Leaky Director Networks and Innovation Herding

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Abstract

We first document that, despite potential legal issues, overlapping directors are surprisingly prevalent among direct competitors. Using panel data regressions and plausibly exogenous shocks, we find that competing firms in markets with dense overlapping-director networks experience innovation herding, lose product differentiation, and ultimately perform poorly. Novel text-based network propagation tests of technologies show that intellectual property leakage plays a role as firms with dense overlapping director networks experience faster propagation of technologies to competitors. Our findings suggest a coordination problem where industry participants cannot stop rivals from earning small gains from leakage despite much larger community-wide negative externalities.

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The practice of directors sitting on the boards of competing firms raises legal and ethical questions. Board members might leak corporate opportunities and intellectual property (IP) to direct competitors. The consequences of leakage, moreover, should be amplified when multiple directors overlap across competitors in a given market. As an illustration, if multiple competing-firm directors overlap, IP leakage might propagate through the full competitor network until most initially-proprietary IP becomes entirely communal. Industry participants then become more homogeneous, a form of industry-wide "innovation herding". As proprietary strategies and IP are crucial to gaining an edge in a competitive market, such outcomes can significantly erode product differentiation and impair ex post performance. Although director leakage of privately-established intellectual property is prohibited by the corporate opportunities doctrine, proving violations can be difficult, and leakages could be beneficial in some cases. This paper examines the extent of such leakage and its consequences.

The set of overlapping directors (ODs) economy-wide constitutes a large overlapping director network (henceforth ODN). We refer to the network of overlaps that only includes direct competitors (our primary focus) as a CODN, which is a "localized" sub-network of the ODN. The extent of potential leakage through a given CODN should be highly dependent on the density of the CODN, as a more connected network enables leakages to reach a significant fraction of competitors. For example, in a market of 50 competitors, if the network is thin and just two companies are connected overall, losses of IP would be limited as any leaked IP could propagate to at most one rival. However, if most of these competitors have connected ODs in the CODN, a given firm faces the possibility of losing its proprietary IP to almost all of its rivals. As illustrated by seminal models of differentiation such as Chamberlin (1933), this loss of differentiation would also result in a loss of rents.

Consistent with this logic, we find evidence of significant losses in differentiation and competitive advantage, lower patent values, and poor accounting performance when a firm is surrounded by a more dense CODN. Our results are most consistent with a simple model of coordination failure we present in detail in Section 2. The model has three primary features. First, a dense CODN can trigger innovation herding as technologies propagate to industry rivals, resulting in losses in product differentiation, higher competition, and lower industry-wide profits. Second, as these outcomes are driven by negative network externalities stemming from the actions of others, a firm can experience these negative outcomes even if it is not connected to the network. This is because industry rivals regularly produce correlated innovations (Lemley, 2011), and technologies can enter the leaky network through multiple paths. Third, the model illustrates that coordination failure among rivals ensures that CODNs can be stable even in equilibrium, as negative outcomes are driven by network externalities and firms cannot influence the actions of rivals. We present mechanism tests that support foundational elements of the model. Yet we cannot rule out all alternatives such as more complex communal agency problems where, for example, directors participating in the CODN are entrenched and receive private benefits (such as launching their own startups) from using the leaked technologies. However, our results are strongest in more competitive industries where such weak governance practices are less likely.

An anecdotal example of leakage is the publicly known conflict between Eric Schmidt and Steve Jobs in 2008. Jobs publicly accused Schmidt —at that time a director on the board of Apple and the CEO of Google— of helping Google to develop cellphones that *"physically, technologically and spiritually resembled the iPhone."* Our paper suggests that examples like this could be widespread, and they likely span both major technologies like smart phones, and also more incremental technologies such as a new product feature. Illustrating higher prevalence, we find strong results not only for overlapping director network links, but also using a separate database of other employment links among directors.

We start our summary of results with a new stylized fact: director overlaps across boards of direct competitors are both commonplace and increasing over time.[1] Using the customizable TNIC industry classification (Hoberg and Phillips, 2016), Figure 1 shows with high resolution how the incidence of director overlaps changes as firm-pairs go from being unrelated (no product similarity) to being direct competitors (highest product similarity). OD incidence increases dramatically as firms become closer to being direct competitors, and there is almost no evidence of trend-reversal even for the most similar direct competitors (firm-pairs with the highest 1% product similarities, which are analogous to being in the same 4-digit SIC code). The high and growing prevalence of direct competitor board overlaps suggests that research understanding the consequences of dense

[1] ODs sitting on competing firm boards might violate Section 8 of the 1914 Clayton Act. Yet this section is rarely enforced as explained by legal experts https://www.skadden.com/en/insights/publications/2021/06/the-informed-board/interlocking-boards. For readers interested in the possibility of collusion in this context (not the focus of our study), we refer them to Gopalan, Li, and Zaldokas (2022). We also note that IP leakage and collusion are not mutually exclusive in this context, and show in our Appendices IA1 and IA9 that our results are sharpest in two subsamples where collusion is unlikely (competitive product markets and unstable markets with high levels of R&D).

CODNs is important from both an academic and a regulatory perspective.

Our most central finding is that firms with dense CODNs experience inferior corporate outcomes along many dimensions. Three quasi-natural experiments (discussed below) further suggest that this relationship is likely causal. In particular, we find that the total product market differentiation in the industry *decreases* significantly with CODN density. We also find consequently lower valuations and profits in the form of market-to-book and ROA. Further indicative of redundant innovation, we find fewer patents and a lower value of patents when they are created. These regressions control for firm and year fixed effects, and an array of standard control variables. Our findings support the existence of systematic IP leakage in dense CODNs, and are consistent with innovation herding and losses of valuable product differentiation.

A challenge in our setting is that OD incentives to leak IP are endogenous. For example, ODs might leak more when they are trying to adapt to difficult business conditions. To alleviate this concern, we start with a quasi natural experiment where 9 states (in a staggered fashion) changed their laws to allow the adoption of Corporate Opportunity Waivers (COWs), thus reducing directors' legal consequences of leakage. Prior to such state law changes, the default in the U.S. legal system is that the responsibility of directors to safeguard corporate innovative opportunities is immutable, as directors cannot contract out of this responsibility, and hence leaking corporate innovations exposes directors to significant liability. Because COWs are waivers that can directly reduce this legal liability, the passage of COWs exogenously increases the net incentives directors have to leak information.[2] In our setting, CODNs comprised of firms in states with a higher incidence of COWs are expected to have exogenously higher leakage after the COWs are enacted.

An important detail regarding our identification strategy is that we do not rely on actual firm-level COW adoptions, which can also be endogenous. Instead, we use the plausibly-exogenous state law changes themselves. We thus employ an intent-to-treat framework, which is standard in difference-in-difference tests based on legal changes. For example, this is the same approach used in Fich, Harford, and Tran (2022), who also study COWs. Although all legal shocks have various limitations regarding the exclusion requirement, four aspects suggest that violations are unlikely in our case. First, individual director/firm decisions are unlikely to drive the changes in state

[2] Rauterberg and Talley (2017) provide a detailed summary of these laws, which we further summarize in Section 4.1. The authors also report that over one thousand public U.S. corporations actually adopt COWs once they are allowed by their state of incorporation, indicating that these legal changes have had significant impact on actual practice, ensuring that our quasi natural experiment has power.

laws themselves. Second, treated states passed these laws in order to improve financing for small venture-backed firms (see Eldar, Grennan, and Waldock (2020)), and hence their impact on the public firms in our sample are at least partially "accidental". Third, state adoptions are staggered and our methods are robust to econometric variations, making it unlikely that other events can explain our findings. Fourth, our focus is on treatment effects at the network level, and it is particularly unlikely that a focal firm can influence the state laws of its out-of-state competitors. We uniformly find that our results are stronger when networks are more heavily treated by COWs, suggesting that our results are likely causal, at least in part.

We use two additional sources of plausibly exogenous variation to further assess potential causal mechanisms. Our hypothesis predicts that information leakage is central, and hence our results should be stronger in more opaque information environments (as there are fewer alternative ways for information to leak, and information rents should be larger). In the first test, we thus use 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)). Using a difference-in-differences specification, we indeed find that our results are stronger when information environments become more opaque.

We also use plausibly exogenous variation motivated by the network econometrics literature (see Bramoullé, Djebbari, and Fortin (2009)),[3] and we use second-degree director links as an instrument for first-degree connections. Second-degree linked boards are those where the two boards are connected through a third board. For example, 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 overlap with another firm C's board. Because A and B cannot control director selection at firm C, information flowing through second-degree links is more plausibly exogenous. We find that second-degree links strongly predict first-degree links, and our findings are fully robust to using second-degree links to instrument for CODN density.

Our thesis is that information and IP leakage specifically are important drivers of the outcomes we report. We thus develop highly granular tests based on individual technologies that explore the rate at which technological adoption propagates through competitor networks. We use textual analysis of all 10-K paragraphs where technologies are specifically mentioned, and identify the set

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

of all noun phrases in these paragraphs. We use research assistants to then limit attention to noun phrases that identify specific technologies, which are nouns. After this filtering, we are left with 352 specific technologies. We then examine how each technology propagates through the peer network using firm-technology-year panel data regressions. We first document the validating finding that a focal firm is significantly more likely to adopt a technology if its competitors use the technology ex ante. Second, in a specific test of our proposed mechanism, we show that these adoptions intensify when a focal firm is surrounded by a dense CODN and especially when the CODN is highly treated by the plausibly exogenous COW shock. These results are significant even in rigid models that include firm, and technology by time fixed effects. These technology propagation tests are novel given the existing literature, and provide direct evidence supporting the prediction that technology transfers across competitors are a key consequence of more dense CODNs.

Our measure of OD density is conservative and understates the true level of director connections. OD connections likely correlate with (and consequences are amplified by) directors having social and professional connections beyond boardrooms. We find that OD network density is indeed highly correlated with an alternative director connectedness measure based on directors being linked through employment at country clubs, charities, other corporations, and universities. Remarkably, all of our economic results supporting the leakage hypothesis are robust to using this alternative director employment network instead of our baseline CODN. This result is predicted by our thesis as leaks through this alternative network should have similar consequences and they are also legally governed by the same corporate opportunities doctrine.

The focus of our analysis is on direct competitors, which are substitutes in the product market. A deeper prediction is that IP leakage might in fact be beneficial if IP instead propagates across firms positioned as complements. We identify complements as pairs of firms with material but 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 indeed less likely to be competitors and are more likely to have asset complementarities, as they do more mergers that result in synergies. Consistent with this prediction, we find diametric opposite economic consequences when IP propagates across distant-peer OD links. We find increased product differentiation and improved accounting performance, consistent with mutually beneficial complementarities being realized. These results also provide a benchmark for further understanding our competing-firm OD results, and illustrate that IP leakage can be either costly or beneficial.

We test additional mechanisms suggested by our model. Our model predicts that our results should be stronger when industry rivals are more likely to co-invent similar innovations at roughly the same time (Lemley (2011) illustrates that this is the normal case in practice). We consider two measures of correlated innovation. The first is a measure of ex-ante product homogeneity, as ex post innovations are likely to be more correlated when firms have very similar products. Our second is a measure of low technological breadth, as firms using technologies that draw from multiple disciplines have increased complexity that makes it less likely that inventors are commonly influenced by the same prior ideas (see Stigler (1955) and Landers (2010)). Our results are significantly stronger in the subsamples where correlated innovation is more likely.

Overall, our paper makes three major contributions. First, we propose a novel CODN leakage hypothesis predicting potentially damaging innovation herding and losses in valuable product differentiation in competitor networks. Second, the consequences are negative for firms in these dense CODNs, as they experience inferior outcomes regarding product differentiation, accounting performance, valuations, and innovative uniqueness. Third, we provide a new methodology for modeling the propagation of specific technologies through the product market network. We find that dense CODNs facilitate more technology propagation through the competitor network.

1 Literature Review and Hypothesis

When directors meet, they discuss corporate policies, growth strategies, and future innovation plans. Although such information is sensitive and often proprietary, this information is clearly relevant to the other boards a director might sit on, particularly when she serves competing firms. Due to its high relevance, this information can shape the advice she then gives the other firms for which she serves on the board.

The existing literature supports this foundation. For example, Bouwman (2011) shows that firms in the same director network tend to have related corporate governance practices, and Foroughi, Marcus, Nguyen, and Tehranian (2022) find that director networks affect the adoption of anti-takeover provisions. Similarly, 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, and Cabezon (2023) shows that when two firms share a director, the structure of their executive compensation plans becomes more similar. Board overlaps also influence acquisition patterns, as Stuart and Yim (2010) show that director networks influence which companies become targets, and Renneboog and Zhao (2014) show that, when a bidder and target have a common director, deals are more likely to be completed and negotiations are shorter.

Existing studies also provide supporting evidence that the properties of the overlapping director network affect firm performance. For example, Akbas, Meschke, and Wintoki (2016) find that investors have better predictions for companies with more connected directors; Dass, Kini, Nanda, Onal, and Wang (2014) show that overlapping directors in upstream/downstream industries increase firm value and performance when the information gap between firms is large; Larcker, So, and Wang (2013) find that firms with central boards of directors have superior risk-adjusted stock returns. Burt, Hrdlicka, and Harford (2020) use the stock comovement of OD-connected firms to measure the value that a director can add to a firm.

Other articles study the direct impact of multi-board directors on firm performance. Some suggest that because these 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 OD network density rather than the unconditional effects of own-firm ODs on focal firm performance. Unlike all existing studies, we propose a thesis based on systematic IP leakage and examine performance and innovation using CODN density and firm connectedness. We use quasi-exogenous variation and textual analysis to examine information propagation, its consequences, and director incentives.

1.1 Intellectual Foundation

We develop an intellectual foundation for three core hypotheses regarding CODNs noted below and two auxiliary predictions noted at the end of this section.

H1: A dense CODN can result in propagation of technologies to rivals ("innovation herding"), a loss of product differentiation, and lower profits.

H2: Firms can experience these negative effects even if they are not connected to the CODN.

H3: Dense CODNs can be stable despite low profits due to a coordination problem.

The first hypothesis H1 is intuitive as direct competitors sharing technologies can result in the loss of a proprietary advantage. For example, this is consistent with the free-riding problem in the theories of strategic exploration (i.e., Bolton and Harris (1999), Keller, Rady, and Cripps (2005), and Hoelzemann, Manso, Nagaraj, and Tranchero (2022)) and the intellectual property to generate product differentiation and obtain competitive advantage (i.e., Sutton (2001) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005)). As we are unaware of existing theories illustrating H2 and H3, we develop a simple model of innovation in Appendix A, and we highlight the logic of the simple model's core predictions here.

1.1.1 Model Highlights

We consider a simple model of competing firms endowed with technologies. Each technology can create one novel product feature. Each competitor has a platform that can be used to sell the product features, and market equilibrium for each feature is determined by non-cooperative competition *a-la-Cournot*. Although we model more scenarios in the Appendix, we focus on the most central case here. Suppose there are four competing firms and two innovative technologies T1 and T2. Firms 1 and 2 have discovered technology T1 using their organic R&D efforts, and firms 3 and 4 discovered technology T2.

Our setup thus assumes that competitors tend to organically develop related technologies at the same time, which is the pattern observed in practice for both major innovations as well as secondary innovations (see Lemley (2011) and Section 6 for a summary of this literature and related tests). Our model Appendix A illustrates why this assumption is important, especially regarding H2.

Below we consider scenarios where subsets of these four firms are connected by a leaky CODN. In our setting, leakage entails connected firms sharing their technologies. For any technology a firm wishes to develop into a product, it must pay a development cost d. It will compete with any other firms that also developed the given technology.

We adopt a standard Cournot model of competition for product features that assumes a linear cost function for each technology a firm has developed, and a demand function in each market of the form $P = A - X$, where X is the total quantity of the product feature produced by firms in the market, and A is a constant. In equilibrium, based on the assumed density of the leaky CODN, each technology will be developed by two to four firms, which then compete in Cournot oligopolies. For each technology a given firm i develops, it must choose a quantity x_i to produce as follows:

$$\max_{\{x_i\}} \ \pi = (A - N_c \ x_j^* - x_i)x_i - c \ x_i - d \tag{1}$$

The quantity x_j^* denotes the equilibrium quantity chosen by the symmetric competitors who also developed the given technology, and $N_c \in \{1, 2, 3\}$ denotes how many competitors developed the given technology. Optimal profits therefore depend on how many rivals also developed the given technology, which is influenced by the density of the CODN and how many leakages occur. We consider three cases that illustrate the core predictions of the above hypotheses **H1** to **H3**:

Case 1 [Zero Network Density]: Here we consider the case of no OD connections. This case serves as the baseline for assessing the direct effects of a leaky network. Here, firm i develops the one technology it is endowed with and faces only one competitor in a Cournot duopoly.

Case 2 [Dense CODN and Firm i is Connected]: Suppose all four firms are fully connected to a leaky CODN, and hence both technologies T1 and T2 propagate to all four firms. Here, all firms develop the two technologies and compete in symmetric 4-firm oligopolies for each.

Case 3 [Dense CODN but Firm i is not Connected]: Here all competitors are connected to the CODN (it is dense) but firm i is not connected. In this case, firm i will only develop its one endowed technology, but will still face a 4-firm oligopoly as both technologies will still transmit through the dense network. The result is half the profits relative to Case 1.

We summarize below the profits of firm i for all 3 cases, as derived in the Appendix:[4]

$$\pi^*_{case1} = \frac{1}{9}(A-c)^2 - d, \qquad \pi^*_{case2} = \frac{2}{25}(A-c)^2 - 2d, \qquad \pi^*_{case3} = \frac{1}{25}(A-c)^2 - d$$

Discussion: Comparing Case 1 to Case 2 illustrates theoretical support for **H1**, as a leaky network creates a free-rider problem and lower profits due to innovation herding and a loss of product differentiation in the market. Comparing Case 1 to Case 3 illustrates theoretical support for **H2**, that the negative consequences of a dense leaky CODN can arise even if a given firm i is not connected to the network. The reason is that a firm's own technology would likely leak and transmit through the network anyway, given other members of the CODN hold correlated

[4] We assume throughout that market size (A) is large enough to avoid non-investment scenarios: $A > c + 5\sqrt{d}$.

innovations. Comparing Case 2 to Case 3 provides support for **H3**, as firms gain more from receiving technologies leaked through the network than they lose by risking their own technology. We find strong evidence supporting the foundations for these hypotheses.[5]

Although it is less focal to our empirical tests, which focus on the consequences of a dense CODN, it is natural to ask if a dense CODN can be stable despite its negative consequences. For example, an extreme neoclassical view might be that dense CODNs should never exist as profit maximizing firms will fire all ODs in order to generate the more profitable equilibrium depicted in Case 1 above. One source of network stability could be agency problems, as directors might realize private benefits to leakage. Perhaps more importantly, the model above illustrates that dense CODNs can in fact be stable even in the presence of rational managers and no agency problems. This arises from an inherent coordination problem. Comparing Case 2 to Case 3 shows that it is optimal for firm i to join the CODN network even though higher profits would accrue to the scenario of all firms being disconnected (Case 1). Thus the dense CODN can be stable and self-reinforcing as firms do not regret being connected given that the network is dense. This is a case of coordination failure, as firm i can only choose its own directors, and it has no influence over the OD connections made by the rivals.

As we note in the appendix, if firms can choose to be connected to the CODN or not, there are two pure strategy Nash equilibria. In the first, all firms choose not to connect and Case 1 emerges with high profits. In the second, all firms choose to connect, and Case 2 emerges. This is less profitable than Case 1, but is nevertheless a Nash equilibrium because deviations, as depicted by Case 3, are less profitable than the equilibrium strategy in Case 2. A dense CODN can thus be stable because joining comes with the benefit of receiving technologies, which can render joining superior to disconnecting from the network. This equilibrium is analogous to the prisoner's dilemma and indicates a "tragedy of the commons," as industry participants will effectively over-develop the available technologies and will be collectively worse off as compared to no sharing.

Appendix A reports full model details and also extends the model to explore predictions for research and development spending, where we separately model the costs of (A) innovative research to produce better technology versus (B) development costs to commercialize existing technologies. Development costs are modeled as above, and the extension adds an initial period to the game

[5] Section 6 summarizes the rich existing literature illustrating correlated innovation, reports the results of tests of correlated innovation, and illustrates evidence of CODN stability via OD incentives.

where firms can invest in innovative research (with convex costs) to increase the scale of period two profits. We find that a leaky CODN can result in both higher R&D as firms need to develop more leaked technologies but also fewer patents as firms have a disincentive to produce novel technologies given the lower equilibrium profits associated with a leaky CODN.[6]

We note that our model is only designed to model OD networks among close competitors selling products that are direct substitutes. In the case of firms with complementary products, our model does not apply. We note that technology leakages are simpler and likely value-creating for complementary firms, as leakages between them can improve each firms' products without transmitting the technologies to direct competitors. We thus expect diametrically opposite predictions when OD connections are dense among complementary firms instead of direct competitors. We study complementary firms in Section 3.3 and our results support this additional prediction.

2 Data and Methodology

We use the Boardex and the 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.[7] 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

[6] Our prediction of increased research and development expenses aligns with Mansfield, Schwartz, and Wagner (1981). They show that imitating a technology can be expensive because the imitator does not have the "know-how" to develop and produce the given technology. In their study, the ratio of the imitation cost to the innovation cost is 65% on average.

[7] TNIC firm-by-firm pairwise similarity scores are calculated by parsing the product descriptions from 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.

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) if 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 product differentiation, performance, and innovation. Our baseline regression specification is described in equation (2) below:

$$\text{DEP}_{it} = \alpha_0 + \beta_1 \text{TN4 OD density}_{i,t-1} + \delta \text{ Controls}_{i,t-1} + \mu_i + \gamma_t + \epsilon_{it} \tag{2}$$

Our coefficient of interest is β_1 (role of dense CODN network). We control for the logarithm of total assets, the logarithm of firm age[8], 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 unobservable time-invariant firm 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.

[8]Firm age is listing vintage from the first year the firm appears in the CRSP/COMPUSTAT merged database.

Our dependent variables include measures of product differentiation, performance, innovation, and competitive threats. Our measure of product differentiation is the TNIC total similarity of competitors. Following Hoberg and Phillips (2016), TNIC-4 Total Similarity (*TsimmTN4*) is the sum of the focal firm's product similarity to each of its TNIC4 rivals. To measure competitive threat, we use the Product Market Fluidity measure from Hoberg, Phillips, and Prabhala (2014), which is a measure of how intensively the product market around a firm is evolving in each year.

We use return on assets (ROA) and Tobin's Q to assess firm performance. We define ROA as operating income before depreciation (OIBDP) divided by assets and market-to-book ratio as the market value of the firm divided by the book value ((CSHO*PRCC_F+DLC+DLTT+ PSTKL)/AT).[9]

To measure innovative spending, we use R&D scaled by total assets. 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 measure innovative outcomes, we use the total number of patents filed by the focal firm in a given year and the total value of patents, both scaled by the firm's assets. We obtain patent information from the Kogan, Papanikolaou, Seru, and Stoffman (2017) database, which covers all patent applications filed with (and ultimately granted by) the US Patent and Trademark Office (USPTO) from 1926 to 2020.

Table 1 reports summary statistics, and Table 2 presents the Pearson correlation matrix. *ODdensity* has a mean of 0.012, indicating that 1.2% of all possible permutations of the focal firm's rivals have a common director. This fraction increases to 1.8% 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 4.2. The higher incidence of second-degree links is expected, as networks tend to extend as the degree of connections increases. When we focus on distant competitors (TNIC2-TNIC4), the average OD density is 0.7% for first-degree connections and 1.3 for the 2nd-degree network. A 1% density might seem small. However, in terms of director appointments, 16% of overlapping directors serve two firms in related industries (TNIC2), and 6% serve two firms that are direct competitors (TNIC4). Moreover, 78% of the firms in our sample are connected to the OD network and can reach any other firm in this subsample through boardroom connections if enough degrees of connectedness are considered,[10] and 18.3% of firms have an overlapping director sitting on the board of at least one TNIC4 peer.

[9] PSTKL is set to zero when missing.

[10] This ratio is similar to ratios reported by other studies(e.g., Larcker, So, and Wang (2013) report a ratio of 76%).

This latter 18.3% statistic illustrates non-trivial network connectedness in the part of the network that substantively matters for our thesis. Yet we believe this figure likely significantly understates the true level of director connectedness. For example, if we expand connectedness to also include employment links among directors (which we observe via Boardex), the 18.3% increases to 20%. If we add second-degree connections, this increases further to 25.1%. All additional director connections are governed by the same corporate opportunities doctrine, and as expected, we find similar economic outcomes for these two alternative measures of director connections. Perhaps more importantly, a data limitation is that we cannot observe all of the ways that directors can be connected. For example, some directors might simply be mutual friends who met at major events, or they might be golfing partners. The existence of likely-many unobservable connections reinforces that our results are likely understated, and that director networks can be significantly more dense than the statistics based on observables indicate.

Regarding firm characteristics, our average sample firm has total assets of $3.31 billion, R&D investment equivalent to 4.6% of total assets, ROA of 9.2%, and a market to book ratio of 1.7.

3 Results

3.1 Director overlap and close competitors

Our first result is the stylized fact that firms hire overlapping directors regardless of their product market closeness. 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. 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 of 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 potential risks of leaking IP to competitors and also the Clayton Act's Section 8 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.[11] 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 Overlapping Director network density and firm outcomes

Our central hypothesis is that dense networks can facilitate faster and more intense transfers of technologies and IP across competing firms. In turn, this might result in innovation herding, reduced product differentiation, and ultimately lower profits and firm valuations. We estimate equation (2) using measures of product differentiation, performance, and innovation as the dependent variable. We use firm-year panel-data regressions with standard errors clustered by firm. These regressions also control for firm size, age, market-to-book ratio, and firm and year fixed effects.

Supporting our main hypothesis that a dense CODN can result in a loss of product differentiation, we find that the products developed by firms in more dense CODN networks are increasingly similar. Column (1) of Table 3 shows that ex-ante OD network density indeed predicts higher ex-post TNIC4 product similarity. This finding is significant at the 1% level and indicates that dense director networks are associated with declining product differentiation through innovation herding likely resulting in product revisions that are ultimately highly correlated across firms.[12]

Columns (2) and (3) show that ex-ante TNIC4 OD density is associated with poor ex-post performance in the form of lower ROA and lower valuations in the form of market-to-book. These findings are significant at the 5% level and are consistent with a decrease in product differentiation and a loss of unique proprietary intellectual property resulting in weaker corporate performance. This consequence of IP homogenization is particularly consistent with the implications of Sutton

[11] 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 in one instance. These recent cases 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.

[12] We find consistent results using the TNIC HHI as dense CODNs lead to lower HHIs, indicating more competition.

(2001) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005) when firms are unable to effectively differentiate from competitors. In particular, barriers to entry are then difficult to establish, and competition is difficult to escape via innovation.

Additionally, column (4) shows that firms with higher ex-ante TNIC4 OD density invest more in R&D in the next year. Even though we observe an increase in R&D, columns (5) and (6) show zero or even negative effects on patents. These findings are consistent with R&D that facilitates the development and commercialization of the many ideas circulating in a leaky CODN, without translating into many novel patents. Our tests using plausibly exogenous variation in later sections will provide reinforcing support for this conclusion. Further supporting the innovation herding perspective and increased homogeneity across firms, column (7) shows that firms in more dense CODN networks experience increasingly fluid product markets. This finding indicates an increase in competitive threat as a consequence of a loss of product differentiation. Overall, the results in Table 3 support the predictions of our central hypothesis **H1** that a dense CODN can result in the propagation of technologies to rivals, a loss of product differentiation, and lower profits.

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 connections beyond the board overlaps alone. For example, directors in dense OD networks are also likely connected through employment in country clubs, charities, universities, or other corporations. We use BoardEx[13] to create an alternative pairwise director connection network based on these common past-employment director connections. We define two firms as connected if they have directors that share a job in a third such institution.[14] We then follow the same methodology and create a density measure called *OTHERdensity*. Column (1) of Table 4 shows that our *OTHERdensity* is indeed highly correlated with *ODdensity*. The positive and 1% level significant coefficient supports our intuition that high OD density is indeed correlated with connections beyond overlapping directorships themselves. Hence *ODdensity* is essentially a measure of overall director connectedness, and the level of director connectedness is likely more pervasive than prior studies might suggest.

Columns (2) to (8) of Table 4 then show that our economic findings generally hold if we use

[13]Specifically, we use BoardEx – Company and Organizational Networks.

[14]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%).

OTHERdensity instead of *ODdensity*, illustrating that these additional director connections are also consistent with innovation herding even though the link is through directors having common employment at another institution rather than a common boardroom.[15]

Panel B shows similar results when we use second-degree CODN connections instead of first-degree CODN connections. Second-degree connections occur when two directors serve on a common third board. Our confirming results for both employment connections and second-degree director connections are predicted by our central thesis, as leaks through these alternative networks should have similar consequences as leaks by directors with first-degree connections. In particular, information transmissions in all of these alternative settings are legally governed by the same corporate opportunities doctrine.

Our findings thus far support the importance of the OD network density. We now contrast the role of network density with the own-firm connections. To measure the focal firm's OD connection intensity, we analogously compute the fraction of TNIC4 peers that share a director with the focal firm (*TN4 OD focal*). In Table 5 we now also include *TN4 OD focal* in our baseline estimation. We also include an interaction term between TNIC4 ODdensity and TNIC4 OD focal. In panel A, we maintain our baseline measure of network density using the first-degree TNIC4 OD network. In panel B, we generalize the network and define two TNIC4 competing firms as connected if they share an OD, or if it they have directors sharing employment, or if they have directors that share a second-degree connection. In both panels, we find that our results for network density remain highly significant even controlling for the focal firm's direct connection to the network. These findings support the theoretical importance of the network and our hypothesis **H2**, that firms can experience negative outcomes even holding fixed whether they are not connected to the CODN.

Finally, because innovation is important in our intellectual foundation, Appendix IA1 examines whether our findings are stronger for more innovative firms. Consistent with innovative firms being more sensitive to IP leakages, we indeed find supportive results.

[15] These findings also contribute to previous research that shows that social connections play a role in the spread of information. For example, Hong, Kubik, and Stein (2005), Cohen, Frazzini, and Malloy (2008), and Cohen, Frazzini, and Malloy (2010) show that investors and managers use shared education networks to transfer information and ideas about stocks and investment strategies. Similarly, Kuhnen (2009) and Ferris, Javakhadze, and Rajkovic (2017) find that social ties can alleviate information asymmetry, improving hiring decisions and external financing, respectively.

3.3 Distant Competitors

Our analysis thus far focuses on OD network density within each firm's TNIC4 industry. These peers are "as similar" as are firms in the same four-digit SIC code. We showed that IP leakage to such direct competitors is harmful, consistent with competitors having products that are substitutes. However, as firms become more distant in the product market, it becomes less likely that their products are substitutes, and more likely that they are complements (Hoberg and Phillips (2010), Bena and Li (2014)). In the case of product complements, technology leakages are not necessarily harmful, as they might create product complementarities that are value-creating for both parties. We explore this diametric opposite prediction for complementary firms in this section.

We thus add measures of the density of distant peer OD connections to our regressions. As defined earlier, distant peers are those that are in a focal firm's TNIC-2 industry classification but not in its TNIC-4 classification (similar to being in a common two-digit SIC code but not a common 4-digit SIC code). Panel A of Table 6 displays the results. We generally find diametric opposite results than we did for the competing firm ODs reported earlier. While our baseline TN4 OD density associates with increases in total product similarity and competitive threats, distant peer TN2-TN4 OD density associates with a decrease in both. Further supporting that these activities are complementary, TN2-TN4 OD density also correlates with superior ex post firm performance in the form of ROA and valuation. Moreover, while TN4 OD density associates with decreases in the value of patents, distant peer TN2-TN4 OD density associates with increases.

These findings suggest that when product complementarities exist, information leakages foster innovation that allows for product differentiation and value creation. For example, these firms can develop product improvements without necessarily imposing negative externalities on industry rivals. This is not possible for direct competitors, as very close competitors have very few product complementarities (their products are substitutes). We also note that our findings for more distant peers illustrate that dense OD networks are indeed special for competing firms. The distant-peer findings thus provide a relevant benchmark for understanding close-competitor OD density (the focus of our earlier results) and its link to innovation, market structure, and outcomes.

4 Accounting for Endogeneity

4.1 Corporate Opportunity Waivers

A challenge regarding inferences in our setting is that directors' incentives to leak are endogenous. For example, ODs might leak more when they face difficult business conditions, and the need for this role might correlate negatively with performance and innovation outcomes. To mitigate these endogeneity concerns, we exploit a quasi-natural experiment where nine states (in a staggered fashion)[16] changed their laws to allow the adoption of Corporate Opportunity Waivers (COW), reducing the directors' legal consequences of leaking IP. This experiment yields a plausibly exogenous shock that can be implemented using a difference-in-differences model, such that the shock increases incentives for directors to leak sensitive information through competitor-firm director networks.

4.1.1 Institutional Details

The primary backstop against the leakage of IP to competitors is the legal obligation directors have to faithfully safeguard the firm's intellectual property. Indeed, directors have a fiduciary duty of loyalty to their shareholders by which they are expected to put the welfare of the corporation above their own personal or other business interests. The force of law asserting this duty is the corporate opportunities doctrine, a legal principle that protects corporate ownership of business opportunities from director expropriation. This doctrine specifies that corporate fiduciaries may not appropriate for themselves —or any of her affiliates— a new business opportunity that belongs to the corporation. Specifically, "*the doctrine states that an officer or director of a corporation usurps a business opportunity if: (1) the corporation is financially able to [undertake] the opportunity; (2) the opportunity is within the corporation's line of business; (3) the corporation has an interest or expectancy in the opportunity; and (4) by [pursuing] the opportunity [personally], the corporate fiduciary will thereby be placed in a position inimicable [sic] to his duties to the corporation.*"[17] In our context, transferring IP to a direct competitor directly conflicts with these provisions.

[16]To illustrate that econometric biases relating to heterogeneous treatment effects (see Baker, Larcker, and Wang (2022)) likely cannot explain our results, we document in appendix IA2 that our results are robust to using Delaware's adoption of COWs alone. This test avoids heterogeneous treatment effects as it is implemented as a one-shot difference-in-difference estimation covering a period where no other states adopt COWs. In the same appendix, we show that our results are also robust to using all states except for Delaware, illustrating also that Delaware alone also cannot explain our results.

[17]Rauterberg and Talley (2017)

The duty of loyalty is widely perceived to be immutable to private efforts to dilute, tailor, or eliminate it. Indeed, without specific state laws indicating otherwise, directors cannot use contracts to avoid exposure to the corporate opportunity doctrine, and D&O insurance does not protect them if they violate the doctrine.[18] Companies thus could not contract out of the corporate opportunities doctrine even if they wanted to.[19] However, in early 2000, Delaware changed its laws and was first to allow companies incorporated there to waive this duty of loyalty with "Corporate Opportunity Waivers" (henceforth COWs).[20] Following Delaware's example, eight more states began allowing waivers to the corporate opportunity doctrine in a staggered manner as Table 7 shows.

The advent of COWs is economically important as a significant number of public companies have adopted such waivers. For example, in an exhaustive analysis of U.S. public company filings with the Securities and Exchange Commission, Rauterberg and Talley (2017) find that over one thousand public corporations have adopted COWs. Additionally, two recent studies illustrate that this test is well-positioned to have strong statistical power in our setting, as Fich, Harford, and Tran (2022) and Eldar, Grennan, and Waldock (2020) show in different contexts that this quasi-experiment indeed had a large impact on investment, firm valuations, and venture capital funding.

Our hypothesis predicts that director incentives to leak will increase in dense CODNs where COWs are more prevalent, and hence our findings should be more pronounced in such settings. Indeed, the risk of IP expropriation associated with COWs has been noted by legal practitioners. For example, a legal expert noted that *"It can be problematic for individuals who serve as directors and officers of multiple organizations to ensure they are not taking advantage of corporate opportunities, or perceived to be doing so (...). The flexibility that comes with the option of advance waiver of corporate opportunities may also lead to real competition and conflict of interest issues that may arise from the usurpation by officers, of corporate opportunities that could have benefited the corporation."*[21]. We exploit the staggered adoption of COWs as plausibly exogenous variation

[18] D&O insurance policies do not cover corporate opportunity doctrine violations as they are based on the "presumption that in making a business decision the directors of a corporation acted on an informed basis, in good faith, and in the honest belief that the action taken was in the best interests of the company" (Aronson v. Lewis, 473 A.2d 805, 812 (Del. 1984)). For a detailed discussion, see section I.A in Rauterberg and Talley (2017) or visit https://www.financierworldwide.com/what-is-a-do-insurance-contract-for.

[19] Companies may want to waive the directors' duty of loyalty to increase their ability to raise capital (see Eldar, Grennan, and Waldock (2020) for supporting evidence), especially from private equity, venture capital, or spin-off transactions. They also might want to waive this duty to expand the pool of potential managers they can hire.

[20] On July 1, 2000, the Delaware Assembly amended the state's statutes to add subsection (17) to section 122 of the DGCL, explicitly permitting COWs.

[21] https://nationalmagazine.ca/en-ca/articles/law/opinion/2022/are-waivers-of-corporate-opportunities-a-good-

in the incentives of directors to leak sensitive information through competitor director networks.

4.1.2 Identification Strategy

A crucial aspect of our identification strategy is that we do not rely on firm-level COW adoptions, which are endogenous. Instead, we use the plausibly exogenous state law changes themselves and thus employ an intent-to-treat approach. Our intent-to-treat framework is standard in difference-in-difference tests that are based on legal changes. In the context of COWs, this approach is also used in Fich, Harford, and Tran (2022). We thus use the state of incorporation and the year of observation to define if a company is "treated" by our COW shock. Although no legal shock can perfectly satisfy the exclusion requirement, four aspects of this setting indicate that violations are unlikely. First, broad changes in state laws are likely exogenous to individual director/firm incentives to pursue corporate opportunities. Second, states began to allow COWs in order to improve financing for small venture-backed firms (see Eldar, Grennan, and Waldock (2020)), and hence their impact on the public firms in our sample was at least partially "accidental". Third, state adoptions are staggered, making it unlikely that other changes can explain our findings. Fourth, our focus is on the exogenous influence of COWs at the network level, and it is particularly unlikely that a focal firm can influence the state laws of its largely out-of-state competitors.

We thus create a dummy variable that equals one if a firm's state of incorporation has enacted a law allowing COWs in a past year, and zero otherwise. Hence treated firms are those that gain the possibility of contracting out of the corporate opportunities doctrine. Using this definition, we find that 62% of our sample is treated. As our focus is on network effects, we also calculate the fraction of each firm's TNIC4 rivals that have been treated by the state-level COW shock. We then create a dummy equal to one if this fraction is above the sample-wide median and zero otherwise. This network measure of COW is thus a shifter of network leakage incentives. It also only depends only on state-level legal changes, and our network test thus also uses the exogenous intent-to-treat framework. In particular, it does not depend on actual firm adoptions of COWs.

We interact our key OD density with the resulting TNIC4-COW variable as shown in equation (3) below. Our thesis predicts that if directors' incentives to leak IP drive the negative effects documented in section 3.2, then the negative effects of OD density will be stronger after the TNIC4

idea

network is treated by COWs (a direct shifter of OD incentives to leak). [22]

$$\begin{aligned} \text{DEP}_{it} = \alpha_0 &+ \beta_1 \text{TN4 ODdensity}_{i,t-1} + \beta_2 \text{TN4 ODdensity}_{i,t-1} x \text{TN4 COW above median}_{i,t-1} \\ &+ \beta_3 \text{TN4 COW above median}_{i,t-1} + \ \delta \text{ Controls}_{i,t-1} + \mu_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{3}$$

4.1.3 Results

Table 8 shows the results of estimating equation (3). We find that all of our results are indeed significantly stronger when TN4 COW treatment is high among competing firms in the network. In particular, the cross-term coefficient β_2 is highly significant and has the same sign as β_1 in Table 3. These findings indicate that the higher the fraction of TNIC4 peers treated by the COW shock, the larger is the positive effect of OD density on total similarity, fluidity, and R&D, and the larger the negative effect on ROA and market value. Additionally, we now find a negative and significant effect on the number and the value of patents. This result is another indication of redundant innovation within the network, as the higher R&D we find indeed is accompanied by fewer novel technologies for any one firm to patent. These results further support the importance of network properties specifically being important along with the innovation herding hypothesis and its predicted negative consequences.

As was true for our baseline results, we also note that the negative effects regarding firm outcomes reported here are also stronger for innovative firms (see appendix IA1). In appendix IA4 we also show that all of these findings are also robust to using our alternative OD network based on *OTHER* employment-based director connections and 2nd-degree director connections.

We next test the parallel trends assumption. If our results are causally linked to the COW shock, the coefficient of ODdensity (β_1 in equation (3)) should be constant before the year of treatment, and it should significantly change soon after the year of treatment. To test this assumption, we first decompose our measure of OD density into parts based on each observation's event-time distance to the year of treatment. This approach is similar in spirit to the cohort approach in Fich, Harford, and Tran (2022), although we implement this methodology at the network level. We thus calculate separate measures of ODdensity, where each uses only the OD links of firms treated by COW

[22] Given our interaction term, a potential concern would be if COW affects the likelihood of forming ODs with TN4 peers. In appendix IA3, we show that this is not the case, as COW does not shift network density, indicating that OD networks are fairly stable. This ensures that our findings are driven by changes in the incentives to leak rather than by any changes in the density of the OD network.

in a given event-year. Here T denotes the treatment event year for the given observation and k denotes how many years the observation is from T. As our sample is long, we consider all values of $k \in \{-20, -19, ..., -3, -2, -1, 0, 1, 2, 3, \ldots, 19, 20\}$. We thus have 41 event years to consider and we calculate a separate ODdensity for each of the 41 event-years. This is done by only summing OD links for firms that were treated k years ago when computing ODdensity, and keeping the rest of the calculation as specified above for our baseline ODdensity variable. Finally, using analogous logic, we also calculate a separate measure of ODdensity for firms never treated by COW. Overall we have 42 measures of ODdensity, which together reflect the content of our original ODdensity variable. Then, we estimate equation (4), which is similar to equation (2) but includes the 42 decomposed parts of ODdensity as follows:

$$\begin{aligned}
\text{DEP}_{it} \quad = \quad & \alpha_0 + \beta_0 \text{TN4 ODdensity [Never Treated]}_{i,t} + \beta_1 \text{TN4 ODdensity [ODs treated 20 years from now]}_{i,t} \\
+ \quad & \beta_2 \text{TN4 ODdensity [ODs treated 19 years from now]}_{i,t} + ... + \beta_{19} \text{TN4 ODdensity [ODs treated 1 years from now]}_{i,t} \\
+ \quad & \beta_{20} \text{TN4 ODdensity [Treated in } T]_{i,t} + \beta_{21} \text{TN4 ODdensity [ODs treated 1 year ago]}_{i,t} \\
+ \quad & \beta_{22} \text{TN4 ODdensity [ODs treated 2 years ago]}_{i,t} + ... + \beta_{41} \text{TN4 ODdensity [ODs treated 20 years ago]}_{i,t} \\
+ \quad & \eta \text{TN4 OD focal}_{i,t-1} + \ \delta \text{ Controls}_{i,t-1} + \mu_i + \gamma_t + \epsilon_{it} \qquad (4)
\end{aligned}$$

The parallel-trends assumption is that there is no change in the coefficients of the ODdensities before event-year T and a significant change soon after. Figure 3 shows the estimated coefficients around year T for TN4 product similarity, ROA, market value, investment in R&D, and patents. The results uniformly support the parallel trends assumption.

In appendix IA5, we report the results of analogous COW analysis for the distant competitors' network (TNIC2-TNIC4). Overall we find that COW strengthens the positive effect of dense OD networks with complementary firms, as we observe more product differentiation, less competitive threat, and more R&D. However, these effects are weaker in magnitude than those in the TNIC4 industry. This result is expected since, as we showed earlier, technology sharing with distant rivals is value-creating. Hence COW matters less for these distant rivals because sharing technologies with them is (both before and after a state adopts COWs) consistent with value creation and fiduciary obligations. In Appendix IA3, we explore the findings of a recent working paper by Geng, Hau, Michaely, and Nguyen (2021) that also studies overlapping directors and illustrate why their findings are distinct from ours.

4.2 Second-degree director links

To further mitigate endogeneity concerns, we use second-degree director links as an instrument for first-degree connections.[23] Two boards are second-degree linked if they 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* at the TNIC-4 level 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 then run a 2SLS analysis using *POPODdensity* as an instrument for *ODdensity*. The instrument should be powerful if industries with a high OD density also have more 2nd-degree connections, as both depend on the number of multi-board directors in the industry. The exclusion restriction relies on the assumption that the focal firm can only control the first-degree connection but not the second-degree one (as it involves a third company's board). Column (1) of Table 9 presents the first stage results, and columns (2) to (8) present results for the second stage.

Overall, Table 9 shows that our results are robust to using second-degree director connections. Columns (2) to (4) show that firms surrounded by more dense second degree OD connections have lower product differentiation, ROA and valuations. Columns (5) to (7) show that they do more R&D, and reduce the rate and value of patenting. Column (8) shows that they also face higher product-market fluidity, although this one result is not statistically significant. This analysis illustrates that our results are robust to using plausibly exogenous variation in OD density.

4.3 Opaque information environments

Our hypothesis predicts that information leakage through networks 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

[23] 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)).

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 closures as plausibly exogenous variation in the quality of the information environment around a firm. Hong and Kacperczyk (2010) illustrate that brokerage 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 closures.

We use the I/B/E/S database to assess analyst coverage.[24] To identify brokerage mergers, we obtain merger events from Hong and Kacperczyk (2010) and Chen, Harford, and Lin (2015), and follow their methodology. First, we identify all firms covered by the merger target brokerage house at the moment of the merger or at any moment in the 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.[25] To identify brokerage closures, we obtain closure events from Chen, Harford, and Lin (2015)[26] 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 event. Following the above articles, a treated firm remains 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 (AS). Hence we are assessing the quality of the information environment in the firm's TNIC4 industry. We then estimate equation (2) 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

[24] 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 of I/B/E/S. This is because, in the later years, I/B/E/S dropped many observations from the database and hence the older database is more complete.

[25] 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.

[26] We thank the authors for sharing the list of events.

firm has more firms affected by the analyst opacity shock. Specifically, we estimate equation (5) and predict that β_1 and β_2 will have the same sign across our array of dependent variables.

$$
\begin{aligned}
\text{DEP}_{it} = \alpha_0 &+ \beta_1 \text{TN4 ODdensity}_{i,t-1} + \beta_2(\text{TN4 AS above median}_{i,t-1})\text{x}(\text{TN4 ODdensity}_{i,t-1}) \\
&+ \beta_3 \text{TN4 AS above median}_{i,t-1} + \ \delta \text{ Controls}_{i,t-1} + \mu_i + \gamma_t + \epsilon_{it}
\end{aligned} \tag{5}
$$

Table 10 shows the results of this regression. 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 product similarity, fluidity, and R&D, and the larger the negative effect on the value of patents, ROA, and valuations. These findings are highly significant, and our use of exogenous variation in information environments provides unique support for the information channel at the network level in generating our findings.

4.4 Geographic proximity

Many studies document knowledge spillovers when companies are geographically close (e.g., Jaffe, Trajtenberg, and Henderson (1993), Ellison and Glaeser (1997), Almeida and Kogut (1999), Greenstone, Hornbeck, and Moretti (2010), Matray (2021)). We explore whether our results are potentially explained by these effects. In our first test, we recalculate *ODdensity* only considering overlapping directors of TN4 firms with headquarters in a different city. In Panel A of appendix IA6, we show that all our results hold using this geographically separated version of *ODdensity*. As the overlapping directors used to construct this alternative measure are not geographically proximate, these findings underscore that our results are unlikely to be driven by geographic connections.

In a second test, we compute an alternative geographic-connectedness network based on the location of each firm's headquarters. Specifically, we define two firms as connected if their headquarters are in the same city. We then compute a measure of *CITYdensity* following the same methodology we use for *ODdensity*. We then re-estimate equation (2) while including both *ODdensity* and *CITYdensity* as competing RHS variables. Panel B in appendix IA6 presents the results and shows that all our findings for *ODdensity* are robust. Moreover, we also note that the consequences of geographic connections are different. For example, the *CITYdensity* coefficient has opposite signs when predicting the value of patents, fluidity, and ROA. We also find no significant results for total similarity and valuations. These findings suggest that geographic connections are distinct, and such connections tend to associate with positive knowledge spillovers.

5 Technology Diffusion

Our network leakage hypothesis predicts that information leaks specifically related to intellectual property are important drivers of the firm outcomes we report. In this section, we test this mechanism directly by curating a list of specific technologies firms discuss in their 10-Ks, and examining how these technologies propagate through the network of firm peers.[27] Our prediction of IP propagation is important to test given that innovation herding plays a prominent role in our intellectual foundation. In particular, we examine if our key variables predict intensified IP propagation among rivals, as such would indicate direct evidence of innovation herding as a mechanism.

5.1 Technology Word List

We use the metaHeuristica software platform and first identify all paragraphs in 10-Ks that contain the word root "technol*". We then extract all noun phrases from these paragraphs and limit attention to those appearing in at least ten such paragraphs in any year. This allows us to focus on technologies that are economically relevant. There are 7,380 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 technologies.

We prune the list of 7,380 noun phrases using a research assistant to tag "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 evolve during our sample. Technological phrases that were not ubiquitous at the start of our sample, however, are relevant because they are expected to grow in use and propagate across firms until they hit equilibrium adoption. This propagation through the product market network is precisely what we hope to

[27] In the context of supply chains, Ahern and Harford (2014) is example of an existing paper in corporate finance studying propagation (in their case the propagation of vertically related mergers).

examine in our context of overlapping directors. This process results in 352 unique technologies, which we list in appendix B.

For each of the 352 noun phrase technologies, we also use metaHeuristica to identify which firms mention each technology in each year. For each firm-year, we also compute the fraction of its TNIC4 peers that mention the technology, and we compute an analogous fraction for each firm's outer peers (those in the focal firm's TNIC-2 but not in its TNIC-4). 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 related intensities for its peers.

5.2 Regressions

Our baseline specifications regress the ex-post focal firm technology dummy (from year t) on the fraction of TN4 peers using the technology in the most recent year $t-1$. 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 firm technologies across peers in a CODN when the CODN's network density is high.

Regarding our COW quasi-natural experiment, we additionally predict that CODNs in markets that are highly exposed to COWs will experience even faster technology diffusion than those with low COW exposure. This would indicate that technology propagates faster through CODNs, and innovation herding is more likely, when directors have stronger incentives to leak.

The results are displayed in Table 11. All regressions include stringent firm fixed effects and technology-by-year fixed effects. Column (1) shows that when TN4 peers have a given technology in year $t-1$, focal firms in the network are significantly more likely to adopt the technology in year t. This is particularly true for firms surrounded by a dense CODN. These inferences regarding direct evidence of innovation herding for dense CODNs obtain because both the "TN4 Peers Have Tech in $t-1$" and the cross term with "TN4 OD density" are highly significant at the 1% level. Column (2) next establishes baseline results for the COW shock. We indeed find significantly more propagation when a firm is in a CODN where a higher fraction of its peers are impacted by the COW shock (indicating stronger group incentives to leak technologies through the network). Column (3) shows that the results in the first two columns are also robust when included together.

Finally, column (4) examines the most direct and specific prediction of our thesis: that technological propagation is likely to be most intense when all three of the following conditions are met: the firm is surrounded by a dense CODN, peers have a given technology ex-ante, and a large number of peers are treated by the COW shock. This prediction needs to be tested using a triple interaction, and we include all double and single interactions (as well as the fixed effects) in our specification. Column (4) shows that the key triple interaction is highly significant with a t-statistic of 6.6. These tests support our intellectual foundation and provide rather direct evidence of our hypothesized innovation herding mechanism through dense CODNs.

Table 12 examines these same tests using OD density measured using second-degree director overlaps, which are more exogenous relative to first-degree connections. Our results are fully robust.

6 Theoretical Consistency

We explore two important predictions of the intellectual foundation presented in Section 1.1. First, we examine the prediction that our results should be strongest when firms independently produce correlated innovation. Second, CODNs can be stable even when they are leaky.

6.1 Correlated Innovation

As we noted in Section 1.1, our predictions (especially H2) are strongest when firms tend to invent similar innovations at roughly the same time. We first clarify that our model does not require the more strict assumption that firms independently produce exactly the same technologies. Rather, it only requires that firms in the same industry tend to produce correlated solutions to the same set of product market needs. For example, our model's predictions obtain if one firm produces an induction technology to create a new product feature and another produces a capacitor-based solution to solve the same problem. In this section, we first outline the existing literature documenting correlated innovation, and we then test its predicted relevance in our setting.

6.1.1 Correlated Innovation is the Norm

"Surveys of hundreds of significant new technologies show that almost all of them are invented simultaneously or nearly simultaneously by two or more teams working independently of each other." This quote is from Lemley (2011), who provides a 24-page review of the history of correlated vs

independent innovation in his Section I. We refer readers interested in the complete literature to Lemley (2011).

In practice, and both for game-changing and smaller innovations, correlated innovation is the norm and independent innovation is the exception. Ogburn and Thomas (1922) documents 148 famous cases of simultaneous invention including the telephone, the telegraph, the incandescent electric light, the microphone, the sewing machine, the balloon, the typewriter, electric motors, the induction coil, the ring armature, the self-exciting dynamo, and the use of gasoline engines in automobiles. Regarding smaller inventions, Cotropia and Lemley (2008) report that 90 to 98 percent of modern patent lawsuits are filed against simultaneous inventors, not copiers.

As Lemley (2011) explains, there are three primary reasons for the high prevalence of simultaneous invention, and they especially apply for firms in the same industry (important for our research question). First, most inventions arise as a response to consumer demands, which are typically co-observed by industry participants. Second, many inventions are a response to changes in supply conditions, such as one input suddenly becoming more scarce. In such scenarios, industry rivals are likely to simultaneously develop alternatives. Finally, inventions are likely to co-occur because inventors are commonly influenced by the same prior art (see Stigler (1955) and Landers (2010)). Lemley (2011) illustrates these forces in detail.

6.1.2 Tests of Correlated Innovation

Because correlated innovation is an important assumption in our model of coordination failure, the evidence summarized by Lemley above already provides strong support for our intellectual foundation. Our model further suggests that our main results regarding innovation herding should be even stronger when correlated innovation is especially likely. To test this deeper prediction, we propose that correlated innovation is more likely when industry rivals have more homogeneous products. We measure product homogeneity as the *average* product similarity across TNIC4 peers. The common-consumer-demand channel Lemley notes (summarized above) as a driver of correlated innovation should be strongest in these homogenous markets. Although it is not material to our inferences, to increase the exogeneity of this measure, we impose a three year lag. We create a dummy variable that equals one if a firm's average TNIC4 similarity is above the median, and we interact it with *TN4 ODdensity* in our main regressions. Panel A in Table 13 reports the results, and we find that our main results are indeed stronger when products are more homogeneous.

To test our predictions through the lens of Stigler (1955)'s common influence channel for correlated innovation, we next consider a measure of *Technological Breadth* from Bowen, Fresard, and Hoberg (2023). Breadth is high when a firm's patents are drawn from multiple technological areas. When an industry has a high breadth, the correlation of technologies is expected to be low due to the complexity of drawing ideas from multiple disciplines. The common-influence effect is likely to be weaker in such cases as inventors will face many different influences, making processing costs higher. We thus calculate the average Breadth across all TNIC4 peers and create a dummy variable that equals one if the average TNIC4 Breadth is below the median. We then interact this dummy with *TN4 ODdensity*. Panel B reports the results and we find that all of our main results are indeed stronger when breadth is low.

In appendix IA7, we show that the results of our COW analysis in section 4.1 are also stronger for industries with more homogenous products and lower technological breadth. We estimate a model with a triple interactions between TN4 OD density, TN4 COW, and each indicator of correlated innovation. Our predicted effects are strongest when all three of the following conditions are met: the firm is surrounded by a dense OD network, a large number of peers are treated by the COW shock, and the focal firm is in an industry with more correlated innovation.

In appendix IA8, we find that our main results regarding negative firm outcomes are also stronger for industry laggards than for industry leaders (leaders and laggards are defined as having above vs. below 90th percentile R&D/assets within each firm's TNIC industry, respectively). This result also conforms to predictions as followers are more likely to have correlated innovation than leaders. We thus expect stronger results for followers.[28] In appendix IA9, we also show that our findings are also stronger in markets with more firms. This also aligns with our predictions as the existence of more firms increases the odds of multiple firms discovering correlated technologies.

6.2 Stability of Dense OD Networks

Our hypothesis H3 predicts a coordination problem in which leaky CODNs can be stable and individually optimal despite their collectively negative consequences. The logic echoes the "Tragedy of the Commons," as industry participants find it individually optimal to hire ODs because the

[28]This is also consistent with laggards being particularly sensitive to losing the limited IP they accumulated.

benefits of receiving leaked technology are larger than the costs of having one's own technology leaked (it will be leaked anyway given the presence of correlated innovations by rivals). Our model thus predicts that companies might reward their ODs, as their presence facilitates the receipt of technologies transmitting through the CODN.

We test this prediction in appendix IA10. The results are suggestive, but illustrate that ODs do realize improved career prospects both in terms of higher pay and recommendations to serve on more boards when they work in industries with dense CODNs ex-ante. Moreover, these career benefits are particularly positive when there is also evidence of likely technology transmissions taking place across the boards the director serves.

7 Conclusion

We examine the consequences of dense competing-firm overlapping director networks (CODNs) on firm innovation and product market strategies. We find that CODNs are associated with innovation herding and losses in product differentiation. These losses in valuable differentiation from rivals are accompanied by poor ex post performance in the form of lower profits and lower valuations.

We explore a number of tests to mitigate concerns about endogeneity. Our first uses staggered state-level adoption of corporate opportunity waivers (COW) that directly shift OD incentives to leak IP as the legal consequences of leakage are significantly reduced. A second test follows the network econometrics literature and assesses network density using second-degree director connections, which require that connections must pass through a third company's board (more exogenous as a third firm's board is not controlled by a given firm). Finally, we consider a quasi natural experiment based on plausibly exogenous losses in analyst coverage to causally link our results to the quality of the information environment. These tests support our conclusion that innovation herding likely explains the negative outcomes we report.

Our results are consistent with the leakage of intellectual property to direct competitors, resulting in reduced rents and innovation-herding. Further supporting technology transfers as a mechanism, in a novel test, we identify 352 individual technologies using textual analysis and find significant evidence that technologies propagate faster to competitors when a dense CODN is present and when plausibly exogenous incentives to leak information are stronger.

Our results are predicted by a simple model of coordination failure, where the well-documented presence of correlated innovation among rivals increases firm incentives to hire ODs as they can harvest technologies circulating in the network. Yet this practice creates negative competitive externalities for industry rivals which are unavoidable in equilibrium as participants cannot influence the decisions of their peers. In specialized mechanism tests, we find supporting evidence relating to actual technology propagation, evidence supporting the predicted role of coordinated innovation, and evidence based on overlapping director careers. Our innovation herding hypothesis and our empirical results are both new to the literature.

Appendix A Simple Model

We first consider an illustrative model in which firms operating in a single industry are endowed with technologies. Each technology can create one novel product feature. Each competitor in the industry has a platform that can be used to sell the product features and market equilibrium for each feature is determined by non-cooperative competition *a-la-Cournot*. In particular, competition takes place for each product feature among all companies that have the given technology. This type of setting allows us to model market power and its link to using technology to generate differentiated products. Intuitively, when fewer firms are endowed with a given technology, it is more profitable.

We adopt a standard Cournot model of competition for product features that assumes a symmetric linear cost function $c\ x_t$ for each technology a firm has developed. The demand function in each market is of the form $P_t = A - X_t$. Additionally, we assume that in order to enter the market associated with a given technology and sell its corresponding product feature, the firm must incur in a development cost of d to convert the technology into its product feature. This is akin to the cost of commercializing an invention or technology into a saleable product feature. We assume throughout that market size (A) is large relative to costs in order to avoid uninteresting scenarios where firms do not invest (in particular, we assume $A > c + 5\sqrt{d}$). For simplicity, we will assume there are four firms. This number is adequately rich to generate all of our key predictions without loss of generality.

Crucially given our hypotheses, in some scenarios below, we assume that there exists a leaky network of overlapping directors across competitors. If a firm joins this network —by hiring an OD—, its technology leaks to the other three firms. However, the firm also receives the technologies held by the other connected firms. This framework indicates the intuition that a leaky network generates two-way technology transmissions.

A.1 Uncorrelated Innovation

Overall we find that correlated innovation is important in deriving predictions relevant to network effects in our innovation setting. In order to illustrate its importance, we first solve the model without correlated innovation as a baseline. To model this scenario, we assume that all four firms are endowed with unique technologies. Thus each firm has a different technology than the other three and all innovation is distinct. In such a setting, if a firm does not join a leaky network, it is able to keep its unique technology proprietary and it can monopolize the technology. We denote this scenario as "M" indicating monopolization of individual technologies.

$$\begin{aligned}\max_{\{x_i\}} \pi &= (A - x_i)x_i - cx_i - d \\ &\Rightarrow \pi^M = \frac{1}{4}(A-c)^2 - d\end{aligned}$$

Alternatively, if the firm joins the leaky network, it loses its technology to the other three firms but gains the other three technologies. Thus, if it joins, the firm operates in four oligopolies. We refer to this scenario as "LU" to denote a leaky network for the case of initially uncorrelated technology endowments.

$$\begin{aligned}\max_{\{x_i\}} \pi &= 4(A - 3x_j^* - x_i)x_i - 4cx_i - 4d \\ &\quad \text{with } x_j^* = \arg\max_{x_j} \{4(A - 3x_i - x_j)x_j - 4cx_j - 4d\} \\ \Rightarrow &\quad \pi^{LU} = \frac{4}{25}(A-c)^2 - 4d\end{aligned}$$

Since $\pi^M > \pi^{LU}$ for any $d > 0$, the firm does not have incentives to join the leaky network when technology is uncorrelated. For example, if firms are able to choose whether or not to join the leaky network in this world, a leakage Nash Equilibrium does not exist. Rather, all firms will optimally avoid joining the network. However, going outside the presented model, a leakage equilibrium nevertheless could be supported if directors have agency problems where they are able to extract private benefits from leakage. Additionally, leakage could be supported if the firm is not capable of detecting leakage or its consequences. However, as we show in the next section, for the case of correlated innovation, a leaky network equilibrium does exist even in the absence of both agency problems and behavioral biases.

A.2 Correlated Innovation

We now model the important case of "correlated innovation" by considering a second case in which there are only two technologies, and two of the four firms are endowed with each. If there are no ODs at all, and hence the network has no leaks, we have two firms competing with each other in Cournot duopolies with the following objective function and equilibrium profits (for parsimony, we henceforth refer to this scenario of no leaks as "NL scenario" indicating no leaks).

$$
\begin{aligned}
\max_{\{x_i\}} \ \pi &= (A - x_j^* - x_i)x_i - cx_i - d \\
& \quad \text{with } x_j^* = \arg\max_{x_j} \{(A - x_i - x_j)x_j - cx_j - d\} \\
\Rightarrow & \quad \pi^{NL} = \frac{1}{9}(A-c)^2 - d
\end{aligned}
$$

If, instead, the firm does join a leaky network, it gets to operate in two four-firm oligopolies as both technologies are transferred to all four firms. Profits in this scenario are (for parsimony, we henceforth refer to this scenario with leaks and the firm joining the network as the "LJ scenario"):

$$
\begin{aligned}
\max_{\{x_i\}} \ \pi &= 2(A - 3x_j^* - x_i)x_i - 2cx_i - 2d \\
& \quad \text{with } x_j^* = \arg\max_{x_j} \{2(A - 3x_i - x_j)x_j - 2cx_j - 2d\} \\
\Rightarrow & \quad \pi^{LJ} = \frac{2}{25}(A-c)^2 - 2d
\end{aligned}
$$

To examine if joining a leaky network is optimal, we next examine the case of one firm deviating from the fully leaking network LJ scenario. In particular, this scenario involves a fully leaky OD network including all competitors, but the focal (deviating) firm does not connect. The focal firm will thus operate in only one market, as it only has its one endowed technology in the case of not joining the network (it receives no additional technologies from the network). Yet this firm will still operate in a four-firm oligopoly for its one technology because its technology will be leaked even if it does not join the network. This is because it was not the only firm that generated its endowed technology as innovation is correlated as indicated above. This focal firm's profits are (for parsimony, we henceforth refer to this scenario with leaks and the focal firm not joining the network as "LNJ scenario"):

$$
\begin{aligned}
\max_{\{x_i\}} \ \pi &= (A - 3x_j^* - x_i)x_i - cx_i - d \\
& \quad \text{with } x_j^* = \arg\max_{x_j} \{2(A - 3x_i - x_j)x_j - 2cx_j - 2d\} \\
\Rightarrow & \quad \pi^{LNJ} = \frac{1}{25}(A-c)^2 - d
\end{aligned}
$$

We observe that firms are better off if there is no leaky network at all, as π^{NL} has the highest level of profit among the three scenarios. However, if there exists a leaky network, the firm is better off if it joins the leaky network. This prediction obtains because $\pi^{LJ} > \pi^{LNJ}$.

This finding illustrates a coordination problem among the four firms. Once the leaky network is present, it is self-reinforcing because it is optimal to remain connected. Yet this is not globally optimal as the four firms would all be better off if the leaky network was dissolved. This arises because any one firm can only choose its own directors and has no control over the director choices of its rivals. This is because the game is non-cooperative, and hence any one firm cannot choose the level of leakiness of its network.

A.2.1 Modeling Network Connection as a Choice

Our derivations above take network connections as given, and firms only optimize quantity given the Cournot competition in the market for product features. In this subsection, we continue our focus on the case of correlated innovation and consider expanding the decision set of each firm to also allow it to choose to connect to the leaky network or not.

There are two pure strategy Nash equilibria in this setting. In the first, all firms choose not to connect and a maximum profit equilibrium with zero network connections emerges. Firm profits are π^{NL} as derived above in this equilibrium. In the second, all firms choose to connect despite the fact that profits are lower in this equilibrium than in the first equilibrium. Yet this second equilibrium is a pure strategy Nash Equilibrium because $\pi^{LJ} > \pi^{LNJ}$, as shown above. Thus firms choose to join the leaky network in this case because it is nevertheless more profitable for a firm to remain connected than it is to deviate and disconnect.

This second self-reinforcing low profit Nash equilibrium is similar to the famous Prisoner's Dilemma, which also features an inability to coordinate as a foundation for the low-utility Nash Equilibrium. In our setting of innovative investment, this also indicates a "tragedy of the commons," as industry participants will effectively over-develop the available technologies and will be collectively worse off as compared to the alternative equilibrium of no sharing.

A.2.2 Innovation Comparative Statics

In this final section, we keep our focus on the case of correlated innovation and we further focus on the low profit equilibrium with a leaky network. We now also compare this equilibrium to the high profit equilibrium without a leaky network. We derive comparative statics for how much R&D and patenting we expect in each equilibrium. Importantly, we divide R&D into a development cost to commercialize technologies and a research cost to innovate and create new technologies. We anticipate that patents will be correlated with the research-based investment but not the development investments. Regarding development, we modeled this cost as d for each technology a firm commercializes as noted above.

In order to understand the research costs, we extend the model above and include an initial period (time zero), where firms are no longer endowed with a technology, but instead they must initially choose a scale for their project, which we denote as R. Investing R in research has convex costs of kR^2. We assume that R scales all aspects of the firm and hence final profits earned by the firm are proportional to R. We also note that this extended model nests our original models above. This is because, if we set $R = 1$, we have the equilibrium solutions noted above. In this baseline model with $R = 1$, the equilibrium development expenditures are d, $2d$, and d, respectively, in the NL, LJ, and LNJ cases as described above.

When we generalize the model to allow the initial investment R as a choice variable, all objective functions above scale proportionally by R as do the profits, and hence the equilibrium development levels are Rd, $2Rd$, and Rd in the three cases, respectively. When we solve the model with generalized research investments at time zero (with convex costs as noted above), we find that the optimal levels of research investments in each of the three cases is as follows:

$$R^{NL} = \frac{A^2 - 2Ac + c^2 - 9d}{18k}; \qquad R^{LJ} = \frac{A^2 - 2Ac + c^2 - 25d}{25k}; \qquad R^{LNJ} = \frac{A^2 - 2Ac + c^2 - 25d}{50k}$$

When d and k are positive, these solutions indicate that equilibrium investments in research are higher for the NL scenario than for the LJ scenario. Thus we predict fewer and less valuable patents when a firm is surrounded by a leaky network (LJ) than when it is *not* surrounded by a leaky network (NL). The expressions for development costs go the other way, as the firm with a leaky network must commercialize more technologies. Hence we expect development costs to be higher in the presence of a leaky network even though patents are less common and less valuable.

Appendix B Technology Noun Phrases

We now list the noun phrases used in our technological diffusion tests in Section 5 of the 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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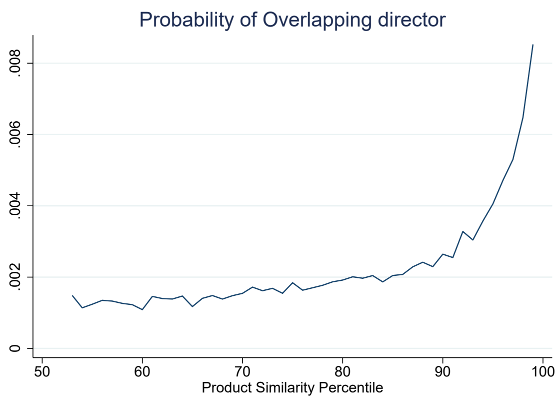
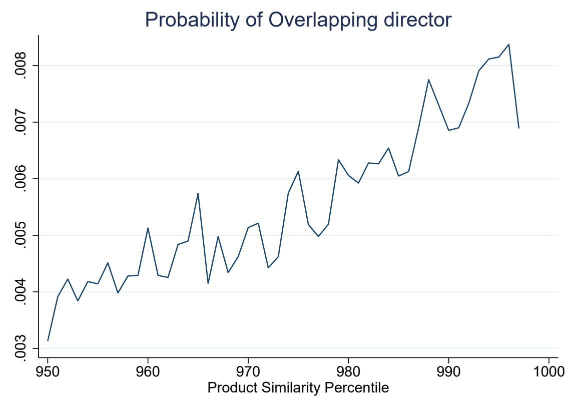
Figure 1: Director overlap by percentile of TNIC Similarity

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.

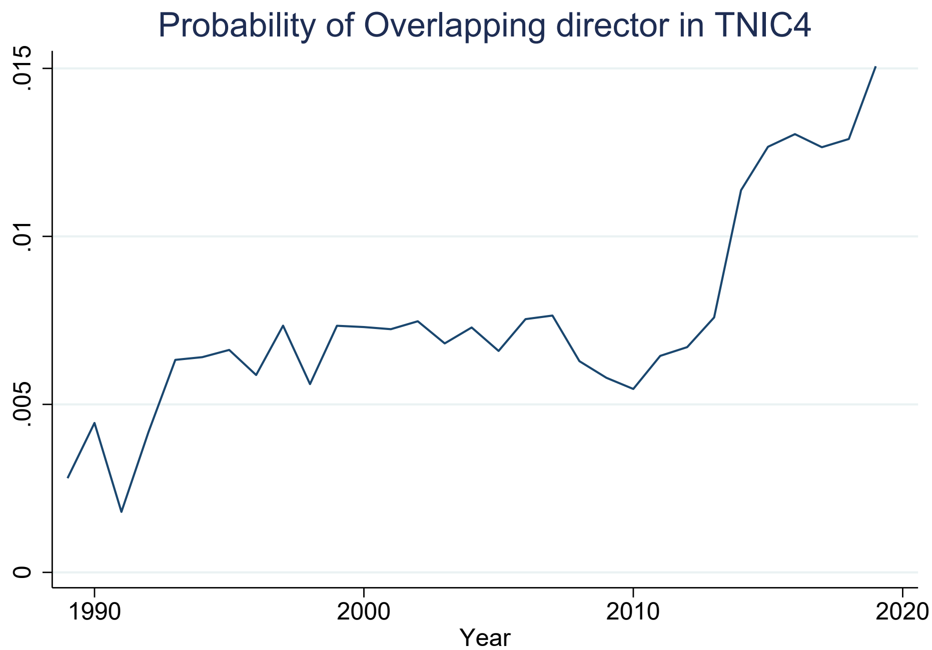
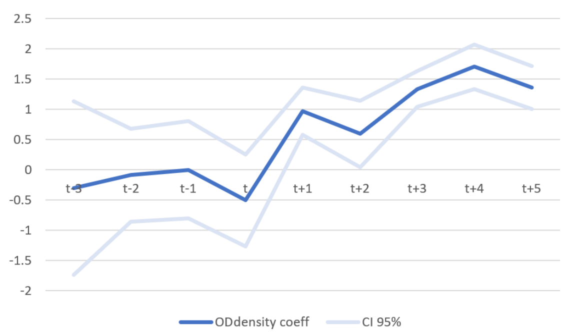
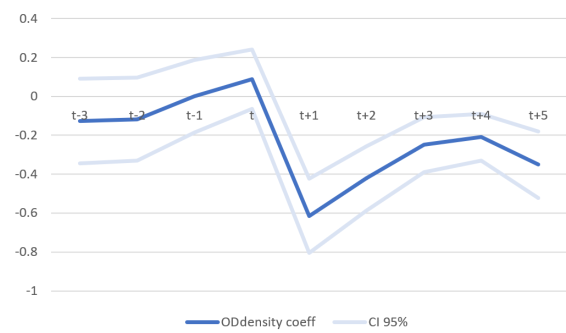


Figure 3: TNIC4 OD density and Corporate Opportunities Waivers: Parallel Trends

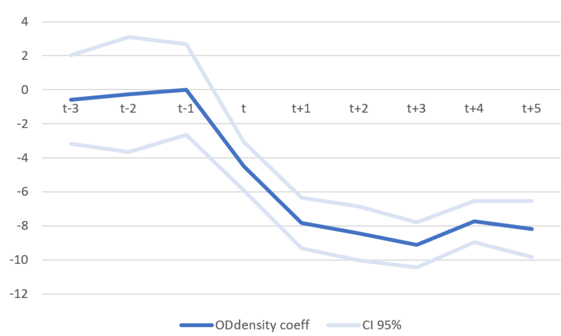
The figure illustrates parallel trends analysis using a 7-year event study window around COW adoptions. Each figure reports the coefficient of highly targeted ODdensity variables, where ODdensity is separately calculated only using OD links of firms treated by COW in a certain event-year. The left-most data point in each graph is based on OD links for firms that will be treated three years into the future. The remaining six data points are based on OD links treated two-years into the future ("t-2") through the year of treatment ("t"), and through the third year after treatment ("t+3"). All of these coefficients are estimated in a regression that includes separate terms for each of the OD links in each year starting from 20 years pre-treatment to 20-years post-treatment. This ensures that each coefficient only compares treated firms in each year to those OD links that are untreated. In particular, the regression also includes the ODdensity of firms that are never treated by COW. Additionally, the regressions include all the controls included in equation (2), firm fixed effects, and year fixed effects.



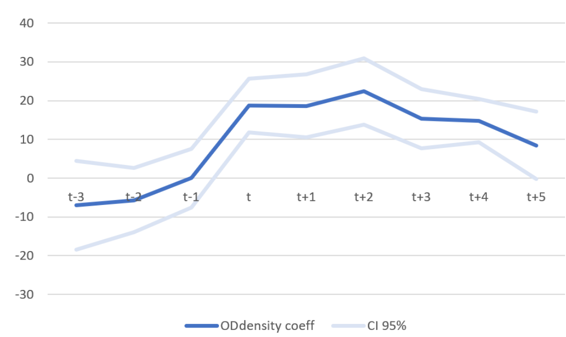
(a) TN4 Prod Similarity



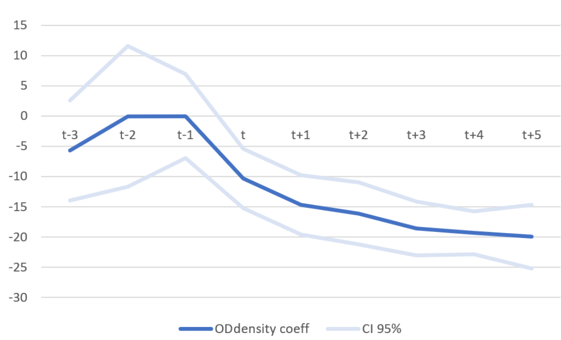
(b) ROA



(c) Market/Book



(d) R&D/assets



(e) Patents/assets

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, firm age, market to book ratio, and ROA are financial indicators from Compustat. 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	42138	.012	.012	0	.05	.01
1st-degree OD density TNIC2-TNIC4	43909	.007	.003	0	.022	.007
2nd-degree OD density TNIC4	42138	.018	.021	0	.083	.011
1st-degree OD focal TNIC4	42181	.008	.018	0	.086	0
1 if OD with TNIC4 peer	43909	.183	.387	0	1	0
XRD/(total assets)	44073	.046	.072	0	.384	.005
Number of patents/(total assets)	44073	.007	.014	0	.114	0
Total Value patents/(total assets)	44073	.031	.081	0	.765	0
TNIC4 Total product similarity	43059	2.702	5.748	.008	54.152	.675
Product market fluidity	43544	6.63	3.22	2.002	20.274	5.993
ROA	44017	.092	.136	-.583	.311	.116
Market to book ratio	43973	1.712	1.163	.169	6.946	1.325
Log of total assets	44073	6.617	1.819	2.823	10.975	6.592
Log of age	44086	2.627	0.8	.693	4.06	2.708

Table 2: Correlations

This table displays the correlation matrix of the main variables.

	TN4 density	TN4 2deg OD density	TN4 OD ODfocal	XRD/ at	pat/ at	val pat/t at	TSim TN4	Fluidity	ROA	mkt/ book
TN4 OD density	1.000									
TN4 2deg OD density	0.409	1.000								
TN4 ODfocal	0.347	0.175	1.000							
XRD/at	0.258	0.242	0.168	1.000						
Pat/at	0.135	0.047	0.093	0.449	1.000					
Val pat/at	0.104	0.048	0.097	0.314	0.665	1.000				
TSimTN4	0.247	0.334	0.213	0.475	0.113	0.107	1.000			
Fluidity	0.226	0.195	0.188	0.349	0.160	0.124	0.604	1.000		
ROA	-0.169	-0.204	-0.111	-0.542	-0.156	0.017	-0.412	-0.312	1.000	
mkt/book	0.117	0.096	0.087	0.360	0.228	0.318	0.226	0.180	0.025	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. In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In columns (2) and (3), the dependent variables are ROA and market to book ratio. In column (4), it is the firm's XRD/(total assets). In column (5), it is the number of patents divided by total assets. In column (6), it is the total value of patents divided by total assets. In column (7), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. Controls include the log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are standardized (z-score) and winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
TN4 OD density in t-1	0.011***	-0.008**	-0.009**	0.004**	0.001	-0.009*	0.021***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.006)	(0.004)
Log of total assets in t-1	0.060***	0.025*	-0.249***	-0.114***	-0.089***	-0.114***	0.078***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.018)	(0.021)	(0.011)
Log of firm age in t-1	-0.025*	0.024*	-0.066***	0.026***	-0.141***	0.006	-0.160***
	(0.013)	(0.014)	(0.019)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.040***	0.167***		-0.017***	0.000	0.064***	0.023***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,457	43,420	43,467	43,471	43,471	43,471	42,935
R-squared	0.870	0.737	0.659	0.906	0.647	0.610	0.800
Adj within R2	0.012	0.053	0.039	0.026	0.011	0.013	0.017
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Table 4: Director links beyond board overlap

This table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density. OD density in this table is built using a company network based on directors' connections different from overlapping company boards. In panel A, two firms are connected if they have directors that share a job in a third institution such as country clubs, charities, universities, etc. In panel B, two firms are connected if the directors serve in a common third board (second-degree connection). Column (1) regresses the alternative OD density on our baseline OD density measure. Column (2) to (8) shows the same analysis of Table 3 using second-degree directors' connections. All variables are standardized (z-score) and 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: OTHER connections

	(1) TN4 OD	(2) TSim $TN4_t$	(3) ROA_t	(4) Mkt/ $Book_t$	(5) XRD_t/ at_t	(6) Pat_t/ at_t	(7) $ValPat_t$/ at_t	(8) $Fluid_t$
TN4 OTHERdensity in t	0.121***							
	(0.006)							
TN4 OTHERdensity in t-1		0.005**	-0.006*	-0.005*	0.001	-0.006	-0.028***	0.036***
		(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.004)
Observations	43,720	42,411	43,814	43,376	43,471	43,471	43,471	42,890
R-squared	0.465	0.870	0.726	0.741	0.911	0.649	0.612	0.800
Adj within R2	0.018	0.012	0.012	0.271	0.074	0.018	0.018	0.018
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: 2nd-degree connections

	(1) TN4 OD	(2) TSim $TN4_t$	(3) ROA_t	(4) Mkt/ $Book_t$	(5) XRD_t/ at_t	(6) Pat_t/ at_t	(7) $ValPat_t$/ at_t	(8) $Fluid_t$
TN4 POPOD density in t	0.231***							
	(0.009)							
TN4 POPOD density in t-1		0.039***	-0.012***	-0.006	0.012***	-0.034***	-0.044***	0.001
		(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)	(0.003)
Observations	43,768	42,457	43,420	43,467	43,471	43,471	43,471	42,935
R-squared	0.485	0.871	0.737	0.659	0.906	0.647	0.611	0.799
Adj within R2	0.055	0.018	0.053	0.039	0.027	0.013	0.015	0.016
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 5: TNIC4 OD density and direct connections to the TNIC4 OD network

This table presents the same analysis of Table 3. The estimation includes an interaction term between TN4 OD density and TN4 OD focal. TN4 OD focal is the fraction of TNIC4 peers that share a director with the focal firm. Both TN4 OD density and TN4 OD focal are standardized such that they have a mean of zero and a st. dev of one. In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In columns (2) and (3), the dependent variables are ROA and market to book ratio. In column (4), it is the firm's XRD/(total assets). In column (5), it is the number of patents divided by total assets. In column (6), it is the total value of patents divided by total assets. In column (7), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. In panel B, the dummy equals one if the focal firm is connected to TN4 rival through an OD, a POP or an OTHER connection. Controls include the log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are standardized (z-score) and 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: connection via OD

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
TN4 OD density in t-1	0.011***	-0.006*	-0.010**	0.005**	0.001	-0.008	0.019***
	(0.002)	(0.003)	(0.005)	(0.002)	(0.005)	(0.006)	(0.004)
OD focal in t-1	-0.002	-0.003	0.011	-0.001	0.009	0.001	0.015***
	(0.004)	(0.005)	(0.007)	(0.004)	(0.007)	(0.009)	(0.005)
(TN4 OD density in t-1)	-0.002	-0.005*	-0.006*	-0.002	-0.008**	-0.009**	-0.011***
x(OD focal in t-1)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.003)
Observations	42,457	43,420	43,467	43,471	43,471	43,471	42,935
R-squared	0.870	0.737	0.659	0.906	0.647	0.610	0.800
Adj within R2	0.012	0.053	0.039	0.026	0.011	0.013	0.018
Controls	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel B: connection via OD, POP OD, or OTHER

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
TN4 OD+POP+OTH density in t-1	0.024***	-0.008**	-0.007**	0.009***	-0.019***	-0.019***	0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.004)
TN4 OD+POP+OTH focal in t-1	-0.010**	-0.000	0.005	-0.001	0.015**	0.002	0.014***
	(0.004)	(0.005)	(0.004)	(0.003)	(0.006)	(0.009)	(0.005)
(TN4 OD+POP+OTH density in t-1)	0.012***	-0.001	-0.003	0.000	-0.018***	-0.016***	-0.012***
x(TN4 OD+POP+OTH focal in t-1)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)
Observations	42,457	43,420	43,376	43,471	43,471	43,471	42,935
R-squared	0.870	0.737	0.741	0.906	0.647	0.610	0.799
Adj within R2	0.015	0.053	0.272	0.026	0.013	0.014	0.017
Controls	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Table 6: Outer ring (TNIC2-TNIC4) 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 columns (2) and (3), the dependent variables are ROA and market to book ratio. In column (4), it is the firm's XRD/(total assets). In column (5), it is the number of patents divided by total assets. In column (6), it is the total value of patents divided by total assets. In column (7), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. Controls include the log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are standardized (z-score) and winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
TN4 OD density in t-1	0.012***	-0.008**	-0.009**	0.004**	0.001	-0.010*	0.022***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.006)	(0.004)
TN2-TN4 OD density in t-1	-0.027***	0.010***	0.009*	0.002	0.007	0.030***	-0.034***
	(0.003)	(0.004)	(0.005)	(0.002)	(0.005)	(0.006)	(0.005)
Log of total assets in t-1	0.060***	0.025*	-0.248***	-0.114***	-0.089***	-0.113***	0.075***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.018)	(0.021)	(0.011)
Log of firm age in t-1	-0.024*	0.023	-0.067***	0.026***	-0.142***	0.005	-0.156***
	(0.013)	(0.014)	(0.019)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.040***	0.167***		-0.017***	0.000	0.064***	0.021***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,457	43,420	43,467	43,471	43,471	43,471	42,935
R-squared	0.870	0.737	0.659	0.906	0.647	0.610	0.790
Adj within R2	0.014	0.053	0.039	0.026	0.011	0.014	0.018
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Table 7: Corporate opportunities waiver adoption timeline

This table presents the States that adopted COW and the date of the adoption.

State	Date
Delaware	July 1, 2000
Oklahoma	November 1, 2001
Missouri	October 1, 2003
Kansas	January 1, 2005
Texas	January 1, 2006
Nevada	October 1, 2007
New Jersey	March 11, 2011
Maryland	October 1, 2014
Washington	January 1, 2016

Table 8: TNIC4 OD density and Corporate opportunities waivers

This table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density. The estimation includes an interaction term between TN4 OD density and a dummy that equals one if the percentage of TNIC4 rivals affected by Corporate Opportunities Waiver is above the median (TN4 COW). In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In columns (2) and (3), the dependent variables are ROA and market to book ratio. In column (4), it is the firm's XRD/(total assets). In column (5), it is the number of patents divided by total assets. In column (6), it is the total value of patents divided by total assets. In column (7), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. Controls include the log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are standardized (z-score) and winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 ODdensity in t-1)	0.029***	-0.013**	-0.026***	0.015***	-0.058***	-0.101***	0.033***
x(TN4 COW in t-1)	(0.005)	(0.006)	(0.008)	(0.004)	(0.010)	(0.013)	(0.006)
TN4 ODdensity in t-1	0.000	-0.003	0.001	-0.001	0.023***	0.028***	0.009**
	(0.003)	(0.004)	(0.005)	(0.002)	(0.006)	(0.008)	(0.004)
TN4 COW in t-1	0.038***	-0.007	-0.027**	0.002	-0.020*	-0.086***	0.049***
	(0.007)	(0.008)	(0.011)	(0.006)	(0.012)	(0.014)	(0.009)
Log of total assets in t-1	0.058***	0.025*	-0.247***	-0.115***	-0.087***	-0.109***	0.075***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.018)	(0.021)	(0.011)
Log of firm age in t-1	-0.027**	0.024*	-0.066***	0.026***	-0.140***	0.010	-0.164***
	(0.014)	(0.014)	(0.019)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.041***	0.166***		-0.017***	-0.001	0.063***	0.023***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,376	43,331	43,378	43,382	43,382	43,382	42,845
R-squared	0.870	0.737	0.659	0.906	0.647	0.613	0.800
Adj within R2	0.014	0.053	0.039	0.026	0.013	0.019	0.020
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Table 9: Instrumental analysis: TNIC4 second-degree OD density

This table presents the results of a 2SLS estimation using the TNIC4 peer-of-peer OD density as an instrument for TNIC4 OD density. Column (1) presents the first stage and columns (2) to (9) the second stage. In column (2), the dependent variable is the firm's total product similarity in its TNIC4 group. In columns (3) and (4), the dependent variables are ROA and market to book ratio. In column (5), it is the firm's XRD/(total assets). In column (6), it is the number of patents divided by total assets. In column (7), it is the total value of patents divided by total assets. In column (8), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. Controls include the log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are standardized (z-score) and winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

	(1) TN4 OD	(2) TSim $TN4_t$	(3) ROA_t	(4) Mkt/ $Book_t$	(5) XRD_t/ at_t	(6) Pat_t/ at_t	(7) $ValPat_t$/ at_t	(8) $Fluid_t$
TN4 POPODdensity in t	0.231***							
	(0.009)							
Inst TN4 ODdensity in t-1		0.171***	-0.053***	-0.032**	0.053***	-0.148***	-0.189***	0.003
		(0.020)	(0.016)	(0.014)	(0.012)	(0.020)	(0.024)	(0.015)
Log of total assets in t-1	0.000**	0.053***	0.027**	-0.177***	-0.117***	-0.082***	-0.105***	0.079***
	(0.000)	(0.011)	(0.013)	(0.009)	(0.010)	(0.018)	(0.022)	(0.011)
Log of firm age in t-1	-0.000	-0.027*	0.024*	-0.010	0.026***	-0.140***	0.008	-0.160***
	(0.000)	(0.014)	(0.014)	(0.012)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	-0.000	0.041***	0.166***	0.404***	-0.017***	-0.000	0.064***	0.023***
	(0.000)	(0.006)	(0.007)	(0.008)	(0.005)	(0.008)	(0.011)	(0.005)
Observations	43,768	43,059	44,017	43,973	44,073	44,073	44,073	43,544
R-squared	0.174							
Adj within R2	0.113							
F-stat	63.09							
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 10: TNIC4 ODdensity and secretiveness

This table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density (de-meaned). The estimation includes an interaction term between OD density and a dummy that equals one if 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)) is above the median (TN4 AS). In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In columns (2) and (3), the dependent variables are ROA and market to book ratio. In column (4), it is the firm's XRD/(total assets). In column (5), it is the number of patents divided by total assets. In column (6), it is the total value of patents divided by total assets. In column (7), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. Controls include the log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are standardized (z-score) and winsorized at the 5-95% level. Standard errors are clustered by firm and reported in parentheses. Significance levels are indicated: *=10%, **=5%, ***=1%.

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 ODdensity in t-1)	0.008**	-0.017**	-0.020**	0.014***	-0.000	-0.029***	0.021***
x(TN4 AS in t-1)	(0.004)	(0.008)	(0.009)	(0.005)	(0.009)	(0.011)	(0.008)
TN4 ODdensity in t-1	0.008***	-0.004	-0.005	0.002	0.002	-0.003	0.015***
	(0.002)	(0.004)	(0.005)	(0.002)	(0.005)	(0.005)	(0.004)
TN4 AS in t-1	0.026***	0.027***	0.028***	-0.019***	0.007	-0.016*	0.036***
	(0.005)	(0.008)	(0.010)	(0.006)	(0.010)	(0.009)	(0.007)
Log of total assets in t-1	0.060***	0.025*	-0.250***	-0.115***	-0.089***	-0.115***	0.076***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.018)	(0.022)	(0.011)
Log of firm age in t-1	-0.026*	0.023	-0.067***	0.026***	-0.142***	0.006	-0.161***
	(0.014)	(0.014)	(0.019)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.040***	0.167***		-0.018***	0.000	0.064***	0.023***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,414	43,376	43,423	43,427	43,427	43,427	42,894
R-squared	0.870	0.737	0.659	0.906	0.647	0.610	0.800
Adj within R2	0.012	0.053	0.039	0.027	0.011	0.013	0.018
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Table 11: 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 in year t. All RHS variables are from year $t-1$ and are characteristics of the TNIC-4 network around the focal firm. One observation is a firm-technology-year. We include three key RHS variables in addition to firm fixed effects, year fixed effects and technology fixed effects. The first key variable is the percentage of the focal firm's TNIC-4 rivals that have the given technology in t-1. The second is the TNIC4 OD density as used in earlier tables. The third is the fraction of the firm's TNIC-4 rivals that have been treated by the Corporate Opportunities Waiver (COW) shock based on their state of incorporation and the year $t-1$. We also include double and triple interactions with these variables. 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 if Focal Firm adopts technology in t			
	(1)	(2)	(3)	(4)
TN4 % Peers Have Tech in t-1	0.543***	0.559***	0.527***	0.546***
	(0.012)	(0.013)	(0.014)	(0.014)
TN4 OD Density in t-1	-0.000		0.000	-0.001
	(0.001)		(0.002)	(0.002)
(Peers Have Tech in t-1)	0.098***		0.094***	0.039**
x(OD Density in t-1)	(0.013)		(0.014)	(0.017)
High TN4 COW in t-1		-0.000	0.000	-0.002
		(0.001)	(0.001)	(0.002)
(Peers Have Tech in t-1)		0.066***	0.058***	0.004
x(High TN4 COW in t-1)		(0.013)	(0.013)	(0.015)
(TN4 OD Density in t-1)				0.007***
x(High TN4 COW in t-1)				(0.002)
(Peers Have Tech in t-1)				0.139***
x(TN4 OD Density in t-1)x(High TN4 COW in t-1)				(0.022)
Observations	896,346	826,217	826,217	826,217
R-squared	0.220	0.219	0.220	0.220
Adj within R2	0.093	0.093	0.093	0.094
Firm FE	YES	YES	YES	YES
Technology x Year FE	YES	YES	YES	YES

Table 12: TNIC4 second-degree 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 in year t. All RHS variables are from year $t-1$ and are characteristics of the TNIC-4 network around the focal firm. One observation is a firm-technology-year. We include three key RHS variables in addition to firm fixed effects, year fixed effects and technology fixed effects. The first key variable is the percentage of the focal firm's TNIC-4 rivals that have the given technology in t-1. The second is the TNIC4 second-degree OD density as used in earlier tables. The third is the fraction of the firm's TNIC-4 rivals that have been treated by the Corporate Opportunities Waiver (COW) shock based on their state of incorporation and the year $t-1$. We also include double and triple interactions with these variables. 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 if Focal Firm adopts technology in t			
	(1)	(2)	(3)	(4)
TN4 % Peers Have Tech in t-1	0.537***	0.559***	0.519***	0.527***
	(0.011)	(0.013)	(0.013)	(0.013)
TN4 OD Density in t-1	-0.004**		-0.004**	-0.006***
	(0.002)		(0.002)	(0.002)
(Peers Have Tech in t-1)	0.115***		0.112***	0.090***
x(OD Density in t-1)	(0.013)		(0.013)	(0.015)
High TN4 COW in t-1		-0.000	-0.000	-0.002
		(0.001)	(0.001)	(0.002)
(Peers Have Tech in t-1)		0.066***	0.065***	0.042***
x(High TN4 COW in t-1)		(0.013)	(0.013)	(0.014)
(TN4 OD Density in t-1)x(High TN4 COW in t-1)				0.005**
				(0.002)
(Peers Have Tech in t-1)				0.062***
x(TN4 OD Density in t-1)x(High TN4 COW in t-1)				(0.022)
Observations	896,346	826,217	826,217	826,217
R-squared	0.220	0.219	0.220	0.220
Adj within R2	0.093	0.093	0.094	0.094
Firm FE	YES	YES	YES	YES
Technology x Year FE	YES	YES	YES	YES

Table 13: TNIC4 OD density and correlated innovation

This table presents the results of the OLS panel regression of different firm policies on TNIC4 OD density. The estimation in Panel A includes an interaction term between TN4 OD density and a dummy that equals one if the average TNIC4 similarity (lagged in three years) is above the median. Panel B includes an interaction term between TN4 OD density and a dummy that equals one if the average TNIC4 Technological Breadth is below the median. Technological Breadth is from Bowen, Fresard, and Hoberg (2023). In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In columns (2) and (3), the dependent variables are ROA and market to book ratio. In column (4), it is the firm's XRD/(total assets). In column (5), it is the number of patents divided by total assets. In column (6), it is the total value of patents divided by total assets. In column (7), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. All variables are standardized (z-score) and 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: Average TNIC4 product similarity

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 OD density in t-1)	0.022***	-0.019***	0.003	0.009**	0.018**	0.001	0.025***
x(Avg TN4sim above median in t-3)	(0.005)	(0.007)	(0.008)	(0.004)	(0.009)	(0.010)	(0.007)
TN4 OD density in t-1	-0.000	0.002	-0.011**	0.000	-0.005	-0.009	0.009**
	(0.002)	(0.004)	(0.005)	(0.003)	(0.006)	(0.006)	(0.004)
Avg TN4 similatity above median in t-3	0.071***	0.003	0.018	0.023***	0.016	0.001	0.060***
	(0.009)	(0.010)	(0.014)	(0.008)	(0.015)	(0.019)	(0.011)
Log of total assets in t-1	0.061***	0.026*	-0.243***	-0.117***	-0.094***	-0.112***	0.080***
	(0.011)	(0.014)	(0.015)	(0.010)	(0.019)	(0.023)	(0.011)
Log of firm age in t-1	-0.023	-0.001	-0.056***	0.032***	-0.154***	0.004	-0.155***
	(0.014)	(0.015)	(0.021)	(0.011)	(0.020)	(0.028)	(0.021)
Market to book ratio in t-1	0.038***	0.170***		-0.014***	0.003	0.070***	0.020***
	(0.007)	(0.007)		(0.005)	(0.009)	(0.012)	(0.005)
Observations	39,969	39,883	39,920	39,924	39,924	39,924	39,674
R-squared	0.863	0.728	0.663	0.906	0.654	0.619	0.799
Adj within R2	0.016	0.055	0.036	0.027	0.012	0.013	0.017
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel B: Average TNIC4 technological breadth

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 OD density in t-1)	0.030***	-0.017**	-0.022**	0.024***	-0.007	-0.049***	-0.008
x(TN4 Breadth below median in t-1)	(0.007)	(0.008)	(0.010)	(0.006)	(0.011)	(0.013)	(0.008)
TN4 OD density in t-1	0.000	-0.005	-0.000	-0.003	0.008	0.012	0.023***
	(0.003)	(0.005)	(0.006)	(0.003)	(0.007)	(0.008)	(0.005)
TN4 Breadth below median in t-1	0.086***	-0.024*	0.016	0.026***	0.032*	0.027	0.080***
	(0.013)	(0.013)	(0.016)	(0.008)	(0.018)	(0.020)	(0.016)
Log of total assets in t-1	0.067***	0.031**	-0.266***	-0.138***	-0.093***	-0.128***	0.080***
	(0.013)	(0.015)	(0.016)	(0.011)	(0.021)	(0.025)	(0.012)
Log of firm age in t-1	-0.037**	0.025	-0.060***	0.031**	-0.168***	0.017	-0.193***
	(0.017)	(0.017)	(0.023)	(0.013)	(0.024)	(0.033)	(0.020)
Market to book ratio in t-1	0.046***	0.156***		-0.020***	-0.006	0.065***	0.027***
	(0.007)	(0.007)		(0.006)	(0.009)	(0.013)	(0.006)
Observations	34,653	34,577	34,613	34,618	34,618	34,618	34,463
R-squared	0.873	0.748	0.662	0.901	0.648	0.619	0.805
Adj within R2	0.018	0.047	0.041	0.032	0.012	0.013	0.023
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Leaky Director Networks and Innovation Herding

Internet Appendix

Not for Publication

Appendix IA1 Cross-sectional test: Innovative Firms

In this appendix, we examine if our findings are more relevant for innovative firms. We expect these results as our thesis is rooted in innovation production, and these firms should be more sensitive to IP leakages. Thus, we focus on the subsample of firms that report R&D expenditure. Panel A shows the results of our main regression on this subsample. Panel B shows the results on the subsample of firms that report zero or missing R&D expenditure. As expected, we indeed find that our results are most relevant for the subsample with positive R&D investments.

Panel A: Firms with XRD>0

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
TN4 OD density in t-1	0.015***	-0.007	-0.016**	0.008**	0.004	-0.014*	0.020***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.008)	(0.009)	(0.005)
Log of total assets in t-1	0.055***	0.074***	-0.309***	-0.208***	-0.151***	-0.208***	0.053***
	(0.017)	(0.019)	(0.020)	(0.015)	(0.027)	(0.031)	(0.014)
Log of firm age in t-1	-0.046*	0.047**	-0.058*	0.067***	-0.251***	0.042	-0.220***
	(0.025)	(0.023)	(0.033)	(0.020)	(0.037)	(0.049)	(0.026)
Market to book ratio in t-1	0.044***	0.145***		-0.029***	-0.006	0.078***	0.027***
	(0.008)	(0.008)		(0.007)	(0.011)	(0.014)	(0.006)
Observations	22,387	22,961	22,983	22,985	22,985	22,985	22,718
R-squared	0.885	0.778	0.645	0.863	0.625	0.636	0.815
Adj within R2	0.011	0.046	0.048	0.050	0.020	0.022	0.024
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel B: Firms with XRD=0

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
TN4 OD density in t-1	0.002	0.002	-0.002	-0.000	0.001	0.007	0.011**
	(0.002)	(0.004)	(0.006)	(0.000)	(0.002)	(0.005)	(0.006)
Log of total assets in t-1	0.060***	-0.026	-0.180***	-0.000	-0.005	0.005	0.113***
	(0.010)	(0.016)	(0.018)	(0.001)	(0.004)	(0.005)	(0.016)
Log of firm age in t-1	-0.013	-0.006	-0.072***	0.001**	0.001	0.013	-0.102***
	(0.013)	(0.017)	(0.022)	(0.000)	(0.005)	(0.010)	(0.025)
Market to book ratio in t-1	0.019***	0.231***		0.001	0.005	0.015*	0.012
	(0.006)	(0.010)		(0.001)	(0.004)	(0.008)	(0.008)
Observations	19,971	20,358	20,383	20,386	20,386	20,386	20,113
R-squared	0.804	0.596	0.651	0.321	0.607	0.554	0.793
Adj within R2	0.010	0.085	0.031	-0.000	0.000	0.005	0.014
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

In panels C and D, we show that the results of our COW analysis in section 4.1 are stronger for innovative firms.

Panel C: Firms with XRD>0

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
(TN4 OD density in t-1)	0.038***	-0.014	-0.033***	0.028***	-0.080***	-0.127***	0.026***
x(TN4 COW in t-1)	(0.008)	(0.009)	(0.012)	(0.007)	(0.015)	(0.018)	(0.008)
TN4 OD density in t-1	0.001	-0.001	-0.002	-0.003	0.036***	0.035***	0.010
	(0.004)	(0.006)	(0.008)	(0.004)	(0.011)	(0.013)	(0.006)
TN4 COW in t-1	0.047***	0.013	-0.004	0.007	0.014	-0.048**	0.058***
	(0.010)	(0.013)	(0.017)	(0.010)	(0.019)	(0.020)	(0.012)
Log of total assets in t-1	0.052***	0.074***	-0.308***	-0.210***	-0.148***	-0.203***	0.051***
	(0.017)	(0.019)	(0.020)	(0.015)	(0.027)	(0.031)	(0.014)
Log of firm age in t-1	-0.050**	0.048**	-0.056*	0.066***	-0.247***	0.050	-0.227***
	(0.025)	(0.023)	(0.033)	(0.020)	(0.037)	(0.049)	(0.025)
Market to book ratio in t-1	0.044***	0.145***		-0.029***	-0.007	0.077***	0.028***
	(0.008)	(0.008)		(0.007)	(0.011)	(0.014)	(0.006)
Observations	22,335	22,905	22,927	22,929	22,929	22,929	22,662
R-squared	0.885	0.777	0.646	0.863	0.626	0.639	0.816
Adj within R2	0.014	0.046	0.048	0.051	0.022	0.028	0.027
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel D: Firms with XRD=0

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
(TN4 OD density in t-1)	0.013***	-0.008	0.002	-0.000	-0.000	-0.003	0.033***
x(TN4 COW in t-1)	(0.004)	(0.008)	(0.010)	(0.000)	(0.003)	(0.005)	(0.010)
TN4 OD density in t-1	-0.003	0.004	-0.003	0.000	0.001	0.008	0.000
	(0.003)	(0.005)	(0.007)	(0.000)	(0.002)	(0.006)	(0.007)
TN4 COW in t-1	0.026***	-0.009	-0.017	-0.001	-0.001	-0.003	0.019
	(0.007)	(0.010)	(0.013)	(0.001)	(0.003)	(0.003)	(0.013)
Log of total assets in t-1	0.059***	-0.025	-0.179***	-0.000	-0.005	0.005	0.111***
	(0.010)	(0.016)	(0.018)	(0.001)	(0.004)	(0.005)	(0.016)
Log of firm age in t-1	-0.013	-0.006	-0.073***	0.001**	0.001	0.012	-0.103***
	(0.013)	(0.017)	(0.022)	(0.000)	(0.005)	(0.010)	(0.025)
Market to book ratio in t-1	0.020***	0.231***		0.001	0.005	0.014**	0.012
	(0.006)	(0.010)		(0.001)	(0.004)	(0.007)	(0.008)
Observations	19,942	20,325	20,350	20,353	20,353	20,353	20,079
R-squared	0.804	0.596	0.651	0.321	0.607	0.557	0.793
Adj within R2	0.012	0.085	0.031	-0.000	0.000	0.005	0.015
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA2 Corporate Opportunity Waivers: Delaware-sensitivity Analysis

In this section, we run the COW analysis only for the period from 1997 to 2002. We choose this window to focus on the Delaware treatment effects alone and 2002 is the last year before another state other than Delaware implements COW. Hence there are no other treated states in this sample other than Delaware. The resulting analysis is a standard one-time difference-in-difference estimation and these results are thus not affected by any potential bias in the coefficients due to any heterogeneous treatment effects over time. The test is also conservative as it only includes two post-treatment years. Panel A shows that all of our results are robust using Delaware alone.

To alleviate any separate concerns that Delaware alone drives our findings, in Panel B, we run the test using all states excluding Delaware (here we restrict the sample to 2003-2019), and our results also remain robust.

Panel A: 1997 - 2002

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 COW in t-1)x(TN4 ODdensity in t-1)	0.005	-0.030**	-0.062***	0.035***	-0.031	-0.235***	0.023**
	(0.006)	(0.015)	(0.019)	(0.010)	(0.023)	(0.036)	(0.011)
TN4 OD Density in t-1	0.005**	-0.004	0.002	-0.007**	0.008	0.016	-0.004
	(0.002)	(0.007)	(0.010)	(0.003)	(0.010)	(0.016)	(0.006)
TN4 COW in t-1	-0.034***	-0.024	-0.154***	0.037***	-0.022	-0.389***	0.041***
	(0.011)	(0.023)	(0.028)	(0.013)	(0.033)	(0.049)	(0.016)
Log of total assets in t-1	-0.012	-0.203***	-0.575***	-0.083***	-0.164***	-0.526***	0.054***
	(0.017)	(0.025)	(0.033)	(0.020)	(0.038)	(0.066)	(0.018)
Log of firm age in t-1	-0.116***	0.117***	-0.026	0.025	-0.048	0.068	-0.132***
	(0.022)	(0.034)	(0.043)	(0.022)	(0.048)	(0.090)	(0.030)
Market to book ratio in t-1	0.019***	0.091***		-0.041***	-0.069***	-0.216***	0.005
	(0.005)	(0.009)		(0.007)	(0.014)	(0.023)	(0.005)
Observations	8,113	8,207	8,216	8,230	8,230	8,230	8,120
R-squared	0.925	0.797	0.767	0.941	0.822	0.775	0.916
Adj within R2	0.021	0.058	0.094	0.027	0.013	0.083	0.010
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel B: 2003 - 2019

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 COW in t-1)x(TN4 ODdensity in t-1)	0.028***	-0.024***	-0.013*	0.006*	-0.011*	-0.007*	0.028***
	(0.004)	(0.007)	(0.008)	(0.004)	(0.006)	(0.004)	(0.006)
TN4 OD Density in t-1	-0.009***	0.007*	-0.005	0.001	0.008**	0.001	-0.006
	(0.002)	(0.004)	(0.005)	(0.002)	(0.004)	(0.003)	(0.004)
TN4 COW in t-1	0.031***	-0.002	-0.006	-0.007	0.023***	0.008*	0.024***
	(0.005)	(0.009)	(0.011)	(0.006)	(0.009)	(0.005)	(0.008)
Log of total assets in t-1	0.102***	0.031*	-0.166***	-0.131***	-0.083***	-0.059***	0.052***
	(0.015)	(0.017)	(0.011)	(0.012)	(0.013)	(0.008)	(0.012)
Log of firm age in t-1	0.045***	-0.022	-0.043***	0.050***	-0.083***	-0.009	-0.110***
	(0.016)	(0.018)	(0.014)	(0.012)	(0.015)	(0.010)	(0.019)
Market to book ratio in t-1	0.035***	0.178***		-0.014**	-0.001	0.014***	0.003
	(0.010)	(0.010)		(0.007)	(0.007)	(0.004)	(0.006)
Observations	31,644	32,440	32,390	32,464	32,464	32,464	32,115
R-squared	0.899	0.773	0.789	0.921	0.715	0.783	0.834
Adj within R2	0.018	0.045	0.244	0.026	0.010	0.010	0.007
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA3 Corporate Opportunity Waivers and OD density

In this section, we test whether COW predicts changes in the frequency of ODs in each firm's TNIC4 peer group. Although COW is a shock to the incentives to leak as penalties are lower, it is possible that COW waivers are used as a tool to recruit directors, and hence we test this prediction for completeness. The results are reported below. We find no significant evidence that ex-ante exposure to COW predicts the ex-post incidence of ODs within TNIC4 industries.

VARIABLES	(1) TN4 OD focal$_t$
COW in t-1	-0.023
	(0.029)
Log of total assets in t-1	0.061***
	(0.015)
Log of firm age in t-1	0.035
	(0.025)
Market to book ratio in t-1	0.005
	(0.008)
Observations	43,221
R-squared	0.467
Adj within R2	0.002
Firm FE	YES
Year FE	YES

Appendix IA4 COW: Director Links Beyond Board Overlap

Panel A: Other connections and COW

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4OTHERdensity in t-1)	0.022***	-0.013*	0.008	0.008*	-0.024***	-0.046***	0.044***
x(TN4 COW in t-1)	(0.005)	(0.007)	(0.006)	(0.004)	(0.008)	(0.009)	(0.006)
TN4OTHERdensity in t-1	-0.005**	-0.002	-0.008**	-0.003	0.004	-0.008	0.017***
	(0.002)	(0.004)	(0.004)	(0.002)	(0.005)	(0.005)	(0.003)
TN4 COW in t-1	0.039***	-0.015*	-0.022***	0.002	-0.021*	-0.086***	0.048***
	(0.007)	(0.009)	(0.008)	(0.006)	(0.012)	(0.014)	(0.009)
Log of total assets in t-1	0.059***		-0.179***	-0.115***	-0.087***	-0.110***	0.074***
	(0.011)		(0.009)	(0.010)	(0.018)	(0.021)	(0.010)
Log of firm age in t-1	-0.026*	-0.063***	-0.010	0.026***	-0.141***	0.008	-0.164***
	(0.014)	(0.015)	(0.012)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.041***			-0.017***	-0.000	0.064***	0.023***
	(0.006)			(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,376	43,521	43,287	43,382	43,382	43,382	42,845
R-squared	0.870	0.729	0.742	0.906	0.647	0.612	0.801
Adj within R2	0.013	0.025	0.272	0.026	0.012	0.017	0.023
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel B: 2nd-degree connections and COW

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 POPODdensity in t-1)	0.095***	-0.019***	-0.013**	0.023***	-0.066***	-0.065***	0.022***
x(TN4 COW in t-1)	(0.011)	(0.007)	(0.006)	(0.006)	(0.009)	(0.013)	(0.007)
TN4 POPODdensity in t-1	0.002	-0.011***	-0.002	0.003	-0.008*	-0.019***	-0.008**
	(0.002)	(0.004)	(0.004)	(0.002)	(0.005)	(0.006)	(0.004)
TN4 COW in t-1	0.037***	-0.016*	-0.022***	0.002	-0.021*	-0.087***	0.049***
	(0.006)	(0.009)	(0.008)	(0.006)	(0.012)	(0.014)	(0.009)
Log of total assets in t-1	0.053***		-0.178***	-0.116***	-0.083***	-0.106***	0.077***
	(0.010)		(0.009)	(0.010)	(0.018)	(0.021)	(0.011)
Log of firm age in t-1	-0.029**	-0.062***	-0.009	0.025**	-0.138***	0.010	-0.163***
	(0.013)	(0.015)	(0.012)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.040***			-0.018***	0.000	0.064***	0.023***
	(0.006)			(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,376	43,521	43,287	43,382	43,382	43,382	42,845
R-squared	0.872	0.730	0.742	0.906	0.648	0.613	0.800
Adj within R2	0.031	0.025	0.272	0.028	0.015	0.019	0.018
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA5 Corporate Opportunity Waivers and distant peers

In this appendix, we run the COW analysis (section 4.1) for distant-peer ODs (TNIC2-TNIC4). We calculate the fraction of distant peers (peers in the TNIC2 group but not in the TNIC4) that are affected by the intent-to-treat COW (COW at the state level), and create a dummy that equals one if this fraction is above the median. We then interact this dummy with the OD density for these distant peers. We find that the positive effect on R&D, and the negative effect on product similarity and fluidity, become stronger with TNIC2-4 COW. These findings align with an increase in complementary leakage fostering product differentiation.

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
(TN2-TN4 OD density in t-1)	-0.028***	-0.010	-0.001	0.011**	-0.020**	-0.040***	-0.037***
x(TN2-TN4 COW in t-1)	(0.005)	(0.007)	(0.009)	(0.005)	(0.009)	(0.011)	(0.007)
TN2-TN4 OD density in t-1	-0.016***	0.010***	0.008*	-0.002	0.005	0.028***	-0.015***
	(0.002)	(0.003)	(0.005)	(0.002)	(0.005)	(0.005)	(0.004)
TN2-TN4 COW in t-1	-0.007	-0.025**	-0.062***	0.007	-0.056***	-0.177***	0.035***
	(0.008)	(0.010)	(0.012)	(0.006)	(0.013)	(0.018)	(0.010)
Log of total assets in t-1	0.057***	0.023*	-0.229***	-0.106***	-0.085***	-0.100***	0.083***
	(0.010)	(0.012)	(0.013)	(0.009)	(0.018)	(0.020)	(0.010)
Log of firm age in t-1	-0.024*	0.024*	-0.070***	0.026***	-0.120***	0.021	-0.159***
	(0.012)	(0.014)	(0.019)	(0.009)	(0.020)	(0.025)	(0.017)
Market to book ratio in t-1	0.038***	0.170***		-0.015***	-0.003	0.065***	0.025***
	(0.006)	(0.006)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	45,534	48,487	48,545	48,550	48,550	48,550	47,805
R-squared	0.869	0.731	0.652	0.904	0.634	0.609	0.798
Adj within R2	0.014	0.055	0.037	0.024	0.010	0.022	0.020
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA6 City density

Panel A of this appendix presents the results of OLS panel data regressions of different firm policies on TNIC4 OD density. TN4 OD density is calculated only considering overlapping directors of TN4 firms with headquarters in a different city. This allows us to separate any plausible geographic effects from our measures of industry OD density as we compute a separate measure of geography effects in the next panel. Panel B thus shows the results of a regression that includes TN4 *ODdensity* and TN4 *CITYdensity* as independent variables. To calculate TN4 *CITYdensity* we consider two firms as connected if their headquarters are in the same city. In column (1), the dependent variable is the firm's total product similarity in its TNIC4 group. In columns (2) and (3), the dependent variables are ROA and market to book ratio. In column (4), it is the firm's XRD/(total assets). In column (5), it is the number of patents divided by total assets. In column (6), it is the total value of patents divided by total assets. In column (7), it is product-market fluidity from Hoberg, Phillips, and Prabhala (2014). Firm and year fixed effects are included. Controls include the percentage of the firm's TN4 peers that are also OD peers, the log of assets in t-1, log of firm age in t-1, and market to book ratio in t-1. All variables are standardized (z-score) and 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: TN4 OD Density only considering TN4 ODs in different cities

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
TN4 OD density in t-1	0.012***	-0.010***	-0.009***	0.005**	0.002	-0.011*	0.022***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)	(0.006)	(0.004)
Log of total assets in t-1	0.060***	0.025*	-0.178***	-0.114***	-0.089***	-0.113***	0.078***
	(0.011)	(0.013)	(0.009)	(0.010)	(0.018)	(0.021)	(0.011)
Log of firm age in t-1	-0.025*	0.024*	-0.010	0.026***	-0.141***	0.006	-0.161***
	(0.013)	(0.014)	(0.012)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.040***	0.167***		-0.017***	0.000	0.064***	0.023***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,457	43,420	43,376	43,471	43,471	43,471	42,935
R-squared	0.870	0.737	0.741	0.906	0.647	0.610	0.800
Adj within R2	0.012	0.053	0.272	0.026	0.011	0.013	0.017
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Panel B: TN4 City Density

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
TN4 OD density in t-1	0.011***	-0.008**	-0.008**	0.003	0.001	-0.012**	0.022***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.006)	(0.004)
TN4 City density in t-1	0.001	0.011**	0.006	0.014***	0.008	0.033***	-0.024***
	(0.004)	(0.005)	(0.005)	(0.003)	(0.007)	(0.009)	(0.006)
Log of total assets in t-1	0.060***	0.025*	-0.179***	-0.114***	-0.089***	-0.114***	0.078***
	(0.011)	(0.013)	(0.009)	(0.010)	(0.018)	(0.021)	(0.011)
Log of firm age in t-1	-0.025*	0.024	-0.010	0.026***	-0.141***	0.006	-0.160***
	(0.013)	(0.014)	(0.012)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.040***	0.167***		-0.018***	0.000	0.064***	0.023***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,457	43,420	43,376	43,471	43,471	43,471	42,935
R-squared	0.870	0.737	0.741	0.906	0.647	0.610	0.800
Adj within R2	0.012	0.053	0.272	0.026	0.011	0.013	0.018
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA7 Cross-sectional test: correlated innovation

In this appendix, show that the results of our COW analysis in section 4.1 are stronger for industries with a higher value of our measure for correlated innovation. In particular, we estimate a model with a triple interaction between TN4 OD density, TN4 COW, and each measure of correlated innovation (high Average TN4 similarity and low TN4 Breadth). We find that all of our predicted effects are strongest when all three of the following conditions are met: the firm is surrounded by a dense OD network, a large number of peers are treated by the COW shock, and the focal firm is an industry with highly correlated innovation. We report results for both measures below.

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
(TN4 OD density in t-1)(TN4COW in t-1)	0.068***	-0.041***	-0.044***	0.028***	-0.107***	-0.160***	0.074***
x(Avg TN4sim above median in t-3)	(0.010)	(0.011)	(0.013)	(0.007)	(0.017)	(0.023)	(0.010)
(TN4 OD density in t-1)	-0.001	0.010	-0.011	-0.001	-0.015	-0.042***	-0.000
x(TN4COW in t-1)	(0.003)	(0.008)	(0.010)	(0.005)	(0.009)	(0.010)	(0.007)
(TN4 OD density in t-1)	-0.002	-0.001	0.015	-0.002	0.052***	0.046***	-0.003
x(Avg TN4sim above median in t-3)	(0.004)	(0.007)	(0.009)	(0.004)	(0.012)	(0.014)	(0.008)
TN4 OD density in t-1	0.001	-0.002	-0.007	0.001	-0.000	0.004	0.010**
	(0.002)	(0.005)	(0.006)	(0.003)	(0.007)	(0.008)	(0.005)
(TN4COW in t-1)	0.014	-0.002	-0.051**	0.045***	-0.063***	-0.158***	0.045***
x(Avg TN4sim above median in t-3)	(0.011)	(0.016)	(0.020)	(0.011)	(0.022)	(0.029)	(0.015)
TN4 COW in t-1	0.032***	-0.002	-0.003	-0.019***	0.015	-0.010	0.028***
	(0.006)	(0.010)	(0.014)	(0.007)	(0.014)	(0.015)	(0.011)
Avg TN4 similatity above median in t-3	0.063***	0.007	0.039**	0.004	0.045***	0.065***	0.040***
	(0.008)	(0.011)	(0.016)	(0.008)	(0.017)	(0.024)	(0.012)
Log of total assets in t-1	0.058***	0.027*	-0.241***	-0.119***	-0.090***	-0.104***	0.077***
	(0.011)	(0.014)	(0.015)	(0.010)	(0.018)	(0.022)	(0.011)
Log of firm age in t-1	-0.026*	0.000	-0.054**	0.031***	-0.150***	0.011	-0.160***
	(0.014)	(0.015)	(0.021)	(0.011)	(0.020)	(0.028)	(0.021)
Market to book ratio in t-1	0.039***	0.170***		-0.014***	0.002	0.069***	0.021***
	(0.007)	(0.007)		(0.005)	(0.009)	(0.012)	(0.005)
Observations	39,899	39,813	39,850	39,854	39,854	39,854	39,604
R-squared	0.864	0.728	0.664	0.906	0.655	0.623	0.800
Adj within R2	0.021	0.055	0.037	0.029	0.015	0.024	0.022
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
(TN4 OD density in t-1)(TN4COW in t-1)	0.070***	-0.001	-0.007	0.036***	-0.120***	-0.174***	0.032***
x(TN4 Breadth below median in t-1)	(0.012)	(0.013)	(0.016)	(0.010)	(0.021)	(0.026)	(0.011)
(TN4 OD density in t-1)	0.006	-0.025***	-0.023**	0.006	-0.022**	-0.049***	0.038***
x(TN4COW in t-1)	(0.005)	(0.009)	(0.010)	(0.005)	(0.011)	(0.012)	(0.009)
(TN4 OD density in t-1)	0.001	-0.023***	-0.019	0.010	0.041***	0.025	-0.009
x(TN4 Breadth below median in t-1)	(0.006)	(0.009)	(0.013)	(0.006)	(0.015)	(0.018)	(0.010)
TN4 OD density in t-1	-0.002	0.003	0.004	-0.005*	0.014*	0.023**	0.011*
	(0.003)	(0.005)	(0.007)	(0.003)	(0.008)	(0.010)	(0.006)
(TN4COW in t-1)	-0.010	-0.039**	-0.167***	-0.009	-0.082***	-0.330***	-0.004
x(TN4 Breadth below median in t-1)	(0.015)	(0.018)	(0.023)	(0.013)	(0.027)	(0.035)	(0.017)
TN4 COW in t-1	0.051***	0.016	0.062***	0.009	0.029	0.092***	0.070***
	(0.008)	(0.013)	(0.016)	(0.008)	(0.017)	(0.019)	(0.013)
TN4 Breadth below median in t-1	0.083***	-0.013	0.068***	0.026***	0.069***	0.146***	0.081***
	(0.012)	(0.013)	(0.017)	(0.008)	(0.019)	(0.023)	(0.017)
Log of total assets in t-1	0.063***	0.031**	-0.264***	-0.140***	-0.088***	-0.118***	0.077***
	(0.013)	(0.015)	(0.016)	(0.011)	(0.020)	(0.024)	(0.012)
Log of firm age in t-1	-0.040**	0.026	-0.057**	0.030**	-0.165***	0.027	-0.198***
	(0.017)	(0.017)	(0.023)	(0.013)	(0.024)	(0.033)	(0.020)
Market to book ratio in t-1	0.047***	0.156***		-0.020***	-0.007	0.060***	0.027***
	(0.007)	(0.007)		(0.006)	(0.009)	(0.012)	(0.006)
Observations	34,586	34,510	34,546	34,551	34,551	34,551	34,396
R-squared	0.873	0.748	0.664	0.901	0.650	0.625	0.806
Adj within R2	0.022	0.047	0.045	0.033	0.015	0.030	0.027
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA8 Leader-Follower Analysis

In this appendix, we examine whether our main results are stronger for industry laggards than for industry leaders. We expect this finding for two reasons. First, industry laggards likely have more correlated innovation as they are following the same leaders. Second, industry-laggard firms might be particularly sensitive to losing the limited IP, and thus might be more sensitive to leakage and losses in differentiation. We define an industry leaders and laggards as having above vs. below the 90th percentile R&D/assets within each firm's TNIC industry, respectively. Panel A below presents the results of this analysis. In particular, we include an interaction term between *ODdensity* and a dummy equal to one if the firm is a laggard. We find that our main effects regarding product differentiation and performance are significantly stronger for industry-laggards. In panel B, we show that this is especially true when examining plausibly exogenous variation from the COW shock.

Panel A: Industry laggards

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
(TN4 ODdensity in t-1)	0.019***	-0.023**	-0.005	0.009	0.007	0.005	0.030***
(Laggard in t-1)	(0.003)	(0.009)	(0.010)	(0.006)	(0.009)	(0.008)	(0.009)
TN4 ODdensity in t-1	-0.007***	0.013	-0.004	-0.004	-0.005	-0.014*	-0.008
	(0.003)	(0.009)	(0.010)	(0.005)	(0.009)	(0.007)	(0.008)
Laggard in t-1	0.032***	0.044***	-0.032**	-0.017**	-0.017	-0.067***	0.157***
	(0.006)	(0.013)	(0.014)	(0.008)	(0.013)	(0.016)	(0.014)
Log of total assets in t-1	0.060***	0.024*	-0.248***	-0.114***	-0.088***	-0.113***	0.076***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.018)	(0.021)	(0.010)
Log of firm age in t-1	-0.025*	0.024	-0.066***	0.026***	-0.141***	0.006	-0.161***
	(0.013)	(0.014)	(0.019)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.040***	0.167***		-0.017***	0.000	0.064***	0.023***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,457	43,420	43,467	43,471	43,471	43,471	42,935
R-squared	0.870	0.737	0.659	0.906	0.647	0.610	0.801
Adj within R2	0.012	0.053	0.039	0.026	0.011	0.013	0.022
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

In panel B, we show that the results of our COW analysis in section 4.1 are stronger for industry laggards. In particular, we estimate a model with a triple interaction between TN4 OD density, TN4 COW and the Laggard dummy. We find that many of our predicted effects are strongest when all three of the following conditions are met: the firm is surrounded by a dense OD network, a large number of peers are treated by the COW shock, and the focal firm is an industry laggard.

Panel B: Industry laggards and COW

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 OD density in t-1)	0.035***	-0.054***	-0.038**	0.019*	-0.064***	-0.099***	0.056***
(TN4COW in t-1)x(Laggard in t-1)	(0.007)	(0.019)	(0.016)	(0.011)	(0.021)	(0.019)	(0.017)
(TN4 OD density in t-1)	-0.005	0.034*	0.015	-0.002	0.001	-0.009	-0.022
x(TN4COW in t-1)	(0.005)	(0.018)	(0.015)	(0.011)	(0.019)	(0.015)	(0.016)
(TN4 OD density in t-1)	0.006*	-0.001	0.007	0.002	0.031**	0.042***	0.008
x(Laggard in t-1)	(0.003)	(0.010)	(0.011)	(0.006)	(0.012)	(0.012)	(0.012)
TN4 OD density in t-1	-0.005*	-0.002	-0.009	-0.003	-0.006	-0.011	0.002
	(0.003)	(0.010)	(0.010)	(0.005)	(0.011)	(0.010)	(0.012)
(TN4COW in t-1)	0.061***	0.039**	-0.052***	-0.011	-0.021	-0.125***	0.178***
x(Laggard in t-1)	(0.009)	(0.016)	(0.014)	(0.009)	(0.016)	(0.023)	(0.017)
(TN4COW in t-1)	0.015*	-0.004	0.016	0.015	0.019	-0.012	-0.027
	(0.008)	(0.023)	(0.019)	(0.013)	(0.021)	(0.022)	(0.020)
(Laggard in t-1)	0.023***	0.043***	-0.019	-0.010	-0.000	-0.035*	0.123***
	(0.006)	(0.015)	(0.013)	(0.008)	(0.014)	(0.021)	(0.016)
Log of total assets in t-1	0.058***	0.025*	0.415***	-0.115***	-0.086***	-0.108***	0.069***
	(0.011)	(0.013)	(0.008)	(0.010)	(0.018)	(0.021)	(0.010)
Log of firm age in t-1	-0.027**	0.023	-0.054***	0.026***	-0.140***	0.010	-0.168***
	(0.013)	(0.014)	(0.012)	(0.010)	(0.019)	(0.026)	(0.018)
Market to book ratio in t-1	0.041***	0.166***		-0.017***	-0.001	0.063***	
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	
Observations	42,376	43,331	43,287	43,382	43,382	43,382	43,044
R-squared	0.870	0.737	0.736	0.906	0.648	0.613	0.801
Adj within R2	0.015	0.054	0.255	0.027	0.013	0.020	0.024
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA9 Cross-sectional test: number of TNIC4 peers

In this appendix, we examine if our findings are stronger in industries with a higher number of rivals as multiple firms are likely to produce related innovation when there are more innovating firms in an industry.

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*. The Table below presents the results. 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.

	(1) TSim TN4$_t$	(2) ROA$_t$	(3) Mkt/ Book$_t$	(4) XRD$_t$/ at$_t$	(5) Pat$_t$/ at$_t$	(6) ValPat$_t$/ at$_t$	(7) Fluid$_t$
(TN4 ODdensity in t-1) x(TN4 peers above median in t-1)	0.022***	-0.038***	0.000	0.017***	0.031***	0.007	0.015*
	(0.006)	(0.007)	(0.010)	(0.005)	(0.011)	(0.012)	(0.008)
TN4 ODdensity in t-1	0.001	0.004	-0.008*	-0.001	-0.007	-0.008	0.008**
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.005)	(0.004)
TN4 peers above median in t-1	0.115***	-0.035***	-0.017	0.027***	-0.014	-0.101***	0.278***
	(0.010)	(0.012)	(0.017)	(0.009)	(0.017)	(0.024)	(0.016)
Log of total assets in t-1	0.057***	0.027**	-0.248***	-0.115***	-0.089***	-0.112***	0.072***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.018)	(0.022)	(0.010)
Log of firm age in t-1	-0.023*	0.024*	-0.067***	0.027***	-0.142***	0.004	-0.155***
	(0.013)	(0.014)	(0.019)	(0.010)	(0.019)	(0.026)	(0.017)
Market to book ratio in t-1	0.040***	0.167***		-0.018***	-0.000	0.064***	0.023***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,457	43,420	43,467	43,471	43,471	43,471	42,935
R-squared	0.871	0.738	0.659	0.906	0.647	0.611	0.805
Adj within R2	0.019	0.054	0.039	0.027	0.012	0.014	0.043
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

In panel B, we show that the results of our COW analysis in section 4.1 are also stronger for industries with a larger number of competitors. In particular, we estimate a model with a triple interaction between TN4 OD density, TN4 COW and a dummy indicating TNIC4 peers are above median. We find that many of our predicted effects are strongest when all three of the following conditions are met: the firm is surrounded by a dense OD network, a large number of peers are treated by the COW shock, and the focal firm is an industry crowded with many firms.

Panel B: Number of peers and COW

	(1) TSim $TN4_t$	(2) ROA_t	(3) Mkt/ $Book_t$	(4) XRD_t/ at_t	(5) Pat_t/ at_t	(6) $ValPat_t$/ at_t	(7) $Fluid_t$
(TN4 OD density in t-1)(TN4COW in t-1) x(TN4 peers above median in t-1)	0.100***	-0.065***	-0.020	0.045***	-0.128***	-0.201***	0.068***
	(0.014)	(0.016)	(0.018)	(0.012)	(0.025)	(0.030)	(0.014)
(TN4 OD density in t-1) x(TN4COW in t-1)	-0.001	0.003	-0.013	0.000	-0.014**	-0.020***	0.001
	(0.002)	(0.006)	(0.008)	(0.003)	(0.007)	(0.008)	(0.006)
(TN4 OD density in t-1) x(TN4 peers above median in t-1)	-0.009	-0.019**	0.006	0.003	0.068***	0.073***	-0.011
	(0.006)	(0.008)	(0.011)	(0.005)	(0.015)	(0.017)	(0.009)
TN4 OD density in t-1	0.001	0.003	-0.003	-0.001	-0.002	-0.002	0.008*
	(0.002)	(0.004)	(0.005)	(0.002)	(0.005)	(0.007)	(0.005)
(TN4COW in t-1) x(TN4 peers above median in t-1)	-0.003	0.020	-0.085***	0.014	-0.064***	-0.217***	0.095***
	(0.012)	(0.017)	(0.023)	(0.011)	(0.023)	(0.030)	(0.016)
(TN4COW in t-1)	0.024***	-0.005	0.011	-0.012**	0.026**	0.038***	-0.002
	(0.004)	(0.010)	(0.013)	(0.005)	(0.011)	(0.013)	(0.009)
(TN4 peers above median in t-1)	0.108***	-0.035***	0.009	0.018**	0.015	-0.019	0.243***
	(0.009)	(0.013)	(0.018)	(0.009)	(0.018)	(0.026)	(0.016)
Log of total assets in t-1	0.054***	0.028**	-0.245***	-0.117***	-0.084***	-0.099***	0.066***
	(0.011)	(0.013)	(0.014)	(0.010)	(0.017)	(0.021)	(0.010)
Log of firm age in t-1	-0.025*	0.024	-0.065***	0.026***	-0.140***	0.010	-0.159***
	(0.013)	(0.014)	(0.019)	(0.010)	(0.019)	(0.026)	(0.017)
Market to book ratio in t-1	0.041***	0.167***		-0.017***	-0.001	0.062***	0.024***
	(0.006)	(0.007)		(0.005)	(0.008)	(0.011)	(0.005)
Observations	42,376	43,331	43,378	43,382	43,382	43,382	42,845
R-squared	0.871	0.737	0.659	0.906	0.648	0.616	0.806
Adj within R2	0.025	0.054	0.040	0.028	0.015	0.028	0.048
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Appendix IA10 Carrer Outcomes

In this section, we examine ODs' career prospects in the presence of a dense leaky CODN. First, we examine if ODs realize improved career prospects (in the form of serving on more boards ex-post, and earning higher compensation ex-post) when they work in dense OD networks ex-ante. Second, we explore whether these ex-post career outcomes are particularly positive when there is also evidence of technology transmissions across the boards the director serves.

IA10.1 OD Density and Career Outcomes

First, for each OD in our 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 of the boards she sits on. We, thus, regress the director's ex post number of boards on the ex-ante one-year-lagged average TN4 OD density of the firms she serves. We include director and year fixed effects. Column (1) in Panel A of Table below shows a positive and highly significant coefficient for the ex-ante TN4 OD density. Column (2) uses exogenous variation, and we interact the ex-ante average TN4 OD density with a dummy that equals one if an above-median fraction of the TN4 rivals of the firms the director serves on are treated by COW. We find that the interaction term is positive and highly significant. This result indicates that the positive impact of OD density on career outcomes (more board seats next year) increases if the OD network is also highly exposed to COW. In column (3) we use second-degree director connections and find similar supportive results.

We extend this analysis to examine director compensation, and we calculate the average compensation each director receives across all boards she sits on.[29] We then regress the log of the average compensation on the one-year-lagged average TN4 OD density of the boards she serves (as above). Panel B of the Table below shows the results. We find a positive and significant effect of ex-ante TN4 OD density on the ex-post average total compensation when the OD network is highly treated by the COW shock. We also find a positive effect using second-degree director connections.

Overall, these findings suggest that the overlapping directors appear to experience better career outcomes in the presence of leaky networks. Moreover, these effects are more pronounced when information leakages through the director network are more likely, as the presence of the COW shock suggests.

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

Panel A: Board Appointments

	Number of boards the OD serves on in t		
Avg TN4 ODdensity in t-1	0.012**	0.001	
	(0.005)	(0.005)	
(Avg TN4 ODdensity in t-1)x(High TN4 COW in t -1)		0.030***	
		(0.008)	
High TN4 COW in t -1		-0.057***	
		(0.009)	
Avg TN4 POPODdensity in t-1			0.015***
			(0.005)
Observations	74,746	74,746	74,746
R-squared	0.527	0.527	0.527
Director FE	YES	YES	YES
Year FE	YES	YES	YES

Panel B: Total Compensation

	Log(1 + total compensation in t)		
Avg TN4 ODdensity in t-1	0.002	-0.014	
	(0.011)	(0.013)	
(Avg TN4 ODdensity in t-1)x(High TN4 COW in t -1)		0.043**	
		(0.019)	
High TN4 COW in t -1		-0.012	
		(0.020)	
Avg TN4 POPODdensity in t-1			0.037***
			(0.011)
Observations	35,230	35,230	35,230
R-squared	0.601	0.601	0.601
Director FE	YES	YES	YES
Year FE	YES	YES	YES

IA10.2 Technology Diffusion and Career Outcomes

We next consider a highly specialized test and examine the career outcomes of ODs in cases where we observe evidence of actual technology transmissions across the boards they serve. We thus test whether observed ex-ante technology diffusion between the overlapping firms that ODs serve also predicts increases in the ex-post number of boards the OD will sit on in the future and on the average compensation they will receive. 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 5, and define an instance of "potential newly leaked technology" in a year t for a given technology as a situation in which two conditions are met: (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 number of boards the OD serves on 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) in Panel A of the Table below displays the results. 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. Column (2) shows that this effect is stronger if the two firms are in dense TN4 OD networks. Column (3) shows that the effect is also stronger if they are more highly treated by the COW shock and column (4) shows that the analysis is robust to using second-degree OD networks.

We extend this analysis to compensation and regress the ex-post log of the average total compensation the OD receives in year t between the two firms on the ex-ante number of newly added "shared technologies" in year $(t-1)$. Column (1) in Panel B of the Table shows a positive and significant effect on compensation following technology sharing between two connected firms. Columns (3) and (4) show that this effect is robust to using second-degree connections and is stronger when the firms' CODN network is highly affected by the COW shock.

Panel A: Board Appointments

	Number of boards the OD serves on in t			
# newly added tech in t-1	0.130***	0.011*	-0.039*	0.006
	(0.028)	(0.006)	(0.023)	(0.006)
(# newly added tech in t-1)x(Avg TN4 ODdensity in t-1)		0.014*		
		(0.007)		
Avg TN4 ODdensity in t-1		-0.010		
		(0.013)		
(# newly added tech in t-1)x(Avg TN4 COW in t-1)			0.071**	
			(0.028)	
Avg TN4 COW in t-1			0.039	
			(0.035)	
(# newly added tech in t-1)x(Avg TN4 POPODdensity in t-1)				0.019***
				(0.005)
Avg TN4 POPODdensity in t-1				0.001
				(0.009)
Observations	492,910	271,710	271,454	271,710
R-squared	0.951	0.857	0.857	0.857
Director FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Panel B: Total Compensation

	Log(1 + total compensation in t)			
# newly added tech in t-1	0.025**	0.022	0.023	0.024*
	(0.012)	(0.015)	(0.053)	(0.014)
(# newly added tech in t-1)x(Avg TN4 ODdensity in t-1)		0.002		
		(0.012)		
Avg TN4 ODdensity in t-1		0.020		
		(0.017)		
(# newly added tech in t-1)x(Avg TN4 COW in t-1)			0.001	
			(0.066)	
Avg TN4 COW in t-1			0.086*	
			(0.047)	
(# newly added tech in t-1)x(Avg TN4 POPODdensity in t-1)				-0.001
				(0.012)
Avg TN4 POPODdensity in t-1				0.039***
				(0.009)
Observations	160,924	140,588	140,572	140,588
R-squared	0.517	0.517	0.517	0.517
Director FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES