

Board Interlocks, Knowledge Spillovers, and Corporate Innovation*

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Abstract: We examine whether interlocking boards of directors help facilitate the transfer of scientific and technical knowledge between firms. To capture exogenous variation in board interlocks, we use a novel identification strategy based on schedule conflicts between firms' annual shareholder meeting dates. For a variety of patent-based measures, we find that a board interlock significantly strengthens the impact of a firm's innovation on other firms' innovation quantity, quality, value, and relatedness. Consistent with theories of board functioning, these spillover effects are reduced when one or both boards in an interlock have a high proportion of outsiders or busy directors. Spillover effects are strengthened, however, when shared directors are younger or have more relevant innovation experience. We also find that higher-quality and more focused patents from originating firms, as well as higher relevance of such patents to interlocking firms' past innovation, can enhance interlock-related spillovers. Overall, our findings suggest that board interlocks are an important channel through which scientific and technical knowledge can flow between firms.

JEL Classification Codes: G30, G34, O32

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1. Introduction

Knowledge spillovers are widely recognized as an important driver of many economic phenomena, such as technological progress (Griliches, 1979), growth in international trade (Grossman and Helpman, 1991), industrial innovation (Giuliani, 2007), and geographic clustering of production (Alcácer and Chung, 2007). Researchers have examined the transfer of scientific and technological knowledge in particular as a key engine of economic growth (e.g., Grossman and Helpman, 1991; Caballero and Jaffe, 1993; Aghion and Howitt, 2005). While various studies have explored how between-firm spillovers of scientific innovation can arise from organizational interactions such as mergers, strategic alliances, supply-chain relationships, or common ownership,¹ very little is currently known about how interlocking boards of directors can serve as a channel of firm-to-firm knowledge transmission.

Board interlocks—situations in which an individual concurrently serves on the boards of two or more companies—are one of the most common types of organizational linkage between public U.S. firms.² Interlocks can help corporate leaders share knowledge (Lorsch and MacIver, 1989) and gain fresh ideas for improving corporate strategy in uncertain environments (Mizruchi, 1996; Haunschild and Beckman, 1998). Interlocks may also enable the transmission of soft information, such as subjective interpretations, hunches, or intuition, that can only be conveyed through face-to-face communication (O'Hagan and Green, 2002). Furthermore, the soft information that firms obtain through interlocks can be more relevant and up-to-date than other types of knowledge because the shared directors in an interlock are able to frequently monitor, advise, and

¹ See, for example, Mowery, Oxley, and Silverman (1996), Bena and Li (2014), Chu, Tian, and Wang (2019), and López and Vives (2019).

² In 2023, about 64% of independent directors of S&P 500 companies served on more than one public-company board. (See, for instance, the 2023 U.S. Spencer Stuart Board Index, <https://www.spencerstuart.com/research-and-insight/us-board-index>.)

communicate with top management at both firms (Carpenter and Westphal, 2001).

Anecdotal evidence suggests that board interlocks may indeed serve as conduits for the between-firm flow of scientific and technical knowledge. Consider, for instance, the case of Netflix, Inc. and Google Inc. Among Netflix's 292 key patents granted as of 2021,³ 25 were filed in 2010 or earlier, and none of these 25 granted patents cited to prior inventions by Google. In 2010, Netflix formed a board interlock with Google by appointing a director who had been on Google's board since 2005. Within a year of the appointment, Netflix began to file for patents that cited one or more of Google's patents.⁴ In fact, more than 30% of the 267 granted key patents that Netflix filed between 2011 and 2021 cited to one or more of Google's patents.⁵ While the foregoing example might simply reflect correlation rather than causation, it is nonetheless consistent with the idea that board interlocks can causally affect the transmission of knowledge between firms.

In this paper, we provide systematic, causal evidence on whether board interlocks help channel firm-to-firm spillovers of scientific and technical knowledge. To do so, we examine detailed data on board interlocks and innovation activity during 2005-2020 for a large sample of firm-pair observations. Unlike most prior work that relies on aggregated R&D-based metrics to study knowledge spillovers between firms, our analysis examines a variety of patent-based measures of innovation by both “source” firms and “downstream” firms.⁶ We employ measures of not only the quantity, quality, and market value of downstream-firm patents, but also the extent to

³ <https://help.netflix.com/en/node/25888>, accessed in April 2024.

⁴ Following the appointment of Ann Mather to Netflix's board in July 2010, the very next patent application by Netflix inventors (filed on July 8, 2011) was for Patent No. US10311386B2, “Identifying Similar Items Based on Interaction History.” This patent cites to 16 other patents, including four held by Google: US8055655B1, US8311950B1, US8825474B1, and US8868570B1.

⁵ The information on citations is extracted from <https://patents.google.com/> (accessed in April 2024).

⁶ Throughout, we define a *source firm* to be a firm that might conduct innovation activities in a given year t . For a source firm, a *downstream firm* is another firm whose innovation activities in year $t+1$ or later could be influenced by the flow of innovation from the source firm. Note that these definitions do not require a source firm to be interlocked with its downstream firms. Nor do these definitions rule out scenarios where a source firm is a downstream firm vis-à-vis other source firms.

which these patents directly cite to source-firm patents. We use these data to address the following questions: Do board interlocks facilitate the transmission of scientific and technical knowledge between firms? If so, under what circumstances are interlocks most effective in channeling such knowledge spillovers?

An ideal experiment for exploring these questions would be one in which directors at a source firm are randomly appointed to the boards of various downstream firms, giving rise to a random pattern of board interlocks. Absent such an experiment, however, any empirical study of interlocks must contend with the fact that board structure is an endogenous response to many different forces (Hermalin and Weisbach, 1998; Adams, Hermalin, and Weisbach, 2010). Indeed, a board interlock may be more likely to arise when two firms are more similar in their R&D policies, innovation activities, or unobservable characteristics. Without accounting for potential sources of endogeneity, attempts to quantify the causal effects of interlocks on knowledge spillovers are likely to yield spurious inferences.

We address this important endogeneity issue with a novel identification approach based on a particular feature of U.S. corporate governance that, in some cases, would make it difficult or impossible for directors to fulfill board obligations with respect to certain pairs of firms. Each year, nearly all public firms in the United States hold annual shareholder meetings for voting on major corporate decisions, including which directors to elect to the board. Two practical aspects of these annual meetings are worth noting. First, director attendance at a firm's annual shareholder meeting is typically mandatory: almost all firms expect their entire board to attend.⁷ Second, annual

⁷ Item 407(b) of the Securities and Exchange Commission's Regulation S-K requires U.S. public firms to disclose in their proxy statements not only their policy on director attendance at the annual shareholder meeting, but also the number of board members who attended the prior year's annual meeting. While director attendance at annual shareholder meetings is not strictly required by law, it is typically a mandatory requirement, and all directors usually do attend (Li and Yermack, 2016). For example, as Apple Inc. states in its 2020 proxy statement to shareholders: "Apple expects all of its directors to attend the Annual Meeting. All directors serving at that time attended the 2019 annual meeting of shareholders."

shareholder meetings tend to cluster in time: about 75% of all annual meetings take place during the months of April, May, or June, and over 80% occur on Tuesdays, Wednesdays, or Thursdays.

Given the temporal clustering of annual meetings and the attendance requirements for directors, we posit that schedule conflicts between two firms' annual shareholder meetings can deter the sharing of directors and provide meaningful, exogenous variation in the likelihood of an interlock. In Section 3, we support this claim by presenting evidence that a schedule conflict between two firms' annual shareholder meeting dates is a strong (negative) predictor of whether a board interlock is present. We also discuss in Section 3 why annual meeting schedule conflicts between two firms can work well as instrumental variables for board interlocks despite the existence of observable or unobservable similarities between the firms. Moreover, using a variety of empirical tests, we find no evidence that firms are deliberately adjusting their meeting dates to cater to the schedules of newly-appointed or soon-to-be-appointed board members.⁸

The first part of our analysis explores the overall impact of board interlocks on spillovers between source firms and downstream firms. Spillover effects are measured by how downstream-firm patenting activity responds to the flow of patents coming from a source firm. We consider four different aspects of downstream innovation: patent volume, patent value, a citation-based measure of patent quality, and the extent to which downstream patents directly cite to a source firm's patents. To help safeguard against firm-level heterogeneity that could confound or add noise to the analysis, we match each downstream firm in an interlocked pair to a non-interlocked, downstream firm with similar industry, geographic location, firm size, and historical patenting activity. We then construct instruments from annual meeting schedule conflicts and use them to estimate two-stage least-squares (2SLS) panel regressions that explain downstream-firm patenting.

⁸ Appendix C provides a detailed discussion of the results of these additional tests.

In these regressions, the coefficient on the interaction between a board interlock dummy and the amount of source-firm patent flow serves to identify whether or not interlocks promote knowledge spillovers.

We find consistent evidence that board interlocks do indeed foster knowledge spillovers between firms. Specifically, our instrumental variables regressions show that the presence of a board interlock leads to a significantly higher sensitivity of downstream innovation to source-firm patent flow. This effect is present for all four of our main downstream innovation measures as well as for several auxiliary measures, including the number of high-value downstream patents, the average breadth of downstream patents, the textual similarity between source patents and subsequent downstream patents, and the degree of commonality in the citations made by source-firm and downstream-firm patents. The economic magnitudes of the effects are notable. For example, when a board interlock is present, the response of a downstream firm's patent quantity to a 1% increase in source-firm patent applications is 0.077 percentage points greater compared to in the non-interlock case. Similarly, the existence of a board interlock implies that the downstream firm's total patent value responds by an extra 0.18 percentage points to a 1% increase in source-firm patent applications.

Next, we turn to an examination of whether the observed effects depend on the composition of source- and downstream-firms' boards. Guided by prior theoretical work, we hypothesize that interlock-related spillover effects will vary with respect to the fractions of outside directors on the interlocked boards. For example, a “management-friendly” board with more insiders may tend to monitor less intensively and hence may encourage the CEO to share more knowledge with board members, resulting in better overall communication and information flow (Adams and Ferreira, 2007). Also, a greater degree of insider control of the board can lead to better information sharing

between management and directors (Raheja, 2005; Harris and Raviv, 2008). In line with these theories, we find that interlock-related spillovers are stronger when neither the source-firm board nor the downstream board is dominated by outside directors.

In additional tests, we examine whether the positive spillover effects of interlocks are weaker in the presence of busy directors on the source and/or downstream boards. Consistent with the notion that a director's effectiveness decreases with their busyness (Fich and Shivadasani, 2006), level of distraction (Falato, Kadyrzhanova, and Lel, 2014), and limited attention (Masulis and Mobbs, 2014), we find that interlocks have a significantly more positive effect on spillovers when the shared director(s) are non-busy or when the two firms' boards are composed of fewer busy directors.

Having found that board characteristics can affect interlock-related spillovers, we then explore whether the individual characteristics of shared director(s) also matter. This issue is of substantial practical interest, for it has a bearing on whether some firms may find it advantageous to recruit directors with certain types of experience or demographic traits. While we find no evidence that a shared director's gender matters for interlock-related spillovers, director age does seem to play a role. Specifically, in line with the notion that a director's effectiveness depends on career concerns (Jiang, Wan, and Zhao, 2016), shared directors who are younger have a more positive effect on knowledge spillovers. We interpret these findings as suggesting that shared directors are not simply passive conduits for knowledge transmission; rather, they play an active, purposeful role in driving the flow of scientific and technical knowledge between firms. We also find that interlock-related spillovers are more pronounced when a shared director's prior innovation experience is more related to the technology space of the interlocked firms. Interestingly, however, having a recent high-tech background by itself does not appear to make a

shared director more effective at facilitating between-firm knowledge flows.

Finally, we examine whether the types of individual patents emanating from a source firm also matter for interlock-related spillovers. In 2SLS regressions, we partition the source-firm patent flow in a given year according to patent characteristics and test whether interlock-based spillovers are stronger for some groups of source patents versus others. Our regressions reveal that board interlocks enhance spillovers more when source-firm patents are of higher quality, exhibit less technological breadth, or are highly related to the downstream firm's past innovation. On the other hand, interlocks matter less for spillovers when a source firm's patents are more closely related to its own established technology space.

Our paper contributes in several ways to research on knowledge spillovers, innovation, and corporate boards. First, our paper extends a growing literature that studies the general implications of board interlocks and overlapping boards for information transmission. Several papers have examined how interlocks relate to the spread of governance practices across firms (Bouwman, 2011) or the diffusion of specific corporate policies, e.g., options backdating (Bizjak, Lemmon, and Whitby, 2009), earnings management contagion (Chiu, Teoh, and Tian, 2013), and disclosure policy (Cai, Dhaliwal, Kim, and Pan, 2014). Other papers have studied how interlocks, or director networks more generally, can facilitate better corporate decision-making and influence firm value (see, e.g., Cai and Sevilir, 2012, Burt, Hrdlicka, and Harford, 2020, and Zhang, 2021). We add to this line of research by focusing on the flow of scientific and technical knowledge and utilizing patent-based measures to provide direct, granular evidence of firm-to-firm knowledge spillovers. Also related to our work are recent studies by Geng, Hau, Michaely, and Nguyen (2023) and Cabezon and Hoberg (2024), who use plausibly exogenous shocks to examine how board interlocks influence knowledge sharing, information leakage, and firm performance. Our work

differs from these studies in that they focus specifically on intra-industry interlocks, while we consider a much larger data sample consisting of both within-industry and cross-industry interlocks.

Our analysis also contributes to a broader understanding of the different mechanisms by which scientific knowledge and, ultimately, technological innovation can diffuse between firms. A large body of literature in business and economics explores how firms can acquire, transmit, or share technology through organizational ties such as mergers (Bena and Li, 2014), strategic alliances (Mowery, Oxley, and Silverman. 1996), supply-chain relationships (Chu, Tian, and Wang, 2019), or common ownership (López and Vives, 2019). To date, however, very little work has studied how the diffusion of scientific knowledge occurs through board interlocks, which represent one of the most common types of formal organizational linkage between U.S. public companies. Our findings help to fill this gap by providing affirmative evidence that shared directors are indeed an important channel for transmitting technological and scientific knowledge across organizational boundaries.

Moreover, we introduce to the literature a novel identification strategy for studying the causal effects of board interlocks. Our instrumental variables approach contrasts with other approaches that researchers have used to tackle the challenging problem of endogeneity in board structures. Such prior approaches have included, for example, using the sudden deaths of directors as unexpected shocks to board composition (Nguyen and Nielsen, 2013; Fracassi and Tate, 2012; Fahlenbrach, Low, and Stultz, 2017); exploiting the passage of the Sarbanes Oxley Act and related regulations that required changes to board composition (e.g., Linck, Netter, and Yang, 2009; Duchin, Matsusaka, and Ozbas, 2010; Guo and Masulis, 2015; Alam, Chen, Ciccotello, and Ryan, 2018); and using local director supply or the introduction of new airline routes to capture

differences in firms' ability to recruit certain types of directors (Knyazeva, Knyazeva, and Masulis, 2013; Bernile, Bhagwat, and Yonker, 2018).⁹ We believe that these prior identification methods, while useful in certain settings, are less well-suited for examining board interlocks because they leave the door open to other, confounding channels by which unobserved factors could be driving outcomes of interest.¹⁰ In other words, while IV approaches based on regulatory shocks, director deaths, or changes in flight routes may capture variation in the structures of individual boards, they are less effective for isolating exogenous variation in the links between boards. From this standpoint, our novel identification method offers a framework that may be useful to researchers for studying how board interlocks impact a variety of outcomes, such as corporate governance practices, product market strategies, or financial reporting.

The remainder of the paper is organized as follows. Section 2 outlines our sample construction, describes our data sources, and provides descriptive statistics on firm and director characteristics. Section 3 explains our instrumental variables approach to capturing exogenous variation in board interlocks. In Section 4, we report our results. Section 5 concludes.

2. Data and Sample

To construct our sample, we start with all U.S. firms covered by the *BoardEx* “Organization Summary–Analytics” dataset. We extract board affiliations of individuals associated with these

⁹ Other papers use mergers, staggered boards, or legislation at the country or state level to draw causal inferences about board and director characteristics. See, for instance, Ahern and Dittmar (2012), Fos and Tsoutsoura (2014), Hauser (2018), and Greene, Intintoli, and Kahle (2020).

¹⁰ For example, if a director is concurrently a member of two firms' boards, the unexpected death of the director would directly eliminate the board interlock. But it would be inappropriate to ascribe all changes in firms' outcomes to the elimination of the interlock because the loss of the director may severely distract colleagues on the board (see Falato, Kadyrzhanova, and Lel, 2014), impairing their ability to guide the firm's decisions. Under the case of a new airline route connecting two cities, the added convenience of traveling between cities may spur the formation of a board interlock between two firms. However, the new airline connection might facilitate more knowledge spillovers through various channels, such as management, employees, shareholders, and other stakeholders who can also travel more easily between the two firms.

firms and then merge the data to the CRSP-Compustat merged database for the time period 2005-2017. From the resulting dataset, we drop observations for which information on a firm’s industry code (SIC) or state of headquarters is unavailable. We also exclude firms that are management investment trusts, unit investment trusts, face-amount certificate offices, or real estate investment trusts (i.e., firms with 4-digit SIC codes of 6722, 6726, or 6798). In addition, we drop individuals who are not board members by relying on the *BoardEx* “Organization Summary–Composition of Officers, Directors, and Senior Managers” file to exclude any observations where an individual is listed in the “Seniority” field as a “Senior Manager.”

Using the calendar year of the “annual report date” recorded in *BoardEx*, we start by identifying, for each year in the sample, all pairs of firms that are interlocked on account of sharing at least one director. Because any knowledge flows that occur through a board interlock may take time to manifest, we only consider a pair of firms to be interlocked as of year t if they share director(s) in both year t and year $t - 1$. For each firm pair, the source firm is the one that might conduct innovation activities in a given year. The other firm in the pair is an interlocked downstream firm whose patenting activities in year $t + 1$ or later might be influenced by the flow of innovation from the source firm. Note that we are able to account for bi-directional knowledge spillovers since each interlocked pair appears twice in the sample of firm pairs.

Next, for each interlocked downstream firm, we identify a group of non-interlocked downstream firms that can serve as potential control firms. These potential control firms include contemporaneous firms that are not interlocked with the relevant source firm but that operate in the same 4-digit SIC industry and are headquartered in the same state as the interlocked downstream firm. Any firms that have a board interlock with the relevant source firm at any time during the period 2005-2019 are excluded from the group of potential controls. After dropping

firm-pair observations where data on main outcome variables or control variables are unavailable¹¹, we restrict the set of potential controls by applying Coarsened Exact Matching (CEM) (see, e.g., Iacus, King, and Porro, 2012) with firm size and the number of patent filings over the past five years as matching variables.¹² As a result of applying CEM, each interlocked downstream firm in each year is matched with a non-interlocked, downstream firm. (Since we match control firms to interlocked downstream firms by year, a given interlocked downstream firm can have different control firms in different years.) If an interlocked downstream firm is not matched to any control firm, we drop it from our sample. We further drop observations where information on annual meeting-date schedule conflicts between paired firms is missing. Our final sample has 128,324 pair-year level observations covering 4,188 unique source firms and 3,887 unique (interlocked and non-interlocked) downstream firms.

From *BoardEx*, we gather additional data on the characteristics of source- and downstream-firm boards, including board size and the percentage of outside directors. We also compile information on two different measures of individual director busyness: (1) the total number of board seats that an individual holds; and (2) the total number of committee roles across all board seats that an individual holds. For shared directors, we gather data from *BoardEx* on age, gender, and past professional experience.

Our source of information on firms' patenting activities is the collection of full-text applications and grant filings available via the Bulk Data Storage System (BDSS) of the U.S.

¹¹ Specifically, the main outcome variables include *Patent volume*, *Direct citations*, *Patent value*, and *Non-self citations*. The control variables include *Firm size*, *ROA*, *R&D*, *Board size* (each measured separately for the source and downstream firms and lagged by one year), *Geographic distance*, and *Technological similarity*.

¹² We employ the user-written Stata package "cem" to implement k-to-k matching. Since the matching in this case may randomly drop observations to maintain an equal number of treated and control units in each strata, we examine a few different random samples and confirm (results not tabulated) that our results are qualitatively robust across these samples.

Patent and Trademark Office (USPTO).¹³ From the BDSS data files, we gather information on application filing and disclosure dates, patent grant dates, applicant names, assignee names, and International Patent Classification (IPC) codes. We also obtain information on patent citations and IPC codes from the *PatentsView* website¹⁴. To merge patent applications to our sample of source and downstream firms, we follow the procedure used by Chen, Hu, Wang, and Wu (2023). This procedure relies on a combination of simple string matching, manual checks, and various machine-learning algorithms to build a name-matching crosswalk between USPTO patent applications and Compustat firms (and their subsidiaries).¹⁵

We also gather comprehensive data on annual shareholder meeting dates from DEF 14A proxy filings filed with the SEC. We apply automated text scraping and text parsing to the SEC EDGAR database¹⁶ to extract all available shareholder meeting dates for all issuers during the sample period.¹⁷ Using various search terms, we filter out dates corresponding to non-regular shareholder meetings such as special shareholder meetings, extraordinary meetings, and consent solicitations. This filtering step leaves us with a sample of annual shareholder meeting dates that we then merge to our main sample of source firms and downstream firms.

Table 1 provides summary statistics for the source firms and their shared directors. The average (median) total assets of firms is \$14.3 billion (\$1.07 billion). The median firm has an ROA

¹³ <https://bulkdata.uspto.gov/>

¹⁴ For applications disclosed between 2001 and 2005, we extract IPC codes directly from the raw filings in the BDSS. For applications disclosed between 2006 and 2021, we use the IPC codes provided by PatentsView. For more details on the PatentsView data, see www.patentsview.org.

¹⁵ As in Chen, Hu, Wang, and Wu (2023), during the matching process we require that a firm be included in both Compustat and Data Axle, a large database that covers corporate parents, subsidiaries, and branches and provides information on the hierarchical position of an entity within its corporate family. We rely on Data Axle because a significant fraction of patent assignees can be subsidiaries or branches of Compustat firms, and accounting for non-parent entities is important for obtaining an overall picture of an organization's innovation activity (see, e.g., Lerner and Seru, 2022).

¹⁶ <https://sec.gov/edgar/search/>

¹⁷ Appendix B provides further details on how we collect and parse annual shareholder meeting dates from EDGAR.

of 0.03 and does not conduct any patenting activity or R&D spending during the year. On average, a board consists of about nine directors, 84% of whom are outsiders. More than 20% of directors are “busy” in that they hold at least three board seats or at least five committee assignments at publicly-traded firms. Among shared directors, the average age is 62, and 13% are female. The median shared director holds three board seats and five committee assignments at public firms. Before joining a source-firm board, 15% of shared directors had recent (in the past three years) employment experience in the technology or life sciences sectors. For those shared directors who had prior experience at firms with patenting activity, the average cosine similarity between vectors representing the director’s innovation experience and the source firm’s technology space is about 0.22.¹⁸

Table 2 presents summary statistics on outcome and control variables¹⁹ for two groups of downstream firms: (1) firms that are board-interlocked with a source firm and (2) CEM-matched firms that do not have an interlock with a source firm. The two groups are comparable along some dimensions but nonetheless differ in terms of firm size, ROA, R&D, board size, geographic distance from the source firm, and similarity to the source firm with regard to technology space. While we control for each of these variables in our regression tests, the substantial differences between the two groups highlight the need to account for observed and unobserved firm-level heterogeneities that could confound any causal relationships that exist between board interlocks and knowledge spillovers.

¹⁸ We construct vectors for measuring a shared director’s innovation experience and a firm’s technology space by counting the number of patent applications filed under various IPC codes. A director’s innovation experience consists of patenting by firms at which he or she was an employee or a board member. In calculating a shared director’s innovation experience, we use the director’s entire history of employment or board service (from 2001 or later) at any firms other than the interlocked firms.

¹⁹ Section 4 gives further details on the construction of key variables, and Appendix A provides a list of variable definitions.

3. Identification Strategy

3.1 Annual Shareholder Meetings and Board Interlocks

Our approach to addressing endogeneity in board interlocks exploits a key institutional detail related to the timing of firms' annual shareholder meetings. With thousands of annual shareholder meetings held in the U.S. each year, it is inevitable that some of the meeting dates will be very close together or even identical. Since directors are almost universally expected to attend their firms' annual shareholder meetings, we contend that a schedule conflict between two firms' annual meetings makes it difficult or impossible for a director to fulfill board obligations at both firms. Thus, our identification strategy consists of using annual meeting schedule conflicts across pairs of firms to build instrumental variables that can capture exogenous variation in the occurrence of board interlocks.

Prior research and anecdotal evidence indicate that firms very often mandate that all of their directors attend the annual meeting of shareholders, and directors generally have strong incentives to do so (see, e.g., Li and Yermack, 2016). Indeed, a longstanding U.S. SEC rule, Item 407(b) of Regulation S-K, requires each public firm to annually disclose not only its policy regarding director attendance at the annual shareholder meeting, but also how many board members attended the prior year's annual meeting. Most firms comply with this rule by openly affirming their commitment to director attendance at the annual meeting.²⁰ Also, given the high degree of importance placed by activists, institutions, and proxy advisors on directors' visibility and accountability to the shareholders who elect them, reputational concerns likely further incentivize boards to strive for 100% director attendance at the annual shareholder meeting.

²⁰ For example, the proxy statement filed by Exxon Mobil on April 7, 2022, states, "As specified in our Corporate Governance Guidelines, it is Exxon Mobil's policy that directors should make every effort to attend the annual meeting of shareholders. All (twelve) directors on May 26, 2021, attended the 2021 annual meeting of shareholders."

For our identification strategy to be effective, it must be the case that a non-negligible number of schedule conflicts exist between pairs of firms' annual shareholder meeting dates. In other words, schedule conflicts must not be so rare that they do not drive any detectable variation in board interlocks. The idea that annual shareholder meeting conflicts occur at a meaningful rate seems plausible in view of the well-known clustering of most U.S. public-firm annual meeting dates during "proxy season," which approximately spans from mid-April to mid-June. Nevertheless, to better gauge the importance of actual and potential schedule conflicts, it is worthwhile to examine how much temporal clustering is present within the proxy season and within different calendar months and weeks.

Figure 1 provides a first look at the extent of temporal clustering in firms' annual shareholder meetings. Panel A shows a breakdown of annual meeting frequencies, by calendar month, across all source-firm and downstream-firm years in our sample during 2005-2017. Notably, May is by far the most popular calendar month for annual shareholder meetings: this month alone accounts for over 42% of meeting dates. About 75% of meetings take place from April to June, and the remaining 25% of meetings are approximately evenly spread out among the other nine months of the year. Meeting dates also tend to cluster on certain days of the week. As seen in Panel B, about 24%, 27%, and 32% of meetings are held on Tuesdays, Wednesdays, and Thursdays, respectively. Only about 16% of meetings take place on Mondays or Fridays, and almost no meetings take place on weekends. Overall, it is clear from Figure 1 that annual shareholder meetings exhibit substantial clustering in terms of both calendar month and day-of-the-week.

Next, to confirm the logic underlying our approach, we consider some basic evidence on whether schedule conflicts in annual meetings are indeed associated with lower probabilities of board interlock. Figure 2 shows a detailed frequency breakdown of the temporal distance, in days,

between the source- and downstream-firm annual meetings for pairs with and without a board interlock. (For expositional convenience, the chart does not include pairs of meetings with temporal distance of more than 10 days.) As seen in the figure, there is a striking difference in the rates with which interlocked pairs and non-interlocked pairs have same-day schedule conflicts. For interlocked firm pairs, only slightly more than 5.20% of the cases involve a direct, same-day schedule conflict. In contrast, the corresponding proportion for non-interlocked firms is about 9.04%, which is over 70% higher than the proportion for interlocked firms. Interestingly, the frequency with which source-downstream firm pairs have annual meetings separated by exactly one day is also lower for interlocked pairs (about 13%) than for non-interlocked pairs (about 15%). This suggests that scheduling constraints for directors continue to be present, albeit to a lesser degree, in the case of annual meeting dates that differ by a single day.

3.2. Instrumental Variables

The above logic motivates the construction of instrumental variables (IVs) that can help address the endogeneity in board interlocks. As a first step in this construction, we estimate OLS regressions that relate the presence of a board interlock between two firms to whether the firms currently have (or recently had) a same-day annual meeting conflict. The sample includes firm-pair-year observations in which each pair consists of a source firm and a downstream firm. Downstream firms include (1) firms that are board-interlocked with the relevant source firm; and (2) matched, contemporaneous, non-interlocked downstream firms selected via Coarsened Exact Matching (CEM) as detailed in Section 2. The dependent variable in the regressions is an indicator equal to one if the downstream firm in a pair is board-interlocked with the source firm from year $t-1$ to t . The main explanatory variable is $\text{Annual meeting overlap}_{ijt}$, a binary variable indicating if source firm i and downstream firm j have the same annual shareholder meeting date

for at least one year during the two-year interval preceding the source firm's fiscal year end. Table 3 reports the regression results. Column (1) is a baseline specification, while Columns (2) to (4) expand the specification by controlling for firm sizes, fixed effects, or both. Firm size is measured as a firm's log-transformed total assets (in millions) and is lagged by one year and winsorized at the 1% and 99% levels. Fixed effects for interlock groups capture time-invariant heterogeneity across interlock groups, where an interlock group is a particular combination of a source firm, a board-interlocked downstream firm, and the downstream firm's CEM-matched, non-interlocked counterparts. As seen in all four regressions, the likelihood of a board interlock is significantly negatively related to the presence of a meeting schedule conflict. These regression results lend further support to our premise that annual meeting schedule conflicts place powerful constraints on firms' ability to form board interlocks.

Taking Column (4) of Table 3 as our preferred specification, we then calculate fitted values to yield $Pr(Interlock)$, the predicted probability of a board interlock for a given firm pair in a given year, and we winsorize it at the 1% and 99% levels. $Pr(Interlock)$ is a key variable that we use repeatedly throughout the main empirical analysis to account for endogeneity in board interlocks. In particular, $Pr(Interlock)$ and its interactions with other covariates will serve as instruments in 2SLS (Two-Stage Least Squares) regressions to examine the causal effects of board interlocks on firm-to-firm spillovers.

For our 2SLS regressions to yield consistent estimates, the instrumental variables must satisfy both relevance conditions and exclusion restrictions. In our main analysis (see Section 4), we confirm that the relevance conditions clearly hold based on the strength of the instruments in 2SLS first-stage regressions. However, it is not as straightforward to establish that our instruments meet the requisite exclusion restrictions. These restrictions amount to the requirement that,

conditional on control variables in a regression, the instruments correlate with downstream-firm innovation outcomes only through the channel of board interlocks (or through the interactions of board interlocks with other covariates). While it is not possible to prove definitively that exclusion is satisfied, the case for our instrumental variables becomes stronger if we can rule out the plausible ways in which exclusion might fail to hold. We therefore proceed to consider some of the main threats to identification in our setting and explain why our inferences are likely to be valid despite such concerns.

One plausible reason that the exclusion restrictions might not hold is if temporal proximity in firms' annual meeting dates correlates with the firms' geographic proximity. For example, annual meeting schedules of paired firms may be impacted by whether they are headquartered in the same city or local region, and it could be the case that geographic proximity, not the presence of an interlock, is the true driver of better knowledge flows between the firms.²¹ This scenario, while not implausible, is less problematic for our analysis for two reasons. First, as discussed in Section 2, we use matching techniques to ensure that each interlocked downstream firm is matched with a non-interlocked downstream firm headquartered in the same state. Second, all of our instrumental variables regressions include a control for the geographic distance between source-firm and downstream-firm headquarters.

Another potential threat to our identification strategy is that annual meeting schedule conflicts could simply be proxying for one or more unobserved dimensions of similarity between firms. For example, it could be that firms with highly similar managerial styles, financial constraints, product qualities, or innovative capacities tend to hold annual shareholder meetings at

²¹ Prior research shows that geographic proximity is an important contributor to knowledge spillovers between firms (see, e.g., Jaffe, Trajtenberg, and Henderson, 1993; Audretsch and Feldman, 1996; Matray, 2021).

around the same time during proxy season, leading to an elevated chance of a schedule conflict. If these between-firm similarities also induce firms to have similar innovation activity, then board interlocks might not be the sole channel through which schedule conflicts correlate with downstream-firm outcomes. Although it is difficult to rule out all of these alternative channels of effect, we note that such channels, even if present, would simply make it more challenging for us to detect interlock-related spillover effects. Indeed, while an unobserved similarity between two firms can be expected to strengthen the observed spillover of knowledge between the firms, it should also raise the chance of a schedule conflict and thus lower the chance of a board interlock.

It is also possible that firms deliberately choose their annual shareholder meeting dates to attract or cater to certain directors who are expected to soon join the board. Under such a scenario, exclusion could fail because annual meeting schedule conflicts themselves would be endogenously determined by some other factor that correlates with both board appointments and downstream innovation behavior. We believe that such a scenario is less plausible for two reasons. First, the shared director(s) in any single interlock usually constitute a relatively small fraction of the two firms' boards. Many other members of the two boards do not participate in the same interlock but have their own busy schedules and professional commitments that could influence how a particular annual shareholder meeting is scheduled. Second, most of the annual meeting dates in our sample follow stable, predictable patterns over time in which firms try to preserve the same calendar month, week-of-the-month, and day-of-the-week from one year to the next. Building on these ideas, we have conducted an extensive set of empirical tests that relate year-to-year changes in annual meeting dates to new director appointments and to the formation of board interlocks. Appendix C provides the details. Taken together, the findings from these tests do not provide any evidence to suggest that firms are endogenously choosing shareholder meeting dates to accommodate the

preferences and constraints of shared directors.

4. Main Results

4.1 Board Interlocks and Knowledge Spillovers

We first investigate the effects of board interlocks on different spillover metrics. *Ceteris paribus*, the presence of a board interlock with a source firm can enable a downstream firm to better acquire scientific and technological knowledge and ultimately incorporate it into its own innovation activities. For example, a shared director may be able to rapidly convey knowledge and insights about a new innovation from a source firm to an interlocked downstream firm through face-to-face communication with top management or fellow board members. Much of this knowledge may be soft information that complements what is available to the wider public through other channels, such as public patent disclosures, financial statements, or corporate news announcements. Consequently, the presence of a board interlock may make a downstream firm's innovation more sensitive to variations in the flow of innovation from the source firm.

To examine this prediction, we first estimate baseline OLS regressions that relate a board interlock to the quantity, relatedness, market value, and quality of a downstream firm's innovation that takes place after source-firm patenting in a given year t . We capture these four different aspects of knowledge spillover with the following variables: *Patent volume*, the log-transformed number of patent applications filed by a downstream firm in year $t + 1$; *Direct citations*, the log-transformed number of patent applications filed by a downstream firm from year $t + 1$ to $t + 3$ that cite the source firm's year t patent applications; *Patent value*, the log-transformed total value of all patent applications²² that a downstream firm files in year $t + 1$; and *Non-self citations*, the

²² We impute individual patent values from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017). Specifically, for each patent we use Equation (3) in Kogan, Papanikolaou, Seru, and Stoffman

log-transformed total number of non-self citations (through December 2021) of patent applications filed by a downstream firm in year $t + 1$.²³

The main explanatory variable of interest is $\text{Log source patents} \times \text{Interlock}$, an interaction between the quantity of source-firm innovation and an indicator for a board interlock. In addition to including the interaction and the standalone variables Interlock and $\text{Log source patents}$, we control for important firm characteristics, such as Firm size , ROA , R\&D , and Board size , each of which is measured separately for source and downstream firms. To ensure our results are not driven by downstream firms' geographic proximity to the source firm, we control in each regression for the geographic distance between source-firm and downstream-firm headquarters. We also control for the 3-digit IPC-vector based cosine similarity between the source and downstream firms' patent applications in the past three years. The elements of a firm's IPC vector are the counts of patent applications filed under the corresponding IPC codes within the specified time window.²⁴ Moreover, we include interlock-group fixed effects and year fixed effects to further mitigate biases from other potential sources of heterogeneity. Specifically, we estimate regressions of the following form:

$$\begin{aligned} \text{Outcome}_{j,t+n} = & \alpha + \beta_1 \times \text{Log source patents}_{it} \times \text{Interlock}_{ijt} + \beta_2 \times \text{Interlock}_{ijt} \\ & + \beta_3 \times \text{Log source patents}_{it} + \gamma_1 Z_{it} + \gamma_2 Z_{jt} + \gamma_3 Z_{ijt} + FEs + \epsilon_{jit} \end{aligned} \quad (1)$$

(2017) to calculate its value as $\text{Economic value} = (1 - \underline{\pi})^{-1} \frac{1}{N_j} E[v_j|R_j]M_j$, where $\underline{\pi}$, the unconditional probability of successful patent application, is taken to be 56%; N_j is the number of patent applications a firm filed on the same day; and M_j is the firm's market capitalization five trading days prior to the application announcement date t . We then aggregate the *Economic value* of all patent applications filed by a firm during the year to construct *Patent value*. The value is set to 0 if the firm does not file any patent in a given year.

²³ Since the BDSS "Patent Application Full Text Data" files do not include information on citations, we construct patent citation measures by merging the "Patent Grant Bibliographic Text Data" files, which cover patent applications that eventually receive grants, to the citation data obtained from the PatentsView database (<https://patentsview.org/>). Note that our constructed outcome variables do not include two groups of granted applications: (1) those that did not have an assignee reported when published in the "Patent Application Full Text Data"; and (2) those that became grants prior to public disclosure of the application and hence were not included in the "Patent Application Full Text Data."

²⁴ If a patent has multiple unique 3-digit IPC codes, we add one to the count of each of these IPC codes to account for this patent.

where $Outcome_{j,t+n}$ is a measure of downstream-firm j 's innovation activity from year $t+1$ to year $t+n$, $\log source\ patents_{it}$ is the log-transformed number of patent applications filed in year t by source firm i , and $Interlock_{ijt}$ is an indicator for the presence of a board interlock between firms i and j in year t . Z_{it} and Z_{jt} denote sets of control variables for the source and downstream firms, respectively. Z_{ijt} denotes control variables for a given source-downstream-firm pair. Interlock-group and year fixed effects are included. In the model, the coefficient of interest is β_1 , which captures the influence of a board interlock on the sensitivity of a downstream firm's innovation to source-firm patent flows.

Table 4 presents the baseline OLS regression results. In line with the notion that board interlocks can facilitate knowledge spillovers between the two firms, the coefficient on our main variable of interest is positive and statistically significant for all four outcome measures. The results are also economically significant. For example, based on the estimates in Column (1), the effect of a one-standard-deviation increase in log source firm patents (1.624 in our sample) on log downstream patent volume is 0.05 greater when a board interlock is present versus when one is not.

It is worth noting that, despite the positive and significant coefficient on the interaction term, the coefficients on the stand-alone variables $Interlock$ and $\log source\ patents$ are often negative. While negative signs for the stand-alone coefficients may seem counterintuitive, we believe they can be explained as follows. First, in the absence of a board interlock, more patenting by a source firm does not necessarily enhance downstream innovation. In fact, more source-firm innovation could reduce downstream innovation either because of economic competition and rivalry effects within a technology space (e.g., Bloom, Schankerman, and Van Reenen, 2013) or because of the legal protections afforded to source firms through the U.S. patenting system. Second, if two firms

are board-interlocked but the source firm does not actively innovate, then the interlock might distract shared directors, thus undermining their advisory capacity and their ability to facilitate knowledge spillovers.

Since the OLS regressions do not address endogeneity issues, we are not able to draw solid conclusions about the effects of interlocks. Thus, we estimate Two-Stage Least Squares (2SLS) regressions to shed light on the causal relation between board interlocks and knowledge spillovers. Towards this end, we first calculate fitted values from Column (4) of Table 3 and winsorize the values at 1% and 99% to yield $\Pr(\text{Interlock})$, the predicted probability of a board interlock. We then estimate 2SLS regressions as in Equation (1), where the endogenous variables, $\text{Log source patents}_{it} \times \text{Interlock}_{ijt}$ and Interlock_{ijt} , are instrumented by the two instruments $\text{Log source patents}_{it} \times \Pr(\text{Interlock})_{ijt}$ and $\Pr(\text{Interlock})_{ijt}$ to form a just-identified model.

Columns (1) and (2) in Table 5 report the first-stage 2SLS results. The coefficients on the two corresponding instrumental variables are both significantly positive, indicating high correlations between our IVs and the endogenous variables. In addition, the Sanderson-Windmeijer multivariate F-statistic in each regression is significant, rejecting a weak instruments hypothesis.²⁵ These results confirm that our instruments satisfy the relevance conditions necessary for drawing valid inferences from 2SLS estimation. Columns (3) to (6) report second-stage results using the two instrumented variables as regressors. Consistent with the OLS regression estimates in Table 4, the coefficient on the main variable of interest is significantly positive in all regressions. In particular, Column (3) indicates that a board interlock strengthens spillover effects with regards

²⁵ In a linear model with multiple endogenous variables, the Sanderson-Windmeijer conditional F-test provides information on whether instruments have sufficient statistical power to separately provide sources of exogenous variation for each endogenous regressor (Sanderson and Windmeijer, 2016). Untabulated results show that the Cragg-Donald F-statistic, which examines whether the entire equation is weakly identified, is also statistically significant.

to the overall volume of downstream patenting. Column (4) shows that a board interlock significantly increases spillover effects in terms of patents that directly cite source patents during the 3-year period following source-firm innovation. As seen in Column (5), a board interlock leads to a significant increase in spillovers as measured by the sensitivity of aggregated patent application values filed by downstream firms in year $t + 1$. Furthermore, Column (6) shows that, when an interlock is present, the spillover effect of source firm innovation is significantly greater in terms of non-self citations for downstream patents. In each case, the weak instrument hypothesis is further rejected by the Kleibergen-Paap Wald F-statistic. For robustness, we conduct additional tests like those in Table 5 except using four alternative measures of downstream innovation quality and relatedness: *Alt_Common citations*, *Alt_Similar100*, *Alt_Patent breadth*, and *Alt_High-value patents*, all defined as in Appendix A. Untabulated results show that board interlocks significantly increase spillover effects with regards to these alternative measures.

4.2 Heterogeneity of Interlock-Related Spillovers

Having shown that board interlocks help foster knowledge spillovers from source firms to downstream firms, we next investigate whether key characteristics of boards and directors influence these spillover effects. In particular, we examine the moderating effects of board busyness and the proportion of outside directors on the board. We also explore whether spillover effects vary with shared directors' busyness, demographic characteristics, technical backgrounds, and innovation experience. To proceed, for a given characteristic, we construct a binary measure of the characteristic ("Heterogeneity") and interact it with the log of source-firm patents and the board interlock indicator. The resulting triple interaction is our main variable of interest. We estimate 2SLS panel regressions in a just-identified model and instrument for the endogenous

variables with four different IVs: $Heterogeneity \times Log\ source\ patents \times Pr(Interlock)$, $Log\ source\ patents \times Pr(Interlock)$, $Heterogeneity \times Pr(Interlock)$, and $Pr(Interlock)$. The regressions have the form

$$\begin{aligned}
Outcome_{j,t+n} = & \alpha + \beta_1 Heterogeneity_{ijt} \times Log\ source\ patents_{it} \times Interlock_{ijt} \\
& + \beta_2 Heterogeneity_{ijt} \times Interlock_{ijt} \\
& + \beta_3 Log\ source\ patents_{it} \times Interlock_{ijt} + \beta_4 Interlock_{ijt} \\
& + \beta_5 Heterogeneity_{ijt} \times Log\ source\ patents_{it} + \beta_6 Heterogeneity_{ijt} \\
& + \beta_7 Log\ source\ patents_{it} + \gamma_1 Z_{it} + \gamma_2 Z_{jt} + \gamma_3 Z_{ijt} + FEs + \epsilon_{jit}
\end{aligned} \tag{2}$$

where $Outcome_{j,t+n}$ is the downstream firm's innovation outcome after source-firm innovation. $Log\ source\ patents_{it}$ is the number of patent applications filed by source firm i in year t . $Heterogeneity_{ijt}$ is an indicator that captures a firm, board, or shared-director characteristic. In untabulated tests, we confirm that the first-stage results of estimating Equation (2) yield a positive and significant correlation between our IVs and the endogenous variables, indicating that our instrumental variables satisfy the relevance condition. In the sections below, we discuss the second-stage results for each of our tests of treatment heterogeneity.

4.2.1 Board Composition

The first board-level characteristic that we examine is the presence of outside directors. Theoretical models suggest that a high proportion of outside directors on the board may be associated with weaker information exchange between the CEO and board members. For instance, Adams and Ferreira (2007) argue that a CEO may be reluctant to share information to outside

board members because disclosing his private information will make the board more informed and more able to monitor him intensively. Also, according to the models of Raheja (2005) and Harris and Raviv (2008), an outsider-dominated board can lead to worse information sharing. Based on these theoretical implications, we predict that outsider-dominated boards are associated with weaker interlock-related spillover effects.

Table 6 reports second-stage 2SLS regressions examining the effects of board composition. Our main variable of interest is the triple interaction of *Log source patents*, *Interlock*, and *Outsider dominated*. The *Outsider dominated* variable is an indicator variable equal to one if at least 85% of directors on either the source-firm board or the downstream-firm board are outside directors, where an outside director is defined as an individual who is a Non-Executive Director (NED) as per the *BoardEx* Company Profile dataset. As seen in Columns (1) to (4), the coefficient on the main variable is significantly negative for all specifications, suggesting that interlock-related spillover effects are relatively weaker when at least one firm in the interlocking pair has an outsider-dominated board. This evidence is consistent with the notion that knowledge spillovers depend not only on the presence of a board interlock, but also on directors' ability to exchange information with management at source and downstream firms.

4.2.2 Board and Shared-Director Busyness

Next, we investigate whether the knowledge spillover effects of board interlocks vary with the busyness of boards and shared directors. Empirical research shows that board busyness can be detrimental to firm performance (Fich and Shivadasani, 2006; Hauser, 2018). A related line of research finds that director distraction hurts board monitoring quality and shareholder value (e.g., Falato, Kadyrzhanova, and Lel, 2014). In contrast, Field, Lowry, and Mkrtchyan (2013) find that,

for less-established firms, busy directors can contribute positively to firm value through advising rather than monitoring. Within the context of knowledge spillovers, we expect that directors who are distracted by fiduciary duties in multiple firms and roles will be less effective in communicating and sharing scientific knowledge with colleagues. Thus, we hypothesize that busy boards and busy shared directors are associated with weaker interlock-related spillover effects. To examine this prediction, we use two measures of director busyness. First, we use the number of board seats held in different firms as a measure of the overall extensity of a director's service. We follow prior literature (e.g., Ferris, Jagannathan, and Pritchard, 2003) and define a director as busy if he or she holds at least three board seats in a given year. While this traditional busyness measure reflects a director's service along the extensive margin, the precise workload that a director has on a given board is also important. Therefore, we rely on directors' committee service to construct an alternative measure of busyness. Under this measure, a director is busy if he or she holds at least five committee seats across all boards on which he or she serves. For each of our two measures, we construct an indicator variable, *Busy board*, which equals one if the source or downstream firm has a board for which more than one-third of members are busy.

Panel A of Table 7 shows the results of second-stage 2SLS regressions examining the effects of board busyness on interlock-related spillovers. In Columns (1) to (4), which define busyness based on directors' held board seats, the coefficient on the main variable (i.e., the triple interaction of *Log source patents*, *Interlock*, and *Busy board*) is significantly negative for patent volume, value, and quality, while it is insignificant for patent relatedness. When board busyness is defined based on directors' committee assignments (Columns (5) to (8)), the coefficient for the main variable is negative in all four specifications. Taken together, the results suggest that interlocks become a less

efficient conduit for information transfer when a substantial number of source or downstream directors are preoccupied by high workloads.

In Panel B, we turn our focus to shared directors and investigate whether interlock-related spillover effects are weakened when individual shared directors in an interlock group are busy. We construct an indicator at the yearly downstream-firm level, *Busy director*, that equals one if all shared directors between an interlocked pair firms are busy. Note that control firms by definition are not part of an interlock and have no shared directors per se. As a result, while the value of *Busy director* is based on the characteristics of shared directors, that value is assigned within a treat-control group to both the treated (interlocked) downstream firm and its matching (non-interlocked) control. Proceeding in this fashion allows us to effectively compare an interlocked firm against the counterfactual represented by its matching control within the same interlock group.²⁶

As in Panel A of Table 7, we employ two distinct measures that capture shared-director busyness along two different dimensions: held board seats and committee service roles. Specifically, the first measure is an indicator equal to one if every shared director in an interlocking firm pair holds at least three board seats in a given year. The second measure is an indicator equal to one if every shared director in an interlocking firm pair holds at least five total committee roles (across all their board seats) in a given year. Our main variable of interest is the triple interaction of *Log source patents*, *Interlock*, and *Busy director*. As seen in Columns (1) to (8) of Panel B, the coefficient on the main variable is significantly negative in all eight specifications, suggesting that a high workload—either in terms the number of held board seats or the number of committee service roles—compromises shared directors' ability to facilitate information flow between source and downstream firms.

²⁶ We also use a similar approach when examining the effects of other shared-director characteristics in Section 4.2.3.

4.2.3 Demographic Characteristics of Shared Directors

We next investigate how the spillover effects of board interlocks vary with the demographic characteristics of individual shared directors. Understanding which shared director characteristics matter most in the context of knowledge spillovers is important because boards may seek to recruit and select certain types of directors to maximize the benefits from potential knowledge spillovers.

We focus first on two demographic characteristics of shared directors: age and gender. The existing literature shows that younger managers or directors have more career concerns and reputational incentives, which could encourage them to exert more effort as board members (Gibbons and Murphy 1992; Chevalier and Ellison 1999; Jiang, Wan, and Zhao, 2016). Therefore, we expect the knowledge spillover effects of board interlocks to be more pronounced when shared directors are relatively young. A large body of literature also investigates the impact of female board representation on firm value (e.g., Ahern and Dittmar, 2012; Matsa and Miller, 2013; Bernile, Bhagwat, and Yonker, 2018). In the context of knowledge spillovers, the potential effects of director gender are ambiguous. On the one hand, prior empirical work finds some evidence that female directors can spur innovation (Chen, Leung, and Evans, 2018). On the other hand, female directors may be stricter, more independent monitors compared to their male counterparts (Adams and Ferreira, 2009; Adams et al., 2010), which could reduce the management team's willingness to share information with the board.

The second group of characteristics that we explore pertain to shared directors' professional backgrounds. Intuitively, having a recent technical background or some experience with innovations in a relevant technology area could enable a shared director to absorb and convey knowledge more efficiently. Therefore, we hypothesize that if a shared director has a recent

technical background or previously served at other firms that developed innovations in relevant technology areas, then interlock-related spillover effects should be stronger. We measure a director's technical background by his or her employment in the past three years in the technology and life-sciences sectors, each of which accounts for a large proportion of all U.S. patents. We define these two sectors based on SIC codes as detailed in the SEC's Division of Corporation Finance Office assignment.²⁷ When tracking a director's employment history, we exclude any firms that the director is affiliated with through current-year employment or board service.

To measure shared directors' innovation experience related to source and downstream firms, we compile information on each shared director's employment and board directorship record prior to the interlock formation (and excluding the interlocked firms). All patent applications filed by firms during a director's historical employment or board service are counted as part of the director's innovation experience. We use total patent counts in each IPC code to form a director's 3-digit IPC-based innovation experience vector.²⁸ Next, for a source firm or downstream firm in a given year, we represent the technology space with a vector of 3-digit IPC counts corresponding to all patent applications filed by the firm in the past three years. The cosine similarity between a director's innovation experience vector and a firm's technology space vector provides a measure of relatedness between the two. When computing cosine similarities, we restrict the sample to cases where a director has at least some innovation experience. Also, we set the innovation similarity equal to zero when an interlocked firm does not have any patent applications with which to calculate its technology space.

²⁷ In particular, we use the U.S. Securities and Exchange Commission (SEC) Division of Corporation Finance Office assignment: <https://www.sec.gov/corpfin/division-of-corporation-finance-standard-industrial-classification-sic-code-list>. The office assignments that we count toward a director's technical background include "Office of Technology" and "Office of Life Sciences".

²⁸ We include all patent applications published by the USPTO BDSS on April 15, 2001, or later when computing directors' experience vectors.

Table 8 reports the results of these regressions. Our main variable of interest is the interaction of *Log source patents*, *Interlock*, and an indicator that captures a particular characteristic of shared-director(s) in an interlock group. Note that, as with the earlier tests in Section 4.2.2, matching control firms by construction have no shared directors. Therefore, within an interlock group in a given year, we assign the same value for the shared-director characteristic to both the interlocked and non-interlocked downstream firms. This approach ensures that we can control for heterogeneity across interlock groups and draw meaningful inferences about how the impact of a shared-director characteristic differs when an interlock is present versus when one is not.

In Panel A, *Young director* indicates that at least one shared director in an interlock group is 63 (the sample median) or younger. In line with our predictions, the coefficient on the main variable is significantly positive in all specifications. This suggests that younger shared directors are better at facilitating knowledge spillovers in terms of downstream patent volume, relatedness, value, and quality.

The regressions in Panel B examine the effects of shared directors' gender on interlock-related knowledge spillovers. *Female* is an indicator equal to one if at least one shared director in an interlock group is female. In contrast to the results for shared-director age, the coefficient on the triple interaction term involving *Female* is insignificant, regardless of whether the dependent variable is downstream firms' innovation quantity, relatedness, market value, or quality. Hence, we conclude there is little evidence that a shared director's gender either strengthens or weakens the knowledge spillovers arising from a board interlock.

In Panel C, *High tech experience* is an indicator equal to 1 if at least one shared director in an interlock group has high-tech employment experience in the past 3 years. Interestingly, we do not find any positive effects of shared directors' technical background on interlock-related

spillovers: the coefficient on the main explanatory variable is insignificant in all four specifications. In contrast, Panel D shows that the relatedness between shared directors' innovation experience and interlocked firms' technology space plays an important role in influencing spillovers. *Related experience* is a binary variable equal to one when the innovation similarities between shared director(s) and the two interlocked firms (i.e., source and downstream) are each above their respective sample medians. As seen in Columns (1) to (4), the coefficient on the triple interaction term is always significantly positive. Taken together, the results in Panels C and D suggest that having a general technical background alone does not make a shared director a better conduit for inter-firm knowledge transmission. Having relevant innovation experience, in contrast, is a key determinant of how effectively shared director(s) can facilitate knowledge spillovers.

4.3 The Nature of Source-Firm Innovation

Our previous tests confirm the view that the knowledge spillover effects of interlocks are influenced by the quality of communication among board members as well as by the individual characteristics of shared directors. In this section, we turn to the question of whether different types of patent flow from the source firm lead to heterogeneous effects. Of particular interest is whether and how the spillover effects of board interlocks are altered when the flow of patenting from the source firm displays (1) high quality, (2) high breadth, or (3) a high degree of technological proximity to prior innovation by the source or downstream firm.

To explore the impact of heterogeneity in the quality of source-firms' patent flows, we construct a variable, *Log high-value source patents*, which is the log-transformed number of patent applications filed by the source firm in year t that have values above the median value among all patent applications filed between 2005 and 2017. We impute individual patent values from stock-

market announcement returns following the methodology of Kogan, Papanikolaou, Seru, and Stoffman (2017). A corresponding variable, *Log low-value source patents*, is the log-transformed count of patents not defined as high-value. We then separately interact *Log high-value source patents* and *Log low-value source patents* with the board interlock indicator and include the interaction terms and stand-alone variables in a 2SLS regression. Using three IVs (*Log high-value source patents* \times *Pr(Interlock)*, *Log low-value source patents* \times *Pr(Interlock)*, and *Pr(Interlock)*) to instrument for the three endogenous variables, we estimate 2SLS regressions with the following form:

$$\begin{aligned}
 Outcome_{j,t+n} = & \alpha + \beta_1 Log\ high-value\ source\ patents_{it} \times Interlock_{ijt} \\
 & + \beta_2 Log\ low-value\ source\ patents_{it} \times Interlock_{ijt} + \beta_3 Interlock_{ijt} \\
 & + \beta_4 Log\ high-value\ source\ patents_{it} + \beta_5 Log\ low-value\ source\ patents_{it} \\
 & + \gamma_1 Z_{it} + \gamma_2 Z_{jt} + \gamma_3 Z_{ijt} + FEs + \epsilon_{ijt}
 \end{aligned} \tag{3}$$

where *Outcome*_{*j,t+n*} is a measure of downstream-firm *j*'s innovation activity from year *t+1* to year *t+n*, *Log high-value source patents*_{*it*} is the log-transformed number of high-value patent applications filed in year *t* by source firm *i*, and *Log low-value source patents*_{*it*} is the log-transformed number of all other patent applications filed by source firm *i* in year *t*. A comparison of β_1 and β_2 indicates whether board interlocks have more positive spillover effects for higher-value source-firm patents. In other tests, we examine the effects of additional types of source-patent heterogeneity on interlock spillover effects by replacing *Log high-value source patents* (*Log low-value source patents*) in equation (3) with alternative measures: *Log high-breadth source patents* (*Log low-breadth source patents*), *Log downstream-similar source patents* (*Log*

downstream-nonsimilar source patents), and *Log core source patents (Log peripheral source patents)*.

Untabulated results from first-stage regressions of estimating the model in Equation (3) show that the instrumental variables are strong and satisfy the relevance condition. Next, we proceed to outline our predictions and findings for each of the source patent features mentioned above. Griffith, Harrison, and Van Reenen (2006) find that knowledge spillovers are more likely to happen when downstream firms have more to learn from the source firm. Since higher-quality source-firm patents may contain more valuable information for downstream firms to learn from, we expect that source-patent quality positively reinforces the knowledge spillover effects of board interlocks.

Panel A of Table 9 examines the effects of quality heterogeneity. To save space, we do not report coefficient estimates for the stand-alone patent-flow variables. As seen in Columns (1) to (4), the coefficient on the interaction term between *Log high-value source patents* and *Interlock* is significantly positive in all specifications. In contrast, none of the regressions has a significant coefficient for *Log low-value source patents × Interlock*. F-tests for differences in the coefficients reject the null hypothesis of equality. Overall, the results support our prediction that higher-quality source-firm patent flow strengthens the spillover effects of board interlocks with respect to the quantity, value, quality, and relatedness of downstream innovation.

Next, we turn to another important characteristic of source-firm patents: patent breadth. A priori, patent breadth could have two contrasting effects on interlock-related spillovers. On the one hand, existing literature shows that overlapping innovations within a technology space tend to yield more spillovers (e.g., Bloom, Schankerman, and Van Reenen, 2013). From this viewpoint, broad patents may enhance interlock-related spillover effects because such patents are inherently more likely than narrow patents to overlap with other innovations. On the other hand, patents with

a very wide scope across technical classes may cover newer technologies or may be less familiar to shared directors, thus making it more difficult for downstream firms to benefit from knowledge spillovers via an interlock.

Panel B of Table 9 examines the moderating role of patent breadth on interlock spillover effects. Following prior work (e.g., Lerner, 1994), we construct a measure of patent breadth by counting the number of unique 4-digit IPC codes associated with a patent. A high-breadth patent is defined as one that has breadth above the median value across all patent applications filed between 2005 and 2017; all other patents are categorized as low-breadth. Columns (1) to (4) show that low-breadth patent flow exhibits strong and positive interlock-based effects with respect to all four downstream innovation outcomes. By contrast, high-breadth patent flow has either negative or insignificant effects. F-tests confirm that the two coefficients are significantly different from each other. Overall, the results support the view that low-breadth patents lend themselves better to firm-to-firm knowledge spillovers via board interlocks.

We next examine the effects of technological similarity between source-firm patent flow and the prior innovation of a downstream firm. Existing research (see, e.g., Chu, Tian, and Wang, 2019; Myers and Lanahan, 2022) provides mixed evidence on how technological similarity between different firms' innovation can be expected to influence spillovers. On the one hand, high similarity between a source firm's patenting and a downstream firm's prior patenting may lead to weaker interlock spillover effects because the knowledge flowing from the source firm might already be familiar to the downstream firm. On the other hand, knowledge from source-firm innovation that pertains to more familiar technologies may be easier for shared directors to absorb and convey to downstream firms.

To construct the technology similarity measure, we first vectorize the 3-digit IPC codes for each source-firm's patent application filed in the current year. We also vectorize the count of 3-digit IPC codes for all downstream-firm's patent applications filed in the past three years. We then compute the cosine similarity between each source-patent vector and the downstream-firm vector. Using the 75th percentile across all cosine similarities in a given year as a cutoff, we define *Downstream-similar source patents* to be the number of patent applications filed during the year by a source firm for which the computed similarity exceeds the cutoff. All other source-firm patents during the current year, plus cases where the downstream firm did not file any patents in the past three years, are defined as *Downstream-nonsimilar source patents*.

As shown in Panel C, the coefficient on the interaction *Log downstream-similar source patents* \times *Interlock* is significantly positive in all specifications. By comparison, the coefficient on *Log downstream-nonsimilar source patents* \times *Interlock* is substantially smaller in magnitude and is only significant in two specifications. In all cases, differences between the two coefficients are statistically significant. Based on these results, we conclude that interlock-related spillover effects are stronger when the source-firm patent flow is more technologically similar to a downstream firm's recent patenting activities.

Finally, we investigate the effects of similarity between a source-firm's innovation in the current year and its own already-established technology space. When a source firm's innovation is similar to its own prior innovation, the patent flow may convey less new information to downstream firms in light of what has already been gleaned from the source firm's public disclosures about older technologies. Therefore, we predict that novel source-firm patents, compared to patents derived from the existing technology space, will lead to stronger interlock spillover effects.

To examine this notion, we construct a measure of how related each current-year source patent is to the source firm's own prior innovation. Specifically, we construct vectors of 3-digit IPC codes for each current-year source-firm patent application and for the source firm's total patenting over the prior three years (i.e., the source firm's established technology space). We then compute the cosine similarity between each source-patent vector and the source-firm's technology space. We define *Core source patents* to be the number of current-year source patents for which the cosine similarity to the source firm's technology space is above the 75th percentile of all cosine similarities in the year, while *Peripheral source patents* is the number of all other current-year source patents. Panel D reports the results of our tests related to core and peripheral source-firm innovation. In all columns, the coefficient on *Log peripheral source patents × Interlock* is significantly positive, and F-tests confirm that the coefficient is significantly different from the non-positive coefficient for *Log core source patents × Interlock* in columns (1), (3), and (4). In column (2), the coefficient on *Log core source patents × Interlock* is significantly positive for the citation-based relatedness measure, but it is not significantly different from the coefficient for *Log peripheral source patents × Interlock*. Overall, the results from Panel D suggest that dissimilarity between a source firm's current patent flow and its already-established technology space strengthens interlock spillover effects in terms of innovation quantity and quality.

5. Conclusion

A well-established literature suggests that many economic phenomena arise from human interactions that convey knowledge across firm boundaries. Yet, there has been a lack of direct evidence on the informational role played by one of the most common types of organizational links between public U.S. firms, namely, interlocking boards of directors. In this paper, we fill this gap

by using detailed data on directors, board interlocks, and patenting activity to empirically examine whether interlocks serve as a conduit for the between-firm transmission of scientific and technological information. To address the endogenous nature of interlocks, we employ a novel identification approach based on schedule conflicts between firms' annual meeting dates that would make it difficult or impossible for a director to simultaneously fulfill board obligations with respect to certain pairs of firms. We use these schedule conflicts to capture exogenous variation in the probabilities of board interlocks across firm pairs, thus enabling us to study how interlocks causally affect the sensitivity of downstream firms' innovation to the flow of innovation emanating from source firms.

We find evidence that board interlocks significantly enhance the inter-firm transmission of scientific and technological knowledge. Specifically, the presence of an interlock strengthens the impact of source-firm patenting on the subsequent quantity, quality, market value, and relatedness of downstream-firm patenting. Consistent with prior work on board functioning, we find that the spillover effects of interlocks depend on the structure and composition of boards. For example, interlock-related spillovers are weaker in the presence of outsider-dominated boards, busy boards, or busy shared directors, but such spillovers are more pronounced when shared directors are younger or have innovation experience in the technological areas of the interlocked firms. The type of innovation flowing from the source firm also matters: interlock-related spillovers are stronger when source-firm patents have higher quality, narrower scope, or less (more) similarity to the source firm's (downstream firm's) prior innovation. Taken together, these results show that board interlocks constitute an important channel through which scientific knowledge and technology can flow between organizations and across the boundaries of firms.

Our work also has implications for practitioners. Recently, a growing amount of attention has focused on the use of “overboarding” or “overcommitting” policies at U.S. corporations that aim to limit the number of outside directorships that a board member can hold. Leading proxy vote advisory services (e.g., Institutional Shareholder Services (ISS) and Glass Lewis & Co.) as well as prominent investment advisers (such as the Vanguard Group) have formulated guidelines that indicate voting against executive directors who hold more than a prescribed number of outside board seats (usually one or two).²⁹ The intent of such measures is to prevent the distraction of board members and insiders, ensuring they have adequate time and attention to fulfill their board duties. Our research findings suggest, however, that restrictive overboarding policies may sometimes also have other effects, such as weakening knowledge spillovers by limiting the formation of useful board interlocks.

²⁹ See the ISS 2024 U.S. proxy voting guidelines at <https://www.issgovernance.com/policy-gateway/voting-policies/>; Glass-Lewis’s 2024 proxy voting policies (U.S.) at <https://www.glasslewis.com/voting-policies-2024/>; and Vanguard’s 2023 proxy voting policy at <https://www.georgesondigital.com/us/insights/proxy-solicitation/vanguard-2023-voting-policy-updates>.

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Appendix A: Variable Index

Variables	Definition
Main Variables	
<i>% Busy directors</i>	The percentage of directors who are defined as busy directors.
<i>% Outside directors</i>	The percentage of non-executive directors. Non-executive directors are identified based on the “NED” variable in the BoardEx company profile data.
<i>Annual meeting overlap</i>	An indicator equal to 1 if the source firm and the downstream firm share the same annual meeting date for at least one year during the two-year interval preceding the source firm’s fiscal year end.
<i>Board size</i>	The number of directors on the board in a given year.
<i>Busy board</i>	An indicator equal to 1 if more than one-third of directors on the source board or the downstream board are defined as busy directors.
<i>Busy director</i>	An indicator equal to 1 if all shared directors in a given firm-pair are busy. Two different definitions of director busyness are used: (1) a director holds at least three board seats during the year, and (2) a director holds at least five committee assignments during the year.
<i>Core source patents, Peripheral source patents</i>	A Core source patent is a patent of the source firm whose similarity (based on 3-digit IPC codes) to the source firm’s own patent applications filed in the past three years is above the 75th percentile in a given year. A Peripheral source patent is any source-firm patent that is not defined as Core.
<i>Downstream-similar patents</i>	Source-firm patents whose similarity (3-digit IPC based) to the downstream-firm patent applications that are filed in the past three years is above the 75th percentile of a given year. <i>Downstream-nonsimilar</i> patents are those not defined as <i>Downstream-similar</i> .
<i>Direct citations</i>	The log-transformed number of patent applications filed by a downstream firm from year $t+1$ to year $t+3$ that cite the corresponding source firm’s patent applications filed in year t .
<i>Female</i>	An indicator equal to 1 if at least one shared director is female.
<i>Firm size</i>	Total assets (in millions).
<i>Geographic Distance to source-firm HQ</i>	The geographic distance (in miles) between the source-firm and downstream-firm headquarters’ locations.
<i>Granted patents</i>	Patent applications that have been granted. Grants are counted to 2021.
<i>High breadth patents</i>	Patents whose IPC-based breadth is above the median of all patent applications filed between 2005 and 2017. IPC-based breadth is measured by the number of unique 4-digit IPC codes a patent filing has. <i>Low-breadth</i> patents are those not defined as <i>High-breadth</i> .
<i>High tech exp</i>	An indicator equal to 1 if at least one shared director has employment experience in the high-tech or life science sectors in the past three years. The two sectors are defined based on the SEC Division of Corporation Finance Office assignment. When tracking a director’s past

	employment, we exclude any firm the director is serving at in the current year.
<i>High value patents</i>	Patents whose value is above the median of all patent applications filed between 2005 and 2017. Patent values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017). <i>Low-value</i> patents are those not defined as <i>High-value</i> .
<i>Interlock</i>	An indicator equal to 1 if a board interlock exists, i.e., if the downstream firm in a pair shares at least one director with the source firm from year t-1 to year t.
<i>Non-self citations</i>	The log-transformed total number of citations, excluding self-citations, received up to December 2021 by a downstream firm's patent applications filed in year t+1.
<i>Outsider dominated</i>	An indicator equal to 1 if at least 85% of directors on either the source-firm board or the downstream-firm board are non-executive directors.
<i>Patent value</i>	The log-transformed aggregated value, in millions, of a downstream firm's patent applications filed in year t+1 (set to zero if the downstream firm does not file any patents during the year), where values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017).
<i>Patent volume</i>	The log-transformed number of patent applications filed by downstream firms, year t+1.
<i>Pr(Interlock)</i>	The predicted probability from Table 3, regression (4) that a board interlock with the source firm is present.
<i>R&D</i>	The R&D expenditures (in millions). Missing values of R&D are replaced with 0.
<i>Related experience</i>	An indicator equal to 1 if the average similarity between shared directors' innovation experience and the source firm's and the interlocked downstream firm's recent innovation activities are both above the sample median. Similarity in innovation is measured as described in the Section 4.2.3.
<i>ROA</i>	Return on assets.
<i>Similarity based on 3-digit IPC</i>	The cosine similarity between two vectors of 3-digit IPC codes that are contained in patent applications filed in a specified time window. Each element of a 3-digit IPC vector is the count of patent applications filed under the corresponding IPC code by a firm (or firms) within the given time window. Details of computing the cosine similarity are described in Section 2.
<i>Source firm, downstream firm</i>	A <i>source firm</i> is defined as a firm that might conduct innovation activities in a given year t . For a source firm, a <i>downstream firm</i> is another firm whose innovation activities in year $t+1$ or later could be influenced by the flow of innovation from the source firm. Note that these definitions do not require a source firm to be interlocked with its downstream firms. Nor do these definitions rule out scenarios where a source firm is a downstream firm vis-à-vis other source firms.

Young director An indicator equals 1 if at least one shared director is 63 years old or younger.

Alternative measures of downstream innovation (all log-transformed in tests)

<i>Alt_Common citations</i>	The number of patent applications filed by a downstream firm from year t+1 to t+3 that cite the same patents as the corresponding source firm's patent applications filed in year t.
<i>Alt_High value patents</i>	The number of patent applications filed by a downstream firm in year t+1 whose value is above the median of all patent applications filed between 2005 and 2017. Patent values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017).
<i>Alt_Patent Breadth</i>	The number of unique 4-digit IPC codes in all patents filed by a downstream firm in year t+1.
<i>Alt_Similar 100</i>	The total number of patent pairs where one patent in the pair was filed by the downstream firm in year t+1, the other patent is filed by the source firm in year t, and the downstream-firm patent is one of the 100 most similar patents to the source-firm patent. The similarity is based on patent filing texts using the method of Whalen, Lungeanu, DeChurch, and Contractor (2020).

Appendix B: Automated Collection of Data on Annual Shareholder Meeting Dates

We gather information on the dates of annual shareholder meetings by using automated scraping and text parsing of firms' DEF 14A filings (definitive proxy filings) from the SEC EDGAR database at <https://www.sec.gov>. The procedure is implemented as follows. First, we use the SEC EDGAR Master Index quarterly files to download the text of every DEF 14A filed during the period 2002 to 2023. We apply a Python script to clean each text file by removing tags, extra spaces, and other extraneous text characters. Then, for each cleaned text file, we apply a second script that uses cueing terms and phrases to identify each location in the text where a notice is being given to shareholders about an upcoming annual meeting of shareholders. The cueing terms and phrases include, for example, "Notice of," "Annual meeting," "Annual general meeting," "Annual stockholders' meeting," and "Regular meeting of shareholders," among others. Because not all shareholder meetings are annual (regular) meetings, in another step we use additional terms and phrases to filter out notices of upcoming special shareholder meetings, extraordinary meetings, and consent solicitations. Further details of the exact algorithms and filtering phrases that we use in the above steps are available upon request.

For each candidate annual meeting announcement identified with the above procedure, we gather any nearby text in the filing that contains information on a specific date (month, day, and year). The date text gathered in this manner is converted into a standardized date format. If multiple such dates are obtained from a single proxy filing, we keep the date that appears first in the filing text. Next, we check each prospective annual meeting date against the proxy statement's filing date and omit any announced meeting dates that predate the day on which the proxy statement was filed with the SEC. This filtering step ensures that our procedure is not erroneously picking up instances in the proxy statement where a firm is simply making a reference to an annual shareholder meeting

held in a prior year. Overall, we obtain 132,477 announced annual shareholder meeting dates over the time period from January 2002 to February 2023.

To verify that the annual meeting date information from our automated procedure is accurate, we randomly select a subset of 100 firm-years from our sample and manually review each associated DEF 14A proxy statement from the SEC EDGAR website to ascertain the firm's true annual meeting date. We confirm in all 100 checked cases that our automated procedure for text parsing identifies the correct annual shareholder meeting date as announced in the proxy statement.

We merge the annual meeting date information to our main sample of source-firm years, keeping any meeting dates that lie within a two-year interval surrounding a source firm's fiscal year-end date. Specifically, for a given source firm in a given year, we gather all of the firm's annual meeting dates that occur within the daily interval (-732,0] relative to Day 0 (the source firm's fiscal year-end) and then keep the most recent one in each calendar year. Including annual shareholder meeting dates that fall within this two-year interval preceding the fiscal year end allows us to capture annual meeting schedule conflicts for this time interval relative to a particular source-firm year. Note that, when checking for schedule conflicts between a source firm's annual meeting and that of a downstream firm, we consider source/downstream meeting-date pairs that have the smallest temporal difference (even if the two meetings occur in different calendar years).

Appendix C: Empirical Evidence on Whether Firms Schedule Annual Meetings to Cater to Individual Directors

A potential threat to the validity of our identification approach is that firms might endogenously choose their annual shareholder meeting dates to accommodate individuals who recently joined (or will soon join) the board. For example, suppose a downstream firm appoints a director with valuable innovation experience—thus creating a board interlock—and deliberately schedules the upcoming annual shareholder meeting a week later than expected to ensure that the new director can attend. Under such a scenario, the exclusion restriction would fail to hold for our instrumental variables because the likelihood of a meeting conflict would correlate with downstream innovation outcomes through a channel other than board interlocks. In this Appendix, we conduct several empirical analyses to investigate whether firms might plausibly be scheduling their annual shareholder meetings to cater to shared directors.

We start by documenting some key patterns in annual shareholder meeting dates that help establish a baseline of what constitutes a predictable or “stable” meeting schedule from one year to the next. First, as Figure C1 shows, firms generally keep their meetings on the same day of the week from year to year. For instance, for annual shareholder meetings held on Thursday (the most popular day for annual meetings), over two-thirds of the following year’s annual meetings also occur on Thursday. With regards to the total length of time between annual meetings, close to half of firm-year observations (46%) in our sample have an annual meeting that is exactly 52 weeks (= 364 days) after the firm’s previous annual meeting. The popularity of choosing exactly 52 weeks between annual meetings may be due to simplicity or to logistical convenience. Indeed, not only is 52 weeks very close to a full year, it also has the advantage of automatically preserving the same day of the week from year to year. Note, however, that 52 weeks is not quite a full calendar year of 365 or 366 days, and adhering to a 52-week increment over time will gradually move the

schedule forward on the calendar and eventually push the meeting date to an earlier week of the month or even to an entirely different month. Therefore, it is not surprising that the second most-common time interval between two consecutive annual meetings is exactly 53 weeks (this accounts for about 11% of all firm-year observations). Many of these 53-week increments represent a periodic “reset” that keeps the annual meeting date within the same ordinal week of the month, e.g., the third Wednesday of June or the last Monday of August.³⁰

By tracking firms’ meeting schedules over the sample period, we also uncover other possible reasons for why some firms do not use a 52-week/53-week scheduling strategy every year. For instance, a firm may wish to avoid holding its annual meeting too close to a national holiday or a long weekend. Also, after a firm changes its fiscal year end, it may change its annual shareholder meeting date to better align with the timing of financial statement filings. Because such changes are likely exogenous with respect to board interlocks, they are much less concerning for our identification strategy. Nevertheless, to better isolate and detect any catering motive behind firms’ scheduling of annual meetings, we control for national holidays, long weekends, and fiscal year-end changes in all of our regression tests below.

We now turn to a question that is critical to the validity of our instrumental variables: Do firms sometimes deviate from a predictable 52-week/53-week scheduling policy to accommodate the preferences and constraints of newly-appointed directors? To investigate this issue, we define an indicator variable, *Typical annual meeting date_t*, that equals one if a firm’s annual meeting date

³⁰ Wal-Mart’s scheduling of annual shareholder meetings is an example of this type of predictable pattern. During the sample period, Wal-Mart’s annual shareholder meeting always occurs on the first Friday in June. In most years, this positioning on the June calendar is maintained by simply holding the annual meeting exactly 52 weeks after the previous one. However, in 2008 and 2013, using a 52-week increment would have required the annual meeting to take place on the last Friday in May, so Wal-Mart instead used an increment of 53 weeks in those two years. Other examples of well-known firms that use similar scheduling patterns include Texas Instruments and Ford Motor Co. While these firms almost always hold their annual shareholder meetings exactly 52 weeks after the previous one, in 2016 TI used a 53-week increment to keep its meeting on the third Thursday of April (April 21st, 2016), and in 2015 Ford used a 53-week increment to keep its meeting on the second Tuesday of May (May 14th, 2015).

in fiscal year t is either (i) exactly 52 weeks after the annual meeting held in $t-1$; or (ii) exactly 104 = 52×2 weeks after the annual meeting held in $t-2$.³¹ We then define the dependent variable in our regressions, *Atypical annual meeting date_t*, to be one minus *Typical annual meeting date_t*.

Our first set of regressions directly examines whether a firm's unusual scheduling of its annual shareholder meeting is associated with one or more new director appointments. In Table C1, we regress *Atypical annual meeting date_t* on *New director appointments_t*, an indicator equal to one if and only if at least one new director joins the board during the year. Along with controls for firm and board characteristics, we include several dummy variables that account for possible exogenous reasons, as mentioned above, for an atypical annual meeting date: (1) the need to keep the meeting in the same ordinal week of the month; (2) the need to keep the meeting within the same calendar month; (3) avoidance of time conflicts with national holidays or long weekends; and (4) a change in fiscal year end. Column (1) shows a baseline regression that includes controls for the four exogenous circumstances that might prompt unusual meeting scheduling, as well as firm fixed effects and industry-by-year fixed effects. Column (2) further includes annual meeting calendar month and day-of-the-week fixed effects. The regressions in Columns (3) to (4) parallel those in Columns (1) to (2) except that they also include firm-level controls and board-level controls. Overall, the results in Columns (1) to (4) do not reveal any evidence that new or pending director appointments are associated with higher likelihoods of choosing atypical annual meeting dates.

The remainder of Table C1 conducts sharper tests by restricting the sample to firm-years where schedule conflicts are more pervasive *a priori* and, thus, where firms are more likely to

³¹ Condition (ii) captures the idea that, because directors usually remain on the board for more than one year, it is unlikely that a firm would shift its annual meeting date to accommodate a new director and, just one year later, revert the annual meeting date back to the original 52-week schedule.

require unusual annual meeting dates to accommodate directors. First, as described in the main text (see Panel A of Figure 1), firms' annual meetings cluster strongly in the spring "proxy season," with more than 40% of annual meetings taking place in May alone and about three quarters of annual meetings taking place from April through June. Columns (5) and (6) show that, contrary to what a catering scenario would imply, the coefficient for *New director appointments_t* is insignificant when considering firm-years with a prior-year annual meeting held in April-June or in May. Since meeting dates also tend to cluster on Thursdays (32%), Wednesdays (27%), and Tuesdays (24%), Column (7) (Column (8)) further restricts the sample to firm-years where the prior annual meeting was held in May and also fell on a Tuesday, Wednesday, or Thursday (on a Wednesday or Thursday). The coefficient on *New director appointments_t* remains statistically insignificant.

In a second group of tests, we examine whether firms are more likely to choose atypical annual meeting dates when they appoint directors who have more scheduling constraints. We define a *multiple-board director* (*single-board director*) to be a director who already holds (who does not hold) board seat(s) at other firm(s) when being appointed to a new board. Under a catering story, firms are more likely to adjust their annual meeting date schedules when they appoint multiple-board directors than when they appoint single-board directors. We test this hypothesis in Table C2 with several different regressions explaining *Atypical annual meeting date*. Column (1) regresses *Atypical Annual Meeting Date_t* on binary variables indicating that, during the year, a firm appointed (1) at least one new multiple-board director but no single-board directors; and (2) at least one single-board director but no multiple-board directors. Contrary to the catering story, the regression generates insignificant coefficients for both indicators. We also estimate regressions on the subsample of firm years with at least one new director appointment. In these regressions, we

test how each of the following four variables relates to the chance of an atypical annual meeting date: (1) a binary variable indicating that at least one of the new appointees is a multiple-board director; (2) the percentage of appointees who are multiple-board directors; (3) an indicator that all appointees are multiple-board directors; and (4) an indicator that all appointees are single-board directors. As seen in the table, all four regressions yield insignificant coefficients, casting further doubt on the catering story.

Our third set of tests is based on the occurrence of unusual annual meeting dates surrounding the formation of new board interlocks. For these tests, we use subsamples of firm pair-years in which one of the firms in a pair-year appoints at least one new director from the other firm, thus creating an interlock. We define an indicator, $\text{Close annual meeting date}_{t-1}$, to be equal to one if the two paired firms' annual meeting dates in the previous year were no more than one day apart.³² We then regress $\text{Atypical annual meeting date}_t$, our indicator for an unusual meeting date in the current year, on $\text{Close annual meeting date}_{t-1}$ and on various firm-level controls. The idea behind this group of tests is straightforward: if firms adjust their annual shareholder meeting dates to cater to new directors joining the board, then this type of schedule adjustment should be more likely to happen when recent history indicates that there is a high *ex ante* probability of schedule conflict. In Columns (1) to (3) of Table C3, we estimate the regressions on various subsamples according to what kind(s) of shared directors are appointed in the current year. The table shows that, regardless of whether the regression is run using all interlock-forming appointments or just a subset of them (i.e., busy-director appointments or appointments of non-busy directors), the coefficient for $\text{Close annual meeting date}_{t-1}$ is insignificant. Thus, we conclude that even when the *ex ante*

³² In untabulated tests, we use different definitions of $\text{Close annual meeting date}_{t-1}$, such as the requirement that two firms' annual meetings last year were in the same month and on the same day of the week; were less than three days apart; or were less than four days apart. These alternative definitions yield similar qualitative results compared to those from the one-day-apart definition.

probability of schedule conflict is relatively high, firms do not appear to be adjusting their annual meeting dates to cater to newly-appointed directors.

Figure C1: Annual Shareholder Meeting Day-of-the-Week: Current Year Versus Prior Year

This figure shows the frequencies with which firms hold their annual shareholder meeting on the same day-of-the-week or on a different day-of-the-week compared to the prior year.

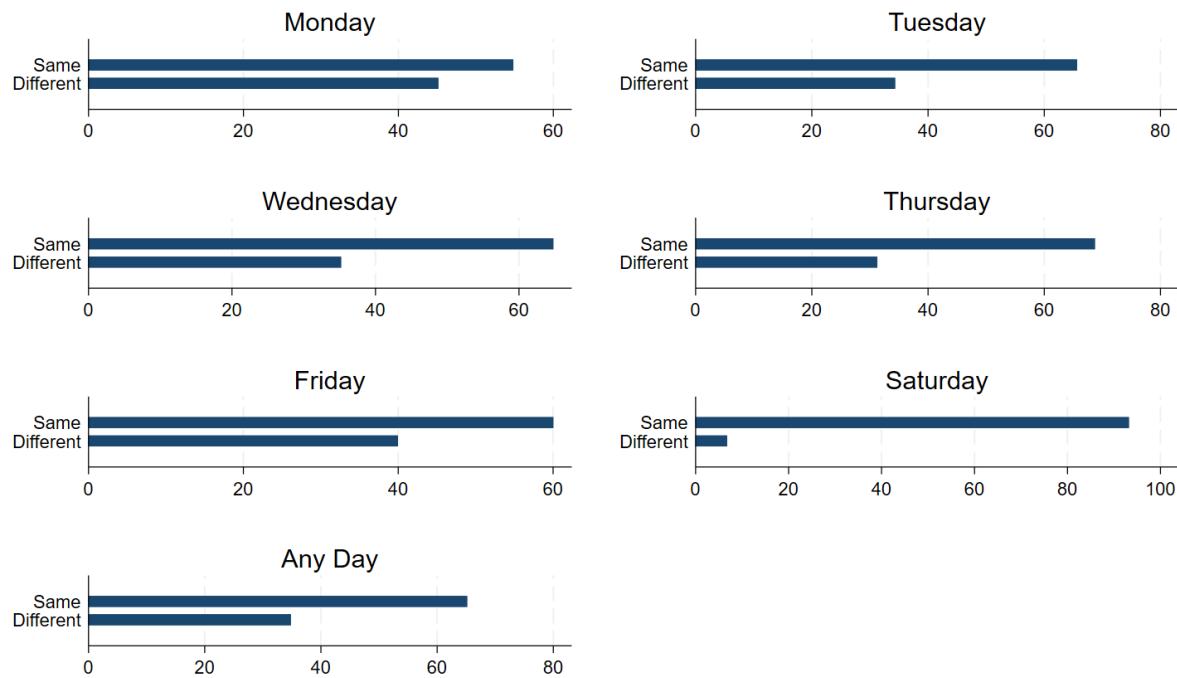


Table C1. Annual Meeting Dates and New Director Appointments

This table reports OLS regressions that predict changes in annual shareholder meeting dates on the basis of new director appointments. The sample consists of firm-year observations of *BoardEx* firms during 2005-2017 for which annual meeting dates are available for years $t-2$ to t . Columns (1) to (4) use the full sample. Column (5) uses the subsample of firm-year observations where the annual meeting in year $t-1$ occurs between April and June, while column (6) uses firm-years where the annual meeting in year $t-1$ is held in May. Column (7) further restricts the subsample in Column (6) to those firm-years where the annual meeting in year $t-1$ falls on Tuesday, Wednesday, or Thursday. Column (8) restricts the subsample in Column (6) to firm-years where the annual meeting in year $t-1$ is on a Wednesday or Thursday. The dependent variable, *Atypical annual meeting date*, is a binary variable equal to one if the annual meeting in year t is neither exactly 52 weeks after the annual meeting in year $t-1$ nor exactly 104 (= 52×2) weeks after the annual meeting in year $t-2$. *New director appointments* indicates that at least one new director appointment occurs in year t . *Expected month change* is an indicator equal to one if the expected annual meeting date in year t (i.e., the date that is exactly 52 weeks after the annual meeting in year $t-1$) falls in a different month than the one for year $t-1$. *Expected holiday/long weekend* is an indicator equal to one if the expected annual meeting date in year t is no more than one day away from a national holiday or long weekend. National holidays and long weekends are defined based on NYSE daily trading data. *Expected different week of the month* indicates the expected annual meeting date in t falls in a different week of the month compared to last year, and thus the firm would need to use a 53-week calendar increment to keep the annual meeting date in the same week of the month. *Fiscal year-end change* indicates that the month of a firm's fiscal year end is not the same as that for the previous year. *Firm size* is measured as total assets (in millions). *ROA* is return on assets. *Board size* is the total number of directors. *% Outsiders* is the percentage of board members who are non-executive directors. *Number of busy directors* is the number of directors who hold at least three board seats in the given year. *Firm size*, *Board size*, and *Number of busy directors* are all log-transformed. Continuous variables are winsorized at the 1% and 99% levels. Columns (1) and (3) control for firm fixed effects and industry-by-year fixed effects (industries are defined at the SIC 4-digit level). In all other columns, we also include fixed effects for annual meetings' calendar month and day-of-the-week. Standard errors, clustered at the firm level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

(continued)

Table C1, continued

	Dependent variable: <i>Atypical annual meeting date</i>							
	Full sample				Subsample: <i>Annual meeting</i> $t-1$ was held ...			
	(1)	(2)	(3)	(4)	April - June	May	May & Tue.-Thu.	May & Wed.-Thu.
<i>New director appointments</i>	0.009 (0.006)	0.009 (0.006)	0.009 (0.006)	0.009 (0.006)	0.008 (0.008)	0.011 (0.012)	0.013 (0.013)	0.030 (0.026)
<i>Expected month change</i>	0.030 (0.019)	0.042** (0.018)	0.029 (0.019)	0.041** (0.018)	0.037 (0.025)	-0.024 (0.040)	-0.005 (0.046)	0.131* (0.071)
<i>Expected holiday/long weekend</i>	0.130*** (0.019)	0.132*** (0.019)	0.130*** (0.019)	0.132*** (0.019)	0.148*** (0.025)	0.059 (0.043)	0.044 (0.073)	
<i>Expected different week of the month</i>	0.696*** (0.013)	0.696*** (0.013)	0.696*** (0.013)	0.696*** (0.013)	0.736*** (0.016)	0.826*** (0.024)	0.856*** (0.027)	0.917*** (0.055)
<i>Fiscal year-end change</i>	0.381*** (0.054)	0.421*** (0.057)	0.388*** (0.053)	0.428*** (0.057)	0.132 (0.183)	0.451 (0.334)	0.753*** (0.136)	-0.458 (0.336)
<i>Firm size</i>			-0.007 (0.010)	-0.004 (0.009)	-0.002 (0.013)	-0.049*** (0.019)	-0.042** (0.021)	0.001 (0.036)
<i>ROA</i>			-0.055** (0.022)	-0.047** (0.021)	-0.068** (0.031)	-0.050 (0.048)	-0.043 (0.050)	-0.006 (0.076)
<i>Board size</i>			-0.010 (0.032)	-0.006 (0.032)	0.024 (0.042)	-0.053 (0.061)	0.028 (0.067)	0.056 (0.138)
<i>% Outsiders</i>			0.036 (0.064)	0.047 (0.064)	-0.007 (0.093)	0.140 (0.137)	0.079 (0.146)	-0.163 (0.225)
<i>Number of busy directors</i>			0.008 (0.010)	0.006 (0.010)	-0.009 (0.013)	0.001 (0.019)	0.012 (0.020)	-0.014 (0.039)
Observations	31,543	31,543	31,514	31,514	18,938	10,010	8,248	2,280
R-squared	0.420	0.427	0.420	0.427	0.462	0.507	0.536	0.723
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry \times Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Calendar month FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes

Table C2: Annual Meeting Date Changes and New Board Appointments: Multiple-Board Directors Versus Single-Board Directors

This table reports OLS regressions that link changes in annual meeting dates to new appointments of directors who do or do not hold other board seat(s) at the time of appointment. The sample consists of firm-year observations of *BoardEx* firms during 2005-2017 for which annual meeting dates are available for years $t-2$ to t . The dependent variable, *Atypical annual meeting date*, is a binary variable equal to one if the annual meeting in year t is neither exactly 52 weeks after the annual meeting in year $t-1$ nor exactly 104 ($= 52 \times 2$) weeks after the annual meeting in year $t-2$. Column (1) employs the full sample. Multiple-board (single-board) directors are those who hold more than one (only one) board seat in year t , including the new appointment during the year. *Only multiple-board new appointees* (*Only single-board new appointees*) is a binary variable indicating that a firm appoints at least one multiple-board director (one single-board director) but no single-board directors (no multiple-board directors) during the year. Columns (2) to (4) use a subsample where the firm appoints at least one new director during the year. *Any multiple-board new directors* is an indicator equal to one if at least one of the firm's newly-appointed directors during the year is a multiple-board director. *% Multiple-board new directors* is the percentage of newly appointed directors in a firm-year who are multiple-board directors. Control variables include *Expected month change*, *Expected holiday/long weekend*, *Expected different week of the month*, *Fiscal year-end change*, *Firm size*, *ROA*, *Board size*, *% Outsiders*, and *Number of busy directors*, all defined as in Table C1. Continuous variables are winsorized at the 1% and 99% levels. All regressions include firm fixed effects, industry-by-year fixed effects, and fixed effects for annual meetings' calendar month and day-of-the-week. Standard errors, clustered at the firm level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent variable: <i>Atypical annual meeting date</i>					
	Full sample	Firm-years with at least one new appointment			
	(1)	(2)	(3)	(4)	(5)
<i>Any multiple-board new appointees</i>		0.008 (0.012)			
<i>% multiple-board new appointees</i>			-0.009 (0.014)		
<i>Only multiple-board new appointees</i>	-0.003 (0.010)			-0.022 (0.014)	
<i>Only single-board new appointees</i>	-0.000 (0.007)				-0.008 (0.012)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	31,514	11,636	11,636	11,636	11,636
R-squared	0.427	0.565	0.565	0.565	0.565
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry \times Year FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes	Yes	Yes

Table C3. Annual Meeting Date Changes around the Formation of Board Interlocks

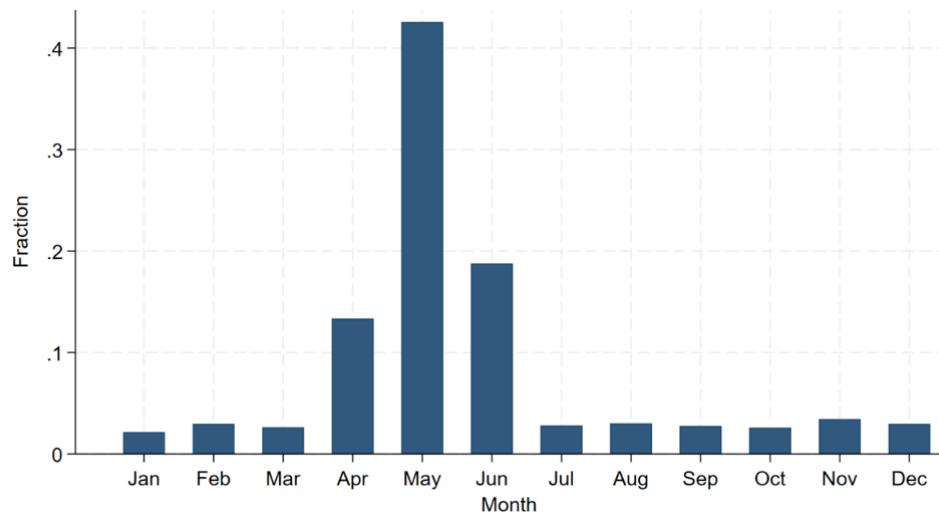
This table reports OLS regressions that examine whether changes in firms' annual shareholder meeting dates are linked to a high ex ante likelihood of an individual director's schedule conflict arising from the formation of a new board interlock. Regressions are based on firm pair-year observations in which one of the firms in a pair-year appoints at least one new director from the other firm, thus creating a new board interlock. Both firms in a given pair-year are required to have annual meeting dates available for years $t-2$ to t . The "receiving" firm within a given pair-year is the firm that appoints at least one director in year t who was already on the board of the other firm (the "sending" firm). The dependent variable, *Atypical annual meeting date (receiving firm)*, is a binary variable indicating that the annual meeting of the receiving firm in year t is neither exactly 52 weeks after the annual meeting in year $t-1$ nor exactly 104 ($= 52 \times 2$) weeks after the annual meeting in year $t-2$. *Close annual meeting date_{t-1}* indicates that the previous year's difference between annual meeting dates of the receiving firm and the sending firm was less than or equal to one day. Control variables for the receiving firm include *Expected month change*, *Expected holiday/long weekend*, *Expected different week of the month*, *Fiscal year-end change*, *Firm size*, *ROA*, *Board size*, *% Outsiders*, and *Number of busy directors*, all defined as in Table C1. Continuous variables are winsorized at the 1% and 99% levels. All regressions include receiving firm's industry-by-year fixed effects, and fixed effects for the receiving firm's annual meeting calendar month and day-of-the-week. Standard errors, clustered at the industry level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent variable: <i>Atypical annual meeting date (receiving firm)</i>			
Interlock-forming director appointments			
	All director appointments	Non-busy director appointments	Busy director appointments
	(1)	(2)	(3)
<i>Close annual meeting date_{t-1}</i>	-0.007 (0.027)	-0.078 (0.052)	0.019 (0.021)
<i>Controls</i>	Yes	Yes	Yes
Observations	7,684	2,730	4,524
R-squared	0.504	0.475	0.656
Industry \times Year FEs	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes
Calendar month FEs	Yes	Yes	Yes

Figure 1: Calendar-Month and Day-of-the-Week Distribution of Annual Meeting Dates

This figure shows the frequency distribution of firms' annual meetings by calendar month and by day-of-the-week. Panel A shows the distribution of annual meetings across calendar months. Panel B presents the day-of-the-week distribution of annual shareholder meetings.

Panel A. Calendar-Month Distribution of Annual Shareholder Meeting Dates



Panel B. Day-of-the-Week Distribution of Annual Shareholder Meeting Dates

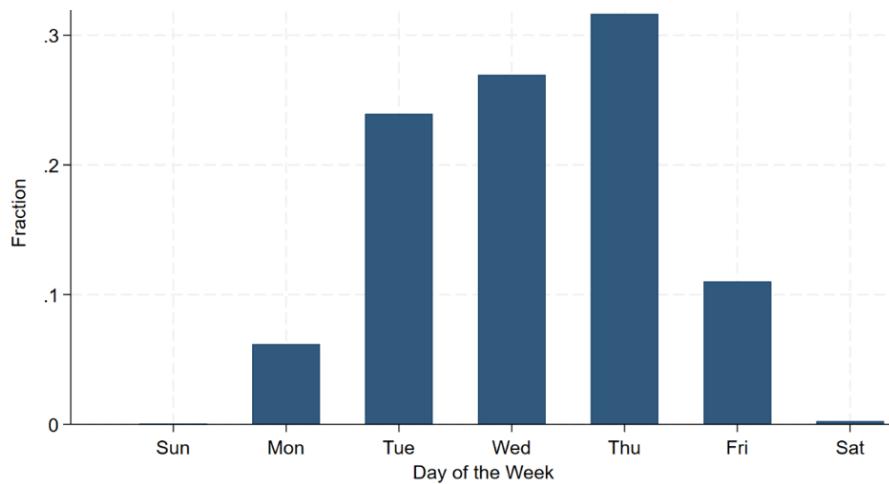


Figure 2. Number of Days Between Source and Downstream Firms' Annual Shareholder Meeting Dates for Interlocked and Non-Interlocked Pairs

This figure shows frequency distributions for the number of days separating the annual meeting dates of interlocked and non-interlocked pairs of source/downstream firms. For expositional convenience, the sample of firm pairs is restricted to those for which the two firms' annual meeting dates are no more than 10 days apart.

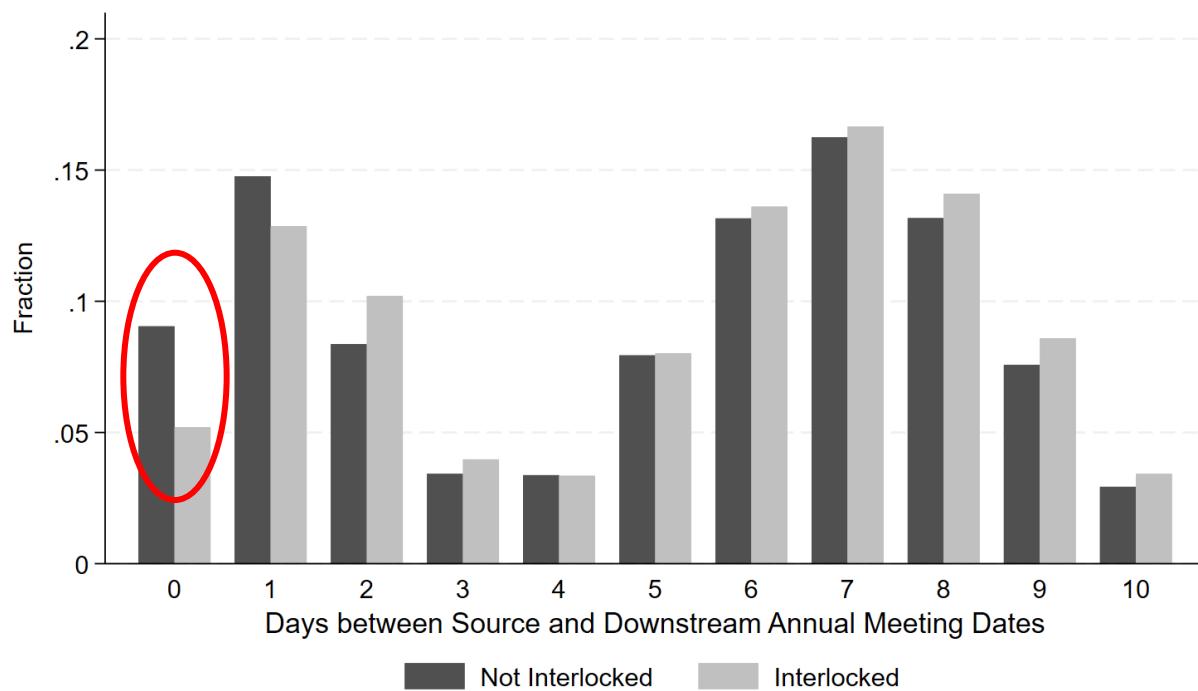


Table 1. Summary Statistics: Firm, Board, and Director Characteristics of Source Firms

This table presents summary statistics for firm, board, and director characteristics corresponding to “source” firms from our main test sample. We define a source firm to be a firm that might conduct innovation activities in a given year t (More details are in footnote 6 and Section 2). The sample period is 2005-2017, and the unit of observation is the source firm-year. Board characteristics are from *BoardEx*. Patent data are obtained from the USPTO Bulk Data Storage System (BDSS). Other firm characteristics are from the Compustat/CRSP merged database. *Firm size* is total assets, in millions. *ROA* is the return on assets. *R&D* is research and development expense, with missing values set to zero. *Patents* is the number of patent applications filed by the source firm during the year. *Avg. patent value* is the average value, in millions, of a source firm’s patent applications filed in year t , where values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017). *Avg. patent breadth* is the average IPC-based breadth of a source firm’s patent applications filed in year t , where patent breadth is measured by the number of unique 4-digit IPC codes a patent filing has. For *Avg. patent value* and *Avg. patent breadth*, we only include observations where the source firm files at least one patent applications in the give year. *Similarity to interlocked down (Similarity to non-interlocked down)* is the average cosine similarity between a source firm’s patent applications filed in year t and all of its interlocked downstream (the CEM matched non-interlocked downstream) firms’ patent applications filed in the past three years. *Similarity to own* is the cosine similarity between a source firm’s patent applications filed in year t and its own patent applications filed in the past three years. The cosine similarities are calculated using the 3-digit IPC vectors formed by counting the number of patent applications filed under each IPC code in a firm within a time window. More details of computing the cosine similarity are described in Section 2. The value of similarity observations is set to zero if one or more of the paired firms do not file any patent in the given period. *Board size* is the number of directors on the source-firm board. *% Outside directors* is the percentage of non-executive directors. *% Busy directors (seats)* and *% Busy directors (committeees)* measure the percentages of source-firm directors who hold at least 3 board seats and at least 5 committee assignments, respectively. The table also reports statistics for individual characteristics of shared directors who provide an interlock between a source firm and a downstream firm. The unit of observation is the source firm-shared director-year, and we restrict the sample to observations where data on the relevant shared director characteristic is non-missing. The individual director characteristics include the following: *Director age*; *Female*; # of board seats held; # of committee roles held; *High tech experience*, an indicator equal to 1 if the shared director has employment experience in the high-tech/life science sector in the past 3 years (when tracking a director’s past employment, we exclude any firm on whose board the director serves in the current year); and *Innovation experience similarity*, the cosine similarity between the source firm and the shared director’s 3-digit IPC code vectors. The source firm’s vector is based on its patent applications filed in the past 3 years, and the shared director’s vector is based on the patent applications filed by his or her historical employers and firms where they serve as directors (the given source firm is excluded when constructing the shared director’s vector). More details on the formation of the shared director’s innovation experience vector are provided in Section 2.

(continued)

Table 1, continued

	Obs.	Mean	Std	p5	Median	p95
Firm Characteristics						
Firm Size (\$M)	26,114	14,281.31	97,594.51	30.03	1,068.21	41,247
ROA	26,112	-0.06	0.95	-0.55	0.03	0.16
R&D (\$M)	26,117	109.80	642.01	0	0	329.56
Patents	26,117	21.96	201.69	0	0	57
Avg. patent value (\$M)	11,514	44.23	120.38	0.54	11.51	189.84
Avg. patent breadth	11,715	2.38	1.70	1	1.98	5.33
Similarity to interlocked down	26,117	0.08	0.19	0	0	0.53
Similarity to non-interlocked down	26,117	0.07	0.16	0	0	0.46
Similarity to own	26,117	0.24	0.34	0	0	0.95
Board Characteristics						
Board Size	26,117	8.86	2.47	5	9	13
% Outside directors	26,117	0.84	0.08	0.67	0.86	0.92
% Busy directors (seats)	26,117	0.21	0.17	0	0.18	0.50
% Busy directors (committees)	26,117	0.26	0.18	0	0.23	0.58
Shared director Characteristics						
Director age	56,034	62.37	8.02	48	63	74
Female	56,042	0.13	0.33	0	0	1
Board seats held	56,042	2.95	1.15	2	3	5
Board committee roles held	55,299	5.70	3	2	5	11
High tech experience	55,706	0.15	0.36	0	0	1
Innovation experience similarity	26,953	0.22	0.32	0	0.02	0.94

Table 2. Summary Statistics: Characteristics of Downstream Firms

This table presents summary statistics for the firm characteristics, board characteristics, and innovation outcomes of “downstream” firms in our main test sample. The sample is based on firm-pair-years, each of which includes a source firm and a downstream firm. Downstream firms include (1) firms that are board-interlocked with the relevant source firm; and (2) contemporaneous, non-interlocked downstream firms that are each matched to an interlocked downstream firm via Coarsened Exact Matching (CEM) as detailed in Section 2. The sample period covers 2005-2017. Board characteristics are from *BoardEx*. Patent data are from the USPTO Bulk Data Storage System (BDSS). The citation data are from *PatentsView*. Other firm characteristics are from Compustat/CRSP merged database. *Firm size* is total assets, in millions of dollars. *ROA* is the return on assets. *R&D* is research and development expense, in millions, with missing values treated as 0. *Geographic distance to source-firm HQ* is the geographic distance, in miles, between the source-firm and downstream-firm headquarter locations. *Patent similarity to source-firm* is the “technological similarity” between the downstream firm and its paired source firm, where technological similarity is measured by the cosine similarity between two vectors of 3-digit IPC codes that are contained in patent applications filed in the past three years. Each element of a 3-digit IPC vector is the count of patent applications filed under the corresponding IPC code by a firm within the given time window. Details of computing the cosine similarity are described in Section 2. Similarity is set to zero when one or both of the paired firms do not file any patents in the past three years. *Board size* is the number of directors on the downstream-firm board. *% Outside directors* is the percentage of non-executive directors on the downstream-firm board. *% Busy directors (seats)* and *% Busy directors (committees)* measure the percentages of downstream-firm directors who hold at least 3 board seats or at least 5 committee assignments, respectively. *Patent volume* is the number of patent applications filed by a downstream firm in year $t+1$. *Direct citations* is the number of patent applications filed by a downstream firm from year $t+1$ to year $t+3$ that cite the corresponding source firm’s patent applications filed in year t . All citations received up to December 2021 are included. *Patent value* is the aggregated value of a downstream-firm’s patent applications filed in year $t+1$, where values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017). *Non-self citations* is the total number of citations, excluding self-citations, received up to December 2021 by a downstream firm’s patent applications filed in year $t+1$. *Patent volume*, *Direct citations*, *Patent value*, and *Non-self citations* are log-transformed.

(continued)

Table 2, continued

	Board Interlock with Source-Firm						No Board Interlock with Source Firm					
	Obs.	Mean	Std	p5	p50	p95	Obs.	Mean	Std	p5	p50	p95
Downstream Firm Characteristics												
Firm size (\$M)	64,162	9,782	38,703.43	37.7	1,431	44,615	64,162	5,493.97	36,866.61	14.54	456.29	210,44.31
ROA	64,161	-0.07	0.83	-0.61	0.02	0.16	64,152	-0.15	3.42	-0.77	0.01	0.16
R&D (\$M)	64,162	175.23	794.94	0	5.08	685	64,162	78.73	475.27	0	0.84	233.31
Geo. dist. to source-firm HQ	64,162	800.94	837.64	2.8	527.5	2,551.2	64,162	828.97	827.88	6.4	551.35	2,548.5
Patent similarity to source-firm	64,162	0.16	0.31	0	0	0.94	64,162	0.13	0.28	0	0	0.89
Downstream Board Characteristics												
Board size	64,162	9.20	2.50	6	9	13	64,162	8.15	2.44	5	8	13
% Outside directors	64,162	0.85	0.07	0.7	0.88	0.92	64,162	0.82	0.1	0.6	0.86	0.92
% Busy directors (seats)	64,162	0.27	0.18	0	0.25	0.6	64,162	0.16	0.17	0	0.13	0.5
% Busy directors (committees)	64,162	0.30	0.19	0	0.29	0.64	64,162	0.20	0.18	0	0.17	0.56
Downstream Innovation Outcomes												
Patent volume	64,162	1.2	1.58	0	0	4.48	64,162	0.82	1.3	0	0	3.66
Direct citations	64,162	0.003	0.06	0	0	0	64,162	0.002	0.05	0	0	0
Patent value	64,162	2.42	3.07	0	0	8.46	64,162	1.56	2.51	0	0	7.06
Non-self citations	64,162	1.01	1.82	0	0	5.30	64,162	0.64	1.43	0	0	4.11

Table 3. Annual Meeting Dates and Board Interlocks

This table reports the results of OLS regressions that use annual shareholder meeting date conflicts to predict the likelihood of a board interlock between two firms. The sample consists of firm-pair-years, each of which includes a source firm and a downstream firm. Downstream firms include (1) firms that are board-interlocked with the relevant source firm; and (2) contemporaneous, non-interlocked downstream firms that are matched to an interlocked downstream firm via Coarsened Exact Matching (CEM) as detailed in Section 2. The dependent variable is an indicator equal to one if, for a given pair-year, the downstream firm shares a director with the source firm from year $t-1$ to year t . *Annual meeting overlap* is a binary variable indicating that the source firm and downstream firm in a pair share the same annual meeting date for at least one year during the two-year interval preceding the source firm's fiscal year end. *Firm size* is one-year lagged, log-transformed total assets (in millions) and is winsorized at the 1% and 99% levels. Columns (3) and (4) include year fixed effects as well as fixed effects for interlock groups, where an interlock group is a particular combination of a source firm, its board-interlocked downstream firm, and the CEM-matched, non-interlocked downstream firms. Standard errors are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Annual meeting overlap	-0.107*** (0.009)	-0.118*** (0.009)	-0.142*** (0.012)	-0.145*** (0.011)
Firm size (Source)		-0.018*** (0.001)		-0.003 (0.006)
Firm size (Downstream)		0.059*** (0.001)		0.118*** (0.001)
Interlock-Group FEs	No	No	Yes	Yes
Year FEs	No	No	Yes	Yes
Observations	128,324	128,324	128,324	128,324
R-squared	0.001	0.062	0.001	0.122

Table 4. Board Interlocks and Knowledge Spillovers – OLS

This table reports the results of OLS regressions that examine whether board interlocks facilitate knowledge spillovers. The unit of observation is the firm-pair-year, each of which has one source firm and one downstream firm. Downstream firms include (1) firms that are board-interlocked with the corresponding source firm; and (2) contemporaneous, non-interlocked downstream firms that are matched to an interlocked downstream firm via Coarsened Exact Matching (CEM) as detailed in Section 2. The sample period is from 2005 to 2017. The dependent variables of interest include four different measures of downstream-firm innovation activity: *Patent volume*, the log-transformed number of patent applications filed by a downstream firm in year $t+1$; *Direct citations*, the log-transformed number of patent applications filed by a downstream firm during year $t+1$ to year $t+3$ that cite source-firm patent applications filed in year t ; *Patent value*, the log-transformed aggregated value, in millions, of a downstream firm's patent applications filed in year $t+1$ (set to zero if the downstream firm does not file any patents during the year), where values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017); and *Non-self citations*, the log-transformed total number of non-self citations received up to December 2021 by the downstream firm's patent applications filed in year $t+1$. *Log source patents* is the log-transformed number of patent applications filed by the source firm during the year. *Interlock* is an indicator equal to 1 if a board interlock exists, i.e., if the downstream firm in a pair shares at least one director with the source firm from year $t-1$ to year t . *Geographic distance* is the distance, in miles, between the source-firm and downstream-firm headquarters. *Technological similarity* is the similarity between the technology spaces of the source and downstream firms, where similarity is measured as the cosine similarity between two vectors of 3-digit IPC codes that are contained in patent applications filed in the past three years. Each element of a 3-digit IPC vector is the count of patent applications filed under the corresponding IPC code by a firm within the given time window. Details of computing the cosine similarity are described in Section 2. The value of *Technological similarity* is set to 0 when no patents are filed by at least one of the paired firm in the given period. Other control variables, described in Tables 1 and 2, include *Firm size*, *ROA*, *R&D*, and *Board Size* (each variable is measured separately for the source and downstream firms and is lagged by one year). *Firm size*, *ROA*, *R&D*, *Board size*, *Geographic distance*, and *Technological similarity* are winsorized at the 1% and 99% levels and (except for *ROA* and *Technological similarity*) are log-transformed. Each regression includes year fixed effects as well as fixed effects for interlock groups, where an interlock group is a particular combination of a source firm, its board-interlocked downstream firm, and the CEM-matched, non-interlocked downstream firms. Standard errors, clustered at the interlock-group level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

(continued)

Table 4, continued

	Patent volume (1)	Direct citations (2)	Patent value (3)	Non-self citations (4)
Log source patents × Interlock	0.032*** (0.006)	0.001** (0.000)	0.064*** (0.012)	0.033*** (0.007)
Interlock	-0.037*** (0.011)	-0.002*** (0.000)	-0.065*** (0.021)	-0.043*** (0.013)
Log source patents	-0.031*** (0.006)	-0.000 (0.001)	-0.061*** (0.011)	-0.050*** (0.009)
Firm size (source)	-0.004 (0.010)	0.000 (0.000)	-0.025 (0.020)	0.028* (0.016)
ROA (source)	0.023 (0.021)	0.001 (0.001)	0.113*** (0.039)	-0.006 (0.027)
R&D (source)	0.006 (0.010)	-0.000 (0.000)	0.012 (0.019)	-0.063*** (0.014)
Board size (source)	0.005 (0.026)	0.000 (0.002)	0.047 (0.050)	0.024 (0.037)
Firm size (downstream)	0.146*** (0.004)	0.001*** (0.000)	0.413*** (0.009)	0.151*** (0.005)
ROA (downstream)	0.024 (0.016)	-0.000 (0.000)	0.200*** (0.029)	-0.017 (0.019)
R&D (downstream)	0.365*** (0.006)	0.002*** (0.000)	0.671*** (0.011)	0.384*** (0.007)
Board size (downstream)	0.166*** (0.021)	-0.002** (0.001)	0.335*** (0.040)	0.065*** (0.023)
Geographic distance	-0.003 (0.005)	-0.000 (0.000)	0.004 (0.009)	-0.005 (0.006)
Technological similarity	0.571*** (0.024)	0.009*** (0.001)	1.093*** (0.044)	0.389*** (0.029)
Interlock-group FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	128,324	128,324	128,324	128,324
R-square	0.71	0.27	0.72	0.64

Table 5. Board Interlocks and Knowledge Spillovers – 2SLS

This table reports the results of Two-Stage Least Squares (2SLS) regressions that examine whether board interlocks facilitate knowledge spillovers. The sample consists of firm-pair-years, each of which has one source firm and one downstream firm. Downstream firms include (1) firms that are board-interlocked with the corresponding source firm in a pair; and (2) non-interlocked downstream firms that are matched to an interlocked downstream firm via Coarsened Exact Matching (CEM) as detailed in Section 2. The sample period is from 2005 to 2017. The dependent variables of interest include four different measures of downstream-firm innovation activity: *Patent volume*, the log-transformed number of patent applications filed by a downstream firm in year $t+1$; *Direct citations*, the log-transformed number of patent applications filed by a downstream firm during year $t+1$ to year $t+3$ that cite source-firm patent applications filed in year t , where citations are counted up to December 2021; *Patent value*, the log-transformed aggregated value, in millions, of a downstream firm's patent applications filed in year $t+1$ (set to zero if the downstream firm does not file any patents during the year), where values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017); and *Non-self citations*, the log-transformed total number of non-self citations received up to December 2021 by the downstream firm's patent applications filed in year $t+1$. *Log source patents* is the log-transformed number of patent applications filed by the source firm during the year. *Interlock* is an indicator equal to 1 if a board interlock exists, i.e., if the downstream firm in a pair shares at least one director with the source firm from year $t-1$ to year t . The two instruments are $Pr(Interlock)$ and $Log\ source\ patents \times Pr(Interlock)$, where $Pr(Interlock)$ is the predicted probability from Table 3, regression (4) that a board interlock with the source firm is present. *Geographic distance* is the distance, in miles, between the source-firm and downstream-firm headquarters. *Technological similarity* is the similarity between the technology spaces of the source and downstream firms, where similarity is measured as the cosine similarity between two vectors of 3-digit IPC codes that are contained in patent applications filed in the past three years. Each element of a 3-digit IPC vector is the count of patent applications filed under the corresponding IPC code by a firm within the given time window. Details of computing the cosine similarity are described in Section 2. The value of *Technological similarity* observations where no patents are filed by at least one of the paired firms in the given period is set as 0. Other control variables, described in Tables 1 and 2, include *Firm size*, *ROA*, *R&D*, and *Board size* (each variable is measured separately for the source and downstream firms and is lagged by one year). $Pr(Interlock)$, *Firm size*, *ROA*, *R&D*, *Board size*, *Geographic distance*, and *Technological similarity* are winsorized at the 1% and 99% levels and (except for $Pr(Interlock)$, *ROA*, and *Technological similarity*) are log-transformed. Columns (1) and (2) represent the first-stage regressions predicting the two endogenous variables, *Interlock* and $Log\ source\ patents \times Interlock$. Columns (3) to (6) show the results of second stage 2SLS regressions. Each regression includes year fixed effects as well as fixed effects for interlock groups, where an interlock group is a particular combination of a source firm, its board-interlocked downstream firm, and the CEM-matched, non-interlocked downstream firms. Standard errors, clustered at the interlock-group level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

(continued)

Table 5, continued

	First Stage		Second Stage			
	Log source patents × Interlock	Interlock	Patent volume	Direct citations	Patent value	Non-self citations
	(1)	(2)	(3)	(4)	(5)	(6)
Log source patents	1.413*** (0.02)	0.095*** (0.01)				
× Pr(Interlock)						
Pr(Interlock)	1.334*** (0.17)	1.880*** (0.09)				
<i>Instrumented:</i>						
Log source patents			0.077*** (0.015)	0.008*** (0.001)	0.180*** (0.027)	0.070*** (0.019)
× Interlock						
Interlock			-0.250*** (0.084)	-0.014*** (0.004)	-0.586*** (0.158)	-0.265** (0.106)
Log source patents	-0.212*** (0.01)	-0.050*** (0.00)	-0.054*** (0.009)	-0.004*** (0.001)	-0.119*** (0.016)	-0.069*** (0.012)
Firm size (source)	0.005 (0.01)	0.002 (0.00)	-0.004 (0.011)	0.000 (0.000)	-0.027 (0.021)	0.028* (0.016)
ROA (source)	0.004 (0.01)	-0.001 (0.00)	0.023 (0.021)	0.001 (0.001)	0.113*** (0.039)	-0.006 (0.027)
R&D (source)	0.004 (0.00)	0.002 (0.00)	0.006 (0.010)	0.000 (0.000)	0.012 (0.019)	-0.063*** (0.014)
Board size (source)	-0.004 (0.01)	0.004 (0.01)	0.005 (0.026)	0.000 (0.002)	0.048 (0.050)	0.024 (0.037)
Firm size (downstream)	-0.217*** (0.02)	-0.141*** (0.01)	0.159*** (0.008)	0.001** (0.000)	0.443*** (0.014)	0.166*** (0.009)
ROA (downstream)	-0.171*** (0.02)	-0.098*** (0.01)	0.007 (0.018)	-0.000 (0.001)	0.159*** (0.032)	-0.036* (0.021)
R&D (downstream)	0.007 (0.01)	0.001 (0.00)	0.363*** (0.006)	0.001*** (0.000)	0.666*** (0.012)	0.383*** (0.007)
Board size (downstream)	0.420*** (0.03)	0.327*** (0.02)	0.216*** (0.032)	-0.001 (0.002)	0.456*** (0.061)	0.122*** (0.038)
Distance	-0.069*** (0.01)	-0.074*** (0.00)	-0.016** (0.007)	-0.001 (0.000)	-0.027* (0.014)	-0.019** (0.009)
Similarity	0.176*** (0.03)	0.085*** (0.01)	0.576*** (0.025)	0.008*** (0.001)	1.105*** (0.046)	0.398*** (0.030)
Interlock-group FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sanderson-Windmeijer F	1,178.65	452.57	N/A	N/A	N/A	N/A
Kleibergen-Paap F	N/A	N/A	226.42	226.42	226.42	226.42
Observations	128,324	128,324	128,324	128,324	128,324	128,324

Table 6. Board Interlocks and Knowledge Spillovers: The Effects of Board Composition

This table reports the results of second-stage 2SLS regressions relating the spillover effects of board interlocks to the proportion of outside directors on the board. The sample consists of firm-pair-year observations as described in Table 5. The dependent variables, all log-transformed, include *Patent volume*, *Direct citations*, *Patent value*, and *Non-self citations*, described in Table 5. *Log source patents* is the log-transformed number of patent applications filed by the source firm during the year. *Interlock* is an indicator equal to 1 if a board interlock exists, i.e., if the downstream firm in a pair shares at least one director with the source firm from year t-1 to year t. *Outsider dominated* indicates that at least 85% of directors on either the source-firm board or the downstream-firm board are outside directors. Outside directors are identified based on the “NED” variable in *BoardEx* company profile data. The four endogenous variables involving *Interlock* are instrumented with *Outsider dominated* \times *Log source patents* \times *Pr(Interlock)*, *Outsider dominated* \times *Pr(Interlock)*, *Log source patents* \times *Pr(Interlock)*, and *Pr(Interlock)*, where *Pr(Interlock)* is the predicted probability from Table 3, regression (4) that a board interlock with the source firm is present. Control variables, described in Tables 5, include *Firm size*, *ROA*, *R&D*, *Board size* (each variable is measured separately for the source and downstream firms and is lagged by one year), *Geographic distance*, and *Technological similarity*. *Pr(Interlock)*, *Firm size*, *ROA*, *R&D*, *Board size*, *Geographic distance*, and *Technological similarity* are winsorized at the 1% and 99% levels and (except for *Pr(Interlock)*, *ROA* and *Technological similarity*) are log-transformed. All regressions include year fixed effects as well as fixed effects for interlock groups, where an interlock group is a particular combination of a source firm, its board-interlocked downstream firm, and the CEM-matched, non-interlocked downstream firms. Standard errors, clustered at the interlock-group level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Patent volume (1)	Direct citations (2)	Patent value (3)	Non-self citations (4)
<i>Instrumented:</i>				
Outsider dominated	-0.141*** (0.036)	-0.008** (0.004)	-0.400*** (0.066)	-0.208*** (0.047)
\times Log source patents \times Interlock				
Outsider dominated \times Interlock	0.687*** (0.109)	0.002 (0.004)	1.610*** (0.225)	0.522*** (0.138)
Log source patents \times Interlock	0.201*** (0.036)	0.016*** (0.004)	0.530*** (0.066)	0.255*** (0.048)
Interlock	-0.877*** (0.146)	-0.015** (0.007)	-2.054*** (0.292)	-0.742*** (0.184)
Outsider dominated	0.060*** (0.017)	0.003** (0.001)	0.176*** (0.031)	0.073*** (0.021)
\times Log source patents				
Outsider dominated	-0.314*** (0.050)	-0.001 (0.002)	-0.742*** (0.102)	-0.198*** (0.062)
Log source patents	-0.106*** (0.017)	-0.006*** (0.002)	-0.272*** (0.033)	-0.134*** (0.023)
Controls	Yes	Yes	Yes	Yes
Interlock-group FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Kleibergen-Paap F	100.24	100.24	100.24	100.24
Observations	128,324	128,324	128,324	128,324

Table 7. Board Interlocks and Knowledge Spillovers: The Effects of Board and Director Busyness

This table reports the results of second-stage 2SLS regressions relating the spillover effects of board interlocks to board and shared director busyness. The sample consists of firm-pair-year observations as described in Table 5. The dependent variables of interest, all log-transformed, include *Patent volume*, *Direct citations*, *Patent value*, and *Non-self citations*, described in Table 5. Two alternative definitions of director busyness are used: (1) a director holds at least three board seats during the year; and (2) a director holds at least five committee assignments during the year. Panel A examines the effects of board-level busyness. *Busy board* is an indicator equal to 1 if more than 1/3 of directors on the source board or the downstream board are busy directors. Panel B examines the effects of busyness among shared directors in an interlock. *Busy director* is an indicator that equals one if all shared directors in a treat-control-group are busy. *Log source patents* is the log-transformed number of patent applications filed by the source firm during the year. *Interlock* is an indicator equal to 1 if a board interlock exists, i.e., if the downstream firm in a pair shares at least one director with the source firm from year $t-1$ to year t . The four endogenous variables involving *Interlock* are instrumented with *Busy board (Busy director)* \times *Log source patents* \times *Pr(Interlock)*, *Busy board (Busy director)* \times *Pr(Interlock)*, *Log source patents* \times *Pr(Interlock)*, and *Pr(Interlock)*, where *Pr(Interlock)* is the predicted interlock probability from Table 3, regression (4). Control variables in each regression are described in Tables 5 and include *Firm size*, *ROA*, *R&D*, *Board size* (each variable is measured separately for the source and downstream firms and is lagged by one year), *Geographic distance*, and *Technological similarity*. *Pr(Interlock)*, *Firm size*, *ROA*, *R&D*, *Board size*, *Geographic distance*, and *Technological similarity* are winsorized at the 1% and 99% levels and (except for *Pr(Interlock)*, *ROA* and *Technological similarity*) are log-transformed. Each regression includes year fixed effects as well as fixed effects for interlock groups, where an interlock group is a particular combination of a source firm, its board-interlocked downstream firm, and the CEM-matched, non-interlocked downstream firms. Standard errors, clustered at the interlock-group level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Table 7, continued

	Panel A: Board Busyness							
	Busy Director: Holds At Least 3 Board Seats				Busy Director: Holds At Least 5 Committee Seats			
	Patent volume	Direct citations	Patent value	Non-self citations	Patent volume	Direct citations	Patent value	Non-self citations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Instrumented:</i>								
Busy board × Log source patents	-0.114*** (0.025)	0.000 (0.002)	-0.280*** (0.047)	-0.116*** (0.031)	-0.110*** (0.025)	-0.006** (0.003)	-0.249*** (0.046)	-0.113*** (0.032)
× Interlock								
Busy board × Interlock	0.502*** (0.067)	0.003 (0.002)	1.550*** (0.131)	0.404*** (0.084)	0.431*** (0.069)	0.006*** (0.002)	1.238*** (0.133)	0.548*** (0.087)
Log source patents × Interlock	0.142*** (0.022)	0.008*** (0.002)	0.328*** (0.041)	0.142*** (0.028)	0.150*** (0.023)	0.012*** (0.002)	0.340*** (0.042)	0.144*** (0.029)
Interlock	-0.518*** (0.099)	-0.015*** (0.005)	-1.411*** (0.190)	-0.487*** (0.125)	-0.531*** (0.104)	-0.018*** (0.005)	-1.388*** (0.197)	-0.621*** (0.132)
Busy board × Log source patents	0.052*** (0.012)	-0.000 (0.001)	0.116*** (0.023)	0.046*** (0.016)	0.050*** (0.013)	0.003** (0.001)	0.116*** (0.023)	0.051*** (0.016)
Busy board	-0.203*** (0.033)	-0.001 (0.001)	-0.603*** (0.063)	-0.139*** (0.041)	-0.185*** (0.032)	-0.002** (0.001)	-0.514*** (0.061)	-0.225*** (0.040)
Log source patents	-0.082*** (0.011)	-0.003*** (0.001)	-0.177*** (0.021)	-0.096*** (0.015)	-0.085*** (0.012)	-0.005*** (0.001)	-0.189*** (0.022)	-0.100*** (0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interlock-group FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	111.50	111.50	111.50	111.50	110.21	110.21	110.21	110.21
Observations	128,324	128,324	128,324	128,324	128,324	128,324	128,324	128,324

(continued)

Table 7, continued

	Panel B: Busyness of Shared Directors							
	Busy Director: Holds At Least 3 Board Seats				Busy Director: Holds At Least 5 Committee Seats			
	Patent volume	Direct citations	Patent value	Non-self citations	Patent volume	Direct citations	Patent value	Non-self citations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Instrumented:</i>								
Busy director × Log source patents	-0.097*** (0.030)	-0.005* (0.002)	-0.242*** (0.053)	-0.091** (0.036)	-0.137*** (0.027)	-0.009*** (0.003)	-0.245*** (0.048)	-0.145*** (0.033)
× Interlock								
Busy director × Interlock	0.254*** (0.084)	0.005* (0.003)	0.850*** (0.159)	0.233** (0.103)	0.194** (0.076)	0.008*** (0.003)	0.484*** (0.143)	0.232** (0.094)
Log source patents × Interlock	0.146*** (0.028)	0.011*** (0.002)	0.349*** (0.049)	0.134*** (0.034)	0.170*** (0.025)	0.015*** (0.003)	0.347*** (0.043)	0.169*** (0.031)
Interlock	-0.423*** (0.117)	-0.017*** (0.005)	-1.167*** (0.221)	-0.424*** (0.146)	-0.384*** (0.109)	-0.019*** (0.005)	-0.919*** (0.203)	-0.426*** (0.137)
Busy director × Log source patents	0.044*** (0.015)	0.003** (0.001)	0.125*** (0.028)	0.062*** (0.019)	0.059*** (0.014)	0.004*** (0.001)	0.113*** (0.025)	0.074*** (0.018)
Busy director	-0.136*** (0.043)	-0.003** (0.001)	-0.463*** (0.081)	-0.157*** (0.053)	-0.101*** (0.039)	-0.004*** (0.001)	-0.252*** (0.073)	-0.123** (0.049)
Log source patents	-0.086*** (0.015)	-0.005*** (0.001)	-0.206*** (0.026)	-0.112*** (0.019)	-0.095*** (0.014)	-0.007*** (0.001)	-0.196*** (0.024)	-0.120*** (0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interlock-group FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F	100.90	100.90	100.90	100.90	108.42	108.42	108.42	108.42
Observations	128,324	128,324	128,324	128,324	128,324	128,324	128,324	128,324

Table 8. Board Interlocks and Knowledge Spillovers: Characteristics of Shared Directors

This table reports the results of second-stage 2SLS regressions regarding the spillover effects of board interlocks to the individual characteristics of the shared directors. The sample consists of firm-pair-year observations as described in Table 5. The dependent variables, all log-transformed, include *Patent volume*, *Direct citations*, *Patent value*, and *Non-self citations*, described in Table 5. Panels A, B, C, and D, respectively, examine how the spillover effects of board interlocks are affected by shared directors' age, gender, high-tech professional experience, and related innovation experience. *Young director* is an indicator equal to one if at least one shared director is 63 years of age or younger. *Female* indicates at least one shared director is female. *High tech experience* is a dummy variable equal to 1 if at least one shared director has employment experience in the high-tech or life sciences sectors in the past 3 years (see Section 4.2.3 for more details). *Related experience* indicates that the average similarity between shared directors' innovation experience and the source firm's and interlocked downstream firm's recent innovation activities are both above the sample median. Similarity in innovation is measured by the 3-digit IPC code vectors as described in Section 4.2.3. In Panels A through D, we restrict the sample to observations where data on the relevant shared director characteristic is non-missing. To save space, coefficient estimates and standard errors are shown only for the endogenous (instrumented) variables. *Log source patents* is the log-transformed number of patent applications filed by the source firm during the year. *Interlock* is an indicator equal to 1 if a board interlock exists, i.e., if the downstream firm in a pair shares at least one director with the source firm from year $t-1$ to year t . The four endogenous variables in each regression are instrumented with *Characteristic* \times *Log source patents* \times *Pr(Interlock)*, *Characteristic* \times *Pr(Interlock)*, *Log source patents* \times *Pr(Interlock)*, and *Pr(Interlock)*, where *Characteristic* indicates a particular type of shared-director characteristic and where *Pr(Interlock)* is the predicted probability of a board interlock from Table 3, regression (4). The stand-alone variables *Characteristic* and *Log source patents*, and the interaction term *Characteristic* \times *Log source patents* are included in all regressions. Other control variables in each regression, described in Tables 5, include *Firm size*, *ROA*, *R&D*, *Board size* (each variable is measured separately for the source and downstream firms and is lagged by one year), *Geographic distance*, and *Technological similarity*. *Pr(Interlock)*, *Firm size*, *ROA*, *R&D*, *Board size*, *Geographic distance*, and *Technological similarity* are winsorized at the 1% and 99% levels and (except for *Pr(Interlock)*, *ROA* and *Technological similarity*) are log-transformed. Each regression includes year fixed effects as well as fixed effects for interlock groups, where an interlock group is a particular combination of a source firm, its board-interlocked downstream firm, and the CEM-matched, non-interlocked downstream firms. Standard errors, clustered at the interlock-group level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

<i>Instrumented variables</i>	Patent volume (1)	Direct citations (2)	Patent value (3)	Non-self citations (4)
Panel A: Director Age				
Young director \times Log source patents \times Interlock	0.079*** (0.025)	0.005*** (0.002)	0.110** (0.046)	0.091*** (0.032)
Young director \times Interlock	-0.200*** (0.070)	-0.004* (0.002)	-0.328** (0.129)	-0.059 (0.087)
Log source patents \times Interlock	0.036* (0.020)	0.005*** (0.001)	0.122*** (0.037)	0.019 (0.025)
Interlock	-0.149* (0.089)	-0.011*** (0.004)	-0.415** (0.168)	-0.236** (0.112)
Kleibergen-Paap F	110.07	110.07	110.07	110.07
Observations	127,070	127,070	127,070	127,070

(continued)

Table 8, continued

<i>Instrumented variables</i>	Patent volume (1)	Direct citations (2)	Patent value (3)	Non-self citations (4)
Panel B: Gender				
Female × Log source patents	-0.010 (0.033)	-0.003 (0.002)	-0.029 (0.058)	-0.039 (0.041)
× Interlock				
Female × Interlock	0.156* (0.093)	0.003 (0.003)	0.575*** (0.171)	0.013 (0.116)
Log source patents × Interlock	0.080*** (0.018)	0.009*** (0.001)	0.186*** (0.031)	0.079*** (0.022)
Interlock	-0.280*** (0.091)	-0.014*** (0.005)	-0.683*** (0.171)	-0.272** (0.116)
Kleibergen-Paap F	106.09	106.09	106.09	106.09
Observations	127,086	127,086	127,086	127,086
Panel C: High-Tech Work Experience				
High tech experience × Log source patents × Interlock	0.004 (0.030)	0.003 (0.003)	-0.083 (0.052)	-0.006 (0.039)
High tech experience × Interlock	0.031 (0.087)	-0.002 (0.003)	0.715*** (0.153)	0.091 (0.113)
Log source patents × Interlock	0.081*** (0.016)	0.008*** (0.001)	0.198*** (0.029)	0.072*** (0.020)
Interlock	-0.275*** (0.086)	-0.014*** (0.004)	-0.740*** (0.164)	-0.291*** (0.109)
Kleibergen-Paap F	109.44	109.44	109.44	109.44
Observations	126,642	126,642	126,642	126,642
Panel D: Related Innovation Experience				
Related experience × Log source patents × Interlock	0.104*** (0.033)	0.010*** (0.003)	0.120** (0.053)	0.147*** (0.041)
Related experience × Interlock	0.245** (0.113)	-0.009 (0.006)	1.120*** (0.181)	-0.091 (0.143)
Log source patents × Interlock	-0.011 (0.019)	0.003*** (0.001)	-0.026 (0.037)	-0.008 (0.023)
Interlock	-0.151 (0.104)	-0.009* (0.005)	-0.612*** (0.196)	-0.096 (0.133)
Kleibergen-Paap F	89.24	89.24	89.24	89.24
Observations	70,272	70,272	70,272	70,272

Table 9. Board Interlocks and Knowledge Spillovers: Characteristics of Source-Firm Patent Flow

This table reports the results of second-stage 2SLS regressions that explain interlock-related spillover effects in terms of different types of innovation from source firms. The sample consists of firm-pair-year observations as described in Table 5. The dependent variables, all log-transformed, include *Patent volume*, *Direct citations*, *Patent value*, and *Non-self citations*, described in Table 5. *Interlock* is an indicator equal to 1 if a board interlock exists, i.e., if the downstream firm in a pair shares at least one director with the source firm from year $t-1$ to year t . Panels A, B, C, and D, respectively, partition the flow of source-firm patents according to whether or not patents have high value, have high IPC-based breadth, are highly similar to the downstream firm's past innovation, and are highly similar to the source firm's own past innovation. *High-value* patents are those whose value is above the median of all patent applications filed between 2005 and 2017. Patent values are imputed from stock-market announcement returns as in Kogan, Papanikolaou, Seru, and Stoffman (2017). *High-breadth* patents are those whose IPC-based breadth is above the median of all patent applications filed between 2005 and 2017. IPC-based breadth is measured by the number of unique 4-digit IPC codes a patent filing has. *Downstream-similar* patents are those whose similarity to the downstream-firm patent applications that are filed in the past three years is above the 75th percentile of a given year. *Core* patents are those whose similarity to their firm's own patent applications filed in the past three years is above the 75th percentile of a given year. Similarity is measured as the cosine similarity between two vectors of 3-digit IPC codes that are contained in patent applications filed in a specified time window. Each element of a 3-digit IPC vector is the count of patent applications filed under the corresponding IPC code by a firm within the given time window. Details of computing the cosine similarity are described in Section 2. *Low-value*, *Low-breadth*, *Downstream-nonsimilar*, and *Peripheral* are source firm patent applications filed during the year that are not defined as *High-value*, *High-breadth*, *Downstream-similar*, and *Core*, respectively. All of the measures count source-firm patent applications filed in year t and are log-transformed. To save space, coefficient estimates and standard errors are shown only for the endogenous (instrumented) variables. The three endogenous variables in each panel are instrumented with *Log source patents of a given type* \times *Pr(Interlock)*, *Log other source patents* \times *Pr(Interlock)*, and *Pr(Interlock)*, where, in Panels A to D, *source patents of a given type* are source patents defined as *High-value*, *High-breadth*, *Downstream-similar*, and *Core*, respectively, while *other source patents* are those defined as *Low-value*, *Low-breadth*, *Downstream-nonsimilar*, and *Peripheral*; *Pr(Interlock)* is the predicted probability of a board interlock from Table 3, Column (4). The stand-alone variables are included in all regressions. Other control variables in each regression, described in Tables 5, include *Firm size*, *ROA*, *R&D*, *Board size* (each variable is measured separately for the source and downstream firms and is lagged by one year), *Geographic distance*, and *Technological similarity*. *Pr(Interlock)*, *Firm size*, *ROA*, *R&D*, *Board size*, *Geographic distance*, and *Technological similarity* are winsorized at the 1% and 99% levels and (except for *Pr(Interlock)*, *ROA* and *Technological similarity*) are log-transformed. Each regression includes year fixed effects as well as fixed effects for interlock groups, where an interlock group is a particular combination of a source firm, its board-interlocked downstream firm, and the CEM-matched, non-interlocked downstream firms. The table also reports, for each regression, the p-value from an F-test for coefficient differences between different types of source patents. Standard errors, clustered at the interlock-group level, are reported in parentheses below coefficient estimates. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

(continued)

Table 9, continued

<i>Instrumented variables</i>	Patent volume (1)	Direct citations (2)	Patent value (3)	Non-self citations (4)
Panel A: High Value Patents				
Log high-value source patents	0.090*** (0.020)	0.008*** (0.002)	0.207*** (0.034)	0.100*** (0.026)
× Interlock				
Log low-value source patents	-0.003 (0.021)	0.001 (0.002)	-0.015 (0.037)	-0.025 (0.027)
× Interlock				
Interlock	-0.217*** (0.081)	-0.010** (0.004)	-0.496*** (0.151)	-0.228** (0.102)
Coefficient diff. tests P value	0.01**	0.04**	<0.01***	<0.01***
Kleibergen-Paap F	151.23	151.23	151.23	151.23
Observations	128,324	128,324	128,324	128,324
Panel B: Patent Breadth				
Log high-breadth source patents	-0.087*** (0.029)	-0.008*** (0.003)	-0.041 (0.051)	-0.609*** (0.037)
× Interlock				
Log low-breadth source patents	0.147*** (0.025)	0.015*** (0.002)	0.216*** (0.042)	0.529*** (0.033)
× Interlock				
Interlock	-0.245*** (0.083)	-0.013*** (0.004)	-0.552*** (0.155)	-0.307*** (0.106)
Coefficient diff. tests P value	<0.01***	<0.01***	<0.01***	<0.01***
Kleibergen-Paap F	152.46	152.46	152.46	152.46
Observations	128,324	128,324	128,324	128,324
Panel C: High Similarity to Downstream Innovation				
Log downstream-similar source patents × Interlock	0.178*** (0.031)	0.026*** (0.004)	0.609*** (0.050)	0.133*** (0.037)
Log downstream-nonsimilar source patents × Interlock	0.032** (0.016)	0.001 (0.001)	0.006 (0.028)	0.052*** (0.020)
Interlock	-0.270*** (0.082)	-0.017*** (0.005)	-0.655*** (0.155)	-0.295*** (0.104)
Coefficient diff. tests P value	<0.01***	<0.01***	<0.01***	0.08*
Kleibergen-Paap F	153.71	153.71	153.71	153.71
Observations	128,324	128,324	128,324	128,324

Table 9, continued

<i>Instrumented variables</i>	Patent volume (1)	Direct citations (2)	Patent value (3)	Non-self citations (4)
Panel D: High Similarity to Own Innovation				
Log core source patents	-0.017 (0.022)	0.009*** (0.002)	0.032 (0.036)	-0.056** (0.027)
× Interlock				
Log peripheral source patents	0.088*** (0.016)	0.005*** (0.001)	0.179*** (0.028)	0.088*** (0.020)
× Interlock				
Interlock	-0.243*** (0.083)	-0.012*** (0.004)	-0.565*** (0.156)	-0.253** (0.105)
Coefficient diff. tests P value	<0.01***	0.20	<0.01***	<0.01***
Kleibergen-Paap F	151.71	151.71	151.71	151.71
Observations	128,324	128,324	128,324	128,324