Do board connections between product market peers impede competition?

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Abstract

After a new direct board connection is formed to a product market peer, a firm's gross margin increases by 0.8 p.p. Gross margin also rises by 0.4 p.p. after a new connection is formed to a peer indirectly through a third intermediate firm. Board connections have positive profitability spillovers on the closest rivals, and the effects are stronger when the newly connected peers share major corporate customers, have more similar business descriptions, or are located closer to each other. Using retail scanner data, we further provide direct evidence that new board connections are related to higher product prices of consumer goods.

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

JEL Classification: G34, G38, L22

Director networks can enable the flow of information between firms and help coordinate anti-competitive behavior. Recognizing this, Section 8 of the Clayton Antitrust Act of 1914 (the Clayton Act) has largely prohibited firms with substantial overlap in their activities from sharing directors and officers on their boards and such practices are actively monitored by the US antitrust authorities.[1]

Despite its stringency and effective enforcement, the Clayton Act leaves room for director networks to serve an anti-competitive role and product-market director interlocks might be more prevalent than expected. First, in a rapidly changing environment of business strategies and product lines, such as in the technology sector, it may be challenging to determine which firms compete with one another at a given point in time.[2] Second, information can flow across competing firms not only through a directly shared common director but in general through the broader director network. Since directors routinely sit on multiple firm boards, firms can become linked through a director network via another firm. In this paper we map the director networks of firms that compete in the product market to explore their anti-competitive role and find that such direct connections and indirect connections (through an intermediate firm) are not only common but are associated with higher firm profitability and increased product prices.

We begin by mapping the director network of product market peer firms based on the Hoberg-Phillips industry classification (Hoberg and Phillips, 2010, 2016) to identify instances when such firms are closely linked through the board director network. 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. The fact that we have 1,493 instances of direct board connections between firms that are potentially in the same product market space – at least according to the Hoberg-Phillips classification

[1] E.g., on June 21, 2021, the Department of Justice (DoJ) announced that two board members of Endeavor Group Holdings Inc. have resigned their positions from the board of Live Nation Entertainment Inc. after the department expressed concerns that these firms are direct competitors in the entertainment ticketing business and the interlocking directorate has the potential to harm competition (Department of Justice, 2021). A newly appointed head of the DoJ's antitrust unit Jonathan Kanter highlighted in May, 2022 that one area of focus for the agency is "interlocking directorates" (Financial Times, 2022).

[2] E.g., in 2018, DoJ raised concerns about cable operator Comcast appointing executives of its NBC Universal broadcast subsidiary to the board of Hulu, a video streaming service provider in which Comcast held a 30% stake. As streaming was increasingly seen as competing with cable, DoJ asserted that Comcast's representatives on Hulu's board potentially ran afoul of Clayton Act (Delrahim, 2018).

– indicates the possibility of imperfect enforcement of the Clayton Act restrictions on board connections between competing firms.[3]

We find that the firms with board connections have more similar product descriptions – as measured using the cosine similarity score – than a random pair of firms from the same Hoberg-Phillips industry. The connected firms are also more likely to be from the same Standard Industrial Classification (SIC) or Global Industry Classification Standard (GICS) industry. These observations indicate that board interlocks do appear between firms that have similar products and thus likely compete in the product markets. Such new appointments of connected directors of product-market peers tend to have positive cumulative abnormal returns (CARs) around the announcement dates.

Our main analysis adopts a difference-in-differences model to study the relationship between new board connections between product market peers and newly connected 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 the same 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 new board appointment ("treatment" or "event"). We find that the set of treated and control firms are indistinguishable in terms of the matching co-variates in the year prior to treatment. The first difference in our model is between the treated and control firms while the second difference is between the time period before and after treatment. In our empirical model, we include firm fixed effects and within-industry year fixed effects.

We mainly focus on firm profitability as the outcome variable. We capture profitability in different ways looking at the gross margin, the operating margin, and the return on assets (ROA). We find that firm profitability significantly increases in the three years after which this 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. Our estimates are economically significant. In the three years following an

[3]For example, our data shows that board interlock arose when Dr. Sharad Mansukani, who had been on the board of Surgical Care Affiliates Inc., was appointed as a director for Kindred Healthcare Inc. in 2015. Another example in the data is when Terry Wright, a long-time independent director of Southwest Gas Holdings Inc., was appointed as an independent director to the board of Golden Entertainment Inc. in 2015. At that time the board of Southwest Gas Holdings Inc. was also directly connected to the board of Boyd Gaming Corp. via Bob Boughner. Thus, an indirect connection formed between Golden Entertainment Inc. and Boyd Gaming Corp., which are competitors in the gaming and hospitality businesses.

indirect connection to a product market peer, a firm's gross margin, operating margin and ROA increase by 0.4 p.p., 0.8 p.p., and 0.6 p.p. respectively. The estimates are even larger following a direct connection to a product market peer and, respectively, are 0.8 p.p., 1.4 p.p., and 0.9 p.p. These increases represent 1.6%, 11%, and 10% of the mean values of the variable in question for the treated firms in the year prior to treatment. We do not see any differential pre-existing trends in profitability between the treated and control firms.

Changes to the board of directors of a firm could be endogenous to the future prospects of the firm. For example, firms that anticipate an improvement in their performance could afford appointing a director who is a better expert in their industry and thus likely connected to another product market peer. Also, the directors of a firm with improving prospects could be more valued in the director labor market and thus more likely to be appointed to the boards of product market peers. In our further tests, we focus on new connections that do not arise from the changes in the treated firm's board and are thus more exogenous.

In particular, we study indirect connection events and isolate the subset of events that arise due to changes in the board of an intermediate firm or a product market peer, i.e., when the treated firm does not appoint directors from peers or intermediate firms and neither of its present directors gets new appointments to the boards of peers or intermediate firms. We deem these events more likely to be exogenous to the treated firm's future prospects and still find a similar increase in its profitability.

While our findings are consistent with board connections facilitating anti-competitive practices, the literature on director networks (see, e.g., Bouwman (2011)) suggests that board connections can also improve profitability by propagating governance practices that could enhance the internal efficiency of the firm. We next design tests to distinguish our proposed anti-competitive mechanism from this internal efficiency mechanism.

First, we zoom into the retail sector and find evidence that board connections are related to coordinated product price movements based on the Nielsen Retail Scanner Data, which contains detailed information on product-level prices in the consumer goods sector. When new board connections among firms selling in the same product category get formed, the product prices of treated firms rise 0.08% faster per quarter relative to untreated firms in the same product category, which translates into a 0.32% annualized difference. We interpret this as direct evidence that board connections could enable anti-competitive practices.

Second, we implement a series of cross-sectional tests for our main results. We sort events based on a range of characteristics and then employ a triple-differences model. We find that connections to peers that share major corporate customers, have more similar businesses according to the cosine similarity score of firms' product descriptions, or are closer geographically have stronger effects on firm profitability. We also see stronger effects in industries where the potential benefits of coordination are greater.

Third, we investigate the spillover effects of board connections on the closest common rivals of newly connected firms. Suppose board connections enable anti-competitive practices such as price-fixing. In such a case, we could expect that the closest rivals operating in the same industry are able to follow so-called "umbrella pricing" and also raise prices (Bos and Harrington, 2010). However, if board connections enhance firms' internal efficiency, those rivals not involved in the newly formed network will be put at a relative disadvantage and could see their profitability worsening when faced with more efficient rivals. We find evidence supportive of the former, which is more consistent with the anti-competitive explanation.

Fourth, we document how board connections relate to detected collusion cases. We find that while two directly connected firms have a probability of 0.058% of having an active detected collusion case and it is 0.061% for a firm-pair with one degree of separation, this probability becomes 0.017% for the firm-pairs with two degrees of separation and 0.004% for the firm-pairs with three degrees of separation. This strong associative relationship also suggests that director networks can play a role in facilitating anti-competitive practices.

We conduct a number of robustness tests, including a placebo test showing that non-peer board connections do not display such a concurrent increase in profitability. Importantly, we also discuss that board overlaps might be associated with concurrent increases in within-industry common ownership (Azar, 2022). We indeed document that those firms experiencing new board connections are more likely to have a concurrent increase in within-industry common ownership than the control firms. However, we also show that common ownership does not fully explain the effects that board connections have on firm performance.

This paper provides large-sample evidence that board connections between product market peers are related to better overall operating performance which is consistent with the anticompetitive effects. The literature previously investigated other aspects of the board connections between product market peers. Nili (2021) documented the widespread prevalence of horizontal directors in the US. Buch-Hansen (2014) found no correlation between direct or indirect board ties and detected cartels in the sample of European firms. Westphal and Zhu (2019) surveyed a moderately-sized sample of firms to show that a CEO feels less uncertain about the competitive landscape in the product market if she has friends on the board of a competing firm. Geng et al. (2021) found that reducing legal risk of sharing information outside of the board of directors increases the frequency of board overlap, which is then associated with higher sales revenue and profit margin. Barone et al. (2022) showed that prohibiting interlocking directorates among banks reduces the interest rates of loans extended by previously interlocked banks. Cabezon and Hoberg (2022) discussed the intellectual property leakage between product market peers connected through the boards of directors. Compared to this literature, we look at a broader firm sample and document the pervasiveness of both direct and, importantly, indirect board connections between firms in the same product space and their positive effects on connected firms' profitability.

This paper also contributes to the literature on firm conduct that facilitates anti-competitive practices. Recent literature has extensively looked at whether sharing common investors between the firms contributes to higher product prices (see, e.g., Azar et al. (2018); Anton et al. (2021)). Tacit coordination can also be achieved with financial documents (Bourveau et al., 2020). Moreover, Ha et al. (2021) found that directors might design executive compensation schemes that motivate product market coordination. We highlight board connections as one of the forms how tacit coordination in product markets can be made easier.

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., 2013; Drobetz et al., 2018; Gopalan et al., 2021) and focuses on how such roles change when the boards of directors can be used to coordinate product market behavior between the 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, the network of directors. At the firm level, prior research has found that the network of directors enhances firm value (Bakke et al., 2021), 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, 2022), and greater stock price synchronicity (Khanna and Thomas, 2009). This network has also been shown to influence 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 via this network, and Intintoli et al. (2018) showed that more connected directors have better career prospects. We restrict our attention to connections with competitors and posit that this economically important class of connections is associated with better future firm profitability. We also provide a novel reduced-form identification strategy of indirect connection formation, which bypasses the concern that the formation of new connections could correlate with unobservable future prospects and allows us to identify their treatment effects.

1 Hypothesis Development

Successful coordination among competitors yields monopolistic profits, which can be divided among these competitors and thus 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 the price at a high 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, an equilibrium with successful tacit coordination might be challenging to sustain, as it can be optimal for the participating firms to deviate and engage in predatory behaviors, such as cutting prices or entering into their competitor's market segment (Wiseman, 2017). Second, 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). Third, explicit collusion is illegal and suspected colluding firms might face legal actions (Department of Justice and Federal Trade Commission, 2000).

We argue that board connections are one way to facilitate anti-competitive practices by alleviating the aforementioned hurdles to successful coordination. Board connections might give opportunities for direct communication between the competing firms about their product market strategies or labor and supply chain policies. Moreover, the professional and personal interactions between directors can help build trust among competing firms and make deviations from coordination less likely to occur. In this sense, board connections can be considered as a kind of relational contract as in Baker et al. (2002). Also, even the interactions among directors of competing firms on the boards of other unrelated firms could facilitate coordination. Observing the rival firms' director voting behavior on third boards could improve understanding of how decisions in the rival firms are made, which could then be internalized into more informed reaction functions for firms' strategic interactions.[4]

While the Clayton Act prohibits interlocking directorates among competing firms, it falls unto the burden of regulators to consider whether two firms share the same product market and can be perceived to be competing. In today's overlapping product markets, product market definition is often challenging.[5]

Nonetheless, there are several reasons why board connections to product market peers might not lead to a higher gross profit margin. First, one may argue that the role of directors is to monitor the behavior of managers and does not entail interfering with firms' product market strategies. Second, when the potential gains from coordination are large, firms might have found alternative vehicles to facilitate and sustain coordination, so the treatment of

[4]Directors might also be better aware of other firms' financial policies, and influence them to be less aggressive, in turn making the strategic competition less fierce.

[5]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 of the Company's top ten competitors," Amazon identified 1,700 companies, including "a discount surgical supply distributor and a beef jerky company."

board connections would have null effects. Third, board connections might be correlated with busier directors simultaneously sitting on more boards, which might hinder directors' ability to perform their duty in a single firm (Core et al., 1999; Fich and Shivdasani, 2006). Hence, it remains an empirical question whether board connections to product market peers lead to easier coordination in product markets and thus superior profitability.

2 Data and Sample Description

2.1 Data

We primarily draw our data from three sources: Compustat, BoardEx, and the 10-K Text-based Network Industry Classifications (TNIC) in the Hoberg-Phillips Data Library.

We put the following restrictions to construct the sample from the set of firms in the intersection of Compustat and BoardEx: (1) the firm is not in the financial and utilities industry (SIC between 6000 and 6999, or SIC 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 start from the Individual Profile Employment dataset provided by BoardEx and we use entries where the type of employment is a board position. From this raw data, we construct annual network snapshots, with the nodes as the firms, and the edges as the pairwise direct connections (i.e., interlocking directorates).

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

Our main variables are defined as follows. We define assets as the natural logarithm of the firm's total assets in millions of dollars, gross margin as the ratio of gross profit to sales, operating margin as the ratio of operating income before depreciation and amortization to sales, ROA as the ratio of operating income before depreciation and amortization to total assets, sales growth as the percentage change of sales relative to the prior year, and Tobin's Q as the ratio of the market value of equity plus book value of debt over total assets.[6] All financial and accounting variables are winsorized at the 1% and 99% percentiles.

2.2 New board connections

Our main empirical exercise is an event study of instances when a firm forms a new board connection to a product market peer. We focus on 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 directly but they have at least one member of their respective boards serve on the board of a third firm. We expect that forming a new direct board connection to a product market peer will correspond to a stronger effect on the firm profitability than forming an indirect one.

We define "treated" firms to be those firms that form a new board connection with a product market peer. Our treated sample then consists of all firms that form a new direct or indirect board connection with a product market peer during the period 1999-2018. We study these firms for the 7-year period around the year when they form the new connection. When identifying these instances of newly formed board connections, we ensure that the firm does not have any prior indirect or direct 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 the firm profitability changes following the formation of the new board connection ("event"). To control for general industry trends in the outcome variables, we match each treated firm to a control firm that is from the same industry and has similar firm characteristics in the year before treatment. More specifically, for each treated firm-year, we look for one control firm-year, and we match with replacement. The matching takes the following steps. 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

[6]Please see Table A1 in the Internet Appendix for the definitions of all variables we use in our analysis.

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 one 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.

2.3 Sample description

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.[7] 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%). [8]

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. The data show that board connections to peers tend to occur in firms that are larger, have higher gross margin and Tobin's Q, and faster sales growth. Consistent with Geng et al. (2021), such connections are also more likely among research and development (R&D) intensive firms. The operating margin in treated firms, however, are lower than average as these firms also have higher selling, general, and administrative (SG&A) expenses.[9] The treated and control firms are balanced in terms of

[7]Unconditional on being product market peers, board connections are quite prevalent in our sample. 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 6.1 we show that connections to a non-peer firm are not associated with increases in profitability.

[8]Figure A1 in the Internet Appendix shows that new board connections are spread out through 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%) exist for longer than 8 years.

[9]We also compare how directors involved in these new connections differ from an average director in the

the variables used in matching. The control firms are also similar to the treated firms in terms of almost all other co-variates not used in the matching.[10]

In Table 3, 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). We find that the average CAR after a firm announces the appointment of a director who cross-sits on the board of a peer firm is 0.83%. When a director cross-sits 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, suggesting that the market reacts positively to such appointments.

In Figure 1, we compare the product market similarity of newly connected firms to that of all firm-pairs in an Hoberg-Phillips industry. Panel A studies direct connections and Panel B studies indirect connections. In both Panels, the green line plots the distribution of the cosine similarity of only the newly connected firm-pairs while the orange line plots the distribution of the cosine similarity of all firm-pairs in an Hoberg-Phillips industry. We find that not only does the green line lie to the right of the orange line but its peak is also to the right of the peak of the orange line. This observation highlights that the newly connected firm-pairs tend to have a higher cosine similarity score than average Hoberg-Phillips industry peers, suggesting that businesses of the newly connected firm-pairs appear more similar – at least in their descriptions – as compared to average Hoberg-Phillips industry peers.

In Table 4, we check the likelihood that the newly connected pairs of firms are in the same SIC or GICS industry. We also compare that likelihood to the probability of Hoberg-Phillips

treated firms. Table A2 in the Internet Appendix shows that, while those connected directors cross-sit on more boards and are more likely to be non-executive directors, their length of professional experience and educational level do not differ from that of an average director.

[10]As we discuss in Section 3.2, we do not see differential pre-trends in the outcome variables between treated and control firms, which makes it unlikely that any residual unbalancedness in firm characteristics is driving our main results. Nevertheless, in the robustness tests reported in Section 6.2.3, we expand the list of matching co-variates to include these additional variables and repeat our analysis. We find our baseline results to be robust.

industry peers being in the same SIC or GICS industry. Our comparison indicates that the newly connected pairs of firms are more likely to be in the same SIC and GICS industry as compared to an average pair of product market peers and this holds for both direct and indirect connections. If anything, the fractions are even slightly larger for the indirect new connections.

In sum, the evidence in both Figure 1 and Table 4 indicates that the new board connections occur between peer firms that have more similar products than average Hoberg-Phillips product market peers.

3 Main Results

3.1 Difference-in-differences regression

Our objective is to estimate the impact of new board connections to product market peers on firm performance and value. To do this, we estimate a difference-in-differences model within our sample of treated and control firms. The first difference is taken between the time period before and after the treatment while the second difference is between the treated and control firms. Our empirical model is then:

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times DirectTreated_{i,c} + \alpha_3 \times IndirectTreated_{i,c} \\
&+ \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} \\
&+ \theta_i + \theta_{j,t} + e_{i,j,c,t},
\end{aligned}
\tag{1}
$$

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 all 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, ROA, and sales growth. $Post_{c,t}$ is a dummy variable that takes a value of 1 for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year.[11] $DirectTreated_{i,c}$ is a dummy variable equal to one for the treated firms

[11] $Post_{c,t}$ is not absorbed by industry-times-calendar year fixed effects because treatments occur in different years for different cohorts.

that experience a 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.[12] Our coefficients of interest are β_1 and β_2. They identify the change in the outcome variable for treated firms that respectively form a direct and an indirect board connection with a product market peer.

We include two sets of fixed effects. First, we include firm fixed effects θ_i.[13] Next, we include industry-times-calendar year fixed effects, $\theta_{j,t}$ to control for wider industry-specific shocks, where industries are defined based on the Fama-French 48-industry classification.[14]

Throughout the paper, we cluster standard errors at the firm level to address serial correlation within a firm affecting our statistical inference (Bertrand et al., 2004). Our methodology of pooling cohorts of treated and control observations together and estimating a difference-in-differences model bears resemblance to Gormley and Matsa (2011), Deshpande and Li (2019), and Cengiz et al. (2019).

Table 5 reports the results from estimating the above regression in our sample. From the first three columns, we see that profitability uniformly increases in the three years after the firm forms a new board connection with its product market peer. There is also some weak evidence that the increase in profitability is greater following a direct connection as compared to that following an indirect connection.

Our estimates are economically meaningful. In column (1), we see 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.[15]

[12] $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ are not absorbed by firm fixed effects only because a firm might be treated with a new direct connection in one year and act as a control or be treated with a new indirect connection in another year.

[13] Section 6.3 shows that our results are unaffected if instead we use firm-cohort fixed effects as in Gormley and Matsa (2011).

[14] Section 6.3 shows that our results are unaffected if instead we use SIC-3 or FIC-200 classifications, where the latter is a version of the Hoberg-Phillips 10-K Text-based Fixed Industry Classifications.

[15] 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, due to an operating leverage effect, we would expect the increase in operating margin to be larger compared to gross margin if firms are gaining more pricing

Consistent with firms limiting the expansion of their output while increasing their profitability following new board connections to their product market peers, in column (4), we report that the sales growth decreases by 2.3 p.p. after a firm forms a new direct connection with an industry peer. That said, we find no statistically significant effect on sales growth after a firm forms an indirect connection with a product market peer.

We report the results based on a few additional outcome variables in Table A3 in the Internet Appendix. We show a similar increase in profitability when we study the markups calculated via the production approach following De Loecker et al. (2020). Also, we find that total sales increase at a faster pace relative to the cost of goods sold, consistent with firms gaining pricing power. However, we find no evidence of reduced SG&A costs or increase in capital expenditure or R&D, or altered size of total assets.

3.2 Dynamic specification

We next document the dynamics of the change in performance around new board connections. These tests should also allow us to study if there are any differential pre-existing trends in the outcome variables between the treated and control firms. To do this, we estimate the following regression within our sample:

$$\begin{aligned}
Y_{i,j,c,t} \;=\; & \alpha_1 \times DirectTreated_{i,c} + \alpha_2 \times IndirectTreated_{i,c} \\
+\; & \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
+\; & DirectTreated_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) \\
+\; & IndirectTreated_{i,c} \times (\sum_{s=-3}^{-2} \delta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \delta_s \times \mathbb{1}(\tau = s)_{c,t}) \\
+\; & \theta_i + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned} \tag{2}$$

where 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 turns on if the observation is s years before the treatment (for $s = -3, -2$) or if the observation is s years after the treatment (for $s = 0, 1, 2, 3$). We

power and thus total sales of treated firms expand at a faster rate than COGS and SG&A expenses, which is consistent with findings in Table A3 in the Internet Appendix.

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 of year s relative to their difference in the baseline year.

We plot the coefficient estimates of γ_s and δ_s in Figure 2. 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 for both direct and indirect connection events. This confirms the absence of pre-existing trends. Focusing on Panel A1, which reports the results for the direct connections, we find 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 some time to get used to understanding the firm(s) and the board(s) before having an impact on performance. In Panel A2, we report the results for the indirect connections, showing a similar pattern, albeit smaller in economic magnitude. We find similar patterns for operating margin and ROA, as reported in Panels B1-2 and C1-2.

4 Third-Party Initiated Board Connection Changes

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. Indeed, new connections arising from changes to a firm's board could be endogenous to the firm's expected operating performance. For example, better-performing firms could afford appointing directors who are experts in their industry and thus also connected to product market peers. Also, the directors of a firm whose prospects are improving may be more valued in the director labor market and thus more likely to be appointed to the board of a product market peer.

In this section, we focus on new connections that are not related to the changes in the focal (i.e., treated) firm's board, nor to the changes in other appointments of the focal firm's directors. We look at the changes in connections arising from changes to a non-treated firm's board that are likely to be a more exogenous set of events. This may enable us to better identify the causal effect of board connections to product market peers on firm performance.

In particular, to identify new board connections initiated due to changes on the board of a third firm, we focus on indirect connections and look at the indirect board connections to product market peers that are initiated due to the changes in the board of either the intermediate firm or the product market peer. In these events, the focal firm is already directly connected with the intermediate firm prior to the treatment year. In the treatment year, there is a change in the board of either the intermediate firm or the product market peer. That is we focus on the instances when (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. At the same time, changes on the focal firm's own board do not result in any direct or indirect connection between the focal firm and its product market peers. Thus, in these events, the new connection between the focal firm and its peer is not due to any changes to the board composition of the focal firm. To this extent we expect these connections to be more exogenous to the future prospects of the focal firm.[16]

Figure 3 illustrates an example, where Firm 1 is the focal firm and Firm 3 is a product market peer of Firm 1. In the year prior to the event, Firm 1 and an intermediate firm, Firm 2, are directly connected through Director A who serves on the boards of both firms. Firm 1 does not have any direct or indirect connection to Firm 3. In the event year, Firm 2 forms a new direct connection 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 gets to have an indirect connection with Firm 3, and this new connection is purely a result of changes in the composition of the board of directors 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.

Out of the 4,085 events of indirect board connections in our overall sample, we find that 2,114 are initiated due to changes on the board of a firm other than the treated firm. Within this subsample, we estimate a regression (1) and present the results in Table 6.

[16] We provide further details in Internet Appendix IA.2

Consistent with our prior evidence, in column (1) we see that gross margin of the treated firm increases by 0.7 p.p. in the three years following the initiation of an indirect board connection to a product market peer. As a comparison, our baseline results that include all indirect board connections reveal that gross margin increases by 0.4 p.p. following a new indirect board connection to a product market peer. This suggests that, if anything, those board appointments that might be considered as more endogenous to the prospects of the treated firm appear to bias our baseline estimates downwards. From columns (2) and (3), we find that consistent with our baseline estimates our results are not sensitive to how we measure firm profitability.

Our results are economically significant. The increase in operating margin and ROA are 8.5% and 10% of the mean values for the treated firms in the year before treatment. In unreported tests, we find that the exogenous board connections to product market peers do not have a statistically significant effect on sales growth.

In Figure 4, we present the corresponding results of the dynamic model presented in equation (2) on the subsample of exogenous board connections. We find that across the measures of profitability there is no pre-existing difference between the treated and control firms. We also show that the profitability significantly increases in the three years following the initiation of a new indirect board connection, independent of the measures employed.

5 Anti-competitive Effects

Our results are consistent with the interpretation that board connections to product market peers may facilitate anti-competitive practices among competing firms.

While anti-competitive practices enabled by board connections can come in a wide variety of forms, strategies, and markets, we acknowledge that board connections can improve a firm's profitability without anti-competitive coordination. For instance, Bouwman (2011) shows 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, 2021). If these practices that spread through board connections can enhance a firm's internal efficiency, board connections can have positive effects on firm profitability, but such an effect would not necessarily be of concern for antitrust policymakers.

We have already documented that the sales growth decreases after the new connections, and we do not find an increase in R&D expenditure or a decrease in SG&A costs. Both are inconsistent with the efficiency-enhancing explanation. To further disentangle between the anti-competitive and the internal efficiency mechanisms, we first look for direct evidence of coordination in the product market prices of treated firms using scanner data in the consumer goods industry. Next, we examine the effects of new board connections using a range of cross-sectional tests. Further, we investigate the spillover effects of new board connections to the closest rivals of those newly connected firms. Finally, we link the board network connections to the detected collusion cases.

5.1 Evidence from product prices in the consumer goods sector

In order to corroborate the interpretation that our results relate to an anti-competitive mechanism, in this section we provide direct evidence on how board connections affect product pricing in one particular sector, the consumer goods. We utilize the Nielsen Retail Scanner Data, which contain prices from more than 90 participating retail chains across the US.[17] The price data are weekly and at a level as fine as each store and each individual Universal Product Code (UPC), which is a 12-digit barcode that identifies a unique traded item in stores. We adopt a similar event study methodology as our main test and look at how prices of products change after their producers form board connections to product market peers.

By narrowing down on the product prices, we can directly observe and measure firm's actual behavior in its product markets. We can also sharpen the definition of product market competitors. In particular, we can define peers as firms that sell in the same "product module" or "product group" based on Nielsen Retail Scanner Data definitions.[18]

[17]Prior research using this dataset has studied the product market impacts of common ownership (Aslan, 2022), private equity deals (Fracassi et al., 2022), taxation (Baker et al., 2020), and credit market disruption (Granja and Moreira, 2022; Kabir, 2022).

[18]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" contains 19 "product modules", which include "Cheese-Natural-Mozzarella","Cheese-Natural-American Colby", "Cheese-Natural-American Cheddar".

5.1.1 Sample construction of the product price test

We start from the universe of Nielsen 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, as the GS1 Company Database does not provide linkage information between itself and BoardEx, we match producers in GS1 Company Database to firms in BoardEx based on their name strings. We are able to match producers of a total of 2,715,025 UPCs to BoardEx, which account for 44.6% of all UPCs and 63.4% of the total sales in the Nielsen Retail Scanner Data.[19]

We construct events of changes in board connections to product market peers in the same manner as for baseline results reported in Section 2.2. Differently from our main tests for which we require a treated firm to be publicly listed and thus have financial information, in this set of tests treated firms can be both public and private. Also, as we have firm outcomes at a higher frequency, we define board connection events at the quarterly level.

We build the relationship network based on all firm personnel but require the person connecting product market peers to be a director in at least one side of the connected firm-pair. When using a "product module" as the product category, which is the finest level in the data, we find 52 pairs of product market peers that form new direct board connections and 778 that form indirect ones. Using a higher level aggregation of a "product group" and thus larger size of each "industry", we instead find 74 pairs that form new direct board connections and 1,067 for indirect ones. We provide results for both of these classifications.

We pool direct and indirect board connections together. To sharpen the definition of our treatment, we define new connections at the firm times product category times 3-digit zip code area level. That is, for each 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 cutoff, we say that these two firms *in this area* are treated. By applying the cutoff, we identify the actual product market overlap and rule out situations when two firms both operate in the same product

[19] Details of the matching procedure are provided in Internet Appendix IA.4

category and the same geographic area but between themselves have inconsequential market share in that area.

We estimate a price inflation index (PPI) as our outcome variable following Aslan (2022). We define the set of products (UPCs) that firm i sells in product category j and 3-digit zip code area z and quarter t as its product portfolio and denote it as $U_{i,j,z,t}$. The share of revenue of each product u within the product portfolio is $w_{u,z,t}$, which sums up to 1 for a product portfolio, that is, $\Sigma_{u \in U_{i,j,z,t}} w_{u,z,t} = 1$. We define the value-weighted dollar price of product u in area z in quarter t to be $p_{u,z,t}$. The price inflation index $P_{i,j,z,t}$ of firm i in product category j and area z and quarter t is then:

$$P_{i,j,z,t} = \Sigma_{u \in U_{i,j,z,t-1}} w_{u,z,t-1} \times (p_{u,z,t}/p_{u,z,t-1} - 1). \tag{3}$$

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 $P_{i,j,z,t}$ if the total sales are below \$5,000 (\$10,000) or the market share is below 5% (1%) for firm i in product module (group) j and area z in the current quarter t or the prior quarter $t-1$. $P_{i,j,z,t}$ is winsorized at 1% and 99%.

We keep observations 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 1 for treated units in the quarters post treatment and 0 elsewhere.

5.1.2 Results of the product price test

Equipped with this sample, we estimate the following difference-in-differences regression,

$$P_{i,j,z,t} = \alpha \times Treated_{i,j,z} \times Post_{i,j,z,t} + \theta_{i,j,z} + \theta_{j,t} + \theta_{z,t} + e_{i,j,z,t}. \tag{4}$$

We include firm times product category times area fixed effects $\theta_{i,j,z}$ so that we are capturing the differential trends in PPI between the treated units and the control units rather than their baseline differences. We also include product category times quarter fixed effects $\theta_{j,t}$, so that we are doing within-industry comparison with those firms that operate in the same industry but are not treated serving as the benchmark. We also include area times 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. To account for within-firm correlation in pricing across time and location, we cluster the standard errors at the firm level.

In Table 7 column (1), we report the results using "product module" as our product category with a cutoff of at least 10% on the joint market share of newly connected firms in the local market. We find that in the quarters post board connections, the per-quarter increase in product price is 0.08% faster for treated firms than untreated firms, which corresponds to a 0.32% annualized difference. As a comparison, the average annual inflation rate during our sample period is 1.83%. In columns (2) and (3), we apply the cutoffs of 5% and 3% on the joint market share of treated firms in the local area. In columns (4)-(6), we use "product group" as the product category instead and repeat the aforementioned tests. While the broader classification leads to larger numbers of firms in each product category and more instances of connected firm-pair's, the products are less similar. Consistent with this, we find that the magnitude of estimated treatment effects is smaller than in columns (1)-(3). Overall, these results provide evidence that board connections are related to the coordinated product price behavior.

5.2 Cross-sectional heterogeneities

In this section, we perform five cross-sectional tests to further investigate the anti-competitive effects. Specifically, we examine how the effects of board connections on profitability vary with: (1) whether the newly connected peers share common customers; (2) the similarity in business descriptions of newly connected peers; (3) the geographical distance of newly connected peers; (4) the Herfindahl–Hirschman Index (HHI) of the treated firm's industry; (5) the returns to scale of the treated firm's industry.

To test our predictions, we estimate the following triple-differences model:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times Treated_{i,c} + \alpha_3 \times EventCharacteristic_c \\ &+ \alpha_4 \times Post_{c,t} \times EventCharacteristic_c + \alpha_5 \times Treated_{i,c} \times EventCharacteristic_c \\ &+ \beta_1 \times Treated_{i,c} \times Post_{c,t} + +\beta_2 \times EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t} \\ &+ \theta_i + \theta_{j,t} + e_{i,j,c,t}, \end{aligned} \tag{5}$$

where $EventCharacteristic_c$ is a sorting variable in the cross-section. It equals to one for the time series of both the treated firm and its control firm if the new connections are in the top half in terms of a certain characteristic.

5.2.1 By whether the newly connected peers share common major corporate customers

We expect the coordination benefits to be the strongest when two firms share major corporate customers. To identify customer-supplier relationships in the network, we utilize firms' self-reported major customers, from the WRDS Supply Chain dataset.[20] We find that out of all events, 383 of them are between peer firms that share a major customer.

Panel A of Table 8 reports results from our triple-difference regressions. For brevity, we pool events of new direct and indirect connections together and we only report the coefficients on the double-difference terms and the triple-difference terms. We indeed find that the effects are stronger when firms share major customers. While firms' gross margin (operating margin/ROA) rises by 0.4 p.p. (0.8 p.p./0.7 p.p.) when newly connected firms do not share major customers, the change becomes 1.3 p.p. (2.6 p.p./1.7 p.p.) when they do.

5.2.2 By similarity in the business descriptions between new connections

We next sort the events based on the degree of similarity in business descriptions between the connected firms, defined as the cosine similarity scores of these descriptions. We define a dummy variable, $TopSimilarity$, which equals one for the treated and control firms involved in events in which the new connections have a cosine similarity score above the sample median and additionally are in the same SIC-3 industry. We then implement the triple-differences regression model (5).

Panel B of Table 8 reports results from our triple-difference regressions. Consistent with Section 3, the coefficients on the double-difference terms are positive for all three outcome variables and statistically significant for operating margin and ROA. The triple-difference terms are also positive and are statistically significant for operating margin and ROA. New

[20] Please see Cen et al. (2016), Cen et al. (2017), and Cohen and Frazzini (2008) for the details on the construction of corporate customer-supplier data.

board connections lead to a 0.3 p.p. (0.6 p.p./0.5 p.p.) increase in gross margin (operating margin/ROA) for the subset of events where $TopSimilarity$ is equal to zero, and these effects become 1.0 p.p. (2.0 p.p./1.3 p.p.) when $TopSimilarity$ is equal to one. This provides strong evidence that the effects of new board connections are stronger between peers with more similar business descriptions and presumably operating closer in their product spaces.

5.2.3 By geographical distance between new connections

A firm is more likely to share the product market with its peers that are geographically closer. Such peers are also more likely to be competitors with the treated firm in the raw material and labor markets. Hence, we examine whether the effects are stronger when the new connections are geographically closer. We obtain the geographical distance between the zip codes (*addzip*) of the treated firm and its newly connected peer. We sort events in each year based on this distance. Then we define an indicator variable, $CloseDistance$, which equals one for the time series of both the treated firm and its control if the events are in the bottom half in terms of the geographical distance between the treated firm and its new connections, and zero otherwise. Using this sorting variable, we estimate the triple-difference regression model (5).

Panel C of Table 8 reports results from these triple-difference regressions. The sign and magnitude of the double-difference terms are consistent with the results in Section 3. Moreover, the triple-difference terms are positive and statistically significant for operating margin and ROA. The effects are about twice larger when the new board connections are between firms that are located closer to each other. Overall, we find supportive evidence that the effects of new board connections are stronger between geographically closer peers.

5.2.4 By HHI of the treated firm's industry

Firms in more concentrated industries could find it more beneficial to coordinate product market actions (Motta, 2004; Huck et al., 2004). To test if our results are stronger in more concentrated industries, we sort firms based on the HHI developed in Hoberg and Phillips (2016) and provided in the Hoberg-Phillips Data Library and develop an indicator $TopHHI$, which equals one if the firm is in the top half in terms of the HHI of its industry.

Panel D of Table 8 reports results from triple-difference regressions (5). We see that the effects are indeed stronger in more concentrated industries, but the differential effects are not statistically significant. Hence, we do not find conclusive evidence over how the effects of new board connections vary with industry concentration.

One potential reason for the lack of significance could be that firms in more concentrated industries might have alternative effective mechanisms to coordinate their behavior. We also recognize that the measures of HHI estimated based on publicly listed firm data might not reflect the actual degree of concentration in the industries (Ali et al. (2008)).

5.2.5 By returns to scale of the treated firm's industry

As an alternative to the HHI data based on publicly listed firms, we use the returns to scale in an industry as a proxy for the extent of competition. An industry is more likely to be oligopolistic if it exhibits increasing returns to scale. Following Dong et al. (2019), we estimate a two-factor Cobb-Douglas production function for each two-digit industry using data of the year 1999. As described in Table A1, we classify the firms according to whether the industry in which they operate is experiencing above median returns to scale and estimate triple-difference regressions.

Panel E of Table 8 reports the results. The effects of new board connections are stronger in industries that exhibit greater returns to scale – forming new board connections is followed by an increase in gross margin (operating margin/ROA) of 0.8 p.p. (1.6 p.p./1.1 p.p.) in industries with top half $ReturntoScale$, while the rise is 0.4 p.p. (0.5 p.p./0.4 p.p.) in industries with bottom half $ReturntoScale$.

5.3 Spillover effects

To further distinguish between the anti-competitive and efficiency-enhancing mechanisms, we also investigate the effects of new board connections on the common closest rivals of the newly connected firms. Suppose board connections enable anti-competitive practices such as price-fixing or suppressing labor or raw material prices. In such cases, we could expect that the closest rivals of the newly connected firms are also able to benefit from coordinating rivals. For example, they could also raise the prices of the product to the same level as that of the product sold by newly connected firms being "under the umbrella of the cartel" (Bos and Harrington, 2010). Even if they are not aware that their rivals became connected, they could simply follow the upward pricing trend in the market caused by the connected firms and benefit as free-riders (Deneckere and Davidson, 1985). However, if board connections enhance the internal efficiency of newly connected firms, their closest rivals could be put at a disadvantage, which can translate into worse firm profitability when faced with more efficient rivals. Hence, the direction of these spillover effects can help us establish the mechanism that drives an increase in the profitability of treated firms.

We identify firms subject to the spillovers (spillover firms) based on the events we identified in Section 2.2. Specifically, we define spillover firms to be firms that are among the ten closest Hoberg-Phillips peers of both sides of the new board connections and are not treated with new board connections themselves in the event year. Next, we repeat the matching procedure as in Section 2.2 with the sole difference that we additionally require that the control firms are not subject to the spillovers in the event year. Our sample includes 686 unique spillover firm-years from new direct board connections, and 2,478 unique spillover firm-years from new indirect board connections.

Equipped with this matched sample, we estimate the following regression:

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times DirectSpillover_{i,c} + \alpha_3 \times IndirectSpillover_{i,c} \\ &+ \beta_1 \times DirectSpillover_{i,c} \times Post_{c,t} + \beta_2 \times IndirectSpillover_{i,c} \times Post_{c,t} \\ &+ \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{6}$$

We report the results in Table 9. We find some evidence supportive of positive spillover effects. While the average gross margin of spillover firms from direct board connections does not evolve differently relative to control after the event, their operating margin and ROA significantly increase with magnitudes of 1.0 p.p. and 0.6 p.p. When we look at the spillover firms from indirect board connections, the estimated effects of the spillovers are positive but not statistically significant with magnitudes around 0.2 p.p. to 0.3 p.p..

In Figure 5, we plot the coefficient estimates from a dynamic specification. Spillover firms do not trend differently relative to the control firms prior to the event, and consistent with

Table 9 we see statistically significant and positive coefficients on the operating margin and ROA after the events when we focus on the firms subject to the spillovers from the direct board connections. Overall, these evidence corroborates the anti-competitive explanation of our main results.

5.4 Convicted collusion cases

Finally, we provide descriptive analysis on how new board connections relate to actual detected collusion cases. We acknowledge the caveats of studying detected cartels, as only about 10% to 30% of all cartel conspiracies are discovered (Connor, 2014), and those detected ones may not be the most economically important ones. Hence, the analysis in this section is only suggestive.

We obtain information on convicted collusion cases from the Private International Cartels database (Connor, 2020). We restrict the sample to firms headquartered in the US and hand-match those firms to the universe of firms we described in Section 2.2. Based on this data, we construct a firm-pair-year level indicator of whether two firms are in an active detected cartel in a certain year. We also construct the degree of separation of each firm-pair in the network described in Section 2, which is the minimum number of intermediate nodes (i.e., firms) between two nodes that can connect these two nodes together. We exclude firm-pairs that are unconnected in the director network or connected but with a degree of separation above four.

In Figure A2 in the Internet Appendix we plot the probability of a firm-pair having an active cartel in a certain year, conditional on the degree of separation of these two firms in the director network. We find that while two directly connected firms (zero degree of separation) have a probability of 0.058% of having an active detected cartel and it is 0.061% for a firm-pairs with one degree of separation, this probability becomes 0.017% for a firm-pairs with two degrees of separation and 0.004% for a firm-pairs with three degrees of separation. This strong associative relationship suggests the possibility of the director network's role in facilitating anti-competitive practices.

We defer a more detailed description of analysis using detected cartel cases to Section IA.3 in the Internet Appendix.

6 Robustness Tests

In this section, we share a number of robustness tests for our main results in Section 3. We first conduct a placebo test using non-product market peers. We also show that our main results are robust to alternative choices in the matching procedure, the specification of fixed effects, and industry classification. Lastly, we confirm the robustness of our main results to controlling for common ownership as well as customer-supplier relationships.

6.1 A placebo test using non-product market peers

We conduct a placebo test where instead of product market peers we study the effects of newly formed connections to non-product market peers on firm performance. We construct the sample as follows. For every firm-year in the Compustat-BoardEx merged data set, we start by generating a random group of firms that we designate as the "pseudo industry" corresponding to that firm-year. We use this pseudo industry in place of the Hoberg-Phillips industry to identify direct and indirect board connections. We ensure that none of the firms in the pseudo industry are actually in the same 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 a new connection to an actual product market peer. Effectively, we thus study how firm connections to non-product market peers affect performance after we keep the sizes of the pool of firms similar between actual product market peers (Hoberg-Phillips industry) and non-product market peers (pseudo industry).

For each pseudo treated firm, we identify a control firm using the same matching procedure as in our main analysis. Then we estimate the regression (1) and report the results in Table 10. We fail to find a statistically significant increase in profitability following the establishment of a board connection to a non-product market peer firm. These results confirm that the effects we document do not come mechanically from any board connections but arise due to board connection to product market peers.

6.2 Robustness to alternative matching schemes

6.2.1 Retain two or three matches instead of one

In the baseline tests, we employ one control firm for each treated firm. The choice of how many control firms to use involves a trade-off between the efficiency and bias of our estimators. By retaining more control firms, we obtain more precise estimates at the cost of potentially greater bias due to the treated and control firms being less similar.

We now repeat the matching process with two or three control firms for each treated firm. As before, we require an exact match on Fama-French 17 industry and quantiles of the matching co-variates. This results in a lack of more than one control firm for some treated firms. For our 5,578 treated firms, we find 9,677 controls when we retain the two closest matches and 12,809 control firms when we retain the three closest matches. While the matching co-variates are no longer balanced statistically in the year prior to the event, we still find that the estimated effects of new board connections presented in Panels A and B of Internet Appendix Table A4 are virtually identical to those in Table 5.

6.2.2 Match on number of new appointments during the event year

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 extra effort at the beginning of their tenure, possibly due to career concerns. Although this is not a concern in the tests that focus on a more exogenous set of indirect connections, it could partially explain the findings in our baseline tests. Indeed, in our main sample, treated firms appoint on average one new director during the event year, while control firms appoint an average of 0.64 directors.

To address this concern, 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. For 706 events of new direct connections and 2,224 events of new indirect connections, an exact match can be found and this constitutes our sample in Panel C of Table A4. We see that our main results are unaffected.

6.2.3 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. However, unbalancedness remains for other co-variates. As we do not see pre-trends in Figure 2, it is highly unlikely that any residual unbalancedness in firm characteristics is driving our main findings.

Also, we include extra co-variates in addition to assets, gross margin, and Tobin's Q. In particular, we sequentially add operating margin, sales growth, ROA, R&D to assets, and CAPEX to assets, and respectively report results in Panels E, F, G, H, and I in Table A4. Our main results hold under the new matching schemes.

6.2.4 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 during the three years prior to the event or the three years post the event. To avoid such treatments affecting our estimates, we additionally require that the control firm is never treated during the [-3, 3] window around the event year in Panel J of Table A4. In Panel K, we additionally require that the control firm is never treated both during or before the [-3, 3] window. Our main results are unaffected by these alternative matching choices.[21]

6.3 Robustness to alternative specifications of fixed effects

In all regressions we estimate, we include industry-times-year fixed effects and firm-specific fixed effects. With the industry-times-year fixed effects we can further rule out the possibility that some industry-level trends coincide with our events of new connections. Panels A and B of Table A5 in the Internet Appendix show that our results are robust to using alternative industry definitions such as SIC-3 and FIC-200 to define industry-times-year fixed effects. This gives us confidence that our estimates are not capturing industry-level common trends.

[21]As we use stacked regression estimators and already-treated firms never act as effective control units in Panel K of Table A4, our results stand to the critique in Baker et al. (2022) on difference-in-differences estimates.

Second, in all specifications we include firm fixed effects and so we are comparing differences in the post-to-prior changes between treated and control firms. Panel C of Table A5 shows the results when we instead control for firm-cohort fixed effects, where a cohort corresponds to observations of a treated firm and its matched control. Thus we have a fixed effect for each time a firm appears as a treated or a control firm in our sample. These fixed effects are more granular than firm fixed effects and our results are robust to including them.

6.4 Robustness to alternative industry classification

In Internet Appendix Table A6, we further provide robustness to the definitions of product market peers. Instead of defining them according to Hoberg-Phillips classification, Panel A uses the competitors disclosed by firms and recorded in FactSet Supply Chain Relationships (formerly, Revere) database. Panel B instead defines product market peers based on being in the same SIC-3 industry, while Panel C uses SIC-4 industry. Further, Panels D and E use GICS 6-digit industry and GICS 8-digit industry. We find confirming evidence of an increase in profitability after new product-market peer board connections get formed.

6.5 Board connections or common ownership?

An active ongoing debate studies the role of common ownership in firm's anti-competitive behavior (Azar et al., 2018, 2022; Nain and Wang, 2018; Koch et al., 2021). For instance, Azar et al. (2018) find a positive correlation between common ownership concentration and flight ticket prices and discuss various potential mechanisms how common ownership can affect firm behavior. Indeed, one such mechanism can be shared board connections. 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 different firms, these directors might still belong to the same network and be more likely than a random director to simultaneously sit on a third intermediate firm. Indeed, Azar (2022) has shown a substantial overlap between firm common ownership and board interlock networks.

Noting these findings, we further study the possibility that the profitability-enhancing effects of board connections we discover purely stem from common ownership. We conduct the following robustness test. We use the firm-pair level measures of common ownership developed in Gilje et al. (2020) (GGL_{linear}, GGL_{fitted}, and GGL_{full_attn}).[22] We first examine whether new board connections are associated with an increase in common ownership. We find that, around the treatment year, treated firms experience a larger increase in common ownership with its product market peers than control firms. The post-minus-prior increase in the mean GGL_{linear} ($GGL_{fitted}/GGL_{full\_attn}$) between treated firms and their product market peers is 1.42 (35.85/1554.59) on average. For control firms, it is 1.12 (33.85/1558.01). A two-sample t-test yields a t-statistic of 2.20 (1.42/0.09). Hence, there is an associative relationship between new board connections and concurrent increases in within-industry common ownership. We also find that, consistent with Azar (2022), the establishment of new board connections is associated with a higher *level* of common ownership.

We next estimate the double-differences regressions (1) by additionally controlling for concurrent *changes* in within-industry common ownership,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times Treated_{i,c} + \beta_1 \times Treated_{i,c} \times Post_{c,t} \\ &+ \gamma_1 \times \Delta(CommonOwnership)_{i,c} \times Post_{c,t} + \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned} \tag{7}$$

In this regression we pool events of new direct and indirect connections together. $\Delta(CommonOwnership)_{i,c}$ is the change in the mean common ownership between a firm and all of its Hoberg-Phillips product market peers from $\tau = -3, -2, -1$ to $\tau = 0, 1, 2, 3$. We scale it by its sample standard deviation. It is a constant for each time series of length 7 (from τ = -3 to +3). We report results in Table 11.

We find that, holding concurrent changes in within-industry common ownership constant, treated firms experience significantly higher growth in profitability compared to control firms. The coefficient estimates are similar to our main results in Table 5. This suggests that the profitability-enhancing effects of board connections are not fully capturing effects of potential concurrent increases in within-industry common ownership and presents a related

[22]Please see Table A1 in the Internet Appendix for detailed descriptions of these measures.

but distinct anti-competitive practice.

We also find a strong positive associative relationship between changes in within-industry common ownership and the changes in profit margin. For example, when using GGL_{linear} as the measure, a one standard deviation increase in the post-minus-prior change in within-industry common ownership is associated with a 0.3 p.p. increase in the change of gross margin. While these coefficients do not necessarily bear a causal interpretation, their signs are consistent with anti-competitive effects of common ownership.[23]

6.6 Executive vs. non-executive directors and inbound vs. outbound appointments

Competition-sensitive information is more likely to flow across firms when directors involved in the board connections are also executives in the same firm, as such directors are likely more engaged in firms' product market decisions than an average director. Therefore, we expect stronger effects when directors linking competing firms are also executives.

We consider that an event of new direct connection involves executives if the director linking the newly connected firms is either an executive in the treated firm or an executive in its newly connected peer based on the Non-Executive Director indicator in BoardEx. Similarly, in the case of new indirect connections between product market peers A and C via an intermediary firm B, we classify the events to involve executive directors if director X who connects firms A and B is an executive in A, or director Y who connects firms B and C is an executive in C. Out of all 1,493 events of new direct connections, 1,098 only involve non-executive directors while 395 involve an executive director. Of the 4,085 events of new indirect connections, 2,886 only involve non-executive directors only and 1,199 also involve an executive director.

Next, we pool the four kinds of events identified above together and estimate double-differences regressions. Results are reported in Table A7 in the Internet Appendix. We

[23]In untabulated tests, we find that the estimated effects of board connections are positive after controlling for an alternative common ownership measure κ (Amel-Zadeh et al., 2022) and are statistically significant when we use ROA as the outcome variable. Moreover, changes in the average κ between a firm and its product market peers are also positively correlated with changes in its profit margin. The sample size might be limited though as κ is only available for single-class S&P500 firms and we are only able to construct within-industry average κ for 13.7% of all observations.

find that the effects of board connections that involve executives are consistently stronger than those that only involve non-executive directors. Moreover, we still find positive and mostly statistically significant effects when looking at events that only involve non-executive directors, suggesting that the anti-competitive effects are not limited to executives.

In 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 the anti-competitive mechanism than with internal efficiency improvements. The latter is more likely to be effectuated by newly appointed inbound directors.

6.7 Robustness to customer-supplier connections

One might argue that the Hoberg-Phillips industry classification can capture customer-supplier relationships instead of product market rivalry, as a customer firm and its supplier can also have similar languages in their business descriptions. Such connections may have positive effects on a firm's profitability, for reasons outside the scope of anti-competitive practices. 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 events used in Table 5, only 68 of them are between pairs of customer-supplier firms based on the WRDS Supply Chain dataset. We then estimate the double-differences regressions (1) by additionally controlling for such events. We report results in Table A9 in the Internet Appendix. Our main results hold if we focus on board connections between firms that are not customer-supplier pairs. We find some weak evidence that board connections have stronger effects on profitability when the two firms are not only Hoberg-Phillips peers but also a pair of customer-supplier firms.

6.8 Connected director deaths

We also study instances of the deaths of directors who cross-sit on the boards of product market peers. We find 51 such instances and construct a treatment-control matched sample as before. The results are reported in Table A10 in the Internet Appendix. We find that the affected firm's gross margin (operating margin/ROA) drops by 1.8% (3.1%/1.7%) following the death of the connected director, and the double-difference terms are statistically significant for operating margin and ROA. Despite the small sample size, this finding is consistent with the discontinuation of coordination after the death of the linking director.

7 Conclusion

Taking advantage of the networks formed by interlocking directorates and the text-based 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 an average of 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 unlikely to be correlated with future firm prospects.

It is worth noting that we remain agnostic over the specific market, strategy, and format of anti-competitive practices that board connections facilitate between peer firms. Connected firms might engage in market segmentation and target separate product categories, demographic groups, or geographic areas, and wield market power in their respective market segments, or they might sell in the same market and fix the product prices at a high level. The coordination can come via pure information exchange, or alternatively the social network could bring trust among competing firms and make market segmentation or price-fixing more sustainable. Using scanner data, we do however find that such connections are associated with higher product prices in the consumer goods sector.

We also want to point out that we cannot speak to the full extent of the board's role in anti-competitive practices or its economic consequences for firms, as we identify the effects of incremental board connections to product market peers rather than the stock of board connections. We provide robust inferences for the effects of the first, but we are unable to identify the effects of the latter due to the lack of valid (natural) experiments. Thus, it would be more valuable to view our results in a qualitative rather than quantitative way. We are also in no way quantifying the economic impacts of anti-competitive behavior among firms in general or discussing broader welfare implications.

Still, with that said this paper has several important regulatory implications. First, our results indicate the role of directors in anti-competitive practices and provide support for the current ban on interlocking directorates between competing firms. Second, the results suggest that text-based analyses are powerful in identifying competitors in the marketplace and can have the potential to aid the execution of antitrust regulations. In addition, we find that indirect connections via an intermediate firm also have positive effects on profitability even though their economic magnitudes are smaller than those of direct connections. This argues for going beyond interlocking directorates and putting restraints on indirect board connections between competitors as well, especially in cases where the detrimental effects of anti-competitive practices on consumer welfare are substantial.

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Table 1: Industry distribution of events

Fama-French industry code (48 industries)	# of New Direct Connections	%	# of New Indirect Connections	%
Agriculture	2	0.0%	1	0.1%
Food Products	14	0.3%	2	0.1%
Candy and Soda	3	0.1%	2	0.1%
Beer and Liquor	5	0.1%	2	0.1%
Recreation	1	0.0%	0	0.0%
Entertainment	35	0.9%	10	0.7%
Printing and Publishing	18	0.4%	4	0.3%
Consumer Goods	6	0.1%	3	0.2%
Apparel	22	0.5%	7	0.5%
Healthcare	151	3.7%	55	3.7%
Medical Equipment	317	7.8%	155	10.4%
Pharmaceutical Products	460	11.3%	227	15.2%
Chemicals	57	1.4%	6	0.4%
Rubber and Plastic Products	2	0.0%	0	0.0%
Construction Materials	20	0.5%	2	0.1%
Construction	30	0.7%	5	0.3%
Steel Works Etc	27	0.7%	2	0.1%
Machinery	137	3.4%	51	3.4%
Electrical Equipment	25	0.6%	6	0.4%
Automobiles and Trucks	33	0.8%	2	0.1%
Aircraft	26	0.6%	2	0.1%
Shipbuilding, Railroad Equipment	9	0.2%	0	0.0%
Defense	5	0.1%	0	0.0%
Non-Metallic and Industrial Metal Mining	5	0.1%	3	0.2%
Coal	6	0.1%	2	0.1%
Petroleum and Natural Gas	326	8.0%	99	6.6%
Communication	2	0.0%	0	0.0%
Personal Services	38	0.9%	4	0.3%
Business Services	840	20.6%	307	20.6%
Computers	322	7.9%	109	7.3%
Electronic Equipment	509	12.5%	214	14.3%
Measuring and Control Equipment	145	3.5%	41	2.7%
Business Supplies	17	0.4%	2	0.1%
Shipping Containers	2	0.0%	0	0.0%
Wholesale	92	2.3%	26	1.7%
Retail	273	6.7%	95	6.4%
Restaraunts, Hotels, Motels	68	1.7%	32	2.1%
Banking	2	0.0%	2	0.1%
Insurance	2	0.0%	0	0.0%
Trading	4	0.1%	0	0.0%
Almost Nothing	27	0.7%	13	0.9%
Total	4,085	100.0%	1,493	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

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.

Table 3: 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

Note: This table reports the average CARs during a seven-day window around the announcement dates of director appointments that cause board connections between product market peers to form. 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.

Table 4: Proportion of newly connected peers that are in the same SIC/GICS industry

	Direct New Connections		**Indirect New Connections**	
	(1)	(2)	(3)	(4)
	Newly Connected Peers	All H-P peers	Newly Connected Peers	All H-P Peers
Using SIC Industry Classification				
Same SIC-2 industry	62.0%	50.4%	65.3%	51.1%
Same SIC-3 industry	55.2%	44.7%	58.5%	45.2%
Same SIC-4 industry	34.4%	26.4%	40.3%	26.5%
Using GICS Industry Classification				
Same GGROUP Industry	75.2%	61.7%	76.1%	61.6%
Same GIND Industry	58.6%	45.8%	61.6%	45.2%
Same GSUBIND Industry	44.2%	34.2%	48.9%	33.5%

Note: Columns (1) and (3) report the proportion of newly connected Hoberg-Phillips peers that are in the same SIC/GICS industry as the treated firms. Columns (2) and (4) report the proportion of all Hoberg-Phillips peers of the treated firm that are in the same SIC/GICS industry as the treated firm, averaged across all the treated firms. A two-sample T-test between columns (1) and (2) or between columns (3) and (4) shows a difference significant at the 1% level.

Table 5: Double-difference regressions

	(1) Gross Margin	(2) Operating Margin	(3) ROA	(4) Sales Growth
Post	-0.007***	-0.008***	-0.007***	-0.020***
	(-4.27)	(-4.77)	(-6.12)	(-5.23)
DirectTreated × Post	0.008**	0.014***	0.009***	-0.023***
	(2.45)	(3.86)	(3.52)	(-2.60)
IndirectTreated × Post	0.004*	0.008***	0.007***	-0.004
	(1.88)	(3.59)	(4.01)	(-0.75)
Observations	68,690	68,534	68,602	67,033
Firm FE	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1
Within R-squared	0.001	0.001	0.002	0.002
P-value from a Test of DirectTreated × Post = IndirectTreated × Post	0.24	0.12	0.42	0.04

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

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times DirectTreated_{i,c} + \alpha_3 \times IndirectTreated_{i,c} \\ &+ \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

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 1 for both treated and control firms for the years τ = 0, 1, 2, and 3, where $\tau = 0$ is the treatment year, and is 0 for the years τ = -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 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. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. We omit coefficients of $DirectTreated_{i,c}$ and $IndirectTreated_{i,c}$ from the table. Table A5 shows that results in this table are robust to alternative specification of fixed effects. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We also report the p-value from a test for the equality of the effects of a direct connection and the effects of an indirect connection.

Table 6: Double-difference regressions, using the exogenous subset of events

	(1) Gross Margin	(2) Operating Margin	(3) ROA	(4) Sales Growth
Post	-0.009***	-0.011***	-0.010***	-0.023***
	(-3.34)	(-4.23)	(-5.17)	(-3.79)
ExogenousTreated × Post	0.007**	0.011***	0.009***	-0.008
	(2.25)	(2.99)	(3.63)	(-0.95)
Observations	26,065	26,016	26,032	25,473
Firm FE	Yes	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm
# of Matched Controls	1	1	1	1
Within R-squared	0.001	0.002	0.002	0.002

Note: This table reports results from the following regression using the subset of events that are deemed to be more exogenous,

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

Here $Post_{c,t}$ is 1 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. $ExogenousTreated_{i,c} \times Post_{c,t}$ is the double difference term, the coefficient of which is the estimated effects of exogenous new board connection with peer firms. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. T-stats are in parentheses. We omit coefficients of $ExogenousTreated_{i,c}$ from the table. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Effects on product market price using retail scanner data

	(1) Price Inflation Index	(2) Price Inflation Index	(3) Price Inflation Index	(4) Price Inflation Index	(5) Price Inflation Index	(6) Price Inflation Index
Treated × Post	0.0007654	0.0007468	0.0007253	0.0006388	0.0006244	0.0006308
	(2.02)	(1.99)	(1.95)	(2.15)	(2.08)	(2.17)
Observations	42,737,380	42,714,241	42,650,014	32,518,690	32,834,146	33,417,503
Firm × Module × Zip3 FE	Yes	Yes	Yes			
Module × Quarter FE	Yes	Yes	Yes			
Firm × Group × Zip3 FE				Yes	Yes	Yes
Group × Quarter FE				Yes	Yes	Yes
Zip3 × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Cutoff on Market Share	10%	5%	3%	5%	3%	1%
Within R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Note: This table reports results from the following regression,

$$p_{ijzt} = \alpha \times Treated_{ijz} \times Post_{ijzt} + \theta_{ijz} + \theta_{jt} + \theta_{zt} + e_{ijzt}$$

where p_{ijzt} is the price inflation index (PPI) of firm i in industry j in 3-digit zip code area z in quarter t. $Treated_{ijz} \times Post_{ijzt}$ equals 0 for those firm-industry-zip3 combinations that are never treated and for treated firm-industry-zip3 in quarters prior to the treatment and equals 1 for treated firm-industry-zip3 in quarters post the treatment. θ_{ijz} are firm times industry times zip3 fixed effects. θ_{jt} are industry times quarter fixed effects. θ_{zt} are area times quarter fixed effects. In columns (1)-(3), we use "product module" as the product category that we use to define product market peers, while in columns (4)-(6), we use "product group" instead. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Effects of new connections in the cross-section

	Gross Margin	Operating Margin	ROA
Panel A: By whether newly connected peers share major corporate customers			
Treated × Post	0.004**	0.008***	0.007***
	(2.06)	(3.67)	(4.02)
Treated × Post × If Share Major Customers	0.009	0.018**	0.010
	(1.08)	(2.12)	(1.62)
Observations	68,690	68,534	68,602
Panel B: By similarity in business descriptions between newly connected peers			
Treated × Post	0.003	0.006**	0.005***
	(1.41)	(2.45)	(2.80)
Treated × Post × Top Score	0.007	0.014***	0.008**
	(1.44)	(2.85)	(2.52)
Observations	68,690	68,534	68,602
Panel C: By geographical distance between newly connected peers			
Treated × Post	0.004	0.006**	0.005**
	(1.60)	(2.20)	(2.28)
Treated × Post × Close Distance	0.001	0.007*	0.005*
	(0.39)	(1.65)	(1.67)
Observations	63,289	63,136	63,203
Panel D: By HHI of the treated firm's industry			
Treated × Post	0.003	0.008**	0.006***
	(1.22)	(2.58)	(2.89)
Treated × Post × Top HHI	0.004	0.004	0.002
	(0.98)	(1.02)	(0.80)
Observations	68,532	68,376	68,431
Panel E: By returns to scale of the treated firm's industry			
Treated × Post	0.004	0.005*	0.004*
	(1.63)	(1.67)	(1.77)
Treated × Post × Top Returns to Scale	0.004	0.011**	0.007**
	(1.02)	(2.49)	(2.01)
Observations	65,006	64,868	64,908
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

Note: This table reports results from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times Treated_{i,c} + \alpha_3 \times EventCharacteristic_c \\
&+ \alpha_4 \times Post_{c,t} \times EventCharacteristic_c + \alpha_5 \times Treated_{i,c} \times EventCharacteristic_c \\
&+ \beta_1 \times Treated_{i,c} \times Post_{c,t} + +\beta_2 \times EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t} \\
&+ \theta_i + \theta_{j,t} + e_{i,j,c,t},
\end{aligned}
$$

Here $Treated_{i,c}$ equals 1 for the time series of a firm experiencing new direct or indirect connections to product market peers, and 0 otherwise. In this regression we pool events of new direct and indirect connections together. $Post_{c,t}$ is 1 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 1 for the time series of both the treated firm and its control if the new connections are in the top or bottom half in terms of a certain characteristic. $Treated_{i,c} \times Post_{c,t}$ 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 0. $EventCharacteristic_c \times Treated_{i,c} \times Post_{c,t}$ is the triple-difference term, the coefficient of which is the estimated incremental effects of new connections where $EventCharacteristic_c$ takes the value of 1 relative to where $EventCharacteristic_c$ takes the value of 0. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects, which use the Fama-French 48-industry classification. 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: Spillover effects of board connections to closest rivals

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.002	-0.005***	-0.005***
	(-1.48)	(-2.61)	(-3.81)
DirectSpillover × Post	-0.002	0.010**	0.006**
	(-0.57)	(2.29)	(2.06)
IndirectSpillover × Post	0.002	0.003	0.002
	(0.93)	(1.05)	(0.86)
Observations	40,885	38,361	38,381
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Within R-squared	0.000	0.001	0.001

Note: This table reports results from the following regression using the sample of firms subject to spillover effects from new board connections,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times DirectSpillover_{i,c} + \alpha_3 \times IndirectSpillover_{i,c} \\ &+ \beta_1 \times DirectSpillover_{i,c} \times Post_{c,t} + \beta_2 \times IndirectSpillover_{i,c} \times Post_{c,t} + \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Post_{c,t}$ is 1 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. $DirectSpillover_{i,c}$ equals 1 for the time series of a firm affected by spillover from new direct connections. $IndirectSpillover_{i,c}$ equals 1 for the time series of a firm affected by spillover from new indirect connections. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. We omit coefficients of $DirectSpillover_{i,c}$ and $IndirectSpillover_{i,c}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: A placebo test using non-product market peers

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	0.000	-0.000	-0.004
	(0.08)	(-0.10)	(-1.30)
PseudoDirectTreated × Post	0.012	-0.004	-0.001
	(0.67)	(-0.28)	(-0.06)
PseudoIndirectTreated × Post	0.001	-0.001	0.004
	(0.17)	(-0.12)	(1.09)
Observations	10,329	10,302	10,303
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Within R-squared	0.000	0.000	0.000

Note: This table reports results from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times PseudoDirectTreated_{i,c} + \alpha_3 \times PseudoIndirectTreated_{i,c} \\ &+ \beta_1 \times PseudoDirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times PseudoIndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_i + \theta_{j,t} + e_{i,j,c,t} \end{aligned}$$

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 1 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 1 for the time series of a firm experiencing direct connections to pseudo peers. $PseudoIndirectTreated_{i,c}$ equals 1 for the time series of a firm experiencing indirect connections to pseudo peers. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. We omit coefficients of $PseudoDirectTreated_{i,c}$ and $PseudoIndirectTreated_{i,c}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Robustness to controlling for concurrent changes in common ownership

	Gross Margin	Operating Margin	ROA
Panel A: Using GGL_{linear}			
Treated × Post	0.004	0.009***	0.008***
	(1.39)	(3.22)	(3.57)
Δ(Common Ownership) × Post	0.003**	0.005***	0.004***
	(2.49)	(3.93)	(3.71)
Panel B: Using GGL_{fitted}			
Treated × Post	0.004	0.009***	0.008***
	(1.41)	(3.25)	(3.59)
Δ(Common Ownership) × Post	0.005***	0.008***	0.004***
	(4.68)	(5.98)	(3.58)
Panel C: Using GGL_{full_attn}			
Treated × Post	0.004	0.009***	0.008***
	(1.39)	(3.22)	(3.58)
Δ(Common Ownership) × Post	0.003***	0.002*	0.000
	(2.71)	(1.86)	(0.02)
Observations	40,408	40,302	40,343
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1

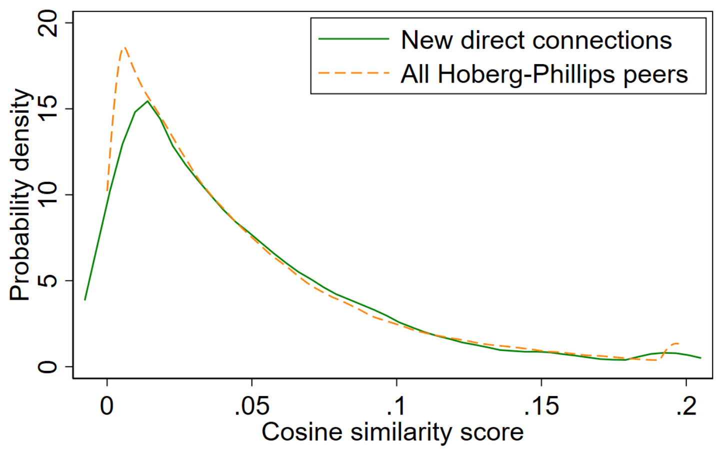
Note: This table reports results from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times Treated_{c,t} + \beta_1 \times Treated_{i,c} \times Post_{c,t} \\ &+ \gamma_1 \times \Delta(CommonOwnership)_{i,c} \times Post_{c,t} + \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Post_{c,t}$ is 1 for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. $Treated_{i,c}$ equals 1 for the time series of a firm experiencing new direct or indirect connections to product market peers, and 0 otherwise. In this regression we pool events of new direct and indirect connections together. $\Delta(CommonOwnership)_{i,c}$ is the change in the mean common ownership between a firm and all its Hoberg-Phillips product market peers from $\tau = -3, -2, -1$ to $\tau = 0, 1, 2, 3$. It is a constant for each time series of length 7 (from τ = -3 to +3). We use firm-pair level measures of common ownership as constructed in Gilje et al. (2020), which are GGL_{linear}, GGL_{fitted}, and GGL_{full_attn}. The sample size shrinks relative to Table 5 as the measures of common ownership are only available for the years 2000-2012. For brevity, only coefficients of $Treated_{i,c} \times Post_{c,t}$ and $\Delta(CommonOwnership)_{i,c} \times Post_{c,t}$ are reported in the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

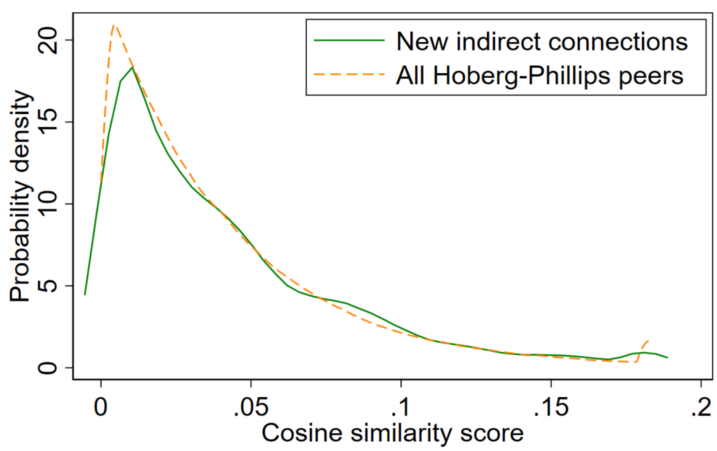
Figure 1: Distribution of cosine similarity score

Panel A: Similarity between new direct connections



Note: The average score is 0.046 for new direct connections and 0.046 for all Hoberg-Phillips peers. The p-value is 0.91 in a two-sample T-test and 0.43 in a Kolmogorov–Smirnov test.

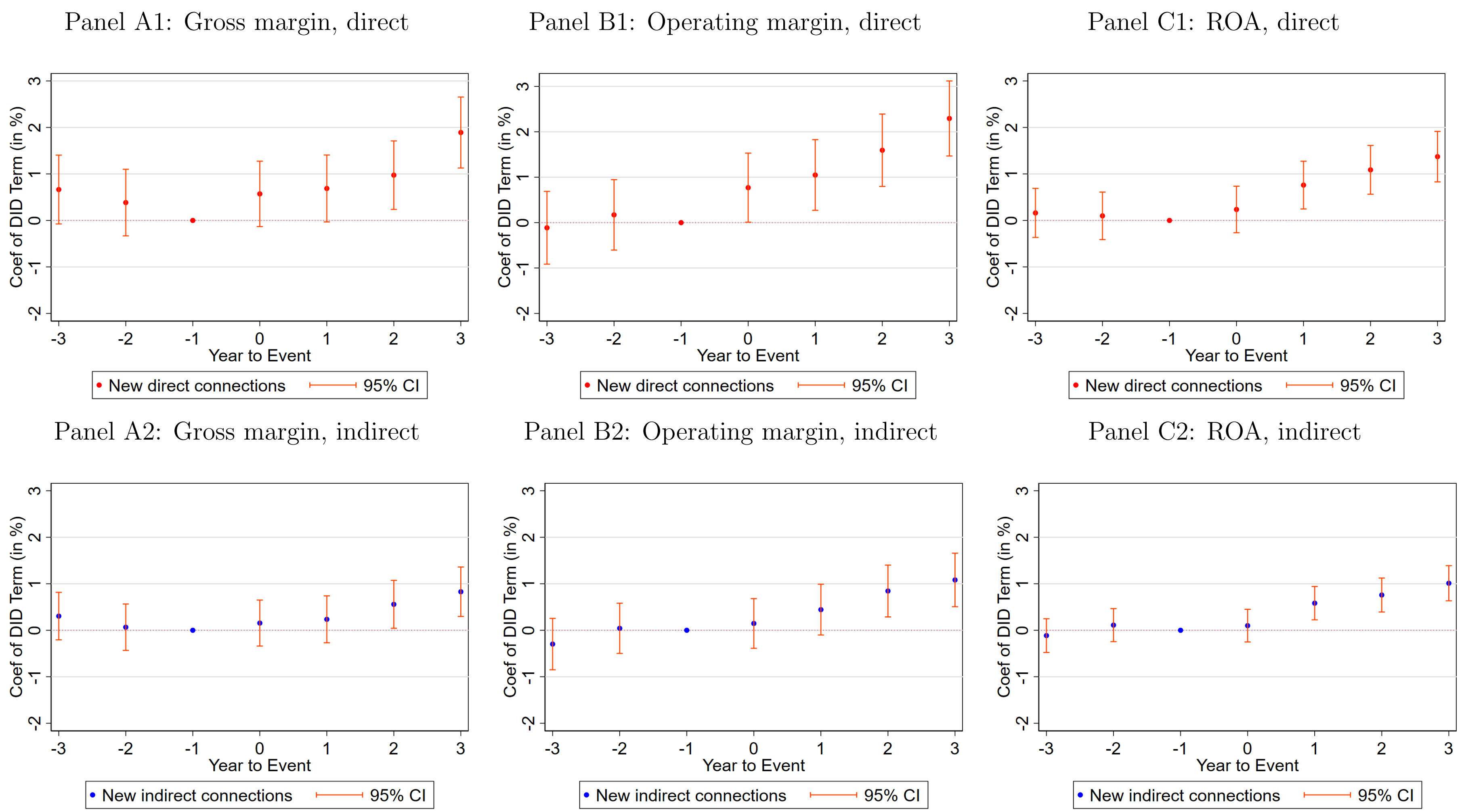
Panel B: Similarity between new indirect connections



Note: The average score is 0.042 for new indirect connections and 0.041 for all Hoberg-Phillips peers. The p-value is 0.03 in a two-sample T-test and 0.01 in a Kolmogorov–Smirnov test.

Note: This figure presents the empirical distribution of the cosine similarity score between the treated firms and their newly connected Hoberg-Phillips peers, along with the cosine similarity score between the treated firms and all their Hoberg-Phillips peers. The scores are winsorized at the 99% percentile.

Figure 2: Plots of the dynamics of the difference between treated and control firms

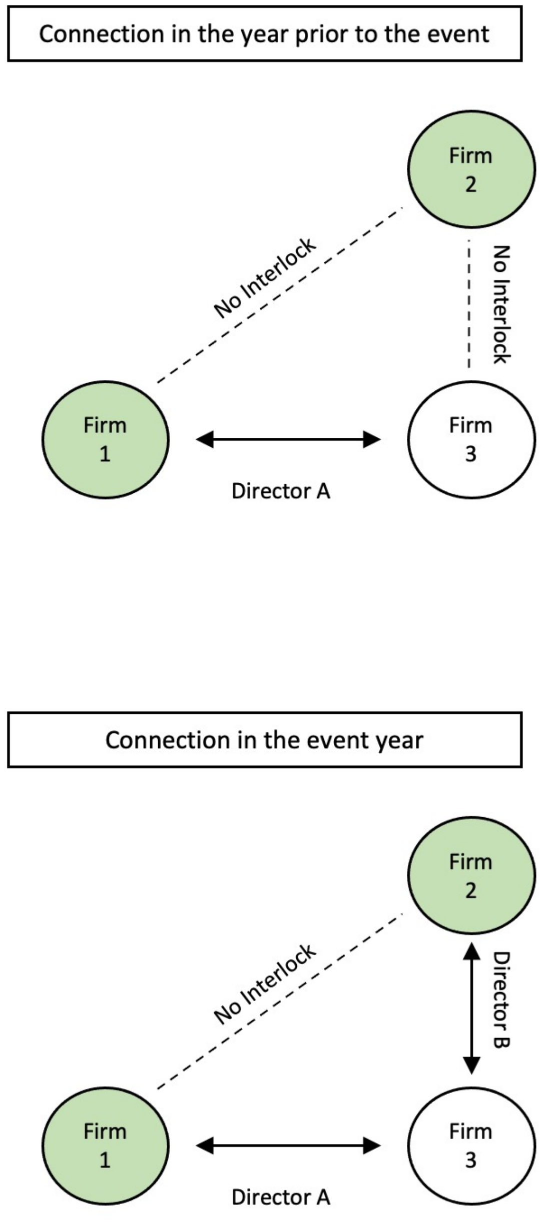


Note: This figure plots coefficients from the following regression,

$$\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times DirectTreated_{i,c} + \alpha_2 \times IndirectTreated_{i,c} \\
&+ \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
&+ DirectTreated_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) \\
&+ IndirectTreated_{i,c} \times (\sum_{s=-3}^{-2} \delta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \delta_s \times \mathbb{1}(\tau = s)_{c,t}) \\
&+ \theta_i + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}$$

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 turns on if the observation is s years before the treatment (for $s = -3, -2$) or if the observation is s years after the treatment (for $s = 0, 1, 2, 3$). 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 of year s relative to their difference in the baseline year. Standard errors are clustered at the firm level.

Figure 3: Illustration of third-party initiated board connection changes



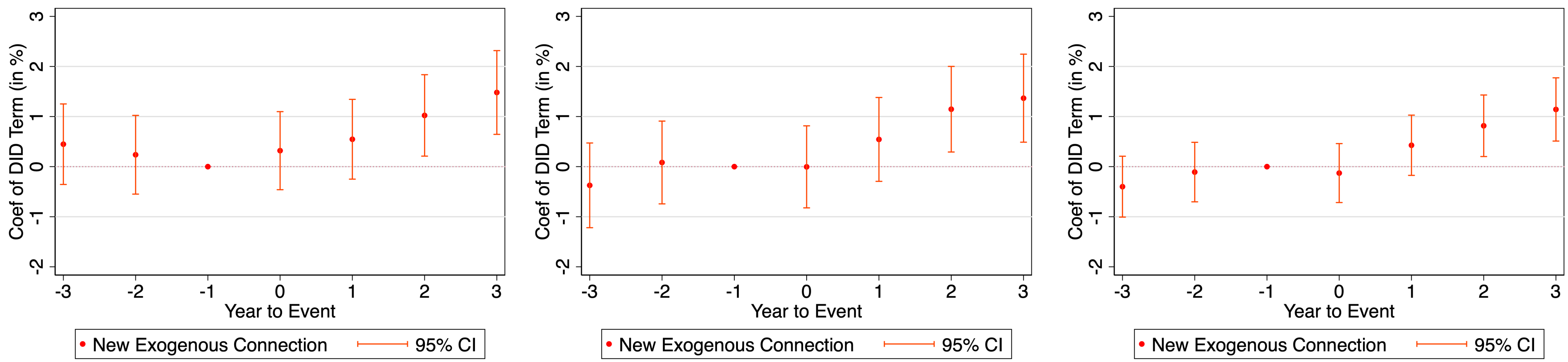
Note: This figure illustrates the third-party initiated board connection changes we use in Section 4. Firm 1 is the treated firm and firm 2 is its product market peer. Firm 3 is the intermediate firm.

Figure 4: Plots of the dynamics of the difference between treated and control firms, using the exogenous subset of events

Panel A: Gross margin

Panel B: Operating margin

Panel C: ROA



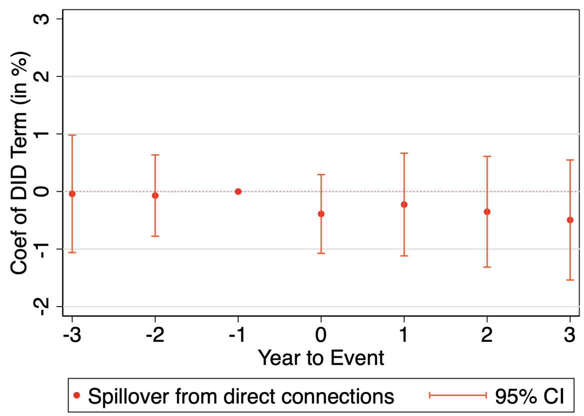
Note: This figure plots coefficients from the following regression,

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times ExogenousTreated_{i,c} + \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\ &+ ExogenousTreated_{i,c} \times (\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}) + \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

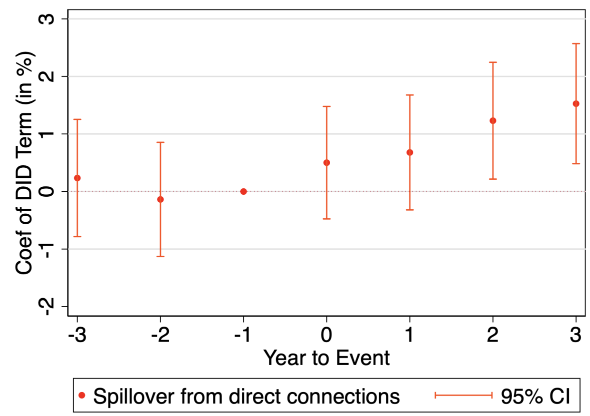
Here t represents the calendar year and τ represents the year relative to the treatment. $\mathbb{1}(\tau = s)_{c,t}$ is a dummy variable that turns on if the observation is s years before the treatment (for $s = -3, -2$) or if the observation is s years after the treatment (for $s = 0, 1, 2, 3$). We 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 of year s relative to their differences in the baseline year. Standard errors are clustered at the firm level.

Figure 5: Plots of the dynamics of the difference between firms subject to spillover effects and control firms

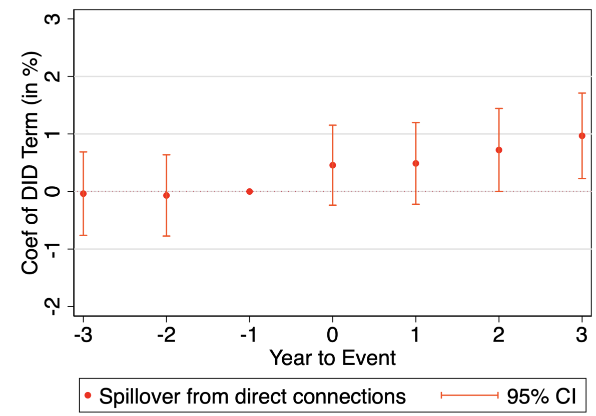
Panel A1: Gross margin, direct



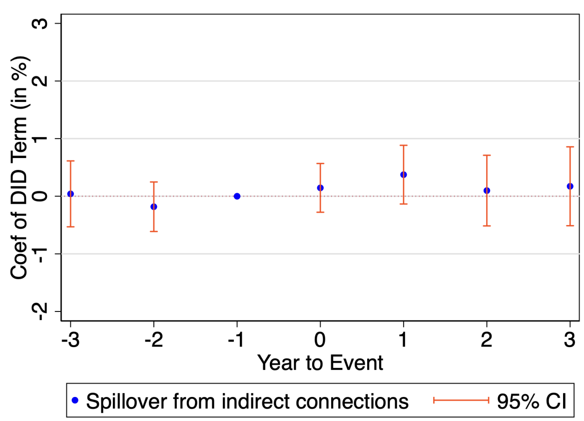
Panel B1: Operating margin, direct



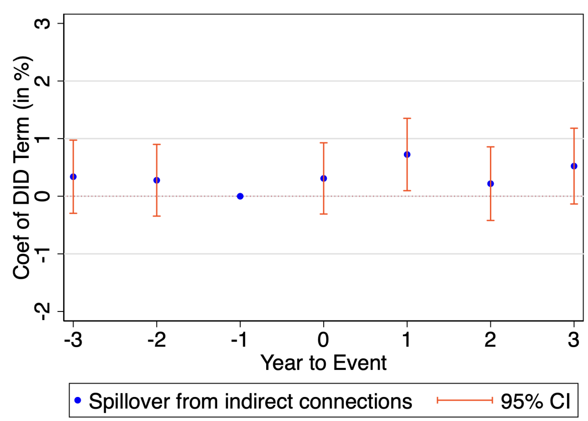
Panel C1: ROA, direct



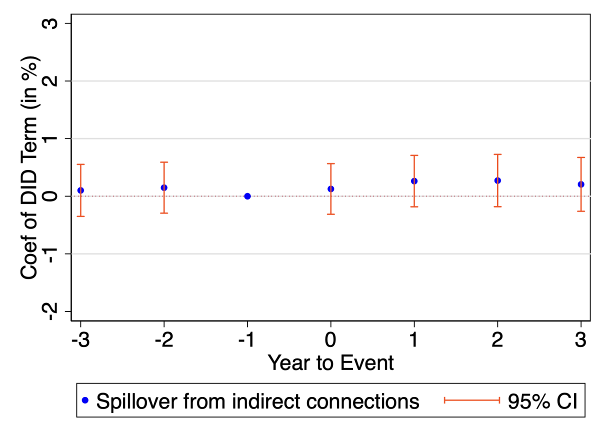
Panel A2: Gross margin, indirect



Panel B2: Operating margin, indirect



Panel C2: ROA, indirect



Note: This figure plots coefficients from the following regression,

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times \mathit{DirectSpillover}_{i,c} + \alpha_2 \times \mathit{IndirectSpillover}_{i,c} \\
&+ \sum_{s=-3}^{-2} \beta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \beta_s \times \mathbb{1}(\tau = s)_{c,t} \\
&+ \mathit{DirectSpillover}_{i,c} \times \Big(\sum_{s=-3}^{-2} \gamma_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \gamma_s \times \mathbb{1}(\tau = s)_{c,t}\Big) \\
&+ \mathit{IndirectSpillover}_{i,c} \times \Big(\sum_{s=-3}^{-2} \delta_s \times \mathbb{1}(\tau = s)_{c,t} + \sum_{s=0}^{3} \delta_s \times \mathbb{1}(\tau = s)_{c,t}\Big) \\
&+ \theta_i + \theta_{j,t} + e_{i,j,c,t}.
\end{aligned}
$$

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 turns on if the observation is s years before the treatment (for $s = -3, -2$) or if the observation is s years after the treatment (for $s = 0, 1, 2, 3$). 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 firms subject to spillover effects and control firms of year s relative to their differences in the baseline year. Standard errors are clustered at the firm level.

Internet Appendix

IA.1 Supplemental 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*)
Tobin's Q	The ratio of market value of equity plus book value of debt over total assets (*(at + csho* $\times$ *prcc f - ceq) / at*)
Panel B: Indicator variables used in regressions	
DirectTreated	A dummy that equals 1 for the time series of a firm experiencing new direct connections to product market peers
IndirectTreated	A dummy that equals 1 for the time series of a firm experiencing new indirect connections to product market peers
Post	It equals 0 for τ = -3, -2, -1 and 0, and equals 1 for τ = 1, 2, and 3
ExogenousTreated	A dummy that equals 1 for the time series of a firm experiencing new indirect connections to product market peers that occur due to changes on the board of another firm rather than itself
PseudoDirectTreated	A dummy that equals 1 for the time series of a firm experiencing direct connections to pseudo peers
PseudoIndirectTreated	A dummy that equals 1 for the time series of a firm experiencing indirect connections to pseudo peers

Table A1: List of variables (continued)

Panel C: Sorting variables	
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. 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. This score is developed in Hoberg and Phillips (2010, 2016) and provided in the Hoberg-Phillips Data Library
Top Similarity	A dummy that equals 1 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 some new connections are in the same SIC-3 industry as the treated firm
Geographical Distance	Geographical distance between the ZIP codes (*addzip*) of the treated firm and its newly connected peer. If a treated firm is incrementally connected to multiple peer firms, it takes the value of the smallest distance
Close Distance	A dummy that equals 1 for the time series of both the treated firm and its control if the new connections are in the bottom half in terms of Geographical Distance between the treated firm and its new connections
HHI	The Herfindahl-Hirschman of the industry that the treated firm is in. This measure is developed in Hoberg and Phillips (2016) and provided in the Hoberg-Phillips Data Library
Top HHI	A dummy that equals 1 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
Returns to Scale	The estimated returns to scale of the industry that the treated firm is in. Following Dong et al. (2019), we estimate a two-factor Cobb-Douglas production function for each SIC-2 industry using data of the year 1999 and OLS regressions. We proxy for the firm's output by its sales (*sale*), for the firm's labor by the number of its employees (*emp*), and for the firm's capital by the firm's property, plant, and equipment (*ppent*). We then add the coefficients for the proxies for labor and capital, which is our measure of an industry's returns to scale

Table A1: List of variables (continued)

Panel C: Sorting variables (continued)	
Top Returns to Scale	A dummy that equals 1 for the time series of both the treated firm and its control if the industry of the treated firm is in the top half in terms of Returns to Scale
Panel D: Other variables	
GGL_{linear}	The firm-pair-year level measure of common ownership developed in Gilje et al. (2020), which is defined as $$GGL_{linear}(A,B) = \sum_{i=1}^{I} \alpha_{i,A} g(\beta_{i,A}) \alpha_{i,B},$$ where $\alpha_{i,A}$ is the fraction of firm A's shares held by investor i, $\alpha_{i,B}$ is the fraction of firm B's shares held by investor i, and $\beta_{i,A}$ is the weight of firm A in investor i's portfolio. Function g describes how the likelihood of an investor being attentive is increasing in how important a stock is in this investor's portfolio. It is assumed to take a linear form
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 all its Hoberg-Phillips product market peers from $\tau = -3, -2, -1$ to $\tau = 0, 1, 2, 3$. For each treated firm, we calculate the average common ownership measure between it 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

Table A2: Characteristics of directors involved in board connections

	Connected Directors			Other Directors		
	Mean	SD	N	Mean	SD	N
Age	58.6	8.3	6,999	59.1	9.4	39,555
Is Female	0.12		6,999	0.10		39,555
Is Non-Executive Director	0.89		6,999	0.81		39,555
Total Number of Seats	3.1	1.3	6,999	1.8	1.1	39,555
Years of Experience	30.3	9.6	6,999	30.6	10.6	39,555
Highest Education Degree						
Undergraduate	30.3%			31.8%		
Master	48.3%			45.6%		
Doctoral	21.4%			22.6%		
Total	100%		6,780	100%		36,793
Source of Nomination						
Nominated by Search Firms	26.5%			24.4%		
CEO Recommendation	8.5%			8.9%		
Nominated by Other Insiders	3.4%			1.8%		
Nominated by Independent Directors	8.1%			9.4%		
Merger	2.6%			4.7%		
Nominated by Shareholders	1.3%			1.5%		
Promotion	2.8%			3.3%		
Nominated by the Nominating Committee	46.8%			46.0%		
Total	100%		468	100%		2,361

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. *Total Number of Seats* is the number of board seats in different firms that a director simultaneously holds on in the treatment year. *Source of nomination* uses the board of directors nomination data constructed in Akyol and Cohen (2013).

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	0.013*	0.026***	0.020***	-0.030***	0.023***	0.016	0.038***	-0.077***
	(1.84)	(2.84)	(2.92)	(-3.01)	(2.79)	(1.40)	(3.64)	(-4.07)
DirectTreated × Post	0.029**	0.022	0.017	0.037*	-0.003	0.007	-0.019	-0.011
	(2.01)	(1.26)	(1.23)	(1.80)	(-0.17)	(0.31)	(-0.96)	(-0.26)
IndirectTreated × Post	0.007	-0.002	-0.005	0.028**	-0.016	-0.030*	-0.014	-0.033
	(0.65)	(-0.16)	(-0.53)	(2.10)	(-1.31)	(-1.83)	(-0.98)	(-1.19)
Observations	68,690	68,654	65,692	63,067	68,766	68,293	44,275	67,904
Firm 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
Within R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002

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

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times DirectTreated_{i,c} + \alpha_3 \times IndirectTreated_{i,c} \\ &+ \beta_1 \times DirectTreated_{i,c} \times Post_{c,t} + \beta_2 \times IndirectTreated_{i,c} \times Post_{c,t} + \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

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 production approach, following De Loecker et al. (2020). 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. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Robustness to alternative matching schemes

	Gross Margin	Operating Margin	ROA
Panel A: Choose two controls for each event			
DirectTreated × Post	0.008***	0.014***	0.010***
	(2.65)	(4.02)	(3.91)
IndirectTreated × Post	0.004**	0.009***	0.008***
	(2.10)	(4.00)	(4.65)
Observations	94,120	93,938	94,026
Panel B: Choose three controls for each event			
DirectTreated × Post	0.008***	0.013***	0.009***
	(2.63)	(3.76)	(3.57)
IndirectTreated × Post	0.004**	0.008***	0.007***
	(2.03)	(3.66)	(4.25)
Observations	11,3475	113,225	113,319
Panel C: Match additionally on number of new appointments during the event year			
DirectTreated × Post	0.012***	0.014***	0.008**
	(2.59)	(2.86)	(2.33)
IndirectTreated × Post	0.004	0.010***	0.009***
	(1.28)	(3.28)	(3.41)
Observations	36,715	36,666	36,696
Panel D: Match using Operating Margin instead of Gross Margin			
DirectTreated × Post	0.008**	0.011***	0.006**
	(2.21)	(2.87)	(2.30)
IndirectTreated × Post	0.005**	0.007***	0.006***
	(2.15)	(2.77)	(3.08)
Observations	60,679	60,633	60,684
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Table A4: Robustness to alternative matching schemes (continued)

	Gross Margin	Operating Margin	ROA
Panel E: Match additionally on Operating Margin			
DirectTreated × Post	0.007**	0.010***	0.005*
	(2.07)	(2.61)	(1.90)
IndirectTreated × Post	0.004*	0.006**	0.005**
	(1.92)	(2.35)	(2.46)
Observations	60,648	60,596	60,653
Panel F: Match additionally on Sales Growth			
DirectTreated × Post	0.009**	0.014***	0.009***
	(2.48)	(3.48)	(3.05)
IndirectTreated × Post	0.004	0.008***	0.007***
	(1.61)	(3.11)	(3.81)
Observations	57,882	57,772	57,820
Panel G: Match additionally on ROA			
DirectTreated × Post	0.009**	0.013***	0.006**
	(2.52)	(3.37)	(2.30)
IndirectTreated × Post	0.006**	0.008***	0.005***
	(2.43)	(3.25)	(2.89)
Observations	60,604	60,552	60,618
Panel H: Match additionally on R&D to Assets			
DirectTreated × Post	0.006	0.014***	0.009***
	(1.63)	(3.15)	(2.78)
IndirectTreated × Post	0.003	0.008***	0.006***
	(1.24)	(2.80)	(2.91)
Observations	45,157	45,061	45,102
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Table A4: Robustness to alternative matching schemes (continued)

	Gross Margin	Operating Margin	ROA
Panel I: Match additionally on CAPEX to Assets			
DirectTreated × Post	0.008**	0.014***	0.008***
	(2.21)	(3.55)	(2.94)
IndirectTreated × Post	0.005**	0.009***	0.007***
	(2.09)	(3.70)	(3.82)
Observations	60,515	60,409	60,463
Panel J: Require that the control firm is never treated during [–3,3]			
DirectTreated × Post	0.011***	0.015***	0.010***
	(2.68)	(3.47)	(3.12)
IndirectTreated × Post	0.005*	0.007**	0.006**
	(1.87)	(2.14)	(2.31)
Observations	52,361	52,198	52,251
Panel K: Require that the control firm is never treated before or during [–3,3]			
DirectTreated × Post	0.011***	0.016***	0.009***
	(2.65)	(3.64)	(2.81)
IndirectTreated × Post	0.006**	0.008**	0.005**
	(1.99)	(2.45)	(2.09)
Observations	48,562	48,406	48,454
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes

Note: This table report coefficients for the regression in Table 5 if alternative matching schemes are used. Panel A (B) uses a matching scheme that retains 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 uses a matching scheme that additionally requires the control firm being never treated from τ = -3 to +3. Panel K uses a matching scheme that additionally requires the control firm being never treated before $\tau = +3$. Otherwise, the variables and specifications are defined as in Table 5.

Table A5: Robustness to alternative fixed effects

	Gross Margin	Operating Margin	ROA
Panel A: SIC-3 × Year FE and Firm FE			
DirectTreated × Post	0.008**	0.015***	0.010***
	(2.54)	(4.03)	(4.08)
IndirectTreated × Post	0.004*	0.008***	0.008***
	(1.67)	(3.32)	(4.31)
Panel B: FIC-200 × Year FE and Firm FE			
DirectTreated × Post	0.008***	0.013***	0.008***
	(2.58)	(3.77)	(3.16)
IndirectTreated × Post	0.003	0.006***	0.006***
	(1.11)	(2.79)	(3.45)
Panel C: FF-48 × Year FE and Firm-Cohort FE			
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)

Note: This table report coefficients for the regression in Table 5 if alternative fixed effects are used. Regressions in Panel A use SIC-3 industry times year fixed effects and firm fixed effects. Regressions in Panel B use FIC-200 industry times year fixed effects and firm fixed effects. FIC-200 industry classification is provided in the Hoberg-Phillips Data Library. Regressions in Panel C use Fama-French 48-industry times year fixed effects and firm-cohort fixed effects. Otherwise, the variables and specifications are defined as in Table 5.

Table A6: Robustness to using alternative industry classification

	Gross Margin	Operating Margin	ROA
Panel A: Using FactSet to identify peer firms			
DirectTreated × Post	0.007	0.016**	0.010**
	(1.07)	(2.04)	(2.04)
IndirectTreated × Post	0.003	0.008**	0.006***
	(0.95)	(2.50)	(2.76)
Observations	20,998	20,521	20,539
Panel B: Using SIC-3 to identify peer firms			
DirectTreated × Post	0.006**	0.013***	0.010***
	(2.21)	(4.07)	(4.43)
IndirectTreated × Post	0.005**	0.010***	0.009***
	(2.54)	(4.79)	(5.17)
Observations	81,338	81,159	81,242
Panel C: Using SIC-4 to identify peer firms			
DirectTreated × Post	0.004	0.013***	0.007**
	(0.90)	(2.96)	(2.42)
IndirectTreated × Post	0.007***	0.010***	0.007***
	(2.81)	(3.69)	(3.56)
Observations	53,065	52,955	53,020
Panel D: Using GICS-6 to identify peer firms			
DirectTreated × Post	0.004*	0.007***	0.004**
	(1.92)	(3.01)	(2.30)
IndirectTreated × Post	0.003**	0.005***	0.004***
	(2.00)	(2.63)	(2.72)
Observations	100,941	100,762	100,828
Panel E: Using GICS-8 to identify peer firms			
DirectTreated × Post	0.006*	0.010***	0.006**
	(1.80)	(2.98)	(2.52)
IndirectTreated × Post	0.003*	0.006***	0.006***
	(1.80)	(2.91)	(3.62)
Observations	72,090	71,947	71,995

Note: This table report coefficients for the regression in Table 5 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. Otherwise, the variables and specifications are defined as in Table 5.

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

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.007***	-0.008***	-0.007***
	(-4.26)	(-4.78)	(-6.12)
DirectTreated, Is Not Exec. × Post	0.007*	0.013***	0.009***
	(1.83)	(3.35)	(3.13)
DirectTreated, Is Exec. × Post	0.011**	0.015**	0.010**
	(2.29)	(2.37)	(2.14)
IndirectTreated, Is Not Exec. × Post	0.002	0.006**	0.007***
	(0.88)	(2.25)	(3.42)
IndirectTreated, Is Exec. × Post	0.009**	0.014***	0.008***
	(2.54)	(3.90)	(3.02)
Observations	68,690	68,534	68,602
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Within R-squared	0.001	0.002	0.002

Note: This table reports results from the following regression

$$
\begin{aligned}
Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times DirectTreatedIsNotExec_{i,c} + \alpha_3 \times DirectTreatedIsExec_{i,c} \\
&+ \alpha_4 \times IndirectTreatedIsNotExec_{i,c} + \alpha_5 \times IndirectTreatedIsNotExec_{i,c} \\
&+ \beta_1 \times DirectTreatedIsNotExec_{i,c} \times Post_{c,t} + \beta_2 \times DirectTreatedIsExec_{i,c} \times Post_{c,t} \\
&+ \beta_3 \times IndirectTreatedIsNotExec_{i,c} \times Post_{c,t} + \beta_4 \times IndirectTreatedIsExec_{i,c} \times Post_{c,t} \\
&+ \theta_i + \theta_{j,t} + e_{i,j,c,t}
\end{aligned}
$$

using the sample of events of connections to product market peers. Here $Post_{c,t}$ is 1 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 1 for the time series of a firm experiencing direct connections to product market peers and only non-executive directors are involved. $DirectTreatedIsExec_{i,c}$ equals 1 for the time series of a firm experiencing direct connections to product market peers and directors who are also executives are involved. $IndirectTreatedIsNotExec_{i,c}$ equals 1 for the time series of a firm experiencing indirect connections to product market peers and only non-executive directors are involved. $IndirectTreatedIsExec_{i,c}$ equals 1 for the time series of a firm experiencing indirect connections to product market peers and directors who are also executives are involved. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. We omit coefficients of $DirectTreatedIsNotExec_{i,c}$, $DirectTreatedIsExec_{i,c}$, $IndirectTreatedIsNotExec_{i,c}$ and $IndirectTreatedIsNotExec_{i,c}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Double-difference by inbound vs outbound directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	-0.007***	-0.008***	-0.007***
	(-4.27)	(-4.77)	(-6.11)
DirectTreated, Inbound × Post	0.006	0.015***	0.013***
	(1.44)	(3.06)	(3.82)
DirectTreated, Outbound × Post	0.010**	0.013**	0.005
	(2.23)	(2.52)	(1.42)
IndirectTreated	0.004*	0.008***	0.007***
	(1.88)	(3.59)	(4.01)
Observations	68,690	68,534	68,602
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Within R-squared	0.001	0.002	0.002

Note: This table reports results from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times DirectTreatedInbound_{i,c} + \alpha_3 \times DirectTreatedOutbound_{i,c} \\ &+ \alpha_4 \times IndirectTreated_{i,c} + \beta_1 \times DirectTreatedInbound_{i,c} \times Post_{c,t} \\ &+ \beta_2 \times DirectTreatedOutbound_{i,c} \times Post_{c,t} + \beta_3 \times IndirectTreated_{i,c} \times Post_{c,t} \\ &+ \theta_i + \theta_{j,t} + e_{i,j,c,t} \end{aligned} \tag{8}$$

using the sample of events of connections to product market peers. Here $Post_{c,t}$ is 1 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 1 for the time series of a firm experiencing direct connections to product market peers and the connections are caused by new appointments to the treated firm's board. $DirectTreatedOutbound_{i,c}$ equals 1 for the time series of a firm experiencing 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 1 for the time series of a firm experiencing indirect connections to product market peers. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. We omit coefficients of $DirectTreatedInbound_{i,c}$, $DirectTreatedOutbound_{i,c}$, $IndirectTreated_{i,c}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Robustness to controlling for connections between customer-supplier firms

	(1) Gross Margin	(2) Operating Margin	(3) ROA
NonCusSupTreated × Post	0.005**	0.010***	0.007***
	(2.40)	(4.27)	(4.44)
CusSupTreated × Post	0.004	0.018*	0.016***
	(0.68)	(1.87)	(2.83)
Observations	68,690	68,534	68,602
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	1	1	1
Within R-squared	0.001	0.001	0.002

Note: This table reports results from the following regression

$$\begin{aligned} Y_{i,j,c,t} &= \alpha_1 \times Post_{c,t} + \alpha_2 \times NonCusSupTreated_{i,c} + \alpha_3 \times CusSupTreated_{i,c} \\ &+ \beta_1 \times NonCusSupTreated_{i,c} \times Post_{c,t} + \beta_2 \times CusSupTreated_{i,c} \times Post_{c,t} \\ &+ \theta_i + \theta_{j,t} + e_{i,j,c,t}. \end{aligned}$$

Here $Post_{c,t}$ is 1 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. In this regression we pool events of new direct and indirect connections together. $NonCusSupTreated_{i,c}$ equals 1 for the time series of a firm experiencing new direct or indirect connections to a product market peer that is not its customer or supplier firm. $CusSupTreated_{i,c}$ equals 1 for the time series of a firm experiencing new direct or indirect connections to a product market peer that is a customer or supplier firm of its. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. We omit coefficients of $Post_{c,t}$, $NonCusSupTreated_{i,c}$ and $CusSupTreated_{i,c}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Effects of the death of connected directors

	(1) Gross Margin	(2) Operating Margin	(3) ROA
Post	0.024	0.017	0.020
	(1.59)	(0.90)	(1.55)
DeathTreated × Post	-0.018	-0.031*	-0.017**
	(-1.16)	(-1.88)	(-2.07)
Observations	1,137	1,137	1,137
Firm FE	Yes	Yes	Yes
FF48 × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
# of Matched Controls	3	3	3
Within R-squared	0.004	0.006	0.011

Note: This table reports results from the following regression

$$Y_{i,j,c,t} = \alpha_1 \times Post_{c,t} + \alpha_2 \times DeathTreated_{i,c} + \beta_1 \times DeathTreated_{i,c} \times Post_{c,t} + \theta_i + \theta_{j,t} + e_{i,j,c,t}.$$

Here $DeathTreated_{i,c}$ equals 1 for the time series of a firm experiencing the death of a director that cross-sits on the board of a product market peer. $Post_{c,t}$ is 1 for both treated and control firms for the years $\tau = 0$, 1, 2, and 3, where $\tau = 0$ is the treatment year. The coefficient of $DeathTreated_{i,c} \times Post_{c,t}$ is the estimated effects of the death of a connected director. θ_i are firm fixed effects. $\theta_{j,t}$ are industry times year fixed effects based on the Fama-French 48-industry classification. We omit coefficients of $DeathTreated_{i,c}$ from the table. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Director network and detected cartel cases

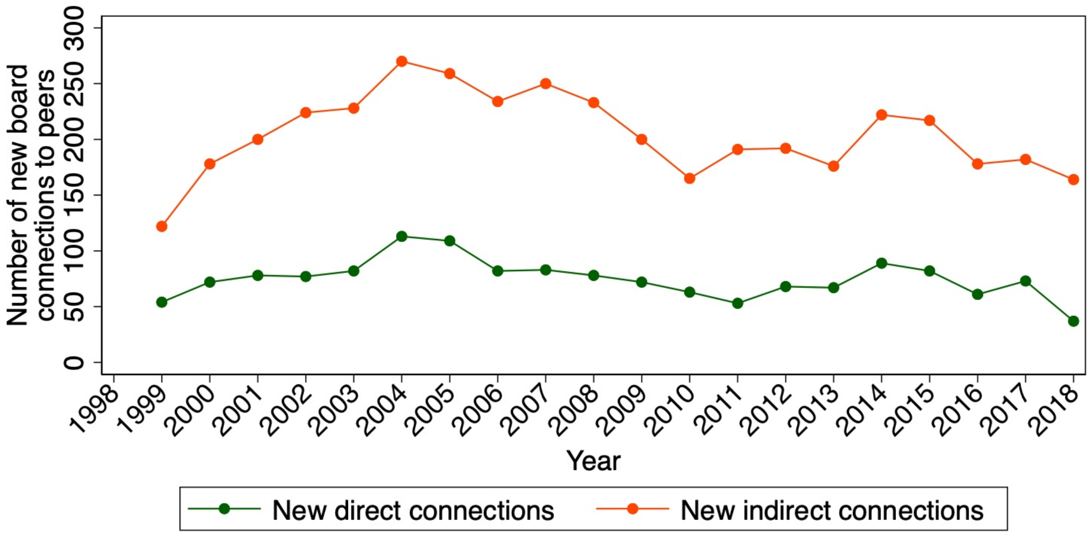
	(1) Prob. of active detected cartel (%)	(2) Prob. of active detected cartel (%)	(3) Prob. of active detected cartel (%)
Degree of separation = 0	0.058***	0.043***	0.025***
	(33.38)	(24.70)	(11.62)
Degree of separation = 1	0.060***	0.053***	0.005***
	(84.82)	(74.30)	(7.32)
Degree of separation = 2	0.017***	0.014***	–0.000
	(52.28)	(41.54)	(–1.00)
Degree of separation = 3	0.003***	0.002***	–0.000
	(16.23)	(11.07)	(–0.81)
Cosine similarity score		0.285***	0.074***
		(72.05)	(12.18)
Is H-P peer		0.036***	–0.007***
		(41.31)	(–6.86)
Observations	53,893,933	53,893,933	53,893,933
Year FE	No	Yes	Yes
Firm-pair FE	No	No	Yes

Note: This table reports results from the following regression

$$\begin{aligned} Prob(\text{Having an active detected cartel})_{i,j,t} &= \sum_{m=0}^{4} \beta_m \times \mathbb{1}(\text{Degree of separation is } m)_{i,j,t} \\ &+ \; Control_{i,j,t} + \theta_t + \theta_{i,j} + e_{i,j,t}. \end{aligned}$$

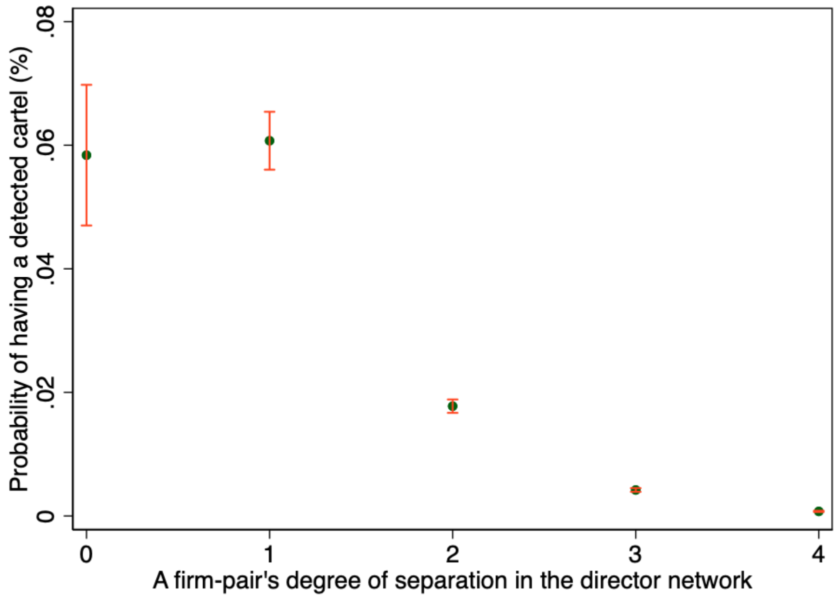
using the sample of firm-pair's with the degree of separation in the director network less than or equal to 4. Firm-pair's with a degree of separation of 4 serve as the omitted category. T-stats are in parentheses. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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: Director network and detected cartel cases



Note: This figure plots the probability of a firm-pair in a certain year being in an active detected cartel case, conditional on each level of minimum distance between the firm-pair in the director network.

IA.2 Definition of the more exogenous subset of events

In our paper, the changes refer to the scenarios of both a firm appointing new directors, and existing directors taking on new roles at other firms. Both kinds of changes on the board of the treated firm could be related to certain future prospects of this treated firm. Our more exogenous subset of events aims to avoid such changes that can be directly linked to firms future prospects. In this section, we describe how we define and operationalize the more exogenous subset of events.

We consider such an exogenous set of events of new board connections to peer firms that occur solely due to changes on the board of a third firm. To identify this exogenous subset of events, we first identify the complement set of it, which are events that occur at least partly due to changes on the board of the treated firm itself. Note that by definition new direct connections take place because of changes to the board of the treated firm, so our more exogenous events only consider (a subset of) new indirect connections.

In particular, we consider that an event is a *not* exogenous one, if either:

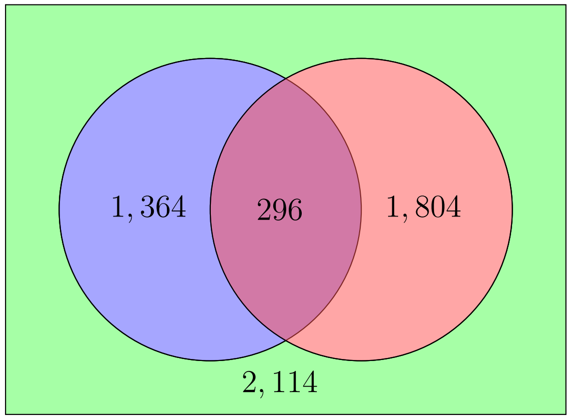
1. the appointment of new directors to the treated firm triggers new connections between the treated firm and its product market peers, and/or

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

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

The logic can be represented using the following Venn diagram.

Figure A3: Definition of the exogenous subset of events



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

IA.3 Director network and detected cartels

We obtain information on convicted cartels from the Private International Cartels database (Connor, 2020). We restrict the sample to firms headquartered in the US, and hand-match those firms to the universe of firms we described in Section 2. Equipped with these cartels cases, we construct a firm-pair-year level indicator of whether two firms are in an active detected cartel in a certain year. We also construct the degree of separation of each firm-pair in the network, which is the minimum number of intermediate firms that can connect these two firms together. Hence, two directly connected firms have a degree of separation of zero and two indirectly connected firms have a degree of separation of one. We exclude firm-pairs that are unconnected in the director network or connected but with a degree of separation above four.

We first plot the probability of a firm-pair having an active detected cartel in a certain year, conditional on the degree of separation of these two firms 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 probit model on this sample:

$$\begin{aligned} Prob(\text{Having an active detected cartel})_{i,j,t} &= \sum_{m=0}^{4} \beta_m \times \mathbb{1}(\text{Degree of separation is } m)_{i,j,t} \\ &+ Control_{i,j,t} + \theta_t + \theta_{i,j} + e_{i,j,t}. \end{aligned}$$

where i and j are indexes for the pair firm i and firm j and t is the index for the calendar year. We report the results in Table A11. Column (1) reports the probability of having an active detected cartel, with firm-pairs of degree of separation 4 being the baseline group. As firms 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 two firms' business descriptions as well as an indicator for whether the two firms are in the same Hoberg-Phillips industry. In column (3) we additionally include firm-pair fixed effects. Across all these specifications, the associative relationship between the degree of separation in the director network and the probability of having an active cartel all holds and remains statistically significant.

IA.4 Matching Nielsen Retail Scanner Data to BoardEx

We start by matching the Nielsen Retail Scanner Data (Nielsen) to producers in the GS1 Company Database. Universal Product Code (UPC) is the unit at which prices are recorded in Nielsen 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. (2020), we start from the set of all UPCs in the Nielsen 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., 2020). Hence, if for a UPC one of the four candidate prefixes belong 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.[24] 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 the Nielsen Retail Scanner Data.

[24]We clean the firm names by dropping suffixes such as "Co", "Inc", and "Corp" and removing special characters before matching by the name string.