Directors Networks and Innovation Herding

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Abstract

This paper examines the role of overlapping board networks on firm innovation, competition, and performance. First, we document that, despite the Clayton Act, overlapping directors are surprisingly most prevalent among competitor firm pairs. Using panel data regressions with rigid controls and plausibly exogenous shocks, we find that competing firms in markets with dense director overlaps engage in innovation herding, experience losses in product differentiation, and ultimately perform poorly. We validate these findings using novel network propagation tests of individual technologies, which show that firms with overlapping directors experience larger and faster propagation of technology transfers to their product market peers. Our results are most consistent with an agency conflict that is new to the literature, as directors can realize better career outcomes by leaking sensitive information across boards, even though a consequence of repeated leakage can be value destruction.

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> No person shall, at the same time, serve as a director or officer in any two corporations that are ... competitors
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> *Clayton Act of 1914, Section 8*

Although the practice of directors sitting on the boards of competing firms is not legal in many cases[1] due to the high risk of anti-competitive practices, Section 8 of the 1914 Clayton Act is rarely enforced.[2] Using the highly customizeable TNIC industry classification (see Hoberg and Phillips (2016)), which provides a spatial product market distance for every pair of firms, we first examine with high resolution how the incidence of U.S. public firm director overlaps changes as firms become closer to being direct competitors. Surprisingly given the Clayton Act's restrictions, Figure 1 illustrates that the incidence of overlapping directors increases steadily as firms become closer to being direct competitors, and reaches a peak for pairs of companies that are quite likely to be direct competitors (firm-pairs with the highest 1% product similarities are analogous to being in the same four-digit SIC code). In fact, we only see a slight decline in overlapping director incidence when we zoom in even further and look at the 0.5% most related firm-pairs in the economy. Furthermore, the prevalence of this practice has increased over time, especially during the last decade. We conclude that the lack of enforcement or applicability of Section 8 has led to an equilibrium where directors regularly sit on the boards of competing firms.

The stylized fact in Figure 1 and its consequences have not been studied in the literature to our knowledge. Because the potential for strategic interactions across competing boards is high, the consequences can be important. The Clayton Act aims to prohibit this practice primarily due to the risk of damage to consumer welfare relating to market power. These overlapping directors (ODs) indeed have incentives to collude as they often own equity stakes in the companies they serve, and the value of these stakes will increase under collusion. Yet we note that these directors might also have other incentives that differ from non-overlapping directors. For example, directors are privy to proprietary information about each firm's business strategy, its growth opportunities, and how it

[1] Exceptions to Section 8's prohibition include banks, smaller firms, and a one year post-acquisition grace period.

[2] The law firm Skadden notes on their website "It has been more than 40 years since the federal government has filed suit under Section 8." The website goes on to note that Section 8 concerns led to changes in the boards of Apple and Google, and the Trump and Obama administrations each invoked Section 8 concerns in one instance. These recent references to Section 8 indicate that Section 8 is relevant and still applies, but overall, serious challenges relating to Section 8 are rare. See https://www.skadden.com/en/insights/publications/2021/06/the-informed-board/interlocking-boards.

plans to innovate and differentiate itself from its competitors. As we explain below, the possibility of leaking proprietary information about innovation across boards might provide private benefits to the ODs, but firm welfare could be reduced (in contrast to the collusion hypothesis, which unambiguously predicts increased valuations). To understand strategic decisions, the incentives and consequences of at least three parties needs to be considered: consumers, the firm, and the directors themselves.[3]

Although the primary concern of Section 8 of the Clayton Act is to protect against collusion, we find no evidence that competing-firm ODs increase collusive practices. Both in tests of association, and in tests that use second-degree peer-of-peer director links (which are less endogenous), we find that the presence of ODs is associated with lower (not higher) profits in the form of return on assets and also lower market valuations. Some readers might find this result to be surprising given the incentives to collude. However, the absence of collusive evidence is consistent with ODs (and their lawyers) being aware of the Clayton Act and its salience, and with these directors being careful to avoid discussions of prices in their meetings in order to avoid litigation. In particular, we propose that both regarding collusion and regarding the potential agency conflicts we discuss next, that directors face both costs and benefits to various strategic interactions across their overlapping boards. Our evidence regarding collusion is that the costs of potential litigation likely exceed the benefits at least from the perspective of ODs, whose careers would be particularly susceptible to legal consequences should collusion be detected by regulatory authorities.

ODs might face strategic incentives other than collusion. One relates to valuable proprietary intellectual property. In a competitive market, intellectual property is particularly important, as both Sutton (2001) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005) predict that managers might use innovation to generate product differentiation and escape from competition. Because intellectual property can be pivotal to securing protection from competitors, it is natural to ask how a director who sits on competing boards will manage his or her knowledge about each firm's IP and competition strategy. We propose that ODs can have strong incentives to leak sensitive IP across the two competing boards they serve. These incentives can be especially compelling if ODs can represent the leaked innovative ideas as their own original thinking. In such a scenario,

[3] Although it is beyond the scope of our study, third parties including suppliers or larger customers can also face consequences such as how future contracts might be negotiated. We leave deeper analysis of these parties' outcomes to future research.

the receiving board will view the director as being highly innovative, and as a consequence of the resulting enhancement of stature, the director might receive stronger recommendations to other boards. In turn, this will create enhanced career opportunities and increase the utility of the leaking director. The original owner of the leaked intellectual property (the competing firm), while harmed by this practice, will likely be unaware of the leak and attribute the competitor's similar innovation strategy to bad luck. Because the director in this scenario realizes enhanced career outcomes at the expense of the firms they serve, this would constitute a new agency problem relating to IP management that is not discussed in the existing literature.

The damage associated with leaking intellectual property might be modest if it is leaked to just one of many potential competitors. ODs might internalize this fact, and feel that the career benefits associated with leaking information might outweigh the costs they incur in the form of reduced value of their equity stake. Yet if the incentives to leak are strong, and director connections are frequent in the competitor network, leaked information can recursively leak to more and more peers. In the most extreme case of frequent recursive leakage, every firm's intellectual property will leak to every peer in the industry, leaving no competitive advantage to any firm. In this scenario, directors might paradoxically feel even more compelled to leak because doing so provides career benefits, and the information will leak through other connections anyway if the given director chooses not to leak. The important conclusion from this discussion is that the tradeoffs ODs face can strongly favor leaking information, and these incentives depend in part on market structure. Subsample tests we report later support these predictions.

Overall, our paper makes three major contributions. First, as noted above, we document the new stylized fact that overlapping directors tend to cluster across competing firms despite Section 8 of the Clayton Act discouraging this practice. Second, we document that the consequences of ODs spanning competing firms are in fact negative, as these firms experience inferior outcomes in accounting terms, valuations, and innovative positioning. These results are consistent with information leakage through OD networks and a loss of product differentiation resulting in inefficient innovation herding. Third, we provide a new methodology ideally suited for modeling the propagation of specific technologies through the product market space. In our context, this methodology illustrates that competing-firm OD networks facilitate more technology propagation through the competitor network, and moreover, these networks also speed the propagation of technological adoption. Taken together, along with supporting evidence of a role for informational opacity and improved OD career outcomes, our findings are most consistent with a new agency problem relating to incentives to leak valuable intellectual property across boards when ODs operate across competing firm pairs. We now summarize our empirical methods and results.

Our first set of empirical tests examine the relationship between the ex-ante density of the competing-firm OD network around a firm, and ex-post corporate outcomes. We find that dense competing-firm OD networks associate with inferior corporate outcomes along many dimensions. These firms experience lower valuations, lower profits, and lower sales growth. Regarding innovation, these firms spend more on R&D, but the R&D is correlated and redundant across peers, as product market fluidity increases even as the total product market similarity of these peers also increases. These results suggest that innovation in these markets does not increase product differentiation, but instead is consistent with innovation herding. The inferior performance outcomes are not consistent with collusion, but are consistent with valuation losses from information leakages through the OD network that induce losses in valuable product differentiation and inefficient innovation herding. Because we later document suggestive evidence that these ODs experience private benefits in the form of better career outcomes, these results are consistent with an agency conflict generating gains for directors at the expense of the firms they serve.

Further empirical tests reveal that competing-firm ODs are special. We contrast the effects for these ODs with those of ODs who overlap on the boards of more distant (less likely to be direct competitor) peers. We identify more distant peers as those with lower pairwise product similarity scores (below the top 1% but still in the top 5%). Hoberg and Phillips (2010) and Bena and Li (2014) find evidence that these more distant peers are less likely to be competitors and are more likely to have asset complementarities, as they are more likely to do mergers that result in product market and technological synergies. Illustrating that competing-firm ODs are indeed different, we find diametrically opposite results for these distant-peer ODs. In particular, more distant OD relationships are associated with improved accounting performance and increased product differentiation (consistent with mutually beneficial asset complementarities being realized). These results provide a relevant benchmark for our competing-firm ODs, and illustrate that incentives indeed vary for the more controversial case of competing-firm boards.

A key challenge in our setting is that OD relationships are endogenous. For example, firms might hire overlapping directors when they wish to collaborate, and the need for doing so might correlate negatively with performance. To mitigate endogeneity concerns, we rerun our primary analysis using only second-degree director links. Second-degree linked boards are those where there is no direct OD link between them, but the two boards are connected through OD relationships to a common third board. For example, two firms A and B would have a second-degree board link if A and B have no overlapping directors, but both firms have a director that overlaps with another firm C. Because A and B cannot control the director selections made at firm C, any information flowing through second degree links is less likely to be driven by endogenous director selection by A and B. The use of second-degree network connections to reduce endogeneity concerns is motivated by theoretical work in network econometrics (see Bramoullé, Djebbari, and Fortin (2009)).[4] Our findings noted above for competitor ODs are fully robust to using this more stringent test based on second degree links. To further mitigate the potential impact of omitted variables, we also control for firm fixed effects and an array of standard control variables. We also consider a quasi natural experiment (discussed next).

Our hypothesis predicts that information leakage is a primary mechanism driving firm outcomes. Hence our results should be stronger when firms are in more opaque information environments (as there are fewer alternative ways beyond ODs for information to leak). We test this opacity hypothesis using an exogenous shock to the information environment in the form of lost analyst coverage due to broker closures and mergers (see, e.g., Hong and Kacperczyk (2010). and Chen, Harford, and Lin (2015)). As the loss of analyst coverage increases opacity, ODs become marginally more important as information intermediaries following losses of coverage. Using a difference-in-differences specification, we indeed find that all of our main results for competing-firm ODs are indeed stronger when information environments become more opaque. These findings are highly significant, providing rather unique support for the importance of the information channel in generating our findings of inferior performance and loss of product differentiation when ODs span competing-firm boards.

Our hypothesis predicts that information leaks specifically related to technologies and intellectual property are important drivers firm outcomes. Given the importance of intellectual property protection, we develop highly granular tests based on individual technologies to explore the rate

[4]See Cohen-Cole, Kirilenko, and Patacchini (2014) for an example of a recent application in finance.

at which technological adoption transmits through the product market. We use textual analysis of all 10-K paragraphs where technologies are specifically mentioned, and identify the set of all noun phrases in these paragraphs. We use noun phrases to limit attention to terms that plausibly identify individual technologies, which are nouns. After filtering noun phrases based on minimum frequency, and validating using a research assistant, we identify 352 specific technologies. We then examine how each technology propagates through the peer network using firm-technology-year panel data regressions. We first document that a focal firm is significantly more likely to adopt a technology over the next three years if its competitors use the technology ex ante. Second, we show that adoption is significantly more likely when a firm is surrounded by a dense OD network. We also find that not only is the likelihood of adoption higher in the presence of a dense OD network, but adoption is also faster. These results are highly significant using a rigorous methodology where we include firm, technology and time fixed effects. These tests are novel given the existing literature and provide rather direct evidence supporting our prediction that technology transfers are strongly related to the presence of ODs.

Given the possibility that poor firm outcomes might be related to agency concerns and information leakage, we test whether the ODs in our sample indeed realize improved career prospects when they serve on competing-firm boards. We thus examine the ex-post number of boards these directors serve on and their total compensation as a function of their ex-ante service on overlapping boards. We find confirming evidence that these directors indeed serve on more boards and receive higher compensation ex-post. We also find that these ex post career outcomes are particularly good when there is also evidence of potential IP leakage across the boards the director serves in the form of technology transfers. Although these results are only suggestive, they are consistent with directors elevating their career status by sharing potentially sensitive information about intellectual property across competitor firm boundaries. In particular, these directors might be seen as particularly innovative and creative by their peers, and hence might receive more consideration for additional board positions.

We also note one limitation of our study that can motivate future research. In particular, although we explore highly specialized tests including technology propagation, and although we consider plausibly exogenous variation from a quasi natural experiment and second-degree director links, it is difficult to fully establish causality on all aspects of documenting a potential new agency conflict. Hence, future research further exploring causal links remains highly fruitful.

1 Literature Review and Hypothesis

Our thesis is that director networks are porous when it comes to intellectual property. This is because directors have access to sensitive and strategic information about the firm, and even though they are required to keep it private, information flows through networks are difficult to prevent. The consequences of this information transmission through director networks are especially relevant when these networks involve competing firms.

Recent papers study the role of social connection in the spread of information. For example, Hong, Kubik, and Stein (2005) show that investors spread information and ideas about stocks to one another through word-of-mouth communication. They find that a mutual fund manager is more likely to buy (or sell) a particular stock if other managers in the same city are buying (or selling) that same stock. Cohen, Frazzini, and Malloy (2008) use social networks to identify information transfer in security markets. They focus on connections between mutual fund managers and corporate board members via shared education networks and find that portfolio managers place larger bets on connected firms and perform better when they do.

Similarly, Cohen, Frazzini, and Malloy (2010) find that analysts outperform on their stock recommendations when they have an educational link to the company. Kuhnen (2009) finds that fund directors and advisory firms that manage the funds hire each other preferentially based on the intensity of their past interactions. Ferris, Javakhadze, and Rajkovic (2017) show that social ties alleviate information asymmetry and agency problems, which in turn leads to a decrease in the cost of equity.

Director networks are more connected when directors hold multiple board seats (often referred to as *busy directors*). A vast body of literature broadly studies the impact of these directors on firm performance. Some studies suggest that because multiple-board directors have high qualifications, they have a positive impact on performance (Ferris, Jagannathan, and Pritchard (2003), Masulis and Mobbs (2011), and Field, Lowry, and Mkrtchyan (2013)), while others propose that they are too busy to perform well (Core, Holthausen, and Larcker (1999), Fich and Shivdasani (2006), and Ahn, Jiraporn, and Kim (2010)). Our focus is different, as we focus on competing-firm overlaps and we do not examine the unconditional effects of overlapping directors on firm performance.

Instead, we examine performance and innovation in cross-section as we compare (A) firms facing dense overlapping director networks to those facing low-density networks and (B) director overlaps among competing firms to director overlaps among more distantly related firms. (C) We also focus on consequences for information transmission.

When directors meet with other directors, they discuss corporate policies, growth strategies, and future innovation plans of the firm. Although such information is sensitive and often proprietary, this information is clearly relevant to the multiple boards a director might sit on, particularly when the firms she serves are in the same or related product markets. Due to its high relevance and salience, the existence of this information can shape the advice she then gives the other firms for which she also sits on the board. Such transmission can be accidental (directors might inadvertently confuse who ultimately owns a given piece of information) or it can be driven by incentives (a director might see a career boost to bringing more novel ideas to a second board even if the ideas were not developed by her own original thinking).

The existing literature supports this foundation for our work. For example, information flowing through director networks can influence corporate governance practices. Bouwman (2011) shows that firms in the same director networks tend to have similar corporate governance practices, and Foroughi, Marcus, Nguyen, and Tehranian (2019) find that director networks affect the adoption of anti-takeover provisions. Flows through overlapping director networks can also influence executive compensation. Fernandes, Ferreira, Matos, and Murphy (2013) show that non-US firms with a high fraction of directors that also sit on boards of US firms adopt CEO pay practices similar to that of US CEOs. Board overlaps also influence acquisition patterns as Stuart and Yim (2010) show that director networks influence which companies become targets in change-of-control transactions. Similarly, Renneboog and Zhao (2014) find that when a bidder and a target have one or more directors in common, the probability of completion increases and negotiations become shorter.

Existing studies also provide evidence supporting our assumption that overlapping directors can influence the information environment outside the firm's boundaries. Akbas, Meschke, and Wintoki (2016) provide evidence that investors are more informed when trading stocks of companies with more connected board members. Specifically, they find that investors better predict outcomes of upcoming earnings surprises and firm-specific news sentiment for companies with more connected directors. Dass, Kini, Nanda, Onal, and Wang (2014) show that overlapping directors of upstream/downstream industries increase firm value and firm performance, and this effect is especially relevant when the information gap between firms is large. Larcker, So, and Wang (2013) show that firms with central boards of directors earn superior risk-adjusted stock returns and experience higher future return-on-assets growth. Burt, Hrdlicka, and Harford (2020) use overlapping directors to study abnormal comovement of connected firms, and report that an overlapping director can influence firm value by almost 1% per year. They also show that this effect is not immediately reflected in stock prices.

In this paper, we study the consequences of dense overlapping director networks on innovation strategies, individual technology adoption, product placement strategies, and subsequent performance. We especially focus on the case of direct competitors with connected directors, as the high prevalence of these connections we report is surprising given the Clayton Act's requirements. These markets are also interesting because the potential for strategic information sharing is particularly high. Our central hypothesis is that dense networks facilitate faster and more intense transfers of technologies across competing firms. In turn, this might reduce product differentiation and ultimately decrease profits and firm valuations.

1.1 Agency Hypothesis

We hypothesize that directors have private incentives to share innovative information with competitors due to a new agency problem not discussed in the literature. When firms are in related markets, and especially when they are competitors, information held by one firm can be particularly valuable to another. As this information is valuable, directors who regularly leak such information can improve their career trajectories as they become increasingly known for innovative thinking. This is especially true if the receiving board is unaware of the true source of the information.

The agency hypothesis is best illustrated through an example. Suppose Jim serves as a director for two auto companies A and B. He learns from sitting on A's board that A is developing driving automation technology. Suppose it is early in this technological cycle and other firms are not thinking about this possibility, and for example, this idea never came up in the board discussions at firm B. Jim has to decide if he will honor his fiduciary responsibility to firm A and avoid mentioning this technology when he attends B's board meeting. Because the other members of B's board do not overlap with A's board, one option Jim might consider is to propose automation to

B's board while allowing others to view the idea as his original thinking. This will increase his reputation for creative thinking and increases the likelihood that he will be recommended to other boards.

The example above indicates an agency conflict because Jim's decisions result in a private benefit (his career) but imposes a cost on the firm he represents (firm A), which loses its intellectual property in the form of product strategy to a competitor. If overlapping director networks are particularly dense in a product market, this process can repeat, and ultimately, all competitors in the market will simultaneously start investing in automation technology, a form of innovation herding. The consequence will then be a global loss of product differentiation, inefficient redundancies in R&D spending, and lower valuations and profits due to competition in less differentiated markets.

The damage caused by such an agency conflict is likely to be largest when the directors overlap on the boards of direct competitors, as such companies are positioned in the market as direct substitutes. Hence, any loss of differentiation is likely to be unambiguously harmful to the original firm that is losing its proprietary advantage. As firms become more distant in the product market, it becomes more likely that they are less positioned as product market substitutes, and more likely that they might offer complementary products. In these cases, the incentives directors have to leak technology might actually create value, as it can accelerate technology spillovers that might be value creating for both the original innovator and the receiver. Repeated leakage of technology through indirectly related firms (who are not direct competitors) might further increase value. We use TNIC industry classifications, which allow us to distinguish between near and far peers to test this auxiliary hypothesis. We indeed find that leakage across competitors appears to be harmful, and leakage across more distant peers is value creating.

We also expect these overlapping director incentives to be particularly strong in markets where innovation tends to be more opaque. Such opacity would indicate that there are fewer overall channels for technology leakages to flow through. This increases the marginal relevance of the overlapping director network as a plausible channel that can still operate even when technologies are not publicly disclosed. We test this hypothesis by examining plausibly exogenous variation in the quality of firm informational environments and find supportive evidence.

Finally, we emphasize that a tension associated with this hypothesis is the awareness of the receiving board as to the source of the leaked information. If the board is aware that the leaked information is not due to the original thinking of the leaking board member, the ability of Jim in our example to realize private benefits might be diminished or even negative. For example, firm B might terminate Jim after receiving the information due to fears that he might leak their secrets too. Directors might then become less willing to refer Jim to future boards. Because identifying or proving the source of new ideas is difficult, the upside associated with leaking innovation can exceed the downside of potential discovery of the leak.

1.2 Collusion Hypothesis

Director overlap across direct competitors is disallowed by the Clayton Act due to the potential for anticompetitive activity. Yet as we reported earlier, this aspect of the Clayton Act is not widely enforced. This motivates the hypothesis that overlapping directors might indeed influence firm outcomes due to their incentives to collude. As directors frequently hold equity stakes either organically or through their compensation, they would indeed have incentives to participate in collusion as doing so will increase profits and, ultimately, the value of their equity positions. This hypothesis obtains through the same logic as does the prediction that common ownership can create collusion incentives. These incentives are illustrated by He and Huang (2017) and Azar, Schmalz, and Tecu (2018), although the results have been called into question by Dennis, Gerardi, and Schenone (2021), Koch, Panayides, and Thomas (2021), and Lewellen and Lowry (2021). In our context, the overlapping directors might also provide a mechanism for communicating the information needed to support a collusive market outcome.

Of course, collusion through board communications is explicitly illegal, and is why the Clayton Act prohibits overlapping directors among competitors. For this reason, it is likely that directors serving on competitor boards are briefed by lawyers regarding the legal liability that such actions would entail. This can increase the dis-incentives these directors have to engage in collusion, as the legal consequences of “getting caught” can be significant and include both fines and jail time.

The most salient prediction of the collusion hypothesis is that dense overlapping director networks will associate with higher profits and higher market valuations. As part of our main tests, we examine this prediction and do not find support. In particular, the evidence instead suggests that overlapping director networks among competitors reduce both profits and firm valuations.

2 Data and Methodology

We use the Boardex and ISS Directors Databases to create our network of directors. We restrict the analysis to the sample of firms covered by these two databases. We then follow Hoberg and Phillips (2016) and use the 10-K Text-based Network Industry Classification (TNIC) to identify close and distant competitors based on product-market similarity.[5] TNIC industry memberships are firm-specific and time-varying: every firm has its unique set of rivals, which can change over time. The continuous nature of the data also allows the researcher to measure relatedness with any level of granularity, as is needed in our study. We also use accounting and firm data from CRSP/COMPUSTAT, and we winsorize all variables at 5% and 95% level. We also exclude financial firms (SIC codes 6000 to 6999) and utilities (SIC codes 4900 to 4999). The final sample of firms consists of 4,800 firms and 44,000 firm-year observations between 1990 and 2019.

We define two firms as close competitors if they are in the same TNIC-4 industry group. The TNIC-4 specification is highly granular and only deems firm pairs to be in the same industry if they have pairwise similarities in the top 1% of all pair similarities. This 1% threshold indicates the same level of granularity as four-digit SIC codes and hence TNIC-4 is constructed to be "as coarse" as are four-digit SIC codes.

We define two firms to be connected (overlapping directors) when they share at least one director. To measure the director network density around each firm, we use the local clustering measure, which is used to identify cliques in the social networks literature (see, e.g.,Granovetter (1973); Watts and Strogatz (1998)). We thus compute Overlapping-director density (*ODdensity*) as the average overlapping-director incidence among each focal firm's set of TNIC-4 competitors. Therefore, *ODdensity* is simply the fraction of all the TNIC-4 pairwise permutations that have an observed overlapping director. A high value would indicate a firm that is in a product market with a high rate of director overlaps.

We are interested in examining the effect of *ODdensity* on firm innovation, competition, and performance. Our baseline regression specification is described in equation (1) below:

[5]TNIC firm-by-firm pairwise similarity scores are calculated by parsing the product descriptions from the firm 10Ks and using the cosine similarity method to compute continuous measures of product similarity for every pair of firms in our sample in each year. For any two firms i and j in a given year, their resulting product similarity is a real number in the interval [0,1] indicating the product market similarity of firms i and j.

$$\text{DEP}_{it} = \alpha_0 + \beta_1 \text{TN4 ODdensity}_{i,t-1} + \ \delta_1 \ \text{Controls}_{i,t-1} + \mu_i + \gamma_t + \epsilon_{it} \tag{1}$$

Our coefficient of interest is β_1. We control for the logarithm of total assets, the logarithm of firm age[6], and the market to book ratio. We include firm fixed effects and year fixed effects, and cluster standard errors by firm. Thus, the regression considers only within-firm variation and controls for any time-invariant unobservable characteristics that might affect the dependent variable.

To contrast the effects of ODs spanning the boards of close competitors with those of ODs spanning the boards of more distant rivals, we also calculate the director network density of distant peer firms. We define these more distant peers as those with TNIC similarities below the top 1%, but still in the top 5%. Using TNIC nomenclature, we refer to this group as *TNIC2-TNIC4*, as these competitors are in the TNIC-2 classification but are not in the TNIC-4 classification. To build intuition, this is analogous to being in the same two-digit SIC code (so these firms are related) but not being in the same four-digit SIC code (so they are unlikely to be direct competitors). We then proceed to calculate the OD density of each firm's *TNIC2-TNIC4* peers using the same local clustering network formulation described above.

Our dependent variables include measures of innovative investment, competition, product market strategies, and performance. To measure innovative spending, we use R&D scaled by total sales (lagged in one year). We replace R&D with zero when it is missing, although we obtain similar results if we instead replace missing R&D with the industry mean (Koh and Reeb (2015)).

To examine product market strategies, we focus on two variables: product differentiation and competitive threat. Our measure of product differentiation is the TNIC total similarity of competitors. Specifically, TNIC-4 Total Similarity (*TsimmTN4*) is the sum of the focal firm's similarity to each of its TNIC4 rivals. To measure competition threat, we use the Product Market Fluidity measure from Hoberg, Phillips, and Prabhala (2014), a measure of how intensively the product market around a firm is evolving in each year.

Finally, we use return on assets (ROA), growth opportunities, and sale growth to assess firm performance. We define ROA as operating income before depreciation (OIBDP) divided by assets, market to book ratio ((CSHO*PRCC_F+DLC+DLTT+PSTKL)/AT),[7] and sales growth as the

[6]Firm age is a listing vintage relative to the first year the firm first appears in the CRSP/COMPUSTAT merged database.

[7]PSTKL is set to zero when missing.

logarithmic growth in sales relative to the prior year.

Table 1 reports summary statistics, and Table 2 presents the Pearson correlation matrix. *ODdensity* has a mean of 0.011, indicating that the average firm and its TNIC-4 competitors shares a director with 1.1% likelihood. This value increases to 1.7% if we consider second-degree connections (boards that are connected through a common overlap with any third company's board), which we examine in section 3.3. The higher incidence of second-degree links is expected, as networks tend to extend as the degree of connections increases. However, when we focus on distant competitors (TNIC2-TNIC4), the average OD density is 0.7% if we consider first-degree connections and 1.2 if we consider the 2nd-degree network. This value is expected to be lower as the incidence of connections deteriorates with product distance. A 1% density might seem small. However, 78% of the firms in our sample are connected to the OD network through a multiple-board director. Since we show that both 1st-degree and 2nd-degree links generate our results, a high TNIC4 density level indicates that many board or personal connections exist in this space, and all boards are more likely to be connected directly or indirectly.

We believe our measure of OD density is conservative, and our findings likely understate the true impact of director connections. In particular, dense OD networks likely correlate with directors having more social connections overall even beyond common board overlap. For example, directors in dense OD networks are also likely connected through country clubs, charities, universities, and such. We use BoradEx data to create an enhanced network in which two firms are linked if they have directors that share a job in a third institution.[8] Using this network, we follow the same methodology and create a density measure called *OTHERdensity*. Indeed, we find that *OTHERdensity* and *ODdensity* are highly correlated. Moreover, all the economic results we describe in the following sections hold if we use the *OTHERdensity* instead of *ODdensity*.[9]

Regarding firm characteristics, our average sample firm has total assets of $3,305 million, R&D investment equivalent to 4.5% of total assets, ROA of 9.8%, a market to book ratio of 1.7, and yearly sales growth of 13.7%.

[8]These other associations include private companies (45%), charities (21%), universities (17.6%), clubs (14%), medical institutions (1.2%), sporting (0.6%), government (0.5%), and armed forces (0.03%).

[9]Appendix A presents the analysis using *OTHERdensity*.

3 Results

3.1 Director overlap and close competitors

Our very first finding is that firms hire overlapping directors regardless of their closeness in the product market. Panel (a) of Figure 1 plots the percentage of firm-pairs that share a director based on how similar their products are. We report results for each percentile of product similarity, where percentiles are based on annual sorts of TNIC pairwise product similarity. The figure shows that the incidence of overlapping directors increases steadily as pairwise product similarity increases, and this trend reaches a peak for pairs of companies that are very similar and that are likely to be direct competitors (the 1% most related firm-pairs in the economy). As noted earlier, being in the top 1% most similar TNIC firm pairs is analogous to being in the same four-digit SIC code (as 1% of randomly drawn firm pairs are in the same SIC-4). We only observe a slight decline in the prevalence of overlapping directors when we zoom in even further and look at the 0.5% most related firm-pairs in the economy, as panel (b) of Figure 1 indicates. In particular, panel (b) is a close-up on the 5% most related firm-pairs of panel A. Hence overlapping directors are most likely when a pair of firms are likely to be direct competitors.

The high prevalence of these connections is surprising given the Clayton Act's prohibition of competing-firm board overlaps. The lack of enforcement or the applicability of Section 8 has thus led to an equilibrium where directors regularly sit on boards of competing firms. We also note that the practice of competing-firm overlapping directors has increased over time. In particular, Figure 2 plots competing-firm TNIC4 OD incidence over time, and shows that TNIC4 OD incidence increased in the early 1990s, was then stable in the 2000s, and further increased after 2010.

3.2 Director network density and firm outcomes

Because information can flow through director networks, our central hypothesis is that dense networks might facilitate faster and more intense transfers of technologies across competing firms. In turn, this might reduce product differentiation and ultimately decrease profits and firm valuations. We estimate equation (1) using various measures of innovation, competition, and performance as the dependent variable to test this hypothesis.

Our regression models are firm-year panel regressions that include firm and year fixed effects, and cluster standard errors by firm. Column (1) of Table 3 shows that firms with higher ex-ante TNIC4 OD density invest more in R&D in the next year. These regressions also control for firm size, age, and market-to-book ratios, and the firm fixed effects absorb any time-invariant firm characteristics. Our finding regarding R&D is significant at the 1% level, and is consistent with innovation being important regarding how ODs interact with the firms they represent. In particular, higher R&D is consistent with leakages of forward-looking strategic information about innovation inducing firms in the product market to invest more on R&D. The results of this R&D will also ultimately prove to be highly correlated across competing firms.

Supporting this interpretation, columns (2) and (3) show that ex ante OD network density also predicts ex post product market developments, favoring increasingly active and yet similar product evolution paths. Indeed, we find that OD network density predicts higher TNIC4 product market similarity and also higher product market fluidity. Both coefficients are significant at the 1% level. These findings indicate that dense director networks are associated with declining product differentiation through innovative shifts in product changes that are ultimately highly correlated across firms. This "innovation herding" ultimately leads firms to converge over time.

Additionally, columns (4), (5), and (6) show that ex ante TNIC4 OD density is associated with poor ex post performance in the form of lower ROA, lower valuations in the form of market-to-book, and lower sales growth. These findings are significant at the 5% level and are consistent with a decrease in product differentiation and proprietary intellectual property resulting in lower corporate performance. This consequence of IP degradation is particularly consistent with the implications of Sutton (2001) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005) when firms are unable to use R&D to differentiate. In particular, barriers to entry are difficult to establish, and competition is difficult to escape via innovation. Furthermore, these results contradict the collusion hypothesis since its most salient prediction is that dense overlapping director networks should result in higher (not lower) profits and market valuations.

Overall, the results in Table 3 support the array of predictions associated with the hypothesis that sensitive information leaks through competitor-firm director networks. Such leakage gives rise to ex post innovation herding, less product-market differentiation and poor performance.

A key aspect of our analysis is that we focus on OD network density within each firm's TNIC4 industry. Among these competitors, our prediction is that IP leakage is unambiguously harmful to the firm losing its IP, as these firms have products positioned in the market as direct substitutes. However, we note that as firms become more distant in the product market, it becomes less likely that their products are positioned as substitutes, and more likely that their products are complements (Hoberg and Phillips (2010), Bena and Li (2014)). In these cases, technology leakages are not necessarily harmful, as complementarities might lead them to be value-creating. We thus explore this prediction further and we contrast the effects associated with close competitor ODs with those of ODs who overlap on the boards of more distant competitors.

Specifically, we define more distant competitors as those with TNIC pairwise similarities that are below the top 1% but still in the top 5%. We then calculate the OD density of these "*TNIC2-TNIC4*" peers surrounding each firm. Finally, to compare the effects of OD density across close competitors versus these distant peers, we include both densities as key independent variables in our main regressions as shown in equation (2):

$$\text{DEP}_{it} = \alpha_0 + \beta_1 \text{TN4 ODdensity}_{i,t-1} + \beta_2 \text{TN2-TN4 ODdensity}_{i,t-1} + \ \delta_1 \ \text{Controls}_{i,t-1} + \mu_i + \gamma_t + \epsilon_{it} \quad (2)$$

Table 4 displays the results of this regression. Importantly, we find diametric opposite results for the distant-peer ODs as we did for the competing firm ODs reported earlier. Even though distant peer TN2-TN4 OD density is also associated with increases in R&D, the results on product differentiation and firm performance are in the opposite direction. While TN4 OD density associates with increases in Total Similarity and Fluidity, distant peer TN2-TN4 OD density associates with decreases in both. The negative effect of distant peer OD density on Total Similarity and Fluidity implies that the ODs in this outer ring of similarity share ideas that actually help these companies to differentiate their products and avoid competitive threats. Further supporting that these activities are indeed complementary, columns (3) shows that TN2-TN4 OD density also predicts superior ex post firm performance, as the TN2-TN4 OD density is a positive and significant predictor of ROA.

These findings suggest that when product complementarities exist, information leakages foster innovation that allows for product differentiation and, consequently, firm value creation. In the outer ring of more distant peers, there exist many opportunities for information leakage that are not harmful to the sender or receiver of the leaked IP. Consequently, ODs spanning distant peers can both increase the value of their equity stakes by sharing mutually beneficial ideas, and also increase their reputation for creative thinking and their career prospects at the same time. This is not possible for ODs who span the boards of direct competitors since very close competitors do not have product complementarities, as their products are too similar and are pure substitutes. This renders all IP leakages to be harmful, and leaking IP in this setting for improved career prospects would constitute a novel agency conflict not discussed in the existing literature.

We also note that our findings for more distant peers illustrate that incentives and consequences of ODs are indeed special for competing firms. The distant-peer findings thus provide a relevant benchmark for understanding OD density and its link to market structure.

3.3 Second-degree director links

A challenge regarding inferences in our setting is that directors are endogenously selected and matches with firms are not random. Hermalin and Weisbach (2001) and Adams, Hermalin, and Weisbach (2010) indeed argue that because board members are chosen, firm and board characteristics are endogenously related. In our setting for example, two firms might hire the same director due to her potential to help the firms collaborate, and the need for this role might correlate negatively with performance. If this is the case, our findings might result from low-performance industries being more likely to have more dense OD networks.

To mitigate these endogeneity concerns, we rerun our primary analysis using only second-degree director links.[10] Two boards are second-degree linked if there is no direct OD link between them, but the two boards are connected through OD relationships to a common third board. For example, two firms A and B would have a second-degree board link if A and B have no overlapping directors, but both firms have a director that overlaps with another firm C. Because A and B cannot control the director selections made at firm C, any information flowing through second-degree links is unlikely to be driven by endogenous director selection by A and B. Using the second-degree network of directors, we create *POPODdensity* in the exactly the same way we create our baseline density variable *ODdensity*, but we assess the prevalence of second-degree links instead of first-degree links. We run this test for TNIC4 competitors and for TNIC2-TNIC4 competiors and we re-estimate equation (1) and equation (2). Table 5 and Table 6 present the results of these estimations. Importantly, results for both tests are similar to those in Tables 3 and 4 (although we

[10] The use of second-degree network connections to reduce endogeneity concerns is motivated by theoretical work in network econometrics (see Bramoullé, Djebbari, and Fortin (2009)).

are now focusing on second-degree connections).

Overall, Table 5 shows that all our results for close competitors described above are fully robust to using second-degree director connections. Columns (1) and (2) show that firms surrounded by more dense peer-of-peer OD connections invest more in R&D but indeed also reduce product differentiation.[11] At the same time, columns (4), (5), and (6) show that they also reduce ROA, valuations, and sales growth.

Table 6 shows that our earlier results for distant competitors are also robust to using second-degree director connections. Specifically, columns (2) and (3) show that an increase in peer-to-peer OD network density across distant competitor boards is associated with higher product differentiation.

3.4 Opaque information environments

Our hypothesis predicts that information leakage is a primary mechanism driving firm outcomes. We thus expect the influence of overlapping director incentives to leak technologies to be particularly strong in markets where the information environment is more opaque. The intuition is that the marginal relevance of the OD network as a means of information transfer increases when there are fewer alternative channels for information to flow through.

To test this hypothesis, we consider shocks that result in lost analyst coverage due to brokerage mergers or broker closures as plausibly exogenous variation in the quality of the information environment around a firm. Hong and Kacperczyk (2010) illustrate that broker mergers are exogenous to firm' characteristics, and when two brokerage houses have a different analyst covering the same firm before the merger, the combined brokerage resulting from the merger will dismiss at least one of the analysts to reduce redundancy. This reduces the number of analyst reports covering the given firm. Kelly and Ljungqvist (2012) analogously show that brokerage closures are motivated by business strategy rather than by the characteristics of the firms they cover. Hence, when a brokerage house closes, firms lose analyst coverage for exogenous reasons. We follow Chen, Harford, and Lin (2015) and use the combination of both brokerage mergers and brokerage closures. We use the I/B/E/S database to assess analyst coverage.[12] To identify firms treated by the brokerage

[11] Column (3) shows that they also face higher competitive threats –measured as product-market fluidity–, although this result is not statistically significant.

[12] From 1989 to 2006, we use an old version of the I/B/E/S dataset. From 2006 to 2019, we use the current version

mergers, we obtain merger events from Hong and Kacperczyk (2010) and Chen, Harford, and Lin (2015), and follow their same methodology. First, we identify all firms covered by the merger target brokerage house at the moment of the merger or at any moment in 12 months before the merger. Second, we identify all firms covered by the acquirer during this same window. Third, we identify the firms covered by the acquirer 12 months after the merger. We then define a firm to be treated if it is in all three lists.[13] To identify firms affected by brokerage closures, we obtain closure events from Chen, Harford, and Lin (2015)[14] and define a firm to be treated if the closing brokerage covered it 12 months before the closure date. Finally, we define a firm as being treated by our unified variable, "analyst opacity shock", if it is either treated by a merger or a closure loss of coverage. Following the above articles, we consider a firm treated to be treated for one year after the event.

For each focal firm in each year, we compute the fraction of its TNIC4 rivals that are affected by the analyst opacity shock. Hence we are assessing the quality of the information environment in the firm's TNIC4 industry. We then estimate equation (1) including an interaction term between the percentage of TNIC4 rivals affected by the opacity shock and *TN4 ODdensity*. Our hypothesis predicts that the impact of OD density should be stronger when the TNIC4 industry of the focal firm has more firms affected by the analyst opacity shock. Specifically, we estimate equation (3) and predict that β_1 and β_2 will have the same sign across our array of dependent variables.

$$\begin{aligned} \text{DEP}_{it} = \alpha_0 &+ \beta_1 \text{TN4 ODdensity}_{i,t-1} + \beta_2 (\text{Analyst Shock TNIC4}_{i,t-1})\text{x}(\text{TN4 ODdensity}_{i,t-1}) \\ &+ \beta_3 \text{Analyst Shock TNIC4}_{i,t-1} + \ \delta_1 \ \text{Controls}_{i,t-1} + \mu_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{3}$$

Panel A of Table 7 shows the results using our baseline first-degree OD network and Panel B reports results using our more exogenous second-degree OD network. We find that all of our results for competing-firm ODs are indeed stronger when information environments become more opaque. In particular, we find that the cross term coefficient β_2 is highly significant and has the same sign of the *TN4 ODdensity* coefficient β_1. These findings indicate that the higher the percentage of TNIC4 peers affected by the opacity shock, the larger the positive effect of OD density on R&D, total similarity, and fluidity, and the larger the negative effect on ROA and valuations.

of I/B/E/S. The reason is that, in the later years, I/B/E/S dropped many observations from the database and hence the older database is more complete.

[13] As in Hong and Kacperczyk (2010), we also drop firms with a CRSP share code that is not 10 or 11. Additionally, we drop firms with a stock prices below $5.

[14] We thank Jarrad Harford for sharing the list of events with us.

These findings are highly significant, and our use of exogenous variation in information environments provides unique support for the importance of the information channel in generating our findings of inferior performance and loss of product differentiation when ODs span competing-firm boards.

3.5 Technology diffusion

Our hypothesis predicts that information leaks specifically related to technologies and intellectual property are important drivers of the firm outcomes we report. In this section, we test this hypothesis directly by curating a list of specific technologies firms discuss in their 10-Ks, and then examining how the mentions of these specific technologies propagate through the network of firm peers. Our key prediction is that the presence of dense OD networks will increase the intensity (and speed) of technological propagation from a focal firm's peers to the focal firm itself, and also the rate of propagation of technologies from more distant peers through the inner competitor network of close peers, and to the focal firm itself.

3.5.1 Technology Word List

We use the metaHeuristica software platform and first identify all paragraphs in all 10-Ks that use the word root "technol*" somewhere in the paragraph. We then extract all noun phrases from these paragraphs and limit attention to any noun phrases that appear in at least ten such paragraphs in any year during our sample. The latter condition allows us to focus on themes that are economically relevant for the firm. There are 7380 noun phrases satisfying these criteria. We focus on noun phrases to identify specific technologies, which are nouns. Although a large number of these noun phrases are specific technologies, we also note that most of the noun phrases in these paragraphs are not actual technologies. This is because companies discuss many issues in the context of paragraphs that mention technology beyond the specific technologies they use.

We thus prune the list of 7380 noun phrases using a research assistant to tag which of the 7380 noun phrases constitute "specific technologies that were not ubiquitous as of the mid 1990s". Technologies that were ubiquitous at that time, such as light bulbs, are not interesting because they are not expected to undergo any relevant evolution during our sample. Technological phrases that were not ubiquitous at the start of our sample, however, are relevant because new technologies are expected to grow in use and propagate across firms until they hit an equilibrium adoption. This growth and spread through the product market network is precisely what we hope to measure and examine in our context of overlapping directors. This process of noun-phrase curation results in 352 unique technologies, which we list in appendix B.

For each of the 352 technologies, we also use the metaHeuristica platform to identify which firms mention the given technology in each year. For each focal firm in each year, we compute the fraction of its inner TNIC4 peers that mention the word as the fraction of the firm's TNIC-4 peers that mention the word in their 10-K, and we compute an analogous fraction for each firm's outer peers (those in the focal firm's TNIC-2 peers that are not in its TNIC-4 peers). We thus obtain a firm-year-technology panel database where we have a dummy indicating if the focal firm uses the given technology in the given year, and also the fraction of the focal firm's inner and outer peers that use the given technology.

3.5.2 Regressions

Our baseline regressions regress the ex-post focal firm technology dummy (from year t) on the fraction of inner or outer peers using the technology either in the most recent year $t-1$ or three years past $t-3$. We then interact these RHS variables with the TNIC4 density of overlapping directors. We predict that the interaction will be positive and significant, indicating that ODs are associated with larger propagation of peer firm technologies to a focal firm when ODs are present. We additionally predict that interactions with the year $t-1$ peer variables will be stronger when ODs are present than are interactions with the $t-3$ peer values. This result would indicate specifically that technology propagates faster in the presence of ODs.

The results are displayed in Table 8. Panel A shows that when inner peers have a given technology in year $t-1$, the focal firm is significantly more likely to adopt the technology in year t, and this is particularly true when the focal firm is surrounded by a relatively dense network of competing-firm ODs. Both the level coefficient and the cross term for OD density are highly significant at the 1% level, indicating that technology propagation through the competing-firm network is more intense when overlapping ODs are present. The table also shows that some technologies take longer to propagate, as the year $t-3$ peer variable is also significant. Yet the interaction of this more deeply lagged coefficient with the OD density is not significant, indicating that the impact of ODs on technology propagation is faster than is the normal propagation that takes place in the absence of OD relationships. These results are highly significant and control for any time-invariant firm and technology characteristics, as we include firm, technology and time fixed effects.

Panel B of Table 8 repeats the tests in Panel A for technologies held by outer more distant peers. Here the experiment examines if dense OD networks also help to propagate more distant technologies all the way to the focal firm. We again find that the OD density cross term for year $t-1$ outer peer technologies is positive and highly significant, confirming that dense OD networks also increase the intensity of outer technology propagation. We also find that the three-year lagged cross term is negative, illustrating that the density of the OD network is particularly effective at speeding technology transfers from these more distant peers. In particular, taken together, the larger positive coefficient for the one year lag and the negative three year lag indicates that the OD effect shifts propagation away from deeper lags and toward the faster one year lag.

Table 9 examines these same tests using OD density measured using second degree director overlaps, which are more exogenous relative to first degree connections. The table shows that our results are fully robust. In particular, we again find that technologies are more likely to propagate when peers mention the technology ex-ante, and this process both (A) becomes more intense and (B) becomes faster when the focal firm is surrounded by a more dense competing-firm OD network.

3.6 Cross-sectional test: more competitive industries

In this section, we examine a subsample of firms where our hypothesis predicts stronger results. Specifically, we expect our findings to be more relevant in industries with more competitors since directors face stronger overall incentives to leak information. The reason is that the relative cost of sharing information is smaller when there are more firms in the market since the OD might expect that their actions will not impact the overwhelming majority of competitors, as only the one competitor they leak to will get the intellectual property leak. Leaking to such a small fraction of the overall market will have less adverse impact on the director's equity stake. Yet the career boost they get from bringing innovative ideas to the second board is likely to be just as large regardless of how many other firms are in the market. Hence the net incentives to leak (benefit minus cost) are likely to be larger in competitive markets.

To test this prediction, we count the number of TNIC4 rivals of each firm and create a dummy variable that equals one if the number of TNIC4 rivals of the focal firm is above the median. We then interact this dummy with *TN4 ODdensity*. Table 10 presents the results of this estimation using a first-degree OD network (panel A) and a second-degree OD network (panel B). In both panels, we find that our results are indeed stronger when the number of TNIC4 peers is above the median. Across our dependent variables, the estimated coefficient of the cross term has the same sign as the *TN4 ODdensity* coefficient, and the cross term is highly significant for almost all the dependent variables. This suggests that the magnitude of the reduction in product differentiation and performance is significantly larger when the firm has more rivals. These findings are consistent with ODs sharing more information when the relative cost of doing so is lower. Additionally, these findings also are difficult to square with the collusion hypothesis, since coordination is more difficult when there are more competitors.

3.7 Career prospects

Because ODs have incentives consistent with potential agency conflicts and private benefits, and because we find poor firm outcomes when competing-firm ODs are present, we focus on testing for private benefits in this section. In particular, we run suggestive analysis examining if ODs realize improved career prospects (in the form of serving on more boards ex-post, and also getting higher compensation ex post) when they serve on competing-firm boards ex-ante. We also explore whether these ex post career outcomes are particularly good when there is also evidence of potential IP leakage across the boards the director serves in the form of technology transfers.

We run a director-level analysis. First, for each OD in the sample, we calculate the number of boards she sits on in a given year. We also calculate the average TN4 OD density of all the firms she sits on. Then we regress the log of the ex post number of boards on the ex-ante one-year-lagged average TN4 OD density of her board position firms. In this regression, we include director and year fixed effects. Column (1) of Table 11 shows the results. We find a positive and highly significant effect of ex-ante TN4 OD density and the ex-post number of boards the OD sits on. Specifically, a one-standard-deviation increase in OD density is associated with a 0.3% higher likelihood of the OD sitting on a new board next year. This suggests that, despite the finding that competing-firm ODs are associated with lower firm value and higher incidences of technology leakage, that the overlapping directors themselves appear to experience better career outcomes in the presence of these networks. This finding is consistent with private benefits that accrue to the directors but not the firms they work for. Column (1) in Panel B shows that this effect is robust to using more exogenous second-degree director connections.

We extend this analysis to examine whether OD density affects directors' compensation. First, for each director in the sample, we calculate the average total compensation she receives in a given year across all the boards she sits on.[15] We then regress the log of the average compensation on the ex-ante one-year-lagged average TN4 OD density of her board position firms. Column (2) of Table 11 shows the result of this regression, which includes director and year fixed effects. We find a positive and highly significant effect of ex-ante TN4 OD density and the ex-post average compensation. Specifically, a one-standard-deviation increase in OD density is associated with a 1.4% rise in the director's total compensation. Columns (3) and (4) show that this effect is robust to considering equity compensation (stock and option awards) and non-equity compensation (salary, bonus, pension, and other compensation) separately. Column (5) shows that the finding is also robust to excluding the new companies that the director has in the next year (in case she starts serving in a new board). Panel B shows similar results when using second-degree director connections.

In a second analysis, we run a highly specialized test and examine the career outcomes of ODs that are plausibly associated with specific evidence of leaked information across the boards they serve. In particular, we test whether observed ex-ante technology diffusion between the overlapping firms that ODs serve specifically also predicts increases in the ex post number of boards the OD will sit on in the future. To implement this test, we first count the number of newly added "shared technologies" across the overlapping firms each OD jointly serves in each year. We use the 352 technologies from section 3.5, and define an instance of "potential newly leaked technology" in a year t for a given technology as situations in which two conditions are satisfied: (A) only one of the two firms in the overlapping pair used the technology in year $t-1$, and (B) BOTH use the technology in year t. We then regress the ex-post log of the number of boards the OD has in year t on the ex-ante number of newly added "shared technologies" between the two firms the OD serves (from $t-1$). We include director and year fixed effects. Column (1) of Table 12 displays the results.

[15] We obtain compensation data from BoardEx - Annual Remuneration.

We find a positive and significant effect of technology sharing between the two firms that share an OD and the number of boards that the same OD will sit on next year. This finding supports the conclusion that ODs receive more ex-post board invitations when they sit on the boards of firm pairs that experienced likely technology transfers in the prior year.

We extend this analysis to examining directors' compensation. We regress the ex-post log of the average total compensation the OD receives in year t on the ex-ante number of newly added "shared technologies" between the two firms the OD serves lagged in one year ($t-1$). Column (2) of Table 12 shows the result of this regression, which includes director and year fixed effects. We find a positive and significant effect of technology sharing between the two firms that share an OD and the ex-post average compensation. Columns (3) and (4) show that this effect is robust to separately considering equity and non-equity compensation.

Panel B of Table 12 shows that these results are robust to only including TN4 pairs. We note that even though the statistical significance is lower due to the limited power of only considering firms that share a director in the same TN4 group, the magnitude of the coefficients is the same.

Although these results are merely suggestive, they are consistent with directors elevating their career status by potentially sharing sensitive information about intellectual property across competitor firm boards. In particular, these directors might be seen as particularly innovative by their peers and hence might receive stronger references when they are being considered for additional board positions. Although these findings are consistent with private benefits and a new agency conflict not reported in the existing literature, we also note that these tests are not causal in nature. Hence, we believe that future research further examining director careers in this context could be particularly compelling.

4 Conclusion

We document a surprising high-prevalence of director overlaps among firms that are product market competitors. This finding is controversial given that this practice is generally disallowed by Section 8 of the Clayton Act on the grounds that it can facilitate anti-competitive practices. We thus explore the consequences of these overlaps on many dimensions. Despite the incentives to collude, we find no evidence that these overlapping directors are materially engaged in anti-competitive policies. In particular, firms in markets with more dense overlapping director networks experience significantly lower profits and lower market valuations, which is diametrically opposite the predictions of collusion. This finding is consistent with overlapping directors facing tradeoffs, and the potential legal and reputational costs of detected collusion outweigh the benefits that might accrue to their stock options by embracing collusion.

Yet these overlapping directors might face other incentives beyond collusion. We propose and test the hypothesis that these directors can have strong incentives to leak proprietary intellectual property across the competing boards they serve. For example, by leaking IP, such directors can earn a reputation for innovative thinking and can improve their career prospects. Overall, this hypothesis would result in innovation herding and reduced product differentiation as leaked information would become increasingly common across competing firms. This hypothesis can then explain why firms surrounded by dense OD networks experience lower (not higher as predicted by collusion) profits and valuation ratios ex post. This hypothesis would also predict lower product differentiation and enhanced technology propagation through the network of firms in afflicted markets. Our evidence strongly supports all of these predictions. In a particularly novel and compelling test, we identify 352 individual technologies using textual analysis and find significant evidence that these technologies propagate to competitors more intensely and faster when a dense network of competing firm ODs is present around a given firm.

We explore a number of tests to mitigate concerns about endogeneity in this setting, as director choices are not random. One such test follows the network econometrics literature and assesses network density using second-degree director overlaps, which require that connections must pass through a third company's board, which is more exogenous as the third firm's board selection is not under the control of the focal connected firms. We also include rigid firm fixed effects, and we consider a quasi natural experiment based on plausibly exogenous losses in analyst coverage due to brokerage consolidation to causally link our results to the quality of the information environment, as required by the information leakage hypothesis. These findings, along with our highly specialized tests of technological propagation, all support the conclusion that information leakage specifically relating to intellectual property likely explains at least a portion of our findings. Yet despite these specialized tests, one limitation is that full causality is difficult to establish, and hence future studies further exploring causality in this setting remain fruitful.

Appendix A Director Links Beyond Board Overlap

This appendix uses the Boardex dataset[16] to create a company network based on directors' connections different from overlapping company boards. Specifically, we define two firms as connected if they have directors that share a job in a third institution such as country clubs, charities, universities, etc. We then calculate the density of these "*OTHER*" peers surrounding each firm and estimate equation (1).

Column (1) shows that *OTHERdensity* is a good predictor of *ODdensity*, supporting the intuition that OD density network is measuring overall connectedness. Columns (2) to (7) show that all our findings hold if we use *OTHERdensity* instead of *ODdensity*. In particular, Columns (2), (3), and (4) show that firms surrounded by more dense *OTHER* director connections invest more in R&D but indeed also reduce product differentiation. At the same time, columns (5), (6), and (7) show that they also reduce ROA, valuations, and sales growth.

In Panel B we use peer-of-peer *OTHER* connections and find the same results.

Panel A: first-degree Directors Network

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	tn4 ODdensity$_t$	XRD$_t$/at$_{t-1}$	TSimTN4$_t$	Fluidity$_t$	ROA$_t$	Growth_Opp$_t$	Sale_Growth$_t$
TNIC4 OTHERdensity in t-1	0.003***	0.036***	0.062***	0.076***	-0.104**	-0.900**	-0.364**
	(0.000)	(0.014)	(0.013)	(0.014)	(0.044)	(0.354)	(0.142)
Log of total assets in t-1	0.000***	-1.160***	0.338***	0.267***	0.164	-20.534***	-7.333***
	(0.000)	(0.068)	(0.062)	(0.038)	(0.168)	(0.995)	(0.406)
Log of firm age in t-1	0.000	0.066	-0.132*	-0.516***	0.355**	-1.449	-3.297***
	(0.000)	(0.059)	(0.071)	(0.059)	(0.169)	(1.242)	(0.506)
Market to book ratio in t-1	-0.000	0.301***	0.227***	0.075***	2.325***	46.740***	4.777***
	(0.000)	(0.030)	(0.036)	(0.018)	(0.086)	(0.911)	(0.230)
Observations	41,991	43,990	42,912	43,398	43,872	43,827	43,921
R-squared	0.100	0.102	0.037	0.178	0.100	0.338	0.106
Number of gvkey	4,841	4,971	4,893	4,946	4,952	4,951	4,957
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

[16]Specifically, we use BoardEx - Company and Organizational Networks.

Panel B: Second-degree Directors Network

VARIABLES	(1) tn4 ODdensity$_t$	(2) XRD$_t$/at$_{t-1}$	(3) TSimTN4$_t$	(4) Fluidity$_t$	(5) ROA$_t$	(6) Growth_Opp$_t$	(7) Sale_Growth$_t$
TNIC4 POP OTHERdensity in t-1	0.000***	0.047***	0.028**	0.119***	-0.226***	-0.526*	-0.812***
	(0.000)	(0.014)	(0.013)	(0.013)	(0.045)	(0.312)	(0.150)
Log of total assets in t-1	0.000***	-1.160***	0.340***	0.266***	0.169	-20.554***	-7.314***
	(0.000)	(0.068)	(0.062)	(0.038)	(0.168)	(0.995)	(0.406)
Log of firm age in t-1	0.000	0.065	-0.132*	-0.519***	0.361**	-1.441	-3.275***
	(0.000)	(0.059)	(0.071)	(0.059)	(0.170)	(1.241)	(0.504)
Market to book ratio in t-1	-0.000	0.302***	0.227***	0.076***	2.322***	46.736***	4.770***
	(0.000)	(0.030)	(0.036)	(0.018)	(0.086)	(0.912)	(0.229)
Constant	-0.003***	10.500***	0.295	7.154***	5.572***	181.412***	47.421***
	(0.001)	(0.513)	(0.539)	(0.521)	(1.289)	(11.766)	(3.533)
Observations	41,991	43,990	42,912	43,398	43,872	43,827	43,921
R-squared	0.058	0.102	0.036	0.180	0.101	0.338	0.107
Number of gvkey	4,841	4,971	4,893	4,946	4,952	4,951	4,957
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix B Technology Noun Phrases

In this appendix, we provide a list of the noun phrases used in our technological diffusion tests in Section 3.5 of this paper.

List of Technology Noun Phrases: 1xrtt, 3d printing, 3g networks, 3g tech, 3g technology, 3g wireless, 4g lte, 4g wireless, 5g mobile, 5g technologies, 5g technology, 5g wireless, a-chip, acid batteries, adas, adc, adc technology, adsl2, advanced metering infrastructure, analog cellular, android, angioplasty, antisense drugs, antisense technology, apis, artificial intelligence, ash removal system, asic, asics, autonomous driving, autonomous vehicles, biomarkers, biosimilars, blockchain, blockchain technology, bmc, broadband access, bvs2, c1 expression system, c1 host technology, c1 technology, carbon capture, carbon nanotubes, cas9, cas9 technology, cdma, cdma technology, cdma2000, cell phone, cell phones, cellular mobile telephones, cellular networks, cellular telephones, checkpoint inhibitors, chip sets, circuit board, circuit boards, clean coal technologies, clean energy technologies, cloning, closed cycle cooling, cloud, cloud applications, cloud computing, cloud environments, cloud infrastructure, cloud offerings, cloud platform, cloud services, cloud solutions, cloud technologies, cloud technology, cmos, computer vision, connected home, core dna delivery technology, corn oil extraction technologies, cpe, cpu, crispr, dark fiber, data warehousing, dense wavelength division multiplexing, desalination, digital cameras, digital compression technology, digital signal processors, digital subscriber line, direct broadcast satellite, dna delivery technology, dna microarrays, dna screening, drones, drug discovery technologies, dsl, dsl services, dsl technology, duplex technology, e-mail, electric vehicle, electrodes, electronic warfare, electroporation, embryonic stem cells, encapsulation technology, ethernet, evlt, excimer laser technology, excimer lasers, fiber lasers, fiber network, fiber optic, fiber optic cable, fiber optics, fiberglass, flash memory, flat panel, flat panel display, flat panel display technology, flat panel displays, flue gas desulfurization, flue gas desulfurization equipment, fpgas, fuel cell technologies, fuel cell technology, fuel cell vehicles, fuel switching, gas turbines, gbps, gene delivery technology, gene editing, gene editing technologies, gene therapies, genetic engineering, genome editing, genome editing technologies, genome editing technology, genotyping, global positioning system, gprs, gprs technology, gps, gps technology, gpus, gsm technology, gtc, gtl technology, handheld computers, haptics, hard disk drives, hdtv, hes cells, home automation, hspa, hybrid mrna technology, hydraulic fracturing operations, iaas, igcc, image capture, immtor technology, instant messaging, interactive television, ion batteries, iq technology, knockout mice, lan, lans, laser, laser beam, laser printers, laser technology, laser vision correction, lcd, led, led lighting, leds, liquid crystal display, liquid crystal displays, lnp technology, local area network, local area networks, local loop, lte, m2m, machine learning, machine vision, machine vision systems, magnetic resonance imaging, mammography, mammography systems, mass spectrometry, membrane technology, memory chips, microarrays, microcomputers, microdisplays, micron process technology, microphones, microspheres, microturbines, mm wafers, mobile app, mobile phone, mobile phones, mobile technologies, mobile telephone control units, mobile tv, monoclonal antibody, motherboards, mouse technology, mp3, mr3 technology, mri, mri systems, mri technology, mrna technology, nanometer process technology, natural gas processing, netbooks, ngs, notebook pcs, nuclear transfer technology, ofdma, oled displays, oled technologies, oled technology, oleds, operating system, optical fiber, optical signals, optical technology, pacs, papnet, pcb, pcr, pda, pdas, pegylation technology, personal digital assistant, personal digital assistants, pet technology, phage display technology, photomasks, photovoltaic solar cells, positron emission tomography, post-combustion control technologies, power grid, power inlay technology, private cloud, prk, protein engineering technology platform, psd, public cloud, pulse combustion technology, pv modules, pv solar, qds, quantum dots, radio frequency identification, rechargeable batteries, recombinant dna technology, recombinant proteins, rf filters, rf products, rfics, rfid, rfid technology, rnai, rnai technology, rnai therapeutic, rnai therapeutics, robots, rom drives, sales force automation, satellite, satellite radio, satellite systems, satellites, scanner, scr, scs, search engine optimization, search engines, selective catalytic reduction, selective catalytic reduction technology, semiconductor wafers, sensor, sensor technology, sfd technology, sige, silicon wafers, sips, sirna, small molecule drugs, smart card, smart card technology, smart cards, smart grid, smart grid technology, smart home, smart meters, smart phone, smart phones, smartphone, smartphones, sms, solar modules, solar panels, specific emission control technologies, sram, ssds, stem cell, stem cell research, stem cell technologies, stem cell technology, stem cells, sulfate concentrations, svp technology, t therapies, taeus technology, tap technology, tdma, tdma technology, text imaging solutions, tft, therapeutic vaccines, thin film solar, tma, tmr, tomography, transdermal patch, ultrasound technology, usb, video compression technology, virtual private networks, vocalid, voip, wan, water purification, wide area networks, wifi, wind turbines, wireless broadband, wireless internet, wireless local loop, wireless phones, wireless telephones, x-ray, x-rays, xmap technology, zfns, zfp technology.

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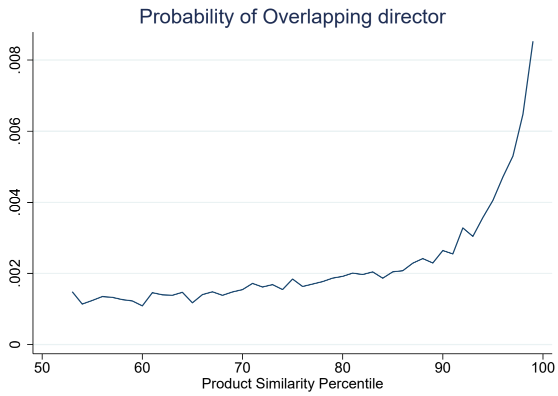
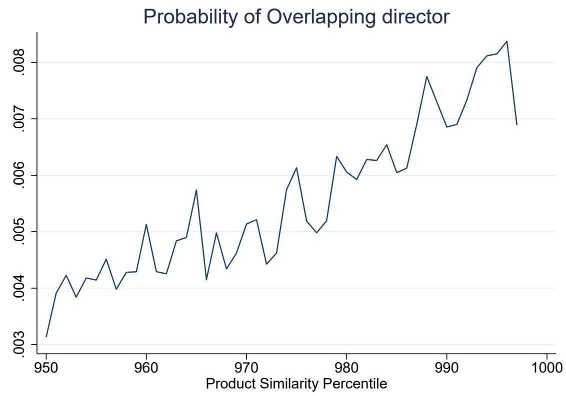
Figure 1: Director overlap by percentile of TNIC Similarity

The figure shows the average director overlap for firm-pairs that are in the same percentile of TNIC product similarity. Panel A uses all firms. Panel B focuses on pair of firms with similarity above percentile 95.



(a) All TNIC



(b) 5% most related firm-pairs

Figure 2: TNIC4 Director overlap over time

The figure shows a time-series plot of the average director overlap for TNIC4 firm-pairs.

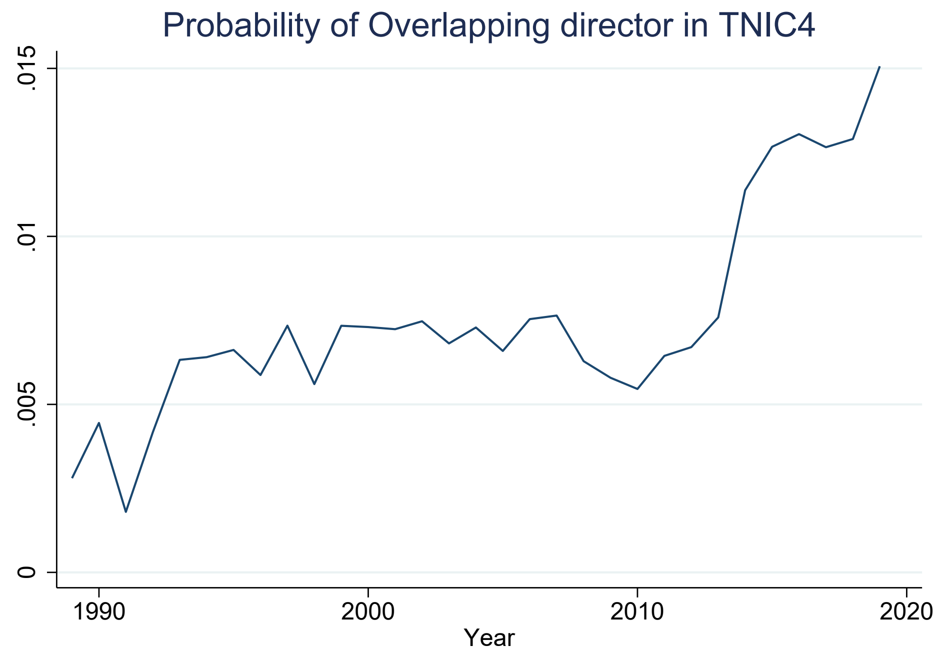


Table 1: Summary Statistics

This table presents the summary statistics of the main variables. Financial firms and utilities are excluded. Total assets, R&D expenditure, sales, firm age, market to book ratio, and ROA are financial indicators from Compustat and CRSP. Firm age is computed using the first effective date of the current link. R&D was set to zero when missing. ROA is the operating income before depreciation (oibdp) over assets. All non-binary variables are yearly winsorized at the 5-95% level.

	Obs	Mean	Std. Dev.	Min	Max	P50
1st-degree OD Density TNIC4	44224	.011	.012	0	.05	.009
2nd-degree OD Density TNIC4	44224	.017	.021	0	.083	.01
TNIC4 Total product similarity	44224	2.587	5.542	.009	54.152	.636
1st-degree OD Density TNIC2-TNIC4	44224	.007	.003	0	.022	.007
2nd-degree OD Density TNIC2-TNIC4	44224	.012	.007	0	.053	.011
Log of total assets	44164	6.618	1.811	2.781	11.012	6.588
XRD/(total assets in t-1)	44224	.045	.067	0	.274	.005
ROA	44117	.098	.12	-.378	.313	.117
Log of sale growth	44156	.083	.272	-4.338	4.357	.068
Market to book ratio	44067	1.696	1.127	.167	6.763	1.324
Product market fluidity	43865	6.657	3.442	.328	34.7	5.98

Table 2: Correlations

This table displays the correlation matrix of the main variables.

	TN4 OD Density	TN2-TN4 OD Density	TN4 POP Density	TN2-TN4 POP Density	TSim TN4	Fluidity Fluidity	XRD/ at t-1	ROA	Market to-book	Sale Growth
TN4 OD Density	1.000									
TN2-TN4 OD Density	0.161	1.000								
TN4 POPOD Density	0.172	0.113	1.000							
TN2-TN4 POPOD Density	0.113	0.354	0.187	1.000						
TSimTN4	0.011	-0.094	0.047	-0.084	1.000					
Fluidity	-0.019	-0.197	-0.026	-0.208	0.611	1.000				
XRD/at t-1	0.010	-0.044	0.028	-0.093	0.422	0.336	1.000			
ROA	-0.016	0.058	-0.016	0.068	-0.372	-0.302	-0.400	1.000		
Market-to-book	-0.009	-0.041	0.004	-0.044	0.209	0.172	0.406	0.074	1.000	
Sale Growth	-0.012	-0.028	-0.021	-0.045	0.080	0.072	0.083	0.173	0.197	1.000

Table 3: TNIC4 first-degree OD density and firm outcomes

This table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density (standardized). In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In column (2), the dependent variable is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). In columns (3), (4), (5), and (6), the dependent variables are XRD/(total assets in t-1), ROA, Log of sale growth, and market to book ratio, multiplied by 100. Firm and year fixed effects are included. Controls include log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	XRD_t/at_{t-1}	$TSimTN4_t$	$Fluidity_t$	ROA_t	Mkt_book_t	$Sale\_Growth_t$
TNIC4 ODdensity in t-1	0.036***	0.062***	0.076***	-0.104**	-0.900**	-0.364**
	(0.014)	(0.013)	(0.014)	(0.044)	(0.354)	(0.142)
Log of total assets in t-1	-1.160***	0.338***	0.267***	0.164	-20.534***	-7.333***
	(0.068)	(0.062)	(0.038)	(0.168)	(0.995)	(0.406)
Log of firm age in t-1	0.066	-0.132*	-0.516***	0.355**	-1.449	-3.297***
	(0.059)	(0.071)	(0.059)	(0.169)	(1.242)	(0.506)
Market to book ratio in t-1	0.301***	0.227***	0.075***	2.325***		4.777***
	(0.030)	(0.036)	(0.018)	(0.086)		(0.230)
Observations	43,990	42,912	43,398	43,872	43,827	43,921
R-squared	0.102	0.037	0.178	0.100	0.338	0.106
Number of gvkey	4,971	4,893	4,946	4,952	4,951	4,957
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 4: Outer ring (TNIC2-TNIC4) first-degree ODdensity and firm outcomes

This table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density (standardized) and TNIC2-TNIC4 OD density (standardized). In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In column (2), the dependent variable is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). In columns (3), (4), (5), and (6), the dependent variables are XRD/(total assets in t-1), ROA, Log of sale growth, and market to book ratio, multiplied by 100. Firm and year fixed effects are included. Controls include log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

VARIABLES	(1) XRD_t/at_{t-1}	(2) $TSimTN4_t$	(3) $Fluidity_t$	(4) ROA_t	(5) Mkt_book$_t$	(6) Sale_Growth$_t$
TN4 ODdensity in t-1	0.035**	0.067***	0.080***	-0.109**	-1.008**	-0.366**
	(0.014)	(0.013)	(0.014)	(0.044)	(0.497)	(0.143)
TNIC2-TNIC4 ODdensity in t-1	0.041***	-0.156***	-0.122***	0.151***	1.091*	0.051
	(0.015)	(0.018)	(0.017)	(0.050)	(0.589)	(0.161)
Log of total assets in t-1	-1.159***	0.336***	0.265***	0.166	-28.071***	-7.332***
	(0.068)	(0.062)	(0.038)	(0.168)	(1.586)	(0.406)
Log of firm age in t-1	0.065	-0.125*	-0.511***	0.348**	-7.684***	-3.299***
	(0.059)	(0.070)	(0.059)	(0.169)	(2.017)	(0.506)
Market to book ratio in t-1	0.301***	0.228***	0.076***	2.323***		4.777***
	(0.030)	(0.036)	(0.018)	(0.086)		(0.230)
Observations	43,990	42,912	43,398	43,872	43,920	43,921
R-squared	0.102	0.039	0.180	0.101	0.130	0.106
Number of gvkey	4,971	4,893	4,946	4,952	4,957	4,957
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 5: TNIC4 second-degree OD density and firm outcomes

This table presents the results of the OLS panel regression of different firm policies on TNIC4 peer-of-peer OD density (standardized). In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In column (2), the dependent variable is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). In columns (3), (4), (5), and (6), the dependent variables are XRD/(total assets in t-1), ROA, Log of sale growth, and market to book ratio, multiplied by 100. Firm and year fixed effects are included. Controls include log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

VARIABLES	(1) XRD_t/at_{t-1}	(2) $TSimTN4_t$	(3) $Fluidity_t$	(4) ROA_t	(5) Mkt_book_t	(6) $Sale\_Growth_t$
TNIC4 POPODdensity in t-1	0.038**	0.224***	0.002	-0.144***	-1.021***	-0.277*
	(0.015)	(0.026)	(0.011)	(0.046)	(0.373)	(0.148)
Log of total assets in t-1	-1.162***	0.319***	0.254***	0.174	-20.476***	-7.323***
	(0.068)	(0.061)	(0.035)	(0.168)	(0.995)	(0.406)
Log of firm age in t-1	0.064	-0.147**	-0.487***	0.364**	-1.382	-3.280***
	(0.059)	(0.070)	(0.054)	(0.169)	(1.243)	(0.505)
Market to book ratio in t-1	0.301***	0.225***	0.073***	2.326***		4.780***
	(0.030)	(0.036)	(0.017)	(0.086)		(0.230)
Observations	43,990	42,912	43,398	43,872	43,827	43,921
R-squared	0.102	0.043	0.197	0.100	0.338	0.106
Number of gvkey	4,971	4,893	4,946	4,952	4,951	4,957
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 6: Outer ring second-degree ODdensity and firm outcomes

This table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density (standardized) and TNIC2-TNIC4 OD density (standardized). Both densities are calculated using the peer-of-peer OD network. In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In column (2), the dependent variable is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). In columns (3), (4), (5), and (6), the dependent variables are XRD/(total assets in t-1), ROA, Log of sale growth, and market to book ratio, multiplied by 100. Firm and year fixed effects are included. Controls include log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

VARIABLES	(1) XRD_t/at_{t-1}	(2) $TSimTN4_t$	(3) $Fluidity_t$	(4) ROA_t	(5) Mkt_book_t	(6) $Sale\_Growth_t$
TNIC4 POPODdensity in t-1	0.037**	0.233***	0.017	-0.142***	-0.955**	-0.279*
	(0.015)	(0.026)	(0.012)	(0.046)	(0.375)	(0.148)
TNIC2-TNIC4 POPODdensity in t-1	0.000	-0.102***	-0.190***	-0.022	-0.743	0.032
	(0.017)	(0.018)	(0.020)	(0.055)	(0.543)	(0.164)
Log of total assets in t-1	-1.162***	0.324***	0.280***	0.175	-20.438***	-7.325***
	(0.069)	(0.061)	(0.038)	(0.168)	(0.995)	(0.406)
Log of firm age in t-1	0.064	-0.132*	-0.490***	0.367**	-1.279	-3.284***
	(0.059)	(0.070)	(0.058)	(0.169)	(1.245)	(0.506)
Market to book ratio in t-1	0.301***	0.224***	0.072***	2.325***		4.780***
	(0.030)	(0.036)	(0.018)	(0.086)		(0.230)
Observations	43,990	42,912	43,398	43,872	43,827	43,921
R-squared	0.102	0.044	0.181	0.100	0.338	0.106
Number of gvkey	4,971	4,893	4,946	4,952	4,951	4,957
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 7: TNIC4 ODdensity and secretiveness

Panel A of this table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density (de-meaned). Panel B uses peer of peer OD network. The estimation includes an interaction term between OD density and the percentage of TNIC4 rivals affected by a decrease in analysts coverage due to broker closures and mergers, as in Chen, Harford, and Lin (2015). In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In column (2), the dependent variable is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). In columns (3), (4), (5), and (6), the dependent variables are XRD/(total assets in t-1), ROA, Log of sale growth, and market to book ratio, multiplied by 100. Firm and year fixed effects are included. Controls include log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

Panel A: first-degree Directors Network

VARIABLES	(1) XRD_t/at_{t-1}	(2) $TSimTN4_t$	(3) $Fluidity_t$	(4) ROA_t	(5) Mkt_book_t	(6) $Sale\_Growth_t$
TNIC4 ODdensity in t-1	0.028**	4.057***	0.049***	-0.035	-0.569	-0.483***
	(0.014)	(1.096)	(0.014)	(0.045)	(0.362)	(0.151)
(Analyst Shock TNIC4 in t-1)x(TNIC4 ODdensity in t-1)	0.013**	1.115**	0.022***	-0.087***	-0.450***	0.136*
	(0.007)	(0.493)	(0.004)	(0.019)	(0.136)	(0.075)
Analyst Shock TNIC4 in t-1	-0.015**	0.024***	0.057***	0.031*	0.344***	0.025
	(0.007)	(0.007)	(0.004)	(0.018)	(0.131)	(0.071)
Observations	43,990	42,912	43,398	43,872	43,920	43,921
R-squared	0.102	0.039	0.189	0.101	0.131	0.107
Number of gvkey	4,971	4,893	4,946	4,952	4,957	4,957
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Panel B: second-degree Directors Network

VARIABLES	(1) XRD_t/at_{t-1}	(2) $TSimTN4_t$	(3) $Fluidity_t$	(4) ROA_t	(5) Mkt_book_t	(6) $Sale\_Growth_t$
TNIC4 POPODdensity in t-1	0.016	10.203***	-0.016	-0.091*	-0.408	-0.381**
	(0.016)	(1.270)	(0.012)	(0.049)	(0.390)	(0.153)
(Analyst Shock TNIC4 in t-1)x(TNIC4 POPODdensity in t-1)	0.025***	0.697*	0.014***	-0.059***	-0.699***	0.111
	(0.006)	(0.375)	(0.004)	(0.018)	(0.136)	(0.068)
Analyst Shock TNIC4 in t-1	-0.018***	0.023***	0.063***	0.010	0.369***	0.048
	(0.007)	(0.007)	(0.004)	(0.017)	(0.125)	(0.065)
Observations	43,990	42,912	43,398	43,872	43,920	43,921
R-squared	0.103	0.047	0.188	0.101	0.131	0.107
Number of gvkey	4,971	4,893	4,946	4,952	4,957	4,957
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 8: TNIC4 OD density and technology diffusion

This table presents the results of an OLS panel regression. The dependent variable is a dummy that equals one if the focal firm has a specific technology. The first independent variable is the percentage of the focal firm's TNIC rivals with that given technology in t-1. The second independent variable is the percentage of the focal firm's TNIC rivals with the given technology in t-3. The other variables are TNIC4 OD density and its interactions with the other variables. Panel A uses TNIC4 rivals and Panel B uses TNIC2-TNIC4 rivals. Firm fixed effects, technology fixed effects, and year fixed effects are included. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

Panle A: Adoption of inner rivals' technologies

	1 if Focal Firm adopts technology in t
TNIC Inner rivals have technology in t-1	0.385***
	(0.009)
TNIC4 ODdensity in t-1	0.000
	(0.001)
(TNIC Inner rivals have technology in t-1)x(TNIC4 ODdensity in t-1)	0.077***
	(0.012)
TNIC Inner rivals have technology in t-3	0.351***
	(0.009)
(TNIC Inner rivals have technology in t-3)x(TNIC4 ODdensity in t-1)	0.008
	(0.012)
Observations	835,230
R-squared	0.229
Number of gvkey	4,028
Firm FE	YES
Technology FE	YES
Year FE	YES

Panle B: Adoption of outer rivals' technologies

	1 if Focal Firm adopts technology in t
TNIC Outer rivals have technology in t-1	0.812***
	(0.013)
TNIC4 ODdensity in t-1	0.001**
	(0.000)
(TNIC Outer rivals have technology in t-1)x(TNIC4 ODdensity in t-1)	0.205***
	(0.017)
TNIC Outer rivals have technology in t-3	0.360***
	(0.013)
(TNIC Outer rivals have technology in t-3)x(TNIC4 ODdensity in t-1)	-0.147***
	(0.019)
Observations	4,226,713
R-squared	0.166
Number of gvkey	4,972
Firm FE	YES
Technology FE	YES
Year FE	YES

Table 9: TNIC4 peer-of-peer OD density and technology diffusion

This table presents the results of an OLS panel regression. The dependent variable is a dummy that equals one if the focal firm has a specific technology. The first independent variable is the percentage of the focal firm's TNIC rivals with that given technology in t-1. The second independent variable is the percentage of the focal firm's TNIC rivals with the given technology in t-3. The other variables are TNIC4 OD density and its interactions with the other variables. Panel A uses TNIC4 rivals and Panel B uses TNIC2-TNIC4 rivals. Firm fixed effects, technology fixed effects, and year fixed effects are included. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

Panle A: Adoption of inner rivals' technologies

	1 if Focal Firm adopts technology in t
TNIC Inner rivals have technology in t-1	0.380***
	(0.008)
TNIC4 POPODdensity in t-1	-0.003*
	(0.002)
(TNIC Inner rivals have technology in t-1)x(TNIC4 POPODdensity in t-1)	0.092***
	(0.012)
TNIC Inner rivals have technology in t-3	0.351***
	(0.008)
(TNIC Inner rivals have technology in t-3)x(TNIC4 POPODdensity in t-1)	0.004
	(0.012)
Observations	835,230
R-squared	0.234
Number of gvkey	4,028
Firm FE	YES
Technology FE	YES
Year FE	YES

Panle B: Adoption of outer rivals' technologies

	1 if Focal Firm adopts technology in t
TNIC Outer rivals have technology in t-1	0.822***
	(0.012)
TNIC4 POPODdensity in t-1	-0.000
	(0.000)
(TNIC Outer rivals have technology in t-1)x(TNIC4 POPODdensity in t-1)	0.172***
	(0.018)
TNIC Outer rivals have technology in t-3	0.335***
	(0.012)
(TNIC Outer rivals have technology in t-3)x(TNIC4 POPODdensity in t-1)	-0.088***
	(0.019)
Observations	4,226,713
R-squared	0.166
Number of gvkey	4,972
Firm FE	YES
Technology FE	YES
Year FE	YES

Table 10: TNIC4 ODdensity and number of rivals

Panel A of this table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density (standardized). Panel B uses peer-of-peer OD network. The estimation includes an interaction term between OD density and a dummy that equals one if the number of TNIC4 rivals is above the median. In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In column (2), the dependent variable is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). In columns (3), (4), (5), and (6), the dependent variables are XRD/(total assets in t-1), ROA, Log of sale growth, and market to book ratio, multiplied by 100. Firm and year fixed effects are included. Controls include log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

Panel A: first-degree Directors Network						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	XRD_t/at_{t-1}	$TSimTN4_t$	$Fluidity_t$	ROA_t	Mkt_book_t	$Sale\_Growth_t$
TNIC4 ODdensity in t-1	0.009	0.003	0.030**	0.048	-0.954*	-0.197
	(0.013)	(0.011)	(0.013)	(0.048)	(0.504)	(0.150)
(Number of TNIC4 rivals above median in t-1)x(TNIC4 ODdensity in t-1)	0.077**	0.134***	0.065**	-0.491***	0.145	-0.542*
	(0.035)	(0.035)	(0.030)	(0.097)	(1.121)	(0.315)
Number of TNIC4 rivals above median in t-1	0.190***	0.662***	0.930***	-0.485***	-1.934	-0.514
	(0.067)	(0.057)	(0.057)	(0.160)	(1.916)	(0.459)
Observations	43,990	42,912	43,398	43,872	43,920	43,921
R-squared	0.102	0.044	0.197	0.101	0.130	0.107
Number of gvkey	4,971	4,893	4,946	4,952	4,957	4,957
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Panel B: second-degree Directors Network						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	XRD_t/at_{t-1}	$TSimTN4_t$	$Fluidity_t$	ROA_t	Mkt_book_t	$Sale\_Growth_t$
TNIC4 POPODdensity in t-1	0.006	0.057***	-0.001	-0.054	-0.367	-0.375***
	(0.012)	(0.010)	(0.012)	(0.042)	(0.365)	(0.143)
(Number of TNIC4 rivals above median in t-1)x(TNIC4 POPODdensity in t-1)	0.115***	0.614***	-0.046	-0.329***	-2.493***	0.425
	(0.043)	(0.085)	(0.033)	(0.123)	(0.909)	(0.355)
Number of TNIC4 rivals above median in t-1	0.196***	0.653***	0.945***	-0.505***	-1.813	-0.583
	(0.068)	(0.057)	(0.058)	(0.160)	(1.263)	(0.460)
Observations	43,990	42,912	43,398	43,872	43,827	43,921
R-squared	0.103	0.061	0.196	0.101	0.338	0.106
Number of gvkey	4,971	4,893	4,946	4,952	4,951	4,957
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 11: TNIC4 OD density and OD career prospects

This table presents the results of OLS panel regressions. The dependent variable in column (1) is the logarithm of the number of boards an OD sits on in a given year. In column (2) the dependent variable is the logarithm of the average total compensation (salary, bonus, pension, stock, options, and other compensation) a director receives in all the boards she sits on in a given year. The dependent variable in column (3) is the logarithm of the average equity compensation (stock and options). In columns (4), it is the logarithm of the average non-equity compensation (salary, bonus, pension, and other compensation). In columns (5) the dependent variable is the logarithm of the average total compensation (salary, bonus, pension, stock, options, and other compensation) excluding new boards that the director starts serving in year t. In Panel A, the primary independent variable is the average first-degree TN4 OD density of the firms the OD sits on. In Panel B, it is the average second-degree TN4 OD density of the firms the OD sits on. Director and year fixed effects are included. All variables are winsorized at the 5-95% level. Standard errors are clustered by director and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

Panel A: first-degree Directors Network

VARIABLES	(1) lg(# boards)$_t$	(2) Total Compensation$_t$	(3) Equity Compensation$_t$	(4) Non-equity Compensation$_t$	(5) Total Compensation$_t$
Avg TN4 ODdensity of OD's firms in t-1	0.003***	0.014**	0.016**	0.005	0.015**
	(0.001)	(0.006)	(0.007)	(0.006)	(0.007)
Observations	68,180	68,180	68,180	68,180	64,635
R-squared	0.690	0.729	0.709	0.717	0.650
Director FE	YES	YES	YES	YES	
Year FE	YES	YES	YES	YES	

Panel B: second-degree Directors Network

VARIABLES	(1) lg(# boards)$_t$	(2) Total Compensation$_t$	(3) Equity Compensation$_t$	(4) Non-equity Compensation$_t$	(5) Total Compensation$_t$
Avg TN4 POPODdensity of OD's firms in t-1	0.002*	0.019***	0.019***	0.020***	0.024***
	(0.001)	(0.006)	(0.007)	(0.005)	(0.007)
Observations	68,180	68,180	68,180	68,180	64,635
R-squared	0.689	0.729	0.709	0.717	0.650
Director FE	YES	YES	YES	YES	
Year FE	YES	YES	YES	YES	

Table 12: Technology transfers and OD career prospects

This table presents the results of OLS panel regressions. The primary independent variable is the number of newly added technologies between the overlapping firms of the OD in year t-1 relative to year t-2. The dependent variable in column (1) is the logarithm of the number of boards an OD sits on in a given year. In column (2), the dependent variable is the logarithm of the average total compensation (salary, bonus, pension, stock, options, and other compensation) a director receives in all the boards she sits on in a given year. The dependent variable in column (3) is the logarithm of the average equity compensation (stock and options). In columns (4), it is the logarithm of the average non-equity compensation (salary, bonus, pension, and other compensation). Panel A uses the whole sample of pair of firms with OD directors. Panel B only includes TN4 pairs of firms. Director and year fixed effects are included. All variables are winsorized at the 5-95% level. Standard errors are clustered by director and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

Panel A: Whole sample

	(1)	(2)	(3)	(4)
VARIABLES	$\lg(\#\ \text{boards})_t$	Total Compensation$_t$	Equity Compensation$_t$	Non-equity Compensation$_t$
Number of newly added technologies in year t-1 relative to year t-2	0.003*	0.048**	0.047**	0.033*
	(0.002)	(0.022)	(0.021)	(0.017)
Observations	106,752	106,752	106,752	106,752
R-squared	0.722	0.717	0.712	0.701
Director FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel B: TNIC 4

	(1)	(2)	(3)	(4)
VARIABLES	$\lg(\#\ \text{boards})_t$	Total Compensation$_t$	Equity Compensation$_t$	Non-equity Compensation$_t$
Number of newly added technologies in year t-1 relative to year t-2	0.002	0.057*	0.054*	0.033
	(0.003)	(0.032)	(0.031)	(0.025)
Observations	8,744	8,744	8,744	8,744
R-squared	0.787	0.793	0.788	0.773
Director FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES