Board Connections, Firm Profitability, and Product Market Actions

Finance Working Paper N° 996/2024
January 2026

Radhakrishnan Gopalan
Washington University in St Louis

Renping Li
Tulane University

Alminas Zaldokas
National University of Singapore and ECGI

ECGI Working Paper Series in Finance

Board Connections, Firm Profitability, and Product Market Actions

Working Paper N° 996/2024

January 2026

Radhakrishnan Gopalan

Renping Li

Alminas Zaldokas

We thank Nesma Ali, Meghana Ayyagari, Felipe Cabez´on, Paul Calluzzo, Ran Duchin, Kornelia Fabisik, Armando Gomes, Todd Gormley, Sangeun Ha, Lina Han, Harald Hau, Jiekun Huang, Mark Leary, Jaejin Lee, Cyrus Mevorach, Roni Michaely, Abhiroop Mukherjee, Mikael Paaso, Thomas Schmid, David Schwartzman, Janis Skrastins, Denis Sosyura, Hannes Wagner, Tracie Woidtke, Fan Yang, Mu-Jeung Yang, Shan Zhao, Xiao Zhao, and seminar participants at Washington University in St. Louis, HKUST, Aalto University, Wilfred Laurier University, the 4th Endless Summer Finance Conference on Financial Intermediation and Corporate Finance 2022, New Zealand Finance Meeting 2022, SFS Cavalcade AsiaPacific 2022, MFA 2023, Chinese Economists Society North America Conference 2023, IIOC 2023, NFI-Oxford Conference on Common Ownership, Experimental IO and Governance 2023, FIRS 2023, CICF 2023, European Winter Finance Summit 2024, University of Delaware Weinberg Center/ECGI Corporate Governance Symposium 2024, SFS Cavalcade North America 2024, and AFA 2025 for helpful comments. Alminas ˇ Zaldokas acknowledges the General Research Fund of the Hong Kong Research Grants Council for the financial support provided for this project (Project Number: 16513216). Our analysis is based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Abstract

A firm's gross margin increases by 0.8 p.p. after forming a new direct board connection to a product market peer. Gross margin also rises by 0.4 p.p. after a connection is formed to a peer indirectly through a third intermediate firm. Further, using barcode-level data of 2.7 million products, we show that new board connections are related to higher consumer good prices, a greater tendency for market allocation, and slower new product introductions. The effects are stronger when the newly connected peers share corporate customers or have similar business descriptions and hold when controlling for other inter-firm relationships.

Keywords: board of directors, interlocking directorships, product market coordination, antitrust

JEL Classifications: G34, G38, L22

Radhakrishnan Gopalan
Professor of Finance
Washington University in St. Louis
One Brookings Drive
St. Louis, MO 63130-4899, United States
phone: + 1 314 935 9196
e-mail: gopalan@wustl.edu

Renping Li*
Assistant Professor of Finance
Tulane University
Goldring/Woldenberg Complex
New Orleans, LA 70118, USA
e-mail: renpingli@wustl.edu

Alminas Zaldokas
Associate Professor of Finance
National University of Singapore
21 Lower Kent Ridge Road
Singapore 119077,
e-mail: alminas@nus.edu.sg

*Corresponding Author

Board Connections, Firm Profitability, and Product Market Actions *

Radhakrishnan Gopalan **Renping Li** **Alminas Žaldokas**

October 2025

Abstract

A firm's gross margin increases by 0.8 p.p. after forming a new direct board connection to a product market peer. Gross margin also rises by 0.4 p.p. after a connection is formed to a peer indirectly through a third intermediate firm. Further, using barcode-level data of 2.7 million products, we show that new board connections are related to higher consumer good prices, a greater tendency for market allocation, and slower new product introductions. The effects are stronger when the newly connected peers share corporate customers or have similar business descriptions and hold when controlling for other inter-firm relationships.

Keywords: board of directors, interlocking directorships, product market coordination, antitrust

JEL Classification: G34, G38, L22

*Radhakrishnan Gopalan passed away in December 2022. He was a Professor of Finance at Olin Business School, Washington University in St. Louis. Renping Li is an Assistant Professor of Finance at Freeman School of Business, Tulane University. Alminas Žaldokas is an Associate Professor of Finance at the National University of Singapore. Emails: rli17@tulane.edu and alminas@nus.edu.sg. A previous version of the paper was circulated under the title "Do Board Connections between Product Market Peers Impede Competition?" We thank Nesma Ali, Meghana Ayyagari, Felipe Cabezón, Paul Calluzzo, Ran Duchin, Kornelia Fabisik, Armando Gomes, Todd Gormley, Sangeun Ha, Lina Han, Harald Hau, Jiekun Huang, Mark Leary, Jaejin Lee, Cyrus Mevorach, Roni Michaely, Abhiroop Mukherjee, Mikael Paaso, Thomas Schmid, David Schwartzman, Janis Skrastins, Denis Sosyura, Hannes Wagner, Tracie Woidtke, Fan Yang, Mu-Jeung Yang, Shan Zhao, Xiao Zhao, and seminar participants at Washington University in St. Louis, HKUST, Aalto University, Wilfred Laurier University, the 4th Endless Summer Finance Conference on Financial Intermediation and Corporate Finance 2022, New Zealand Finance Meeting 2022, SFS Cavalcade Asia-Pacific 2022, MFA 2023, Chinese Economists Society North America Conference 2023, IIOC 2023, NFI-Oxford Conference on Common Ownership, Experimental IO and Governance 2023, FIRS 2023, CICF 2023, European Winter Finance Summit 2024, University of Delaware Weinberg Center/ECGI Corporate Governance Symposium 2024, SFS Cavalcade North America 2024, and AFA 2025 for helpful comments. Alminas Žaldokas acknowledges the General Research Fund of the Hong Kong Research Grants Council for the financial support provided for this project (Project Number: 16513216). Our analysis is based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

"For too long, our Section 8 enforcement (of the ban on director interlocks among competitors) has essentially been limited to our merger review process. We are ramping up efforts to identify violations across the broader economy, and we will not hesitate to bring Section 8 cases to break up interlocking directorates."

(The DOJ's recent crackdown on director interlocks is an) "effective way of deconcentrating the United States economy today."

- Jonathan Kanter (2022a; 2023)

Board connections can enable the flow of information between firms and help coordinate product market actions. Recognizing this, Section 8 of the 1914 Clayton Antitrust Act (the Clayton Act) prohibits firms with substantial overlap in their activities from sharing directors. However, historically, the enforcement of the interlock restrictions has been limited to the context of merger reviews and regulators rarely proactively searched for Section 8 violations in the broader economy (Demblowski, 2022; Department of Justice, 2022a; Sher et al., 2022). Indeed, in an environment of rapidly changing business strategies and product lines, such as in the technology sector, it is challenging to determine which firms compete with one another at a given point in time and more so which of these connections have anti-competitive effects.

After the Biden Administration ramped up the enforcement of the Clayton Act (Department of Justice, 2022b, 2023), discussion revolving around director interlocks between competing firms has drawn increasing public attention. Yet, the evidence on the implications of these connections is limited. In this paper we map the director networks of firms that compete in the product markets, explore the anti-competitive role of these networks, and find that the board connections between product market peers are not only common but are also associated with higher firm profitability, increased product prices, a greater tendency for market allocation, and slower new product introductions.

We first define product market peer firms based on the Hoberg-Phillips industry classification (Hoberg and Phillips, 2010, 2016). Combined with BoardEx, we identify instances when such firms are closely linked through the director networks. We consider that two firms have a *direct* board connection if they share a director, and that two firms have an *indirect* board connection if they do not share board members directly but a member of their respective boards serves on the board of the same intermediate firm. In the twenty-year period of 1999-2018, we identify 1,493 instances of new direct connections to a product market peer and 4,085 instances of new indirect connections to a product market peer. These 1,493 instances of direct board connections between firms that are potentially in the same product market space — according to the Hoberg-Phillips classification — indicate the possibility of imperfect enforcement of the Clayton Act restrictions on director interlocks between competing firms.

Our first analysis adopts a stacked difference-in-differences model to study the relationship between new product-market-peer board connections and firm profitability. For every firm that forms a new board connection ("treated" firm), we identify a control firm that is from the same year and industry as the treated firm and is the closest to the treated firm in terms of total assets, gross margin, and Tobin's Q in the year before the formation of board connections ("treatment" or "event"). These matched pairs of firms are indistinguishable in terms of the matching co-variates in the year prior to treatment.

We find that firm profitability significantly increases in the three years after a firm forms a board connection to a product market peer. The increase happens both following a direct and following an indirect connection and is robust to how we measure profitability. In particular, in the three years following an indirect connection, a firm's gross margin, operating margin, and return on assets (ROA) increase by 0.4 p.p., 0.8 p.p., and 0.7 p.p., respectively, suggesting economically significant effects. The estimates are even larger following a direct connection and, respectively, are 0.8 p.p., 1.4 p.p., and 0.9 p.p. We do not see differential pre-existing trends in profitability between the treated and control firms.

Our interpretation that these board connections hinder competition faces a few alternative interpretations. First, the changes to the board of directors are likely endogenous to the firm's future prospects. For example, firms that anticipate an improvement in their performance could afford appointing a director who is an expert in their industry and thus likely connected to a product market peer. Moreover, board connections can also improve profitability by propagating governance practices that could enhance a firm's internal efficiency (see, e.g., Bouwman (2011)), and new directors can otherwise benefit the firm with their industry experience. There can also be innovation collaboration and knowledge and technology spillovers, and our findings might be explained by other confounding network ties such as shared educational backgrounds or other non-board activities.

To address these concerns, we first zoom into newly formed indirect connections and isolate a particular subset of connections that are formed because of changes to the board of an intermediate firm and not because of changes to the board of the treated firm, nor the new appointments of its present directors. That is, we look at cases where the intermediate firm that already shares a director with the treated firm appoints another director from the peer firm, or the peer firm appoints another director from the intermediate firm. We deem these events less likely to be caused by the treated firm's unobservable future prospects and find a similar increase in treated firms' profitability after forming these indirect connections.

Second, we study firm actions in the product markets using barcode-level price data. Taking advantage of the NielsenIQ Retail Scanner Data, which contain detailed information on store-specific barcode-level prices for over 2.7 million consumer goods, we examine how new board connections are related to product prices. We employ a tightly-specified difference-in-differences model that controls for within-product-module and within-geographic-area time trends and makes use of within-firm-and-time variation for firms that sell in multiple product modules. We find that after board connections are formed, the prices of products in categories that overlap with a firm's newly directly connected peer grow 0.22 p.p. faster per quarter than products of the same firm in categories that do not overlap with its connected peer. This translates into a 0.88 p.p. annualized difference. Indirect connections have smaller yet also statistically significant effects of 0.06 p.p. per quarter.

We also examine how these new board connections relate to market allocation, another type of coordination when firms adjust their product offerings to avoid head-on competition (Belleflamme and Bloch, 2004; Sullivan, 2020; De Leverano, 2023). The Federal Trade Commission (FTC) states that it is "almost always illegal" for firms to divide sales territories or assign customers (Federal Trade Commission, 2022). Based on the cosine similarity between a firm-pair of their geographic distribution of sales, we find that after indirect connections product market peers grow more distant in terms their geographic presence, while we do not observe such behavior after direct connections. We interpret both the rise in price and the drop in similarity as evidence that board connections enable product market coordination.

In the context of another product market outcome — new product introductions — we show that this key source of consumer welfare creation (Granja and Moreira, 2022) slows down after product-market-peer board connections. The number of new products introduced per quarter drops by 2.21 following a direct board connection to a product market peer and 1.13 following an indirect one. While one could argue that board connections could help facilitate new product creation, which could compensate consumers for the rise in prices, we find evidence of the opposite. This is consistent with board connections reducing the need for firms to expand or defend market shares with new products and further lends support to an overall negative effect on the consumer welfare.

Third, we directly test alternative explanations beyond anti-competitive coordination. We do not find evidence that product-market-peer board connections significantly affect patenting output, R&D collaboration, labor costs, or governance practices. The increases in profitability hold when controlling for measures of director experience. Our findings are also robust to controlling for customer-supplier relationships, joint ventures, strategic alliances, linkages via common ownership (Azar, 2022; Gilje et al., 2020; Amel-Zadeh et al., 2022), or other network ties such as shared non-board work experience, education, non-business activities, or common ethnic origin.

Fourth, we document how board connections relate to convicted collusion cases. We find that directly connected firms have a 0.058% probability of having an active convicted collusion case, while it is 0.061% for indirectly connected firms. However, for firms that are more distant in director networks such probability is much lower, e.g., it is 0.017% for firm-pairs with two degrees of separation and 0.004% for firm-pairs with three degrees of separation. This strong associative relationship further suggests that director networks can play a role in facilitating coordination.

Fifth, we examine the heterogeneity in the profitability effects of these new board connections. We sort new connections based on a range of firm and firm-pair characteristics and estimate triple-difference models. We first find that the introduction of Corporate Opportunity Waivers (COWs) in some states, which reduced the legal risks of a director serving on multiple boards, increases both the frequency and the profit-enhancing effects of board connections. We also show greater effects for connections to peers that share major corporate customers and to peers with higher cosine similarity score in terms of product descriptions.

Moreover, effects are more pronounced when these connected product market peers share multiple directors or when the new director is more central in the director networks (Larcker et al., 2013; El-Khatib et al., 2015; Fogel et al., 2021; Bakke et al., 2024).

We finish with a range of robustness tests. We show that non-product-market-peer board connections do not display similar effects on profitability. Our findings are also robust to alternative industry classifications, matching methodologies, and regression specifications. Based on a specification curve analysis — in which we plot the empirical distribution of coefficient estimates across all possible combinations of specification choices — and joint inference, we conclude that our findings exhibit robustness to alternative specifications and are unlikely to occur by chance under the null hypothesis of no effect.

To summarize, this paper provides large-sample evidence that board connections between product market peers are related to better overall profitability, higher product prices, a greater tendency for market allocation, and slower new product introductions, which are consistent with product market coordination. The literature has been investigating various aspects of board connections between product market peers. Geng et al. (2023) found that a reduction in the legal risks of sharing information outside of the board increases the frequency of director interlocks, which is then associated with higher profit margins and sales revenue. Barone et al. (2025) showed that restricting director interlocks among banks in Italy reduces the interest rates on loans extended by previously interlocked banks. Cabezon and Hoberg (2025) discussed the intellectual property leakage between product market peers connected through directors.

Compared to this contemporaneous literature, we look at a broader firm sample and document the pervasiveness of both direct and indirect board connections between product market peers. Moreover and likely more importantly, our multi-product barcode-level data allow us to identify the effects of board connections on both price and non-price coordination.

The paper also contributes to the literature on firm conduct and inter-firm linkages that facilitate coordination. Tacit coordination can be achieved with financial disclosure (Bourveau et al., 2020) or executive compensation (Ha et al., 2024). Recent literature has also extensively looked at whether sharing common investors contributes to product market coordination (see, e.g., He and Huang (2017); Azar et al. (2018); Antón et al. (2023); Aslan

(2023)). We highlight board connections as one way in which tacit coordination in product markets can be facilitated among commonly owned firms but also among firms without common ownership.

In addition, this paper speaks to our understanding of the dual role of directors as both advisors and monitors in a firm (Güner et al., 2008; Adams and Ferreira, 2009; Duchin et al., 2010; Dass et al., 2014; Drobetz et al., 2018; Gopalan et al., 2021) and focuses on how such roles change when the directors can help coordinate product market actions between competing firms. Relatedly, Campello et al. (2017) showed that independent directors suffer personal costs from cartel prosecutions and they take actions to mitigate those costs.

Finally, we add to the literature on social networks and, in particular, on the network of directors. Prior research has documented that this network influences director-level outcomes. Goergen et al. (2019) provided evidence that more connected directors make more profitable insider trades, which corroborates the existence of information exchange between directors. Intintoli et al. (2018) showed that more connected directors have better career prospects. At the firm level, the network of directors enhances firm value (Bakke et al., 2024), affects investment decisions (Fracassi and Tate, 2012; Chuluun et al., 2017), disclosure (Intintoli et al., 2018), and governance policies (Coles et al., 2020; Renneboog and Zhao, 2014; Bouwman, 2011), and is associated with better merger outcomes (Cai and Sevilir, 2012; El-Khatib et al., 2015), more intellectual property leakage (Cabezon and Hoberg, 2025), and greater stock price synchronicity (Khanna and Thomas, 2009). We restrict our attention to connections between product market peers and posit that this economically important class of connections is associated with better firm profitability and greater coordination in product markets.

1 Hypothesis

Successful coordination among competing firms yields supra-competitive profits, which can exceed their respective profits under oligopolistic competition. Among many ways, such coordination can, for example, come in the form of price-fixing schemes, in which two firms competing in the same market agree to fix product market prices at a higher-than-competitive level, or market allocation, in which competing firms agree to each serve a separate product category, geographic area, or demographic group.

Although the benefits might be substantial to the shareholders of participating firms, successful coordination is hard to achieve for several reasons. First, explicit collusion is illegal and might invite legal actions (Department of Justice and Federal Trade Commission, 2000). Much of the coordination is then tacit. Second, a tacit coordination equilibrium might be challenging to sustain, as it can be optimal for the participating firms to engage in opportunistic deviations, such as undercutting prices or entering into their competitor's market segment (Wiseman, 2017). Third, communication channels among competing firms might be imperfect, so crucial competition-sensitive information such as distribution, marketing, and pricing schemes might not reach or be trusted by the rival decision-makers (Kandori and Matsushima, 1998; Genesove and Mullin, 2001; Awaya and Krishna, 2016).

We argue that board connections can alleviate the aforementioned hurdles and facilitate anti-competitive coordination. Board connections might give opportunities for direct communication between the competing firms about their product market strategies. Moreover, the professional and personal interactions between directors in competing firms can help build affinity and trust and make deviations less likely to occur. In this sense, board connections can be considered as a kind of relational contract as in Baker et al. (2002), in which the exchange of sensitive information is even unnecessary for competition to be hindered. Also, even the interactions among directors of competing firms on the boards of other unrelated firms could facilitate coordination. Observing rival firm directors' voting behavior on third boards could improve the understanding of how decisions in rival firms are made, which could then be internalized as more informed reaction functions for firms' strategic interactions. Directors might also become better aware of other firms' financial policies, and influence them to be less aggressive, in turn making the strategic competition less fierce.

The Clayton Act bans director interlocks if the individual competitive sales are more than \$4,525,700, more than 2% of total individual sales for both firms, *and* more than 4% of total sales for either firm, where competitive sales are defined as the gross revenues for all products and services sold by one firm in competition with the other (Federal Trade Commission, 2023). In reality, regulators have rarely proactively searched for these violations. Moreover, it is the burden of regulators to consider whether two firms share the same product market and can be perceived to be competing. Competitive sales are usually analyzed and determined on a case-by-case basis by industry experts and in today's overlapping product markets, product market definition is often under debate.[1] We hypothesize that, due to such limitations on enforcement, many board connections between product market peers can be anti-competitive.

2 Firm Profitability and Product Market Actions

We first examine the effects of board connections on firm profitability. Next, we look for direct evidence using barcode-level data in the consumer goods sector.

2.1 Effects on firm profitability

2.1.1 Data

In our large sample analysis on board connections and firm profitability, we draw data from three sources: Compustat, BoardEx, and the 10-K Text-based Network Industry Classifications (TNIC) in the Hoberg-Phillips Data Library. We construct the sample from the set of firms in the intersection of Compustat and BoardEx and put the following restrictions: (1) the firm is not in the financial industry or the utilities industry (SIC between 6000 and 6999, or between 4900 and 4999); (2) the firm-year has inflation-adjusted total assets above \$10 million and sales above \$4 million in 2018 dollars; (3) the gross margin and operating margin for the firm-year are both above -50%.

To construct the network of directors, we use the BoardEx Individual Profile Employment Dataset and require the type of employment to be a board position. From this, we construct annual network snapshots, with the firms as the nodes and the pairwise direct connections

[1] As an example, in its response to the inquiry of the United Kingdom's Competition Market Authority, Facebook said that it saw its market share as the "time captured by Facebook as a percentage of total user time spent on the Internet, including social media, dating, news, and search platforms". Similarly, Amazon (2020) reported that it "accounts for less than 1% of the \$25 trillion global retail market and less than 4% of retail in the US", suggesting that it defines its relevant market as not only online but also offline retail markets. In fact, when the Antitrust Subcommittee of the U.S. House of Representatives requested Amazon for a list its top competitors, Amazon identified 1,700 companies, including "a discount surgical supply distributor and a beef jerky company".

(director interlocks) as the edges. We then find board connections between firms that are product market peers based on the Hoberg-Phillips classification, which is calibrated to be as fine as the SIC-3 industries (Hoberg and Phillips, 2010, 2016). In particular, this classification determines firm's competitors by calculating the textual similarity scores of a firm's 10-K product descriptions with other firms and retaining those to which the score is above a certain threshold.

We define our main variables as follows. Gross margin is the ratio of gross profit to sales, operating margin is the ratio of operating income before depreciation and amortization to sales, ROA is the ratio of operating income before depreciation and amortization to total assets, assets is the natural logarithm of the firm's total assets in millions of dollars, and Tobin's Q is the ratio of the market value of equity plus book value of debt over total assets. Internet Appendix Table A1 tabulates the definitions of all variables we use in our analysis. All financial and accounting variables are winsorized at the 1% and 99% percentiles.

2.1.2 Sample description

We conduct a stacked difference-in-differences analysis of instances when a firm forms a new board connection to a product market peer. We study both direct and indirect board connections between product market peers. We define that two firms have a *direct* board connection if they share a director, and we define that two firms have an *indirect* board connection if they do not share any board members but a member of their respective boards serves on the board of the same intermediate firm. We expect that forming a new direct board connection to a product market peer has a stronger effect on firm profitability than forming an indirect one.

Our "treated" firms consist of all firms that form a new direct or indirect board connection with a product market peer during the period 1999-2018. When identifying these instances of newly formed board connections, we ensure that the firm does not have any pre-existing direct or indirect board connection with its newly connected peers. We further ensure that, in the instances of forming an indirect connection, the firm does not concurrently form a direct connection with any of its peers.

We study how firm profitability changes following the formation of such connections. We construct a treatment-control matched sample. For each treated firm, we look for one control firm, and we match with replacement. First, following Fracassi and Tate (2012), we require that the control firm is in the same Fama-French 17 industry as the treated firm, and the control firm itself is not treated in the event year. Second, we look for candidate control firms in the same quantiles of assets, gross margin, and Tobin's Q and rank them by their Mahalanobis distance to the treated firm based on these three characteristics in the year prior to the treatment. Finally, we retain the one candidate control firm with the smallest Mahalanobis distance to the treated firm. That forms each cohort of treated and control firms. Our final sample comprises of a stacked set of these cohorts of treated and control firms for the treatment year, the three-year period before, and the three-year period after treatment — i.e., from year -3 to year +3 where year 0 refers to the treatment year.

Our sample consists of 1,493 events of new direct connections to product market peers, and 4,085 events of new indirect connections to product market peers via an intermediate firm.[2] [3] These newly connected product market peers share multiple directors in 10.1% of the cases. Table 1 reports the distribution of the treated firms' Fama-French 48 industries. The five industries with the most newly formed connections are business services (accounting for 20.6% of all events), electronic equipment (13.0%), pharmaceutical products (12.3%), medical equipment (8.5%), and computers (7.7%).

Table 2 reports the summary statistics for the treated and control firms in the year prior to the treatment (i.e., the year for which firm characteristics are used in the matching procedure) and also for all firms in Compustat. Board connections to peers tend to occur in firms that are larger and have higher gross margin and Tobin's Q and faster sales growth. Consistent with Geng et al. (2023), such connections are also more likely among research and development (R&D) intensive firms. The operating margin in treated firms, however, is lower than average as these firms also have higher selling, general, and administrative

[2]Unconditional on being product market peers, board connections are quite prevalent. Over our sample period, we observe 57,809 new board connections formed between product and non-product market peers, of which 56.8% involve direct connections. A firm is on average directly connected to 4.4 firms and indirectly connected to 25.0 firms. In Section 4.2.2, we show that connections to a non-product market peer are not associated with increases in profitability.

[3]Internet Appendix Figure A1 shows that new board connections are spread throughout our sample period. 51.8% (69.1%) of the new direct (indirect) connections last for less than 4 years, 38.0% (27.1%) last for 4 to 8 years, while 10.2% (3.8%) last for longer than 8 years.

(SG&A) expenses. In addition, the treated and control firms are balanced in terms of the variables used in matching. In the tests reported in Section 4.3, we expand the set of matching co-variates and find the baseline estimates to be robust.

We also compare how directors involved in these new connections differ from an average director in the treated firms. Internet Appendix Table A2 shows that those connecting directors cross-serve on more boards, have higher director centrality (Larcker et al., 2013; Fogel et al., 2021; Bakke et al., 2024), and are more likely to be non-executive directors. In contrast, their professional experience and educational level are close to those of an average director.[4]

2.1.3 Profitability

We study the impact of new board connections to product market peers on firm performance. To do this, we estimate a difference-in-differences model on our sample of treated and control firms. Our methodology of pooling observations of cohorts of treated and control firms together and estimating a difference-in-differences model follows Gormley and Matsa (2011), Gormley and Matsa (2016), and Gormley et al. (2023). The first difference is taken between the time period before and after the event while the second difference is between the treated and control firms. Our empirical model is then:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}, \end{aligned} \tag{1}$$

where i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of the observations of a treated firm and its matched control, and t is the index for each calendar year.

$Y_{i,j,c,t}$ is one of our outcome variables: gross margin, operating margin, and ROA. $Post_{c,t}$ is a dummy variable that takes a value of one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. $DirectTreated_{i,c}$ ($IndirectTreated_{i,c}$)

[4] In Internet Appendix IA2, we find an average cumulative abnormal return (CAR) of 0.78% upon the announcement of connected directors' appointments, which is larger than the average CAR around the announcement of non-interlocking appointments.

is a dummy variable equal to one for the treated firms that experience a direct (indirect) board connection to a product market peer. We include two sets of fixed effects: firm-by-cohort fixed effects $\theta_{i,c}$ and industry-by-calendar-year fixed effects $\theta_{j,t}$ where industries are based on the Fama-French 48-industry classification. The latter controls for wider industry-specific shocks. $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ are left out of the regression as they are absorbed by the firm-by-cohort fixed effects. The coefficients of interest are β_1 and β_2, which identify the change in the outcome variable for treated firms that respectively form a direct or an indirect board connection with a product market peer. We cluster standard errors at the firm level to address serial correlation within a firm (Bertrand et al., 2004).

Table 3 reports the findings from estimating the above regression. Columns (1)-(3) show that profitability uniformly increases in the three years after a firm forms a new board connection with its product market peer. Also, the increase in profitability is greater following a direct connection as compared to that following an indirect connection, albeit the differences are weak in terms of the statistical significance.

Our estimates are economically meaningful. Column (1) suggests that the gross margin increases by 0.8 p.p. for a firm that forms a direct board connection with a product market peer. This is a 1.6% of the mean gross margin of the treated firms in the pre-treatment year. As reported in columns (2)-(3), our estimates of the increase in operating margin and ROA for a firm that forms a direct connection are 1.4 p.p. and 0.9 p.p., which constitute a much larger 11% and 10% of their respective mean values in the pre-treatment year.[5]

In Internet Appendix Table A3, we report the findings for several other variables. Consistent with firms gaining market power, we find that the sales increase at a faster pace relative to the cost of goods sold and also see an increase in the markup calculated following Ayyagari et al. (2023). However, we find no evidence of reduced SG&A costs or increase in capital expenditure or R&D. If anything, we see a small drop in the size of total assets.

We next document the dynamics of the change in performance around new board connections. We estimate a dynamic version of regression (1) with the year prior to the event as the

[5]Gross margin is $\frac{\text{Sales-COGS}}{\text{Sales}} = 1 - \frac{\text{COGS}}{\text{Sales}}$ and operating margin is $\frac{\text{Sales-COGS-SG\&A}}{\text{Sales}} = 1 - \frac{\text{COGS}}{\text{Sales}} - \frac{\text{SG\&A}}{\text{Sales}}$, where COGS refers to costs of goods sold. Hence, if firms gain more pricing power after forming board connections and thus the sales expand at a faster rate than COGS and SG&A expenses, due to an operating leverage effect, we would expect the increase in operating margin to be larger compared to the increase in gross margin.

baseline year. We plot the coefficient estimates in Figure 1. Panels A1 and A2 report that there is no statistically significant difference in the gross margin between the treated and control firms in the years prior to the treatment. This suggests the absence of pre-existing trends. Panel A1, which reports the findings for the direct connections, shows that the gross margin of treated firms increases significantly starting from the second year following the formation of a new connection. Furthermore, the magnitude of the increase gets larger in the third year. This is consistent with the new director taking time to understand the board dynamics and the potential for coordination. Panel A2 reports the findings for the indirect connections, showing a similar pattern, albeit smaller in the magnitude. We also find similar patterns for operating margin and ROA, as reported in Panels B1-2 and C1-2.

2.2 Evidence from barcode-level data

Next, we provide direct evidence on how board connections affect competition outcomes based on barcode-level data. These evidence helps corroborate the interpretation that our findings of profitability increase entail an anti-competitive mechanism. We rely on NielsenIQ Retail Scanner Data, which contain data on prices and revenues from retail chains across the US. Prior research has used this data to study the product market impacts of private equity (Fracassi et al., 2022), credit market disruption (Granja and Moreira, 2022; Kabir, 2022), ownership structure (Aslan, 2023), and taxation (Baker et al., 2023). We extract prices and revenues at the weekly frequency and at a level as fine as each store and each Universal Product Code (UPC), which is a 12-digit barcode that identifies a unique traded item.

This granular data allow us to quantify firm's actual pricing and product placement decisions. We can also sharpen the definition of product market competitors. Product data are organized in a hierarchical structure, with around 125 "product groups" and 1,100 "product modules". For example, the "product group" labelled as "Cheese" has 19 "product modules", which include "Cheese-Natural-Mozzarella","Cheese-Natural-American Colby", and "Cheese-Natural-American Cheddar". We define peers as firms that sell in the same "product module". We adopt a similar difference-in-differences framework as in the prior section and look at how the prices of products, the tendency for market allocation, and the rate of new product introductions change after firms form board connections to product market peers.

2.2.1 Sample description

We use the universe of NielsenIQ Retail Scanner Data in 2006-2020, which contain 6,087,712 distinct UPCs and record total annual sales of \$260.7 billion on average. We start by matching each UPC to a producer based on the UPC prefix data provided in the GS1 Company Database. We are able to assign producer information to 77.1% of all UPCs. Next, we match producers in GS1 Company Database to firms in BoardEx based on their name strings. We are able to match producers of 2,715,025 UPCs to BoardEx, which account for 44.6% of all UPCs and 63.4% of the total sales in the NielsenIQ Retail Scanner Data. The details of the matching procedure are provided in Internet Appendix IA3.

The relevant changes in board connections are defined in the same manner as in Section 2.1. As we have outcomes at a higher frequency, we define board connection events at the quarterly level. Differently from our prior tests for which treated firms are publicly listed, in this analysis treated firms can be either publicly listed or privately held. While many of the privately held firms do not maintain formal board of directors, BoardEx reports leadership information for these firms, including CEOs and other senior managers. To ensure that these firms are included in our analysis, here we consider cases where the connecting individuals hold board positions at both sides of the connected firm-pair, or where the connecting individuals are a board member in one firm and hold a non-board senior executive position at the other. We find 52 pairs of product market peers that form new direct board connections and 778 that form indirect ones.

We construct three groups of outcome variables that respectively capture the average price, the firm-pairs' tendency for market allocation, and new product introductions. First, we construct a price index following Aslan (2023). We define the set of products (UPCs) that firm i sells in product module m and 3-digit zip code area z and quarter t as its product portfolio and denote it as $U_{i,m,z,t}$. The share of revenue of each product u within the product portfolio is $w_{u,z,t}$, which sums up to one for a product portfolio — i.e., $\Sigma_{u \in U_{i,m,z,t}} w_{u,z,t} = 1$. We denote the average dollar price of product u in area z in quarter t as $p_{u,z,t}$. The price index $P_{i,m,z,t}$ of firm i in product module m and area z and quarter t is then:

$$P_{i,m,z,t} = \Sigma_{u \in U_{i,m,z,t-1}} w_{u,z,t-1} \times (p_{u,z,t}/p_{u,z,t-1} - 1). \tag{2}$$

$P_{i,m,z,t}$ thus reflects the weighted average of firm i's UPC price changes in a product module m in area z in quarter t, weighted by the firm i's one-quarter lagged UPC revenue shares within product module m. We exclude a UPC if the unit price in the current quarter is below 33% or above 300% of the prior quarter. We also exclude an observation $P_{i,m,z,t}$ if quarterly sales are below \$5,000 or the market share is below 1% for firm i in product module m and area z in the current quarter t or the prior quarter $t-1$. $P_{i,m,z,t}$ is winsorized at the 1% and 99% percentiles.

Second, we obtain the firm-pair-quarter-level cosine similarity of the geographic distribution of sales. That is, different from the price index, we aggregate observations across geographic areas to the firm-pair i and j and quarter t level. We restrict the analysis to pairs of firms that sell in the same product module and have quarterly sales above \$100,000. We represent a firm i's share of sales in each 3-digit zip code area in quarter t as a vector $v_{i,t}$ and calculate the cosine similarity for each firm-pair i and j:

$$s_{i,j,t} = \frac{v_{i,t} \cdot v_{j,t}}{\|v_{i,t}\| \|v_{j,t}\|}. \tag{3}$$

Third, we calculate $N_{i,t}$, the rate at which a firm introduces new products. Following Granja and Moreira (2022), we identify the timing of a product's introduction by observing the first sale of the product in the dataset. We then calculate the number of new products (UPCs) that a firm introduces in a quarter, both in total and in product modules that the firm did or did not have a presence in prior quarters. We winsorize the variables at the 1% and 99% percentiles and also generate logged versions as $log(N_{i,t} + 1)$.

We provide summary statistics of these variables in Internet Appendix Table A4. We keep all observations of untreated units and the observations of all treated units in a $[-6, 8]$ time window around the treatment, where quarter 0 is the quarter in which new board connections are formed. The $Treated \times Post$ variable equals one for treated units in the quarters post treatment and zero otherwise.

2.2.2 Product prices

Compared to the tests for profitability effects discussed in Section 2.1, we sharpen the treatment definition. In particular, we define new connections at the firm times product module times 3-digit zip code area level. That is, for each newly-connected firm-pair, we zoom into each 3-digit zip code area that both firms operate in and calculate the sum of their market shares within this area in the quarter right before the treatment. If their joint market share exceeds a threshold, we say that these two firms *in this area* are treated. By applying the threshold, we identify the actual product market overlap and exclude situations where two firms both operate in the same product module and the same geographic area but they have inconsequential market share in that area.

We then estimate the following tightly-specified difference-in-differences regression,

$$\begin{aligned} P_{i,m,z,t} = {} & \alpha_1 \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} + \alpha_2 \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ & + \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned} \tag{4}$$

We include firm-by-product-module-by-area fixed effects $\theta_{i,m,z}$ so that we are capturing the differential trends in outcome variables between the treated units and the control units rather than their baseline differences. We also include product-module-by-quarter fixed effects $\theta_{m,t}$ and firm-by-quarter fixed effects $\theta_{i,t}$ to partial out within-product-module and within-firm time trends. As the same firm can produce in many product modules, and the peer firm it forms a board connection with might produce in some but not all the same product modules, we can exploit within-firm-and-time variations between product modules that are affected by the new connection and those that are not. In addition, we include area-by-quarter fixed effects $\theta_{z,t}$ to control for local economic dynamics that could correlate with the level of concentration in the local product markets and affect prices. We cluster the standard errors at the firm level.

We report our findings in Panel A of Table 4. In column (1), we use a minimum 10% threshold on the joint market share of the treated firm and its newly connected peer in the local market. We find that in the quarters post direct board connections, the per-quarter increase in product prices is 0.22 p.p. faster for treated firms in their product modules that are affected by direct board connections compared to the rest, which corresponds to a 0.88 p.p. annualized difference. For indirect connections, the effects are 0.06 p.p. per quarter, which is consistent with direct connections having a more prominent role at facilitating product market coordination than indirect connections. Both effects are statistically significant. In columns (2) and (3), we apply the thresholds of 5% and 3% on the market share in the local area. The magnitude of the estimated treatment effects slightly decreases, which is consistent with a larger combined market share making coordination easier.

2.2.3 Market allocation

We next direct our attention to market allocation. The FTC deems agreements among competitors to divide sales territories or assign customers as "almost always illegal" based on the rationale that such arrangements are essentially agreements not to compete (Federal Trade Commission, 2022). Prior research has studied how firms could utilize tacit market allocation to profit (Sullivan, 2020; De Leverano, 2023). We formally test how the tendency for product market peers to compete head-on changes after board connections. We estimate the model on the firm-pair i and j and quarter t panel:

$$\begin{aligned} s_{i,j,t} = {} & \alpha_1 \times DirectTreated_{i,j} \times Post_{i,j,t} + \alpha_2 \times IndirectTreated_{i,j} \times Post_{i,j,t} \\ & + \theta_t + \theta_{i,j} + e_{i,j,t}, \end{aligned} \tag{5}$$

where i and j are indices for the firm-pair i and j, t indexes the quarter, and $s_{i,j,t}$ is the cosine similarity score of the geographic distribution of the two firms' sales portfolios. We include firm-pair fixed effects $\theta_{i,j}$ and quarter fixed effects θ_t, and cluster standard errors at the firm-pair level.

We report our findings in Table 5. Column (1) shows that cosine similarity score falls by 0.0037 on average after firm-pairs form indirect board connections, which is 3.69% of the within-firm-pair standard deviation (0.1004). However, we do not observe a drop in this score following direct connections. Columns (2) and (3) further indicate that the findings are robust to measuring the similarity of firm-pairs' sales by county or by designated marketing area (DMA). These findings suggest that product market peers adjust their geographic distribution and tilt away from one another after the formation of board connections, which is consistent with board connections enabling deliberate market allocation to avoid head-on competition.

This evidence also enlightens us about the differential mechanisms underlying direct and indirect board connections. While direct connections have much stronger effects on product market prices than indirect connections, likely because price coordination is more difficult to achieve, we find that only indirect connections are related to market allocation. Indirect board connections are less effective at sustaining anti-competitive coordination and deterring deviation. Under direct board connections, competing firms can stay in the same geographical areas and at the same time raise prices. Under indirect connections, however, such coordination on price is more likely to fail. Anticipating this, firms have the incentive to adjust their geographical positioning and tilt away from each other, not least because this strategy could create commitment that is costly to reverse.

2.2.4 New product introductions

We also examine how board connections affect new product introductions. If such connections soften product market competition, we expect firms to introduce fewer new products as they have a reduced need for expanding or defending market shares with new products. Following Granja and Moreira (2022), we calculate the number of new products a firm introduces in a quarter and estimate the model on the firm i and quarter t panel:

$$\begin{aligned} N_{i,t} = {} & \alpha_1 \times DirectTreated_i \times Post_{i,t} + \alpha_2 \times IndirectTreated_i \times Post_{i,t} \\ & + \theta_i + \theta_t + e_{i,t}. \end{aligned}$$

where $N_{i,t}$ is the number of new products. We include firm fixed effects θ_i and quarter fixed effects θ_t, and cluster standard errors at the firm level.

We report the findings in Table 6, which shows that the number of new products that a firm introduces in a quarter drops by 2.21 following a direct board connection to a product market peer and 1.13 following an indirect one. The drop happens both in product modules in which the firm had a presence in prior quarters and in new product modules in which the firm did not have a presence in prior quarters. We obtain qualitatively consistent findings when using logged versions of the outcome variables.

As the introductions of new products require costly investments in development and distribution (Granja and Moreira, 2022), the drop we find could have contributed to the increased firm profitability after board connections. These findings also provide incremental insight over the potential consumer welfare effects of board connections. While one could argue that board connections could facilitate new product creation, we find evidence of the opposite. This further lends support to an overall negative effect on the consumer welfare.

3 Mechanisms

Our findings are consistent with the interpretation that board connections to product market peers facilitate product market coordination among competing firms. That being said, new board connections can be endogenous to firm current and expected operating performance. Alternatively, board connections can improve firm profitability without anti-competitive coordination. For instance, Bouwman (2011) showed that good corporate governance practices can propagate across firms via the network of directors. The newly appointed board members might also have connections to regulators and thus be in high demand among industry peers (Emery and Faccio, 2025). Board connections could also facilitate knowledge and technology spillovers. If board connections facilitate the spread of corporate governance practices that enhance a firm's internal efficiency or new directors otherwise benefit the firm with knowledge and technology spillovers, they can have positive effects on firm profitability without any anti-competitive concerns.

We conduct a range of tests to address both endogeneity concerns and alternative explanations. First, we conduct analysis on board connections that are either initiated by non-focal firms or arise due to mergers between non-focal firms. In these cases, board connections result from changes to the board of a non-focal firm rather than the treated (focal) firm. Hence, at least these particular board connections are not a direct choice of the treated firm and thus are less likely to be driven by its *own* unobservable future prospects. Second, we thoroughly discuss the alternative explanations and test them in the data. Third, we link the board connections to the convicted collusion cases. Finally, we examine a range of cross-sectional heterogeneities in the profitability effects.

3.1 Endogeneity concerns

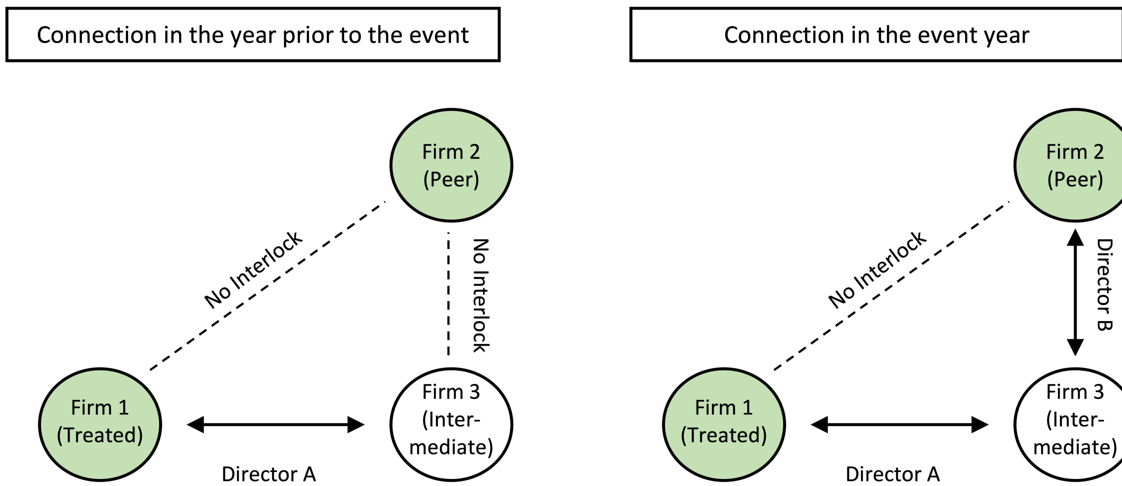
New board connections can be endogenous to firm current and expected operating performance. For example, firms might be more likely to choose to initiate board connections when they anticipate heightened competition and downward profitability trends, reflecting adverse selection that creates a negative bias in our baseline estimates. Alternatively, better-performing firms could afford appointing directors who are experts in their industry and thus also on the board of a product market peer, leading to positive selection. To circumvent these concerns, we focus on newly built connections that are unrelated to the focal firm's appointment actions.

3.1.1 Non-focal-firm-initiated board connections

We note that new board connections to a product market peer can arise either from changes to a firm's board or from changes to the board of a connected firm. In the first test, we focus on new connections that are formed not because of changes to the focal (i.e., treated) firm's board, nor because of changes to other appointments of the focal firm's directors. That is, we look at new connections that are formed because of changes to a non-focal firm's board and thus are less likely to be caused by the future prospects of the focal firm.

More specifically, we focus on the cases when the focal firm is already interlocked with the intermediate firm prior to the event year. In the event year, the board changes in either the intermediate firm or the product market peer. That is, either (1) the intermediate firm appoints a new director who is also on the board of a product market peer of the focal firm, or (2) a product market peer appoints a director who is also on the board of the intermediate firm. Consequently, the focal firm forms a new indirect connection to a product market peer via the intermediate firm, but such a new connection between the focal firm and its peer is not due to any changes in the board composition of the focal firm.

Graph 1: Illustration of non-focal-firm-initiated board connections



Note: This graph illustrates an example of the non-focal-firm-initiated board connection changes. Firm 1 is the treated firm (i.e., the focal firm), Firm 2 is its product market peer, and Firm 3 is the intermediate firm. We provide further details in Internet Appendix IA4.

Graph 1 illustrates an example, where Firm 1 is the focal firm and Firm 2 is a product market peer of Firm 1. In the year prior to the event, Firm 1 and an intermediate firm, Firm 3, are interlocked through Director A who serves on the boards of both firms. Firm 1 does not have any direct or indirect connection to Firm 2. In the event year, Firm 2 becomes interlocked with Firm 3 via Director B. This can be either due to Firm 2 newly appointing Director B, who is also on the board of Firm 3, or due to Director B, who has always been on the board of Firm 2, additionally taking on a board position in Firm 3. Either way, Firm 1 now has an indirect connection with Firm 2, and this new connection is purely a result of changes in the composition of the boards of either the intermediate firm or a product market peer. It is not due to any change in the composition of Firm 1's board or due to changes in the directorships of any of its directors.

We construct a sample using only such focal firms (i.e., Firm 1 in Graph 1) as the treated firms and using the same control firms as we used in the difference-in-differences model (1). Out of the 4,085 events of indirect board connections in our overall sample, we find that 2,114 are initiated due to changes to the board of a firm other than the treated firm. Using only such connections, we present the findings in Panel A of Table 7. Consistent with our prior findings, column (1) shows that the gross margin of the treated firm increases by 0.7 p.p. in the three years following the formation of a non-focal-firm-initiated indirect board connection to a product market peer. Columns (2) and (3) imply that, consistent with our baseline estimates, our findings are not sensitive to how we measure firm profitability.

The effects are economically significant. The increase in gross margin, operating margin, and ROA are 1.4%, 7.7%, and 10% of the mean values for the treated firms in the year before treatment, respectively. Figure 2 presents the corresponding findings in a dynamic model. Across the measures of profitability, we do not see pre-existing difference between the treated and control firms, and instead find that profitability significantly increases in the three years following the initiation of such indirect board connections.

While the new board connections of the treated firms are not due to any changes to their own boards in the tests reported in Panel A of Table 7, the intermediate firm could still be fundamentally similar to the treated firm. Hence, certain unobservable factors might drive both board changes in the intermediate firm and also the future performance of the treated firm. This could be a particular concern if the treated and the intermediate firms are product market peers themselves. Indeed, the intermediate firm is a Hoberg-Phillips peer of the treated firm in 35.6% of the cases. In Panel B of Table 7, we re-estimate the difference-in-differences regressions excluding cases where the intermediate firm is a product market peer of the treated firm and find similar estimates.

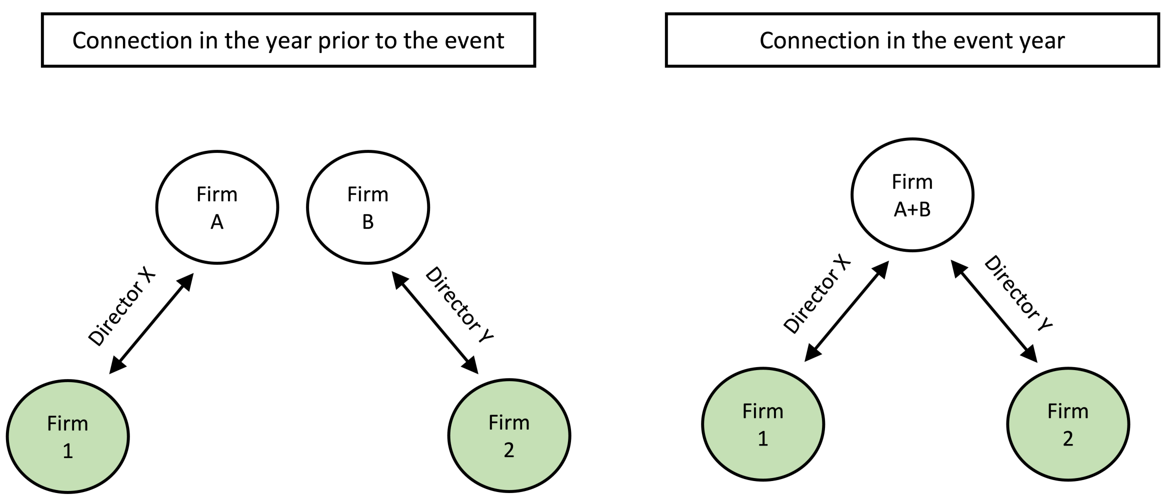
Notably, the point estimates for the profit-enhancing effects of non-focal-firm-initiated connections (0.7 p.p., 1.0 p.p., 0.9 p.p.) are consistently larger than those based on all indirect board connections (0.4 p.p., 0.8 p.p., 0.6 p.p.). Furthermore, our findings of higher product prices in Section 2.2 are consistent for such non-focal-firm-initiated board connections. We show this in Panel B of Table 4. We also find that the estimated effects on product prices for non-focal-firm-initiated board connections are approximately 50% greater than those based on all indirect board connections. These indicate that estimates based on all board connections may be biased downwards, potentially because firms are more likely to choose to initiate board connections when they anticipate heightened competition and downward profitability trends — i.e., when they are endogenously affected by the industry trends.

Overall, we find evidence of increased profitability and product prices in cases where the new board connections are less likely to be caused by unobservable focal firm future prospects.

3.1.2 Merger-induced indirect board connections

We further focus on an even smaller sample of firms to abstract from the remaining concerns that certain unobservable future prospects of both the peer firm and the treated firm affect the creation of the non-focal-firm-initiated connection. We look at the indirect connections induced by the merger activity of two intermediate firms.

Graph 2: Illustration of merger-induced board connections



Note: This graph illustrates an example of the merger-induced board connection changes. Firm 1 and Firm 2 are product market peers. Firm A and Firm B engage in a merger. Director X cross-serves on Firm 1 and Firm A and stays on the board of the combined firm after the merger. Director Y cross-serves on Firm 2 and Firm B and stays on the board of the combined firm after the merger.

Consider the situation where Firm 1 shares a director with Firm A, Firm 2 shares a director with Firm B, and Firm 1 and Firm 2 are product market peers. When Firm A and Firm B engage in a merger, it is possible that the merged firm has directors from both merging firms, and as a result now the merged firm might share directors with both Firm 1 and Firm 2, giving rise to an indirect connection between Firm 1 and Firm 2. In these cases, treated firms (i.e., Firm 1 and Firm 2) do not experience mergers themselves. Graph 2 illustrates such situations by showing the connectedness before and after the merger. Becher et al. (2019) showed that acquiror directors often and target directors sometimes remain in the combined firm after a merger. In our sample, we find 60 instances of merger-induced new indirect connections.

Internet Appendix Table A5 reports the estimated effects of such connections and Internet Appendix Figure A2 reports the dynamics. We find that after a firm experiences merger-induced board connections, its gross margin, operating margin, and ROA rise by 0.2 p.p., 3.1 p.p. and 2.8 p.p., respectively. Despite the small sample size, the increase is statistically significant for operating margin and ROA. Becher et al. (2019) found that directors who remain on the board after mergers, especially those from the target firm, are a highly selected group that more often have experiences of serving as a CEO. Director appointment during normal times, instead, occurs for more routine reasons such as diversity, financial expertise, and retirement. It is possible that certain characteristics of the connecting directors in these merger-induced connections are also conducive to easier coordination, which might explain larger estimates compared to the baseline findings.

Finally, one concern could be that we might be capturing the direct product market spillover effects that a merger between Firms A and B has on Firms 1 and 2 (Eckbo, 1983). In Panel B, we alter the matching procedure and require that the control firm has a director who cross-serves on the board of a firm experiencing a merger as well, but such a merger does not lead to new board connections of the control firm to its product market peers. That is, both treated and control firms have directors in firms experiencing mergers. We show that the findings remain similar, and gross margin, operating margin, and ROA rise by 0.9 p.p., 3.4 p.p. and 2.5 p.p., respectively.

3.2 Addressing alternative explanations

To discipline alternative explanations, we systematically discuss mechanisms through which product-market-peer board connections may causally affect firm profitability. Broadly, board connections can improve profit margins by increasing revenues or reducing costs. On the revenue side, profit gains could come from higher prices due to anti-competitive coordination or from new product introductions facilitated by knowledge and technology spillovers. In addition, board connections may reduce two key frictions – information asymmetry and moral hazard – enabling firms to explore new business opportunities and expand into previous overlooked but profitable areas. That is, firms could learn about promising business opportunities from their peers (non-innovation knowledge spillovers), or learn about and adopt effective governance practices that align incentives and reduce managerial slack (governance spillovers). On the cost side, there can be reduced production costs through technology spillovers, improved governance practices that curtail the waste of resources, or coordination in the labor markets (e.g., non-poaching agreements) that lowers labor expenses.

Apart from these causal explanations, board connections may not directly improve firm outcomes, neither on the revenue or cost side. Rather, the observed increase in profitability may be explained by some other correlated network ties that have those above-mentioned effects.

We first note that some of the previously reported evidence already does not support alternative explanations beyond anti-competitive coordination. We show that firm profitability and product prices increase (Tables 3 and 4), there is a greater tendency for market allocation (Table 5), new product introductions slow down (Table 6), and there is no statistically significant change in SG&A costs (Internet Appendix Table A3). Neither the observed increase in product prices nor the decline in product innovation supports the interpretation that profits increase because of the knowledge and technology spillovers. The increased tendency for market allocation suggests that firms are not sharing information about how to crowd into the same profitable business segments, but are instead coordinating to avoid overlaps in their businesses. We also do not find evidence of reduced SG&A costs, which does not support the propagation of profit-enhancing governance practices.

Moreover, in Internet Appendix IA5, we provide additional evidence by directly testing those alternative explanations beyond anti-competitive coordination, aiming to address them and also to thoroughly understand the economic implications of product-market-peer board connections. In summary, we do not find evidence that board connections are related to improved corporate governance in terms of the proportion of independent directors, CEO duality, or the level and pay-performance sensitivity of executive compensation (Core and Guay, 2002; Coles et al., 2006; Appel et al., 2016; Heath et al., 2021). Furthermore, we do not see significant changes in the wage bill or the labor share. The increases in profitability are also consistent when controlling for measures of director experience or the density of other network ties such as educational background, non-board work experience, other non-business-related activities, and ethnic origin.

We also do not find that connected firms produce more patents or collaborate more in R&D. Notably, our findings do not contradict those of Cabezon and Hoberg (2025). The latter paper proposed a theoretical framework in which director networks facilitate information leakage and reduce firm differentiation, leading to two empirical predictions. First, at the industry level, denser director networks are related to greater innovation herding and lower profitability. This is shown in Cabezon and Hoberg (2025), which employed variations in *industry-level connectedness* and thus capture the industry-wide externalities. Second, if we turn away from industry-level connectedness and instead explore the *within-industry variations* in terms of whether an individual firm is part of the network, the framework predicts that joining the network is still optimal and profit-enhancing for the firm. This is precisely what we document throughout our paper. In this regard, our paper pins down anti-competitive coordination as another reason why director networks are stable and self-reinforcing, complementing those discussed in Cabezon and Hoberg (2025). We discuss the relationship of the two papers in greater details in Internet Appendix IA6.

3.3 Convicted collusion cases

Do board connections also relate to the actual convicted collusion cases? We obtain data on convicted collusion cases from the Private International Cartels Database (Connor, 2020). We acknowledge the caveats of studying convicted cases, as only about 10% to 30% of all collusion conspiracies are detected (Connor, 2014), and those detected may not be the most economically important ones.

We restrict the sample to firms headquartered in the US and hand-match these firms to the universe of firms described in Section 2.1.2. We then construct a firm-pair-year level indicator of whether two firms are in an active convicted collusion scheme in a certain year. We also construct the degree of separation of each firm-pair in the director networks, which is the minimum number of intermediate nodes (i.e., firms) between two nodes that can connect them together. We exclude firm-pairs that are unconnected in the director networks or connected but with a degree of separation above four.

In Internet Appendix Figure A3, we plot the probability of a firm-pair having an active convicted collusion scheme, conditional on the degree of separation of these two firms. While a directly connected firm-pair (i.e., with zero degree of separation) has a 0.058% probability of having an active convicted collusion scheme and this probability is 0.061% for firm-pairs indirectly connected (i.e., with one degree of separation), it becomes 0.017% for firm-pairs with two degrees of separation and 0.004% for firm-pairs with three degrees of separation. Reversing the exercise, we see that out of firm-pairs with convicted collusion schemes, 3.5% are directly connected while 26.8% are indirectly connected via an intermediate firm. This strong associative relationship further suggests the director networks' role in facilitating anti-competitive coordination. We defer a detailed analysis of convicted collusion to Internet Appendix IA7.

3.4 Cross-sectional heterogeneities

We next perform tests on the cross-sectional heterogeneities in the profitability effects discussed in Section 2.1. We focus on scenarios where the anti-competitive effects are likely to be stronger. Specifically, we examine how the effects of board connections on profitability vary with: (1) exposure to Corporate Opportunity Waiver (COW); (2) whether the newly connected firm-pairs share common corporate customers; (3) the similarity in business descriptions of newly connected firm-pairs; (4) the Herfindahl–Hirschman Index (HHI) of the treated firm's industry.

To test our predictions, we extend the baseline specification (1) and estimate the following triple-difference model:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times Post_{c,t} \times EventCharacteristic_c \\ &+ \beta_1 \times Treated_{i,c} \times Post_{c,t} + +\beta_2 \times EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}, \end{aligned} \tag{6}$$

where $EventCharacteristic_c$ is a cross-sectional sorting variable. It equals one for the time series of both the treated firm and its control if the new connections are exposed to COWs, share common corporate customers, or are in the top or bottom half in terms of a certain other characteristic. For brevity, we pool events of new direct and indirect connections together into $Treated_{i,c}$. $Treated_{i,c}$, $EventCharacteristic_c$, and $EventCharacteristic_c \times Treated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$.

3.4.1 By exposure to Corporate Opportunity Waivers (COWs)

Before the staggered introduction of COWs in some states, directors were subject to corporate opportunity doctrine, which prohibits directors from pursuing outside corporate opportunities without first presenting them to the company on the board of which they serve. The introduction of COWs reduced the legal risk of sharing information outside the board. Geng et al. (2023) suggested that COW introduction led to an increase in the frequency of board overlaps. Following Eldar and Grennan (2024), we consider a firm to be subject to COWs in or after the year when the law was introduced in the firm's state of incorporation.

We study whether the previously estimated profitability effects of board connections are larger when COWs are in place.[6] Indeed, Panel A of Table 8 shows that effects of board connections are concentrated in firm-years with COWs. This evidence suggests that legal changes in recent decades might have exacerbated both the formation and anti-competitive effects of board connections.

3.4.2 By whether the newly connected firm-pairs share corporate customers

We expect the coordination benefits to be stronger when two firms share major corporate customers. To identify customer-supplier relationships, we rely on firms' self-reported major customers from the WRDS Supply Chain Dataset, the construction of which is detailed in Cen et al. (2016), Cen et al. (2017), and Cohen and Frazzini (2008). We find that out of all events, 6.9% are between firm-pairs that share a major customer. Panel B of Table 8 reports estimates from the triple-difference regressions. In the case of operating margin, we

[6]Internet Appendix Table A6 shows that board connections to product market peers are more frequent when COWs are in effect. We find that firms are 2.3 p.p. more likely to form new board connections to product market peers when COWs are in effect, which is a 25% increase relative to the unconditional mean of 9.1 p.p.

find that the effects are stronger when firms share major customers. While it rises by 0.9 p.p. when newly connected firm-pairs do not share major customers, the change becomes 2.7 p.p. when they do.

3.4.3 By similarity in the business descriptions between connected firm-pairs

We next sort the new board connections based on the cosine similarity scores of business descriptions between the connected firm-pairs. We define a dummy variable, *TopSimilarity*, which equals one for the treated and control firms involved in events in which the connected firm-pairs have a cosine similarity score above the sample median and additionally are in the same SIC-3 industry. Panel C of Table 8 reports estimates from the triple-difference regressions. The triple-difference terms are positive and statistically significant for operating margin and ROA. New board connections lead to a 0.2 p.p. (0.6 p.p.; 0.5 p.p.) increase in gross margin (operating margin; ROA) for board connections where *TopSimilarity* is equal to zero, and these effects become 1.0 p.p. (1.9 p.p.; 1.4 p.p.) when *TopSimilarity* is equal to one. This provides evidence that the effects of new board connections are stronger between firm-pairs with more similar business descriptions and presumably operating closer in the product space. Importantly, this finding also attenuates the concern that the Hoberg-Phillips classification does not capture the extent of product market rivalry.

3.4.4 By HHI of the treated firm's industry

Firms in more concentrated industries could find it easier to coordinate product market actions (Motta, 2004; Huck et al., 2004). To test if the effects are stronger in more concentrated industries, we sort firms based on the HHI provided in Hoberg and Phillips (2016) and define *TopHHI* to equal one if the firm is in the top half in terms of its industry's HHI. Panel D of Table 8 reports estimates from triple-difference regressions. We see that the effects are indeed stronger in more concentrated industries, but the differential effects are not statistically significant. One potential reason for the lack of significance could be that firms in more concentrated industries might have alternative mechanisms to coordinate their actions. We also recognize that the HHI estimated based on the data of publicly listed firms might not reflect the actual degree of industry concentration (Ali et al., 2008). Possibly, this could also mean that the overall degree of industry concentration is not a necessary condition to take advantage of product-market-peer board connections.

3.5 Director and connection characteristics

We look at how effects may vary by director and connection characteristics: whether directors act as executives, whether director appointments are inbound or outbound, the strength of connections, the centrality of the connected directors, and whether the connected directors are busy with serving on the board of other (non-peer) firms.

First, we examine whether product market peers are connected through executives. Using the Non-Executive Director Indicator from BoardEx, we find that 26.5% of the new direct connections involve an executive, as do 29.4% of the indirect connections. In Internet Appendix Table A7, we find positive and mostly statistically significant effects for connections involving only non-executive directors, suggesting that coordinating behavior also occurs through non-executive board members. The effects are weakly stronger for connections that involve executives though, consistent with executives being more likely to engage in firms' product market actions.

Second, in Internet Appendix Table A8, we compare new appointments to the board of the treated firm (i.e., inbound directors) to the cases when existing directors in the treated firm are appointed to a peer firm (i.e., outbound directors). We find no consistent pattern in the differences between the effects. These findings are more consistent with an anti-competitive interpretation than with internal efficiency improvements, as the latter is more likely to be effectuated by newly appointed inbound directors.

Third, we examine how the effects vary with connection strength in Internet Appendix Tables A9 and A10. We observe substantially stronger effects when multiple directors connect the competing firms, compared to cases with a single connecting director. For example, the magnitudes of increases in operating margin and ROA are more than twice as large. These findings are consistent with the notion that multiple board connections lead to more coordination.

Fourth, the effects are also stronger when the newly connected firm or the new director occupies a more central position in the director networks (Larcker et al., 2013; El-Khatib et al., 2015; Fogel et al., 2021; Bakke et al., 2024). This is consistent with such connections significantly boosting firm access to competition-sensitive information. The new director contributes additional information to what is already available in the director network and more so if they are connected to more firms, especially better-connected ones. Thus, a firm benefits not just from forming a connection to one firm, but also from the broader networks that the new connection brings access to. We present these findings in Internet Appendix Tables A11 and A12.

Fifth, we examine how the effects of product-market-peer board connections vary with the busyness of the connecting director serving on the treated firm's board (Fich and Shivdasani, 2006; Falato et al., 2014; Hauser, 2018). We define a director as busy if the number of board positions that she holds at non-product-market-peer firms exceeds a threshold of one (Panel A) or two (Panel B) in Internet Appendix Tables A13 and A14. We find that effects are attenuated when directors are busy, suggesting that busyness impairs their ability to facilitate anti-competitive coordination. The findings are similar if we instead define a busy director as one that is burdened with committee obligations (Jiraporn et al., 2009; Falato et al., 2014; Chen and Guay, 2020).

We provide a more thorough discussion of our findings in Internet Appendices IA8, IA9, and IA10. Taken together, they are consistent with directors facilitating the flow of competition-sensitive information across firms — a functionality that is strengthened by the intensity and breadth of connections, yet impaired by director busyness.

4 Robustness Tests and Additional Evidence

In this section, we report a range of robustness tests. First, we confirm the robustness of our findings to controlling for customer-supplier relationships, joint ventures and strategic alliances, as well as common ownership. Next, we show our findings to be robust to alternative commonly used industry classifications but not present under pseudo industry classifications using non-product market peers. We then show that our findings are robust to alternative choices in the matching procedure and the regression specifications. Finally, we summarize and systematically assess the robustness of our findings using a specification curve analysis.

4.1 Controlling for confounding inter-firm relationships

4.1.1 Customer-supplier relationships

One might argue that a firm and its suppliers can also have similar languages in their business descriptions and the Hoberg-Phillips industry classification might capture such relationships. Board connections between such firms may have positive effects on a firm's profitability for reasons outside of the scope of product market coordination. To address this concern, we check if any of the new board connections we identify are between customer and supplier firms. We find that out of all new board connections in Section 2.1.2, 68 are between pairs of customer-supplier firms based on the WRDS Supply Chain Dataset. As reported in Panel A of Table 9, our main findings are very similar if we focus on board connections between firms that are not customer-supplier pairs.

4.1.2 Joint ventures and strategic alliances

We also investigate the possibility that the profitability increase comes from the formation of joint ventures or strategic alliances that are associated with new board connections to solidify the relationships. Using the Securities Data Company (SDC) Database, we find that 213 new connections are between firms that ever started joint ventures or formed strategic alliance during our sample period. In Panel B of Table 9, we show that baseline estimates are robust to excluding such relationships. This increases our confidence that we are not capturing effects of such explicit agreements among firms that antitrust authorities cleared to be benign and not anti-competitive in nature.

4.1.3 Common ownership

Further, recent research has studied the role of common ownership in anti-competitive conduct (Azar et al., 2018, 2022; He and Huang, 2017; Nain and Wang, 2018; Koch et al., 2021). An increase in common ownership between the treated firm and its product market peers can be accompanied by the establishment of new board connections. For example, an investor may appoint the same directors to its portfolio firms in the same industry. Even when a common investor appoints different directors to its portfolio firms, these directors might still belong to the same network and be more likely than a random director to simultaneously serve on a third intermediate firm. Indeed, Azar (2022) showed a substantial overlap between firm common ownership and board interlock networks.

Noting the prior evidence, we further address the possibility that the profit-enhancing effects of board connections that we discover stem from common ownership. We use the firm-pair level measures of common ownership developed in Gilje et al. (2020) (GGL_{linear}, GGL_{fitted}, and GGL_{full_attn}) and Amel-Zadeh et al. (2022) (kappa, κ). As κ is only available for single-class S&P 500 firms and we are able to construct within-industry average κ for 13.7% of all observations, the sample size when using the latter measure is smaller. We estimate the double-difference regression (1) and additionally control for pre- versus post-period *changes* in within-industry common ownership $\Delta(CommonOwnership)_{i,c}$,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times Treated_{i,c} \times Post_{c,t} \\ &+ \gamma_1 \times \Delta(CommonOwnership)_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{7}$$

We construct $\Delta(CommonOwnership)_{i,c}$ in two ways, based on common ownership with all of a firm's product market peers or only with its newly connected product market peers. First, we calculate $\Delta(CommonOwnership)_{i,c}$ as the mean of common ownership between a treated or control firm and all of its Hoberg-Phillips product market peers during [0, +3] minus the mean during [-3, -1]. It is a constant for each time series of seven years (from τ = -3 to +3). We then scale it by its sample standard deviation. We report the findings controlling for $\Delta(CommonOwnership)_{i,c}$ in Panels C-F in Table 9. Alternatively, we also calculate $\Delta(CommonOwnership)_{i,c}$ as the change in mean common ownership between a treated firm and its newly connected peers, and let it take a value 0 for control firms. For these we report the findings in Panels G-I.

We find that controlling for the dynamic effects of concurrent changes in within-industry common ownership, treated firms still experience significantly higher growth in profitability compared to control firms. The coefficient estimates are similar to our findings in Table 3. In addition, we show that the product market price effects are robust to controlling for common ownership, as discussed in Internet Appendix IA11. These suggest that the profit-enhancing effects of board connections do not simply reflect potential concurrent increases in within-industry common ownership, but rather represent a related but distinct phenomenon.

4.1.4 Other network ties

Product market peers can be linked via other network ties. We may undercount how many and how dense network ties are or capture the confounding effects of these ties. In Internet Appendix IA12, we consider network ties via directors' shared non-board work experience, education, other non-business-related activities, and ethnic origin. We also examine past board connections, which are the cases where two product market peers each have a director, and these two directors historically served together on the board of a common third firm.

We find that these network ties have limited effects compared to concurrent board interlocks. In Internet Appendix Tables A15 and A16, we observe that firm profitability and product prices increase, albeit with substantially smaller magnitudes compared to board interlocks, when a firm appoints a director with shared *non-board work* or *educational* experiences with directors in product market peers. Such patterns are not present for the rest of the network ties we examine.

4.2 Robustness to alternative industry classifications

4.2.1 Commonly used alternative industry classifications

In Internet Appendix Table A17, we provide evidence on robustness to the definitions of industry peers. Instead of defining them according to the Hoberg-Phillips classification, Panel A uses the competitors disclosed by firms and recorded in the FactSet Supply Chain Relationships (formerly, Revere) Database. Panel B defines industry peers based on the SIC-3 industry, while Panel C uses the SIC-4 industry. Further, Panels D and E use the GICS 6-digit and 8-digit industries, and Panel F uses TNIC-4. We find consistent evidence of an increase in profitability after firms form new industry peer board connections. In Internet Appendix Table A18 we also replicate heterogeneity tests under alternative industry classifications and find that effects are also mostly stronger when Corporate Opportunity Waivers (COWs) are in effect, or when connections are between peers that share major corporate customers or have higher cosine similarity in business descriptions.

4.2.2 Pseudo industries

We further conduct a test in which, instead of actual product market peers, we study the effects of connections to non-product market peers — i.e., we use pseudo industry classifications. We construct the sample as follows. We start by generating a random group of firms that we designate as the "pseudo industry" for each firm-year. We use this pseudo industry in place of the Hoberg-Phillips industry to identify new board connections. We ensure that none of the firms in the pseudo industry are actually in the Hoberg-Phillips industry and keep the size of the pseudo industry to be the same as the Hoberg-Phillips industry. We exclude the pseudo events that coincide with connections to actual product market peers. Effectively, we study how board connections to non-product market peers affect performance while keeping the sizes of the pool of firms similar between actual product market peers (Hoberg-Phillips industry) and non-product market peers (pseudo industry).

We then estimate the regression (1) and report the findings in Internet Appendix Table A19. We do not find a statistically significant increase in profitability following the establishment of board connections to non-product market peers. That is, not all board connections matter: the effects we document earlier do not come mechanically from any board connections but arise from board connections to product market peers.

4.3 Robustness to alternative matching schemes

4.3.1 Use two or three matches instead of one

Our baseline tests use one control firm for each treated firm. We repeat the matching process with two or three control firms for each treated firm. The estimated effects of new board connections presented in Panels A and B of Internet Appendix Table A20 are virtually identical to those in Table 3.

4.3.2 Match on the number of new appointments during the event year

Treated firms appoint on average one new director during the event year, while control firms appoint an average of 0.64 directors. We next address the concern that the appointment of new directors to the board by itself might have positive effects on profitability. For instance, new directors might put in extra effort at the beginning of their tenure, possibly due to career concerns. The pseudo industry tests reported in Section 4.2.2 partially address this concern. In those cases in Section 3.1.1 in which we study non-focal-firm-initiated board connections, the pure new-appointment effect is also not a concern. Still, in Panel C of Internet Appendix Table A20 we refine the matching procedure and incrementally require that the treated firm and its control have exactly the same number of newly appointed directors during the event year. Our estimates are similar to those in Table 3.

4.3.3 Match additionally on other co-variates

Table 2 shows that treated and control firms are not statistically significantly different in terms of co-variates used in matching. Also, we do not see pre-trends in Figure 1, so any residual unbalancedness in firm characteristics is unlikely to be confounding our main findings. Nevertheless, we now provide robustness tests where we match additionally on other co-variates. In Panel D of Internet Appendix Table A20, we examine the robustness using operating margin instead of gross margin in the matching scheme. We also sequentially add operating margin, sales growth, ROA, R&D to assets, and capital expenditures to assets to the matching scheme, and report the findings in Panels E, F, G, H, and I of Internet Appendix Table A20, respectively. We match on all variables in Panel J of Internet Appendix Table A20. Our findings under the new matching schemes remain robust.

4.3.4 Require that the control firm is never treated before or during [-3, 3]

In the matching process, we require that the control firm is not treated in the event year. Nonetheless, it is possible that it might be treated a few years before the event or right after. To avoid these cases affecting our estimates, in Panel K of Internet Appendix Table A20 we additionally require that the control firm is never treated during the [-3, 3] window around the event year. In Panel L of Internet Appendix Table A20, we additionally require that the control firm is never treated both during or before the [-3, 3] window. Our findings are unaffected by these choices. As we use stacked regression estimators and already-treated firms never act as effective control units in Panel L, our estimates stand to the critique in, e.g., Baker et al. (2022), on the interpretation of difference-in-differences estimates.

4.4 Robustness to alternative regression specifications

We provide additional robustness tests with regard to the regression specifications. First, in Panel A of Internet Appendix Table A21, we report effects of direct and indirect connections consistent with Table 3 when they are estimated with separate regressions. Second, Panels B and C show that the estimates are robust to defining industry-by-year fixed effects based on the SIC-3 or FIC-200 industry classifications. This gives us further confidence that our estimates are not capturing industry-level common trends. Third, Panel D shows that our findings are robust to including cohort-by-year fixed effects, which control for within-cohort time trends in a granular manner. Finally, in our baseline tests, we cluster the standard errors at the firm level. It is possible that the outcome variables of connected firm-pairs are positively correlated and treating them as independent units could lead us to inflating the power of the tests. Hence, we define a new unit of clustering, which is all observations of a connected firm-pair for treated firms and all observations of a single firm for control firms. As shown in Panel E of Internet Appendix Table A21, while the T-stats drop slightly for some estimates, they all remain statistically significant.

4.5 Specification curve analysis

We also conduct a specification curve analysis (Simonsohn et al., 2020; Cookson, 2018; Bernstein et al., 2022; Cookson et al., 2025). This analysis allows us to systematically assess the sensitivity of our findings to sample and regression specification choices and also to make joint inference. Specifically, we estimate our baseline profitability effects of board connections using all possible combinations of industry classifications (Internet Appendix Table A17), matching schemes (Internet Appendix Table A20), number of matches (Internet Appendix Table A20), and regression specifications (Internet Appendix Table A21). We then rank the coefficient estimates of all specifications from the smallest to the largest and plot the empirical cumulative distribution function. This forms our observed specification curve.

We present our findings in Figure 3. Across all empirical specifications, we consistently find positive estimates for the profit-enhancing effects of board connections, supporting the robustness of our findings. Notably, the point estimates for effects of direct connections are larger than those for indirect connections across the entire distribution, consistent with with our main findings.

Next, we conduct joint inference by answering the question: Considering the full set of reasonable specifications jointly, how inconsistent are the results with the null hypothesis of no effect? Following the procedure proposed by Simonsohn et al. (2020) for non-experimental data, we generate bootstrapped specification curves as benchmarks for comparison, for which we force the null hypothesis of no effect on the data. The detailed steps are provided in the notes under Figure 3. We plot the median as well as the 2.5th and 97.5th percentiles of the bootstrapped specification curves. Comparing the observed specification curve to these bootstrapped ones enables us to assess how extreme the observed specification curve would be under the null hypothesis. We find that the observed specification curve lies almost entirely above the upper bound of the 95% confidence bands of bootstrapped specification curves. This indicates that it is unlikely that the null hypothesis of no effect holds and our findings occur only by chance.

4.6 Connected director deaths

We next study instances of the deaths of interlocked directors. The death of a director breaks the connection between two firms. We find 51 instances where director death breaks direct connections and construct a treatment-control matched sample as before. The findings are reported in Internet Appendix Table A22. Despite the small sample, we find in Panel A that the affected firm's gross margin (operating margin; ROA) drops by 1.8 p.p. (3.1 p.p.; 1.8 p.p.) following the death of the connected director. The double-difference terms are statistically significant for operating margin and ROA.

Further, in Panel B, we examine the effects of director deaths that sever indirect board connections. In Panel C, we specifically focus on non-focal director death. As expected, the sample size is small. There are 91 cases in which deaths sever indirect connections between product market peers, among which 49 are attributable to the death of a non-focal director, meaning the focal firm did not lose its own director. Employing difference-in-differences regressions, we find that ROA decreases by 1.6 p.p. following deaths that sever indirect connections. When focusing on non-focal director deaths, ROA decreases by 2.4 p.p. Our findings with non-focal director deaths provide support for the value of product-market-peer board connections aside from individual director talent.

5 Conclusion

Taking advantage of the networks formed by director interlocks and the Hoberg-Phillips industry classification, we find that board connections to product market peers have positive profitability implications. Specifically, a firm's gross margin rises by 0.8 p.p. after forming new direct connections to product market peers and by 0.4 p.p. after forming new indirect connections to product market peers via an intermediate firm. We address endogeneity concerns by exploring the network structure and focusing on new connections that are not a direct choice of the treated firm.

Connected firms might engage in market allocation and target separate product categories, demographic groups, or geographic areas, and wield market power in their respective market segments. Alternatively, they might sell in the same market and fix the product prices. The coordination can come via pure information exchange, or alternatively interactions among directors can build trust and affinity among competing firms and make market allocation or price-fixing more sustainable. We remain agnostic over the specific strategy and form of anti-competitive practices that board connections facilitate. Using barcode-level data, we do however find that such connections are associated with higher product prices, a greater tendency for market allocation, and slower new product introductions.

This paper has regulatory implications. First, our findings indicate the role of directors in anti-competitive coordination and provide support for the current ban on director interlocks between competing firms. Second, we find that indirect connections via an intermediate firm also have positive, albeit smaller, effects on firm profitability and prices, and in fact even stronger effects on market allocation. This argues for going beyond director interlocks and putting restraints on indirect board connections between competitors as well, especially in cases where the detrimental effects of anti-competitive coordination on consumer welfare are substantial.

References

Acemoglu, D. and P. Restrepo (2019): "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33, 3–30.

Adams, R. B. and D. Ferreira (2009): "Women in the Boardroom and Their Impact on Governance and Performance," *Journal of Financial Economics*, 94, 291–309.

Akyol, A. C. and L. Cohen (2013): "Who Chooses Board Members?" in *Advances in Financial Economics*, Emerald Group Publishing Limited, vol. 16, 43–77.

Ali, A., S. Klasa, and E. Yeung (2008): "The Limitations of Industry Concentration Measures Constructed with Compustat Data: Implications for Finance Research," *The Review of Financial Studies*, 22, 3839–3871.

Amazon (2020): "Statement by Jeffrey P. Bezos, Founder & Chief Executive Officer, Amazon before the U.S. House of Representatives, Committee on the Judiciary, Subcommittee on Antitrust, Commercial, and Administrative Law," *House Committee on the Judiciary*, available at `https://docs.house.gov/meetings/JU/JU05/20200729/110883/HHRG-116-JU05-Wstate-BezosJ-20200729.pdf`.

Amel-Zadeh, A., F. Kasperk, and M. C. Schmalz (2022): "Mavericks, Universal, and Common Owners - The Largest Shareholders of U.S. Public Firms," Working paper.

Antón, M., F. Ederer, M. Giné, and M. Schmalz (2023): "Common Ownership, Competition, and Top Management Incentives," *Journal of Political Economy*, 131, 1294–1355.

Appel, I. R., T. A. Gormley, and D. B. Keim (2016): "Passive Investors, Not Passive Owners," *Journal of Financial Economics*, 121, 111–141.

Arora, A., S. Belenzon, L. Cioaca, L. Sheer, H. M. J. Shin, and D. Shvadron (2024a): "DISCERN 2.0: Duke Innovation & SCientific Enterprises Research Network Dataset," Tech. rep., available at `https://doi.org/10.5281/zenodo.13153196`.

Arora, A., S. Belenzon, L. Cioaca, L. Sheer, and D. Shvadron (2024b): "Back to the Future: Are Big Firms Regaining their Scientific and Technological Dominance? Evidence from DISCERN 2.0," Tech. rep.

Aslan, H. (2023): "Common Ownership and Creative Destruction: Evidence from US Consumers," *Review of Finance*, 28, 865–896.

Awaya, Y. and V. Krishna (2016): "On Communication and Collusion," *American Economic Review*, 106, 285–315.

Ayyagari, M., A. Demirgüç-Kunt, and V. Maksimovic (2023): "The Rise of Star Firms: Intangible Capital and Competition," *The Review of Financial Studies*, 37, 882–949.

Azar, J. (2022): "Common Shareholders and Interlocking Directors: The Relation Between Two Corporate Networks," *Journal of Competition Law & Economics*, 18, 75–98.

Azar, J., S. Raina, and M. Schmalz (2022): "Ultimate Ownership and Bank Competition," *Financial Management*, 51, 227–269.

Azar, J., M. C. Schmalz, and I. Tecu (2018): "Anticompetitive Effects of Common Ownership," *The Journal of Finance*, 73, 1513–1565.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022): "How Much Should We Trust Staggered Difference-in-Differences Estimates?" *Journal of Financial Economics*, 144, 370–395.

Baker, G., R. Gibbons, and K. J. Murphy (2002): "Relational Contracts and the Theory of the Firm," *The Quarterly Journal of Economics*, 117, 39–84.

Baker, S. R., S. Sun, and C. Yannelis (2023): "Corporate Taxes and Retail Prices," Working paper.

Bakke, T.-E., J. R. Black, H. Mahmudi, and S. C. Linn (2024): "Director Networks and Firm Value," *Journal of Corporate Finance*, 102545.

Barone, G., F. Schivardi, and E. Sette (2025): "Interlocking Directorates and Competition in Banking," *The Journal of Finance*, 80, 1963–2016.

Becher, D., R. A. Walkling, and J. I. Wilson (2019): "Understanding the Motives for Director Selection," Working paper.

Belleflamme, P. and F. Bloch (2004): "Market Sharing Agreements and Collusive Networks," *International Economic Review*, 45, 387–411.

Bernstein, A., S. B. Billings, M. T. Gustafson, and R. Lewis (2022): "Partisan Residential Sorting on Climate Change Risk," *Journal of Financial Economics*, 146, 989–1015.

Bertrand, M., E. Duflo, and S. Mullainathan (2004): "How Much Should We Trust Differences-In-Differences Estimates?" *The Quarterly Journal of Economics*, 119, 249–275.

Bonacich, P. (1972): "Factoring and Weighting Approaches to Status Scores and Clique Identification," *The Journal of Mathematical Sociology*, 2, 113–120.

Bourveau, T., G. She, and A. Žaldokas (2020): "Corporate Disclosure as a Tacit Coordination Mechanism: Evidence from Cartel Enforcement Regulations," *Journal of Accounting Research*, 58, 295–332.

Bouwman, C. H. S. (2011): "Corporate Governance Propagation through Overlapping Directors," *The Review of Financial Studies*, 24, 2358–2394.

Cabezon, F. and G. Hoberg (2025): "Leaky Director Networks and Innovation Herding," *The Review of Financial Studies*, Forthcoming.

Cai, Y. and M. Sevilir (2012): "Board Connections and M&A Transactions," *Journal of Financial Economics*, 103, 327–349.

Campello, M., D. Ferrés, and G. Ormazabal (2017): "Whistle-Blowers on the Board? The Role of Independent Directors in Cartel Prosecutions," *Journal of Law and Economics*, 60, 241–268.

Cen, L., S. Dasgupta, and R. Sen (2016): "Discipline or Disruption? Stakeholder Relationships and the Effect of Takeover Threat," *Management Science*, 62, 2820–2841.

Cen, L., E. L. Maydew, L. Zhang, and L. Zuo (2017): "Customer–Supplier Relationships and Corporate Tax Avoidance," *Journal of Financial Economics*, 123, 377–394.

Chen, K. D. and W. R. Guay (2020): "Busy Directors and Shareholder Satisfaction," *Journal of Financial and Quantitative Analysis*, 55, 2181–2210.

Chen, X. (2025): "How Do Private Firms Affect Common Ownership-Driven Collusion among Public Firms?" Working paper.

Chuluun, T., A. Prevost, and A. Upadhyay (2017): "Firm Network Structure and Innovation," *Journal of Corporate Finance*, 44, 193–214.

Cohen, L. and A. Frazzini (2008): "Economic Links and Predictable Returns," *The Journal of Finance*, 63, 1977–2011.

Coles, J., N. Daniel, and L. Naveen (2020): "Director Overlap: Groupthink versus Teamwork," Working paper.

Coles, J. L., N. D. Daniel, and L. Naveen (2006): "Managerial Incentives and Risk-Taking," *Journal of Financial Economics*, 79, 431–468.

Connor, J. (2014): "Price-Fixing Overcharges: Revised 3rd Edition," *SSRN Electronic Journal*.

——— (2020): "Private International Cartels Full Data 2019 edition. (Version 2.0)," .

Cookson, J. A. (2018): "When Saving is Gambling," *Journal of Financial Economics*, 129, 24–45.

Cookson, J. A., C. Fox, J. Gil-Bazo, J. F. Imbet, and C. Schiller (2025): "Social Media as a Bank Run Catalyst," *Journal of Financial Economics*, Forthcoming.

Core, J. and W. Guay (2002): "Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price and Volatility," *Journal of Accounting Research*, 40, 613–630.

Dass, N., O. Kini, V. Nanda, B. Onal, and J. Wang (2014): "Board Expertise: Do Directors from Related Industries Help Bridge the Information Gap?" *The Review of Financial Studies*, 27, 1533–1592.

De Leverano, A. (2023): "Collusion Through Market Sharing Agreements: Evidence from Québec's Road Paving Market," Working paper.

Demblowski, D. (2022): "Analysis: DOJ Is Shaking Up World of Interlocking Directorates," *Bloomberg Law*, available at `https://news.bloomberglaw.com/bloomberg-law-analysis/analysis-doj-is-shaking-up-world-of-interlocking-directorates`.

Department of Justice (2022a): "Assistant Attorney General Jonathan Kanter Delivers Opening Remarks at 2022 Spring Enforcers Summit," *Office of Public Affairs, Department of Justice*, available at `https://www.justice.gov/opa/speech/assistant-attorney-general-jonathan-kanter-delivers-opening-remarks-2022-spring-enforcers`.

——— (2022b): "Directors Resign from the Boards of Five Companies in Response to Justice Department Concerns about Potentially Illegal Interlocking Directorates," *Office of Public Affairs, Department of Justice*, available at `https://www.justice.gov/opa/pr/directors-resign-boards-five-companies-response-justice-department-concerns-about-potentially`.

——— (2023): "Justice Department's Ongoing Section 8 Enforcement Prevents More Potentially Illegal Interlocking Directorates," *Office of Public Affairs, Department of Justice*, available at `https://www.justice.gov/opa/pr/justice-department-s-ongoing-section-8-enforcement-prevents-more-potentially-illegal`.

Department of Justice and Federal Trade Commission (2000): "Antitrust Guidelines for Collaborations Among Competitors," *Federal Trade Commission*.

Donangelo, A., F. Gourio, M. Kehrig, and M. Palacios (2019): "The Cross-Section of Labor Leverage and Equity Returns," *Journal of Financial Economics*, 132, 497–518.

Drobetz, W., F. von Meyerinck, D. Oesch, and M. Schmid (2018): "Industry Expert Directors," *Journal of Banking & Finance*, 92, 195–215.

Duchin, R., J. G. Matsusaka, and O. Ozbas (2010): "When Are Outside Directors Effective?" *Journal of Financial Economics*, 96, 195–214.

Eckbo, B. (1983): "Horizontal Mergers, Collusion, and Stockholder Wealth," *Journal of Financial Economics*, 11, 241–273.

El-Khatib, R., K. Fogel, and T. Jandik (2015): "CEO Network Centrality and Merger Performance," *Journal of Financial Economics*, 116, 349–382.

Eldar, O. and J. Grennan (2024): "Common Venture Capital Investors and Startup Growth," *The Review of Financial Studies*, 37, 549–590.

Emery, L. P. and M. Faccio (2025): "Exposing the Revolving Door in Executive Branch Agencies," *Journal of Financial and Quantitative Analysis*, 60, 1625–1655.

Falato, A., D. Kadyrzhanova, and U. Lel (2014): "Distracted Directors: Does Board Busyness Hurt Shareholder Value?" *Journal of Financial Economics*, 113, 404–426.

Federal Trade Commission (2022): "Market Division or Customer Allocation," *Competition Guidance, Federal Trade Commission*, available at `https://www.ftc.gov/advice-guidance/competition-guidance/guide-antitrust-laws/dealings-competitors/market-division-or-customer-allocation`.

——— (2023): "FTC Announces 2023 Update of Size of Transaction Thresholds for Premerger Notification Filings and Interlocking Directorates," *Office of Public Affairs, Federal Trade Commission*, available at `https://www.ftc.gov/news-events/news/press-releases/2023/01/ftc-announces-2023-update-size-transaction-thresholds-premerger-notification-filings-interlocking`.

Fich, E. M. and A. Shivdasani (2006): "Are Busy Boards Effective Monitors?" *The Journal of Finance*, 61, 689–724.

Fogel, K., L. Ma, and R. Morck (2021): "Powerful Independent Directors," *Financial Management*, 50, 935–983.

Fracassi, C., A. Previtero, and A. Sheen (2022): "Barbarians at the Store? Private Equity, Products, and Consumers," *The Journal of Finance*, 77, 1439–1488.

Fracassi, C. and G. Tate (2012): "External Networking and Internal Firm Governance," *The Journal of Finance*, 67, 153–194.

Genesove, D. and W. P. Mullin (2001): "Rules, Communication, and Collusion: Narrative Evidence from the Sugar Institute Case," *American Economic Review*, 91, 379–398.

Geng, H., H. Hau, R. Michaely, and B. Nguyen (2023): "Does Board Overlap Promote Coordination Between Firms?" Working paper.

Gilje, E. P., T. A. Gormley, and D. Levit (2020): "Who's Paying Attention? Measuring Common Ownership and its Impact on Managerial Incentives," *Journal of Financial Economics*, 137, 152–178.

Goergen, M., L. Renneboog, and Y. Zhao (2019): "Insider Trading and Networked Directors," *Journal of Corporate Finance*, 56, 152–175.

Gopalan, R., T. A. Gormley, and A. Kalda (2021): "It's Not so Bad: Director Bankruptcy Experience and Corporate Risk-taking," *Journal of Financial Economics*, 142, 261–292.

Gormley, T. A., M. Jha, and M. Wang (2023): "The Politicization of Social Responsibility," Working paper.

Gormley, T. A. and D. A. Matsa (2011): "Growing Out of Trouble? Corporate Responses to Liability Risk," *The Review of Financial Studies*, 24, 2781–2821.

——— (2016): "Playing it Safe? Managerial Preferences, Risk, and Agency Conflicts," *Journal of Financial Economics*, 122, 431–455.

Granja, J. and S. Moreira (2022): "Product Innovation and Credit Market Disruptions," *The Review of Financial Studies*, 36, 1930–1969.

Güner, A. B., U. Malmendier, and G. Tate (2008): "Financial Expertise of Directors," *Journal of Financial Economics*, 88, 323–354.

Ha, S., F. Ma, and A. Žaldokas (2024): "Motivating Collusion," *Journal of Financial Economics*, 154, 103798.

Hafner, L., T. P. Peifer, and F. S. Hafner (2024): "Equal Accuracy for Andrew and Abubakar—Detecting and Mitigating Bias in Name-Ethnicity Classification Algorithms," *AI & Society*, 39, 1605–1629.

Hauser, R. (2018): "Busy Directors and Firm Performance: Evidence from Mergers," *Journal of Financial Economics*, 128, 16–37.

He, J. J. and J. Huang (2017): "Product Market Competition in a World of Cross-Ownership: Evidence from Institutional Blockholdings," *The Review of Financial Studies*, 30, 2674–2718.

Heath, D., D. Macciocchi, R. Michaely, and M. C. Ringgenberg (2021): "Do Index Funds Monitor?" *The Review of Financial Studies*, 35, 91–131.

Henderson, M. T., I. Hutton, D. Jiang, and M. Pierson (2023): "Lawyer CEOs," *Journal of Financial and Quantitative Analysis*, 1–37.

Hoberg, G. and G. Phillips (2010): "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis," *The Review of Financial Studies*, 23, 3773–3811.

——— (2016): "Text-Based Network Industries and Endogenous Product Differentiation," *Journal of Political Economy*, 124, 1423–1465.

Huck, S., H.-T. Normann, and J. Oechssler (2004): "Two Are Few and Four Are Many: Number Effects in Experimental Oligopolies," *Journal of Economic Behavior & Organization*, 53, 435–446.

Intintoli, V. J., K. M. Kahle, and W. Zhao (2018): "Director Connectedness: Monitoring Efficacy and Career Prospects," *Journal of Financial and Quantitative Analysis*, 53, 65–108.

Jiraporn, P., M. Singh, and C. I. Lee (2009): "Ineffective Corporate Governance: Director Busyness and Board Committee Memberships," *Journal of Banking & Finance*, 33, 819–828.

Kabir, P. (2022): "Consumer Welfare and Product Creation: The Credit Supply Channel," Working paper.

Kandori, M. and H. Matsushima (1998): "Private Observation, Communication and Collusion," *Econometrica*, 66, 627–652.

Kanter, J. (2023): "Remarks at the 2023 American Bar Association Antitrust Spring Meeting," *Antitrust Division, Department of Justice*.

Khanna, T. and C. Thomas (2009): "Synchronicity and Firm Interlocks in an Emerging Market," *Journal of Financial Economics*, 92, 182–204.

Koch, A., M. Panayides, and S. Thomas (2021): "Common Ownership and Competition in Product Markets," *Journal of Financial Economics*, 139, 109–137.

Kogan, L., D. Papanikolaou, L. Schmidt, and B. Seegmiller (2025): "Technology and Labor Displacement: Evidence from Linking Patents with Worker-Level Data," Working paper.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman (2017): "Technological Innovation, Resource Allocation, and Growth," *The Quarterly Journal of Economics*, 132, 665–712.

Larcker, D. F., E. C. So, and C. C. Wang (2013): "Boardroom Centrality and Firm Performance," *Journal of Accounting and Economics*, 55, 225–250.

Lewellen, J. and K. Lewellen (2022): "Institutional Investors and Corporate Governance: The Incentive to Be Engaged," *The Journal of Finance*, 77, 213–264.

Lewellen, K. and M. Lowry (2021): "Does Common Ownership Really Increase Firm Coordination?" *Journal of Financial Economics*, 141, 322–344.

Motta, M. (2004): *Competition Policy*, Cambridge University Press.

Nain, A. and Y. Wang (2018): "The Product Market Impact of Minority Stake Acquisitions," *Management Science*, 64, 825–844.

Peters, R. H. and L. A. Taylor (2017): "Intangible Capital and the Investment-Q Relation," *Journal of Financial Economics*, 123, 251–272.

Renneboog, L. and Y. Zhao (2014): "Director Networks and Takeovers," *Journal of Corporate Finance*, 28, 218–234.

Sher, S. A., M. Y. Hale, J. T. Hahn, K. Biagioli, R. S. Crauthers, and J. Philipoom (2022): "DOJ Launches Enforcement Initiative Against "Interlocking Directorates"," *Wilson Sonsini Goodrich & Rosati*, available at `https://www.wsgr.com/en/insights/doj-launches-enforcement-initiative-against-interlocking-directorates.html`.

Simonsohn, U., J. P. Simmons, and L. D. Nelson (2020): "Specification Curve Analysis," *Nature Human Behaviour*, 4, 1208–1214.

Sullivan, C. (2020): "The Ice Cream Split: Empirically Distinguishing Price and Product Space Collusion," Working paper.

Terbeck, H., V. Rieger, N. Van Quaquebeke, and A. Engelen (2022): "Once a Founder, Always a Founder? The Role of External Former Founders in Corporate Boards," *Journal of Management Studies*, 59, 1284–1314.

Wiseman, T. (2017): "When Does Predation Dominate Collusion?" *Econometrica*, 85, 555–584.

Table 1: Industry distribution of events

Fama-French industry	# Direct	%	# Indirect	%	# Total	%
Agriculture	1	0.1%	2	0.0%	3	0.1%
Food Products	2	0.1%	14	0.3%	16	0.3%
Candy & Soda	2	0.1%	3	0.1%	5	0.1%
Beer & Liquor	2	0.1%	5	0.1%	7	0.1%
Recreation	0	0.0%	1	0.0%	1	0.0%
Entertainment	10	0.7%	35	0.9%	45	0.8%
Printing & Publishing	4	0.3%	18	0.4%	22	0.4%
Consumer Goods	3	0.2%	6	0.1%	9	0.2%
Apparel	7	0.5%	22	0.5%	29	0.5%
Healthcare	55	3.7%	151	3.7%	206	3.7%
Medical Equipment	155	10.4%	317	7.8%	472	8.5%
Pharmaceutical Products	227	15.2%	460	11.3%	687	12.3%
Chemicals	6	0.4%	57	1.4%	63	1.1%
Rubber & Plastic Products	0	0.0%	2	0.0%	2	0.0%
Construction Materials	2	0.1%	20	0.5%	22	0.4%
Construction	5	0.3%	30	0.7%	35	0.6%
Steel Works Etc	2	0.1%	27	0.7%	29	0.5%
Machinery	51	3.4%	137	3.4%	188	3.4%
Electrical Equipment	6	0.4%	25	0.6%	31	0.6%
Automobiles & Trucks	2	0.1%	33	0.8%	35	0.6%
Aircraft	2	0.1%	26	0.6%	28	0.5%
Shipbuilding, Railroad Equipment	0	0.0%	9	0.2%	9	0.2%
Defense	0	0.0%	5	0.1%	5	0.1%
Non-Metallic & Industrial Metal Mining	3	0.2%	5	0.1%	8	0.1%
Coal	2	0.1%	6	0.1%	8	0.1%
Petroleum & Natural Gas	99	6.6%	326	8.0%	425	7.6%
Communication	0	0.0%	2	0.0%	2	0.0%
Personal Services	4	0.3%	38	0.9%	42	0.8%
Business Services	307	20.6%	840	20.6%	1,147	20.6%
Computers	109	7.3%	322	7.9%	431	7.7%
Electronic Equipment	214	14.3%	509	12.5%	723	13.0%
Measuring & Control Equipment	41	2.7%	145	3.5%	186	3.3%
Business Supplies	2	0.1%	17	0.4%	19	0.3%
Shipping Containers	0	0.0%	2	0.0%	2	0.0%
Wholesale	26	1.7%	92	2.3%	118	2.1%
Retail	95	6.4%	273	6.7%	368	6.6%
Restaraunts, Hotels, Motels	32	2.1%	68	1.7%	100	1.8%
Banking	2	0.1%	2	0.0%	4	0.1%
Insurance	0	0.0%	2	0.0%	2	0.0%
Trading	0	0.0%	4	0.1%	4	0.1%
Almost Nothing	13	0.9%	27	0.7%	40	0.7%
Total	1,493	100.0%	4,085	100.0%	5,578	100.0%

Note: This table reports the distribution of treated firms in the Fama-French 48-industry classification.

Table 2: Comparison of treated and matched control firms

	Treated			Control					Compustat Sample	
	Mean	SD	N	Mean	SD	N	Dif	T-stat	Mean	SD
Variables used in matching										
Assets	6.71	1.85	5,578	6.68	1.86	5,578	0.04	1.0	6.58	2.04
Gross Margin	0.51	0.26	5,578	0.51	0.24	5,578	0.00	0.9	0.42	0.24
Tobin's Q	2.67	2.03	5,578	2.62	1.88	5,578	0.06	1.6	1.82	1.40
Variables not used in matching										
Operating Margin	0.13	0.20	5,571	0.17	0.18	5,558	–0.04	–12.0	0.18	0.19
ROA	0.09	0.12	5,571	0.13	0.11	5,558	–0.03	–15.2	0.09	0.11
Sales Growth	0.22	0.50	5,253	0.17	0.38	5,291	0.05	5.5	0.14	0.38
SG&A to Sales	0.41	0.27	5,248	0.35	0.24	5,320	0.06	11.6	0.28	0.20
Depreciation & Amortization to Sales	0.07	0.10	5,571	0.07	0.10	5,558	0.00	1.0	0.06	0.08
R&D to Assets	0.11	0.11	4,507	0.07	0.08	3,918	0.03	15.4	0.06	0.08
CAPEX to Assets	0.05	0.06	5,561	0.05	0.06	5,553	–0.00	–1.2	0.04	0.06
Firm Age	24.45	17.55	5,578	26.76	18.30	5,578	–2.32	–6.8	26.76	20.40

Note: This table reports the summary statistics for the treated and control firms in the year prior to the treatment (i.e., the year for which firm characteristics are used in the matching procedure) and also for all firms in Compustat. In Internet Appendix Table A20, we add operating margin, sales growth, ROA, R&D to assets, and capital expenditures to assets to the matching scheme, and show that our findings remain robust.

Table 3: Double-difference regressions

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.007***	-0.008***	-0.007***
	(-4.08)	(-4.47)	(-5.61)
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.29)	(3.84)	(3.41)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.81)	(3.38)	(3.74)
Observations	68,682	68,526	68,594
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.878	0.746	0.667
P-value from a Test of DirectTreated × Post = IndirectTreated × Post	0.26	0.09	0.36

Note: This table reports estimates from the following regression using the sample of all events,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $DirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a new direct board connection to a product market peer while $IndirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a new indirect board connection to a product market peer. $DirectTreated_{i,c} \times Post_{c,t}$ and $IndirectTreated_{i,c} \times Post_{c,t}$ are the double-difference terms, the coefficient estimates of which are the estimated effects of new board connections to product market peers. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. We also report the p-value from a test for the equality of the effects of direct connections and the effects of indirect connections. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Effects on product market price using barcode-level data

	(1) Price Index	(2) Price Index	(3) Price Index
Panel A: Using all events			
DirectTreated × Post	0.00223***	0.00187**	0.00171**
	(2.67)	(2.20)	(1.98)
IndirectTreated × Post	0.00063***	0.00057***	0.00056***
	(3.13)	(2.67)	(2.75)
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.342	0.343	0.343
Panel B: Using non-focal-firm initiated subset of events			
NFFInitiatedTreated × Post	0.00092***	0.00086***	0.00083***
	(3.07)	(2.89)	(2.92)
Observations	48,608,899	48,131,202	47,920,471
Adjusted R-squared	0.346	0.348	0.348
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%

Note: Panel A of this table reports estimates from the following regression,

$$\begin{aligned} P_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} + \alpha_2 \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned}$$

Panel B of this table reports estimates from the following regression,

$$P_{i,m,z,t} = \alpha \times NFFInitiatedTreated_{i,m,z} \times Post_{i,m,z,t} + \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}.$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. $DirectTreated_{i,m,z} \times Post_{i,m,z,t}$ ($IndirectTreated_{i,m,z} \times Post_{i,m,z,t}$; $NFFInitiatedTreated_{i,m,z} \times Post_{i,m,z,t}$) equals zero for those firm-product-module-zip3 combinations that are never treated and for treated firm-product-module-zip3 in quarters prior to the treatment of direct (indirect; non-focal-firm-initiated) board connections. It equals one for treated firm-product-module-zip3 in quarters post the treatment. $\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Effects on cosine similarity of geographic distribution using barcode-level data

	(1) Similarity by Zip-3	(2) Similarity by County	(3) Similarity by DMA
DirectTreated × Post	0.0048	0.0033	0.0053
	(0.87)	(0.64)	(0.94)
IndirectTreated × Post	-0.0037**	-0.0051***	-0.0044***
	(-2.35)	(-3.91)	(-2.66)
Observations	23,051,386	23,051,386	23,051,386
Firm-Pair FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Clustering	Firm-Pair	Firm-Pair	Firm-Pair
Adjusted R-squared	0.878	0.892	0.873

Note: This table reports estimates from the following regression,

$$s_{i,j,t} = \alpha_1 \times DirectTreated_{i,j} \times Post_{i,j,t} + \alpha_2 \times IndirectTreated_{i,j} \times Post_{i,j,t} + \theta_t + \theta_{i,j} + e_{i,j,t}$$

where i and j are indices for the pair firm i and firm j and t is the index for the quarter. $DirectTreated_{i,j} \times Post_{i,j,t}$ ($IndirectTreated_{i,j} \times Post_{i,j,t}$) equals zero for those firm-pairs that are never treated and for treated firm-pairs in quarters prior to the treatment of direct (indirect) board connections. It equals one for treated firm-pairs in quarters post the treatment. We include firm-pair fixed effects $\theta_{i,j}$ and quarter fixed effects θ_t. T-stats are in parentheses. Standard errors are clustered at the firm-pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Effects on new product introductions using barcode-level data

Panel A: Using all events

	(1) New Products Total	(2) New Products Old Lines	(3) New Products New Lines	(4) New Products Total Logged	(5) New Products Old Lines Logged	(6) New Products New Lines Logged
DirectTreated × Post	-2.21***	-1.92***	-0.19***	-0.09***	-0.08***	-0.07***
	(-2.98)	(-2.62)	(-2.72)	(-2.99)	(-2.81)	(-2.78)
IndirectTreated × Post	-1.13***	-1.00***	-0.07***	-0.06***	-0.05***	-0.03***
	(-3.49)	(-3.24)	(-3.03)	(-4.42)	(-4.44)	(-3.03)
Observations	269,232	269,232	269,232	269,232	269,232	269,232
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R-squared	0.786	0.795	0.152	0.706	0.727	0.165

Panel B: Using non-focal-firm-initiated subset of events

	(1) New Products Total	(2) New Products Old Lines	(3) New Products New Lines	(4) New Products Total Logged	(5) New Products Old Lines Logged	(6) New Products New Lines Logged
NFFInitiatedTreated × Post	-0.85**	-0.73*	-0.06*	-0.05***	-0.05***	-0.02*
	(-1.97)	(-1.86)	(-1.72)	(-2.66)	(-2.90)	(-1.73)
Observations	261,802	261,802	261,802	261,802	261,802	261,802
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R-squared	0.766	0.777	0.140	0.674	0.696	0.153

Note: Panel A of this table reports estimates from the following regression,

$$\begin{aligned} N_{i,t} &= \alpha_1 \times DirectTreated_i \times Post_{i,t} + \alpha_2 \times IndirectTreated_i \times Post_{i,t} \\ &+ \theta_i + \theta_t + e_{i,t}. \end{aligned}$$

Panel B of this table reports estimates from the following regression,

$$N_{i,t} = \alpha \times NFFInitiatedTreated_i \times Post_{i,t} + \theta_i + \theta_t + e_{i,t}.$$

Here $N_{i,t}$ is the number of all new products that firm i introduces in quarter t for column (1) of Panels A and B. It is the number of new products in product modules in which firm i had a presence in prior quarters for column (2), and the number of new products in product modules in which firm i did not have a presence in prior quarters for column (3). We use the logged value of one plus the prior three variables in columns (4), (5), (6). $DirectTreated_i \times Post_{i,t}$ ($IndirectTreated_i \times Post_{i,t}$; $NFFInitiatedTreated_i \times Post_{i,t}$) equals zero for the observations of a firm that never formed a direct (indirect; non-focal-firm-initiated) board connection with a product market peer which renders a joint pre-treatment market share in a local market above 5%, or for the observations of a firm that ever formed such a board connection in quarters prior to the treatment. It equals one for the observations of a firm that ever formed such a board connection in quarters post the treatment. θ_i are firm fixed effects. θ_t are quarter fixed effects. The outcome variables are winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Double-difference regressions, using non-focal-firm initiated board connections

	Gross Margin	Operating Margin	ROA
Panel A: Using all non-focal-firm initiated events			
Post	–0.006**	–0.011***	–0.009***
	(–2.45)	(–3.88)	(–4.30)
NFFInitiatedTreated × Post	0.007**	0.010***	0.009***
	(2.02)	(2.79)	(3.50)
Observations	26,060	26,010	26,026
Adjusted R-sqaured	0.894	0.764	0.696
Panel B: Require that the intermediate firm is not a product market peer of the treated firm			
Post	–0.009***	–0.011***	–0.008***
	(–2.96)	(–3.51)	(–3.37)
NFFInitiatedTreated × Post	0.007*	0.010***	0.008***
	(1.94)	(2.61)	(2.64)
Observations	16,927	16,905	16,913
Adjusted R-sqaured	0.909	0.777	0.702
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: Panel A of this table reports estimates from the following regression using the subset of events that are non-focal-firm-initiated,

$$Y_{i,j,c,t} \quad = \quad \alpha_1 \times Post_{c,t} + \beta_1 \times NFFInitiatedTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Panel B reports estimates from the above regression using non-focal-firm-initiated board connections for which the intermediate firm is not a product market peer of the treated firm. Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $NFFInitiatedTreated_{i,c} \times Post_{c,t}$ is the double-difference term, the coefficient of which is the estimated effects of non-focal-firm-initiated new board connections with peer firms. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Cross-sectional heterogeneities in the effects of new board connections

	Gross Margin	Operating Margin	ROA
Panel A: By whether corporate opportunity waivers (COWs) are in effect			
Treated × Post	–0.001	–0.003	0.001
	(–0.73)	(–0.61)	(0.36)
Treated × Post × COWs In Effect	0.008	0.017***	0.009*
	(1.62)	(3.23)	(2.16)
Observations	68,669	68,508	68,576
Panel B: By whether newly connected firm-pairs share major corporate customers			
Treated × Post	0.004	0.009***	0.007***
	(1.51)	(3.39)	(3.77)
Treated × Post × If Share Major Customers	0.013	0.018**	0.010
	(1.39)	(1.96)	(1.59)
Observations	68,669	68,508	68,576
Panel C: By similarity in business descriptions between newly connected firm-pairs			
Treated × Post	0.002	0.006**	0.005**
	(0.93)	(2.34)	(2.56)
Treated × Post × Top Similarity	0.008	0.013**	0.009**
	(1.45)	(2.50)	(2.53)
Observations	68,669	68,508	68,576
Panel D: By HHI of the treated firm's industry			
Treated × Post	0.003	0.008**	0.007***
	(1.06)	(2.45)	(2.82)
Treated × Post × Top HHI	0.003	0.003	0.002
	(0.74)	(0.77)	(0.56)
Observations	68,512	68,351	68,406
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times Post_{c,t} \times EventCharacteristic_c + \beta_1 \times Treated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Treated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to product market peers, and zero otherwise. In this regression we pool events of new direct and indirect connections together. $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. $EventCharacteristic_c$ is a sorting variable in the cross-section. It equals one for the time series of both the treated firm and its control if COWs are in effect in the event year in the state where the treated firm was incorporated (Panel A), the newly connected firms share common corporate customers (Panel B), or are in the top or bottom half in terms of a certain characteristic (Panels C-D). $Treated_{i,c} \times Post_{c,t}$ is the double-difference term, the coefficient of which is the estimated effects of new connections in the subsample where $EventCharacteristic_c$ takes the value of zero. $EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t}$ is the triple-difference term, the coefficient of which is the estimated incremental effects of new connections where $EventCharacteristic_c$ takes the value of one relative to where $EventCharacteristic_c$ takes the value of zero. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$, $EventCharacteristic_c$, and $EventCharacteristic_c \times Treated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. For brevity, only coefficients of the double-difference and triple-difference terms are reported in the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Robustness to controlling for other inter-firm relationships

	Gross Margin	Operating Margin	ROA
Panel A: Control for customer-supplier relationships			
NonCusSupTreated × Post	0.004*	0.010***	0.007***
	(1.89)	(3.87)	(4.10)
CusSupTreated × Post	0.005	0.020**	0.019***
	(0.82)	(2.19)	(3.37)
Observations	68,669	68,508	68,576
Panel B: Control for joint ventures and strategic alliance			
NonAllianceTreated × Post	0.004*	0.010***	0.008***
	(1.88)	(4.02)	(4.42)
AllianceTreated × Post	0.005	0.002	–0.004
	(0.65)	(0.31)	(–0.82)
Observations	68,669	68,508	68,576
Panel C: Control for CO to all peers using kappa, κ (Amel-Zadeh et al., 2022)			
Treated × Post	0.005	0.009*	0.007*
	(1.00)	(1.69)	(1.82)
Δ(Common Ownership) × Post	0.000	0.005**	0.004*
	(0.20)	(2.11)	(1.88)
Observations	8,636	8,625	8,625
Panel D: Control for CO to all peers using GGL_{linear} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.24)	(3.17)	(3.52)
Δ(Common Ownership) × Post	0.004***	0.005***	0.004***
	(2.68)	(3.74)	(3.58)
Observations	40,401	40,295	8,625
Panel E: Control for CO to all peers using GGL_{fitted} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.25)	(3.18)	(3.53)
Δ(Common Ownership) × Post	0.006***	0.008***	0.004***
	(4.71)	(5.82)	(3.63)
Observations	40,401	40,295	40,336

Table 9: Robustness to controlling for other inter-firm relationships (continued)

	Gross Margin	Operating Margin	ROA
Panel F: Control for CO to all peers using GGL_{full_attn} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.24)	(3.17)	(3.53)
Δ(Common Ownership) × Post	0.003***	0.003**	0.000
	(3.05)	(2.02)	(0.34)
Observations	40,401	40,295	40,336
Panel G: Control for CO to new connections using GGL_{linear} (Gilje et al., 2020)			
Treated × Post	0.005	0.011***	0.008***
	(1.56)	(3.45)	(3.52)
Δ(Common Ownership) × Post	–0.001	–0.001	–0.000
	(–0.87)	(–1.02)	(–1.20)
Observations	41,151	41,044	4,449
Panel H: Control for CO to new connections using GGL_{fitted} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.008***
	(1.45)	(3.20)	(3.36)
Δ(Common Ownership) × Post	0.001	0.002	0.001
	(0.71)	(1.32)	(0.69)
Observations	41,151	41,044	41,083
Panel I: Control for CO to new connections using GGL_{full_attn} (Gilje et al., 2020)			
Treated × Post	0.004	0.010***	0.009***
	(1.35)	(3.26)	(3.46)
Δ(Common Ownership) × Post	0.001	0.000	–0.000
	(0.79)	(0.37)	(–0.32)
Observations	41,151	41,044	41,083
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: Panel A of this table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times NonCusSupTreated_{i,c} \times Post_{c,t} + \beta_2 \times CusSupTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $NonCusSupTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that is not its customer or supplier firm. $CusSupTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that is also a customer or supplier firm of its. Panel B of this table reports estimates from the following regression

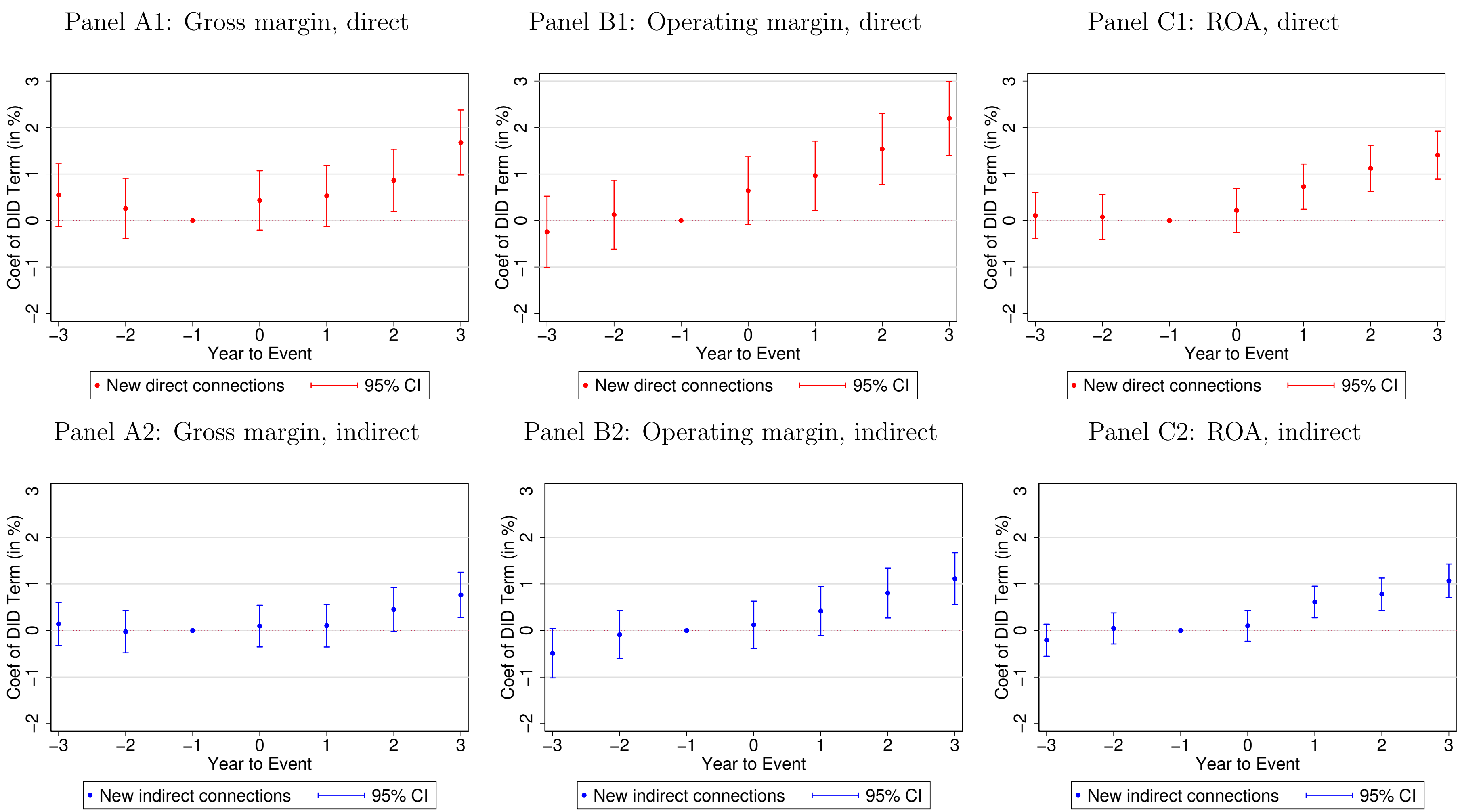
$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times NonAllianceTreated_{i,c} \times Post_{c,t} + \beta_2 \times AllianceTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $NonAllianceTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that it never formed strategic alliance or started joint venture with during the sample period. $AllianceTreated_{i,c}$ equals one for the time series of a firm forming new direct or indirect connections to a product market peer that it ever formed strategic alliance or started joint venture with during the sample period. Panels C to I of this table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times Treated_{i,c} \times Post_{c,t} + \gamma_1 \times \Delta(CommonOwnership)_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

To obtain $\Delta(CommonOwnership)_{i,c}$, in Panels C to F we calculate the mean of common ownership (CO) between a treated or control firm and all of its Hoberg-Phillips product market peers during [0, +3] minus the mean during [-3, -1]. In Panels H to I, we calculate the mean of common ownership (CO) between a treated firm and its newly connected product market peers during [0, +3] minus the mean during [-3, -1]. In these four panels, for control firms, we set $\Delta(CommonOwnership)_{i,c}$ to 0. $\Delta(CommonOwnership)_{i,c}$ is a constant for each time series of seven years (from τ = -3 to +3). We then scale it by its sample standard deviation. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. In these regressions we pool events of new direct and indirect connections together. $Treated_{i,c}$, $NonCusSupTreated_{i,c}$, $CusSupTreated_{i,c}$, $NonAllianceTreated_{i,c}$, $AllianceTreated_{i,c}$, $\Delta(CommonOwnership)_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. For brevity, we omit coefficients of $Post_{c,t}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1: Plots of the dynamics of the difference between treated and control firms

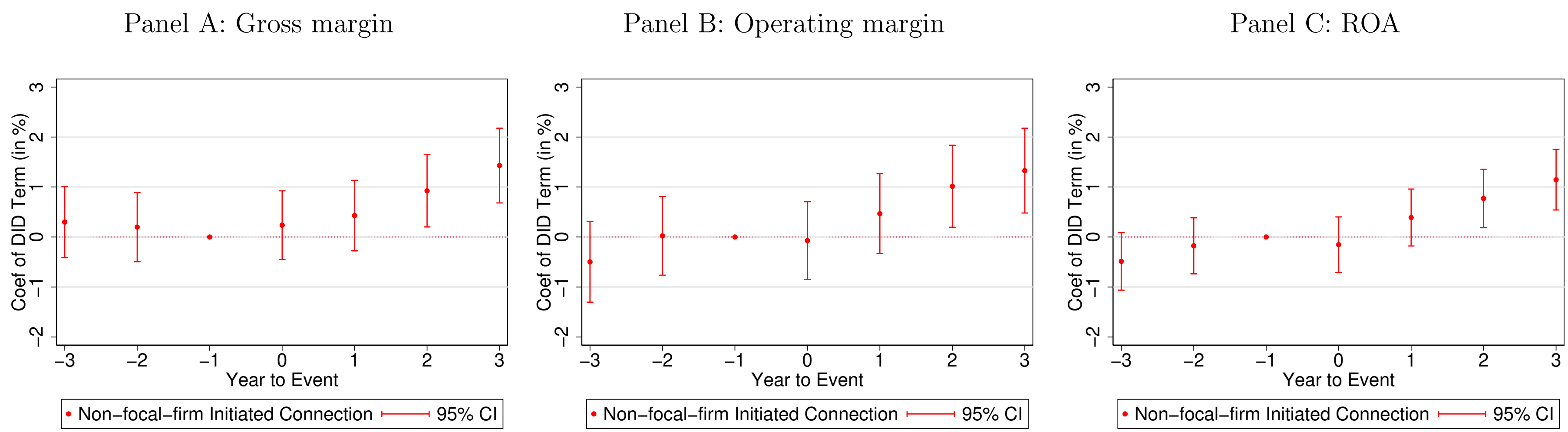


Note: This figure plots coefficients from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} \quad = \quad & \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
+ \quad & DirectTreated_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) \\
+ \quad & IndirectTreated_{i,c} \times (\sum_{s=-3}^{-2} \delta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \delta_s \times \mathbb{1}(\tau = s)_{c,t}) \\
+ \quad & \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that is equal to one for year $\tau = s$ relative to treatment year, with $s = -3, -2, 0, 1, 2, 3$. We omit the dummy variables for the year prior to the event (i.e., $\tau = -1$), which forms the baseline year. Thus all the effects we document are relative to this year. The estimates of γ_s and δ_s capture the difference in outcome variables between treated and control firms $-s$ years before the treatment (for $s = -3, -2$) or s years after the treatment (for $s = 0, 1, 2, 3$) relative to their difference in the baseline year. $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. Standard errors are clustered at the firm level.

Figure 2: Plots of the dynamics of the difference between treated and control firms, using the non-focal-firm-initiated board connections

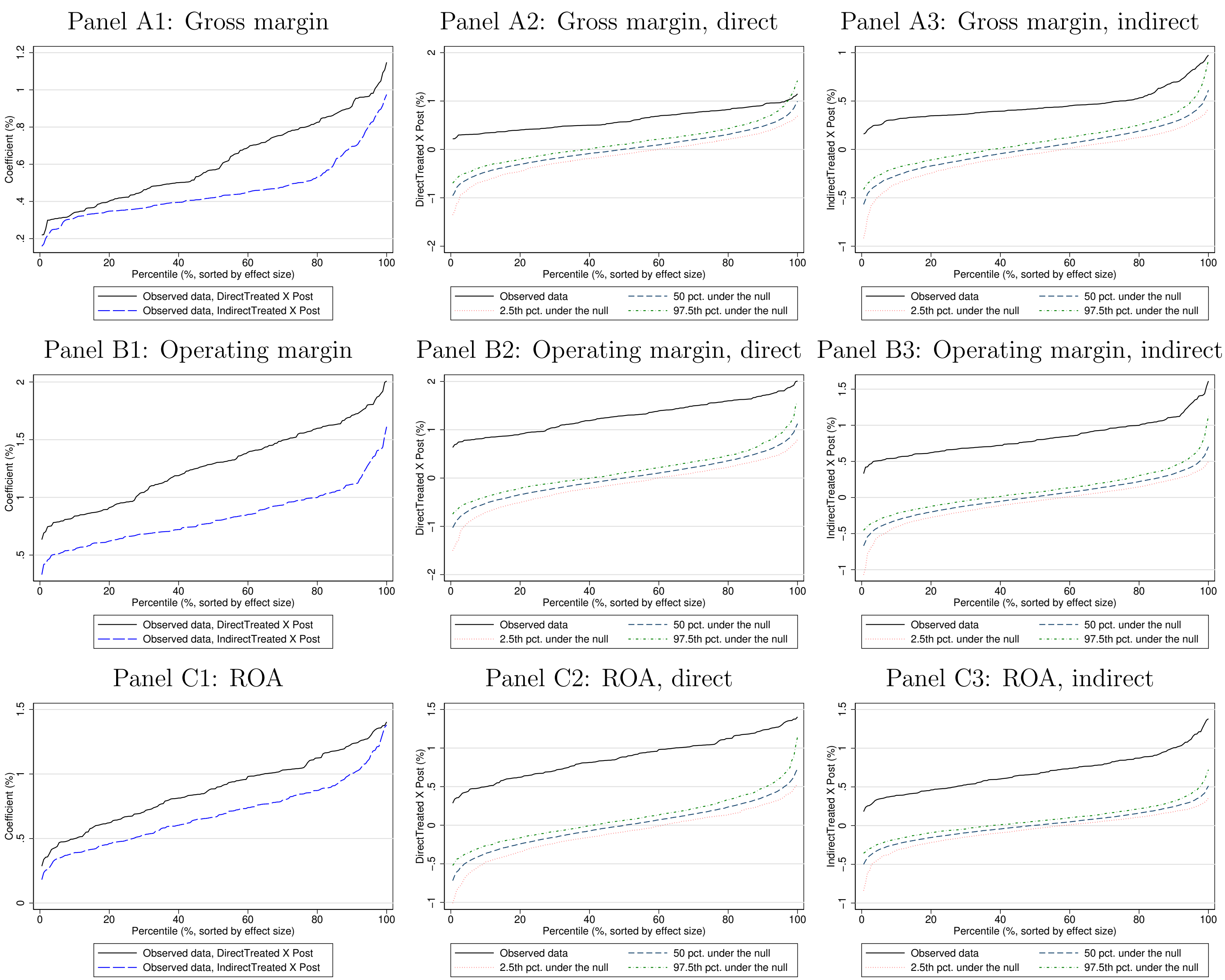


Note: This figure plots coefficients from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} \quad &= \quad \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
&+ \quad NFFInitiatedTreated_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that is equal to one for year $\tau = s$ relative to treatment year, with $s = -3, -2, 0, 1, 2, 3$. We omit the dummy variables for the year prior to the event (i.e., $\tau = -1$), which forms the baseline year. Thus all the effects we document are relative to this year. The estimates of γ_s capture the difference in outcome variables between treated and control firms $-s$ years before the treatment (for $s = -3, -2$) or s years after the treatment (for $s = 0, 1, 2, 3$) relative to their differences in the baseline year. $NFFInitiatedTreated_{i,c}$ is left out of the regressions as they are absorbed by $\theta_{i,c}$. Standard errors are clustered at the firm level.

Figure 3: Specification curve analysis



Note: In this figure, we conduct a specification curve analysis to assess the robustness of our findings to sample and regression specification choices and make joint inference (Simonsohn et al., 2020; Cookson, 2018; Bernstein et al., 2022). We proceed in the following steps:

1. We estimate the profit-enhancing effects using all possible combinations of industry classifications (Internet Appendix Table A17), matching schemes (Internet Appendix Table A20), number of matches (Internet Appendix Table A20), and regression specifications (Internet Appendix Table A21). We rank the coefficient estimates from the smallest to the largest, and plot the empirical cumulative distribution function (with the cumulative probability on the horizontal axis and coefficient estimates on the vertical axis). This is our observed specification curve.

2. We conduct inferences by assessing the plausibility of our observed specification curve under the null hypothesis. Following the steps proposed in Simonsohn et al. (2020) for non-experimental data, we generate bootstrapped specification curves as benchmarks for comparison, for which we force the null hypothesis of no effect on the data:

   (a) For a given specification, we estimate the model using the observed data and obtain coefficient estimates.

   (b) We then construct counterfactual dependent variables under the null. That is, we subtract the fitted treatment effects (i.e., the product of $TreatedDirect \times Post$ and the coefficient estimate for it, plus the product of $TreatedIndirect \times Post$ and the coefficient estimate for it) from the dependent variables. With the original independent variables and these modified dependent variables, the null hypothesis of no effect is forced on the data.

   (c) We draw with replacement a random sample of the same size as the original data and we estimate this specification on the drawn sample. The draw is at the treatment-control firm-pair level.

   (d) We repeat the previous step for 200 times with a fixed sequence of random seeds.

   (e) We repeat all previous steps for each specification. We now have 200 bootstrapped sets of estimates, each covering all possible specifications, resulting in 200 bootstrapped specification curves.

   (f) For each percentile in the empirical distribution of coefficient estimates, we rank the values from the 200 bootstrapped empirical curves. We then obtain the 2.5th, 50th, and 97.5th percentiles among these values. These form the median and 95% confidence bands of the bootstrapped specification curves constructed under the null hypothesis, which we plot alongside the observed specification curve.

In Panels A1, B1, and C1, we plot the observed specification curves for the effects of board connections on gross margin, operating margin, and ROA, respectively. In Panels A2 and A3 (B2 and B3; C2 and C3), we separately plot the observed specification curves for the effects of direct and indirect board connections on gross margin (operating margin; ROA). We also plot median and 95% confidence bands of the bootstrapped specification curves constructed under the null hypothesis.

Internet Appendix

IA1 Supplementary Tables and Figures

Table A1: List of variables

Panel A: Financial and accounting variables	
Assets	The natural logarithm of the firm's total assets (*log(at)*)
Gross Margin	The ratio of gross profit to sales (*gp/sale*)
Operating Margin	The ratio of operating income before depreciation and amortization to sales (*oibdp/sale*)
ROA	The ratio of operating income before depreciation and amortization to total assets (*oibdp/at*)
Sales Growth	The percentage change of sales relative to the prior year (*(sale-l.sale)/l.sale*)
Panel B: Indicator variables used in regressions	
DirectTreated	A dummy variable that equals one for the time series of a firm forming new direct connections to product market peers
IndirectTreated	A dummy variable that equals one for the time series of a firm forming new indirect connections to product market peers
Post	A dummy variable that equals zero for τ = -3, -2, -1, and equals one for τ = 0, 1, 2, and 3, where τ is the event year
NFFInitiatedTreated	A dummy variable that equals one for the time series of a firm forming non-focal-firm initiated new board connections to product market peers
MergerInducedTreated	A dummy variable that equals one for the time series of a firm forming merger-induced new board connections to product market peers
PseudoDirectTreated	A dummy variable that equals one for the time series of a firm forming direct connections to pseudo industry peers
PseudoIndirectTreated	A dummy variable that equals one for the time series of a firm forming indirect connections to pseudo industry peers

Table A1: List of variables (continued)

Panel C: Sorting variables	
COWs In Effect	A dummy variable that equals one if COWs are in effect in the current year in the state where the firm was incorporated, following Eldar and Grennan (2024)
If Share Major Customers	Whether the connected firm-pair has common major customer firms, i.e., those accounting for more than 10% of their total sales according to their annual disclosure
Similarity Score	The cosine similarity scores between the treated firm and its new connections (Hoberg and Phillips, 2010, 2016). If an event involves a new connection between a treated firm and multiple product market peers, it takes the value of the largest cosine similarity score
Top Similarity	A dummy that equals one for the time series of both the treated firm and its control if the new connections are in the top half in terms of the cosine similarity score between the treated firm and its new connections, and the new connections are in the same SIC-3 industry as the treated firm
HHI	The Herfindahl-Hirschman index of the text-based industry that the treated firm is in (Hoberg and Phillips, 2016)
Top HHI	A dummy that equals one for the time series of both the treated firm and its control if the treated firm is in the top half in terms of HHI among all treated firms treated in the same year

Table A1: List of variables (continued)

Panel D: Other variables	
κ	The firm-pair-year level measure of common ownership developed in Amel-Zadeh et al. (2022)
GGL_{linear}	The firm-pair-year level measure of common ownership developed in Gilje et al. (2020)
GGL_{fitted}	A version of common ownership measure developed in Gilje et al. (2020) that uses a non-parametric fitted attention function estimated with voting data
GGL_{full_attn}	A version of common ownership measure developed in Gilje et al. (2020) that assumes full attention, i.e., $g = 1$
$\Delta(CommonOwnership)$	The change in the within-industry common ownership, i.e., the mean common ownership between a firm and its product market peers from $\tau = -3, -2, -1$ to $\tau = 0, 1, 2, 3$. We calculate both $\Delta(CommonOwnership)$ to all of a firm's Hoberg-Phillips product market peers and also $\Delta(CommonOwnership)$ to a firm's newly connected product market peers. For the former, for each treated firm, we calculate the average common ownership measure between the firm and all of its Hoberg-Phillips product market peers. We do it separately for each year from $\tau = -3$ to $\tau = 3$. Then we take a prior-event average using $\tau = -3, -2, -1$, and a post-event average using $\tau = 0, 1, 2, 3$, and take the post-minus-prior difference. We arrive at a constant for each time series of length 7 (from τ = -3 to +3). We do the same calculation for each control firm around the treatment year of the treated firm it is matched to. Finally, we scale this measure by its sample standard deviation. For the latter, we do the same calculation for treated firms but using the common ownership measure to its newly connected product market peers only. For control firms, we set $\Delta(CommonOwnership)$ to 0

Table A2: Characteristics of directors involved in board connections

	Directors Involved			Other Directors			
	Mean	SD	N	Mean	SD	N	T-Stat
Age	58.6	8.3	6,999	59.1	9.4	39,555	-4.55
Is female	0.12		6,999	0.10		39,555	5.08
Is non-executive director	0.89		6,999	0.81		39,555	16.13
Total number of seats	2.6	1.3	6,999	1.8	1.1	39,555	48.5
Years of experience	30.3	9.6	6,999	30.6	10.6	39,555	-2.37
Tenure	9.3	5.3	6,999	10.5	5.5	39,555	-17.36
Highest education degree							
Undergraduate degree	30.3%			31.8%			-2.44
Master	48.3%			45.6%			4.10
Doctoral	21.4%			22.6%			-2.18
Total	100%		6,780	100%		36,793	
Source of nomination							
By search firms	26.5%			24.4%			0.96
CEO recommendation	8.5%			8.9%			-0.28
By other insiders	3.4%			1.8%			2.23
By independent directors	8.1%			9.4%			-0.89
Merger	2.6%			4.7%			-2.03
Nominated by shareholders	1.3%			1.5%			-0.33
Promition	2.8%			3.3%			-0.56
By the nominating committee	46.8%			46.0%			0.32
Total	100%		468	100%		2,361	
Centrality							
Degree centrality	0.0007	0.0003	6,999	0.0004	0.0003	39,555	77.1
Closeness centrality	0.1338	0.0123	6,999	0.1272	0.0137	39,555	128.6
Betweenness centrality	0.0008	0.0008	6,999	0.0003	0.0005	39,555	50.57
Eigenvector centrality	0.0014	0.0041	6,999	0.0008	0.0026	39,555	11.83

Note: This table reports the characteristics of directors in treated firms that are involved in the board connections and of other directors in the treated firms. *Age*, *Is Female*, *Is Non-Executive Director*, *Total Number of Seats*, *Years of Experience*, and *Highest Education Degree* are based on BoardEx. *Years of Experience* is the number of years since the director first served any role that is recorded in BoardEx. *Tenure* is the number of years that the director serves in the treated firm since initial appointment. *Total Number of Seats* is the number of board seats in different firms that a director simultaneously holds in the treatment year. *Source of nomination* uses the board of directors nomination data constructed in Akyol and Cohen (2013). *Director centrality* is constructed following Fogel et al. (2021) and Bakke et al. (2024).

Table A3: Double-difference regressions, using other outcome variables

	(1) ln(Sales)	(2) ln(COGS)	(3) ln(SG&A)	(4) Markup	(5) ln(Assets)	(6) ln(CAPEX)	(7) ln(R&D)	(8) Tobin's Q
Post	-0.014**	-0.003	0.000	-0.019***	-0.004	-0.012	0.008	-0.044**
	(-2.31)	(-0.33)	(0.01)	(-4.43)	(-0.53)	(-1.09)	(0.81)	(-2.10)
DirectTreated × Post	0.028*	0.024	0.013	0.021***	-0.010	-0.009	-0.021	-0.046
	(1.80)	(1.27)	(0.83)	(2.59)	(-0.56)	(-0.36)	(-1.00)	(-0.99)
IndirectTreated × Post	0.002	-0.005	-0.013	0.019***	-0.026**	-0.045**	-0.021	-0.052*
	(0.13)	(-0.37)	(-1.16)	(3.03)	(-2.01)	(-2.51)	(-1.34)	(-1.71)
Observations	68,669	68,633	65,638	48,272	68,745	68,266	44,202	67,878
Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1	1	1	1	1
Adjusted R-squared	0.977	0.971	0.975	0.905	0.970	0.934	0.967	0.691

Note: This table reports estimates from the following regression using the sample of all events,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Column (1) uses $ln(Sales)$, the natural logarithm of total sales ($sale$) as the outcome variable. Column (2) uses the logarithm of the cost of good sold ($cogs$). Column (3) uses the logarithm of selling, general and administrative costs ($xsga$). Column (4) uses the markup calculated using the cost share approach and adjusting for intangible capital, following Peters and Taylor (2017) and Ayyagari et al. (2023). Column (5) uses the logarithm of assets (at). Column (6) uses the logarithm of capital expenditure ($capex$). Column (7) uses the logarithm of R&D expenditure (xrd). Column (8) uses Tobin's Q. All outcome variables are winsorized at their 1% and 99% percentiles. $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ are left out of the regressions as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Summary statistics of variables based on barcode-level data

	Mean	Min	p10	p25	Median	p75	p90	Max	N
Panel A: Price index									
Price Index (%)	0.44	-18.10	-5.68	-2.12	0.13	2.69	6.74	22.86	53,157,657
Quantity Index (%)	3.96	-66.60	-26.43	-12.74	-0.47	13.40	34.23	300.00	53,157,657
Panel B: Similarity of geographic distribution									
By Zip-3	0.24	0.00	0.00	0.02	0.13	0.38	0.68	0.93	64,041,688
By County	0.43	0.00	0.04	0.15	0.38	0.71	0.90	0.98	64,041,688
By DMA	0.31	0.00	0.00	0.03	0.21	0.53	0.80	0.96	64,041,688
Panel C: Number of new products introduced									
Total in a Quarter	7.37	0.00	0.00	0.00	0.00	2.00	12.00	202.00	274,100
New Products in Existing Product Lines	6.86	0.00	0.00	0.00	0.00	1.00	10.00	192.00	274,100
New Products in New Product Lines	0.28	0.00	0.00	0.00	0.00	0.00	0.00	9.00	274,100
log(Total in a Quarter + 1)	0.71	0.00	0.00	0.00	0.00	1.10	2.56	5.31	274,100
log(New Products in Existing Product Lines + 1)	0.65	0.00	0.00	0.00	0.00	0.69	2.40	5.26	274,100
log(New Products in New Product Lines + 1)	0.11	0.00	0.00	0.00	0.00	0.00	0.00	2.30	274,100

Note: This table reports summary statistics for variables constructed based on the barcode-level data. Variables in Panels A and C are winsorized at the 1% and 99% percentiles. We report the sample mean, sample minimum, 10%, 25%, 50%, 75%, 90% percentiles, sample maximum, and number of observations in each column.

Table A5: Double-difference regressions, using merger-induced board connections

	Gross Margin	Operating Margin	ROA
Panel A: Baseline matching scheme			
Post	0.002	–0.008	–0.004
	(0.24)	(–0.73)	(–0.49)
MergerInducedTreated × Post	0.002	0.031**	0.028**
	(0.15)	(2.02)	(2.56)
Observations	1,279	1,279	1,279
Adjusted R-sqaured	0.918	0.766	0.656
Panel B: Require that control firm directors also cross-sit on M&A firms			
Post	0.009	0.015	0.011
	(1.04)	(1.15)	(1.35)
MergerInducedTreated × Post	0.009	0.034*	0.025**
	(0.64)	(1.89)	(2.17)
Observations	1,420	1,420	1,420
Adjusted R-sqaured	0.902	0.757	0.742
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	3	3	3

Note: This table reports estimates from the following regression using the merger-induced board connections,

$$Y_{i,j,c,t} = \alpha_1 \times Post_{c,t} + \beta_1 \times MergerInducedTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $MergerInducedTreated_{i,c} \times Post_{c,t}$ is the double-difference term, the coefficient of which is the estimated effects of merger-induced new board connection with peer firms. Panel A uses the same matching procedure as described in Section 2.1.2. To address the concern that mergers might have spillover effects, Panel B further requires in the matching procedure that the control firm has a director who cross-serves on the board of a firm experiencing merger, but such a merger does not lead to new board connections of the control firm to its product market peers. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $MergerInducedTreated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Corporate Opportunity Waivers (COWs) and the frequency of board connections

	(1)
	Prob. of forming new connection
COWs In Effect	0.023***
	(3.95)
Observations	55,880
Firm FE	Yes
FF48 × Year FE	Yes
Clustering	Firm

Note: This table reports estimates from the following linear probability regression

$$\mathbb{1}(\text{Forming a new board connection to a product market peer})_{i,j,t} = \beta \times \mathit{COWsInEffect}_{i,t} + \theta_i + \theta_{j,t} + e_{i,j,t}.$$

Here $\mathit{COWsInEffect}_{i,t}$ equals one if COWs are in effect in year t in the state where firm i was incorporated. θ_i are firm fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Double-difference regressions by executive versus non-executive directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.007***	-0.007***	-0.007***
	(-3.88)	(-4.31)	(-5.50)
DirectTreated, Is Not Exec. × Post	0.007*	0.013***	0.008***
	(1.75)	(3.19)	(2.93)
DirectTreated, Is Exec. × Post	0.008*	0.015**	0.009**
	(1.65)	(2.32)	(1.98)
IndirectTreated, Is Not Exec. × Post	0.001	0.006**	0.006***
	(0.63)	(2.23)	(3.25)
IndirectTreated, Is Exec. × Post	0.008**	0.011***	0.005**
	(2.04)	(2.92)	(2.05)
Observations	68,682	68,526	68,594
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.878	0.746	0.667

Note: This table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} \\ &+ \beta_1 \times DirectTreatedIsNotExec_{i,c} \times Post_{c,t} + \beta_2 \times DirectTreatedIsExec_{i,c} \times Post_{c,t} \\ &+ \beta_3 \times IndirectTreatedIsNotExec_{i,c} \times Post_{c,t} + \beta_4 \times IndirectTreatedIsExec_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $DirectTreatedIsNotExec_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and only non-executive directors are involved. $DirectTreatedIsExec_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and directors who are also executives are involved. $IndirectTreatedIsNotExec_{i,c}$ equals one for the time series of a firm forming indirect connections to product market peers and only non-executive directors are involved. $IndirectTreatedIsExec_{i,c}$ equals one for the time series of a firm forming indirect connections to product market peers and directors who are also executives are involved. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $DirectTreatedIsNotExec_{i,c}$, $DirectTreatedIsExec_{i,c}$, $IndirectTreatedIsNotExec_{i,c}$, and $IndirectTreatedIsExec_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Double-difference regressions by inbound versus outbound directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.007***	-0.008***	-0.007***
	(-4.07)	(-4.46)	(-5.60)
DirectTreated, Inbound × Post	0.006	0.014***	0.012***
	(1.40)	(2.91)	(3.68)
DirectTreated, Outbound × Post	0.009**	0.013***	0.005
	(2.03)	(2.58)	(1.34)
IndirectTreated	0.004*	0.008***	0.006***
	(1.81)	(3.38)	(3.74)
Observations	68,682	68,526	68,594
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.878	0.746	0.667

Note: This table reports estimates from the following regression

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreatedInbound_{i,c} \times Post_{c,t} \\
&+ \beta_2 \times DirectTreatedOutbound_{i,c} \times Post_{c,t} + \beta_3 \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $DirectTreatedInbound_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and the connections are caused by new appointments to the treated firm's board. $DirectTreatedOutbound_{i,c}$ equals one for the time series of a firm forming direct connections to product market peers and the connections are caused by existing directors of the treated firm getting appointed to a peer firm. $IndirectTreated_{i,c}$ equals one for the time series of a firm forming indirect connections to product market peers. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $DirectTreatedInbound_{i,c}$, $DirectTreatedOutbound_{i,c}$, and $IndirectTreated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Effects on firm profitability by the number of connecting directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
OneDirector × DirectTreated × Post	0.008**	0.010**	0.007**
	(2.25)	(2.29)	(2.23)
MultipleDirector × DirectTreated × Post	0.005	0.032*	0.017*
	(0.37)	(1.87)	(1.69)
OneDirector × IndirectTreated × Post	0.002	0.006**	0.005**
	(0.87)	(2.23)	(2.45)
MultipleDirector × IndirectTreated × Post	0.009**	0.015***	0.011***
	(2.56)	(3.24)	(3.40)
Observations	68,682	68,526	68,594
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.878	0.747	0.667

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times OneDirector_c \times Post_{c,t} + \alpha_2 \times MultipleDirector_c \times Post_{c,t} \\ &+ \beta_1 \times OneDirector_c \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times MultipleDirector_c \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_3 \times OneDirector_c \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_4 \times MultipleDirector_c \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $OneDirector_c$ ($MultipleDirector_c$) equals one for both treated and control firms if there is a single connecting director (there are multiple connecting directors) between the treated firm and its product market peers. For indirect connections, we say that there are multiple connecting directors if (1) the treated firm and the intermediate firm share multiple directors, (2) the intermediate firm and the peer firm share multiple directors, or (3) there are multiple intermediate firms connecting competing firms. $DirectTreated_{i,c}$ ($IndirectTreated_{i,c}$) is a dummy variable equal to one for the treated firms that experience a new direct (indirect) board connection to a product market peer. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. Coefficient estimates of $OneDirector_c \times Post_{c,t}$ and $MultipleDirector_c \times Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Effects on product prices by the number of connecting directors

	(1) Price Index	(2) Price Index	(3) Price Index
OneDirector × DirectTreated × Post	0.00209***	0.00171**	0.00157*
	(2.54)	(2.04)	(1.82)
MultipleDirector × DirectTreated × Post	0.00849***	0.00969**	0.00969**
	(2.66)	(2.12)	(2.12)
OneDirector × IndirectTreated × Post	0.00083***	0.00073***	0.00070***
	(3.89)	(3.38)	(3.37)
MultipleDirector × IndirectTreated × Post	-0.00058	-0.00046	-0.00033
	(-1.17)	(-1.04)	(-0.82)
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.370	0.371	0.372
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%

Note: This table reports estimates from the following regression,

$$\begin{aligned}
P_{i,m,z,t} &= \alpha_1 \times OneDirectorDirectTreated_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_2 \times MultipleDirectorDirectTreated_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_3 \times OneDirectorIndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_4 \times MultipleDirectorIndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\
&+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}.
\end{aligned}$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. $OneDirectorDirectTreated_{i,m,z} \times Post_{i,m,z,t}$ ($MultipleDirectorDirectTreated_{i,m,z} \times Post_{i,m,z,t}$, $OneDirectorIndirectTreated_{i,m,z} \times Post_{i,m,z,t}$, $MultipleDirectorIndirectTreated_{i,m,z} \times Post_{i,m,z,t}$) equals one for firm-product-module-zip3 treated with direct (direct; indirect; indirect) connections with single (multiple; single; multiple) connecting directors in quarters post the treatment. For indirect connections, we say that there are multiple connecting directors if (1) the treated firm and the intermediate firm share multiple directors, (2) the intermediate firm and the peer firm share multiple directors, or (3) there are multiple intermediate firms connecting competing firms. $\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Effects on firm profitability by the centrality of connecting directors or the newly connected peers

	Gross Margin	Operating Margin	ROA
Panel A: By centrality of the connecting director			
DirectTreated × Centrality < Median × Post	0.003	0.010**	0.008**
	(0.71)	(2.02)	(2.13)
DirectTreated × Centrality ≥ Median × Post	0.010**	0.017***	0.010***
	(2.02)	(3.19)	(2.68)
IndirectTreated × Centrality < Median × Post	0.003	0.004	0.005**
	(0.90)	(1.33)	(2.01)
IndirectTreated × Centrality ≥ Median × Post	0.005	0.013***	0.009***
	(1.49)	(3.84)	(3.81)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.770	0.699
Panel B: By the number of peers reachable to the connecting director			
DirectTreated × Centrality < Median × Post	0.001	0.007	0.008**
	(0.26)	(1.63)	(2.21)
DirectTreated × Centrality ≥ Median × Post	0.014**	0.022***	0.011***
	(2.28)	(3.67)	(2.73)
IndirectTreated × Centrality < Median × Post	0.004	0.004*	0.004**
	(1.46)	(1.67)	(2.05)
IndirectTreated × Centrality ≥ Median × Post	0.003	0.016***	0.012***
	(0.79)	(3.40)	(3.67)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.770	0.699
Panel C: By centrality of the newly connected firm			
DirectTreated × Centrality < Median × Post	0.007	0.009	0.008*
	(1.14)	(1.52)	(1.67)
DirectTreated × Centrality ≥ Median × Post	0.008	0.014**	0.009**
	(1.60)	(2.38)	(1.96)
IndirectTreated × Centrality < Median × Post	0.004	0.004	0.004
	(1.19)	(1.21)	(1.50)
IndirectTreated × Centrality ≥ Median × Post	0.003	0.013***	0.010***
	(0.94)	(3.54)	(3.89)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.769	0.699
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Centrality < Median_c \times Post_{c,t} + \alpha_2 \times Centrality \geq Median_c \times Post_{c,t} \\ &+ \beta_1 \times Centrality < Median_c \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times Centrality \geq Median_c \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_3 \times Centrality < Median_c \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_4 \times Centrality \geq Median_c \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. In Panel A, we sort treated firms by the director centrality of the connecting director among all directors in the treated firm's product market peers, which varies at the firm-director-year level. In Panel C, we sort treated firms by the firm centrality of the newly connected product market peer. $Centrality \geq Median_c$ equals one for both treated and control firms if the director (firm) centrality of the connecting director in the treated firm (the newly connected product market peer) is above median when sorted within each year in Panel A (C). $Centrality < Median_c$ equals one otherwise. In Panel B, $Centrality \geq Median_c$ equals one if the number of product market peers that the connecting director can reach is above the median when sorted within each year. We say that a director can reach a firm if she sits on their board or if she can reach them via one or two intermediate firms in the director networks. $DirectTreated_{i,c}$ ($IndirectTreated_{i,c}$) is a dummy variable equal to one for the treated firms that experience a new direct (indirect) board connection to a product market peer. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. Coefficient estimates of $Centrality < Median_c \times Post_{c,t}$ and $Centrality \geq Median_c \times Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Effects on product prices by the centrality of connecting directors or the newly connected peers

	Price Index	Price Index	Price Index
Panel A: By centrality of the connecting director			
DirectTreated × Centrality < Median × Post	0.00157	0.00092	0.00037
	(1.52)	(0.94)	(0.35)
DirectTreated × Centrality ≥ Median × Post	0.00369***	0.00385***	0.00372***
	(3.06)	(3.16)	(4.00)
IndirectTreated × Centrality < Median × Post	0.00014	0.00006	-0.00003
	(0.49)	(0.19)	(-0.08)
IndirectTreated × Centrality ≥ Median × Post	0.00106***	0.00101***	0.00107***
	(3.94)	(3.70)	(4.07)
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.370	0.371	0.372
Panel B: By the number of peers reachable to the connecting director			
DirectTreated × Centrality < Median × Post	0.00102	0.00068	0.00078
	(0.78)	(0.51)	(0.59)
DirectTreated × Centrality ≥ Median × Post	0.00325***	0.00283***	0.00246**
	(2.55)	(2.62)	(2.36)
IndirectTreated × Centrality < Median × Post	0.00056**	0.00046*	0.00044*
	(2.28)	(1.73)	(1.83)
IndirectTreated × Centrality ≥ Median × Post	0.00069**	0.00067**	0.00067**
	(2.25)	(2.10)	(2.08)
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.370	0.371	0.372
Panel C: By centrality of the newly connected firm			
DirectTreated × Centrality < Median × Post	0.00192*	0.00171*	0.00147
	(1.72)	(1.65)	(1.51)
DirectTreated × Centrality ≥ Median × Post	0.00255*	0.00198	0.00188
	(1.70)	(1.34)	(1.25)
IndirectTreated × Centrality < Median × Post	0.00059**	0.00042*	0.00038
	(2.24)	(1.68)	(1.62)
IndirectTreated × Centrality ≥ Median × Post	0.00068*	0.00072**	0.00073**
	(1.88)	(2.35)	(2.54)
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.370	0.371	0.372
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%

Note: This table reports estimates from the following regression,

$$\begin{aligned} P_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times Centrality < Median_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_2 \times DirectTreated_{i,m,z} \times Centrality \geq Median_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_3 \times IndirectTreated_{i,m,z} \times Centrality < Median_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_4 \times IndirectTreated_{i,m,z} \times Centrality \geq Median_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned}$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. In Panel A, we sort firm-product-module-zip3 by the director centrality of the connecting director in the treated firm among directors in the treated firm's product market peers. In Panel B, we use the number of product market peers reachable to the connecting director instead. We say that a director can reach a firm if she sits on their board or if she can reach them via one or two intermediate firms in the director networks. In Panel C, we use the firm centrality of the newly connected product market peer. $DirectTreated_{i,m,z} \times Centrality < Median_{i,m,z} \times Post_{i,m,z,t}$ ($DirectTreated_{i,m,z} \times Centrality \geq Median_{i,m,z} \times Post_{i,m,z,t}$; $IndirectTreated_{i,m,z} \times Centrality < Median_{i,m,z} \times Post_{i,m,z,t}$; $IndirectTreated_{i,m,z} \times Centrality \geq Median_{i,m,z} \times Post_{i,m,z,t}$) equals one for firm-product-module-zip3 treated with direct (direct; indirect; indirect) connections with the centrality of the connecting director in the treated firm or the newly connected product market peer below (above; below; above) the median in quarters post the treatment. $\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Effects on firm profitability by the busyness of connecting directors

	Gross Margin	Operating Margin	ROA
Panel A: By busyness of the connecting director, busy = N non-peer appointments > 1			
DirectTreated × DirectorNotBusy × Post	0.008**	0.014***	0.009***
	(2.09)	(3.38)	(3.20)
DirectTreated × DirectorBusy × Post	0.001	0.011	0.006
	(0.10)	(1.57)	(1.14)
IndirectTreated × DirectorNotBusy × Post	0.005*	0.009***	0.007***
	(1.77)	(3.26)	(3.47)
IndirectTreated × DirectorBusy × Post	–0.001	0.005	0.005
	(–0.19)	(1.06)	(1.43)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.769	0.699
Panel B: By busyness of the connecting director, busy = N non-peer appointments > 2			
DirectTreated × DirectorNotBusy × Post	0.008**	0.014***	0.009***
	(2.16)	(3.64)	(3.17)
DirectTreated × DirectorBusy × Post	–0.008	0.003	0.010
	(–0.68)	(0.21)	(1.09)
IndirectTreated × DirectorNotBusy × Post	0.005*	0.010***	0.008***
	(1.93)	(3.66)	(3.99)
IndirectTreated × DirectorBusy × Post	–0.012	–0.009	–0.000
	(–1.35)	(–1.27)	(–0.01)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.769	0.699
Panel C: By busyness of the connecting director, busy = N committee obligations > 1			
DirectTreated × DirectorNotBusy × Post	0.008**	0.016***	0.011***
	(2.00)	(3.46)	(3.48)
DirectTreated × DirectorBusy × Post	0.004	0.006	0.002
	(0.59)	(0.83)	(0.35)
IndirectTreated × DirectorNotBusy × Post	0.005**	0.009***	0.007***
	(1.96)	(3.02)	(3.35)
IndirectTreated × DirectorBusy × Post	–0.001	0.007*	0.007**
	(–0.38)	(1.83)	(2.42)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.769	0.699
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Table A13: Effects on firm profitability by the busyness of connecting directors (continued)

	Gross Margin	Operating Margin	ROA
Panel D: By busyness of the connecting director, busy = N committee obligations > 2			
DirectTreated × DirectorNotBusy × Post	0.007**	0.014***	0.009***
	(2.00)	(3.41)	(3.28)
DirectTreated × DirectorBusy × Post	0.002	0.013	0.005
	(0.28)	(1.33)	(0.61)
IndirectTreated × DirectorNotBusy × Post	0.005*	0.009***	0.007***
	(1.92)	(3.31)	(3.49)
IndirectTreated × DirectorBusy × Post	–0.005	0.003	0.008**
	(–0.96)	(0.66)	(2.11)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.769	0.699
Panel E: By busyness of the connecting director, busy = serving on multiple kinds of committee			
DirectTreated × DirectorNotBusy × Post	0.007**	0.015***	0.010***
	(2.00)	(3.51)	(3.44)
DirectTreated × DirectorBusy × Post	0.004	0.004	0.001
	(0.51)	(0.54)	(0.25)
IndirectTreated × DirectorNotBusy × Post	0.005*	0.008***	0.007***
	(1.80)	(2.96)	(3.47)
IndirectTreated × DirectorBusy × Post	–0.001	0.008*	0.007**
	(–0.39)	(1.95)	(2.13)
Observations	68,669	68,508	68,576
Adjusted R-sqaured	0.900	0.769	0.699
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: In this table, we sort new board connections by the busyness of the connecting directors (i.e., the cross-sitting director for direct connections), or the director shared by the treated firm and the intermediate firm for indirect connections. We report estimates from the following regressions,

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times DirectorNotBusy_c \times Post_{c,t} + \alpha_2 \times DirectorBusy_c \times Post_{c,t} \\
&+ \beta_1 \times DirectorNotBusy_c \times DirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_2 \times DirectorBusy_c \times DirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_3 \times DirectorNotBusy_c \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_4 \times DirectorBusy_c \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

In Panel A (B), we define a connecting director to be busy if the director simultaneously holds more than one (two) board positions in non-product-market-peer firms in the year of the treatment. In Panel C (D), we alternatively define a director to be busy if she serves on more than one (two) committees (nominating, compensation, auditing, etc.). In Panel E, we say that a director is busy if she serves on multiple kinds of committees in the same or different firms.

Table A14: Effects on product prices by the busyness of connecting directors

	Price Index	Price Index	Price Index
Panel A: By busyness of the connecting director, busy = N non-peer appointments > 1			
DirectTreated × DirectorNotBusy × Post	0.00289**	0.00228*	0.00204*
	(2.15)	(1.81)	(1.69)
DirectTreated × DirectorBusy × Post	0.00019	0.00070	0.00080
	(0.21)	(1.00)	(1.14)
IndirectTreated × DirectorNotBusy × Post	0.00067***	0.00063**	0.00058***
	(2.74)	(2.32)	(2.48)
IndirectTreated × DirectorBusy × Post	0.00062***	0.00054**	0.00055**
	(2.65)	(2.21)	(2.02)
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.370	0.371	0.372
Panel B: By busyness of the connecting director, busy = N non-peer appointments > 2			
DirectTreated × DirectorNotBusy × Post	0.00278**	0.00209*	0.00194*
	(2.34)	(1.95)	(1.82)
DirectTreated × DirectorBusy × Post	0.00007	0.00091	0.00078
	(0.09)	(1.35)	(1.02)
IndirectTreated × DirectorNotBusy × Post	0.00076***	0.00069***	0.00069***
	(3.47)	(3.23)	(3.47)
IndirectTreated × DirectorBusy × Post	0.00023	0.00017	0.00010
	(0.61)	(0.41)	(0.25)
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.370	0.371	0.372
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%

Note: This table reports estimates from the following regression,

$$\begin{aligned} P_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times DirectorNotBusy_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_2 \times DirectTreated_{i,m,z} \times DirectorBusy_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_3 \times IndirectTreated_{i,m,z} \times DirectorNotBusy_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_4 \times IndirectTreated_{i,m,z} \times DirectorBusy_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned}$$

In Panel A (B), we define a connecting director to be busy if the director simultaneously holds more than one (two) board positions in non-product-market-peer firms in the year of the treatment. Columns (1)-(3) use 10%, 5%, and 3% joint market-share thresholds, respectively.

Table A15: Effects of other network ties on firm profitability

	Gross Margin	Operating Margin	ROA
Panel A: Connections via shared work experience outside of public firm boards			
OtherNetworkTiesTreated × Post	0.003**	0.002	0.000
	(2.21)	(1.61)	(0.47)
Observations	231,486	220,276	220,330
Adjusted R-squared	0.919	0.847	0.760
Panel B: Connections via education			
OtherNetworkTiesTreated × Post	0.007***	0.006***	0.002*
	(3.67)	(3.40)	(1.88)
Observations	85,412	80,926	80,940
Adjusted R-squared	0.909	0.836	0.777
Panel C: Connections via other activities			
OtherNetworkTiesTreated × Post	0.002	0.004**	0.001
	(1.42)	(2.31)	(0.89)
Observations	95,864	89,830	89,849
Adjusted R-squared	0.921	0.847	0.801
Panel D: Connections via shared ethnic origin			
OtherNetworkTiesTreated × Post	–0.000	–0.001	0.000
	(–0.18)	(–0.61)	(0.24)
Observations	150,195	142,702	142,733
Adjusted R-squared	0.919	0.840	0.782

Note: This table reports estimates from the following regression,

$$Y_{i,j,c,t} \quad = \quad \alpha_1 \times Post_{c,t} + \beta_1 \times OtherNetworkTiesTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $OtherNetworkTiesTreated_{i,c}$ is a dummy variable equal to one for the treated firms that have directors who possess shared non-board work experience (educational experience; non-business-related activities; ethnic origin) with directors in product market peers in Panel A (B; C; D). $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. The treatment year is the year in which directors with these ties begin serving on the boards of the treated firms. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $OtherNetworkTiesTreated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. Coefficients of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A16: Effects of other network ties on product prices

	Price Index	Price Index	Price Index
Panel A: Connections via shared work experience outside of public firm boards			
OtherNetworkTiesTreated × Post	0.00016	0.00024**	0.00023**
	(1.52)	(2.28)	(2.23)
Observations	57,045,513	57,959,595	58,369,975
Adjusted R-squared	0.369	0.366	0.365
Panel B: Connections via education			
OtherNetworkTiesTreated × Post	0.00039	0.00039*	0.00037*
	(1.63)	(1.81)	(1.68)
Observations	53,769,991	53,877,670	53,958,199
Adjusted R-squared	0.373	0.373	0.372
Panel C: Connections via other activities			
OtherNetworkTiesTreated × Post	-0.00024	-0.00016	-0.00017
	(-0.71)	(-0.52)	(-0.56)
Observations	55,023,572	55,235,820	55,332,270
Adjusted R-squared	0.368	0.367	0.367
Panel D: Connections via shared ethnic origin			
OtherNetworkTiesTreated × Post	-0.00008	-0.00003	-0.00002
	(-0.56)	(-0.22)	(-0.17)
Observations	60,847,333	62,310,560	62,863,431
Adjusted R-squared	0.374	0.372	0.372
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%

Note: This table reports estimates from the following regression,

$$P_{i,m,z,t} = \alpha \times OtherNetworkTiesTreated_{i,m,z} \times Post_{i,m,z,t} + \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}.$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. $OtherNetworkTiesTreated_{i,m,z} \times Post_{i,m,z,t}$ equals zero for those firm-product-module-zip3 combinations that are never treated and for treated firm-product-module-zip3 in quarters prior to the treatment of other network ties. It equals one for treated firm-product-module-zip3 in quarters post the treatment. Firms are treated when they appoint directors who possess shared non-board work experience (educational experience; non-business-related activities; ethnic origin) with directors in product market peers in Panel A (B; C; D). $\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A17: Robustness to alternative industry classification

	Gross Margin	Operating Margin	ROA
Panel A: Using FactSet to identify peer firms			
DirectTreated × Post	0.006	0.017**	0.012**
	(0.92)	(2.10)	(2.28)
IndirectTreated × Post	0.003	0.009**	0.007***
	(0.91)	(2.50)	(2.90)
Observations	20,998	20,521	20,539
Panel B: Using SIC-3 to identify peer firms			
DirectTreated × Post	0.004	0.015***	0.012***
	(1.38)	(4.04)	(4.73)
IndirectTreated × Post	0.004*	0.010***	0.009***
	(1.93)	(4.38)	(5.25)
Observations	81,325	81,146	81,229
Panel C: Using SIC-4 to identify peer firms			
DirectTreated × Post	0.003	0.013***	0.007**
	(0.77)	(2.79)	(2.39)
IndirectTreated × Post	0.007***	0.010***	0.007***
	(2.72)	(3.58)	(3.64)
Observations	53,054	52,944	53,009
Panel D: Using GICS-6 to identify peer firms			
DirectTreated × Post	0.004*	0.007***	0.004**
	(1.71)	(2.82)	(2.12)
IndirectTreated × Post	0.003**	0.005**	0.004**
	(2.01)	(2.47)	(2.48)
Observations	100,931	100,751	100,817
Panel E: Using GICS-8 to identify peer firms			
DirectTreated × Post	0.005	0.009***	0.006**
	(1.46)	(2.66)	(2.31)
IndirectTreated × Post	0.003*	0.006***	0.006***
	(1.71)	(2.82)	(3.62)
Observations	72,080	71,937	71,985
Panel F: Using TNIC-4 to identify peer firms			
DirectTreated × Post	0.017*	0.017	0.016**
	(1.71)	(1.54)	(2.32)
IndirectTreated × Post	0.008	0.010*	0.009*
	(1.44)	(1.82)	(1.91)
Observations	18,587	18,253	18,320

Note: This table repors estimates for the regression in Table 3 if alternative industry classifications are used in the definition of product market peers when constructing events of board connections. Panel A uses the competitors disclosed by firms and recorded in FactSet Supply Chain Relationships database. Panel B uses SIC-3 industry. Panel C uses SIC-4 industry. Panel D uses GICS 6-digit industry. Panel E uses GICS 8-digit industry. Panel F uses TNIC-4.

Table A18: Cross-section heterogeneities in the effects of board connections under alternative industry classification

	Gross Margin	Operating Margin	ROA
Panel A: SIC, By whether corporate opportunity waivers (COWs) are in effect			
Treated × Post	0.002	–0.001	0.001
	(0.57)	(–0.37)	(0.27)
Treated × Post × COWs In Effect	0.003	0.018***	0.013***
	(0.79)	(3.99)	(3.81)
Observations	81,325	81,146	81,229
Panel B: SIC, By whether newly connected peers share major corporate customers			
Treated × Post	0.004*	0.010***	0.009***
	(1.67)	(4.31)	(5.40)
Treated × Post × If Share Major Customers	0.013	0.024***	0.010*
	(1.44)	(2.90)	(1.90)
Observations	81,325	81,146	81,229
Panel C: SIC, By similarity in business descriptions between newly connected peers			
Treated × Post	0.001	0.003	0.006***
	(0.59)	(1.32)	(2.78)
Treated × Post × Top Similarity	0.006*	0.018***	0.010***
	(1.70)	(4.49)	(3.59)
Observations	81,325	81,146	81,229
Panel D: SIC, By HHI of the treated firm's industry			
Treated × Post	0.004	0.008***	0.007***
	(1.53)	(2.46)	(2.76)
Treated × Post × Top HHI	0.002	0.004	0.004
	(0.72)	(1.00)	(1.31)
Observations	77,933	77,754	77,821
Panel E: GICS, By whether corporate opportunity waivers (COWs) are in effect			
Treated × Post	0.002	–0.001	–0.001
	(0.96)	(–0.20)	(–0.63)
Treated × Post × COWs In Effect	0.001	0.009**	0.008***
	(0.46)	(2.55)	(2.86)
Observations	100,931	100,751	100,817
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Table A18: Cross-section heterogeneities in the effects of board connections under alternative industry classification (continued)

	Gross Margin	Operating Margin	ROA
Panel F: GICS, By whether newly connected peers share major corporate customers			
Treated × Post	0.003**	0.005***	0.004***
	(2.10)	(2.87)	(2.68)
Treated × Post × If Share Major Customers	0.005	0.005	0.001
	(0.86)	(0.62)	(0.17)
Observations	100,931	100,751	100,817
Panel G: GICS, By similarity in business descriptions between newly connected peers			
Treated × Post	0.001	0.001	0.001
	(0.40)	(0.53)	(0.56)
Treated × Post × Top Similarity	0.006**	0.010***	0.007***
	(2.30)	(3.09)	(2.71)
Observations	100,931	100,751	100,817
Panel H: GICS, By HHI of the treated firm's industry			
Treated × Post	0.005**	0.007**	0.005***
	(2.21)	(2.16)	(2.64)
Treated × Post × Top HHI	0.001	0.004	0.003
	(0.27)	(1.36)	(1.12)
Observations	96,701	96,521	96,574
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: This table examines the cross-sectional heterogeneities in the effects of board connections under alternative industry classifications. Panels A-D use SIC-3 industry. Panels E-H use GICS 6-digit industry. The other definitions follow Table 8.

Table A19: A placebo test using non-product market peers

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.003	-0.003	-0.004
	(-0.84)	(-0.76)	(-1.29)
PseudoDirectTreated × Post	0.010	-0.005	-0.001
	(0.54)	(-0.37)	(-0.12)
PseudoIndirectTreated × Post	0.001	0.001	0.004
	(0.16)	(0.20)	(1.00)
Observations	10,326	10,298	10,299
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.906	0.755	0.679

Note: This table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times PseudoDirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times PseudoIndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t} \end{aligned}$$

using the sample of events of connections to pseudo peers and excluding the overlap of pseudo events with actual events. Here $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. Coefficient on $Post_{c,t}$ is the estimated difference between prior and post for the control firm. $PseudoDirectTreated_{i,c}$ equals one for the time series of a firm forming direct connections to pseudo peers. $PseudoIndirectTreated_{i,c}$ equals one for the time series of a firm forming indirect connections to pseudo peers. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $PseudoDirectTreated_{i,c}$ and $PseudoIndirectTreated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A20: Robustness to alternative matching schemes

	Gross Margin	Operating Margin	ROA
Panel A: Use two controls for each event			
DirectTreated × Post	0.007**	0.014***	0.010***
	(2.21)	(3.85)	(3.67)
IndirectTreated × Post	0.004*	0.009***	0.008***
	(1.94)	(3.72)	(4.30)
Observations	94,083	93,898	93,986
Panel B: Use three controls for each event			
DirectTreated × Post	0.007**	0.014***	0.010***
	(2.24)	(3.78)	(3.59)
IndirectTreated × Post	0.004*	0.009***	0.007***
	(1.96)	(3.64)	(4.21)
Observations	113,418	113,163	113,257
Panel C: Match additionally on the number of new appointments during the event year			
DirectTreated × Post	0.011**	0.014***	0.008**
	(2.29)	(2.74)	(2.16)
IndirectTreated × Post	0.003	0.010***	0.009***
	(1.14)	(3.04)	(3.25)
Observations	36,707	36,657	36,687
Panel D: Match using Operating Margin instead of Gross Margin			
DirectTreated × Post	0.008**	0.011***	0.006**
	(2.26)	(2.86)	(2.20)
IndirectTreated × Post	0.005**	0.007***	0.006***
	(1.99)	(2.59)	(2.84)
Observations	60,656	60,610	60,661
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Table A20: Robustness to alternative matching schemes (continued)

	Gross Margin	Operating Margin	ROA
Panel E: Match additionally on Operating Margin			
DirectTreated × Post	0.008**	0.011***	0.005*
	(2.05)	(2.67)	(1.79)
IndirectTreated × Post	0.004*	0.006**	0.005**
	(1.78)	(2.37)	(2.29)
Observations	60,626	60,574	60,631
Panel F: Match additionally on Sales Growth			
DirectTreated × Post	0.009**	0.014***	0.009***
	(2.26)	(3.36)	(2.88)
IndirectTreated × Post	0.003	0.008***	0.007***
	(1.26)	(2.99)	(3.69)
Observations	57,872	57,762	57,810
Panel G: Match additionally on ROA			
DirectTreated × Post	0.009**	0.013***	0.006**
	(2.40)	(3.30)	(2.07)
IndirectTreated × Post	0.005**	0.008***	0.005**
	(2.14)	(2.98)	(2.50)
Observations	60,583	60,531	60,597
Panel H: Match additionally on R&D to Assets			
DirectTreated × Post	0.006	0.014***	0.009**
	(1.47)	(3.04)	(2.55)
IndirectTreated × Post	0.003	0.008***	0.007***
	(1.04)	(2.64)	(2.73)
Observations	45,145	45,049	45,090
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Table A20: Robustness to alternative matching schemes (continued)

	Gross Margin	Operating Margin	ROA
Panel I: Match additionally on CAPEX to Assets			
DirectTreated × Post	0.008**	0.013***	0.007**
	(2.14)	(3.30)	(2.51)
IndirectTreated × Post	0.004*	0.009***	0.006***
	(1.76)	(3.26)	(3.24)
Observations	60,492	60,386	60,440
Panel J: Match additionally on all variables			
DirectTreated × Post	0.005	0.009**	0.005
	(1.39)	(2.20)	(1.58)
IndirectTreated × Post	0.003	0.006**	0.004*
	(1.24)	(2.09)	(1.95)
Observations	56,560	56,504	56,554
Panel K: Require that the control firm is never treated during [–3, 3]			
DirectTreated × Post	0.010**	0.015***	0.010***
	(2.46)	(3.45)	(3.04)
IndirectTreated × Post	0.004	0.006*	0.005**
	(1.54)	(1.88)	(1.98)
Observations	52,354	52,191	52,244
Panel L: Require that the control firm is never treated before or during [–3, 3]			
DirectTreated × Post	0.010**	0.017***	0.010***
	(2.52)	(3.64)	(2.85)
IndirectTreated × Post	0.005*	0.008**	0.005*
	(1.79)	(2.27)	(1.89)
Observations	48,558	48,402	48,450
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Note: This table reports estimates for the regression in Table 3 if alternative matching schemes are used. Panel A (B) uses a matching scheme that uses two (three) controls for each treated event. Panel C uses a matching scheme that additionally requires an exact match on the number of new appointments to the board during the event year. Panel D uses a matching scheme that matches on operating margin instead of gross margin. Panel E (F; G; H; I) uses a matching scheme that additionally matches on operating margin (sales growth; ROA; R&D to Assets; CAPEX to Assets). Panel J matches on all variables when R&D is non-missing for the treated firm and on all variables but R&D when it is missing. Panel K uses a matching scheme that additionally requires the control firm being never treated from τ = -3 to +3. Panel L uses a matching scheme that additionally requires the control firm being never treated before or during [–3, 3].

Table A21: Robustness to alternative regression specifications

	Gross Margin	Operating Margin	ROA
Panel A: Separately estimating effects of direct and indirect connections			
DirectTreated × Post	0.008*	0.011**	0.008**
	(1.94)	(2.57)	(2.46)
IndirectTreated × Post	0.004*	0.009***	0.007***
	(1.75)	(3.48)	(3.68)
Panel B: SIC-3 × Year FE and Firm × Cohort FE			
DirectTreated × Post	0.008**	0.016***	0.011***
	(2.29)	(4.05)	(4.12)
IndirectTreated × Post	0.004*	0.009***	0.009***
	(1.73)	(3.42)	(4.54)
Panel C: FIC-200 × Year FE and Firm × Cohort FE			
DirectTreated × Post	0.009**	0.013***	0.008***
	(2.48)	(3.51)	(2.96)
IndirectTreated × Post	0.003	0.007***	0.006***
	(1.30)	(2.58)	(3.25)
Panel D: FF-48 × Year FE and Firm × Cohort FE and and Cohort × Year FE			
DirectTreated × Post	0.008*	0.010**	0.007**
	(1.77)	(1.99)	(1.96)
IndirectTreated × Post	0.004**	0.008***	0.006***
	(1.97)	(3.29)	(3.46)
Panel E: Clustering at the connected firm-pair level			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.18)	(3.48)	(3.24)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.83)	(3.25)	(3.63)

Note: Panel A of this table reports estimates for the regression in Table 3 if the effects of direct and indirect board connections are estimated in two separate regressions. Panels B, C, and D of this table report estimates for the regression in Table 3 if alternative fixed effects are used. Regressions in Panel B use SIC-3 industry-by-year fixed effects and firm-by-cohort fixed effects. Regressions in Panel C use FIC-200 industry-by-year fixed effects and firm-by-cohort fixed effects. FIC-200 industry classification is provided in the Hoberg-Phillips Data Library. Regressions in Panel D use FF-48 industry-by-year fixed effects, firm-by-cohort fixed effects, and cohort-by-year fixed effects. Panel E of this table reports estimates for the regression in Table 3 if alternative clustering of standard errors is used. We cluster the standard errors at the unit level, which we define to be all observations of a connected firm-pair for treated firms and all observations of a single firm for control firms. This method of clustering accounts for the possibility that the outcome variables of connected firm-pairs could be positively correlated.

Table A22: Effects of the death of connected directors

	Gross Margin	Operating Margin	ROA
Panel A: Death severs a direct connection			
DeathTreated × Post	-0.018	-0.031*	-0.018**
	(-1.15)	(-1.90)	(-2.17)
Observations	1,137	1,137	1,137
Adjusted R-squared	0.855	0.744	0.690
Panel B: Death severs an indirect connection			
DeathTreated × Post	-0.007	-0.011	-0.016*
	(-0.45)	(-0.71)	(-1.78)
Observations	2,097	1,988	1,988
Adjusted R-squared	0.811	0.761	0.591
Panel C: Non-focal director death that severs an indirect connection			
DeathTreated × Post	-0.000	-0.011	-0.024*
	(-0.00)	(-0.53)	(-1.86)
Observations	819	781	781
Adjusted R-squared	0.931	0.845	0.701
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	3	3	3

Note: This table reports estimates from the following regression

$$Y_{i,j,c,t} = \alpha_1 \times Post_{c,t} + \beta_1 \times DeathTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

In Panel A, $DeathTreated_{i,c}$ equals one for a firm that experiences the termination of direct connections to product market peers due to director death. In Panel B, $DeathTreated_{i,c}$ equals one for a firm that experiences the termination of indirect connections to product market peers due to director death. In Panel C, $DeathTreated_{i,c}$ equals one for a firm that experiences the termination of indirect connections due to the death of a non-focal director (i.e., a director who cross-sits on the boards of the intermediate firm and the product market peer). $Post_{c,t}$ is one for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $DeathTreated_{i,c}$ is left out of the regressions as it is absorbed by $\theta_{i,c}$. Coefficients of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A23: Cumulative abnormal returns (CARs) around announcement dates

	Average CARs	
	(1)	(2)
	Abnormal returns from the market model	Firm returns minus market returns as abnormal returns
Direct Connections	0.83%*	0.91%**
	(1.91)	(2.23)
Observations	396	396
Indirect Connections	0.73%*	0.62%*
	(1.89)	(1.71)
Observations	424	424
Other Appointments	0.23%***	0.22%***
	(4.29)	(4.23)
Observations	25,459	26,821

Note: This table reports the average CARs during a seven-day window around the announcement dates of director appointments. We report CARs both for appointments that cause board connections between product market peers to form and for all other appointments. In column (1), we estimate a market model using stock returns between [-300, -60] calendar days before the announcement dates and the CRSP NYSE/NYSEMKT/Nasdaq Value-Weighted Market Index. Then we calculate abnormal returns using our estimated model. In column (2), we calculate abnormal returns as firm returns minus market returns. We winsorize daily returns at the 1% and 99% percentiles before estimating the market model. We also winsorize CARs at the 1% and 99% percentiles. T-stats are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A24: Summary statistics for additional tests on alternative explanations

	Mean	Min	p10	p25	Median	p75	p90	Max	N
Panel A: Director experience									
Fraction with Scientific Experience (%)	8.81	0.00	0.00	0.00	0.00	14.29	25.00	50.00	68,231
Fraction with Entrepreneurial Experience (%)	31.68	0.00	7.69	15.38	28.57	44.44	60.00	100.00	68,231
Fraction with Legal Experience (%)	7.38	0.00	0.00	0.00	0.00	12.50	20.00	50.00	68,231
Fraction with Financial Experience (%)	17.93	0.00	0.00	9.09	16.67	26.67	37.50	100.00	68,231
Length of Scientific Experience	1.78	0.00	0.00	0.00	0.00	2.80	5.75	11.00	68,231
Length of Entrepreneurial Experience	4.61	0.00	0.29	1.75	4.10	6.67	9.50	17.40	68,231
Length of Legal Experience	0.73	0.00	0.00	0.00	0.00	0.80	2.54	7.00	68,231
Length of Financial Experience	1.72	0.00	0.00	0.33	1.31	2.57	4.00	17.25	68,231
Panel B: Firm innovation									
Total Market Value of Patents ($ Million) (Kogan et al., 2017)	388.90	0.00	0.00	0.00	0.49	62.30	772.95	6170.70	68,935
Total Forward Citations of Patents	407.74	0.00	0.00	0.00	0.00	160.00	994.00	5993.00	68,935
Number of Patents	23.45	0.00	0.00	0.00	1.00	10.00	56.00	339.00	68,935
Panel C: Firm-pair innovation collaboration									
Joint Patent Application (%)	0.05	0.00	0.00	0.00	0.00	0.00	0.00	100.00	130,578
Joint Patent Grant (%)	0.05	0.00	0.00	0.00	0.00	0.00	0.00	100.00	130,578
Joint Venture (%)	0.05	0.00	0.00	0.00	0.00	0.00	0.00	100.00	130,578
Panel D: Firm governance characteristics									
Fraction of Independent Directors (%)	79.28	0.00	62.50	72.73	83.33	87.50	90.91	100.00	68,231
CEO Duality (%)	52.16	0.00	0.00	0.00	100.00	100.00	100.00	100.00	68,231
Log Comp	8.18	5.37	6.75	7.48	8.25	8.93	9.48	10.28	43,628
Pay-Performance Sensitivity (Coles et al., 2006)	323.61	1.75	21.32	49.21	122.62	305.77	723.34	4016.21	41,387

Note: Panel A reports summary statistics for board-level director experience and expertise. Fraction with Scientific Experience (%) is the fraction of directors with a PhD or with prior experience as a scientist, identified with key words “scientific”, “researcher”, “professor”, or “academic” in the role name or the text descriptions in BoardEx. Length of Scientific Experience is the length of prior scientific experience in years, averaged across all board members and treating a PhD as five years of experience. Fraction with Entrepreneurial Experience (%) is the fraction of directors with prior experience as a “founder” (based on the role name or the text descriptions) or with experience of working in the “venture capital” or the “private equity” industries (Terbeck et al., 2022). Length of Entrepreneurial Experience is the length of prior entrepreneurial experience. Fraction with Legal Experience (%) is the fraction of directors with a JD or with prior experience in the “legal” industry. Length of Legal Experience is the length of prior legal experience, treating a JD as four years of experience (Henderson et al., 2023). Fraction with Financial Experience (%) is the fraction of directors with prior experience in the “banking” or “investment” industries or as a finance officer, identified with key words “finance” or “accounting” in the role name or the text descriptions. Length of Financial Experience is the length of prior financial experience.
Panel B reports summary statistics for innovation output. Total Market Value of Patents is the value of all patents for a firm in a certain year, using the stock-price-implied measure of patent value (Kogan et al., 2017) and deflated to 1982 dollars (in millions) using the CPI. Total Forward Citations of Patents is the total forward citations of all patents for a firm in a certain year. Number of Patents is the number of patents for a firm in a certain year.
Panel C reports summary statistics for innovation collaboration in the treatment-control matched firm-pair-year-level sample. Joint Patent Application and Joint Patent Grant are indicators for whether a firm-pair jointly file patent applications or receive patent grants in a certain year (Arora et al., 2024a,b). Joint Venture is an indicator for whether a firm-pair starts a joint venture in a certain year, as recorded in the SDC Database.
Panel D reports summary statistics for corporate governance characteristics. Fraction of Independent Directors (%) is the share of independent directors on the board. CEO Duality (%) is an indicator for whether a firm’s CEO and chairperson is the same person. Log Comp is the natural logarithm of one plus the CEO’s annual compensation in millions of dollars. Pay-performance sensitivity is the dollar change in wealth associated with a 1% change in the firm’s stock price (in $1,000s) (Core and Guay, 2002; Coles et al., 2006).

Table A25: Effects of product-market-peer board connections on firm innovation output

	(1) Total Market Value of Patents	(2) Total Forward Citations of Patents	(3) Number of Patents
DirectTreated × Post	-9.07	-5.52	-0.12
	(-0.57)	(-0.35)	(-0.15)
IndirectTreated × Post	12.45	-11.63	1.61**
	(0.97)	(-1.03)	(2.30)
Observations	68,774	68,774	68,774
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.889	0.876	0.876

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. The outcome variables are (1) the value of all patents granted to firm i in year t, using the stock-price-implied measure of patent value (Kogan et al., 2017) and deflated to 1982 dollars (in millions) using the CPI; (2) the number of total forward citation of all patents granted to firm i in year t; (3) the number of patents that firm i receives in year t. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $DirectTreated_{i,c}$ ($IndirectTreated_{i,c}$) is a dummy variable equal to one for the treated firms that experience a new direct (indirect) board connection to a product market peer. $DirectTreated_{i,c} \times Post_{c,t}$ and $IndirectTreated_{i,c} \times Post_{c,t}$ are the double-difference terms, the coefficient estimates of which are the estimated effects of new board connections to product market peers. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$ and coefficient estimates of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A26: Effects of product-market-peer board connections on firm-pair innovation collaboration

	(1) Joint Patent Application (%)	(2) Joint Patent Grant (%)	(3) Joint Venture (%)
DirectTreated × Post	-0.02	-0.00	0.05
	(-0.87)	(-0.22)	(1.41)
IndirectTreated × Post	-0.00	-0.02	0.01
	(-0.09)	(-1.00)	(0.31)
Observations	130,557	130,557	130,557
Firm-Pair × Cohort FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustering	Firm-Pair	Firm-Pair	Firm-Pair
# of Matched Controls	1	1	1
Adjusted R-squared	0.407	0.393	0.054

Note: This table reports estimates from the following regression,

$$\begin{aligned} Collaboration_{i,k,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,k,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,k,c} \times Post_{c,t} + \theta_{i,k,c} + \theta_t + e_{i,k,c,t}. \end{aligned}$$

Here i and k indicate a firm-pair, c is the index for each cohort which consists of a treated firm-pair and its matched control firm-pair, and t is the index for each calendar year. For each treated firm-pair, we first identify candidate control firm-pairs, which are all firm-pairs with one firm in common with the treated firm-pair. Next, for each treated firm-pair A and B and candidate control firm-pair C and D, we calculate two Mahalanobis distances with seven variables — cosine similarity score (Hoberg and Phillips, 2010, 2016) and assets, gross margin, and Tobin's Q of the firm-pair. For one distance, we compare A to C and B to D along the dimensions of assets, gross margin, and Tobin's Q. For the other, we compare A to D and B to C. We handle arbitrary ordering of firms inside a pair by taking the smaller value as the Mahalanobis distance between the two firm-pairs. We then designate the candidate control firm-pair with the lowest distance to the treated firm-pair as the matched control. In the regression, the outcome variables are indicators for (1) whether a firm-pair jointly files a patent application (Arora et al., 2024a,b); (2) whether a firm-pair jointly receives a patent grant (Arora et al., 2024a,b); (3) whether a firm-pair starts a joint venture. $Post_{c,t}$ is one for both treated and control firm-pairs for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $DirectTreated_{i,k,c}$ ($IndirectTreated_{i,k,c}$) is a dummy variable equal to one for the treated firm-pairs that experience new direct (indirect) board connections. $\theta_{i,k,c}$ are firm-pair-by-cohort fixed effects. θ_t are calendar year fixed effects. Coefficient estimates of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm-pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A27: Effects of product-market-peer board connections on firm governance practices

	(1) ln(SG&A)	(2) Frac. of Ind. Directors (%)	(3) CEO Duality (%)	(4) Log Comp.	(5) PPS
DirectTreated × Post	0.013	-0.13	-0.22	0.01	14.48
	(0.83)	(-0.58)	(-0.19)	(0.58)	(0.87)
IndirectTreated × Post	-0.013	-0.41**	-0.25	0.00	-14.98
	(-1.16)	(-2.53)	(-0.31)	(0.25)	(-1.24)
Observations	65,638	68,073	68,073	43,506	41,269
Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1	1
Adjusted R-squared	0.975	0.740	0.642	0.689	0.689

Note: This table reports estimates from the following regression,

$$Y_{i,j,c,t} \quad = \quad \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. The outcome variable can be (1) the logarithm of SG&A costs in millions; (2) the fraction of independent directors on a firm's board; (3) whether the CEO is also the chairperson; (4) the logarithm of one plus total compensation in millions; (5) delta (pay-performance sensitivity) of executive compensation (Core and Guay, 2002; Coles et al., 2006). $DirectTreated_{i,c}$ ($IndirectTreated_{i,c}$) is a dummy variable equal to one for the treated firms that experience a new direct (indirect) board connection to a product market peer. $DirectTreated_{i,c} \times Post_{c,t}$ and $IndirectTreated_{i,c} \times Post_{c,t}$ are the double-difference terms, the coefficient estimates of which are the estimated effects of new board connections to product market peers. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$ and coefficient estimates of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A28: Effects of product-market-peer board connections on firm-pair governance practice similarity

	(1) Dist. Frac. of Ind. Directors (%)	(2) Dist. CEO Duality (%)	(3) Dist. Log Comp	(4) Dist. PPS
DirectTreated × Post	-0.70***	-1.92	-0.00	53.52
	(-2.77)	(-1.38)	(-0.16)	(1.23)
IndirectTreated × Post	-0.15	0.94	-0.01	12.06
	(-1.32)	(1.40)	(-0.91)	(0.66)
Observations	113,274	113,274	52,576	46,922
Firm-Pair × Cohort FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustering	Firm-Pair	Firm-Pair	Firm-Pair	Firm-Pair
# of Matched Controls	1	1	1	1
Adjusted R-squared	0.556	0.455	0.479	0.798

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,k,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,k,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,k,c} \times Post_{c,t} \\ &+ \theta_{i,k,c} + \theta_t + e_{i,k,c,t}. \end{aligned}$$

Here i and k indicate a firm-pair, c is the index for each cohort which consists of a treated firm-pair and its matched control firm-pair, and t is the index for each calendar year. For each treated firm-pair, we first identify candidate control firm-pairs, which are all firm-pairs with one firm in common with the treated firm-pair. Next, for each treated firm-pair A and B and candidate control firm-pair C and D, we calculate two Mahalanobis distances with seven variables — cosine similarity score (Hoberg and Phillips, 2010, 2016) and assets, gross margin, and Tobin's Q of the firm-pair. For one distance, we compare A to C and B to D along the dimensions of assets, gross margin, and Tobin's Q. For the other, we compare A to D and B to C. We handle arbitrary ordering of firms inside a pair by taking the smaller value as the Mahalanobis distance between the two firm-pairs. We then designate the candidate control firm-pair with the lowest distance to the treated firm-pair as the matched control. In the regression, the outcome variables are the absolute values of the distance in governance characteristics within a firm-pair. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $DirectTreated_{i,k,c}$ ($IndirectTreated_{i,k,c}$) is a dummy variable equal to one for the treated firm-pairs that experience new direct (indirect) board connections. $\theta_{i,k,c}$ are firm-pair-by-cohort fixed effects. θ_t are calendar year fixed effects. Coefficient estimates of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm-pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A29: Effects of product-market-peer board connections on board-level director experience

	(1) Frac. Scientific Exp. (%)	(2) Frac. Entrepreneurial Exp. (%)	(3) Frac. Legal Exp. (%)	(4) Frac. Financial Exp. (%)	(5) Length Scientific Exp.	(6) Length Entrepreneurial Exp.	(7) Length Legal Exp.	(8) Length Financial Exp.
DirectTreated × Post	0.14	-1.36***	-0.16	0.18	-0.00	-0.25***	-0.02	-0.00
	(0.70)	(-3.37)	(-0.93)	(0.67)	(-0.03)	(-4.00)	(-0.88)	(-0.05)
IndirectTreated × Post	-0.11	0.11	-0.05	0.29	0.02	-0.03	-0.01	0.03
	(-0.77)	(0.45)	(-0.45)	(1.55)	(0.75)	(-0.80)	(-0.76)	(1.46)
Observations	68,073	68,073	68,073	68,073	68,073	68,073	68,073	68,073
Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1	1	1	1	1
Adjusted R-squared	0.826	0.810	0.806	0.764	0.841	0.829	0.819	0.789

Note: This table reports estimates from the following regression,

$$Y_{i,j,c,t} \quad = \quad \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. The outcome variables are the fraction of directors with scientific, entrepreneurial, legal, or financial experience in the first four columns and the length of such experience in years averaged across all directors in the next four columns. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $DirectTreated_{i,c}$ ($IndirectTreated_{i,c}$) is a dummy variable equal to one for the treated firms that experience a new direct (indirect) board connection to a product market peer. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$ and coefficient estimates of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A30: Effects on profitability, controlling for board-level director experience

	Gross Margin	Operating Margin	ROA
Panel A: Controlling for fraction with scientific experience			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.35)	(3.85)	(3.31)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.93)	(3.31)	(3.64)
Frac. Scientific Exp.	–0.008	–0.014	–0.012
	(–0.32)	(–0.59)	(–0.74)
Panel B: Controlling for fraction with entrepreneurial experience			
DirectTreated × Post	0.008**	0.014***	0.008***
	(2.48)	(3.80)	(3.24)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.93)	(3.33)	(3.66)
Frac. Entrepreneurial Exp.	0.029**	–0.009	–0.012
	(2.30)	(–0.67)	(–1.14)
Panel C: Controlling for fraction with legal experience			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.36)	(3.85)	(3.30)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.94)	(3.32)	(3.65)
Frac. Legal Exp.	0.012	0.002	–0.003
	(0.39)	(0.06)	(–0.15)
Panel D: Controlling for fraction with financial experience			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.34)	(3.83)	(3.29)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.92)	(3.30)	(3.64)
Frac. Financial Exp.	0.013	0.023	0.009
	(0.77)	(1.41)	(0.75)
Panel E: Controlling for length of scientific experience			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.35)	(3.85)	(3.30)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.95)	(3.33)	(3.67)
Length of Scientific Exp.	–0.001	–0.001	–0.001
	(–1.23)	(–0.95)	(–1.47)

Table A30: Effects on profitability, controlling for firm-average director experience

	Gross Margin	Operating Margin	ROA
Panel F: Controlling for length of entrepreneurial experience			
DirectTreated × Post	0.008**	0.014***	0.008***
	(2.42)	(3.86)	(3.28)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.95)	(3.32)	(3.65)
Length of Entrepreneurial Exp.	0.001	0.000	–0.000
	(1.27)	(0.24)	(–0.45)
Panel G: Controlling for length of legal experience			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.37)	(3.86)	(3.31)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.96)	(3.34)	(3.67)
Length of Legal Exp.	0.003*	0.004**	0.002
	(1.75)	(1.99)	(1.56)
Panel H: Controlling for length of financial experience			
DirectTreated × Post	0.008**	0.014***	0.009***
	(2.35)	(3.84)	(3.30)
IndirectTreated × Post	0.004*	0.008***	0.006***
	(1.93)	(3.32)	(3.66)
Length of Financial Exp.	0.001	0.000	–0.000
	(0.41)	(0.26)	(–0.42)
Observations	67,982	67,826	67,893

Note: This table reports estimates from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \gamma \times DirectorExperience_{i,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

We estimate a version of the the difference-in-differences regressions in Table 3 that additionally controls for the experience of directors on the board. In Panels A, B, C, and D, we control for the fraction of directors with scientific, entrepreneurial, legal, or financial experience, respectively. In the next four panels, we control for the length of such experience averaged across all directors.

Table A31: Effects of product-market-peer board connections on firm labor expenses

	(1) Labor Share	(2) Labor Share (Imputed)	(3) N Employees Logged	(4) Wage Bill Logged
DirectTreated × Post	-0.007	-0.008	-0.010	-0.054
	(-0.95)	(-1.05)	(-1.01)	(-0.65)
IndirectTreated × Post	0.006	-0.001	-0.011	-0.056
	(0.83)	(-0.14)	(-1.50)	(-1.44)
Observations	3,552	59,058	68,093	3,552
Firm × Cohort FE	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1
Adjusted R-squared	0.966	0.906	0.982	0.988

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. The outcome variables are (1) a firm's labor share, defined as total staff expenses (*xlr*) divided by firm sales (*sale*); (2) an imputed labor share following Donangelo et al. (2019), for which a firm's average wage is imputed with the SIC-3 industry mean; (3) logged number of employees (*emp*); (4) logged total wage bill (*xlr*). $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $DirectTreated_{i,c}$ ($IndirectTreated_{i,c}$) is a dummy variable equal to one for the treated firms that experience a new direct (indirect) board connection to a product market peer. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $Treated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$ and coefficient estimates of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A32: Director network and convicted collusion cases

	(1) Prob. of active convicted collusion (%)	(2) Prob. of active convicted collusion (%)
Degree of separation = 0	0.058***	0.043**
	(3.22)	(2.39)
Degree of separation = 1	0.060***	0.053***
	(9.07)	(8.41)
Degree of separation = 2	0.017***	0.014***
	(12.21)	(10.93)
Degree of separation = 3	0.003***	0.002***
	(10.30)	(7.89)
Cosine similarity score		0.285***
		(10.91)
Is H-P peer		0.036***
		(5.73)
Observations	53,893,933	53,893,933
Year FE	No	Yes
Clustering	Firm-Pair	Firm-Pair
Adjusted R-squared	0.000	0.001

Note: This table reports estimates from the following linear probability regression

$$\begin{aligned} \mathbb{1}(\text{Having an active convicted collusion scheme})_{i,j,t} &= \sum_{m=0}^{3} \beta_m \times \mathbb{1}(\text{Degree of separation is } m)_{i,j,t} \\ &+ Control_{i,j,t} + \theta_t + e_{i,j,t}. \end{aligned}$$

using the sample of firm-pairs with the degree of separation in the director network less than or equal to 4. Firm-pairs with a degree of separation of 4 serve as the omitted category. T-stats are in parentheses. Standard errors are clustered at the firm-pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A33: Effects of pre-existing connections becoming stronger on firm profitability

	(1) Gross Margin	(2) Operating Margin	(3) ROA
DirectTreated × Post	0.009	0.009	0.012**
	(0.93)	(0.85)	(2.04)
IndirectTreated × Post	0.007	0.008*	0.003
	(1.60)	(1.79)	(0.86)
Observations	9,106	8,728	8,730
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Adjusted R-squared	0.916	0.812	0.752

Note: This table reports estimates from the following regression and examines scenarios where pre-existing connections become stronger,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $DirectTreated_{i,c}$ is a dummy variable equal to one for treated firms that were directly or indirectly connected to a product market peer in the previous year and start sharing one more director with the same peer in the current year. $IndirectTreated_{i,c}$ is a dummy variable equal to one for treated firms that were directly or indirectly connected to a product market peer in the previous year and acquires an additional indirect board connection with the same peer in the current year. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. Coefficient estimates of $Post_{c,t}$ are omitted for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A34: Effects of pre-existing connections becoming stronger on product prices

	(1) Price Index	(2) Price Index	(3) Price Index
DirectTreated × Post	0.00228	0.00162	0.00122
	(1.43)	(0.97)	(0.82)
IndirectTreated × Post	0.00051**	0.00045*	0.00041*
	(2.10)	(1.88)	(1.96)
Observations	54,020,760	53,849,749	53,793,323
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%
Adjusted R-squared	0.346	0.347	0.348

Note: This table reports estimates from the following regression,

$$\begin{aligned} P_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} + \alpha_3 \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned}$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. $DirectTreated_{i,m,z} \times Post_{i,m,z,t}$ ($IndirectTreated_{i,m,z} \times Post_{i,m,z,t}$) equals one for firm-product-module-zip3 combinations that were directly or indirectly connected to a product market peer in the previous year and start sharing one more director with the same peer (acquire an additional indirect board connection with the same peer) in the current year in quarters post the treatment. $\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A35: Effects of board connections on product prices, controlling for common ownership

	(1) Price Index	(2) Price Index	(3) Price Index
Panel A: Controlling for C-Score			
DirectTreated × Post	0.00222***	0.00186**	0.00171**
	(2.66)	(2.20)	(1.98)
IndirectTreated × Post	0.00063***	0.00057***	0.00056***
	(3.11)	(2.66)	(2.75)
CommonOwnership	0.29281	0.27364	0.26755
	(0.95)	(0.88)	(0.86)
PrivateShare	-0.00275	-0.00294	-0.00301
	(-1.01)	(-1.08)	(-1.10)
CommonOwnership × PrivateShare	1.27225	1.29236	1.25755
	(1.28)	(1.29)	(1.26)
Panel B: Controlling for MHHI			
DirectTreated × Post	0.00223***	0.00187**	0.00171**
	(2.67)	(2.20)	(1.98)
IndirectTreated × Post	0.00063***	0.00057***	0.00056***
	(3.12)	(2.67)	(2.75)
CommonOwnership	0.00196	0.00156	0.00119
	(0.63)	(0.51)	(0.39)
PrivateShare	-0.00287	-0.00306	-0.00315
	(-1.05)	(-1.12)	(-1.15)
CommonOwnership × PrivateShare	0.01775	0.01862*	0.01884*
	(1.64)	(1.70)	(1.70)
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%
Observations	51,547,579	51,392,309	51,351,196
Adjusted R-squared	0.342	0.343	0.343

Note: This table reports estimates from the following regression,

$$\begin{aligned} Y_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} + \alpha_2 \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \beta_1 \times CommonOwnership_{m,z,t} + \beta_2 \times PrivateShare_{m,z,t} \\ &+ \beta_3 \times CommonOwnership_{m,z,t} \times PrivateShare_{m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned}$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. $DirectTreated_{i,m,z} \times Post_{i,m,z,t}$ ($IndirectTreated_{i,m,z} \times Post_{i,m,z,t}$) equals zero for those firm-product-module-zip3 combinations that are never treated and for treated firm-product-module-zip3 in quarters prior to the treatment of direct (indirect) board connections. It equals one for treated firm-product-module-zip3 in quarters post the treatment. $CommonOwnership_{m,z,t}$ is the common ownership measure of the market segment of product module m in zip-3 area z and quarter t. $PrivateShare_{m,z,t}$ is the total market share of private firms in this market segment. We use the C-Score (Lewellen and Lowry, 2021) in Panel A and the MHHI Delta (Azar et al., 2018) in Panel B. $\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A36: Density of other network ties

	Mean	Min	p10	p25	Median	p75	p90	Max	Obs.
Direct connections									
N Connected Peers	0.53	0.00	0.00	0.00	0.00	0.00	2.00	20.00	92,111
Indirect connections									
N Connected Peers	2.11	0.00	0.00	0.00	0.00	1.00	5.00	118.00	92,111
Connections via shared non-board work experience									
N Connected Peers	3.88	0.00	0.00	0.00	0.00	3.00	9.00	200.00	92,111
Connections via education									
N Connected Peers	1.41	0.00	0.00	0.00	0.00	2.00	4.00	38.00	92,111
Connections via other activities									
N Connected Peers	2.04	0.00	0.00	0.00	0.00	1.00	4.00	176.00	92,111
Connections via shared ethnic origin									
N Connected Peers	8.49	0.00	0.00	0.00	0.00	3.00	19.00	269.00	92,111
Past connections									
N Connected Peers	1.97	0.00	0.00	0.00	0.00	0.00	3.00	195.00	92,111

Note: This table shows the density of board interlocks and other network ties between product market peers. We lay out definitions of these network ties here: (1) Direct connections are the cases where the same director simultaneously sits on the boards of two product market peer firms. (2) Indirect connections are the cases where two product market peers Firm 1 and Firm 2 are linked via a third, intermediate firm Firm 3. One director simultaneously sits on the boards of Firm 1 and Firm 3, while another director sits on the boards of Firm 2 and Firm 3. (3) Connections via shared non-board work experiences are the cases where two product market peers each have a director, these two directors have shared work experiences in the same firm. In constructing this network tie, we exclude the cases where both directors act as board directors at this intermediate firm. (4) Connections via education are the cases where two product market peers each have a director and these two directors attended the same school and graduated within one year of each other (Fracassi and Tate, 2012). (5) Connections via other activities are the cases where two product market peers each have a director and these two directors engaged in the same non-business-related activities, such as charitable work or leisure clubs, at the same time. (6) Connections via shared ethnic origin are the cases where two product market peers each have a director and these two directors have shared ethnic origin. We employ the classifier that Hafner et al. (2024) developed with machine learning and use the default "21 nationalities and else" option. We also require that the confidence level of the ethnic classification is in the top 25%, and we exclude the top five ethnic groups as the likelihood of two individuals having social connections is smaller when they belong to a larger ethnic group. (7) Past connections are the cases where two product market peers each have a director and these two directors served on the board of a common third firm at the same time in the past. We report firm-year-level summary statistics for the number of product market peers that a firm has network ties with.

Table A37: Other activities in BoardEx

Other Activity in BoardEx	Count
National Association of Corporate Directors	228
American Heart Association Inc	125
American Academy of Arts and Sciences	122
Biotechnology Innovation Organization	119
Commercial Club of Chicago	116
Aspen Institute	113
Boy Scouts of America	102
American National Red Cross	99
United Way Worldwide	97
Brookings Institution	95
Advertising Council Inc	90
National Association of Manufacturers	89
Business Roundtable	88
National Academy of Sciences	85
Council on Foreign Relations Inc	84
National Venture Capital Association	82
Catalyst Inc	80
New York And Presbyterian Hospital	78
National Research Council	77
Pharmaceutical Research and Manufacturers of America	77
National Association of Real Estate Investment Trusts	76
Partnership for New York City	75
Nature Conservancy	74
YPO Inc	73
American Cancer Society Inc	71
Association for the Advancement of Artificial Intelligence	65
Institute of Electrical and Electronics Engineers Inc	64
Massachusetts Institute of Technology	64
Urban Land Institute	64
Committee for Economic Development of The Conference Board	61
Greater Houston Partnership	61
California Institute of Technology	60
American Institute of Certified Public Accountants	57
National Retail Federation	57
Lincoln Center for the Performing Arts Inc	57
Woodruff Arts Center	55
Electric Power Research Institute Inc	54
John F Kennedy Center for the Performing Arts	54
Center for Strategic and International Studies Inc	53
Institute of Corporate Directors	52

Note: This table shows the 40 most frequent “other activities” in BoardEx. We report the name of the activity and the number of public firm directors involved.

Table A38: Effects of past connections on firm profitability

	(1) Gross Margin	(2) Operating Margin	(3) ROA
PastConnectionsTreated × Post	0.002	0.004*	0.002
	(0.71)	(1.68)	(1.35)
Observations	48,063	45,934	45,946
Adjusted R-squared	0.912	0.831	0.760

Note: This table reports estimates from the following regression,

$$Y_{i,j,c,t} \quad = \quad \alpha_1 \times Post_{c,t} + \beta_1 \times PastConnectionsTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $PastConnectionsTreated_{i,c}$ is a dummy variable equal to one for the treated firms that have past connections to product market peers. In these cases, product market peers Firm 1 and Firm 2 each have Director A and Director B, and these two directors served together on the board of a common third firm Firm 3 in the past. In constructing past connections, we require that by the time the overlap of the tenures of Director A at Firm 1 and Director B at Firm 2 begins, they no longer serve on the board of Firm 3 together, so connections are in the past rather than concurrent. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. The treatment year corresponds to the year when the overlap of the tenures of Director A at Firm 1 and Director B at Firm 2 begins. $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. $PastConnectionsTreated_{i,c}$ is left out of the regression as it is absorbed by $\theta_{i,c}$. Coefficients of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A39: Effects of past connections on product prices

	(1) Price Index	(2) Price Index	(3) Price Index
PastConnectionsTreated × Post	-0.00007	-0.00008	-0.00008
	(-0.20)	(-0.71)	(-0.76)
Observations	56,757,765	58,303,635	58,974,937
Adjusted R-squared	0.366	0.361	0.359
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%

Note: This table reports estimates from the following regression,

$$P_{i,m,z,t} = \alpha \times PastConnectionsTreated_{i,m,z} \times Post_{i,m,z,t} + \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}.$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. $PastConnectionsTreated_{i,m,z} \times Post_{i,m,z,t}$ equals zero for those firm-product-module-zip3 combinations that are never treated and for treated firm-product-module-zip3 in quarters prior to the treatment of past connections. It equals one for treated firm-product-module-zip3 in quarters post the treatment. Here treated firms have past connections to product market peers. $\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A40: Effects of board connections on firm profitability, controlling for the density of other network ties

	Controlling for share of peers connected via other connections			Controlling for number of peers connected via other connections		
	(1) Gross Margin	(2) Operating Margin	(3) ROA	(4) Gross Margin	(5) Operating Margin	(6) ROA
DirectTreated × Post	0.009**	0.013***	0.008***	0.008**	0.013***	0.008***
	(2.56)	(3.52)	(3.22)	(2.57)	(3.59)	(3.11)
IndirectTreated × Post	0.004*	0.006***	0.006***	0.004*	0.007***	0.006***
	(1.87)	(2.63)	(3.54)	(1.93)	(3.02)	(3.64)
Connections via Shared Work Experiences	0.001	-0.024*	-0.015	0.000	0.000	0.000
	(0.09)	(-1.76)	(-1.35)	(0.65)	(0.34)	(0.58)
Connections via Education	0.029	0.017	-0.001	-0.001	-0.003***	-0.002***
	(1.49)	(0.74)	(-0.07)	(-1.17)	(-2.88)	(-3.22)
Connections via Other Activities	0.015	0.015	0.017	-0.001	-0.001	-0.000
	(0.76)	(0.85)	(1.33)	(-0.76)	(-1.00)	(-0.18)
Connections via Ethnic Origin	0.005	0.011	0.002	-0.000	0.000	-0.000
	(0.54)	(0.96)	(0.20)	(-0.48)	(0.63)	(-0.94)
Past Connections	0.002	0.002	0.001	0.000	0.001**	0.000
	(0.82)	(1.14)	(0.74)	(1.63)	(2.22)	(0.91)
Observations	61,986	61,835	61,894	65,853	65,699	65,762
Firm × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1	1	1
Adjusted R-squared	0.880	0.750	0.672	0.880	0.753	0.674

Note: This table reports estimates from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \sum_{\substack{\text{network tie type} \in \\ \{\text{shared work experience, education,} \\ \text{other activities, ethnic origin,} \\ \text{past connections}\}}} \gamma_{\text{network tie type}} \times Density_{i,t,\text{network tie type}} \\
&+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \qquad (8)
\end{aligned}
$$

Here i is the index for each firm, j is the index for each industry, c is the index for each cohort which consists of all observations of a treated firm and its matched control, and t is the index for each calendar year. $Post_{c,t}$ is one for both treated and control firms for years 0, 1, 2, and 3, where year 0 is the treatment year, and is zero for years -3, -2, and -1. $DirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a new direct board connection to a product market peer while $IndirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms that experience a new indirect board connection to a product market peer. $Density_{i,t,\text{network tie type}}$ is the share (number) of product market peers that a firm has network ties to in columns (1)-(3) (columns (4)-(6)). $\theta_{i,c}$ are firm-by-cohort fixed effects. $\theta_{j,t}$ are industry-by-year fixed effects based on the Fama-French 48-industry classification. Coefficient estimates of $Post_{c,t}$ are omitted for brevity. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A41: Effects of board connection terminations on firm profitability

	Gross Margin	Operating Margin	ROA
Panel A: All board connection terminations			
DirectTreated × Post	0.000	0.004	0.003
	(0.02)	(0.91)	(0.96)
IndirectTreated × Post	0.002	0.003	0.002
	(0.78)	(1.51)	(1.15)
Observations	55,615	53,218	53,222
Adjusted R-squared	0.915	0.827	0.737
Panel B: Director no longer holds any position in the same SIC-1 division			
DirectTreated × Post	-0.018**	-0.015*	-0.008
	(-1.99)	(-1.70)	(-1.36)
IndirectTreated × Post	-0.007*	-0.006	-0.003
	(-1.75)	(-1.14)	(-1.39)
Observations	9,013	8,704	8,705
Adjusted R-squared	0.907	0.814	0.775
Panel C: Director no longer holds any position in BoardEx			
DirectTreated × Post	-0.034*	-0.028*	-0.015*
	(-1.76)	(-1.90)	(-1.77)
IndirectTreated × Post	-0.017	-0.016	-0.018*
	(-1.37)	(-1.36)	(-1.72)
Observations	5,141	5,012	5,012
Adjusted R-squared	0.875	0.782	0.775
Firm × Cohort FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: In this table, we examine the effects of board connection terminations on firm profitability. In Panel A, we examine all board connection terminations. In Panels B and C, we examine cases where a board connection terminates and the connecting director no longer stays in the workforce or in the same industry as the product market peers. In Panel B, we require that the director no longer holds any BoardEx position after connection terminations. In Panel C, we require that the director no longer works in the same SIC division after connection terminations. For direct connections, the connecting director is the board member shared by the connected product market peers when connections existed. For indirect connections, the connecting director is either the board member shared by the focal firm and the intermediate firm when connections existed, or the member shared by the product market peer and the intermediate firm, depending on which member no longer constitutes a link in the board connection upon connection termination (thus causing the connection termination).

Table A42: Effects of board connection terminations on product prices

	(1) Price Index	(2) Price Index	(3) Price Index
DirectTreated × Post	0.00040	-0.00072	-0.00081
	(0.27)	(-0.63)	(-0.78)
IndirectTreated × Post	-0.00035	-0.00034	-0.00038
	(-0.81)	(-0.84)	(-0.94)
Observations	50,186,137	49,715,319	49,500,352
Adjusted R-squared	0.343	0.345	0.345
Firm × Product Module × Zip3 FE	Yes	Yes	Yes
Product Module × Quarter FE	Yes	Yes	Yes
Firm × Quarter FE	Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Threshold on Market Share	10%	5%	3%

Note: Panel A of this table reports estimates from the following regression,

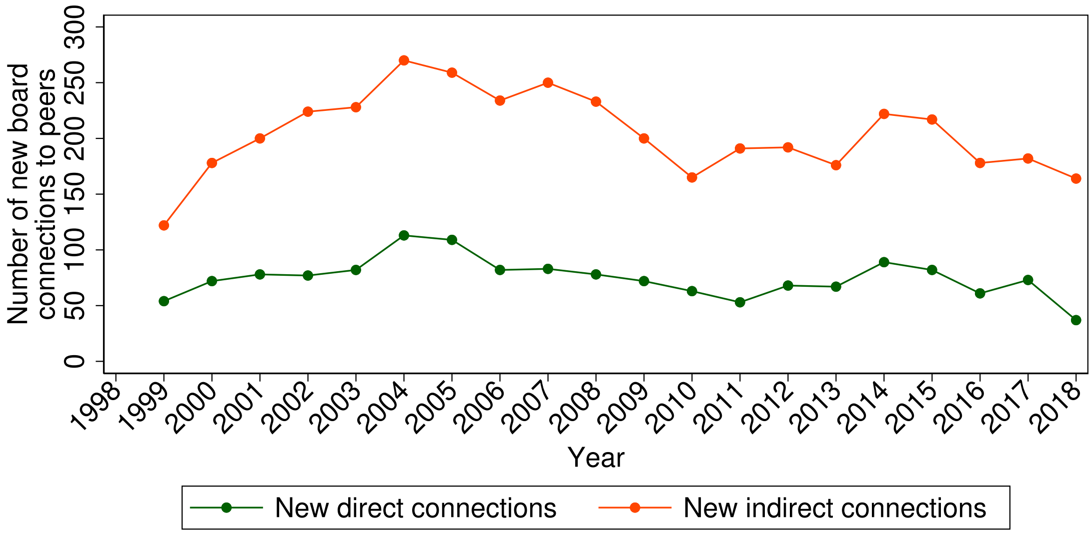
$$\begin{aligned} Y_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} + \alpha_2 \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned}$$

Here $P_{i,m,z,t}$ is the price index of firm i in product module m in 3-digit zip code area z in quarter t. $DirectTreated_{i,m,z} \times Post_{i,m,z,t}$ ($IndirectTreated_{i,m,z} \times Post_{i,m,z,t}$) equals zero for those firm-product-module-zip3 combinations that are never treated and for treated firm-product-module-zip3 in quarters prior to the treatment of terminations of direct board connections (terminations of indirect board connections). It equals one for treated firm-product-module-zip3 in quarters post the treatment. In Panel B (C), we divide treated firm-product-module combinations into cases where the connecting directors continue working in the consumer goods sector (the same product module) and cases where they no longer do so. We then employ the following regression,

$$\begin{aligned} Y_{i,m,z,t} &= \alpha_1 \times DirectorExit_{i,m,z} \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_2 \times NotDirectorExit_{i,m,z} \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_3 \times DirectorExit_{i,m,z} \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_4 \times NotDirectorExit_{i,m,z} \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned}$$

$\theta_{i,m,z}$ are firm-by-product-module-by-zip3 fixed effects. $\theta_{m,t}$ are product-module-by-quarter fixed effects. $\theta_{i,t}$ are firm-by-quarter fixed effects. $\theta_{z,t}$ are area-by-quarter fixed effects. We omitted the coefficient estimates of $NotDirectorExit_{i,m,z} \times DirectTreated_{i,m,z} \times Post_{i,m,z,t}$ and $NotDirectorExit_{i,m,z} \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t}$ for brevity. The outcome variable is winsorized at the 1% and 99% percentiles. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

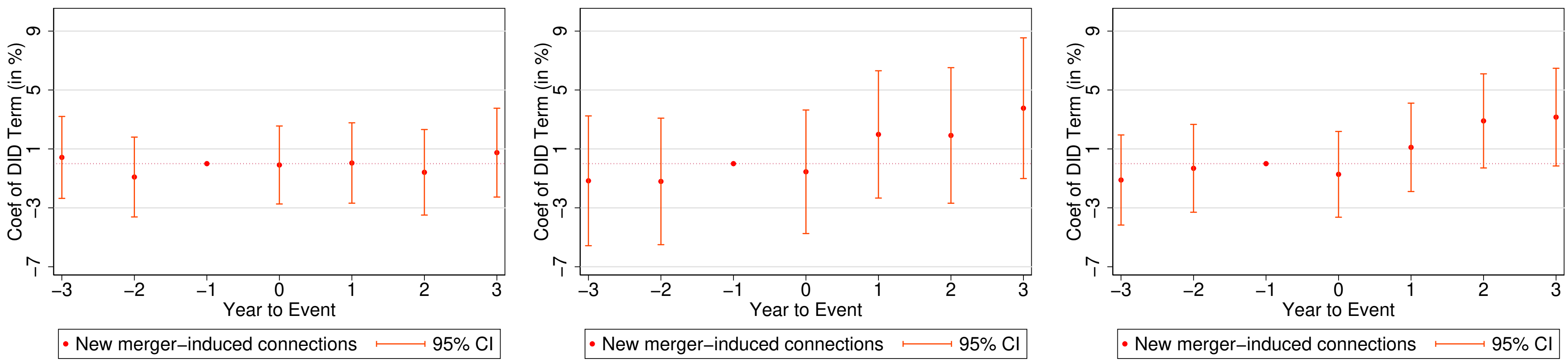
Figure A1: Distribution of new board connections over time



Note: This figure plots the number of new direct and indirect board connections in each year over our sample period of 1999-2018.

Figure A2: Plots of the dynamics of the difference between treated and control firms, using the merger-induced board connections

Panel A: Gross margin | Panel B: Operating margin | Panel C: ROA

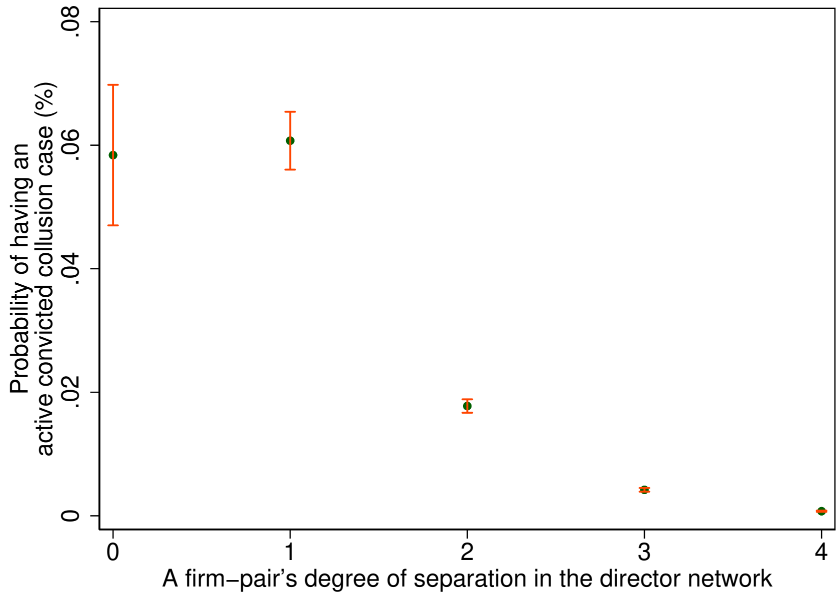


Note: This figure plots coefficients from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} \quad &= \quad \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
&+ \quad MergerInducedTreated_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

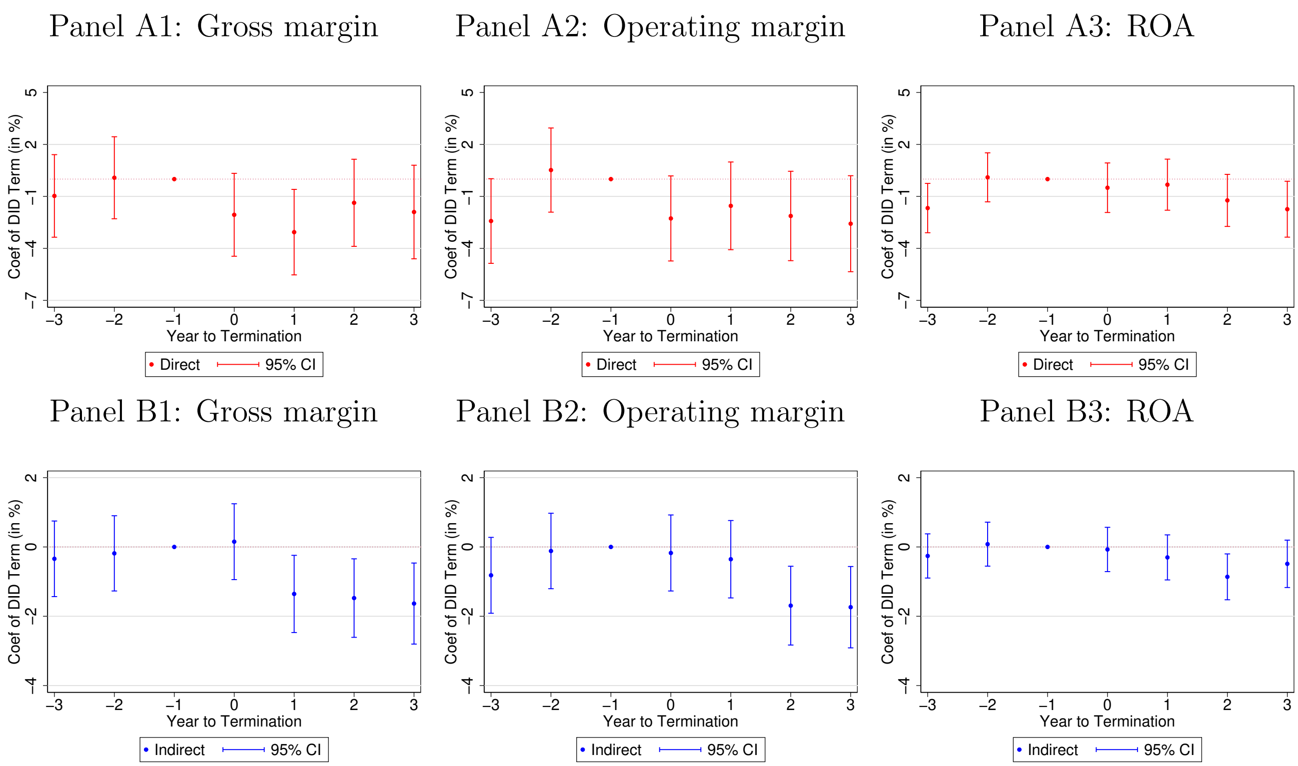
Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that is equal to one for year $\tau = s$ relative to treatment year, with $s = -3, -2, 0, 1, 2, 3$. We omit the dummy variables for the year prior to the event (i.e., $\tau = -1$, which forms the baseline year). Thus all the effects we document are relative to this year. The estimates of γ_s capture the difference in outcome variables between treated and control firms $-s$ years before the treatment (for $s = -3, -2$) or s years after the treatment (for $s = 0, 1, 2, 3$) relative to their differences in the baseline year. $MergerInducedTreated_{i,c}$ is left out of the regression as they are absorbed by $\theta_{i,c}$. Standard errors are clustered at the firm level.

Figure A3: Director network and convicted collusion cases



Note: This figure plots the probability of a firm-pair in a certain year being in an active convicted collusion case, conditional on each level of degree of separation between the firm-pair in the director network.

Figure A4: Dynamics when directors exit the industry and connections terminate



Note: In this figure, we examine the effects of board connection terminations and focus on cases where the connected directors exit the industry — i.e., they no longer work in the same SIC division one year after connection terminations. We plot coefficients from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} \quad = \quad & \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
+ \quad & DirectTreated_{i,c} \times \Big(\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} \Big) \\
+ \quad & IndirectTreated_{i,c} \times \Big(\sum_{s=-3}^{-2} \delta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \delta_s \times \mathbb{1}(\tau = s)_{c,t} \Big) + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that is equal to one for year $\tau = s$ relative to treatment year, with $s = -3, -2, 0, 1, 2, 3$. We omit the dummy variables for the year prior to the event (i.e., $\tau = -1$), which forms the baseline year. Thus all the effects we document are relative to this year. The estimates of γ_s and δ_s capture the difference in outcome variables between treated and control firms $-s$ years before the treatment (for $s = -3, -2$) or s years after the treatment (for $s = 0, 1, 2, 3$) relative to their differences in the baseline year. Panels A1, A2, and A3 report the effects of direct connection terminations, while Panels B1, B2, and B3 report the effects of indirect connection terminations. $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ are left out of the regression as they are absorbed by $\theta_{i,c}$. Standard errors are clustered at the firm level.

IA2 Stock market reaction to director appointments

In Internet Appendix Table A23, we report the cumulative abnormal returns (CARs) in the days around the announcement of director appointments that trigger board connections to peers. We obtain the announcement dates from the Director and Officer Changes Dataset provided by Audit Analytics. We calculate the CARs using the market model and a seven-day window centered around the announcement dates and report the means in column (1). The average CAR after a firm announces the appointment of a director who cross-serves on the board of a product market peer is 0.83%. When a director cross-serves on an intermediate firm that is connected to a peer, the average CAR is 0.73%. In column (2), we report the CARs with the abnormal return calculated as the firm return minus the market return and find similar effects. These announcement returns are statistically significant and are much larger than the CARs around the announcement of non-interlocking appointments as reported in the bottom row, suggesting that the market reacts positively to the appointments under study.

IA3 Matching NielsenIQ Retail Scanner Data to BoardEx

We start by matching the NielsenIQ Retail Scanner Data (NielsenIQ) to producers in the GS1 Company Database. Universal Product Code (UPC) is the unit at which prices are recorded in NielsenIQ Retail Scanner Data, and the first 6-9 digits of it is a prefix that can identify the producer of the product. Each UPC-prefix corresponds to a unique producer. The GS1 Company Database records the name of each producer and the prefixes it owns. Following Baker et al. (2023), we start from the set of all UPCs in the NielsenIQ Retail Scanner Data and obtain their first 6-9 digits, which are our candidate UPC-prefixes. Then we search for these UPC-prefixes in the GS1 Company Database. While the length of a UPC-prefix can vary between 6 to 9, by the rule of its assignment, there will not be a longer UPC-prefix that contains a shorter UPC-prefix as its first many digits (Baker et al., 2023). Hence, if one of the four candidate prefixes for a UPC belongs to a producer in the GS1 Company Database, its producer can be uniquely pinned down. Out of 6,087,712 UPCs, we are able to find producer information for 4,695,783 of them.

Next, we match the producers in the GS1 Company Database to BoardEx. As there is no common identifier among these two databases, we match by the name string. First, we perform an exact match of firm names in the GS1 Company Database to firm names in BoardEx. We clean the firm names by dropping suffixes such as "Co", "Inc", and "Corp" and removing special characters. Second, we use WRDS Company Subsidiary Data to identify subsidiaries of firms in BoardEx and then we do an exact match of firm names in the GS1 Company Database that are still not matched in the prior step to the names of subsidiaries of firms in BoardEx. Third, for the remaining unmatched firm names in the GS1 Company Database, we conduct a fuzzy match between them and firms in BoardEx. We manually check the results from the fuzzy match and make sure we only retain correct matches. Finally, we manually check the top 1,000 UPC-prefixes with the most sales and see if they can be matched to a firm in BoardEx. In this step, we employ Google search and also the location information that is provided in the GS1 Company Database.

We are able to match 2,715,025 UPCs to a firm in BoardEx, which account for 44.6% of all UPCs and 63.4% of the total sales in NielsenIQ.

IA4 Definition of the non-focal-firm-initiated subset of events

Changes to the board of the focal firm could be related to certain future prospects of this focal firm. Our non-focal-firm-initiated subset of events aims to avoid such changes that can be directly linked to firm future prospects. In this section, we describe how we define and operationalize the non-focal-firm-initiated subset of events.

We consider board connections that occur solely due to changes outside of the board of the focal firm. To identify this subset of events, we first identify the complement set of it, which is the set of events that occur at least partly due to changes to the board of the focal firm. Note that by definition new *direct* connections take place because of changes to the board of the focal firm (either appointing new directors or existing directors taking on roles at other firms), so our non-focal-firm-initiated events only consider (a subset of) new *indirect* connections.

In particular, we consider that an event is *not* a non-focal-firm-initiated one, if either:

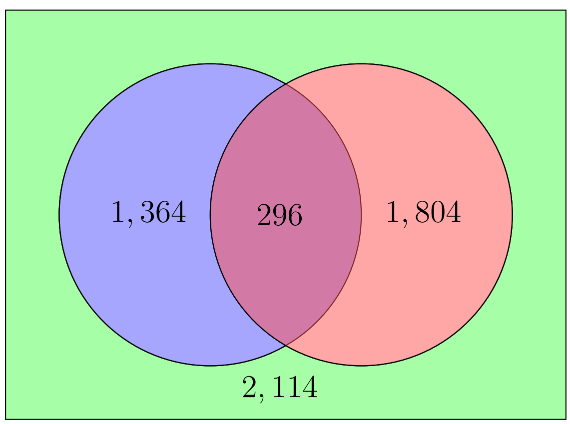
1. the appointment of new directors to the focal firm triggers new connections between the focal firm and its product market peers, and/or

2. new board positions taken by existing directors in the focal firm trigger new connections between the focal firm and its product market peers.

Taking out these *not* non-focal-firm-initiated events from the set of all events, we get the subset of events that we deem to be non-focal-firm-initiated. These events occur solely due to changes to the board of a third intermediate firm or a product market peer, and not due to any changes to the board of the focal firm.

We further decompose how the sample of all new connections relates to non-focal-firm-initiated events with the following Venn diagram:

Figure A5: Definition of the non-focal-firm initiated subset of events



All events of new connections	5,578
Some new connections result from new appointment of directors to the focal firm	1,364 + 296 = 1,660
Some new connections result from existing directors on the focal firm's board taking on directorship elsewhere	1,804 + 296 = 2,100
New connections purely result from changes on boards of other firms (the non-focal-firm initiated subset of events)	2,114

IA5 Examining alternative explanations

In this section, we provide additional evidence by directly testing explanations other than anti-competitive coordination, both to address these explanations and also to better understand the economic implications of product-market-peer board connections. Specifically, we examine the following possibilities:

- Peer-firm board connections facilitate knowledge and technology spillovers;
- Peer-firm board connections facilitate the propagation of profit-enhancing governance practices;
- Peer-firm board connections enhance the board's aggregate experience and expertise, thus improving its governance capacity;
- Peer-firm board connections reduce labor expenses through displacement effects or labor market coordination;
- Peer-firm board connections are correlated with other confounding network ties.

We discuss our findings in turn. Summary statistics for outcome variables examined are reported in Internet Appendix Table A24.

Knowledge and technology spillovers. Board connections may facilitate knowledge and technology spillovers, which can enable firms to reduce production costs or introduce novel products, thereby enhancing profitability. We investigate this mechanism by testing whether:

- Peer-firm board connections affect firm-level patenting outcomes (Kogan et al., 2017);
- Peer-firm board connections facilitate cross-firm collaboration in innovation.

First, we examine whether board connections affect the quantity and quality of firm patenting. Such connections may facilitate communication between firms' R&D departments, potentially fostering innovative ideas that enhance productivity and increase firm profitability. We construct three firm-year-level patenting output measures: (1) the number of patent grants; (2) the total market value of granted patents, capturing the economic value of innovation (Kogan et al., 2017); and (3) the total number of forward citations to granted patents, capturing the scientific value of innovation. In Internet Appendix Table A25, we estimate the following difference-in-differences regression specification:

$$\begin{aligned} Innovation_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{9}$$

As can be seen in Table A25, following product-market-peer board connections, we do not find statistically significant changes in firm patenting output: the number of patent grants; the total market value of granted patents; or the total number of forward citations to granted patents.

Next, we examine whether product market peers more often jointly file patent applications or receive patent grants once they form board connections. We employ a firm-pair-by-year-level treatment-control-matched sample, which consists of both treated and control firm-pairs. To find comparable control firm-pairs, we use a matching procedure based on both individual firm characteristics and firm-pair cosine similarity (Hoberg and Phillips, 2010, 2016). We look at three measures of collaboration: (1) joint patent applications; (2) joint patent grants; and (3) joint ventures. We report our findings from the following difference-in-differences regression specification in Internet Appendix Table A26:

$$\begin{aligned} Collaboration_{i,k,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,k,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,k,c} \times Post_{c,t} + \theta_{i,k,c} + \theta_t + e_{i,k,c,t}. \end{aligned} \tag{10}$$

Indices i and k denote a firm-pair. The specification includes firm-pair-by-cohort fixed effects and year fixed effects. We do not find evidence that connected firms collaborate more in patenting, nor do we observe changes in the likelihood of starting joint ventures.

Our findings indicate that firm patenting and collaboration, while crucial for firm profitability, are not systematically correlated with new product-market-peer board connections.

Propagation of profit-enhancing governance practices. A cross-sitting director may advocate for governance practices that she observes at another firm. Such practices may align incentives and reduce managerial slack, or curtail the waste of resources, thereby improving firm profitability. To assess this mechanism, we examine whether board connections affect a range of governance practices extensively studied in the literature (Core and Guay, 2002; Coles et al., 2006; Appel et al., 2016; Heath et al., 2021), including:

- The proportion of independent directors;
- Whether the CEO also serves as the board chairperson (CEO duality);
- CEO compensation, both in level and in pay-performance sensitivity (PPS).

In addition, we study the effects on SG&A costs as an all-encompassing metric of the effects of improved governance on firms' cost side.

We examine both directional changes and firm-pair similarity in governance practices. Similarity is defined as the absolute difference in a given governance metric. We study similarity in addition to directional changes because the optimal governance practices may vary across sectors. For example, higher PPS may be beneficial in some sectors but counterproductive in others. In such cases, the propagation of better governance practices would manifest as within-industry convergence in governance metrics rather than uniform directional changes.

In Internet Appendix Table A27, we examine the directional changes in (1) share of independent directors; (2) CEO duality; (3) compensation levels; and (4) PPS. We use the treatment-control matched sample as in Table 3 and report estimates from the following difference-in-differences regression specification:

$$\begin{aligned} Governance_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{11}$$

In Internet Appendix Table A28, we instead examine firm-pair similarity in (1) share of independent directors; (2) CEO duality; (3) compensation levels; and (4) PPS. We use a firm-pair-by-year-level treatment-control-matched sample and report estimates from the following regression specification:

$$
\begin{aligned}
|Governance\ Dist|_{i,k,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,k,c} \times Post_{c,t} \\
&+ \beta_2 \times IndirectTreated_{i,k,c} \times Post_{c,t} + \theta_{i,k,c} + \theta_t + e_{i,k,c,t}.
\end{aligned} \tag{12}
$$

We do not find evidence of improved governance practices, i.e., increased board independence (if anything, board independence decreases after indirect connections), reduced CEO duality, or changes in the level or sensitivity of executive compensation, nor do we find consistent evidence of within-firm-pair convergence in governance practices, except for a modest decrease in the firm-pair distance of the independent director share.

Director experience and expertise. Another alternative explanation is that those cross-serving directors may bring superior experience and expertise, thereby improving the board's overall governance and monitoring capacity. For example, a director with legal or financial training may be more effective at corporate oversight, while one with entrepreneurial or scientific experience may be better equipped to navigate the evolving business environments and capitalize on growth opportunities.

To examine this possibility, we leverage the detailed director career histories from BoardEx, covering both board service and other experiences, and construct director-year-level measures of four types of experience: (1) scientific; (2) entrepreneurial; (3) legal; and (4) financial. Specifically, scientific experience is defined as working as a scientist or towards a PhD degree. Entrepreneurial experience is defined as founding a firm or working in the private equity or venture capital industry. Legal experience is defined as experience towards a JD degree or in the legal industry. Financial experience is defined as experience in banks, investment companies, or finance-related corporate roles.

First, we employ the following regression specification in Internet Appendix Table A29, using as outcome variables the share of directors with a given experience or the length of such experience averaged across the board:

$$
\begin{aligned}
Experience_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned} \tag{13}
$$

We do not find statistically significant changes in the board-level (1) scientific; (2) entrepreneurial; (3) legal; or (4) financial experience following the formation of product market peer board connections. These suggest that the newly connected directors do not possess more scientific, entrepreneurial, legal, or financial experience than other directors.

Second, we also re-examine our baseline profit-enhancing effects while controlling for these measures of director experience, using the following regression specification:

$$\begin{aligned} Profitability_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \gamma \times DirectorExperience_{i,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{14}$$

In Panels A to D of Internet Appendix Table A30, we measure director experience as the share of directors with a given experience. We again observe increased firm profitability after the formation of board connections, with coefficient estimates similar to those in Table 3. In the next four panels, we instead control for the length of the experience averaged across the board. We obtain similar findings for our baseline effects. The robustness of the profitability increases is inconsistent with director experience and expertise alone being the underlying mechanism.

Labor cost effects. Board connections could also reduce labor costs for at least two potential reasons. Such connections may facilitate the adoption of labor-displacing technologies (Acemoglu and Restrepo, 2019; Kogan et al., 2025), thereby reducing labor costs and enhancing profitability. Further, board connections could enable anti-competitive coordination in the labor market, suppressing the overall wage bill.

We evaluate these possibilities using the following difference-in-differences regression specification:

$$\begin{aligned} LaborCost_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}, \end{aligned} \tag{15}$$

and examine the effects on (1) the number of employees; (2) the total wage bill; (3) the labor share, defined as total staff expenses (*xlr*) divided by sales (*sale*); and (4) an imputed labor share, for which a firm's wage per employee is imputed using the SIC-3 industry average. The imputed measure is used to address missing data on total staff expenses in financial reports (Donangelo et al., 2019). The findings, reported in Internet Appendix Table A31, show no statistically significant changes in the labor share or the size of employment. These findings do not support the view that board connections facilitate the adoption of labor-displacing technologies or reduce labor expenses through other channels.

In summary, we do not find evidence that product-market-peer board connections significantly affect innovation output, R&D collaboration, labor costs, or governance practices. The increases in profitability hold when controlling for measures of director experience or the density of other network ties. Overall, the evidence does not support these alternative explanations.

IA6 Leaky Director Networks

In this section, we discuss the relationship of our work with Cabezon and Hoberg (2025). Cabezon and Hoberg (2025) proposed a theoretical framework in which director networks facilitate information leakage and reduce firm differentiation. Empirically, they showed a negative relationship between firm profitability and industry-level director network connectedness. In our view, our findings are not inconsistent with their theoretical predictions or empirical findings. Rather, we learn a different aspect of director networks. The differences in the empirical findings arise from the different sources of variation that the two papers exploit.

In the theoretical framework of Cabezon and Hoberg (2025), denser director networks in an industry increase the likelihood of intellectual property leakage, which in turn leads to innovation herding, lost product differentiation, and lower industry-wide profitability. Another valuable insight the model yields is that, from the standpoint of an individual firm, it is still optimal to join the network. This is because the negative externalities of director networks are only partially internalized by an individual firm, yet being in the network enables the firm to receive knowledge from its peers. As a result, director networks are self-reinforcing and there exists a classic coordination failure problem.

The theoretical framework generates two empirical predictions. First, at the industry level, denser director networks should be related to greater innovation herding and lower profitability. This is shown in Cabezon and Hoberg (2025), which employed variation in industry-level connectedness and thus capture the industry-wide externalities. Second, if we turn away from industry-level connectedness and instead exploit the firm-level variation when an individual firm becomes part of the network, the theoretical framework predicts that joining the network is still optimal and profit-enhancing for the firm. This is precisely what we find when examining scenarios where a firm becomes connected to its peers. Hence, our findings are consistent with the theoretical predictions of Cabezon and Hoberg (2025) and can, in this respect, be viewed as providing empirical support for the network's stability and self-reinforcing properties that they discussed.

That being said, we argue that the observed profit increase upon joining the network is not solely a result of receiving knowledge. Rather, it encompasses, to a considerable extent, the benefits of anti-competitive coordination. Leveraging unique product market data, we show that board connections are related to higher product prices and a greater tendency for market allocation, consistent with anti-competitive coordination. In this regard, our paper pins down anti-competitive coordination as another reason why director networks are stable and self-reinforcing, complementing those discussed in Cabezon and Hoberg (2025).

IA7 Director network and convicted collusion cases

We first plot in Internet Appendix Figure A3 the probability of a firm-pair having an active convicted collusion scheme in a certain year, conditional on the degree of separation of this firm-pair in the director network. We find that while this probability is around 0.06% for firm-pairs with a degree of separation of zero or one, it becomes 0.017% for firm-pairs with a degree of separation of two, and diminishes to near zero as the degree of separation further increases.

Next, we estimate the following linear probability model on this sample:

$$
\begin{aligned}
& Prob(\text{Having an active convicted collusion scheme})_{i,j,t} \\
= \ & \sum_{m=0}^{3} \beta_m \times \mathbb{1}(\text{Degree of separation is } m)_{i,j,t} + Control_{i,j,t} + \theta_t + e_{i,j,t},
\end{aligned} \tag{16}
$$

where i and j are indices for the pair firm i and firm j and t is the index for the calendar year. We report the findings in Internet Appendix Table A32. Column (1) reports the probability of having an active convicted collusion scheme, with firm-pairs of degree of separation of four being the baseline group. As firm-pairs closer in the director network might have more similar businesses, which can be a confounding factor that affects the tendency for anti-competitive practices, in column (2) we also control for the cosine similarity of the firm-pair's business descriptions as well as an indicator for whether the firm-pair is in the same Hoberg-Phillips industry. For both specifications, the associative relationship between the degree of separation in the director network and the probability of having an active collusion scheme holds.

IA8 Connection strength

In this section, we study the implications of connection strength. First, we study cases where two previously unconnected firms become connected and examine how effects vary with connection strength, proxied by the number of connecting directors. We consider direct connections to be stronger when the connected firms share multiple directors. For indirect connections, we define greater strength as cases where the treated and the intermediate firms share multiple directors, the intermediate and the peer firms share multiple directors, or there are multiple intermediate firms linking competing firms. We expect greater coordination benefits from stronger connections, and we employ the following regression specification:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times OneDirector_c \times Post_{c,t} + \alpha_2 \times MultipleDirector_c \times Post_{c,t} \\ &+ \beta_1 \times OneDirector_c \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times MultipleDirector_c \times DirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_3 \times OneDirector_c \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \beta_4 \times MultipleDirector_c \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{17}$$

Product market peers share multiple directors in 10.1% of the cases, conditional on them being directly or indirectly connected. In Internet Appendix Table A9, we show that the effects are consistently stronger when product market peers are connected by multiple directors. For example, the effects on ROA more than double in such cases.

In Internet Appendix Table A10, using the NielsenIQ Retail Scanner Data and the following regression specification:

$$\begin{aligned} P_{i,m,z,t} &= \alpha_1 \times OneDirectorDirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_2 \times MultipleDirectorDirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_3 \times OneDirectorIndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \alpha_4 \times MultipleDirectorIndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}, \end{aligned} \tag{18}$$

we also observe stronger product price effects when product market peers become directly connected and share multiple directors (although we do not see such a pattern for indirect connections).

Second, we examine cases in which pre-existing connections between two product market peers become even stronger. Focusing on already connected firm-pairs with a single connection, we identify cases where they form additional direct or indirect connections. Additional direct connections occur when two connected product market peers start sharing one more director. Additional indirect connections occur when an additional director starts cross-serving on the boards of the treated and the intermediate firms, an additional director starts cross-serving on the boards of the intermediate and the peer firms, or there is an additional intermediate firm that connects the treated firm and its peer. These scenarios are distinct from those examined in Table 3, for which no direct or indirect connections existed between the firm-pair in the previous year.

We present our findings in Internet Appendix Table A33. When already connected product market peers form additional direct connections, their gross margin and operating margin change by 0.9 p.p. and 0.9 p.p. to the positive direction, respectively. Their ROA increases by 1.2 p.p., which is statistically significant at the 5% level. For indirect connections, gross margin and ROA change by 0.7 p.p. and 0.3 p.p. to the positive direction. Operating margin experiences a statistically significant increase of 0.8 p.p. We further examine effects on product prices in Internet Appendix Table A34. The prices of products in overlapping product modules grow 0.23 p.p. more per quarter, which has a similar magnitude to those of new direct connections (as reported in Table 4) but is not statistically significant. For indirect connections, we observe a statistically significant effect of 0.05 p.p. These findings are broadly consistent with the notion that adding additional board connections is related to more coordination.

IA9 Network centrality

In this section, we construct centrality measures and examine effect heterogeneity along three dimensions:

- The *director* centrality of the connecting directors (Fogel et al., 2021; Bakke et al., 2024);
- The number of peer firms that these directors can reach;
- The *firm* centrality of the connected peer firms (Larcker et al., 2013).

We agree that analyzing both director centrality and firm centrality — treating directors or firms as nodes in the networks — provides additional insights into how information flows facilitate coordination in overlapping director networks. In addition to centrality, we also use the number of product market peers that the connecting directors can reach as a measure of connectedness, in light of its intuitive interpretation.

We calculate four firm centrality measures following Larcker et al. (2013). First, a firm's degree centrality is defined as the fraction of product market peers with which this firm shares a director. We denote $\delta(i, j)$ as an indicator for whether firms i and j share a director and N_i as the total number of product market peers of firm i. The degree centrality of firm i is

$$\text{Degree}_i = \frac{\sum_{j \neq i} \delta(i, j)}{N_i - 1}. \tag{19}$$

Second, a firm's closeness centrality is measured as the inverse of the average length of the shortest paths from the firm to its product market peers in the director networks. We denote the number of steps in the shortest path between firms i and j as $l(i, j)$. Noting that there may lack a path between a firm i and some product market peers, we denote the fraction of peers that a firm i has a path to as $\frac{n_i}{N_i - 1}$ and the set of such peers as $\mathbb{N}_i$. The closeness centrality is

$$\text{Closeness}_i = \frac{n_i}{N_i - 1} \times \frac{n_i}{\sum_{j \neq i, j \in \mathbb{N}_i} l(i, j)}. \tag{20}$$

The scaler $\frac{n_i}{N_i - 1}$ ensures that firms in a tightly-connected but small "subnetwork" has low centrality (Fogel et al., 2021; Bakke et al., 2024). Third, we calculate betweenness centrality, which measures how frequently a firm lies on the "shortest path" between a randomly selected pair of its product market peers. More formally, denote $m_{j,k}$ as the number of distinct "shortest path" between product market peers j and k, and $m_{j,k}(i)$ the number of such "shortest path" going through a focal firm i. The betweenness centrality is

$$\text{Betweenness}_i = \sum_{j < k, i \neq j, i \neq k} \frac{m_{j,k}(i)/m_{j,k}}{\frac{1}{2}(N_i - 1)(N_i - 2)}. \tag{21}$$

Fourth, we construct eigenvector centrality, which builds on the idea that a board is well-connected if its direct contacts are also well-connected (Bonacich, 1972). It is recursively defined: a firm's eigenvector centrality is a constant scalar times the sum of the eigenvector centrality of all product market peers with which this firm shares a director. Formally,

$$\lambda_i \cdot \text{Eigenvector}_i = A_i \cdot \text{Eigenvector}_i. \tag{22}$$

Eigenvector_i is the eigenvector of matrix A_i (a $N_i \times 1$ vector), and λ_i is the associated eigenvalue.[7]

In addition to firm centrality, we also construct analogous director centrality measures (Fogel et al., 2021). For these, directors are the "nodes" in the network and the firm board that two directors both sit on serves as the "edge". We assess a director's centrality among directors affiliated with product market peers. These measures vary at the director-firm-year level, as the same director serving on multiple boards may have different peer directors depending on the focal firm under consideration. In Internet Appendix Table A2, we compare how directors involved in the product-market-peer connections differ from an average director in the treated firms. Consistent with our expectations, we observe a strong pattern that these directors have higher centrality under every definition.

In sum, we construct four (degree, closeness, betweenness, and eigenvector centralities) $\times$ two (firm centrality and director centrality) centrality measures. Following Larcker et al. (2013), Fogel et al. (2021), and Bakke et al. (2024), we collapse along the first dimension. Specifically, within each year and for each measure, we rank the observations and convert them into percentiles ranging from 0 to 100. We then average across the four percentiles for degree, closeness, betweenness, and eigenvector centralities. This procedure yields two composite measures, one at the firm-year level and one at the director-firm-year level.

We expect stronger effects when the connecting directors have greater connectedness (i.e., higher director centrality or access to many product market peers) as such a director substantially boosts the competition-sensitive information available to the firm. Similarly, we expect stronger effects when the newly connected firms have higher firm centrality. Such firms can serve as conduits between the focal firm and the broader director networks.

We report our findings from the following regression specification, in which we interact

[7] Please refer to, for example, Larcker et al. (2013), Renneboog and Zhao (2014), El-Khatib et al. (2015), Fogel et al. (2021), and Bakke et al. (2024), for the insights on how to interpret them in the context of director networks.

the treated times post indicators with dummies for whether the centrality of the connecting directors or the newly connected firms is above median:

$$\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Centrality < Median_c \times Post_{c,t} + \alpha_2 \times Centrality \geq Median_c \times Post_{c,t} \\
&+ \beta_1 \times Centrality < Median_c \times DirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_2 \times Centrality \geq Median_c \times DirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_3 \times Centrality < Median_c \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_4 \times Centrality \geq Median_c \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \qquad (23)
\end{aligned}$$

We expect the estimated profit-enhancing effects to be greater when centrality is high (β_2 and β_4) than when it is low (β_1 and β_3).

In Internet Appendix Table A11, we report the findings on effect heterogeneity along the following three dimensions:

- The *director* centrality of the connecting directors (Panel A);
- The number of peer firms that these directors can reach (Panel B);
- The *firm* centrality of the connected peer firms (Panel C).

In Panel A, we sort board connections by the director centrality of the connecting director in the treated firm. The estimated profitability effects are consistently greater and are on average twice as large when the connecting director has above-median director centrality.

In Panel B, we sort board connections by the number of product market peers that the connecting directors can reach, which is an intuitive measure of connectedness. A director is considered able to reach a peer firm if she serves on its board or if she can reach it via one or two intermediate firms in the director networks. This measure bears similarity to degree centrality but additionally considers connections via intermediate firms. We find that the profit-enhancing effects are also stronger when the connecting directors are more central in this sense.

In Panel C, we find larger point estimates for the profit-enhancing effects of board connections when the newly connected peer firm has above-median firm centrality. This is consistent with such firms serving as conduits and linking the treated firm to the broader director networks.

Finally, in addition to these profitability effects, we examine the relationship of centrality heterogeneity with the effects on product prices in NielsenIQ Retail Scanner Dataset using the following regression specification:

$$\begin{aligned}
P_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times Centrality < Median_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_2 \times DirectTreated_{i,m,z} \times Centrality \geq Median_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_3 \times IndirectTreated_{i,m,z} \times Centrality < Median_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_4 \times IndirectTreated_{i,m,z} \times Centrality \geq Median_{i,m,z} \times Post_{i,m,z,t} \\
&+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \qquad (24)
\end{aligned}$$

Our findings are reported in Internet Appendix Table A12. Consistent with our prior findings, we observe that the product price effects are larger or at least as large when the connecting directors or the newly connected peer firms are more central in the director networks.

In sum, our findings with both director and firm centralities support the importance of overlapping networks in facilitating anti-competitive coordination. A firm benefits not just from forming a connection to one peer, but also from the broader overlapping networks that the new connection brings access to.

IA10 Director busyness

In this section, we study the implications of director busyness. Having a connected but busy director can have two effects. First, the director may be preoccupied with obligations on other firms' boards and lack the capacity for anti-competitive coordination. Second, busyness may also impair the director's monitoring role (Fich and Shivdasani, 2006; Falato et al., 2014; Hauser, 2018).

We examine how the effects of product-market-peer board connections vary with the busyness of the connecting director that serves on the treated firm's board. In Internet Appendix Table A13, we define a director as busy if the number of board positions that she holds at non-product-market-peer firms exceeds a threshold of one (Panel A) or two (Panel B). The connecting directors are busy in 16.5% (6.2%) of the cases under the former (latter) definition. We focus on non-product-market-peer appointments because we want to step aside from the confounding effects of director centrality within the product-market-peer director networks, which may instead strengthen the coordination benefits. We examine the effects on firm profitability with the following regression specification:

$$\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times DirectorNotBusy_c \times Post_{c,t} + \alpha_2 \times DirectorBusy_c \times Post_{c,t} \\
&+ \beta_1 \times DirectorNotBusy_c \times DirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_2 \times DirectorBusy_c \times DirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_3 \times DirectorNotBusy_c \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \beta_4 \times DirectorBusy_c \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \qquad (25)
\end{aligned}$$

In Panels A and B of Internet Appendix Table A13, we find that the profit-enhancing effects of board connections are concentrated in cases where the connecting directors are classified as not busy. When directors are busy, we do not observe statistically significant effects, and the point estimates are almost always smaller and occasionally negative.

Similarly, in Internet Appendix Table A14, we employ the following regression specification on the NielsenIQ Retail Scanner Dataset:

$$\begin{aligned}
P_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times DirectorNotBusy_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_2 \times DirectTreated_{i,m,z} \times DirectorBusy_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_3 \times IndirectTreated_{i,m,z} \times DirectorNotBusy_{i,m,z} \times Post_{i,m,z,t} \\
&+ \alpha_4 \times IndirectTreated_{i,m,z} \times DirectorBusy_{i,m,z} \times Post_{i,m,z,t} \\
&+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \qquad (26)
\end{aligned}$$

We find that the effects on product market prices are also more pronounced or at least as large when the connecting directors are not busy.

We further expand this analysis by examining the degree of director involvement on other boards. Directors often serve on auditing, compensation, nominating, and other committees.

Prior research (Jiraporn et al., 2009; Falato et al., 2014; Chen and Guay, 2020) suggested that the detrimental effects of director busyness are amplified when directors serve on such committees. In Panels C and D of Table A13, we define a director as busy if she serves on more than one (Panel C) or two (Panel D) such committees. The connecting directors are busy in 23.9% (12.8%) of the cases under the former (latter) definition. In Panel E, a director is considered busy if she serves on multiple types of committees — for example, on both the compensation committee and the auditing committee — in the same or across different firms. Serving on a variety of committees with distinct functionalities is likely more cognitively demanding than specializing in a single area. This happens in 17.6% of the cases. Consistent with this reasoning, we again observe that the effects of board connections are attenuated when directors are busy with committee obligations.

Overall, our findings are consistent with the prior corporate governance literature and suggest that the value directors bring to a firm, including their role in facilitating anti-competitive coordination, can be diminished by their busyness.

IA11 Common ownership and product prices

As shown in Section 4.1.3, our baseline profitability effects were robust to controlling for common ownership. We also examine the robustness of the product price effects controlling for common ownership. Employing the Refinitiv 13F Institutional Holdings dataset, we construct measures of common ownership. Specifically, we compute the following C-index at the product module times quarter times geographic area level:

$$\text{Market-segment-level C-Index}_{m,z,t} = \sum_{j=1}^{J} \sum_{\substack{k=1 \\ k \neq j}}^{K} \sum_{n=1}^{N} w_j \cdot w_k \cdot \mu_{n,j} \cdot \mu_{n,k}. \tag{27}$$

Here j and k denote a pair of public firms with sales in the market segment of product module m in 3-digit zip code area z and quarter t. The terms $\mu_{n,j}$ and $\mu_{n,k}$ represent the ownership shares of institutional investor n in firms j and k, respectively. We use a multiplicative form of ownership shares following Gilje et al. (2020) and Lewellen and Lewellen (2022). w_j and w_k are the market shares of firms j and k in this market segment. The common ownership measure first sums up the ownership overlap of all institutional investors within a firm-pair, and then aggregates across all firm-pair combinations within a market segment. Following Azar et al. (2018), we also compute the MHHI Delta as:

$$\text{MHHI Delta}_{m,z,t} = \sum_{j=1}^{J} \sum_{\substack{k=1 \\ k \neq j}}^{K} \frac{\sum_{n=1}^{N} w_j \cdot w_k \cdot \mu_{n,j} \cdot \mu_{n,k}}{\sum_{n=1}^{N} \mu_{n,j} \cdot \mu_{n,j}}. \tag{28}$$

One caveat is that these measures are based on public firms. Apart from data limitations, privately held firms are less likely to have passive institutional owners that create the commonly discussed common ownership concerns. To address this issue, following Chen (2025), we additionally control for the total market share of private firms in each market segment ($PrivateShare_{m,z,t}$) and its interaction with the common ownership measures. Specifically, we estimate the following regression specification:

$$\begin{aligned} Y_{i,m,z,t} &= \alpha_1 \times DirectTreated_{i,m,z} \times Post_{i,m,z,t} + \alpha_2 \times IndirectTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \beta_1 \times CommonOwnership_{m,z,t} + \beta_2 \times PrivateShare_{m,z,t} \\ &+ \beta_3 \times CommonOwnership_{m,z,t} \times PrivateShare_{m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned} \tag{29}$$

We report the findings in Internet Appendix Table A35. The effects of board connections on product market prices remain robust, with point estimates similar to those in Table 4, indicating that common ownership is not a major omitted confounding factor in our analysis of product prices.

IA12 Other network ties

In this section, we study network ties beyond board interlocks. Firms can potentially be connected via other types of connections. It is not clear a priori whether these network ties facilitate coordination. While under these network ties directors may lack the opportunity to interact face to face or to exchange competition-sensitive information, it is certainly plausible that firms might be inclined to rely on "less visible ties" to avoid antitrust scrutiny. The comparison can help inform the appropriate scope of antitrust regulations — i.e., whether the current ban on board interlocks under Section 8 of the Clayton Act should be expanded.

We examine the implications of four more kinds of network ties.

- Connections via shared non-board work experience outside of public firm boards: These are the cases where product market peers Firm 1 and Firm 2 each have Director A and Director B, and these two directors have shared work experience at the same intermediate firm. In constructing this network tie, we exclude the cases where both directors served as a board member at this intermediate firm.

- Connections via education: These are the cases where product market peers Firm 1 and Firm 2 each have Director A and Director B, and these two directors attended the same educational institution and graduated within one year of each other (Fracassi and Tate, 2012).

- Connections via other activities: These are the cases where product market peers Firm 1 and Firm 2 each have Director A and Director B, and these two directors participated in the same non-business-related activities, such as charitable work or leisure clubs. Following Fracassi and Tate (2012), we require that the director be listed as an officer or director of the organization and not merely a member.

- Connections via common ethnic origin: These are the cases where product market peers Firm 1 and Firm 2 each have Director A and Director B, and these two directors have common ethnic origin inferred based on their names using a machine-learning classification algorithm (Hafner et al., 2024).

In Internet Appendix Table A36, we report firm-year-level summary statistics on the number of product market peers that a firm is connected to via each type of network tie. On average, a firm's board shares a director with 0.53 product market peers and is indirectly connected to 2.11 peers via a third intermediate firm. Its directors collectively have shared work experience outside of public firm boards with directors of 3.88 peers, common educational experience with directors of 1.41 peers, common non-business-related activities (e.g., charitable work, leisure club)[8] with directors of 2.04 peers, and common ethnic origin with

[8]In Internet Appendix Table A37, we present the most common non-business-related activities in our

directors of 8.49 peers. Overall, the density of other network ties is comparable to that of board interlocks.

We examine the profit and price implications of these network ties in Internet Appendix Tables A15 and A16. Our analysis begins with the following regression specification:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times OtherNetworkTiesTreated_{i,c} \times Post_{c,t} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{30}$$

Here, the event time (i.e., time 0) corresponds to the time of the formation of the network tie — i.e., the start of the overlap in the tenures of Director A at Firm 1 and Director B at Firm 2.

We find that gross margin, operating margin, and ROA rise by 0.7 p.p., 0.6 p.p., and 0.2 p.p. after a firm appoints a director who shares educational experience with directors at product market peers. We also observe positive changes in profitability upon the formation of network ties via shared work experience outside of public firm boards and via other activities, but the effects are not always statistically significant and have smaller magnitudes. Gross margin increases by 0.3 p.p. for network ties via shared work experience outside of public firm boards and operating margin changes by 0.2 p.p. Operating margin increases by 0.4 p.p. for network ties via other non-business-related activities. We observe little changes in profitability for network ties via common ethnic origin.

Next, we examine the effects on product prices using the NielsenIQ Retail Scanner Dataset and the following regression specification:

$$\begin{aligned} P_{i,m,z,t} &= \alpha \times OtherNetworkTiesTreated_{i,m,z} \times Post_{i,m,z,t} \\ &+ \theta_{i,m,z} + \theta_{m,t} + \theta_{i,t} + \theta_{z,t} + e_{i,m,z,t}. \end{aligned} \tag{31}$$

We find that when a firm appoints a director who shares educational experience with directors at product market peers, the prices of products in overlapping product modules grow 0.39 p.p. more per quarter. Similarly, in cases of shared work experience outside of public

sample. These include professional associations (e.g., American Heart Association), academic societies (e.g., American Academy of Arts and Sciences), charitable organizations (e.g., The Nature Conservancy), and leisure activities (e.g., Woodruff Arts Center).

firm boards, the prices of products in overlapping product modules grow 0.16 p.p. more per quarter. The magnitudes of these effects amount to 62% and 25%, respectively, of those observed for indirect board connections, as reported in Table 4. We do not observe significant price effects for network ties via other non-business-related activities or common ethnic origin.

We note that our examination of network ties is non-exhaustive, and other social and professional links between competing firms may exist. We address them to the extent possible given data limitations. Nevertheless, those we do examine provide useful examples for understanding the prevalence and implications of such ties. Overall, our findings suggest that while network ties among competing firms besides board interlocks are common, they have limited effects on product prices and profitability. This highlights the importance of face-to-face interactions and shared experience and expertise for facilitating anti-competitive coordination. Indeed, these analyses offer a novel perspective and help sharpen the paper's policy implications that these particular non-board network ties are less likely to provide a stable platform of repeated interactions for product market coordination.

We next examine past connections. These are the cases where product market peers Firm 1 and Firm 2 each have Director A and Director B, and these two directors served together on the board of a common third firm Firm 3 in the past. The event time (i.e., time 0) corresponds to the time when the overlap of the tenures of Director A at Firm 1 and Director B at Firm 2 begins. In constructing past connections, we require that by the time the overlap of the tenures of Director A at Firm 1 and Director B at Firm 2 begins, they no longer serve on the board of Firm 3 together, so connections are in the past rather than concurrent. That is, both directors co-served on the same board in the past and no longer do so when they serve on boards of competing firms.

On average, a firm's board members served on a third firm together with directors of 1.97 product market peers in the past. We report our findings on the effects of past connections in Internet Appendix Tables A38 and A39. We find some evidence of higher firm profitability. Operating margin rises by 0.4 p.p. following the formation of past connections, approximately half the magnitude of that of concurrent board connections. Gross margin and ROA both change by 0.2 p.p. to the positive direction, which are not statistically significant. These findings indicate that past connections have a limited role in facilitating anti-competitive coordination, underscoring the importance of simultaneous board appointments for the transmission of competition-sensitive information.

Overall, we find evidence that network ties via shared working or educational experiences can facilitate coordination and increase profitability, though the effects are smaller in magnitudes compared to those of board interlocks. Other types of network ties and past connections have limited or no effects.

Finally, as a robustness test and to understand whether these other network ties and past connections serve as alternative explanations to our baseline findings, we employ the following regression specification and re-examine the effects of board connections controlling for the density of other network ties and past connections:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \sum_{\substack{\text{network tie type} \in \\ \{\text{shared work experience, education,} \\ \text{other activities, ethnic origin,} \\ \text{past connections}\}}} \gamma_{\text{network tie type}} \times Density_{i,t,\text{network tie type}} \\ &+ \theta_{i,c} + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{32}$$

We report our findings in Internet Appendix Table A40. In columns (1)-(3), we control for the share of product market peers that a firm is connected to via other network ties or past connections. We control for the number of such peers instead in columns (4)-(6). Our main findings that board connections increase firm profitability are robust to these controls, and the point estimates are similar in magnitude.

IA13 Connection terminations

In this section, we examine effects of board connection terminations. Anti-competitive coordination may cease upon board connection terminations, but it is also possible that the same directors continue to facilitate coordination when they no longer cross-serve on boards of competing firms. In addition, they may help establish social and professional ties among themselves or with other members in competing firms. These ties can persist beyond the termination of the original board connection. Therefore, it is ex-ante unclear whether effects would reverse following connection terminations.

We examine the effects of board connection terminations and report our findings in Internet Appendix Tables A41 and A42. We find that on average firm profitability and product prices do not exhibit statistically significant changes following board connection terminations.

Next, we zoom into cases where the connected directors leave the treated firm's industry completely. In these scenarios, directors likely changed career path or retired, and therefore they reduce their face-to-face interactions with industry peers and are less likely to remain as information intermediary among these peers. We restrict the sample to cases where the connected director no longer works in the same SIC division one year after connection termination (Panel B of Internet Appendix A41) or no longer holds any board position (Panel C of Internet Appendix A41). Directors exit the industry in 16.3% of the cases and entirely step down from any board positions in 9.4% of the cases. We observe a reversal in firm profitability in such cases. We further examine the dynamics of firm profitability when the connecting directors exit the industry, and show in Internet Appendix Figure A4 that profitability decreases within one to two years after connection terminations.

Our findings indicate that while reversals can occur, more often the effects of product-market-peer board connections persist. Notably, these results are not inconsistent with those on past connections, for which we observe limited effects. In cases of past connections, directors no longer co-serve on the board of the same intermediate firm when they independently (and without current connection) start serving on the boards of competing firms. During their time at the intermediate firm, they were likely unaware of their future roles at competing firms and thus may not have forged strong bonds. Overall, our findings underscore the necessity of regulatory interventions that prevent the formation of board connections in the first place.

about ECGI

The European Corporate Governance Institute has been established to improve *corporate governance through fostering independent scientific research and related activities.*

The ECGI will produce and disseminate high quality research while remaining close to the concerns and interests of corporate, financial and public policy makers. It will draw on the expertise of scholars from numerous countries and bring together a critical mass of expertise and interest to bear on this important subject.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.

Electronic Access to the Working Paper Series

The full set of ECGI working papers can be accessed through the Institute's Web-site (www.ecgi.global/content/working-papers) or SSRN:

Finance Paper Series	http://www.ssrn.com/link/ECGI-Fin.html
Law Paper Series	http://www.ssrn.com/link/ECGI-Law.html