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Keywords: Labor and Finance, social capital, social connections, directed networks
JEL Classification: G30, G32, L14

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Abstract

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1. Introduction

The role of physical capital, human capital, and intellectual capital in corporations is well studied. Yet, another type of capital, perhaps equally important, has received much less attention: a firm's social capital, consisting broadly of the relationships that a firm and its employees have built with economically related agents outside the firm (Servaes and Tamayo, 2017).[1] Social capital is a broad concept that can be understood as the information, trust, and norms of reciprocity inherent in a social network (Woolcock, 1998). The literature has conceptualized social capital in two complementary ways. One view is that social capital is a societal characteristic that captures the strength of cooperative norms in society (Putnam, 1993, 2000). Studies that rely on this framework measure the social capital of countries or regions through the civic engagement of the population or their willingness to trust each other; these studies conclude that regions with more social capital experience better economic outcomes due to increased trust and cohesiveness (e.g., Knack and Keefer, 1997; La Porta et al., 1997; Guiso et al., 2004, 2008) and that firms operating in these regions have better access to capital (Hasan et al., 2017; Kuchler et al., 2020) and suffer less from agency problems (Hoi et al., 2019).

Another view is that social capital is an individual asset embedded in social networks that enables access to resources and information (Coleman, 1988; Paldam, 2000; Lin, 2002; Burt, 2007). Glaeser et al. (2002) define individual social capital as a person's social characteristics—including social skills, charisma, and the size of their Rolodex—which enable the individual to reap market and non-market returns from interactions with others. At the firm level, individual social capital is important since employees, including management and rank and file, interact directly with business partners, clients, and other stakeholders. However, due to the latent nature

[1] This definition of social capital distinguishes it from relationships within the firm, sometimes referred to as organization capital or corporate culture; for work in this area, see, for example, Eisfeldt and Papanikolaou (2013), Jeffers and Lee (2019), and Graham et al. (2019).

of social networks, how the social capital embodied in employees' connections contributes to firm performance and valuation remains an open question.[2]

The goal of this paper is twofold. First, we aim to establish a causal link between the social capital embedded in employees' networks and firms' performance. To this end, we construct a novel firm-level measure of employee social capital using professional connections that a firm's employees, across all job levels, have built with economically related agents outside the firm. Second, we identify the types of employee connections that are valuable to firms, thus contributing to a more granular understanding of social capital in corporations.

To measure employee social capital, we exploit a unique cultural practice in Asia: the exchange of business cards when forming connections. We obtain proprietary data from the professional networking app Remember, to which users upload business cards they have collected from others. Remember has a near-monopoly of business card management in Korea. We obtain the business card collections uploaded by each user and screen out individuals who are not employees of firms. The data allow us to directly identify the professional networks of individual employees and quantify the connections each employee has built with people outside of their firm. We further map the connections of public firm employees to the financial variables of their employers to obtain a matched employer-employee dataset.

Several aspects of our data are novel and noteworthy. First, our final sample consists of 2.4 million employees, with more than 12 million professional connections among them. The data's broad coverage of employees across ranks, including lower-level managers and rank-and-file employees, allows us to quantify employee social capital at the firm level. Second, because in Asian culture, business cards are typically exchanged in face-to-face meetings, our data depict real-world professional connections more reliably than those from online networking platforms such as LinkedIn and Facebook.[3] Third, while card exchanges are mutual between the two parties,

[2] Limited by data availability on networks, the finance literature that uses the network approach focus almost exclusively on benefits firms obtain from their well-connected executives and board members (e.g., Cai and Sevilir, 2012; Engelberg et al., 2012; Larcker et al., 2013).

[3] As in most other Asian countries, in Korea exchanging business cards in face-to-face meetings is an essential ritual for establishing professional connections. It is not the norm to pass on business cards on behalf of others.

uploading cards to the app is not necessarily mutual because users likely upload only the cards of contacts that they value. Using language from the network literature, we refer to the network as *directed*: each connection is directed from the employee who uploaded the card to the employee whose card was uploaded. This directed feature allows us to determine whether one of the two connected parties values the other party more.

We calculate several connection measures at the individual employee level—*In-degree* (the number of others uploading the employee as a contact), *Out-degree* (the number of business contacts uploaded by the employee), and *Total degree* (the sum of *In-degree* and *Out-degree).* In other words, *In-degree* counts the contacts who remember (apropos the name of the app) or value the employee; *Out-degree* counts the contacts the employee remembers or values. As we discuss below, this distinction allows us to analyze the extent to which social capital—as distinguished by "who knows you" versus "who you know"—matters for firm performance.

We construct firm-level measures of employee social capital (ESC) by averaging the employee-level degree measures (*In-degree*, *Out-degree, Total degree*) within a firm in a given year. Our initial research question is: Does employee social capital contribute to improving firm performance? Drawn from a comprehensive sample of Korean public firms in the OSIRIS Industrials database from 2014 to 2018, our baseline regressions examine the effect of the average *Total degree* of a firm's employees without regard to the direction of connections. We find that firms with higher employee social capital are more profitable and experience higher sales growth in the following year. For instance, firms with a one standard deviation higher lagged *ESC total degree* have a higher return on assets (*ROA*) of 0.4 percentage points and a higher sales growth of 2.1 percentage points. These are considerable economic effects given the mean *ROA* of 4.3 percentage points and the mean sales growth of 4.1 percentage points.

If employee social capital is positively and significantly associated with firm performance, which direction of connection is more valuable? To answer this question, we re-estimate the model when firm-level ESC takes the value of *ESC in-degree* (which measures "who knows you") and *ESC out-degree* (which measures "who you know"). Results show that the positive association with performance arises mainly from *ESC in-degree*, which captures the extent to which a firm's employees are remembered or valued by their external contacts. The estimated effect is statistically significant and economically meaningful. A one standard deviation increase in lagged *ESC in-degree* is associated with a 9.4% increase in *Tobin's q* relative to the sample mean, a 0.9 percentage point increase in *ROA*, and a 4.0 percentage point increase in sales growth. By contrast, the coefficient estimates on *ESC out-degree* are largely insignificant. While the social capital literature argues that networks endow employees with goodwill and better access to resources and information, our findings suggest that the extent to which employees can mobilize these benefits for their employers depends on whether their business contacts value them. In this sense, having a broad network of business contacts who know you is more valuable to your employer than having a broad network of contacts whom you know.[4]

We perform a battery of robustness checks to confirm that the value of employee social capital reflected in "who knows you" is not driven by omitted variables. For example, sales employees who serve as customer touchpoints are active in exchanging cards, such that the observed relation between employee connections and firm performance might reflect their sales effort. To address this concern, we exclude the connections of a firm's customer-facing employees who perform sales functions; our results are robust. Another concern is that well-connected employees might also have high technical skills. Thus, the superior firm performance could be driven by their technical skills, which is part of their human capital, but not their social capital. To address this possibility we follow the strategy in Cohen et al. (2010) and exclude subsamples of firms that are ranked highly by skilled employees and find the results continue to hold.

In addition, our data's coverage of employees across ranks allows us to study employee social capital beyond the executive team. We find that executives are not the only group that has beneficial connections for their firms; employee connections across all job ranks, including the

[4] Although "who you know" may be less useful to employers than "who knows you," "who you know" can be an asset for employees themselves. To the extent that employees uploading contacts from other firms—as measured by *ESC out-degree*—expands outside job opportunities, as shown by Gortmaker et al. (2020) using data from LinkedIn, the resources mobilized through these connections do not necessarily accrue to their current employer.

rank and file, are valuable. For instance, our estimates reveal that connections of non-executive managers have the greatest significance for employer *ROA* and sales growth.

Establishing a causal link between employee social capital and firm performance requires a careful account of the endogeneity of networks. A relevant concern is reverse causality, whereby better firm performance leads to the formation of professional connections. Another concern is that omitted variables that are correlated with both employee social capital and firm performance may be driving our findings. To reinforce the causal interpretation of our results, we exploit the 2016 enactment of the Improper Solicitation and Graft Act (the Act) as an exogenous shock to professional networks in Korea. Intended to curb bribery, the Act makes it illegal for media professionals (such as journalists) and public sector employees (such as civil servants, lawmakers, central bankers, and teachers), and their spouses to accept gifts or meals exceeding a specified limit, regardless of whether they are in exchange for favors. The Act is a suitable identification tool because of the uncertainty in the legislative process and its aggressive enforcement. Evidence suggests that the Act had a chilling effect on meetings and social events with employees in the affected industries. By making firms less able to access the resources and information embedded in their employees' connections to the media and the public sector, the Act was a negative shock to employee social capital.

We use a difference-in-differences framework surrounding the enactment of the Act and set the treatment intensity as the fraction of a firm's preexisting employee social capital derived from its employees' connections with industries subject to the Act. Since some firms are more exposed to the Act than others, we can estimate differences in performance between firms with differential exposure. We find that firms with ESC more exposed to the Act experience a decline in performance after the Act relative to those less exposed. This differential effect does not appear in pre-treatment years but persists over the years following the Act's implementation. Furthermore, the results are robust to matching treatment to control firms based on industry and observable firm characteristics and to excluding firms that are economically linked to the industries directly affected by the Act, such as customers and suppliers of the media and the public sector. Finally, if firms with employee social capital more exposed to the Act also engaged more actively in bribery for resources, the negative effect on their performance might be due to the curb on bribery rather than a reduction in the value of employee social capital. To alleviate this concern, we control for a firm's entertainment expenses, which are shown to include a significant bribe component (Cai et al., 2011; Kang et al., 2020), and find our results remain robust. Moreover, we find that entertainment expenses do not differentially impact firms with employee social capital more exposed to the Act, thus ruling out the reduction in bribery as a potential channel. Altogether, our findings provide compelling evidence for a causal impact of employee social capital on firm performance.

To bolster confidence in our causality tests, we consider some specific economic benefits that firms can derive from their employees' connections with the industries affected by the Act—the media and the public sector. Motivated by the literature on media coverage and firm valuation (e.g., Gurun and Butler, 2012; Ahern and Sosyura, 2014), we predict that media connections of a firm's employees will foster goodwill and boost trust by journalists, which in turn promotes news coverage of the firm, especially news stories with a positive tone. Indeed, we find that employees' media connections lead to substantially more news articles about a firm and to a greater fraction of positive coverage. Moreover, the positive effects diminish after the adoption of the Act, reinforcing our causal inference.

We next investigate the benefits of employee connections with the public sector. Drawing on evidence that public officers allocate significantly more procurement contracts to firms with a connected CEO (Schoenherr, 2019), we expect that employees with public sector connections may also help their firms secure government contracts. Our evidence is consistent with this prediction. For example, a one standard deviation increase in the fraction of employee social capital accumulated from public sector connections leads to a 5.8% increase in the contract volume before the Act and to only a 3.1% increase after the Act.

Connections among individuals lead to reciprocity, trust, and information sharing, according to the social capital literature. While these mechanisms could all be at play, it is challenging to sort out their relative contribution; in our final analysis, we provide evidence for one mechanism—information sharing—by examining employee connections to the investment banking industry. Our results show that firms with more investment banking connections incur lower at-issue bond spreads. Notably, among employees at all job levels, connections between investment bankers and rank-and-file employees are the most significant contributor to lower bond spreads. Since rank-and-file employees of the issuer firm are unlikely to be relevant in developing trust or reciprocity, a likely motivation for investment bankers to remember them is to acquire information in the due diligence investigation. Hence, our evidence suggests that a key mechanism through which employee social capital enhances firm performance is the sharing of information with economically related entities.

In sum, this paper documents that employee social capital enhances employers' performance, thus shedding light on the drivers of firm productivity (Syverson, 2011). By exploiting the directed feature of the network data, we show that the value of employee social capital to a firm comes mainly from employees being valued by their external contacts. Our unique analysis of employees across ranks informs us that connections by all levels of employees matter for firm outcomes. Finally, our analysis of connections with external stakeholders sheds light on the economic benefits that firms can derive from their employee social capital. This study thus contributes to the burgeoning literature on the role of social capital in corporations (e.g., Servaes and Tamayo, 2017; Lins et al., 2017; Hasan et al., 2017; Hoi et al., 2019).[5] Our study uniquely leverages the Asian cultural practice of exchanging business cards, allowing us to measure firm-level social capital by identifying interpersonal networks. Although our evidence draws from Korean firms, the effects of social ties on business outcomes have been documented in diverse business cultures, such as the US (Hochberg et al., 2007), China (Cai and Szeidl, 2017), Germany (Haselmann et al., 2018), and the UK (Rossi et al., 2018), suggesting that the insights are general and broadly contribute to our understanding of social capital.

Our study also extends prior work that focuses on the benefits of managerial networks, such as high announcement returns in mergers and acquisitions (Cai and Sevilir, 2012), better firm

[5] A firm's political capital may be considered to be part of its social capital in broad terms. Studies have examined a firm's political capital accumulated through campaign contributions and executives' connections with politicians (Faccio, 2006; Akey, 2015; Acemoglu et al., 2016; Schoenherr, 2019; Babenko et al., 2020).

performance (Larcker et al., 2013; Cai and Szeidl, 2017), favorable lending terms (Engelberg et al., 2012), and survival during a financial crisis (Babina et al., 2020).[6] Adding to this work, we show that executives are not the only group that possesses beneficial connections for their firms; employee connections (when valued by their external contacts) across all job ranks are valuable.

We organize the paper as follows. Section 2 describes the data and the construction of firm-level employee social capital. Section 3 examines the relation between employee social capital and firm performance. In Section 4, we provide causal evidence by exploiting the 2016 enactment of the Anti-Graft Act as a quasi-natural experiment. We provide additional evidence on the mechanism in Section 5 and conclude in Section 6.

2. Data and Summary Statistics

2.1. Remember, a Professional Networking App

We exploit a unique proprietary database extracted from a professional networking app, Remember*,* which was developed by the Korean mobile and web service provider Drama & Company.[7] Since its launch in January 2014, Remember has become the single most popular professional business card management app in Korea.[8] The app is available free of charge from Google Play and the App Store. As of December 2018, the total number of business cards uploaded was over 140 million; the total number of users was around 2.5 million, which is approximately 18.1% of the total number of full-time employees in Korea (about 13.8 million according to Statistics Korea). The data cover a wide array of sectors, as shown in Table IA.1.

To keep a record of their professional network, users of the app upload the business cards they have collected, either scanning and uploading the business cards by themselves or having the

[6] Other studies point out potential downside associated with executives being well networked: connections could weaken effective monitoring of board members, increase the entrenchment of CEOs, and lead to rent-seeking coalitions (Hwang and Kim, 2009; Khanna et al., 2015; Ishii and Xuan, 2014; El-Khatib et al., 2015; Haselmann et al., 2018).

[7] The company website is http://dramancompany.com; the app is accessible at https://rememberapp.co.kr/home.

[8] Remember has a near monopoly in the business card management industry in Korea, with virtually no domestic competitors. The app won the Google Play Awards in 2015 and 2016 and received the Brand of the Year Korea for four consecutive years, from 2015 through 2018.

app developer scan the cards in bulk for a small fee.[9] Professional typists hired by the app developer hand-type the information on the scanned cards into the database, which renders the network data virtually free of automatic-recognition errors. The app allows users to manage their professional networks on mobile devices or computers, to use search criteria to connect to calls, texts, emails, and addresses, and to add updates about promotions or new job titles. Unlike online networking platforms (e.g., LinkedIn, Facebook, or Twitter), the network of an app-user is not visible to others.

2.2. Business Card Data and Individual Employee-Level Connections

The cultural background of Korea strongly supports the notion that tracking business card exchanges is a useful way to identify employees' professional networks. As in most other Asian countries, in Korea exchanging business cards in face-to-face meetings is more than an exchange of personal details; it is an important ritual for building professional connections. It is widely believed that, besides being an ice breaker, the exchange of business cards can help establish a positive first impression and boost professional credibility.[10] Business cards are also a physical reminder that one has met the contact rather than simply googled them.[11] In addition, exchanging cards helps the two parties bond and build trust by encouraging follow-up social events.

Tracing the exchange of business cards is thus a relatively feasible and reasonable way to identify Koreans' professional networks. From each card uploaded by each app-user, we obtain detailed information about the business contacts, including an individual identifier (uniquely defined by a coded name and coded mobile phone number to comply with user privacy laws), email domain, company name, job position, and timestamp of card registration. The unit of observation in the raw data is the *connection level*—that is, a pair consisting of the app-user and

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[9] Figure IA.1 in the Internet Appendix illustrates how the Remember app appears in the App Store, the app's user interface, and how to upload business cards.

[10] "Why Business Cards Still Matter," BBC, September 2016, https://www.bbc.com/worklife/article/20160914-how-a-small-yet-mighty-bit-of-paper-can-still-get-you-a-job.

[11] As discussed extensively in the *Economist* (May 2015), "business cards are doubly useful. They can be a quick way of establishing connections, particularly in Asia, where they are something of an obsession . . . exchanging business cards still seems to be an excellent way to initiate a lasting relationship. The ritual swapping of paper rectangles may be old-fashioned but on it will go."

the business contact whose card is uploaded. Since our goal is to count connections among employees, we exclude connections that involve individuals who do not have a company name on their card, whose listed email domain is inconsistent with their company, or whose company does not have a Korea Investors Service (KIS) firm identifier.[12] To focus on interfirm connections, we further select connections between employees with different KIS identifiers. Accordingly, each connection involves two employees of different firms: the app-user who uploads the business card and the business contact to whom the card belongs. Internet Appendix I provides an example of the business card data.

In general, cards are mutually exchanged between two parties, but the upload of exchanged cards is not necessarily mutual. For example, Aaron and Bob meet and exchange cards. When Aaron uploads Bob's card, Bob does not necessarily upload Aaron's card. Borrowing terminology from the network literature (e.g., Jackson, 2008; Newman, 2010), our connection-level data are directed. Next, we briefly discuss some commonly used concepts in describing networks. In social networks, individuals, also called *nodes*, form *links* (*connections*) to other individuals; the nodes and links constitute the network. If the links have a specified direction and are not necessarily mutual, we say the network is *directed*.[13] The literature typically visualizes directed networks by drawing links as arrows to indicate the direction. Thus, there can be links pointing inward to and outward from each node. The number of links pointing inward to each node is the *in-degree,* and the number of links pointing outward is the *out-degree*. The *total degree* of a node is the sum of its *in-* and *out-degree*.

Applying these concepts to our data, each connection is a link directed from the user who uploaded the card to the contact whose card was uploaded. The example of Aaron uploading Bob's card is represented graphically by an arrow from Aaron pointing to Bob. This connection counts as an *out-degree* for Aaron, and an *in-degree* for Bob. Because users are most likely to upload only

[12] KIS data contain financial information on both listed and unlisted companies in Korea; firms not covered by KIS are likely businesses without a corporate registration number.
[13] For instance, a network that keeps track of which author cites which other authors, or which person follows which other people on Twitter, would naturally be a directed network. By contrast, professional connections on LinkedIn and friendship networks on Facebook are undirected.

the cards they value and intend to "remember"—as suggested by the name of the app—Aaron uploading Bob's card likely reveals that Aaron considers Bob a valuable connection. We will refer to this observation as Aaron remembers Bob, and Bob is remembered by Aaron. This directed feature is useful for an empiricist attempting to identify the economic value of a connection. We define the degree measures at the employee level as follows. *In-degree* is the number of employees of other firms who have uploaded the employee as a business contact ("who knows you"). *Out-degree* is the number of business contacts of other firms uploaded by the employee ("who you know"). For each employee, *Total degree* is the sum of their *In-degree* and *Out-degree.*[14]

[Table 1 about here]

Panel A of Table 1 describes our sample. Since our interest is in the performance of public firms, we keep only the connections in which at least one of the two individuals is employed by a publicly listed firm. This network consists of more than 12 million connections between 2.4 million employees. Among these employees, 17.4% are app-users, and 43.0% work for public firms. The share of app-users among public firm employees is 11.8%. There are 126,987 firms with KIS identifiers; among them, 1,866 are public firms with OSIRIS Industrials firm identifiers. To analyze the performance of Korean public firms, we use the OSIRIS Industrials database compiled by Bureau van Dijk, which contains financial information on listed industrial companies worldwide.

Panel B of Table 1 presents descriptive statistics of employee-level connections as of December 2018. We begin by summarizing the connections of the 119,423 app-user employees of public firms. *In-degree* shows that an average app-user employee is uploaded as a contact by 26 app-users outside the firm. *Out-degree* shows that the average app-user uploads 57 business contacts from other firms. The sum of the two degrees above, *Total degree*, has a mean of 83. All degree measures have a median much lower than the mean, suggesting that the degree distributions

[14] A reciprocal relationship, which occurs when both parties upload each other's cards, appears as two connections in our data. Put differently, a reciprocal relationship counts toward both the *In-degree* and *Out-degree* for each party, thereby increasing the *Total degree* of each party by two. Consequently, the number of connections of an employee might be greater than the number of business contacts.

are highly right skewed. In the network, there are 896,600 non-app-users working for public firms. Non-app-users enter the network when their cards are uploaded by app-users and thus, by definition, only have links pointing inward. On average, a non-app-user, whose *In-degree* (which also equals *Total degree*) is around five, is uploaded as a contact by five app-users outside the firm. Pooling the app-users and non-app-users together, an average public firm employee in the network is uploaded by seven others as a business contact and has a total degree of 14. We also tabulate *In-degree* by employee job level into executives, non-executive managers, and rank-and-file employees.[15] About 10% of the observed employees are executives, who have the highest average *In-degree* of 13. Non-executive managers make up 57% of our sample and are uploaded as a contact by eight external contacts on average. A third of our sample is rank-and-file employees, who appear to be the least connected with an average *In-degree* of four.

The business card data from Remember have several advantages in identifying employees' professional networks. First, the data's broad coverage of individual employees' connections (including management and rank and file) allows us to map employee-level connections to their employers to construct a matched employer-employee dataset. This feature overcomes a limitation of the corporate finance literature that has focused primarily on managerial networks. Second, because business cards are typically exchanged in a face-to-face meeting, our data depict real-world professional relationships more reliably than online professional or social networks such as LinkedIn. An uploaded business card is a physical imprint that the two people indeed met rather than simply connected via an online invitation. Third, the directed nature of the data allows us to differentiate the value that each of the two parties assigns to the link, thus shedding light on the economic value of the connections. Given that the connections of an employee are not publicly visible, one's *In-degree* and *Out-degree* are unlikely to strategically influence each other.

[15] Job levels classified as executives include chairman, vice chairman, president, deputy president, executive vice president, and senior vice president; job levels classified as non-executive managers include vice president, general manager, department head, deputy general manager, manager, section head; rank-and-file employees include all the other employees without a managerial title.

2.3. Firm-Level Employee Social Capital (ESC)

To examine the extent to which resources inherent in an employee's professional connections contribute to their employer's performance, we construct measures of firm-level employee social capital (ESC) based on the employee-level degree measures. Having access to the connections of the universe of public firm employees would be ideal, but we can only observe connections for those employees who appear in the Remember app. Thus, to identify firm-level ESC, our strategy is to average across the employee-level degree measures to obtain a proxy for the representative employee of each firm.

The decomposition of firm-level employee social capital into *ESC in-degree* and *ESC out-degree* utilizes the direction of connections (as illustrated in Figure IA.2 in the Internet Appendix). The employees of a firm who appear in the network include both app-users and non-app-users. For each app-user, we observe their connections in both directions; the connections of non-app-users can only be observed when their business cards have been uploaded by app-user employees of other firms. Accordingly, *ESC in-degree* is the average *In-degree* across the firm's employees in the network that year; it quantifies the number of times the firm's employees are uploaded as business contacts by employees outside the firm. *ESC out-degree* is the average *Out-degree* across the app-user employees of a firm that year; it quantifies the number of business contacts from other firms uploaded by the firm's app-user employees. Finally, *ESC total degree* is the average *Total degree* across the firm's employees in the network that year.[16]

2.4. Sample Construction and Summary Statistics

To construct our sample, we start with Korean public firms from the annual OSIRIS Industrials database from 2014 through 2018. We match the 1,866 public firms in the network data with OSIRIS Industrials using company names. We use three measures for firm performance: *Tobin's q* is the market value of assets divided by the book value of assets; *ROA* (return on assets)

[16] To reduce measurement error when taking averages, we restrict our sample to firm-year observations with at least ten employees observed in the network. Our results are robust to using alternative thresholds for the minimum number of employees who appear in the network data.

is earnings before interest, tax, depreciation, and amortization (EBITDA) divided by the lagged total assets;[17] *Sales Growth* is the annual log growth rate of sales. The definitions of all variables are provided in Appendix A. We drop firm-year observations with missing data for the main variables in the baseline regressions. To reduce the effects of outliers, we winsorize all potentially unbounded variables at the 1st and 99th percentiles of the distribution. The final sample consists of 5,340 firm-year observations and covers 1,553 unique firms.

[Table 2 about here]

Panel A of Table 2 reports summary statistics for our firm-year sample. *ESC in-degree* has a mean of 3.7 and a median of 3.1; *ESC total degree* has a mean of 6.8 and a median of 5.3. These numbers show that employees of a firm, on average, have 6.8 connections with employees of other firms and that in 3.7 of those connections, they are uploaded as a business contact by others. In comparison, *ESC out-degree* has a mean of 31.0 and a median of 24.2, suggesting that app-user employees of a firm, on average, upload 31 business contacts from other firms; *ESC out-degree* is larger in magnitude than *ESC total degree* because we observe a more complete picture of connections by app-user employees of a firm, as discussed in Panel B of Table 1.[18] The financial variables are comparable in magnitude to those of US firms during the same period; Korean firms have relatively less skewed *Tobin's q,* larger *ROA,* smaller *Sales Growth*, and lower *Book Leverage.* Summary statistics of firm-level ESC measures by sector are reported in Table IA.1 in the Internet Appendix. Aside from the mining and quarrying sector, which has only three public firms, firms in the financial sector (SIC codes 61, 62, 65, 67) have the highest ESC, suggesting that they tend to be central in the network.[19]

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[17] Results are similar when we use EBIT instead of EBITDA to measure *ROA*.

[18] The number of observations of *ESC out-degree* is slightly smaller than that of the other main variables; this is because some firm-year observations have zero app-user employees and thus are missing *ESC out-degree*.

[19] The OSIRIS Industrials database does not include depository institutions (SIC code 60) or insurance companies (SIC codes 63 and 64); however, the business contacts of our focal firm employees are from a wide range of unrestricted employers, including private firms, depository institutions, and insurance companies.

3. Employee Social Capital and Firm Performance: Baseline Analysis

This section provides baseline estimates of the relation between employee social capital, as variously measured by employee connections, and firm performance. In Section 3.1, we examine the importance of *ESC total degree,* which measures the average total connections across employees of a firm, without accounting for the direction of those connections. In Section 3.2, we exploit the directed nature of our network data, considering both *ESC in-degree* and *ESC out-degree* to determine whether there is significance to the direction of connection ("who knows you" versus "who you know"). Section 3.3 provides a variety of robustness tests. Section 3.4 evaluates employee social capital across employees of various ranks.

3.1. Employee Social Capital Measured by Total Degree

We begin our analysis by grouping firm-year observations into above-median and below-median subgroups based on *ESC total degree* within each two-digit Standard Industrial Classification (SIC) industry by year. Panel B of Table 2 summarizes the univariate analysis of the two groups in their observable firm characteristics. The comparison reveals that firms with above-median *ESC total degree* exhibit better firm performance. For example, the average *Sales Growth* for the above-median firms is 5.4%, which is almost twice the average of the below-median firms. Whereas the differences in mean for *ROA* and *Sales Growth* are statistically significant, they are not significant for *Tobin's q*. The two groups do not display significant differences in book leverage, volatility, age, or number of employees. However, firms with above-median ESC are larger in asset size and have higher R&D expenses.

Next, we examine the empirical relation between employee social capital and firm performance, conditioned on observable firm characteristics. Specifically, we estimate the following ordinary least squares (OLS) specification:

$$Y_{i,t} = \beta_0 + \beta_1 \times \ln\left(1+ESC_{i,t-1}\right) + \gamma' X_{i,t-1} + \alpha_{j,t} + \varepsilon_{i,t}, \quad (1)$$

where $Y_{i,t}$ is one of the performance measures (*Tobin's q*, *ROA*, or *Sales Growth*), $ESC_{i,t-1}$ is the one-year lagged firm-level employee social capital measured using *ESC total degree* (the average

Total degree in year *t*-1 across employees of firm *i* who are in the network), $X_{i,t-1}$ is a set of one-year lagged time-varying firm-specific control variables (R&D, book leverage, total assets, stock return volatility, firm age, and number of employees) commonly included in the literature (Anderson and Reeb, 2003), and $\alpha_{j,t}$ is a set of industry-by-year fixed effects. We include two-digit SIC industry-by-year fixed effects in all specifications because our focus is on the cross-section controlling for economy-wide shocks and industry trends. Since our ESC measures are right skewed, we take the log transformation to reduce the effects of outliers, although our results are robust to not taking the log transformation.

[Table 3 about here]

The estimation results are presented in Table 3. The coefficient estimates of employee social capital are positive across all firm performance measures. Consistent with the univariate analysis, the estimated effect is statistically significant on *ROA* and *Sales Growth*, but not on *Tobin's q*. In terms of magnitude, the coefficient estimates on ln(1+*ESC*) in columns (2)–(3) imply that, for a one standard deviation increase in *ESC* from its mean, *ROA* increases by 0.4 percentage points (=0.008×(ln(1+6.836+5.844)−ln(1+6.836))) and *Sales Growth* by 2.1 percentage points. These are considerable economic effects, given the mean *ROA* of 4.3 percentage points and the mean *Sales Growth* of 4.1 percentage points over the sample period.[20] These baseline regressions suggest a positive relation between a firm's performance and its employee social capital based on those employees' total professional connections.

3.2. Direction of Employee Social Capital: In-Degree versus Out-Degree

The results above are based on employees' *Total degree*, namely the total number of connections in the network, without regard to the direction of those connections. To shed more light on the economic value of employees' professional connections, we exploit the directed nature of our data; this allows us to differentiate the direction of connections and thus the relative

[20] Since *ROA* and *Sales Growth* have negative values in the distribution, we do not compute the percentage increase relative to the sample mean when evaluating the economic magnitudes.

importance that each of the two individuals assigns to a relationship. More specifically, by using our decomposition of *ESC total degree* into *ESC in-degree,* which measures "who knows you," and *ESC out-degree*, which measures "who you know," we consider whether the direction of connections matters.

[Table 4 about here]

Panel A of Table 4 reports the results where we re-estimate equation (1) separately for *ESC in-degree* and *ESC out-degree.* The results provide strong evidence suggesting that the direction of connections plays a significant role in firm performance. All coefficient estimates on *ESC in-degree,* reported in columns (1)–(3), are positive and statistically significant at the 1% level. The economic effects on firm performance are substantial: a firm with one standard deviation more *ESC in-degree* has a 9.4% higher *Tobin's q* relative to the sample mean. For the same increase in *ESC in-degree, ROA* increases by 0.9 percentage points and *Sales Growth* by 4.0 percentage points, about twice the magnitude of the estimates in Table 3. By contrast, the coefficient estimates on *ESC out-degree* in columns (4)–(6) are insignificant or borderline significant at the 10% level. The estimated coefficients for *ESC out-degree* and the economic significance are an order of magnitude smaller than those for *ESC in-degree,* which is also confirmed by the one-tailed tests (with p-value < 1%). For example, in comparison with the 9.4% increase in *Tobin's q* for *ESC in-degree* above, a one standard deviation increase in *ESC out-degree* from its mean is associated with only a 1.8% increase in *Tobin's q*.

These findings suggest that the economic value of employee social capital to a firm comes mainly from employees' connections with external contacts who remember or value the firm's employees. While the literature suggests that social ties are associated with goodwill, valuable resources, and information (e.g., Coleman, 1988; Granovetter, 2005),[21] the extent to which employees can leverage these benefits for their employers depends on whether the employees are

[21] Coleman (1988) compares social capital with human capital. Putnam (2000) notes that social connections lead to reciprocity, trust, and better sharing of information. Relatedly, Lin (2002) highlights two key elements in the definition of social capital: resources embedded in social relations and the ability to access these resources.

valued by their business contacts. Although out-degree business contacts are less useful to their employers, individuals can benefit personally from having a broad network of out-degree business contacts. For example, studies show that social networks are a useful resource for individuals seeking outside job opportunities (e.g., Lin et al., 1981; Granovetter, 1973, 1995; Lin and Dumin, 1986). If employees uploading contacts from other firms—as measured by *ESC out-degree*—reflects employees' desire and efforts to switch employers,[22] the resources mobilized through these connections do not necessarily accrue to their current employer. Overall, our evidence shows that employee social capital is valuable; however, compared with remembering and valuing others, being remembered and valued by others is a more robust indicator of employee social capital that can benefit firms. In other words, "who knows you" is more important than "who you know" as a source of value creation for employers.

3.3. Robustness Tests: "Who Knows You" versus "Who You Know"

We conduct robustness tests to show that potential differences between app-users and non-app-users, reciprocal connections, or omitted factors such as sales productivity and employee hard skills do not drive the results that "who knows you" matters more than "who you know."

App-users versus non-app-users. App-users, by nature, are likely to be more tech-savvy, better connected, and more socially active than non-app-users. As noted earlier, only app-users can upload others' cards; hence, *ESC in-degree* reflects connections with external contacts who are app-users, whereas *ESC out-degree* reflects connections with external contacts who may or may not be app-users. A concern is that our decomposition of employee social capital by the direction of connections may pick up differences between app-users and non-app-users. To address this concern, in Panel B of Table 4, we examine *ESC in-degree* of non-app-user employees in columns (1)–(3) and *ESC out-degree* to external contacts who are app-users in columns (4)–(6). If our results are indeed driven by the connections of app-user employees or the connections to

[22] This mechanism is consistent with the evidence in Gortmaker et al. (2020). They analyze micro-level data from LinkedIn and find that, after learning about their firms' credit deterioration, workers start initiating connections on LinkedIn more frequently; this is followed by an increased likelihood of a job change afterward.

external app-users, we should expect *ESC in-degree* of non-app-user employees to lose significance, and *ESC out-degree* to app-users to be significant. Our results indicate the opposite: *ESC in-degree* continues to be significant, and *ESC out-degree* is only marginally significant. This test suggests that our results concerning the direction of connections are not an artifact of the asymmetry between app-users and non-app-users.

Removing reciprocal connections. A reciprocal connection, in which the two parties upload each other's cards, counts toward the *in-degree* and *out-degree* for both parties. Reciprocal connections do not differentiate the direction since they represent cases where both parties "remember each other." To isolate the impact of reciprocal connections, we exclude them in constructing firm-level employee social capital and re-estimate equation (1) separately for *ESC nonreciprocal in-degree* and *ESC nonreciprocal out-degree.* Our results in Panel B of Table 4 show that the in-degree coefficients continue to be positive and statistically significant at the 1% level. The out-degree coefficients remain virtually unchanged from Panel A, and the differences between the two sets of coefficients become substantially larger. When considering nonreciprocal connections, firms benefit more from their employees being remembered by others than the other way around, corroborating our finding that the direction of connections indeed matters.

Alternative measures for firm-level ESC. We consider three alternative measures for firm-level *ESC* to address potential confounding factors. First, employees in sales departments serve as customer touchpoints and are particularly active in exchanging business cards. Thus the observed positive association between *ESC in-degree* and sales growth might merely reflect their sales efforts or business transactions. To alleviate this concern, we calculate *ESC: Excl. Sales* by excluding the connections of a firm's customer-facing employees who perform sales functions.[23] Second, to address the concern that our results might be driven by multiple employees of the same firm who are each connected to the same highly connected individuals outside the firm, we count

[23] The employees who perform sales functions are identified by job title and department information extracted from their business cards. Examples of relevant job titles related to sales include sales representative, manufacturer's representative, financial advisor, loan consultant; examples of relevant departments involving sales include customer service, sales strategy, dealership, marketing communication, retail advisory, and marketing. Our method identifies 98,404 public firm employees as sales personnel.

the connections to the same outside employee as one connection and obtain a second alternative measure, *ESC: Single Count*. Third, employees' connections might collectively contribute to firm performance; hence, rather than averaging across employees, we calculate *ESC: Sum* as the sum of *In-degree* (or *Out-degree*) across the firm's employees while controlling for the number of firm employees in the network. The results are reported in Panel A of Table IA.2 in the Internet Appendix. For all alternative measures, the coefficients on *ESC in-degree* continue to be positive and statistically significant, while those for *ESC out-degree* are not.

Subsample analysis. We investigate the possibility that highly connected employees might also be highly skilled employees, and it is the employees' skill rather than their connections that drives superior firm performance. Two aspects of employees' skill set are relevant. The first aspect, the social aspect of the skill set—soft skills—is consistent with our argument that employee social capital contributes to performance. Glaeser et al. (2002) note that employees' social capital includes both their intrinsic abilities (e.g., being extroverted or charismatic) and relationships (e.g., a large Rolodex). Hence, we expect that soft skills and charisma help employees impress their business contacts, expand the network of contacts that remember them, and, in turn, contribute to their firms' performance. The second aspect pertains to the non-social element of the skill set, such as technical skills. To alleviate the concern that our results are an artifact of employees with high technical skills driving firm performance, we use a similar strategy as Cohen et al. (2010) and conduct subsample analysis. We first exclude firms that were ranked at least once in the "top 20 companies most wanted by university students" in the period 2015–2018 according to the Job Korea Survey, because these firms tend to attract some of the most talented university graduates. Then we drop financial firms (SIC codes 61, 62, 65, 67), which are also popular among skilled employees. We also exclude large firms that are in the top three percentile of the asset size distribution, which tend to be competitive in the competition for talent. The results, in Panel B of Table IA.2, show that *ESC in-degree* remains positively associated with firm performance, whereas the coefficient estimates of *ESC out-degree* largely remain insignificant, indicating that our results are not an artifact of a selected sample of employees with good "hard skills."

Propensity score matching. We report a propensity score matching analysis in Panel C of Table IA.2, aiming to control for observable firm characteristics. We match the above-median ESC firms with their below-median counterparts on year, industry (two-digit SIC), and the controls in our baseline regression, using the nearest-neighbor-matching algorithm with replacement. Results confirm that firms with above-median *ESC in-degree* reliably see significantly better performance than their matched firms with below-median *ESC in-degree*. However, we do not find such differences among firms with different *ESC out-degree*.

Cross-sectional analysis. We conclude this subsection by investigating employer performance sensitivity to employee social capital across firms. First, if employee social capital indeed boosts firm performance by providing resources and information through interpersonal ties, firms that rely more on labor in the production process will benefit more. To test this prediction, we follow Dewenter and Malatesta (2001), measuring labor intensity as the number of employees divided by inflation-adjusted total assets.[24] As reported in Table IA.3 in the Internet Appendix, the coefficient estimates of *ESC* on *Tobin's q* and *ROA* are significantly larger for firms with higher labor intensity. Second, synergies will emerge if employees share the benefits obtained from their external contacts with coworkers. Hence, firms with more efficient internal communication and information sharing will gain more from employee connections. Eisfeldt and Papanikolaou (2013) note that resources allocated to selling, general, and administrative (SG&A) expenses, which they refer to as part of a firm's organization capital, yield improvements in internal communication systems. Consistent with this idea, the estimated effects of employee social capital on *Tobin's q* and *ROA* is larger for firms with greater organization capital. Third, we find that the estimated effects of *ESC* on *Tobin's q* and *Sales Growth* are greater for firms located outside of industry clusters. Geographic clusters spur information spillover, dissemination, and learning (Jacobs, 1969). Our evidence suggests that the benefits of employees' personal connections are especially important for geographically peripheral firms that lack alternative channels to acquire information

[24] Similar findings obtain for labor intensity proxied by the number of employees divided by inflation-adjusted sales.

and build trust with external stakeholders. These cross-sectional results substantiate our arguments for employee social capital as a productive factor embodied in a firm's workforce.

3.4. Employee Social Capital by Job Level

While executive management makes the major strategic decisions, non-executive employees constitute most of a firm's workforce and closely interact with business partners, clients, media, regulators, and creditors, collectively forming the bulk of their employer's social capital. Understanding the social capital embodied in these employees is potentially important since decision making and information processing within a firm is often decentralized by a hierarchical structure (Radner, 1992). A key advantage of our data is the broad coverage of employees across various job ranks, which allows us to study the social capital embodied in employees beyond the executive team, an aspect scarcely examined in prior literature.

[Table 5 about here]

Table 5 presents results on employee social capital across employees of various ranks. We first identify a firm's employees in the network who are classified as executive management. Results show that the ESC measures are positively associated with all firm performance measures for both executives and non-executives. While our finding echoes existing studies on the value of executive networks, executives are not the only group that has beneficial connections for their firms. Non-executive employees also contribute substantially to their employers' performance. In fact, for *ROA* and *Sales Growth*, the coefficient estimates for the ESC of non-executives are statistically larger than those for the executives. To further understand whose connections are most valuable, we divide non-executive employees into non-executive managers and rank-and-file employees. Based on our estimates, the connections of non-executive managers have the greatest economic significance for *ROA* and *Sales Growth*. For example, a one standard deviation increase in *ESC* of executives, non-executive managers, and rank-and-file employees is associated with an increase in *ROA* of 0.7, 1.3, and 0.8 percentage points, respectively. The result is consistent with the idea that non-executive managers—vice presidents, general managers, department heads, section heads—are on the front line interacting with external stakeholders and responsible for critical day-to-day operations and decision making. Our results also highlight the contribution of rank-and-file employees—who perform the daily tasks without a managerial title—to a firm's social capital, such as gathering information, enhancing trust, and fostering goodwill toward the company.

4. Establishing a Causal Relation between Employee Social Capital and Firm Performance

To establish a causal interpretation of our regression results, we need to address the endogeneity of a firm's employee social capital. An advantage of our social capital measure is that it is based on individual employees' endowed assets embodied in their professional connections. In comparison with physical capital, intellectual capital, and other firm-level social capital measures such as corporate social responsibility activities (Lins et al., 2017), employee social capital is arguably less likely to be endogenous to a firm's policies in response to its growth prospects. Still, a firm's employee social capital may proxy for other variables that are positively linked to firm performance, such as corporate culture or employee satisfaction. Another relevant concern is reverse causality: employees of firms with better performance might be more sought after as business contacts. Using lagged employee social capital measures in the regressions partially alleviates this concern. Nonetheless, in this section we attempt to establish a causal link between employee social capital and firm performance using a quasi-natural experiment.

4.1. The 2016 Anti-Graft Act

We exploit the 2016 enactment of the Improper Solicitation and Graft Act (the Act), also known as the Anti-Graft Act, which imparted a negative shock to professional networks. The Act took effect on September 28, 2016; its purpose was to curb corruption by prohibiting improper solicitations and gifting of money or goods and services. The Act makes it illegal for media professionals (such as journalists) and public sector employees (such as civil servants, lawmakers, and teachers), and their spouses to accept gifts of more than 50,000 Korean won (about 45 USD) or 100,000 won at events such as weddings and funerals; it also limits meal expenditures to 30,000 won per person.[25]

Despite intended to prevent corruption, these gift and meal limits also resulted in fewer social events and meetings with contacts employed in the media and the public sector, thereby restricting firms' ability to leverage their employee social capital. As a culturally ingrained business practice in Korea, corporate employees would regularly treat clients, business partners, and public employees to dinners, drinks, and other entertainments as part of networking (Choi and Storr, 2019). The implementation of the Act, according to an article in *Korea Herald,* has caused significant precautions among businesses in their interactions with the media and the public sector due to the abstract and vague provisions and the lack of precedents. "Companies say they are concerned about how to maintain business relationships they have built with government officials and the media over the years. The law's definition of those related to work is ambiguous…as it excludes socializing as part of business formality." This concern by firms is consistent with the observations that "Korean reporters were intentionally left out of the invitation list in a launch event for Apple's iPhone X" (*Korea Herald*, September 24, 2017), and that "reservation rates of restaurants in Seoul's financial and legal districts and those near government complexes in Sejong and Daejeon, have rapidly dropped" (*Korea Herald*, September 27, 2016).

To provide further evidence on the adverse impact of the Act on social relations with the media and the public sector using our network data, we examine the formation of connections with the affected industries using the following model:

$$\frac{ESC_{i,t}^{Act}}{ESC_{i,t}} = \beta_0 + \beta_1 \times Post_t + \gamma' X_{i,t-1} + \alpha_j + \varepsilon_{i,t}. \quad (2)$$

The outcome variable is the fraction of a firm's employee social capital (*ESC*) that is derived from connections with employees in the industries affected by the Act (ESC^{Act}). We use *ESC in-degree* to measure *ESC* and calculate ESC^{Act} using only the employee connections to industries subject

[25] The upper limits were adjusted in January 2018 to 100,000 won for non-cash gifts and to 50,000 won for cash gifts. We list all industries subject to the Act, together with their industry identifiers in Appendix A.

to the Act (according to the industry codes listed in Appendix A).[26] *Post* is a dummy variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. X is the same set of lagged control variables as in Table 3; α_j is a full set of industry fixed effects. We no longer include year fixed effects due to the dummy variable *Post*. Since the Act became effective in the latter half of 2016, we report results both by excluding and including observations in 2016 in Table IA.4. For both specifications, we obtain a significant and negative coefficient for the dummy variable *Post*. According to our baseline estimation where we exclude observations in 2016, the fraction of employees' connections with individuals in the affected industries dropped by 7.7% after the enactment, relative to its sample mean. This transition is also visualized in Figure IA.3. Comparing the networks before the Act in 2015 and after the Act in 2018, we find a sharp reduction in the fraction of a firm's employee connections to the media and the public sector.

The enactment of the Act serves as a useful identification tool for two reasons. First, enforcement was aggressive, imposing penalties such as imprisonment.[27] Second, it was uncertain whether the Act would be ruled constitutional. Right after bipartisan approval of the Act in 2015, the Korean Bar Association and the Korean Journalists Association filed a court petition questioning the law's constitutionality on the grounds that it threatened freedom of speech. The Constitutional Court upheld the law on July 28, 2016, rejecting the petition. This series of unforeseen events lends credibility to our identifying assumption of orthogonality between the enactment and unobservable covariates that affect corporate performance, after controlling for observable firm characteristics and time-varying industry-specific economic conditions.

[26] Our results in Section 3 show that the economic value of employee social capital to a firm comes mainly from its employees being remembered (uploaded) by others rather than the other way around. Hence, we focus on a firm's *ESC in-degree* for this and the remaining tests.

[27] The Act imposes a punishment of imprisonment for up to three years, or a fine of up to 30 million Korean won (about 27,000 USD) on persons convicted of accepting money or goods (including meals) valued at more than one million won from one person in one installment, regardless of whether such compensation was in exchange for favors or related to the recipient's work. If the money or goods are worth less than one million won, a fine of up to five times the gift's value is imposed.

4.2. Evidence for Causality

We assess the causal effect of employee social capital on firm performance using a difference-in-differences framework surrounding the enactment of the Anti-Graft Act. Since the employee social capital of some firms is more exposed to the Act than others, we can estimate differences in performance between firms with differential exposure.[28] The restrictions of the Act impair the ability of employees to access the resources and information embedded in their existing connections to the media and the public sector; hence, we hypothesize that those firms with greater exposure experienced a bigger reduction in the value of their employee social capital.

We define the treatment intensity as the relative exposure of a firm's ESC to the Act—that is, the fraction of a firm's preexisting employee social capital in year 2015 derived from its employees' connections with industries subject to the Act. The regression model is as follows:

$$Y_{i,t} = \beta_0 + \beta_1 \times Act\ Exposure_i + \beta_2 \times Act\ Exposure_i \times Post_t + \gamma' X_{i,t\text{-}1} + \alpha_{j,t} + \varepsilon_{i,t}. \qquad (3)$$

Treatment intensity is $Act\ Exposure_i = ESC^{Act}_{i,2015}/ESC_{i,2015}$, where $ESC_{i,2015}$ is *ESC in-degree* in 2015, and $ESC^{Act}_{i,2015}$ is *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Act. We measure the treatment intensity in 2015, before the enactment, to isolate it from the dynamic response of a firm's employee social capital to the Act. *Post* is a dummy variable for the years during and after the enactment (2016–2018). *X* is the same set of lagged control variables as in Table 3; $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. The Act generates a negative shock to employees' connections with a specific set of industries, namely the media and the public sector. These connections have a significant and positive impact on firm performance, with the effect concentrated in *Tobin's q*, as reported in Table IA.5 in the Internet Appendix. Thus we focus on *Tobin's q* as our measure of firm performance in testing for causality. Our focus is on β_2, the coefficient of the interaction term, *Act Exposure*×*Post*. If employee social capital indeed has a causal effect on firm performance, we expect firms with ESC more exposed to the Act to

[28] We are not interested in the direct effect of the Act on the affected industries—that is, the change in performance of firms in the media and the public sector—but rather the impact of the reduction in the value of existing employee connections to the two sectors.

derive less value from their employee social capital after the Act than firms that are less exposed. In other words, we expect β_2 to be negative.

Panel A of Table 6 summarizes the results of estimating equation (3). The regression in column (1) excludes observations during the enactment year because the Act only became effective in the latter half of 2016. Consistent with our prediction, the estimate of β_2 is negative and statistically significant at the 1% level, and the estimate of β_1 is positive and significant at the 1% level. Based on these estimates, employee connections to the media and the public sector contribute positively to a firm's *Tobin's q* before the Act; however, the positive impact declines by about 75% (=4.930/6.578) after the Act. For instance, a one standard deviation increase in *Act Exposure* (0.038) leads to an increase in *Tobin's q* by 17.5% (=0.038×6.578/1.432) relative to the sample mean before the Act, but only by 4.4% after. We further include observations in 2016 in column (2) and find little change in the magnitude and significance of our β_2 estimate.

[Table 6 about here]

To test for the presence of pre-trends, in columns (3)–(4) we estimate an augmented version of equation (3) where we interact *Act Exposure* with an indicator variable for each year *t*.[29] Consistent with *Act Exposure* capturing an adverse shock to employee social capital by the Act, the decline in firm performance does not occur prior to the enactment. Starting from the enactment year of 2016, the estimate becomes negative and remains negative and significant at the 1% level; also see Figure IA.4 in the Internet Appendix for an illustration. Our results suggest no preexisting trend in firm performance before the enactment, reinforcing the idea that the Act negatively affects firm performance by reducing employee social capital.

To address the concern that an omitted variable coinciding with the Act might drive our results, we perform a placebo test. We randomly assign a *Pseudo Exposure* to each firm by maintaining the true distribution of *Act Exposure* and re-estimate column (1) in Panel A of Table

[29] In column (3), we set 2015 as the baseline year and omit the 2015 interaction term (the outcome variable in year 2014 is dropped in our baseline analysis because we lag all control variables by one year). To highlight the insignificance of the pre-treatment interaction terms, in column (4) we extend our pre-treatment sample to include year 2014 and set 2014 as the baseline year, omitting the 2014 interaction term.

6. We repeat this procedure a thousand times and obtain the empirical distribution of the coefficient estimate on the interaction term. The true coefficient estimate (−4.930) falls well below the 1% threshold of this distribution, as reported in Table IA.6. This placebo test gives confidence that the negative estimate of β_2 is not driven by omitted shocks other than the enactment of the Act.

The exposure of a firm's employee social capital to the Act is not randomly assigned. Firms with ESC more exposed to the Act tend to be larger in asset size and number of employees. It is likely they also had more frequent business interactions with the media and the public sector by 2015. We perform three robustness checks to address this issue. First, we use propensity score matching to generate a group of control firms similar to the treated firms and conduct the tests within this matched sample. We use a probit model to estimate the probability of being a treated firm (those with above-median exposure in 2015). Then we match each treated firm to a control firm, using nearest neighbor matching with a maximum difference of 0.01 with replacement. Panel B of Table 6 shows that the treated and control firms in the matched sample display indistinguishable observable differences. Columns (1)–(4) estimate the same specifications as in Panel A for the matched sample. The estimates are consistent with those in Panel A, confirming that firms with ESC more exposed to the Act have larger declines in performance after the enactment. As a second robustness test addressing covariate balance, we use the full sample and interact firm-level control variables with the *Post* dummy to control for any observable differences in characteristics related to the treatment that could lead to differences in performance around the enactment. We find the results continue to hold, as reported in Table IA.7.

To alleviate concerns that adverse sectoral shocks to the industries directly affected by the Act could spill over to treated firms through economic linkages rather than employee connections, we conduct subsample analysis in Panel C of Table 6. Firms in the media and the public sector may be highly connected among themselves; therefore, we drop firms that belong to the industries directly affected by the Act (26 unique firms) in column (1) and also drop firms that more broadly belong to the media and the publishing activities sectors (KSIC 58, 59) in column (2). In column (3), we further drop firms in the supplier and customer industries of the media and the public sector identified using Make-and-Use tables following the method in Frésard et al. (2020).[30] In column (4), we focus on the subsample with positive exposure of employee social capital to the Act. Across all these subsamples, the coefficient estimates on the interaction term remain negative and significant at the 1% level. These tests help rule out alternative explanations for our results, such as omitted differences between the treated and control firms and potential economic spillovers.

Finally, we investigate whether a firm's bribery activities could be a confounding factor, i.e., if firms with more employee connections to the media and the public sector also engaged more actively in bribery for resources, the negative effect on their performance might be due to the Act's restriction on bribery activities rather than a reduction in the value of their employee social capital. The limitations imposed on gifts and meal expenditures by the Anti-Graft Act substantially cut related business expenses and were reportedly successful in curbing bribery. For example, major local media such as *Korea Herald* and *Korea Bizwire* reported significant reductions in firms' entertainment expenses. Although this income statement item includes regular expenditures to entertain suppliers and clients, it also captures the excess expenses that are viewed as graft and bribery (Cai et al., 2011; Kang et al., 2020).[31] Accordingly, we control for *Entertainment Expense*, measured as a firm's entertainment expenses in 2015 scaled by total assets, and by SG&A expenses. Results in Panel D of Table 6 suggest that firms' bribery activities are not driving our results. In columns (1)–(2) we add *Entertainment Expense* and its interaction with the *Post* dummy

[30] Examples of supplier industries include manufacturers of newsprint, printing and reproduction of recorded media, infrastructure suppliers, and restaurants; examples of customer industries include the wholesale and retail sectors and sellers of motor vehicles and parts (with significant advertising expenses). To identify supplier and customer industries, we use the 2014 Make-and-Use tables to construct a 328 industry-by-328 industry flow matrix in which each cell indicates the dollar flows from an upstream industry to a downstream industry. Following Fan and Goyal (2006), we define industry j as a customer industry of industry i if the fraction of industry i's total production used by industry j exceeds a threshold (3%), and define industry k as a supplier industry of industry i if the fraction of industry i's total input supplied by industry k exceeds a threshold (3%).

[31] Because of its illicit nature, bribery is not directly observable. Cai et al. (2011) show that entertainment expenses of Chinese firms include "grease money" to obtain better government services. They argue that managers commonly use this accounting category to reimburse expenditures for bribes. At times, phony or inflated receipts are submitted for reimbursement of illegitimate expenses. Similarly, Kang et al. (2020) find that a significant portion of Korean firms' entertainment expenses are bribes paid to public officials. According to the Corporate Tax Act and its Enforcement Decree, entertainment expenses do not include expenses for fringe benefits to a firm's own employees and thus do not reflect corruption by internal employees.

as controls in estimating equation (3) and find our results continue to hold. We also employ a triple-difference model by interacting *Entertainment Expense* with *Act Exposure*×*Post* to examine whether our estimates differ across firms with different entertainment expenses. If the Act negatively affected the performance of more exposed firms by reducing bribery, the estimated effect of *Act Exposure*×*Post* should be more pronounced for firms with high entertainment expenses. Columns (3)–(4) show that the coefficient estimate for the triple interaction term is insignificant, whereas the coefficient estimate for *Act Exposure*×*Post* remains significant.

4.3. Stock Market Reaction to the Court Ruling on the Act

We conduct an event study based on the court ruling that the Anti-Graft Act was constitutional. After bipartisan approval, the Act faced a lengthy petition challenging its scope and constitutionality. The Korean Bar Association and the Korean Journalists Association argued that applying the law to journalists and private school teachers (and their spouses) infringed on freedom of the press and on the rights of private schools. However, the petition was eventually rejected, when seven out of the nine Constitutional Court justices ruled that the Act was constitutional at 2pm on July 28, 2016. We examine stock price reactions around the court ruling for firms differentially exposed to the Act. A negative market reaction for firms with ESC more exposed to the Act will reinforce the causal effect of employee social capital on *Tobin's q*.

[Table 7 about here]

We divide firms into above-median and below-median subgroups based on *Act Exposure,* which is the fraction of employee social capital in 2015 derived from employees' connections with industries subject to the Act. We calculate average cumulative abnormal returns for each subgroup, both CAPM-adjusted and size-adjusted, for various windows around the event date.[32] As reported in Table 7, we find evidence of a negative market reaction to firms with ESC more exposed to the Act. For example, the average cumulative abnormal return over the [−3, 3] event window is

[32] As in La Porta et al. (1997) and Ahern (2009), the size-adjusted abnormal returns are adjusted by the equally weighted returns of a portfolio of ten control stocks matched by size. Ahern (2009) shows that characteristic-based benchmark models tend to reduce bias when firm characteristics are correlated with exposure to the events.

−0.61% (significant at the 5% level) for firms with ESC more exposed to the Act and 0.41% for firms with ESC that is less exposed. The difference between the two groups is statistically significant with a p-value of 0.019. The observation that the return differentials are not significant for the [−1, 1] event window and are increasing with the length of the event windows suggests that firms' social capital exposed to the Act might not be immediately known to the market as employee connections are latent. We also examine the cross-sectional pairwise correlation between *Act Exposure* and the cumulative abnormal returns and find that greater exposure to the Act is significantly associated with more negative stock price reactions. Taken together, the event study results provide confidence that employee social capital indeed adds to firm value.

4.4. Economic Benefit of Employee Connections with the Media and the Public Sector

We proceed to identify the underlying economic benefits that a firm can extract from its employee connections to the industries affected by the Act—the media and the public sector.

We start by confirming that the results in Panel A of Table 6 hold when we examine connections to the media and the public sector separately. The industries affected by the Act are grouped into the media (KSIC 5812, 59114, 5912, 5913, 60, 63910) and the public sector (all other industries listed in Appendix A). We define $Act\ Exposure^{Media}$ ($=ESC_{2015}^{Media}/ESC_{2015}$) as the fraction of *ESC in-degree* in 2015 that is due to connections to employees in the media, and $Act\ Exposure^{Public}$ similarly. The sum of the two treatment intensities equals *Act Exposure* used in Table 6. As shown in Panel A of Table 8, when we re-estimate equation (3) by separately setting the treatment intensity as $Act\ Exposure^{Media}$ and $Act\ Exposure^{Public}$, our early results hold. Before the Act, employee connections to the media have a more substantial positive impact on the firm's *Tobin's q,* relative to connections to the public sector. After the Act went into effect, connections to both sectors display significant reductions in their economic value by as much as 70%.

[Table 8 about here]

We next consider some specific benefits that employers can derive from their employee social capital based on connections with the media and the public sector. First with respect to our analysis of media connection, a large body of literature suggests that media coverage influences the stock markets and firm valuation (Tetlock, 2007; Tetlock et al., 2008; Engelberg and Parsons, 2011; Dougal et al., 2012). In particular, Gurun and Butler (2012) document that local media tend to display a "positive slant" toward local firms by using fewer negative words in news articles and that the positive slant strongly relates to firms' equity value. Relatedly, Ahern and Sosyura (2014) find that firms actively manage media coverage to influence their stock prices.

Like the positive slant when media covers local companies, media connections by a firm's employees may foster goodwill and closer relationships with journalists, leading to a positive slant in news coverage and a positive effect on firm valuation. For instance, reporters who are well connected to a firm's employees may have developed trust in those employees and therefore be more likely to report positive news about the firm. Media connections might also facilitate active media management as in Ahern and Sosyura (2014) by allowing firms to influence the timing and content of media coverage. We thus expect that all else equal, employee connections with the media foster news coverage of the firm, especially news stories with a positive tone.

To test this prediction, we examine the effect of a firm's employee social capital—derived from connections with the media—on media coverage of the firm before and after the Act; the results are reported in columns (1)–(2) in Panel B of Table 8.[33] The dependent variable in column (1) is the log of the weighted count of news articles from RavenPack News Analytics covering a firm in a given year. To measure positive slant by media, we calculate the fraction of news articles covering a firm each year that are associated with positive sentiment (according to the BMQ sentiment series of RavenPack) as the dependent variable in column (2).

In keeping with the notion that media connections promote news coverage, we obtain a significant and positive coefficient on *Act Exposure*^{Media}. The estimated economic effect is sizable. Before the Act, a one standard deviation increase in *Act Exposure*^{Media} increases news articles by 13% (=0.029×4.495) and the positive media coverage ratio by 49.1%. In addition, consistent with

[33] We report results excluding observations in the enactment year of 2016 because the outcome variables reflect the cumulative outcomes throughout the year. Results are robust if we also include the year 2016.

our finding that the Act undermines the benefit of connections, the estimated coefficient for *Act Exposure*^{Media}×*Post* is negative in both columns. Notably, the estimated effect on the positive slant is almost negligible after the Act. Altogether, these findings suggest that connections to the media lead to more frequent media coverage and a greater fraction of media coverage with positive sentiment, enhancing firm valuation. After the adoption of the Act, the positive impact on media coverage declines substantially, consistent with the diminished contribution to *Tobin's q* in Panel A as well as the event study results.

We then turn to investigating the benefits of employee social capital due to connections with the public sector. A nontrivial responsibility of public sector employees is public procurement, which accounts for 10–20% of GDP in developed countries (OECD, 2015). Using data on procurement contracts from the Korea online e-Procurement Service, Schoenherr (2019) documents that CEOs' political connections affect the allocation of public resources: public officers who control the distribution of government contracts allocate significantly more procurement contracts to firms with connected CEOs. Similarly, we expect that firms with employees (including non-executive managers) who are better connected with the public sector may obtain more government contracts, thereby displaying superior performance.

To assess this prediction, we examine the effect of a firm's employee connections with the public sector on public procurement contracting outcomes.[34] The evidence is consistent with our prediction. As shown in columns (3)–(5) in Panel B of Table 8, firms highly connected to public sector employees obtain more public procurement contracts, both in the number of newly signed contracts and the value in Korean won. The estimated effect is larger before the Act and is reduced by about half after the Act. For example, in column (3), a one standard deviation increase in *Act Exposure*^{Public} leads to a 6.8% increase in contract volume before the Act and only 3.4% after.

Overall, the evidence in Tables 6–8 supports the notion that the employee social capital derived from connections with the media and the public sector positively impacts firm performance

[34] We measure the procurement contracting outcomes using the same data source as Schoenherr (2019). The Korea online e-Procurement Service data are managed by the Public Procurement Service, Ministry of Economy and Finance; see http://data.g2b.go.kr:8275/pt/pubdata/moveGnrlzBidPblancNdCntrctPop.do#.

by promoting media coverage of the firm and enhancing its ability to obtain public procurement contracts. A negative shock to employee social capital dampens these economic benefits, resulting in a decline in the effect of employee social capital and firm value.

5. Further Evidence on the Mechanism

Our regression results in Tables 3–5 show a robust positive relation between employee social capital and firm performance. Using a negative shock to professional networks in the context of the Anti-Graft Act, our difference-in-differences analysis provides evidence of causality in Tables 6–8. Based on the social capital literature (e.g., Putnam (2000)), connections among individuals lead to reciprocity, trust, and information sharing. While all of these mechanisms could be at play in contributing to firm performance, in this section, we provide suggestive evidence for one of the mechanisms, namely, information sharing. To do so, we examine how employees' connections to the investment banking industry help to reduce the at-issue bond spreads of their employers by facilitating information sharing between the issuer and the bond underwriters.

The availability of detailed bond issuance terms and information about employee connections to the investment banking industry provide a unique opportunity to analyze the information sharing channel.[35] The public bond market is the primary source of financing for Korean listed firms in our sample period.[36] Financial intermediation theories suggest that investment banks play an integral role in acquiring issuer-specific information such as the line of

[35] A large literature on relationship banking has shown that firms have improved access to bank loans and face lower financing costs when they are better connected with bankers (Bharath et al., 2011; Engelberg et al., 2012; Haselmann et al., 2018; Karolyi, 2018). We focus on the connections with the investment banking industry and the corporate bond market for several reasons. First, public bonds, not bank loans, constitute the lion's share of total debt for large Korean companies. According to the Bank of Korea and Korea Financial Investment Association (KOFIA), the ratio of total outstanding bonds to bank loans steadily increased from 3.5 in 2014 to 4.8 in 2018. Second, detailed data on bond issuance terms allow us to assess the effect on the cost of public bond issuance, whereas comparable data on bank loan contracting terms are scant. Third, bond investors are more sensitive than banks when pricing borrower information into interest spreads (Bharath et al., 2008), making the bond market a more relevant setting for analyzing the information channel.

[36] Since the 1997 Asian financial crisis, authorities in Korea have attempted to increase corporate bond issuance, particularly by large corporations and blue-chip companies (Choi, 2017). Based on the Financial Supervisory Service statistics, the amount of corporate bond issuance accounts for approximately 94% of total securities issued by listed firms between 2014 and 2018.

business, employee relations, and any inside information that may affect security prices (Leland and Pyle, 1977; Campbell and Kracaw, 1980). Hence, all else equal, effective information sharing between the underwriter and the issuer should have a material impact on bond spreads at issuance. More specifically, if employee connections with the investment banking industry bridge the information gap between the issuer and bond investors, we expect firms with more investment banking connections to incur lower bond spreads when issuing public bonds.

To test this prediction, we calculate $ESC^{I\text{-}bank}$, defined as the employee social capital accumulated by connections with the investment banking industry (KSIC 6612), which consists of investment banks and security brokerage companies.[37] We start by examining the relation between connections with employees in the investment banking industry and firm performance in Panel A of Table 9. Consistent with the idea that connections with the investment banking industry make bond issuance more feasible and less costly, we find that $ESC^{I\text{-}bank}$ is positively associated with firm performance across all three performance measures and are statistically significant at the 1% level. A one standard deviation increase in $ESC^{I\text{-}bank}$ from its mean is associated with a 17% increase in *Tobin's q* relative to the sample mean, and an increase of 0.9 percentage points in *ROA* and 2.1 percentage points in *Sales Growth*.[38]

[Table 9 about here]

We proceed to explore the relation between $ESC^{I\text{-}bank}$ and at-issue bond spreads using a comprehensive sample of 480 bond issues in our sample period. The outcome variable, *At-Issue Bond Spread*, is defined as the difference between the bond's yield at issuance and the mark-to-market benchmark yield of a corporate bond portfolio with the same maturity and credit rating.[39]

[37] The Financial Investment Services and Capital Market Act in Korea defines the business scope of the investment banking industry as investment brokerage, investment banking, investment advisory service, and investment trading. Firms in the investment banking industry can neither take deposits nor make loans. These restrictions are analogous to the firewall between commercial banking and investment services established by the Glass-Steagall Act in the US.

[38] We also find a significant and positive association between $ESC^{I\text{-}bank}$ and the likelihood of bond issuance, the amounts of bond issuance, total debt, and firm leverage.

[39] The firm-level and issuance-level controls largely follow Bharath et al. (2011) and Hasan et al. (2017); we only include two-digit SIC industry fixed effects because of the relatively small sample size and the fact that the mark-to-market benchmark yields already control for potential economy-wide shocks.

To validate the mechanism of information sharing, we also separately examine $ESC^{I\text{-}bank}$ across employees of various ranks.

Our regression results in Panel B of Table 9 show a significant and negative relation between $ESC^{I\text{-}bank}$ and at-issue bond spreads. In column (1), we observe a negative coefficient of $ESC^{I\text{-}bank}$, which is statistically significant at the 5% level. A one standard deviation increase in $ESC^{I\text{-}bank}$ from its mean is associated with a reduction of 7.29 basis points in at-issue bond spreads, relative to the sample average benchmark corporate bond yield of 2.70%. The estimate is comparable to that in Hasan et al. (2017), who find that firms headquartered in high-social-capital counties obtain at-issue bond spreads that are, on average, 7.98 basis points lower.

In the rest of the panel, we separately account for $ESC^{I\text{-}bank}$ by employee job level into executives in column (2), non-executive managers in column (3), and rank-and-file employees in column (4). Notably, comparing the coefficient estimates of $ESC^{I\text{-}bank}$ across job levels, we find that the reduction in the at-issue bond spreads is mainly driven by the in-degree connections with the investment banking industry of the issuer's rank-and-file employees. A one standard deviation increase in $ESC^{I\text{-}bank}$ of rank-and-file employees from its mean is associated with a reduction of 7.67 basis points in the at-issue bond spreads, whereas the same increase in $ESC^{I\text{-}bank}$ of executives and of non-executive managers is associated with a reduction of 3.70 and 5.41 basis points, respectively. These results are noteworthy because the rank and file are not likely to be the decision makers about corporate bond issuance or to be relevant for investment bankers' development of trust or expectations of reciprocity. Hence, a more likely motivation for the investment bankers to remember (upload the cards of) the issuer's rank-and-file employees is to acquire information in the due diligence investigation. In this sense, personal connections with the investment banking industry by a firm's assembly line workers, salespeople, and analysts could help channel useful information about their employers, enhance transparency, and lead to lower financing costs.

To further support the information-sharing channel, we focus on a subsample of innovative firms with above-median R&D expenses. Aboody and Lev (2000) show that R&D activities contribute substantially to information asymmetry between managers and investors. Information sharing would therefore be particularly relevant for underwriters in evaluating the credit risk of firms that are more involved in R&D. If information sharing is indeed a pertinent mechanism through which employee connections with the investment banking industry contribute to firm performance, the effect should be more pronounced for innovative firms. The results are reported in Panel C of Table 9. Consistent with our prediction, the coefficient estimates of $ESC^{I\text{-}bank}$ for the subsample of more innovative firms on *Tobin's q*, *ROA*, *Sales Growth*, and *At-Issue Bond Spread* are 1.859, 0.057, 0.182, and −0.891, all significant at the 1% level. These estimates stand in contrast to the untabulated coefficients for the subsamples of less innovative firms of 0.954, 0.035, 0.032, and −0.323. Altogether, our results on connections with the investment banking industry suggest that enhancing information sharing with economically related entities is an essential mechanism through which employee social capital boosts firm performance.

6. Conclusion

This paper provides novel empirical evidence that a firm's social capital derived from its employees' professional connections is a valuable production factor contributing to firm performance. We use a comprehensive dataset from a professional networking app with broad coverage of individual-level connections to measure firm-level employee social capital. Our analysis reveals that employee social capital is robustly and positively associated with firm performance. Our unique network data record the direction of connections, allowing us to determine whether one of the two involved parties values the other more and to investigate whether the direction of connection matters. Our results show that the positive effect on firm performance is primarily the result of external stakeholders remembering and valuing a firm's employees.

To establish a causal interpretation of our results, we exploit the enactment of an Anti-Graft Act in 2016 which was a negative shock to the professional networks. Our evidence suggests that firms with employee connections more exposed to the Act derive less value from employee social capital after the Act than firms that are less exposed. The results support our prediction that employee social capital contributes to improving firm performance, indicating a causal role of employee social capital in creating firm competitiveness and value.

This paper makes several contributions to the literature. First, our study introduces the concept of employee social capital and establishes its contribution to firm performance. We quantify employee social capital at the firm level by identifying interpersonal networks that cover employees at all job levels. Second, our employee social capital measures are directional. Our finding that being remembered by others is more productive than remembering others echoes a popular saying about professional networking: “It is not who you know—it is who knows you.” Third, our analysis of the connections with economically related industries provides novel insight into the economic channels underlying the concomitant benefit of employee connections. One implication of our research is that social ties can be leveraged in business settings. Personal relationships and business contacts endow employees (and their firms) with resources, goodwill, and access to information, constituting an essential form of social capital that is convertible into firm value and performance.

Appendix A: Variable Definitions

Variable Name	Description
<u>*Measures of employee social capital (ESC)*</u>	
ESC in-degree	The average *In-degree*—the number of employees of other firms who have uploaded the employee as a business contact ("who knows you")—across employees of firm *i* who are in the network in year *t*
ESC out-degree	The average *Out-degree*—the number of business contacts of other firms uploaded by the corresponding employee ("who you know")—across app-user employees of firm *i* in year *t*
ESC total degree	The average *Total degree*—the sum of *In-degree* and *Out-degree*—across employees of firm *i* who are in the network in year *t*
ESC in-degree of non-app-user employees	The average *In-degree*—the number of employees of other firms who have uploaded the employee as a business contact ("who knows you")—across non-app-user employees of firm *i* who are in the network in year *t*
ESC out-degree to app-users	The average *Out-degree* to app-users—the number of app-user business contacts of other firms uploaded by the corresponding employee ("who you know")—across app-user employees of firm *i* in year *t*
ESC nonreciprocal in-degree	The average *Nonreciprocal in-degree*—the number of employees of other firms who have uploaded the employee as a business contact, but not reciprocal—across employees of firm *i* who are in the network in year *t*
ESC nonreciprocal out-degree	The average *Nonreciprocal out-degree*—the number of business contacts of other firms uploaded by the corresponding employee, but not reciprocal—across app-user employees of firm *i* in year *t*
ESC: Excl. Sales	*ESC* in which we exclude connections of a firm's customer-facing employees who perform sales functions
ESC: Single Count	*ESC* in which we count multiple connections between the firm's employees and the same outside employee as one connection
ESC: Sum	The sum of *In-degree* (or *Out-degree)* aggregated across employees of firm *i* who are in the network in year *t*
ESC^{Act}	*ESC in-degree* using only the connections to employees in the industries subject to the Anti-Graft Act according to the industry codes in Appendix A
ESC^{Media} (ESC^{Public})	*ESC in-degree* using only the connections to employees in the media (public) sector according to the industry codes in Appendix A
$ESC^{I\text{-}bank}$	*ESC in-degree* using only the connections to employees in the investment banking industry (KSIC 6612 = Securities and commodity contracts brokerage), which consists of investment banks and security brokerage companies
<u>*Other variables*</u>	
Tobin's q	Market value of assets divided by book value of assets, in which market value of assets is the sum of market value of equity (common shares outstanding times fiscal-year closing price) and book value of assets minus book value of equity

ROA	Return on assets, calculated as EBITDA divided by the lagged total assets
Sales Growth	Log growth rate of sales
R&D	The ratio of R&D expenses to sales; the ratio is set equal to zero when R&D expenses are missing
Book Leverage	Total debt (sum of total long-term interest-bearing debt and current long-term debt) divided by total assets
ln(1+*Assets*)	Log of one plus total assets (in million Korean won)
Volatility	Stock return volatility of a firm during the past 24 months
Age	Firm age
ln(1+*Emp*)	Log of one plus total number of employees
Post	An indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise
d_t	An indicator variable for year t
Act Exposure	$ESC_{2015}^{Act}/ESC_{2015}$, that is, the fraction of *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Anti-Graft Act (we use the industry codes listed in Appendix A to identify these connections)
Entertainment Expense	The ratio of a firm's entertainment expenses (an item reported in the financial statement and provided by FnGuide) in 2015 to lagged total assets, or alternatively, to contemporaneous SG&A expenses
Act Exposure$^{Media\ (Public)}$	$ESC_{2015}^{Media\,(Public)}/ESC_{2015}$, that is, the fraction of *ESC in-degree* in 2015 that is due to connections to employees in the media (public) sector subject to the Anti-Graft Act (we use the industry codes listed in Appendix A to identify these connections)
ln(1+*Media Coverage*)	Log of one plus the weighted count of news articles from RavenPack News Analytics covering a firm over a year in which the weight is the relevance score of each article which ranges from 0 to 100%. We only include news articles with relevance scores greater than or equal to 75%.
Positive Media Coverage Ratio	The ratio of positive media coverage to media coverage. Positive media coverage is the weighted count of news articles with BMQ sentiment scores of 100 from RavenPack News Analytics covering a firm over a year. The BMQ sentiment score represents the news sentiment of a given story according to the BMQ classifier, which specializes in short commentary and editorials. We only include news articles with relevance scores greater than or equal to 75%.
ln(1+*# of Proc. Contracts*)	Log of one plus the total number of newly signed procurement contracts of firm i in year t, from the Korea online e-Procurement Service
ln(1+*Tot Amt. of Proc. Contracts*)	Log of one plus the total amount of newly signed procurement contracts of firm i in year t, from the Korea online e-Procurement Service
ln(1+*Tot Amt. of Proc. Contracts / Assets*)	Log of one plus the total amount of newly signed procurement contracts normalized by total assets of firm i in year t, from the Korea online e-Procurement Service

ln(1+*Sales*)	Log of one plus sales
At-Issue Bond Spread	The difference, in percentage, between the bond's yield at issuance and the mark-to-market benchmark yield of a corporate bond portfolio for the same maturity and credit rating from the Korea Financial Investment Association (KOFIA)
PPENT	Net property, plant, and equipment normalized by total assets
Modified Z-Score	Modified Altman's z-score according to Campello et al. (2010) = 3.3 × (earnings before interest and tax / total assets) + 1.0 × (sales / total assets) + 1.4 × (retained earnings / total assets) + 1.2 × (working capital / total assets)
Capital Expenditure	Capital expenditure normalized by total assets
Current Ratio	The ratio of current assets to current liabilities
ln(1+ *Maturity*)	Log of one plus the maturity of the bond (in years)
ln(1+ *Issue Amount*)	Log of one plus the bond issue amount (in billion Korean won)

List of Industries Subject to the Anti-Graft Act

KSIC Code	**Sector**	**Industry**
5812	Media	Publishing of newspapers, magazines, and periodicals
59114	Media	Broadcasting program production
5912	Media	Motion picture, video, and broadcasting program post-production activities
5913	Media	Motion picture, video, and broadcasting program distribution activities
60	Media	Broadcasting activities
63910	Media	News agency activities
6411	Public	Central bank
64991	Public	Public fund management business
6513	Public	Social security insurance
65303	Public	Pension funding
6611	Public	Administration of financial markets
66191	Public	Securities issuance, management, deposit and settlement services
84	Public	Public administration and defense; compulsory social security
85	Public	Education

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Table 1. Descriptive Statistics: Business Card Exchange Network and Employee-Level Connections

Panel A describes the business card exchange network data obtained from a professional networking app, Remember. We obtain de-identified data from all business cards uploaded as of December 31, 2018. From the raw data, we exclude connections that involve individuals with no company name on their card, or whose listed email domain is inconsistent with their company, or whose company does not have a Korea Investors Service (KIS) firm identifier. We obtain our sample by including only connections between employees with different KIS firm identifiers and those in which at least one of the two individuals is an employee of a public firm in the OSIRIS Industrials database. Panel B presents summary statistics of the employee-level connections as of December 2018, based on the 1,016,023 public firm employees of our sample. *In-degree,* which measures "who knows you," is the number of employees of other firms who have uploaded the corresponding employee as a business contact. *Out-degree,* which measures "who you know," is the number of business contacts of other firms uploaded by the focal app-user employee; given the nature of our data, *Out-degree* is only available for the 119,423 public firm employees who are app-users. *Total degree* is the sum of *In-degree* and *Out-degree*. We also tabulate *In-degree* by employee job level into executives (chairman, vice chairman, president, deputy president, executive and senior vice president), non-executive managers (vice president, general manager, department head, deputy general manager, manager, section head), and rank-and-file employees (staff and senior staff).

Panel A. Business Card Exchange Network as of December 2018

Number of connections	12,391,177
Number of employees	2,363,295
Number of employees who are app-users	411,039
Number of employees in public firms	1,016,023
Number of employees in public firms who are app-users	119,423
Number of firms with KIS identifiers	126,987
Number of public firms in OSIRIS Industrials	1,866

Panel B. Employee-Level Connections as of December 2018

	N	Mean	Median	SD	P25	P75
App-users						
In-degree	119,423	26.329	11	50.160	4	27
Out-degree	119,423	56.916	17	116.831	5	56
Total degree	119,423	83.244	30	161.819	11	84
Non-app-users						
In-degree = Total degree	896,600	4.820	2	9.826	1	5
All public firm employees in the network (app-users + non-app-users)						
In-degree	1,016,023	7.348	2	20.710	1	6
Total degree	1,016,023	14.038	2	61.652	1	7
In-degree by employee job level						
Executives	98,864	12.909	2	33.986	1	11
Non-executive managers	581,094	8.198	2	21.703	1	7
Rank and file	336,065	4.242	2	11.069	1	4

Table 2. Summary Statistics: Firm-Year Sample

Panel A presents summary statistics of the main variables for our firm-year sample. *ESC in-degree* is the average *In-degree* across employees of firm *i* who are in the network in year *t*. *ESC out-degree* is the average *Out-degree* across app-user employees of firm *i* in year *t*. *ESC total degree* is the average *Total degree* across employees of firm *i* who are in the network in year *t*. The sample period is 2014–2018. Panel B compares the characteristics of firm-year observations with above-median and below-median *ESC total degree*. For each year, we classify firm-year observations with above-median ESC and below-median ESC based on the median of *ESC total degree* for each two-digit SIC industry. The number of firm-year observations and the mean are presented in columns (1)–(2) for the above-median ESC group and in columns (3)–(4) for the below-median ESC group. Column (5) reports the difference in mean between the two groups, and column (6) reports corresponding t-statistics with the standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A. Firm-Level Employee Social Capital (ESC) Measures and Other Main Variables

	N	Mean	Median	SD	P25	P75
ESC in-degree	5,340	3.676	3.139	2.392	1.976	4.693
ESC out-degree	4,994	30.953	24.167	26.787	12.909	40.304
ESC total degree	5,340	6.836	5.319	5.844	3.000	8.548
Tobin's q	5,340	1.456	1.106	1.099	0.890	1.575
ROA	5,340	0.043	0.042	0.087	0.009	0.082
Sales Growth	5,340	0.041	0.037	0.324	-0.066	0.141
R&D	5,340	0.024	0.003	0.067	0.000	0.022
Book Leverage	5,340	0.101	0.062	0.115	0.001	0.165
ln(1+*Assets*) (in million Korean won)	5,340	12.248	12.013	1.343	11.341	12.950
Volatility	5,340	0.130	0.115	0.068	0.085	0.156
Age	5,340	28.666	25	16.163	16	40
ln(1+*Emp*)	5,340	5.478	5.429	1.154	4.771	6.071

Panel B. Univariate Analysis

	ESC total degree					
	Above Median		Below Median		Above − Below	
	Obs.	Mean	Obs.	Mean	Diff.	T-stat
	(1)	(2)	(3)	(4)	(5)	(6)
ESC in-degree	2,599	4.461	2,741	2.931	1.530***	20.67
ESC out-degree	2,577	42.213	2,417	18.947	23.267***	24.94
ESC total degree	2,599	9.521	2,741	4.290	5.231***	27.74
Tobin's q	2,599	1.478	2,741	1.435	0.043	0.93
ROA	2,599	0.045	2,741	0.040	0.005*	1.65
Sales Growth	2,599	0.054	2,741	0.030	0.024**	2.52
R&D	2,599	0.027	2,741	0.021	0.005*	1.92
Book Leverage	2,599	0.104	2,741	0.099	0.006	1.28
ln(1+*Assets*)	2,599	12.303	2,741	12.197	0.106*	1.80
Volatility	2,599	0.130	2,741	0.130	0.001	0.30
Age	2,599	28.265	2,741	29.047	-0.782	(1.15)
ln(1+*Emp*)	2,599	5.474	2,741	5.481	-0.006	(0.13)

Table 3. Employee Social Capital and Firm Performance: Total Degree

This table reports OLS regression estimates on the relation between employee social capital and firm performance in the following year, without accounting for the direction of connections. We estimate the following specification:

$$Y_{i,t} = \beta_0 + \beta_1 \times \ln\left(1+ESC_{i,t-1}\right) + \gamma' X_{i,t-1} + \alpha_{j,t} + \varepsilon_{i,t},$$

where $ESC_{i,t-1}$ is the measure of one-year lagged firm-level employee social capital using *ESC total degree* of firm i in year t-1; $X_{i,t-1}$ is a set of lagged firm-level control variables commonly included in the literature (Anderson and Reeb, 2003); $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. $Y_{i,t}$ is *Tobin's q* in column (1), *ROA* in column (2), and *Sales Growth* in column (3). Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

	ESC total degree		
Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)
ln(1+*ESC*)	0.084	0.008**	0.038***
	(0.053)	(0.004)	(0.012)
R&D	4.634***	-0.182***	0.420***
	(0.576)	(0.034)	(0.125)
Book Leverage	0.172	-0.138***	0.076
	(0.179)	(0.016)	(0.054)
ln(1+*Assets*)	-0.134***	0.010***	-0.009
	(0.022)	(0.002)	(0.008)
Volatility	3.498***	-0.104***	0.050
	(0.388)	(0.026)	(0.080)
Age	-0.005***	-0.000***	0.000
	(0.001)	(0.000)	(0.000)
ln(1+*Emp*)	0.064***	0.009***	-0.007
	(0.023)	(0.002)	(0.006)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340
Adjusted R^2	0.248	0.148	0.035

Table 4. Employee Social Capital and Firm Performance: "Who Knows You" vs. "Who You Know"

This table reports OLS regression estimates on the relation between employee social capital and firm performance in the following year when we differentiate the direction of connections. Panel A presents the baseline results. Firm-level employee social capital takes the lagged value of *ESC in-degree* ("Who Knows You") in columns (1)–(3) and *ESC out-degree* ("Who You Know") in columns (4)–(6). H_0: *ESC in-degree* – *ESC out-degree* = 0 is based on a one-tailed test on the coefficient estimates of *ESC in-degree* and *ESC out-degree* with p-values in square brackets. Panel B presents robustness checks. In the upper panel, firm-level employee social capital takes the lagged value of *ESC in-degree of non-app-user employees* in columns (1)–(3) and *ESC out-degree to app-users* in columns (4)–(6). In the lower panel, we exclude reciprocal connections in calculating *ESC nonreciprocal in-degree* and *ESC nonreciprocal out-degree.* For both panels, we include the same set of lagged firm-level control variables and industry-by-year fixed effects as in Table 3. The dependent variable is *Tobin's q* in columns (1) and (4), *ROA* in columns (2) and (5), and *Sales Growth* in columns (3) and (6). Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. Baseline Results

	ESC in-degree ("Who Knows You")			*ESC out-degree* ("Who You Know")		
Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+*ESC*)	0.330***	0.021***	0.098***	0.042	0.004*	0.004
	(0.090)	(0.007)	(0.024)	(0.030)	(0.002)	(0.007)
R&D	4.536***	-0.187***	0.397***	4.565***	-0.176***	0.398***
	(0.577)	(0.034)	(0.124)	(0.573)	(0.034)	(0.125)
Book Leverage	0.160	-0.139***	0.073	0.059	-0.134***	0.091
	(0.178)	(0.016)	(0.053)	(0.163)	(0.016)	(0.057)
ln(1+*Assets*)	-0.142***	0.009***	-0.011	-0.126***	0.010***	-0.010
	(0.022)	(0.002)	(0.009)	(0.022)	(0.002)	(0.009)
Volatility	3.504***	-0.103***	0.054	3.618***	-0.106***	0.023
	(0.388)	(0.026)	(0.079)	(0.409)	(0.027)	(0.083)
Age	-0.005***	-0.000***	0.000	-0.005***	-0.000***	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ln(1+*Emp*)	0.079***	0.010***	-0.003	0.075***	0.008***	-0.008
	(0.024)	(0.002)	(0.006)	(0.024)	(0.002)	(0.006)
H_0: *ESC in-degree* – *ESC out-degree* = 0	0.288	0.017	0.094			
[p-value]	[0.000]	[0.004]	[0.000]			
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	4,994	4,994	4,994
Adjusted R^2	0.252	0.150	0.038	0.252	0.142	0.035

Panel B. Robustness Results

Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
	ESC in-degree of non-app-user employees			*ESC out-degree to app-users*		
ln(1+*ESC*)	0.427***	0.029***	0.135***	0.089*	0.005*	0.006
	(0.110)	(0.009)	(0.029)	(0.047)	(0.003)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	4,994	4,994	4,994
Adjusted R^2	0.252	0.151	0.039	0.253	0.142	0.035
	ESC nonreciprocal in-degree			*ESC nonreciprocal out-degree*		
ln(1+*ESC*)	0.517***	0.031***	0.128***	0.026	0.004*	0.005
	(0.115)	(0.009)	(0.029)	(0.025)	(0.002)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	4,994	4,994	4,994
Adjusted R^2	0.254	0.151	0.038	0.252	0.142	0.035

Table 5. Employee Social Capital and Firm Performance: By Employee Job Level

This table reports OLS regression estimates on the relation between employee social capital and firm performance in the following year when we differentiate the connections of employees by their job level. In Panel A, we categorize a firm's employees who are in the network as Executives (chairman, vice chairman, president, deputy president, executive, and senior vice president) or Non-Executive Employees (all other employees). Firm-level employee social capital takes the lagged value of *ESC in-degree* averaged across executives in columns (1)–(3) and averaged across non-executive employees in columns (4)–(6). In Panel B, we categorize a firm's non-executive employees who are in the network into Non-Executive Managers if they have a managerial title (vice president, general manager, department head, deputy general manager, manager, section head) or into Rank-and-File Employees (staff and senior staff). Firm-level employee social capital takes the lagged value of *ESC in-degree* averaged across non-executive managers in columns (1)–(3) and averaged across rank-and-file employees in columns (4)–(6). Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. Group Employees into Executives and Non-Executive Employees

	Executives			Non-Executive Employees		
Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+*ESC*)	0.190***	0.013***	0.050***	0.207**	0.032***	0.090***
	(0.056)	(0.004)	(0.013)	(0.100)	(0.008)	(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,321	5,321	5,321	5,340	5,340	5,340
Adjusted R^2	0.251	0.151	0.036	0.249	0.154	0.037

Panel B. Group Non-Executive Employees into Non-Executive Managers and Rank-and-File Employees

	Non-Executive Managers			Rank-and-File Employees		
Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+*ESC*)	0.159*	0.029***	0.068***	0.136	0.024***	0.084***
	(0.089)	(0.007)	(0.022)	(0.108)	(0.007)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	5,290	5,290	5,290
Adjusted R^2	0.248	0.154	0.036	0.250	0.150	0.036

Table 6. Employee Social Capital and Firm Performance: Causal Evidence

This table provides evidence on the causal effect of employee social capital on firm performance. In Panel A, we estimate the following difference-in-differences model surrounding the enactment of the Anti-Graft Act:

$$Y_{i,t} = \beta_0 + \beta_1 \times Act\ Exposure_i + \beta_2 \times Act\ Exposure_i \times Post_t + \gamma' X_{i,t\text{-}1} + \alpha_{j,t} + \varepsilon_{i,t},$$

where $Y_{i,t}$ is *Tobin's q*, $Act\ Exposure_i = ESC^{Act}_{i,2015}/ESC_{i,2015}$, $ESC_{i,2015}$ is *ESC in-degree* in 2015, and $ESC^{Act}_{i,2015}$ is *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Act. $Post_t$ is an indicator variable that equals one during and after the enactment year (2016–2018) and zero otherwise. d_t is an indicator variable for year t. $X_{i,t\text{-}1}$ is the same set of lagged controls as in Table 3; $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. Column (1) reports results excluding the enactment year (2016); columns (2)–(4) report results including the year 2016. The sample period is 2015–2018 for output variables in columns (1)–(3) and is 2014–2018 for output variables in column (4). Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A. Before and After the Act

Dep. Var.	*Tobin's q*			
	(1)	(2)	(3)	(4)
Act Exposure	6.578***	6.640***	6.642***	5.420***
	(1.273)	(1.272)	(1.272)	(1.050)
Act Exposure × *Post*	-4.930***	-4.726***		
	(1.132)	(1.052)		
Act Exposure × d_{2015}				1.169
				(0.793)
Act Exposure × d_{2016}			-4.155***	-2.973***
			(0.932)	(0.849)
Act Exposure × d_{2017}			-4.730***	-3.540***
			(1.162)	(1.006)
Act Exposure × d_{2018}			-5.162***	-3.980***
			(1.169)	(0.983)
R&D	5.431***	5.066***	5.065***	4.969***
	(0.689)	(0.677)	(0.678)	(0.653)
Book Leverage	0.183	0.233	0.232	0.227
	(0.185)	(0.182)	(0.182)	(0.177)
ln(1+*Assets*)	-0.139***	-0.146***	-0.146***	-0.139***
	(0.025)	(0.023)	(0.023)	(0.022)
Volatility	3.403***	3.400***	3.396***	3.238***
	(0.449)	(0.395)	(0.395)	(0.363)
Age	-0.005***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.001)	(0.001)	(0.001)
ln(1+*Emp*)	0.076***	0.067***	0.067***	0.068***
	(0.024)	(0.023)	(0.023)	(0.023)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including Year 2016	No	Yes	Yes	Yes
Observations	3,778	5,101	5,101	6,048
Adjusted R^2	0.242	0.245	0.245	0.243

Table 6. Employee Social Capital and Firm Performance: Causal Evidence (continued)

Panel B uses a propensity score matched sample to estimate the specifications in Panel A. We use a probit regression to estimate the probability of being a treated firm (those with above-median exposure in 2015) using the sample of 2015 with a set of industry fixed effects and the same set of control variables in 2015 as in Panel A. Each treated firm is matched to a control firm using nearest neighbor with replacement within each two-digit SIC industry, where the maximum absolute difference in propensity scores between the matched observations is 0.01. We first tabulate the means of the matched variables for the treated group (those with above-median exposure) and the control group (those with below-median exposure) in year 2015. We also report the mean differences between the two groups and their corresponding t-statistics based on heteroskedastic-consistent standard errors. We next present the results estimating the specifications in Panel A using the matched sample. We include the same set of lagged control variables and industry-by-year fixed effects as in Panel A. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel B. Matched Sample

	Above Median (Obs. = 635)	Below Median (Obs. = 635)	Above − Below	T-stat
R&D	0.021	0.023	-0.002	-0.54
Book Leverage	0.107	0.109	-0.002	-0.41
ln(1+*Assets*)	12.347	12.304	0.043	0.56
Volatility	0.142	0.148	-0.006	-1.31
Age	29.191	30.710	-1.519	-1.57
ln(1+*Emp*)	5.572	5.565	0.007	0.10

Dep. Var.	*Tobin's q*			
	(1)	(2)	(3)	(4)
Act Exposure	6.507***	6.531***	6.531***	5.521***
	(1.356)	(1.353)	(1.353)	(1.177)
Act Exposure × *Post*	-4.651***	-4.409***		
	(1.232)	(1.140)		
Act Exposure × d_{2015}				0.964
				(0.878)
Act Exposure × d_{2016}			-3.957***	-2.997***
			(1.050)	(1.002)
Act Exposure × d_{2017}			-4.064***	-3.102***
			(1.218)	(1.099)
Act Exposure × d_{2018}			-5.237***	-4.272***
			(1.306)	(1.150)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including Year 2016	No	Yes	Yes	Yes
Observations	3,541	4,811	4,811	5,721
Adjusted R^2	0.266	0.265	0.265	0.264

Table 6. Employee Social Capital and Firm Performance: Causal Evidence (continued)

In Panel C, we re-estimate the specification of column (1) in Panel A using subsamples. Column (1) drops firms that belong to the industries directly affected by the Act (26 unique firms identified according to the industry codes in Appendix A); column (2) additionally drops firms that belong more broadly to the media and the publishing activities sectors (KSIC 58, 59); column (3) further drops firms that belong to the supplier and customer industries of the media and the public sector using detailed Make-and-Use tables; column (4) focuses on a subsample with positive exposure of employee social capital to the Act. In Panel D, we re-estimate the specification of column (1) in Panel A by incorporating an additional variable, *Entertainment Expense*, defined as the ratio of a firm's entertainment expenses in 2015 to lagged total assets in columns (1) and (3) and to *SG&A* expenses in columns (2) and (4). Columns (1)–(2) include *Entertainment Expense* and its interaction with *Post*; columns (3)–(4) employ a triple-difference model by interacting *Entertainment Expense* with *Act Exposure* × *Post*. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel C. Subsamples

Dep. Var.	*Tobin's q*			
	(1)	(2)	(3)	(4)
Act Exposure	8.010***	8.350***	8.190***	6.362***
	(1.419)	(1.535)	(2.232)	(1.363)
Act Exposure × *Post*	-5.884***	-6.211***	-6.376***	-4.760***
	(1.304)	(1.407)	(2.046)	(1.196)
R&D	5.379***	5.950***	6.317***	5.222***
	(0.692)	(0.741)	(1.202)	(0.770)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including Year 2016	No	No	No	No
Observations	3,708	3,464	2,686	3,344
Adjusted R^2	0.247	0.251	0.222	0.234

Panel D. Controlling for Entertainment Expense

Dep. Var.	*Tobin's q*			
	(1)	(2)	(3)	(4)
Act Exposure	8.081***	8.100***	5.532***	6.278***
	(1.527)	(1.570)	(1.601)	(1.925)
Act Exposure × *Post*	-5.390***	-5.333***	-4.218***	-4.767***
	(1.306)	(1.332)	(1.482)	(1.650)
Entertainment Expense	0.531***	-0.014	0.175	-0.049*
	(0.189)	(0.026)	(0.262)	(0.025)
Entertainment Expense × *Post*	-0.322**	-0.013	-0.153	-0.001
	(0.163)	(0.022)	(0.223)	(0.026)
Act Exposure × *Entertainment Expense*			10.183*	1.179
			(5.925)	(0.940)
Act Exposure × *Post* × *Entertainment Expense*			-5.114	-0.422
			(5.216)	(0.758)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including Year 2016	No	No	No	No
Observations	3,009	3,010	3,009	3,010
Adjusted R^2	0.248	0.243	0.250	0.244

Table 7. Stock Market Reaction to the Court Ruling on the Act

This table reports the stock market reaction around July 28, 2016, when the Constitutional Court rejected the petition and ruled that the Anti-Graft Act is constitutional. In Panel A, we report the cumulative CAPM-adjusted abnormal returns in event windows [-1, 1], [-3, 3], and [-5, 5], where day 0 is the date of the announcement. Daily abnormal stock returns are computed based on the market model using the Korean equal-weighted market return as the market proxy. The estimation window is days [-200, -60] prior to the event date. In Panel B, we report the cumulative size-adjusted abnormal returns in the same event windows. Following La Porta et al. (1997) and Ahern (2009), for each event window, we form a size-decile equal-weighted benchmark portfolio using all stocks in that size decile, where size is measured as market capitalization as of one day prior to the start date of the event window. The daily size-adjusted abnormal returns are the difference between raw returns and the corresponding size-decile benchmark portfolios. In both panels, we report the average cumulative abnormal returns for firms with below-median exposure in column (1) and above-median exposure in column (2), where exposure is $Act\ Exposure = ESC_{2015}^{Act}/ESC_{2015}$. We also report the significance based on one-tailed tests that the cumulative abnormal returns are negative for the above-median subgroup. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Column (3) reports the mean difference between the above-median subgroup and the below-median subgroup; column (4) reports corresponding p-values based on one-tailed tests that the return differentials are negative, with the standard errors clustered at the industry (two-digit SIC) level. Column (5) reports the cross-sectional pairwise correlation coefficients between *Act Exposure* and the cumulative abnormal returns, and column (6) reports the corresponding p-values based on one-tailed tests that the correlation coefficients are negative, with the standard errors clustered at the industry (two-digit SIC) level. We exclude penny stocks with stock price less than 1,000 Korean won (about 0.9 USD) as of June 28, 2016, one month prior to the court's ruling.

Panel A. Cumulative CAPM-Adjusted Abnormal Returns

	$Act\ Exposure = ESC_{2015}^{Act}/ESC_{2015}$					
	Below Median	Above Median	Diff Above − Below	P-value	Correlation Coefficient	P-value
	(1)	(2)	(3)	(4)	(5)	(6)
[-1, 1]	0.07%	-0.27%*	-0.34%	0.083	-0.009	0.363
[-3, 3]	0.41%	-0.61%**	-1.02%	0.019	-0.076	0.020
[-5, 5]	0.62%	-1.04%***	-1.66%	0.008	-0.086	0.014
Observations	751	751				

Panel B. Cumulative Size-Adjusted Abnormal Returns

	$Act\ Exposure = ESC_{2015}^{Act}/ESC_{2015}$					
	Below Median	Above Median	Diff Above − Below	P-value	Correlation Coefficient	P-value
	(1)	(2)	(3)	(4)	(5)	(6)
[-1, 1]	0.16%	-0.11%	-0.27%	0.098	-0.004	0.440
[-3, 3]	0.52%	-0.43%**	-0.95%	0.014	-0.065	0.035
[-5, 5]	0.65%	-0.69%***	-1.33%	0.013	-0.071	0.034
Observations	788	782				

Table 8. The Economic Value of Connections with the Media and the Public Sector

In Panel A, we estimate changes in the value of connections with the media and the public sector around the Act using:

$$Y_{i,t} = \beta_0 + \beta_1 \times Act\ Exposure_i^{Media(Public)} + \beta_2 \times Act\ Exposure_i^{Media(Public)} \times Post_t + \gamma' X_{i,t\text{-}1} + \alpha_{j,t} + \varepsilon_{i,t},$$

where $Y_{i,t}$ is *Tobin's q*, $Act\ Exposure_i^{Media}$ is $ESC_{i,2015}^{Media}/ESC_{i,2015}$ for columns (1)–(2) and $Act\ Exposure_i^{Public}$ is $ESC_{i,2015}^{Public}/ESC_{i,2015}$ for columns (3)–(4); $ESC_{i,2015}$ is *ESC in-degree* in 2015; $ESC_{i,2015}^{Media(Public)}$ is *ESC in-degree* in 2015 due to connections to the media (public) sector. $Post_t$ is an indicator variable for during and after the enactment year (2016–2018). $X_{i,t\text{-}1}$ is the same set of lagged controls as in Table 3; $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. Columns (1) and (3) report results excluding the enactment year (2016), whereas columns (2) and (4) report results including 2016. Panel B reports results on the economic benefits of connections with the media and the public sector. $Act\ Exposure_i^{Media}$ is $ESC_{i,2015}^{Media}/ESC_{i,2015}$ for columns (1)–(2) and $Act\ Exposure_i^{Public}$ is $ESC_{i,2015}^{Public}/ESC_{i,2015}$ for columns (3)–(5). Dependent variables in columns (1)–(2) are *Media Coverage*, the weighted count of news articles from RavenPack News Analytics covering a firm in a given year (the weight is the relevance score of each article provided by RavenPack; we only include articles with relevance scores greater than or equal to 75%), and *Positive Media Coverage Ratio*, the fraction of news articles with positive sentiment (according to RavenPack's BMQ sentiment series) covering a firm in a given year. Dependent variables in columns (3)–(5) are the natural logarithms of one plus the number of newly signed procurement contracts, the amount of newly signed procurement contracts, and the amount of procurement contracts normalized by the firm's total assets. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A. The Value of Connections with the Media and the Public Sector: Before and After the Act

	$Act\ Exposure^{Media}$		$Act\ Exposure^{Public}$	
Dep. Var.	*Tobin's q*			
	(1)	(2)	(3)	(4)
$Act\ Exposure^{Media(Public)}$	8.016***	8.070***	6.181**	6.303***
	(1.591)	(1.588)	(2.414)	(2.407)
$Act\ Exposure^{Media(Public)} \times Post$	-5.655***	-5.431***	-4.782**	-4.735**
	(1.398)	(1.290)	(1.981)	(1.899)
R&D	5.455***	5.092***	5.449***	5.085***
	(0.697)	(0.685)	(0.686)	(0.674)
Book Leverage	0.183	0.233	0.185	0.235
	(0.187)	(0.185)	(0.187)	(0.183)
ln(1+*Assets*)	-0.141***	-0.148***	-0.124***	-0.132***
	(0.025)	(0.023)	(0.025)	(0.023)
Volatility	3.377***	3.376***	3.445***	3.443***
	(0.451)	(0.397)	(0.447)	(0.393)
Age	-0.005***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.001)	(0.002)	(0.001)
ln(1+*Emp*)	0.080***	0.070***	0.068***	0.059**
	(0.025)	(0.024)	(0.025)	(0.024)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including Year 2016	No	Yes	No	Yes
Observations	3,778	5,101	3,778	5,101
Adjusted R^2	0.242	0.244	0.234	0.237

Panel B. The Value of Connections with the Media and the Public Sector: Economic Benefits

	Act Exposure^{Media}		*Act Exposure*^{Public}		
Dep. Var.	ln(1+*Media Coverage*)	*Positive Media Coverage Ratio*	ln(1+*# of Proc. Contracts*)	ln(1+*Tot Amt of Proc. Contracts*)	ln(1+*Tot Amt of Proc. Contracts / Assets*)
	(1)	(2)	(3)	(4)	(5)
Act Exposure$^{Media(Public)}$	4.495***	0.437**	3.756***	19.837***	0.091***
	(1.564)	(0.180)	(1.111)	(5.295)	(0.027)
Act Exposure$^{Media(Public)}$ × *Post*	-2.991**	-0.305*	-1.878**	-9.700**	-0.040*
	(1.445)	(0.172)	(0.839)	(4.443)	(0.022)
Tobin's q	0.116***	0.013***	-0.003	-0.015	-0.000*
	(0.017)	(0.004)	(0.008)	(0.041)	(0.000)
Book Leverage	0.131	-0.003	0.094	0.442	-0.003
	(0.158)	(0.027)	(0.125)	(0.538)	(0.002)
ROA	-0.931***	-0.107***	-0.191*	-1.668***	-0.005**
	(0.195)	(0.027)	(0.105)	(0.521)	(0.002)
R&D	0.611**	0.020	-0.367**	-1.883**	-0.013***
	(0.245)	(0.040)	(0.159)	(0.772)	(0.005)
ln(1+*Sales*)	0.267***	0.019***	0.030***	0.229***	-0.000
	(0.025)	(0.003)	(0.011)	(0.055)	(0.000)
Volatility	-0.204	-0.017	0.143	1.049*	0.005
	(0.181)	(0.032)	(0.104)	(0.596)	(0.003)
Age	0.009***	0.001**	0.001	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.004)	(0.000)
ln(1+*Emp*)	0.069***	0.009***	0.107***	0.576***	0.002***
	(0.024)	(0.003)	(0.014)	(0.066)	(0.000)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including Year 2016	No	No	No	No	No
Observations	3,775	3,775	3,775	3,775	3,775
Adjusted R^2	0.343	0.164	0.241	0.264	0.194

Table 9. Employee Social Capital with the Investment Banking Industry

Panel A reports OLS regression estimates on the relation between $ESC^{I\text{-}bank}$, a firm's ESC measured by connections with the investment banking industry (KSIC 6612), and firm performance in the following year. We include the same set of control variables and industry-by-year fixed effects as in Table 3. The dependent variable is *Tobin's q* in column (1), *ROA* in columns (2), and *Sales Growth* in column (3). Panel B reports how $ESC^{I\text{-}bank}$ relates to the bond spreads at issuance. The dependent variable is bond yield spreads at issuance (in percentage), defined as the difference between the bond's yield at issuance and the mark-to-market benchmark yield of a portfolio of corporate bonds with the same maturity and credit rating. Data on bond issuance are from the Korea Financial Investment Association (KOFIA). In columns (2)–(4), we re-estimate column (1) by differentiating $ESC^{I\text{-}bank}$ of employees by their job level as executives, non-executive managers, and rank-and-file employees. Panel C repeats Panel A and column (1) of Panel B for the subsample of more innovative firms, defined as those with above-median R&D for each year. H_0: More Innovative–Less Innovative = 0 is based on a one-tailed test on the coefficient estimates of ln(1+$ESC^{I\text{-}bank}$) for the more innovative firms and the less innovative firms, with p-values in square brackets. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. ESC in-degree with the Investment Banking Industry and Firm Performance

Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)
ln(1+$ESC^{I\text{-}bank}$)	1.461***	0.051***	0.124***
	(0.241)	(0.014)	(0.038)
R&D	4.188***	-0.196***	0.395***
	(0.576)	(0.034)	(0.123)
Book Leverage	0.100	-0.140***	0.071
	(0.175)	(0.016)	(0.054)
ln(1+*Assets*)	-0.173***	0.009***	-0.011
	(0.025)	(0.002)	(0.009)
Volatility	3.497***	-0.103***	0.055
	(0.387)	(0.026)	(0.079)
Age	-0.005***	-0.000***	0.000
	(0.001)	(0.000)	(0.000)
ln(1+*Emp*)	0.126***	0.011***	-0.003
	(0.025)	(0.002)	(0.006)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340
Adjusted R^2	0.270	0.151	0.035

Panel B. At-Issue Bond Spread

Dep. Var.	All Employees	Executives	Non-Executive Managers	Rank-and-File Employees
	At-Issue Bond Spread			
	(1)	(2)	(3)	(4)
ln(1+$ESC^{I\text{-}bank}$)	-0.454**	-0.192	-0.319*	-0.710**
	(0.216)	(0.182)	(0.174)	(0.299)
PPENT	-0.543***	-0.544***	-0.537***	-0.567***
	(0.165)	(0.168)	(0.168)	(0.162)
ln(1+Sales)	0.026	0.013	0.024	0.036
	(0.027)	(0.026)	(0.027)	(0.027)
ROA	0.675	0.658	0.634	0.679
	(0.517)	(0.509)	(0.511)	(0.527)
Volatility	1.614	1.631	1.577	1.637
	(1.196)	(1.210)	(1.188)	(1.181)
Age	0.002**	0.002*	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
ln(1+Emp)	-0.043*	-0.015	-0.035	-0.046**
	(0.023)	(0.021)	(0.022)	(0.023)
Tobin's q	-0.162*	-0.174**	-0.160*	-0.165*
	(0.089)	(0.087)	(0.089)	(0.086)
Modified Z-Score	0.020	0.029	0.024	0.017
	(0.039)	(0.039)	(0.039)	(0.040)
R&D	1.234	1.168	1.247	1.197
	(1.083)	(1.107)	(1.094)	(1.065)
Capital Expenditure	-0.940**	-0.904*	-0.901*	-0.944*
	(0.470)	(0.463)	(0.473)	(0.482)
Current Ratio	-0.090*	-0.086*	-0.087*	-0.078
	(0.049)	(0.050)	(0.048)	(0.049)
ln(1+ *Maturity*)	0.043	0.042	0.043	0.040
	(0.050)	(0.051)	(0.050)	(0.051)
ln(1+ *Issue Amount*)	0.003	-0.001	0.003	0.001
	(0.033)	(0.034)	(0.034)	(0.034)
Fixed Effects	Ind	Ind	Ind	Ind
Observations	480	477	480	480
Adjusted/Pseudo R^2	0.314	0.310	0.311	0.318

Panel C. Subsample of More Innovative Firms

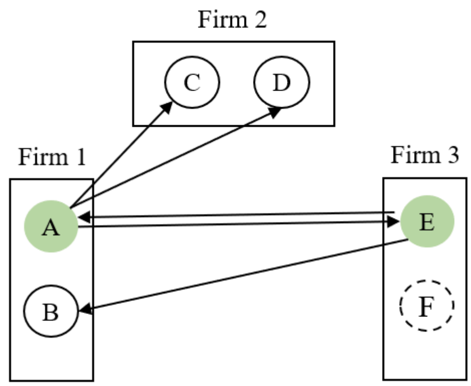
Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*At-Issue Bond Spread*
	(1)	(2)	(3)	(4)
ln(1+$ESC^{I\text{-}bank}$)	1.859***	0.057***	0.182***	-0.891***
	(0.360)	(0.019)	(0.051)	(0.265)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind
Observations	2,669	2,669	2,669	206
Adjusted R^2	0.295	0.201	0.055	0.332
H_0: More Innovative–Less Innovative = 0	0.905	0.022	0.150	-0.568
[p-value]	[0.017]	[0.197]	[0.016]	[0.056]

Internet Appendix

Internet Appendix I: An Example of the Network Data

We use an example to illustrate the data structure of our business card exchange network and the method for constructing the measures of firm-level employee social capital. The example network is given by the following connection-level data, together with the network graph.

Employee_ID_From	Firm_ID_From	Job_From	Employee_ID_To	Firm_ID_To	Job_To
A	1	Staff	C	2	Staff
A	1	Staff	D	2	Vice president
A	1	Staff	E	3	Manager
E	3	Manager	A	1	Staff
E	3	Manager	B	1	Manager



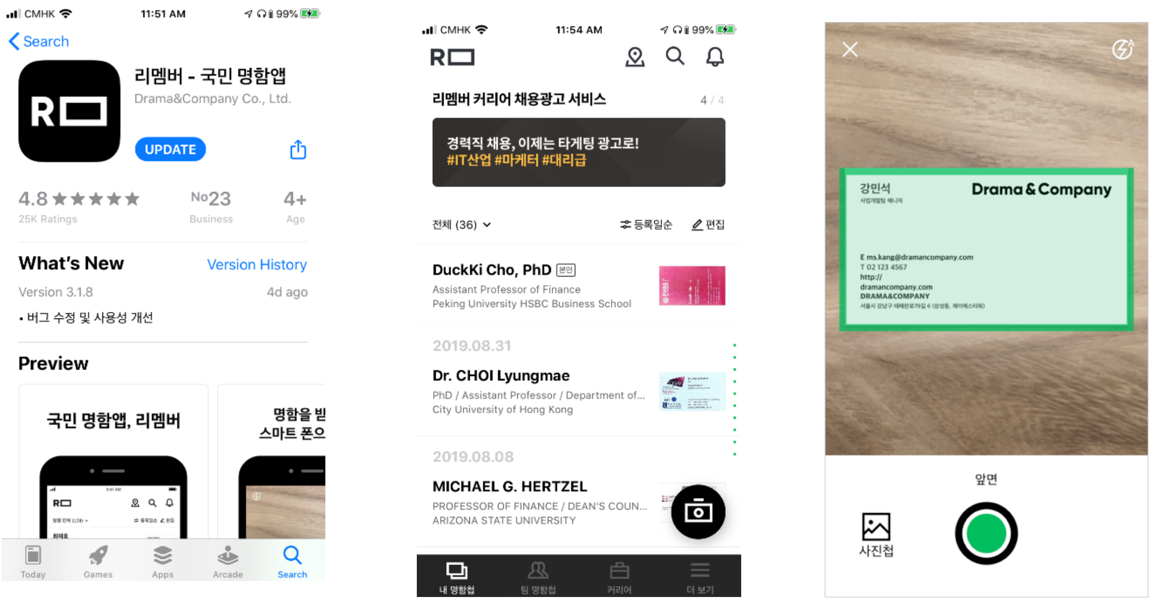
Employees A and E are app-users, and all other employees are non-app-users. Employee F does not appear in the network data. Each connection is a directed link from the app-user employee (Employee_ID_From) who uploads the card to the employee (Employee_ID_To) whose card is uploaded. For example, the first entry shows that employee A, a staff of firm 1, has uploaded a card of employee C, a staff of firm 2. This link counts toward the out-degree for A and the in-degree for C. Based on the connection-level data, we construct the measures of firm-level employee social capital (ESC). *ESC in-degree* is the average *In-degree* across the firm's employees who are in the network. For example, the *In-degree* is one for both A and B, so firm 1's *ESC in-degree* = 1. *ESC out-degree* is the average *Out-degree* across the firm's app-user employees. Firm 1 has only one app-user employee, A, so its *ESC out-degree* equals the out-degree of employee A, which is three. Finally, *ESC total degree* is the average *Total degree* across the firm's employees who are in the network. The total degree is four for employee A and one for employee B, so its *ESC total degree* = 2.5(=5/2). Firm 2 does not have *ESC out-degree* because we can only observe the out-degree of app-users.

Firm_ID	Number of Employees in the Network	Number of App-user Employees in the Network	*ESC in-degree*	*ESC out-degree*	*ESC total degree*
1	2	1	1	3	2.5
2	2	0	1	-	1
3	1	1	1	2	3

Internet Appendix II: Additional Figures and Tables

Figure IA.1. Remember, the Professional Business Card Management App

This figure displays screenshots of the Remember app's user interface. Panel A shows the app available on App Store, Panel B presents the basic user interface, and Panel C illustrates how to scan and upload business cards using the app.



Panel A. Remember on App Store *Panel B. User Interface* *Panel C. Uploading a Card*

Figure IA.2. Construction of Firm-Level ESC from Employee-Level Degree Measures

This figure illustrates the construction of firm-level *ESC in-degree* and *ESC out-degree*. To measure firm-level *ESC in-degree*, we average the *In-degree* of the users and non-users in the network, because they are all capable of being uploaded as business contacts by app-users outside the firm (as illustrated by the solid red arrows pointing inward). To measure firm-level *ESC out-degree*, we average the *Out-degree* of app-users, since these are the only employees we can observe uploading others as business contacts (as illustrated by the dotted blue arrows pointing outward). We measure firm-level *ESC total degree* by averaging the *Total degree* (=*In-degree* + *Out-degree*) across the firm's employees who are in the network.

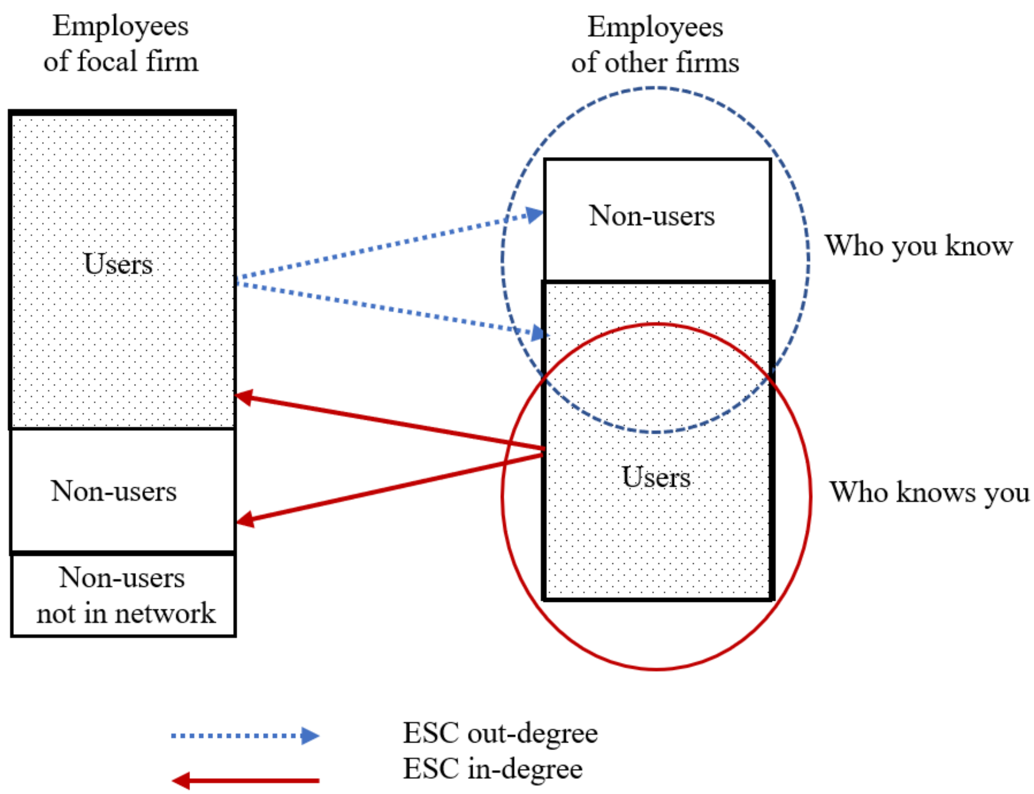
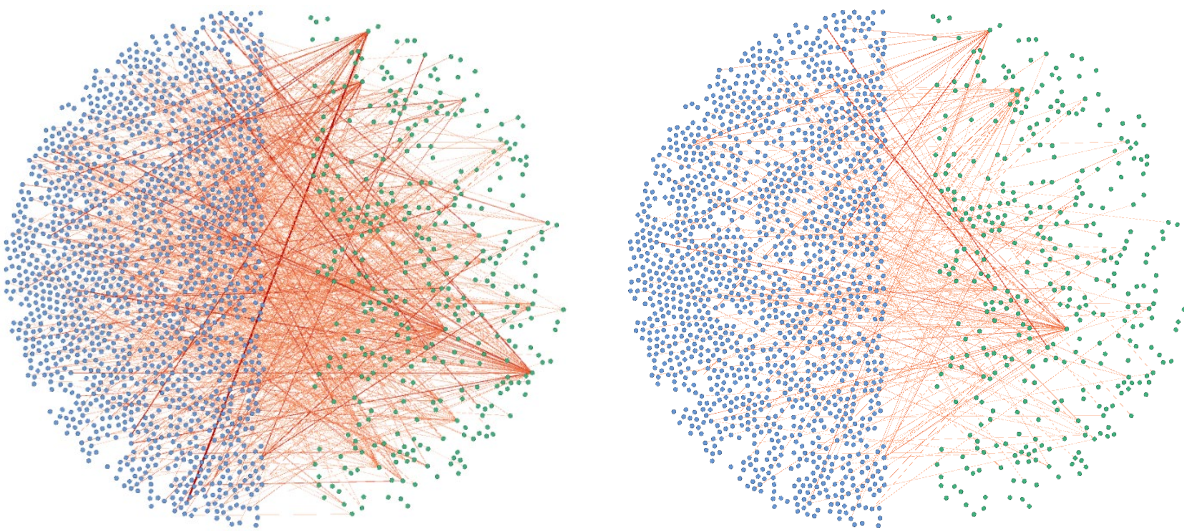


Figure IA.3. Employee Social Capital Before and After the Anti-Graft Act

This figure compares business card exchange networks before and after the enactment of the Anti-Graft Act. Panel A is a snapshot of the network in 2015 (before the Act) and Panel B is a snapshot of the network in 2018 (after the Act). In each panel, the dots in the left semicircle (colored in blue) represent the 1,481 public firms in our main sample of 2015 that are not affected by the Act, whereas dots in the right semicircle (colored in green) represent the 408 public and private firms that belong to industries restricted by the Act. We keep the same set of firms with their locations fixed across the two networks. We draw a line connecting two dots only if the fraction of a firm's ESC subject to the Act, $ESC_{i,t}^{Act}/ESC_{i,t}$, is greater than 3% and the intensity of a link connecting two firms (scaled by $ESC_{i,t}$) is greater than 1%, where $ESC_{i,t}$ is measured as *ESC in-degree*.



Panel A. Before the Act: 2015 *Panel B. After the Act: 2018*

Figure IA.4. Effect of the Exposure of Employee Social Capital to the Act on Firm Performance Year by Year

This figure plots the point estimates of β_t in the following regression:

$$Y_{i,t} = \beta_0 + \beta_1 \times Act\ Exposure_i + \sum_{t=2015}^{2018} \beta_t \times Act\ Exposure_i \times d_t + \gamma' X_{i,t\text{-}1} + \alpha_{j,t} + \varepsilon_{i,t},$$

where $Y_{i,t}$ is *Tobin's q*, $Act\ Exposure_i = ESC^{Act}_{i,2015}/ESC_{i,2015}$, $ESC_{i,2015}$ is *ESC in-degree* in 2015, and $ESC^{Act}_{i,2015}$ is *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Act. d_t is an indicator variable for year t. We extend our pre-treatment sample to include year 2014 and set 2014 as the baseline year, omitting the 2014 interaction term. The vertical bars correspond to the 95% confidence intervals based on standard errors clustered by firm.

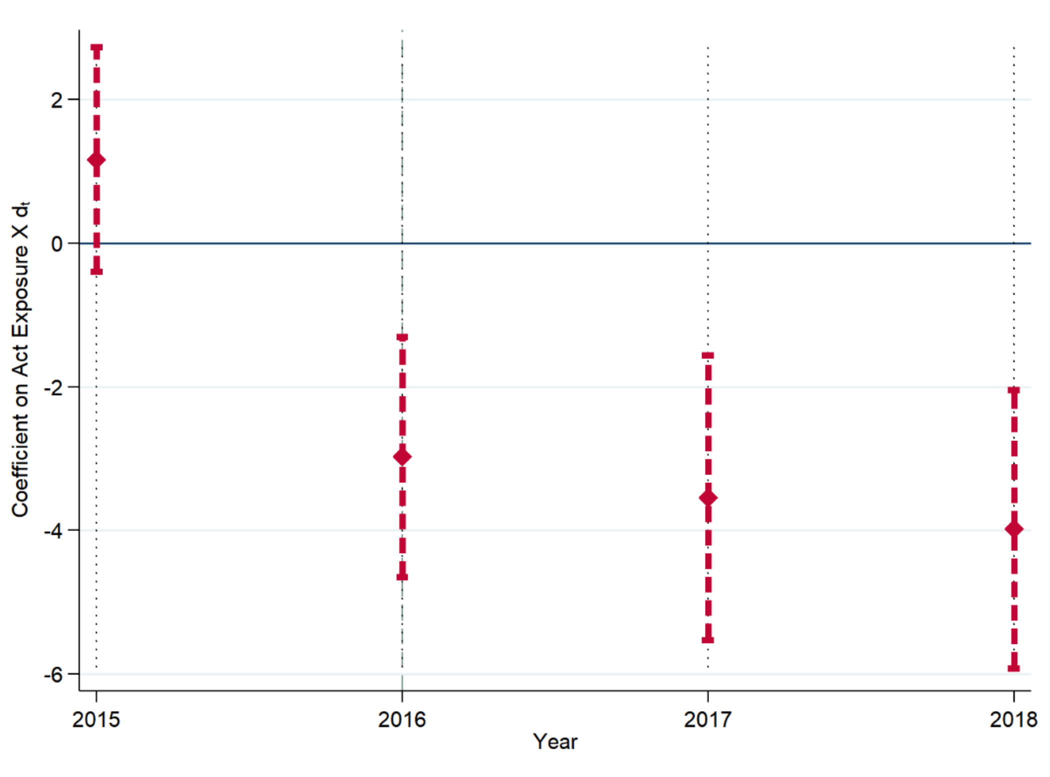


Table IA.1. Descriptive Statistics of the Business Card Exchange Network by Sector

This table presents descriptive statistics by sector (based on the KSIC codes) of the business card exchange network and the firm-level employee social capital measures as of December 2018. We report the number of public firm employees, the number of public firm employees who are app-users, the number of public firms in OSIRIS Industrials, and the average firm-level ESC measures: *ESC in-degree, ESC out-degree,* and *ESC total degree.*

	Business Card Exchange Network			Average Firm-level Employee Social Capital Measures		
	Employee	App-User Employee	Public Firms	*ESC in-degree*	*ESC out-degree*	*ESC total degree*
Agriculture, forestry and fishing	1,172	161	6	2.752	22.890	4.568
Mining and quarrying	32	5	3	18.929	73.000	34.571
Manufacturing	545,205	54,502	1,203	3.273	27.669	5.938
Electricity, gas, steam and air conditioning supply	17,698	1,892	11	3.145	25.507	5.670
Water supply; sewage, waste management, materials recovery	417	65	7	4.073	24.706	7.299
Construction	58,462	8,526	51	3.622	30.050	7.430
Wholesale and retail trade	74,745	8,441	148	3.663	29.820	6.694
Transportation and storage	23,843	2,924	26	3.619	37.821	7.231
Accommodation and food service activities	1,272	211	3	3.327	30.388	6.771
Information and communication	105,078	13,648	211	5.119	42.925	9.905
Financial and insurance activities	141,713	23,286	103	5.758	53.176	12.381
Real estate activities	347	100	2	9.217	92.867	21.470
Professional, scientific and technical activities	27,155	3,057	52	4.707	36.251	8.459
Business facilities management and business support services; rental and leasing activities	12,229	1,764	17	4.049	32.126	7.761
Education	2,289	279	10	4.323	32.527	7.758
Arts, sports, and recreation related services	2,467	317	12	3.315	19.571	5.168
Membership organizations, repair and other personal services	1,899	245	1	2.907	16.040	4.741

Table IA.2. Additional Robustness Results: "Who Knows You" vs. "Who You Know"

This table reports a battery of robustness tests for Table 4. Panel A repeats the analysis in Table 4 with three alternative measures of employee social capital. *ESC: Excl. Sales* is *ESC in-degree* or *ESC out-degree* in which we exclude connections of a firm's customer-facing employees who perform sales functions. *ESC: Single Count* is *ESC in-degree* or *ESC out-degree* in which we count multiple connections to the same outside employee as one connection. *ESC: Sum* is the sum of *In-degree* (or *Out-degree*) aggregated across employees of firm *i* in the network that year. We include an additional control, the number of employees of firm *i* in the network that year. Panel B repeats the analysis in Table 4 using subsamples, which exclude, respectively, firms rated in the "top 20 companies most wanted by university students" in 2015–2018, financial firms (SIC codes 61, 62, 65, 67), or firms in the top three percentile of asset size distribution. In both panels, we include the same set of lagged control variables (unless specified) and industry-by-year fixed effects as in Table 4. The dependent variable is *Tobin's q* in columns (1) and (4), *ROA* in columns (2) and (5), and *Sales Growth* in columns (3) and (6). Standard errors in parentheses are clustered at the firm level. Panel C reports the results of a propensity score matching analysis. We match the above-median ESC firms with their below-median counterparts on year, industry (two-digit SIC), and the controls as in Table 4, using the nearest-neighbor-matching algorithm with a caliper of 0.01, and with replacement. Standard errors in parentheses are bootstrapped based on 500 replications with replacement. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. Alternative Measures of Employee Social Capital

	ESC in-degree ("Who Knows You")			*ESC out-degree* ("Who You Know")		
Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+*ESC: Excl. Sales*)	0.389***	0.020***	0.093***	0.050*	0.003	0.002
	(0.084)	(0.007)	(0.024)	(0.028)	(0.002)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	4,860	4,860	4,860
Adjusted R^2	0.254	0.150	0.037	0.252	0.139	0.038
ln(1+*ESC: Single Count*)	0.361***	0.018**	0.102***	-0.025	-0.002	0.006
	(0.093)	(0.007)	(0.022)	(0.028)	(0.002)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	4,994	4,994	4,994
Adjusted R^2	0.253	0.149	0.039	0.252	0.140	0.035
ln(1+*ESC: Sum*)	0.251***	0.016***	0.067***	-0.004	0.002	0.007
	(0.070)	(0.006)	(0.017)	(0.022)	(0.002)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	4,994	4,994	4,994
Adjusted R^2	0.254	0.150	0.037	0.253	0.142	0.036

Panel B. Subsample Analysis

Dep. Var.	*ESC in-degree* ("Who Knows You")			*ESC out-degree* ("Who You Know")		
	Tobin's q	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
[Excluding Top 20 Companies Most Wanted by University Students]						
ln(1+*ESC*)	0.329***	0.021***	0.083***	0.043	0.004*	0.003
	(0.090)	(0.008)	(0.021)	(0.030)	(0.002)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,258	5,258	5,258	4,913	4,913	4,913
Adjusted R^2	0.258	0.142	0.043	0.258	0.133	0.042
[Excluding Financial Sector]						
ln(1+*ESC*)	0.325***	0.020***	0.100***	0.042	0.004*	0.004
	(0.092)	(0.008)	(0.024)	(0.031)	(0.002)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,263	5,263	5,263	4,919	4,919	4,919
Adjusted R^2	0.253	0.150	0.040	0.254	0.142	0.037
[Excluding Top 3% Companies based on Total Assets]						
ln(1+*ESC*)	0.350***	0.020***	0.079***	0.044	0.004*	0.003
	(0.091)	(0.008)	(0.022)	(0.030)	(0.002)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,129	5,129	5,129	4,786	4,786	4,786
Adjusted R^2	0.257	0.146	0.039	0.256	0.137	0.038

Panel C. Propensity Score Matching

	Tobin's q	*ROA*	*Sales Growth*	Number of Matches
	(1)	(2)	(3)	(4)
Above Median – Below Median	0.203***	0.014***	0.065***	2,456
(*ESC in-degree*)	(0.047)	(0.004)	(0.016)	
Above Median – Below Median	0.025	0.005	-0.002	2,237
(*ESC out-degree*)	(0.047)	(0.004)	(0.015)	

Table IA.3. Employee Social Capital and Firm Performance: Cross-Sectional Analysis

This table shows the cross-sectional analysis of firm performance sensitivity to employee social capital across firms with heterogeneous characteristics. Firm-level employee social capital takes the lagged value of *ESC in-degree*. In Panel A, we group firms into those with above- and below-median labor intensity each year, measured by the ratio of *EMP* and inflation-adjusted total assets. In Panel B, we group firms into those with above- and below-median organization capital each year, measured by the ratio of organization capital and inflation-adjusted total assets. We follow Eisfeldt and Papanikolaou (2013) and Peters and Taylor (2017) to construct the stock of organization capital by accumulating past SG&A spending net of R&D expense using the perpetual inventory method and a depreciation rate of 15%. In Panel C, we group firms into those outside of and those within industry clusters based on the cross-sectional sample in 2017. We define an industry cluster as a city (or cities, if there are ties) that hosts the largest number of firms for each three-digit KSIC industry. H_0: Above − Below = 0 (or H_0: Outside − Within = 0 in Panel C) is based on a one-tailed test with p-values in square brackets. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. By Labor Intensity

Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
	Above Median			Below Median		
ln(1+*ESC*)	0.438***	0.037***	0.077***	0.197*	0.005	0.103***
	(0.140)	(0.013)	(0.028)	(0.110)	(0.008)	(0.038)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	2,669	2,669	2,669	2,671	2,671	2,671
Adjusted R^2	0.185	0.137	0.040	0.344	0.198	0.034
H_0: Above − Below = 0	0.241	0.032	-0.026			
[one-tailed p-value]	[0.076]	[0.012]	[0.722]			

Panel B. By Organization Capital

Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
	Above Median			Below Median		
ln(1+*ESC*)	0.421***	0.032***	0.074*	0.190**	0.012	0.131***
	(0.146)	(0.011)	(0.041)	(0.095)	(0.008)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	2,582	2,582	2,582	2,584	2,584	2,584
Adjusted R^2	0.207	0.195	0.029	0.250	0.109	0.054
H_0: Above − Below = 0	0.231	0.020	-0.057			
[one-tailed p-value]	[0.079]	[0.053]	[0.879]			

Panel C. By Industry Cluster

Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
	Outside Industry Clusters			Within Industry Clusters		
ln(1+*ESC*)	0.420***	0.020**	0.134***	0.207*	0.024**	0.049
	(0.136)	(0.010)	(0.038)	(0.123)	(0.012)	(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	2,852	2,852	2,852	2,488	2,488	2,488
Adjusted R^2	0.269	0.134	0.036	0.221	0.156	0.028
H_0: Outside − Within = 0	0.213	-0.004	0.085			
[p-value]	[0.114]	[0.613]	[0.040]			

Table IA.4. Anti-Graft Act and Employee Social Capital

We examine the adverse impact of the Anti-Graft Act on social relations with the media and the public sector by estimating changes in the fraction of ESC subject to the Act around the enactment as follows:

$$\frac{ESC_{i,t}^{Act}}{ESC_{i,t}} = \beta_0 + \beta_1 \times Post_t + \gamma' X_{i,t\text{-}1} + \alpha_j + \varepsilon_{i,t},$$

where $\frac{ESC_{i,t}^{Act}}{ESC_{i,t}}$ measures the fraction of a firm's employee social capital ($ESC_{i,t}$) that is derived from connections with employees in the industries affected by the Act ($ESC_{i,t}^{Act}$). $Post_t$ is an indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. $X_{i,t\text{-}1}$ is the same set of lagged firm-level control variables as in Table 3; α_j is a full set of two-digit SIC industry fixed effects. We report results excluding the enactment year of 2016 in column (1) and results including the year 2016 in column (2); the sample period is 2015–2018 for output variables. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Dep. Var.	ESC^{Act} / ESC (%)	
	(1)	(2)
Post	-0.266***	-0.260***
	(0.068)	(0.062)
R&D	0.496	0.549
	(0.789)	(0.831)
Book Leverage	-0.284	-0.114
	(0.536)	(0.538)
ln(1+*Assets*)	0.498***	0.492***
	(0.111)	(0.110)
Volatility	1.609*	1.528*
	(0.891)	(0.856)
Age	0.000	0.001
	(0.005)	(0.005)
ln(1+*Emp*)	-0.201*	-0.178
	(0.113)	(0.112)
Fixed Effects	Ind	Ind
Including Year 2016	No	Yes
Observations	4,017	5,340
Adjusted R^2	0.274	0.277

Table IA.5. Employee Social Capital and Firm Performance: Full Measures of Firm Performance

This table presents evidence that a firm's employee social capital due to connections with industries affected by the Anti-Graft Act has a positive impact on firm performance, with the effect concentrated in *Tobin's q*, but not in *ROA* or *Sales Growth*. As in Table 6, we estimate the following difference-in-differences model surrounding the enactment of the Act:

$$Y_{i,t} = \beta_0 + \beta_1 \times Act\ Exposure_i + \beta_2 \times Act\ Exposure_i \times Post_t + \gamma' X_{i,t\text{-}1} + \alpha_{j,t} + \varepsilon_{i,t},$$

where $Y_{i,t}$ is *Tobin's q*, *ROA*, and *Sales Growth*. $Act\ Exposure_i = ESC^{Act}_{i,2015}/ESC_{i,2015}$, $ESC_{i,2015}$ is *ESC in-degree* in 2015, and $ESC^{Act}_{i,2015}$ is *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Act. $Post_t$ is an indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. $X_{i,t\text{-}1}$ is the same set of lagged controls as in Table 3; $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. Columns (1)–(3) report results excluding the enactment year (2016), whereas columns (4)–(6) report results when we include the year 2016. The sample period is 2015–2018 for output variables. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Dep. Var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
Act Exposure	6.578***	0.152	0.178	6.640***	0.156	0.185
	(1.273)	(0.099)	(0.306)	(1.272)	(0.098)	(0.308)
Act Exposure × *Post*	-4.930***	-0.173**	-0.172	-4.726***	-0.148*	-0.193
	(1.132)	(0.087)	(0.338)	(1.052)	(0.080)	(0.339)
R&D	5.431***	-0.158***	0.379***	5.066***	-0.155***	0.439***
	(0.689)	(0.040)	(0.138)	(0.677)	(0.040)	(0.134)
Book Leverage	0.183	-0.132***	0.075	0.233	-0.139***	0.059
	(0.185)	(0.017)	(0.057)	(0.182)	(0.016)	(0.055)
ln(1+*Assets*)	-0.139***	0.010***	-0.006	-0.146***	0.009***	-0.007
	(0.025)	(0.002)	(0.009)	(0.023)	(0.002)	(0.009)
Volatility	3.403***	-0.111***	0.049	3.400***	-0.103***	0.078
	(0.449)	(0.027)	(0.093)	(0.395)	(0.026)	(0.081)
Age	-0.005***	-0.000***	-0.000	-0.005***	-0.000***	0.000
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ln(1+*Emp*)	0.076***	0.010***	-0.007	0.067***	0.010***	-0.007
	(0.024)	(0.002)	(0.007)	(0.023)	(0.002)	(0.006)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including Year 2016	No	No	No	Yes	Yes	Yes
Observations	3,778	3,778	3,778	5,101	5,101	5,101
Adjusted R^2	0.242	0.151	0.035	0.245	0.146	0.031

Table IA.6. Placebo Test: Randomization of the Exposure to the Act

This table reports the empirical distribution of the coefficient estimate on *Pseudo Exposure* × *Post* when re-estimating column (1) in Panel A of Table 6 one thousand times using the bootstrapped sample. To obtain the bootstrapped sample, we randomly assign a false treatment intensity, *Pseudo Exposure*, to each firm by maintaining the true distribution of *Act Exposure*. We also plot the kernel density of the coefficient estimate distribution and draw a vertical line to indicate the actual coefficient of -4.930.

Actual Estimate	Regression Coefficient on *Pseudo Exposure* × *Post*									
Act Exposure × *Post*	Mean	p1	p5	p10	p25	p50	p75	p90	p95	p99
-4.930	0.045	-1.563	-1.081	-0.827	-0.389	0.062	0.476	0.858	1.069	1.687

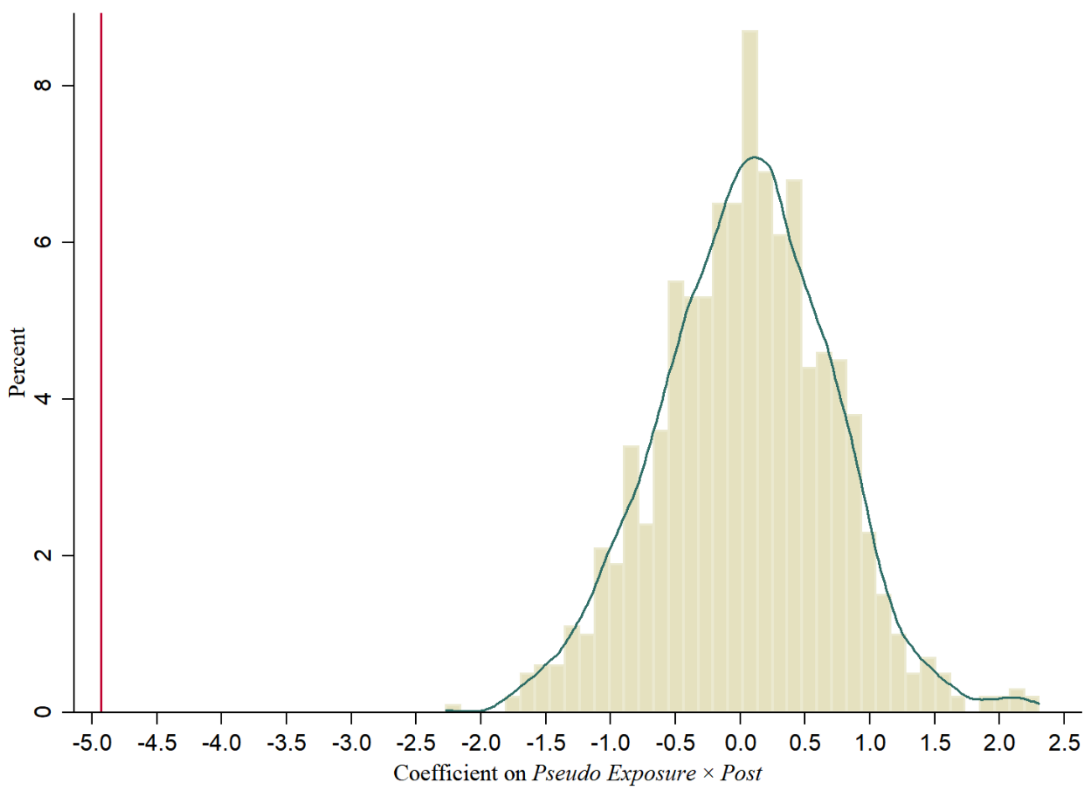


Table IA.7. Robustness Results for the Difference-in-Differences Estimation

This table presents robustness checks for the results in Panel A of Table 6. In addition to including the control variables in estimating equation (3), we also interact these firm-level control variables with the dummy variable $Post_t$. Column (1) reports results excluding the enactment year of 2016; column (2) reports results including the year 2016. The sample period is 2015–2018 for output variables. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Dep. Var.	*Tobin's q*	
	(1)	(2)
Act Exposure	7.380***	7.380***
	(1.319)	(1.318)
Act Exposure × *Post*	-5.847***	-5.544***
	(1.175)	(1.100)
R&D	1.997***	1.997***
	(0.712)	(0.711)
Book Leverage	0.564*	0.564*
	(0.314)	(0.314)
ln(1+*Assets*)	-0.249***	-0.249***
	(0.034)	(0.034)
Volatility	3.742***	3.742***
	(0.666)	(0.666)
Age	-0.010***	-0.010***
	(0.002)	(0.002)
ln(1+*Emp*)	0.137***	0.137***
	(0.038)	(0.038)
R&D × *Post*	4.337***	3.711***
	(0.851)	(0.805)
Book Leverage × *Post*	-0.481	-0.393
	(0.359)	(0.331)
ln(1+*Assets*) × *Post*	0.141***	0.123***
	(0.033)	(0.030)
Volatility × *Post*	-0.334	-0.352
	(0.789)	(0.729)
Age × *Post*	0.008***	0.007***
	(0.002)	(0.002)
ln(1+*Emp*) × *Post*	-0.070*	-0.081**
	(0.036)	(0.034)
Fixed Effects	Ind × Year	Ind × Year
Including Year 2016	No	Yes
Observations	3,778	5,101
Adjusted R^2	0.253	0.252