It's Not Who You Know—It's Who Knows You: Employee Social Capital and Firm Performance†

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Abstract

We show that the social capital embedded in employees' networks translate into superior firm performance. Using unique data from a professional networking app, we measure a firm's social capital derived from employees' connections with external stakeholders. The directed nature of connections allows for identifying if one party in a connection values the other more. Results show that firms with more employee social capital have better performance. The positive effect arises primarily from employees being valued by others and is embodied in employees across all job ranks. We provide causal evidence by exploiting the enactment of an anti-graft act, which imparts a shock to professional networks.

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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 approach views social capital as 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, Sapienza, and Zingales (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, Wu, and Zhang (2019)).

Another paradigm views social capital as an individual asset that is embedded in social networks and enables access to resources and information (Coleman (1988), Paldam (2000), Lin (2002), Burt (2007)). The academic literature that considers the network approach focuses almost exclusively on benefits firms obtain from their well-connected executives and board members (e.g., Cai and Sevilir (2012), Engelberg, Gao, and Parsons (2012), Larcker, So, and Wang (2013)). By contrast, very little is known about the social capital embodied in the broader set of employees through their connections. Although non-executive employees—ranging from lower-level managers to rank and file employees—comprise most of a firm's workforce and directly interact with business partners, clients, and other stakeholders, how their social capital translates to firm performance and valuation remains an open question.

The goal of this paper is twofold. First, we aim to establish a causal link between the social capital embedded in employees' networks and the firm's performance. To this end, we construct a novel firm-level measure of employee social capital using professional connections that a firm's

[1] This definition of social capital is distinguished 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).

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 the understanding of social capital in corporations from a more granular perspective.

To measure employee social capital, we exploit unique proprietary data extracted from a professional networking app, Remember, which is a near-monopoly of business card management in Korea. Recording the business card collections uploaded by each user and screening out individuals who are not employees of firms, yield data that allow us to identify the professional networks among 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 various ranks, including lower-level managers and rank and file employees, allows us to overcome a limitation of the corporate finance literature that has focused mainly on executive and board networks. Second, compared to data from online networking platforms such as LinkedIn and Facebook, our data depict real-world professional connections more reliably because business cards are typically exchanged in face-to-face meetings in Korea.[2] Third, while card exchanges are mutual between the two parties, uploading cards to the app is not necessarily mutual because users likely register only those cards that they value. Using language from the network literature, our network is *directed*; each connection is directed from the employee who registered the card to the employee whose card was registered. This directed feature allows us to identify if one of the two connected parties values the other party more.

We compute several connection measures at the individual employee level—*In-degree* (the number of others registering the employee as a contact), *Out-degree* (the number of business contacts registered by the employee), and *Total degree* (the sum of *In-degree* and *Out-degree).* Using more common language, *In-degree* measures those contacts who remember (apropos the name of the app) or value the employee, whereas *Out-degree* measures those contacts whom the employee remembers or values. As will be discussed below, this distinction allows us to analyze

[2] As in most other Asian countries, in Korea, exchanging business cards in face-to-face meetings is an essential ritual for establishing professional connections.

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 over 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 improved 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 directions of connections. We find that firms with higher employee social capital expect superior profitability and higher sales growth in the following year. For instance, firms with a one standard deviation higher lagged *ESC total degree* display 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 the connections 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 effect on performance arises mainly from *ESC in-degree*, which captures the extent to which a firm’s employees are remembered or valued by their external business 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 points increase in *ROA*, and a 4.0 percentage points increase in sales growth. By contrast, the coefficient estimates on *ESC out-degree* are largely insignificant.

While the evidence above is consistent with the social capital literature indicating 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 that know you is more valuable to your employer than having a broad network of contacts that you know. Despite less useful to their employers, “who you know” can be an asset for employees themselves. To the extent that employees registering contacts from other firms—as measured by *ESC out-degree*—offers outside job opportunities, as shown by Gortmaker, Jeffers, and Lee (2020) using data from LinkedIn, the resources mobilized through these connections do not necessarily accrue to their current employer.

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 reciprocal connections, differences between app-users and non-app-users, or omitted factors such as efforts by sales personnel and employee hard skills. Additionally, our data's coverage of employees across various ranks allows us to study employee social capital beyond the executive team. We find that executives are not the only group that processes beneficial connections for their firms; employee connections across all job ranks, including the rank and file, are valuable. For instance, our estimates reveal that connections of non-executive managers have the greatest significance to employer *ROA* and sales growth.

Establishing a causal link between employee social capital and firm performance requires a careful account of the endogeneity of connections. For instance, a firm's employee social capital might correlate with omitted variables, leading to a spurious relation between ESC and firm performance. Another concern is reverse causality, whereby better firm performance leads to the formation of professional connections. To reinforce the causal interpretation of our results, we exploit the 2016 enactment of the Kim Young-ran Anti-Graft Act as an exogenous shock to professional networks in Korea. Intended to curb bribery, the Act makes it illegal for employees and their spouses in the media (such as journalists) and the public sector (such as civil servants, lawmakers, central bankers, and teachers) to accept gifts or incur meal expenditures exceeding a 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. Anecdotal evidence suggests that the Act had a chilling effect on meetings and social events with employees in the affected industries. Indeed, we find that the composition of firm ESC moves away from connections with the media and public sector employees after the Act. 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 imparts a negative shock to employee social capital.

We estimate a difference-in-differences framework surrounding the enactment of the Act by setting 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 treated firms with ESC more exposed to the Act derive lower value from employee social capital 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. 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. These results add support for a causal impact of employee social capital on performance.

To provide insight into the mechanism driving the improvement in firm performance, 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., Tetlock, Saar-Tsechansky, and Macskassy (2008), Dougal et al. (2012), 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 covering a firm and to a greater fraction of coverage with a positive sentiment. Moreover, the positive effects diminish after the adoption of the Act, reinforcing our causal inference.

We next turn to investigating the economic 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 who are well connected to the public sector may also help their firms secure more 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 connections with the public sector leads to a 5.8% increase in the contract volume before the Act and only a 3.1% increase after the Act.

To further investigate potential channels through which employee social capital might enhance firm performance as well as to bolster confidence in our causality tests, we conclude our analysis by examining connections to economically related industries. Consistent with the notion that employee connections serve as a source of firm competitive advantage by providing better access to resources and information, connections to customer industries are associated with superior profitability and sales growth, accompanied by a reduced cash conversion cycle. In addition, firms with more employee connections with the investment banking industry have greater access to the public bond market and face lower at-issue yield spreads when issuing public bonds.

In sum, this paper documents that employee social capital translates into superior firm performance. Exploiting the directed feature of the network data suggests that the value of employee social capital to a firm comes mainly from employees being valued by their external contacts. Examining employees across various ranks informs that connections by all levels of employees matter for firm outcomes. Finally, our analysis of connections with various external stakeholders sheds light on the economic benefits that firms can derive from their employee social capital. This study thus broadly contributes to the burgeoning literature on the role of social capital in corporations (e.g., Servaes and Tamayo (2017), Lins, Servaes, and Tamayo (2017), Hasan et al. (2017), Hoi, Wu, and Zhang (2019), Huang and Shang (2019)).[3] While our analysis leverages unique data in Korea, the effects of social ties on business outcomes have been documented for countries with diverse business cultures, such as the US (Hochberg, Ljungqvist, and Lu (2007)), Germany (Haselmann, Schoenherr, and Vig (2018)), and China (Cai and Szeidl (2017)), suggesting that the insights are rather general.

Our study also extends prior work that focuses mostly on the benefits of well-connected executives and boards, such as high announcement returns (Cai and Sevilir (2012)), favorable lending terms (Engelberg, Gao, and Parsons (2012)), large abnormal returns (Larcker, So, and Wang (2013)), and survival during a financial crisis (Babina, Garcia, and Tate (2020)).[4] Our findings suggest that executives are not the only group that processes beneficial connections for their firms; employee connections (when valued by their external business contacts) across all job ranks, including the rank and file, 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, where we explore the importance of the directions of connections and employee job ranks. 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 employee connections to economically related industries in Section 5, and conclude in Section 6.

[3] To the extent that a firm's political capital is part of its social capital in broad terms, studies such as Faccio (2006), Akey (2015), Acemoglu et al. (2016), Schoenherr (2019), and Babenko, Fedaseyeu, and Zhang (2020), have examined a firm's political capital accumulated through campaign contributions and executives connected with politicians.

[4] Other studies point out potential downsides associated with executives being well-networked because connections could weaken effective monitoring of board members, increase the entrenchment of CEOs, and lead to rent-seeking coalitions (Hwang and Kim (2009), Khanna, Kim, and Lu (2015), Ishii and Xuan (2014), El-Khatib, Fogel, and Jandik (2015), Haselmann, Schoenherr, and Vig (2018)).

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 a Korean mobile and web service provider called Drama & Company.[5] Since its launch in January 2014, Remember has become the single most popular professional business card management app in Korea.[6] The app is available free of charge from Google Play and the App Store. As of December 2018, the total number of business cards registered was over 140 million; the total number of registered users was around 2.5 million, which is approximately 18.1 percent of the total number of full-time employees in Korea (about 13.8 million according to Statistics Korea). The data have coverage across a wide array of sectors, as shown in Table IA.1 in the Appendix.

[Figure 1 about here]

To keep a record of their professional network, users of the app register the business cards they have collected, either scanning and uploading the business cards by themselves or having the app developer scan the cards in bulk at a minor cost. 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. Figure 1 illustrates the Remember app as depicted on the App Store (in Panel A), the app's user interface (in Panel B), and how to scan business cards (in Panel C). The app allows users to manage their professional networks on mobile devices or computers, and to use search criteria to connect to calls, texts, emails, and addresses and to make 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 by others.

2.2. Business Card Data and Individual Employee-level Connections

The cultural background of South Korea strongly supports the notion that tracking business card exchanges is a useful way to identify employees' professional networks. As in most other

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

[6] The app Remember is 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 to 2018.

Asian countries, exchanging business cards in face-to-face meetings, which goes beyond a simple exchange of personal details, is an important ritual for building professional connections in Korea. It is popularly believed that, besides acting as an ice breaker, business cards can help establish a positive first impression and boost professional credibility.[7] They can also act as a physical reminder that one has met the contact rather than simply googled them (*Economist*, May 2015).[8] In addition, this business practice helps the two parties bond and build trust by encouraging follow-up social events. Hence, tracing the exchange of business cards provides a feasible and reasonable way to identify the professional networks among employees in Korea.

From each card registered by each app-user, we obtain detailed information about the business contact, including an individual identifier (uniquely defined over the coded name and coded mobile phone number to comply with user privacy laws), email domain, company name, job position, and the timestamp of card registration. The unit of observation in the raw data is at the *connection-level*, that is, a pair consisting of the app-user and the business contact whose card is registered. Since our goal is to measure connections among employees, we exclude connections that involve individuals who do not have a 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.[9] To focus on interfirm connections, we further select connections between employees with different KIS firm identifiers. Accordingly, each connection involves two employees of different firms: the app-user who registers the business card and the business contact to whom the card belongs. Internet Appendix I illustrates an example of the business card data.

While, in general, cards are mutually exchanged between two parties, registration of exchanged cards is not necessarily mutual. For example, Aaron and Bob meet and exchange cards. When Aaron registers Bob's card, Bob does not necessarily register Aaron's card. Borrowing terminology from the network literature, this feature of the registration process means that our connection-level data are directed. We draw from Jackson (2008) and Newman (2010) and briefly discuss some commonly used concepts in describing networks. In social networks, individuals,

[7] "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.

[8] As discussed extensively in *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."

[9] 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.

also called *nodes*, form *links* (*connections*) to other individuals; the nodes and links form the network. If the links have a specified direction and are not necessarily mutual, we say the network is *directed*.[10] 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 registered the card to the business contact whose card was registered. The example of Aaron registering 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 register only the cards they value and intend to "remember"—as suggested by the name of the app—Aaron registering Bob's card likely reveals that Aaron considers Bob a valuable connection. For simplicity, 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 registered the employee as a business contact ("who knows you"). *Out-degree* is the number of business contacts of other firms registered by the employee ("who you know"). For each employee, *Total degree* is the sum of their *In-degree* and *Out-degree.*[11]

[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 involved is a public firm employee. 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 fraction of app-users among public firm employees is 11.8%. There are 126,987 firms

[10] 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 take the form of a directed network. By contrast, professional connections on LinkedIn and friendship networks on Facebook are undirected.

[11] A reciprocal relationship, which occurs when both parties register 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.

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 registered as a contact by 26 app-users outside the firm. *Out-degree* shows that an average app-user registers 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 are highly right-skewed.

In the network, there are 896,600 non-app-users working for public firms. Non-app-users only enter the network when their business cards are registered 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 registered 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 registered by seven others as a business contact and has a total degree equal to 14. We also tabulate *In-degree* by employee job levels into executives, non-executive managers, and rank and file employees.[12] 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 registered as a connection 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 4.

The business card data from Remember have several advantages in identifying employee professional networks. First, the data's broad coverage of individual employees' connections (including both rank and file and top management) allows us to map employee-level connections to their employers to construct a matched employer-employee dataset. This feature overcomes a key limitation of the corporate finance literature which has focused primarily on managerial networks. Second, compared with data from online professional or social networks, e.g., LinkedIn,

[12] 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; and rank and file employees include all the other employees without a managerial title.

our data depict real-world professional relationships more reliably because business cards are typically exchanged in a face-to-face meeting. Hence, a registered 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 relative value that each of the two parties assigns to the link, thus shedding light on the economic value of the connections. Given the connections of an employee are not publicly visible, it is less likely that one's *In-degree* and *Out-degree* could strategically influence each other.

2.3. Firm-level Employee Social Capital (ESC)

To examine the extent to which resources inherent in a focal 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. Using the connections of the universe of public firm employees would be ideal; yet, 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. Specifically, *ESC in-degree* is the average *In-degree* across the firm's employees in the network that year. *ESC out-degree* is the average *Out-degree* across the app-user employees of a firm that year. *ESC total degree* is the average *Total degree* across the firm's employees in the network that year.[13]

The decomposition of firm-level employee social capital into *ESC in-degree* and *ESC out-degree* utilizes the directions of connections, as illustrated in Figure 2. 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; in contrast, the connections of non-app-users are only observed when their business cards have been registered by app-user employees of other firms. A firm's *ESC in-degree*, illustrated by links with an arrow pointing inward, quantifies the degree to which the firm's employees are registered as business contacts by employees outside the firm. A

[13] For *ESC in-degree* and *ESC total degree*, we average over all employees (both app-users and non-app-users) in the network because they are all available for registration by app-users outside the firm; when measuring *ESC out-degree*, we average over each firm's app-user employees because only app-users can register cards of others. To reduce measurement error when taking averages, we restrict our sample to firm-year observations with at least 10 employees observed in the network. Our results are robust to using alternative thresholds for the minimum numbers of employees who appear in the professional network data.

firm's *ESC out-degree,* illustrated by links with an arrow pointing outward, quantifies the number of business contacts from other firms registered by the firm's app-user employees.

[Figure 2 about here]

2.4. Sample Construction and Financial Variables

To construct our sample, we start with Korean public firms from the annual OSIRIS Industrials database between 2014 and 2018.[14] 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) is earnings before interest, tax, depreciation, and amortization (EBITDA) divided by the beginning-of-period total assets;[15] *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.

2.5. Summary Statistics

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 these connections, they are registered 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, register 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 earlier in Panel B of Table 1.[16] The financial variables are comparable in magnitude to firms in the US during the same period; Korean

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[14] 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.
[15] Results are similar when we use EBIT instead of EBITDA to measure *ROA*.
[16] 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*.

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 ESCs, suggesting that they tend to be central in the network.

[Table 2 about here]

3. Employee Social Capital and Firm Performance: Baseline Estimations

This section provides baseline estimates of the relation between employee social capital, as variously measured by employee connections, and firm performance. We start our analysis in Section 3.1 by examining the importance of *ESC total degree*, which measures the average total connections across employees of a firm, without accounting for the directions 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 industry by year, where industries are defined using two-digit Standard Industrial Classification (SIC) codes. 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 exhibit 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:

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

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.

[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) and (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.[17] These baseline regressions suggest a positive relation between a firm's performance and its employees' preexisting social capital based on those employees' total professional connections.

[17] 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.

3.2. The Directions of Connections: 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 directions 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 directions of connections and thus the relative 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 directions of connections matter. 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 directions of connections play a significant role in firm performance. We first note that 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, relative to the average *ROA* of 4.3% and the average *Sales Growth* of 4.1% in the sample, and 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. These estimated coefficients for *ESC out-degree* and the economic significance are an order of magnitude smaller than those for *ESC in-degree*. One-tailed tests also confirm that these two sets of coefficients are significantly different from each other (with p-value < 1%). For example, compared 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*.

[Table 4 about here]

These findings suggest that the economic value of employee social capital to a firm comes mainly from those connections with external contacts who choose to remember or value the firm's employees. While connections and social ties are associated with goodwill, valuable resources and information, as suggested by the social capital literature (e.g., Coleman (1988), Granovetter

(2005)),[18] the extent to which the employee can mobilize these benefits for their employers depends on whether the employee is valued by their business contacts. Despite less useful to their employers, remembering a broad network of business contacts can be an asset for individual employees. Studies on social capital (e.g., Lin, Ensel, and Vaughn (1981), Granovetter (1973, 1995), Lin and Dumin (1986)) show that social networks are a useful resource for an individual to obtain job opportunities. If employees registering contacts from other firms—as measured by *ESC out-degree*—reflects employees' intentions and efforts to switch employers,[19] 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 useful connections that employees and their firms can count on. 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 provide a set of robustness tests to confirm that reciprocal connections, potential differences between app-users and non-app-users, omitted factors such as sales productivity and employee hard skills, or observable differences in firms do not drive the results that "who knows you" matters whereas "who you know" does not.

3.3.1. Removing Reciprocal Connections

If Aaron registers Bob's business card and vice versa, these two card registrations correspond to a reciprocal relationship, counting toward the *in-degree* and *out-degree* for both parties. The reciprocal relationships in and of themselves do not differentiate the directions of connections since they represent cases where the two parties "remember each other." To rule out the concern that reciprocal connections might drive our results, we exclude reciprocal connections in constructing firm-level employee social capital and re-estimate equation (1) separately for *ESC*

[18] Coleman (1988) compares social capital with human capital. Putnam (2000) notes that connections among individuals lead to reciprocity, trustworthiness, 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 the resources.

[19] This mechanism is consistent with the evidence in Gortmaker, Jeffers, and Lee (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.

nonreciprocal in-degree and *ESC nonreciprocal out-degree.* Our tests, reported in Panel B of Table 4, show that the in-degree coefficients continue to be positive and statistically significant at the 1% level. Notably, the out-degree coefficients remain virtually unchanged from Panel A, and the differences between the two sets of coefficients become substantially larger. These findings bolster confidence that the directions of connections indeed matter. When considering professional connections that are not reciprocal, a firm benefits more from its employees being remembered (registered) by others than the other way around.

3.3.2. App-users versus Non-app-users

A potential concern is that our decomposition of employee social capital by the directions of connections may pick up unobservable differences between app-users and non-app-users. As noted earlier, an app-user has both *in-degree* and *out-degree* because we observe their connections in both directions. By contrast, non-users have only *in-degree* since they appear in the network only when app-users register their cards. Consequently, we average over both app-users and non-users when computing a firm's *ESC in-degree*, and average over app-users when computing *ESC out-degree*. If non-users behave differently from app-users who might be more tech-savvy and better connected, our *ESC in-degree* measure could be biased. To address this issue, we calculate a firm's *ESC nonreciprocal in-degree* by separately focusing on the app-user employees and non-user employees in the network and comparing how they relate with firm performance. As reported in Panel B of Table 4, the results confirm that employees' app-usage status does not drive our results. Both *ESC nonreciprocal in-degree* of app-users and non-users continue to be positively associated with firm performance. Particularly, in comparison with the estimates using *ESC nonreciprocal out-degree* (of app-users) above, results in columns (1)–(3) suggest that for the same set of app-user employees in a firm, being remembered by others is more useful for their firm than their remembering others.

3.3.3. Additional Robustness Tests

We perform a battery of additional robustness tests to confirm the value of employee social capital, especially the social capital embedded in "who knows you." We consider three alternative measures for firm-level *ESC* to address potential confounding factors. First, it is possible that employees in the sales department often serve as customer touchpoints and are particularly active in exchanging business cards. Thus, the observed positive association between average in-degree and company sales growth might be a mere reflection of their sales effort or business transactions. To alleviate this concern, we calculate ESC: *Excl. Sales* by excluding connections of a firm's customer-facing employees who perform sales functions.[20] Second, to address the concern that our results might be driven by multiple employees within the same firm who are each connected to the same highly connected individuals outside the firm, we count the connections to the same outside employee as one connection and obtain a second alternative measure, *ESC: Single Count*.[21] Third, connections made by employees might collectively contribute to firm performance; hence, rather than averaging across employees, we alternatively calculate *ESC: Total* as the sum of *In-degree* (or *Out-degree*) aggregated across the firm's employees while controlling for the number of firm employees who appear in the network. The results are reported in Panel A of Table IA.2 in the Internet Appendix. Across all three alternative measures, the coefficients on *ESC in-degree* continue to be positive and statistically significant, while those for *ESC out-degree* are not.

Highly connected employees might coincide with a selected sample of intelligent or skilled employees. The social aspect of the skill set—soft skills—support our argument because employees with good soft skills are naturally well-connected. Soft skills and charisma help the employee impress their business contacts, expand their network of "who knows you," and, in turn, are convertible into employer's performance. The non-social aspect of the skill set—hard skills—will pose a concern for our analysis if employee connectivity is correlated with skills orthogonal to social relations. To alleviate this concern, we use a similar strategy as Cohen, Frazzini, and Malloy (2010) and conduct subsample analysis in Panel B of Table IA.2. We first exclude from our analysis if a firm is rated at least once during 2015–2018 as "top 20 companies most wanted by university students" according to a survey by Job Korea as these firms tend to attract talented university graduates. Then we drop financial firms (SIC codes 61, 62, 65, 67), which are also popular among skilled employees and are disproportionately more connected with other firms,

[20] The employees who perform sales functions are identified based on the 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.

[21] Suppose both employees A and B of a firm are connected to an external employee C. Both connections are potentially valuable because A and B could utilize the resources embedded in their relationships to C. In this view, it is natural to count both connections in measuring firm-level ESC. Alternatively, one may argue that B's connection to C might be redundant and does not add value to the firm as a whole. It is then plausible to count these connections as one in the alternative measure, *ESC: Single Count.*

partly due to the nature of their business (e.g., underwriting, information production, advisory role). We also exclude large firms that are in the top three percentile of the asset size distribution, which tend to be more competitive in the war for top talent. Results 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 simply an artifact of a selected sample of employees with good "hard skills."

We also 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 control variables from our baseline regression, using the nearest-neighbor-matching algorithm with replacement. Results show that, as expected, firms with above-median *ESC in-degree* consistently see significantly better performance than their propensity-score matched firms with below-median *ESC in-degree*. However, we do not find such differences among firms with different *ESC out-degree*. Altogether, these robustness results reinforce that reciprocal connections, differences between app-users and non-app-users, or omitted factors related to sales activities and employee skill cannot explain our finding that "who knows you" matters whereas "who you know" does not.

We conclude this subsection by investigating employer performance sensitivity to employee social capital across firms with heterogeneous labor-related characteristics. 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) and Kim (2020) and measure labor intensity by the number of employees divided by deflated assets.[22] 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. In addition, synergy 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 benefit 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 notion, we find that the estimated effects of employee social capital on *Tobin's q* and *ROA* is larger for firms with greater

[22] Similar findings obtain for labor intensity proxied by the number of employees divided by deflated sales.

organization capital. These results further support our arguments for the positive effect of employee social capital as a productive factor embodied in a firm's workforce.

3.4. Employee Social Capital by Job Levels

The social capital of a firm consists of the quality of its relationships with external stakeholders. While executive management makes the major strategic decisions, non-executive employees comprise most of a firm's workforce and closely interact with business partners, clients, media, regulators, and creditors, forming the bulk of their employer's social capital. This aspect is particularly important since decision making and information processing within a firm is often decentralized by a hierarchical structure (Radner (1992)). Our data's key advantage 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 the employee social capital across employees of various ranks. We first divide a firm's employees in the network based on whether they belong to executive management. Results show that the ESC measures are positively associated with all firm performance measures for both groups. While our finding echoes existing studies on the value of executive networks, executives are not the only group that processes 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 who are not in a managerial position. Based on our estimates, the connections of non-executive managers have the greatest significance to *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 notion 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. Notably, our results also uniquely identify 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 useful information, enhancing trust, and fostering the goodwill of the company.

4. Establishing a Causal Relation

To establish a causal interpretation of our regression results, we need to address the potential endogeneity of a firm's employee social capital. An advantage of our employee social capital measure is that it is based on individual employee's endowed assets embodied in their professional connections. Compared with physical capital, intellectual capital, and existing firm-level social capital measures such as corporate social responsibility activities (Lins, Servaes, and Tamayo (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. For example, employee satisfaction may attract in-degree connections while simultaneously enhancing firm performance. 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 might partially alleviate 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 Anti-Graft Act

We exploit the 2016 enactment of the Anti-Graft Act (the Act), also known as the Kim Young-ran Act, which imparts a negative shock to the professional network. The Act took effect on September 28, 2016 to curb corruption by prohibiting improper solicitations and gifting of money or goods and services. As a culturally ingrained practice of business entertainment in South Korea, corporate employees would regularly treat clients, business partners, and public employees to dinners, late-night drinks, and other evening entertainment as part of networking (Choi and Storr (2019)). However, the Act makes it illegal for employees and their spouses in the media (such as journalists) and the public sector (such as government employees and teachers) to accept gifts of more than 50,000 won (about 45 USD) or, at events such as weddings and funerals, of 100,000 won; it also limits meal expenditures to 30,000 won per person.[23] Since the prohibited gifting and meal limits apply regardless of whether they are in exchange for favors, the Act causes significant precautions among businesses in their interactions with the media and the public sector.[24]

Direct consequences of the Act include relatively fewer connections with employees in affected industries. To verify this pattern in our data, we assess the impact of the Anti-Graft Act in reshaping the formation of professional connections with individuals in the affected industries by estimating the following model:

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

where the outcome variable 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 ($ESC_{i,t}^{Act}$). We use *ESC in-degree* to measure *ESC* and calculate ESC^{Act} using only the connections to employees in the industries subject to the Act (we use the industry codes in Appendix A to identify these connections).[25] $Post_t$ is an indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. $X_{i,t-1}$ 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 no longer include year fixed effects due to the dummy variable $Post_t$.

Table IA.4 in the Internet Appendix reports the results. Since the Act became effective in the latter half of 2016, we report results excluding observations in the enactment year of 2016 in column (1) and results by including the year 2016 in column (2). Across both specifications, we obtain a significant and negative coefficient for the indicator variable, *Post*. The economic magnitude is consequential. For instance, according to column (1), the industry composition of a firm's employee social capital moves away from industries that are under scrutiny after the enactment, with a 7.7% decrease in the fraction, ESC^{Act}/ESC, relative to its sample mean. This

[23] The upper limits were adjusted in January 2018 to 100,000 Korean won (about 90 USD) for non-cash gifts, and to 50,000 Korean won (about 45 USD) for cash gifts. We list all industries subject to this Act, together with their industry identifiers in Appendix A.

[24] In response to the Act, corporations imposed precautionary measures and guidelines to avoid any potential violation by their employees due to the joint penal provision, meaning that both the company and the actual offender are subject to punishment.

[25] Our results in Section 3 show that the economic value of employee social capital to a firm mainly comes 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.

transition is visualized in Figure IA.1. Compared with the network before the Act in 2015, the network after the Act in 2018 shows a sharp reduction in the fraction of a firm's employee connections to industries subject to the Act. In effect, the Act reduces the formation and the relative importance of employee social capital based on employees' professional connections with industries affected by the Act.

Although we cannot observe directly, we expect that the Act likely also resulted in fewer social events and meetings with existing business contacts employed in the affected industries. According to the *Korea Herald*, "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 observation 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).

The enactment of the Anti-Graft Act serves as a particularly useful identification tool for two reasons. First, the enforcement was aggressive with penalties such as imprisonment.[26] Second, it was uncertain whether the Act would be ruled constitutional. Right after bipartisan approval of the Act in 2015, many filed petitions 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—orthogonality between the enactment of the Act and unobservable covariates that affect corporate performance, after controlling for observable firm characteristics and time-varying industry-specific economic conditions. Accordingly, such a shock is likely to affect firm performance only through its impact on employees' professional connections and not through other variations between firms that are differentially exposed to the Act.

[26] The Act imposes a punishment of imprisonment of 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 valuables (including meals) valued at more than 1 million Korean won (about 900 USD) 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 valuables are worth less than 1 million Korean won, a fine of up to five times the gift's value is imposed.

4.2. Causal Effect of Employee Social Capital on Firm Performance

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 are able to estimate differences in performance between firms with differential exposure.[27] The Act makes firms less able to access the resources and information embedded in their employees' connections to the media and the public sectors; hence, we hypothesize that those firms with higher exposure experienced a bigger reduction in the value of their employee social capital.

We thus 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 of the Act, to isolate from the dynamic response of a firm's employee social capital to the Act. $Post_t$ is a dummy variable for the years during and after the enactment (2016–2018). $X_{i,t\text{-}1}$ is the same set of lagged firm-level 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 connections with a specific set of industries, namely the media sector (journalists) and the public sector (government employees and teachers). Connections to these affected industries have a significant and positive impact on firm performance, with the effect concentrated in *Tobin's q*.[28] In what follows, we focus on *Tobin's q* as our measure of firm performance in testing for causality. Our primary focus is on β_2, the coefficient of the interaction term, $Act\ Exposure_i \times Post_t$. If the effect of employee social capital on firm performance is indeed causal, we expect that firms with ESC that is more exposed to the

[27] 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 sectors—but rather the impact of the reduction in value of existing employee connections to the media and the public sectors.
[28] The results are reported in Table IA.5 in the Internet Appendix.

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

Panel A of Table 6 summarizes the results estimating equation (3). In column (1), we report results excluding firm-year 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. Additionally, the coefficient estimate of $Act\ Exposure_i$ is positive and significant at the 1% level. Based on these estimates, employee connections to the media and the public sectors contribute positively to a firm's *Tobin's q* before the Act; however, the positive impact reduces by about 75% (=4.930/6.578) after the Act. For example, a one standard deviation increase in $Act\ Exposure_i$ (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 the Act. We further include the firm-year observations during the enactment year of 2016 in column (2) and find little change in the magnitude and significance of our β_2 estimate.

[Table 6 and Figure 3 about here]

To test for the presence of pre-trends, in columns (3) and (4), we estimate an augmented version of equation (3) where we interact $Act\ Exposure_i$ with an indicator variable for each year t.[29] Figure 3 plots the estimates of the interaction terms and their 95% confidence intervals based on standard errors clustered by firm. Consistent with $Act\ Exposure_i$ capturing an adverse shock to employee social capital by the enactment, the reduction in the value of employee social capital does not occur prior to the enactment (also illustrated in Figure 3). Starting from the enactment year of 2016, the estimate becomes negative and remains negative and significant at the 1% level, both economically and statistically. The results in columns (3)–(4) suggest no preexisting trend in firm performance before the enactment, supporting the notion that the Act negatively affects firm performance by impacting employee social capital.

To address the concern that an omitted variable coinciding with the Anti-Graft Act might be driving our results, we perform a placebo test. We randomly assign a $Pseudo\ Exposure_i$ to each

[29] In column (3), we set 2015 as the baseline year and omit the 2015 interaction term (year 2014 for outcome variable 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.

firm by maintaining the true distribution of *Act Exposure*$_i$ and re-estimate column (1) in Panel A of Table 6. We repeat this procedure a thousand times and obtain the empirical distribution of the coefficient estimate on the interaction term (*Pseudo Exposure* × *Post*). As reported in Table IA.6 in the Internet Appendix, the actual coefficient estimate (-4.930) falls well below the 1% threshold of the distribution. To visualize this comparison, we plot the kernel density of the coefficient distribution and draw a vertical line to indicate the actual coefficient estimate. This placebo test assures that the negative estimate of β_2 cannot be obtained randomly or 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 employee social capital more exposed to the Act tend to be larger in both asset size and the number of employees. Likely they also have more frequent business interactions with the media and the public sectors by 2015. We perform three robustness checks to address this issue. First, we use propensity score matching to generate two very similar groups of treated and control firms and conduct the tests within this matched sample. We use a probit regression 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) present estimates for the matched sample using the same specifications as in Panel A. The estimates are consistent with those in Panel A, confirming that firms with ESC more exposed to the Act see 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 firm performance around the enactment. As reported in Table IA.7 in the Internet Appendix, our results continue to hold.

Finally, to alleviate concerns that adverse sectoral shocks to the industries directly affected by the Act spilled over to the 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 sectors may be highly connected among themselves; hence, we drop firms that belong to the industries directly affected by the Act (26 unique firms) in column (1) and additionally drop firms that belong more broadly to the media and the publishing activities industries (KSIC 58, 59) in column (2). In column (3), we further drop firms that belong to the supplier and customer industries of the media and the public sectors using the Make and Use table and an algorithm we will describe in detail in Section 5.1.[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 robustness tests help to rule out alternative explanations of our results, such as omitted differences between the treated and control firms and potential economic spillovers.

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

We next conduct an event study based on the court ruling that the Anti-Graft Act was constitutional. After bipartisan approval in 2015, the Act faced a lengthy petition, challenging its scope and vagueness. The Korean Bar Association and the Korean Journalists Association argued that applying the law to journalists and private school teachers (and their spouses) is an infringement upon freedom of the press and private schools. However, the petition was eventually rejected at 2pm on July 28, 2016, when seven out of the nine justices of the Constitutional Court ruled that the Act was constitutional.

We examine stock price reactions, around the court ruling date, for firms with different fractions of preexisting employee social capital due to its employees' connections with individuals working in industries subject to the Act. A negative stock 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 $Act\ Exposure = ESC_{2015}^{Act}/ESC_{2015}$, which is the fraction of employee social capital in 2015 derived from its employees' connections with industries subject to the Act. We calculate average cumulative abnormal returns for each subgroup, both CAPM-adjusted and size-adjusted, for

[30] Examples of the supplier industries include the manufacture of newsprint, printing and reproduction of recorded media, infrastructure suppliers, and restaurants; examples of the customer industries include the wholesale and retail sectors, sale of motor vehicles and parts (with significant advertising expenses).

various windows around the event date.[31] As reported in Table 7, we find evidence of a negative market reaction to firms with employee social capital more exposed to the Act. For example, the average cumulative abnormal return over the [-3, 3] event window is -0.61% (significant at the 5% level) for the subset of 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 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 it is negative and statistically significant, i.e., greater exposure to the Act is 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 Social Capital with the Media and the Public Sector

Having established a robust and causal relation between employee social capital and firm performance, we proceed to uncover underlying economic channels through which employees' connections to the industries affected by the Act—the media and the public sector—contribute to their employer's performance.

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. We split the industries affected by the Act into the media (KSIC 5812, 59114, 5912, 5913, 60, 63910) and the public sector (all other industries listed in Appendix A). Similarly as ESC_{2015}^{Act}, we define ESC_{2015}^{Media} and ESC_{2015}^{Public} as *ESC in-degree* in 2015 due to connections to the media and the public sector, respectively. We re-estimate equation (3) by setting the treatment intensity as the fraction of a firm's preexisting employee connections to the media and the public sector in 2015. The sum of the two treatment intensities equals that used in Panel A of Table 6.

[Table 8 about here]

[31] 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.

The estimation results in Panel A of Table 8 show that all the results still hold if we separately examine connections to the two sectors affected by the Act. The coefficient estimates of *Act Exposure* remain positive and significant. Before the Act, employee connections to the media have a more substantial positive impact on the employer'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%. These results reinforce the causal role of employee professional connections with the media and the public sector.

We next consider some specific economic benefits that employers can derive from their employee social capital based on connections with the media and the public sector. A large body of literature suggests that media coverage affects firm value by facilitating information dissemination and influencing investor sentiment. For example, Tetlock (2007) finds that negative words used in a *Wall Street Journal* column about the stock market predict aggregate market performance. Tetlock, Saar-Tsechansky, and Macskassy (2008) show that negative words in firm-specific news stories capture firm fundamentals, which investors quickly incorporate into stock prices. Using exogenous scheduling of *Wall Street Journal* columnists, Dougal et al. (2012) establish a causal relation between financial reporting and stock market performance. Liu, Sherman, and Zhang (2014) find that pre-IPO media coverage relates positively to the stock's long-term value and liquidity by increasing investor recognition. Ahern and Sosyura (2014) find evidence that firms actively manage media coverage by originating and disseminating information to the media to influence their stock prices. Studies have also emphasized the role of local media. Engelberg and Parsons (2011) use differences in local media coverage to identify a causal impact of local media on investor trading. In addition, Gurun and Butler (2012) document that media tend to display "positive slant" toward local companies by using fewer negative words in news articles and that the positive slant strongly relates to firm equity values.

Similar to the positive slant when local media report news about local companies, media connections by a firm's employees may foster goodwill and closer relationship with journalists, leading to positive slant in news coverage and a positive effect on firm valuation. For instance, reporters that are well connected to a firm's employees may be biased positively toward the firm due to increased trust and thus may be more likely to promote positive news about the firm. Media connections might also facilitate active media management as in Ahern and Sosyura (2014), so firms may strategically influence the timing and content of media coverage. Therefore, we expect that, all else equal, employee connections with the media promote 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—that is derived from connections with the media sector—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.[32] *Act Exposure* is the fraction of a firm's employee social capital due to connections to the media sector in 2015, $ESC_{2015}^{Media}/ESC_{2015}$. The dependent variable in column (1) is the log of a 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 in a given year that are associated with a positive sentiment (according to RavenPack's BMQ sentiment series) as the dependent variable; results are reported in column (2).

In keeping with the notion that connections with the media promote news coverage, we obtain a significant and positive coefficient on *Act Exposure*. The economic magnitude of the estimated effect is sizable. Before the Act, a one standard deviation increase in *Act Exposure* increases news articles by 13% (=0.029×4.495) and the fraction of positive media coverage by 1%. In addition, consistent with the earlier finding that the Act undermines the positive value of connections, the estimated coefficient for *Act Exposure*×*Post* is negative for both columns. Notably, the estimated effect on the positive slant is almost negligible after the Act. Taken together, these findings suggest that connections to the media lead to more frequent media coverage and to 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 next turn to investigating the economic benefits of employee social capital based on 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 a connected CEO. Similarly, we expect that employees well

[32] 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 instead include the year of 2016.

connected with the public sector may also enhance the ability of their firms to obtain more government contracts, thereby improving their firm's performance.

To assess this prediction, we use the same dataset as in Schoenherr (2019) and examine the effect of a firm's employee connections with the public sector on government procurement contracting outcomes.[33] 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 annual public procurement contracts, both in terms of the number of newly signed contracts and the monetary value in Korean won. The estimated effect is much larger before the Act and is reduced by about half after the Act. The estimated effects are economically sizable. For example, in column (3), a one standard deviation increase in $ESC_{2015}^{Public}/ESC_{2015}$ leads to a 6.8% increase in contract volume before the Act and only 3.4% after the Act.

Overall, the evidence in Tables 6–8 supports the hypothesis that the employee social capital derived from connections with the media and the public sector positively impacts firm performance. Consistent with the social capital literature, the positive impact likely derives from information dissemination, trust, and/or contract execution, which in turn benefits firm value. A negative shock to employee social capital adversely impacts these economic benefits, resulting in a decline in the relation between employee social capital and firm value.

5. Further Evidence on Connections to Economically Related Industries

We have provided evidence suggesting that professional connections translate to superior performance. To further characterize the relation between employee social capital and firm performance, and to bolster support for the validity of our natural experiment, this section provides additional evidence on employee connections to economically related industries.

5.1. Connections to Customer Industries

Although the relation between employee social capital and firm performance is not confined to the consumer channel, consumers constitute a natural group of business contacts to validate such a relation, given that their purchasing behavior clearly affects a company's financial performance and, ultimately, firm value. For example, employees who are well connected to

[33] 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#.

individuals in customer industries may have an advantage in identifying and establishing new customers, strengthening relationships with existing customers, helping their firm stay informed about trade terms, and managing inventories more effectively. Whereas similar benefits may arise from connections to supplier industries, we expect connections to customer industries to be relatively more valuable for several reasons. First, given the importance of revenues from customer sales to firm profitability, we expect that the ability to maintain good relations with existing customers and, especially, to identify new customers is more important to profitability than similar abilities made possible by connections to suppliers. In the parlance of our paper, being valued by customers seems more important than being valued by suppliers. Second, extant evidence similarly suggests such an asymmetry. For example, Hertzel et al. (2008) find that firms experience contagion effects following the financial distress of their customers, but not that of suppliers.

[Table 9 about here]

To identify customer and supplier industries, we measure vertical relatedness using detailed Make-and-Use tables obtained from the Economic Statistics System provided by the Bank of Korea.[34] We then calculate $ESC^{Customer}$ using only the connections to employees in customer industries, weighted by the fraction of an upstream industry's total production used by a downstream industry. We use a similar method to calculate $ESC^{Supplier}$. Panel A of Table 9 reports the results estimating the effects of connections with employees in customer and supplier industries. Consistent with our expectations, $ESC^{Customer}$ displays a significant positive impact on *ROA* and *Sales Growth*, whereas $ESC^{Supplier}$ does not. The estimated effect of connections to customers is economically sizable, translating to an increase of 0.6 percentage points in *ROA* and an increase of 1.5 percentage points in *Sales Growth* when $ESC^{Customer}$ increases by one standard deviation (0.044). These findings highlight the significance of being valued by customers.

[34] We use the 2014 Make-and-Use tables, which cover 384 commodities and 328 industries. The Make table is a commodity-by-industry matrix that provides the dollar value of each commodity produced by each industry as output, and the Use table is a commodity-by-industry matrix that records the dollar value of each commodity purchased by each industry as input. We conform to Frésard, Hoberg, and Phillips (2020) to construct an industry-by-industry flow matrix in which a cell (i, j) indicates the dollar flows from an upstream industry i to a downstream industry j based on the 328 industries. Dividing each cell by the total production of industry i, we construct a new matrix in which each cell records the fraction of industry i's total production used by industry j. Following Fan and Goyal (2006), we use 1%, 3%, and 5% as numerical thresholds to define a vertically related industry-pair: If the flow of goods from industry i to j exceeds the threshold, we define industry j as downstream (customer industry) to industry i.

Next, we examine channels through which connections to customers may lead to improvements in firm performance. Dass et al. (2014) provide evidence suggesting that connections with customer industries allow suppliers to bargain for better trade credit terms and to achieve shorter cash conversion cycles. Motivated by their findings, we examine whether connections to customer industries are associated with a reduced cash conversion cycle (CCC), defined as days in account receivable plus days in inventory minus days in account payable. Panel B of Table 9 reports the results. We find that connections with customer industries predict cash conversion cycles negatively and significantly; the negative coefficient on ESC (-314.32) in column (1) indicates that an increase in ESC of one standard deviation from its mean shortens the cash conversion cycles by more than 12 days. As shown in column (3), this effect comes mainly from fewer days in inventory, which serves as a source of competitiveness for firms.

5.2. Connections to the Investment Banking Industry

There is substantial evidence that firms have improved access to capital and face lower financing costs when they are better connected with bankers or located in areas with higher social capital. For example, repeated borrowing from the same lender translates into lower loan spreads (Bharath et al. (2011)), and bankers extend better loan contract terms and larger loan sizes to firms where they share a social tie with the firm's executives (Engelberg, Gao, and Parsons (2012)). Using executive turnover caused by death, Karolyi (2018) shows that borrowers are more likely to choose personally connected bankers, which results in lower spreads and larger loan amounts. Haselmann, Schoenherr, and Vig (2018) document that common membership at an elite club in Germany increases lending volume granted by connected banks and overall leverage for the borrower firms. Relatedly, Kuchler et al. (2020) show that firms located in areas to which institutional investors are more socially connected obtain better investments. Hasan et al. (2017) show that firms headquartered in high-social-capital counties face lower bank loan spreads and lower at-issue bond spreads.

Motivated by these findings, we investigate employee connections to the financial sector. Given the increasing importance of public bonds as a source of financing to Korean listed firms in our sample period, we focus on connections to the investment banking industry, whose major role is to underwrite bonds.[35] Bharath, Sunder, and Sunder (2008) show that bond investors are more sensitive than banks in pricing borrower risks into interest spreads. Accordingly, if employee connections with the investment banking industry enhance trust and bridge the information gap between bond investors and borrowers, we expect firms with more investment banking connections to have greater access to the public bond market and face lower spreads when issuing corporate bonds. Specifically, we calculate $ESC^{I\text{-}banks}$, which is 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.[36] As the investment banking industry plays an integral role in bond underwriting, we expect that employee connections to this industry will increase performance and firm value by making public bond issuance more feasible and less costly.

[Table 10 about here]

Panel A of Table 10 reports the results of estimating the effects of connections with employees in the investment banking industry on firm performance. Consistent with our expectation, connections with the investment bankers are associated with superior firm performance across all three performance measures and are statistically significant at the 1% level. A one standard deviation increase in $ESC^{I\text{-}banks}$ 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*. These findings illustrate that being valued by investment bankers can be leveraged into better corporate outcomes.

We further investigate potential channels through which employee connections to the investment banking industry enhance firm value and performance. We start by testing whether these connections are associated with lower at-issue bond spreads using a comprehensive sample of 480 bond issues in our sample period. In column (1) of Panel B in Table 10, we examine the at-issue bond yield spread, which is defined as the difference between the bond's yield at issuance

[35] 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)).

[36] Firms that belong to the investment banking industry can neither take deposits nor make loans, analogous to the firewall between commercial banking and investment services by the Glass-Steagall Act in the US. The Financial Investment Services and Capital Market Act defines the business scope of the investment banking industry (KSIC 6612) as investment brokerage, investment banking, investment advisory service, and investment trading; see, for example, https://elaw.klri.re.kr/eng_service/lawView.do?hseq=43324&lang=ENG

and the mark-to-market benchmark yield of a corporate bond portfolio for the same maturity and credit rating.[37] Based on the estimates, we observe a negative and significant (at the 5% level) coefficient of $ESC^{I\text{-}bank}$. A one standard deviation increase in $ESC^{I\text{-}banks}$ from its mean is associated with a reduction of 7 basis points in at-issue bond yield,[38] relative to a sample average benchmark corporate bond yield of 2.7%. The estimate is comparable to that in Hasan et al. (2017), who show that better social capital is associated with a reduction of 7.98 basis points in bond spreads.

To shed light on the relation between $ESC^{I\text{-}banks}$ and credit availability, in column (2) and (3), we turn to the full sample and investigate whether connections with the investment banking industry are associated with a higher likelihood and greater volume of public bond issuance. The conditional logit regression shows that $ESC^{I\text{-}banks}$ is positively related to the likelihood of a firm issuing public bonds in a given year, with significance at the 1% level. Furthermore, borrowers with a one standard deviation higher $ESC^{I\text{-}banks}$ have 9.6% larger bond issuance amounts. Finally, in column (4) and (5), we examine whether the observed increases in corporate bond issuance reflect a substitution for bank loans and other sources of credit, by exploring effects on total debt and leverage. The significant positive coefficients of $ESC^{I\text{-}banks}$ suggest that the increase in credit availability through public bond issuance does not constitute a mere substitution for alternative sources of debt.

Our evidence thus extends the growing literature on relationship lending to direct financing through corporate bonds. Our results suggest that employee social capital due to connections with the investment banking industry is associated with lower bond yields, a higher likelihood of bond issuance, and larger bond issuance amounts. These aspects potentially add to the financial flexibility of the firm and act as a source of value creation.

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[37] The way we measure the bond yield spread controls for credit ratings and the macroeconomic conditions. This adheres to how Korean issuers tap the market prior to issuance and how they disclose the terms of bonds to the market. Take one statement from the bond issuance disclosure for instance, "yields at the issue date will be determined by AA0 (mark-to-market benchmark yields) + 3 bps." The firm-level and issuance-level controls largely follow Bharath et al. (2011), Engelberg, Gao, and Parsons (2012), 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.

[38] Notably, among employees of all job levels, we find that the connections by the rank and file employees are a major contributor to the reduction in bond spreads. Thus, our results seem to be consistent with the notion that personal connections with the borrower's employees assist investment bankers in their due diligence investigation and information acquisition process.

6. Conclusion

This paper provides the first 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 novel data from a professional networking app with broad coverage of individual connections to measure firm-level employee social capital. Consistent with the literature on social capital, our analysis reveals that employee social capital is robustly and positively associated with firm performance, as measured by *Tobin's q*, *ROA*, and *Sales Growth*. Our network data uniquely records the directions of connections, allowing us to assess if one of the two involved parties values the other side more and to investigate whether the directions of connections matter. Our results show that the positive effect on firm performance mainly arises from external stakeholders remembering and valuing a firm's employees.

To establish a causal interpretation of our results, we exploit a negative shock to the professional networks in the context of the 2016 enactment of the Anti-Graft Act. Our evidence suggests that firms with employee connections more exposed to the Act derive lower value from employee social capital after the Act relative to firms that are less exposed. The results support the notion that higher employee social capital contributes to better 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 professional network data cover employees at all job levels. Our measure of employee social capital thus addresses a limitation of existing corporate finance studies that have focused mainly on managerial networks. 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.

An implication of our research is that social ties and professional connections can be leveraged in business settings. Business creation and growth are not isolated processes affected autonomously by a focal firm, but rather collective processes that take place within the interwoven social and economic structures of our increasingly global society. Personal relationships and business contacts endow individual employees (and their firms) with resources and goodwill, 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 registered 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 in other firms registered 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 nonreciprocal in-degree	The average *Nonreciprocal in-degree*—the number of employees of other firms who have registered 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 registered by the corresponding employee, but not reciprocal—across app-user employees of firm i in year t
ESC nonreciprocal in-degree of App-users	The average *Nonreciprocal in-degree* across app-user employees of firm i in year t
ESC nonreciprocal in-degree of Non-app-users	The average *Nonreciprocal in-degree* across non-app-user employees of firm i who are in the network 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: Total	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
$ESC^{Customer}$($ESC^{Supplier}$)	*ESC in-degree* using only the connections to employees in customer (supplier) industries, weighted by the fraction of an upstream industry's total production used by a downstream industry
$ESC^{I\text{-}banks}$	*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

Other variables	
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 beginning-of-period 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
Volatility	Stock return volatility during the past 24 months of a firm
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 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%
ln(1+*Positive Media Coverage Ratio*)	Log of one plus 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 firm total assets of firm i in year t, from the Korea online e-Procurement Service

ln(1+*Sales*)	Log of one plus sales
CCC	Cash conversion cycle = days in inventory + days in AR - days in AP
Days in AR	Collection period = 365 days / accounts receivables turnover, where accounts receivables turnover is a ratio of sales to accounts receivables
Days in Inventory	Inventory conversion period = 365 days / inventory turnover, where inventory turnover is a ratio of COGS to inventory
Days in AP	Payable period = 365 days / accounts payables turnover where accounts payables turnover is a ratio of COGS to accounts payables
At-issue Bond Spreads	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)
Bond Issue	An indicator variable that takes the value of one if a firm has positive bond issuance in a given year
ln(1+*Total Issue Amount*)	Log of one plus the total amount of bond issuance of a firm in a given year
ln(1+*Total Debt*)	Log of one plus total debt (sum of total long-term interest-bearing debt and current long-term debt)
PPENT	Net property, plant, and equipment normalized by total assets
Modified Z-Score	Modified Altman's z-score according to Campello, Graham, and Harvey (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 KRW)

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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Figure 1. The Professional Business Card Networking App—Remember

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*

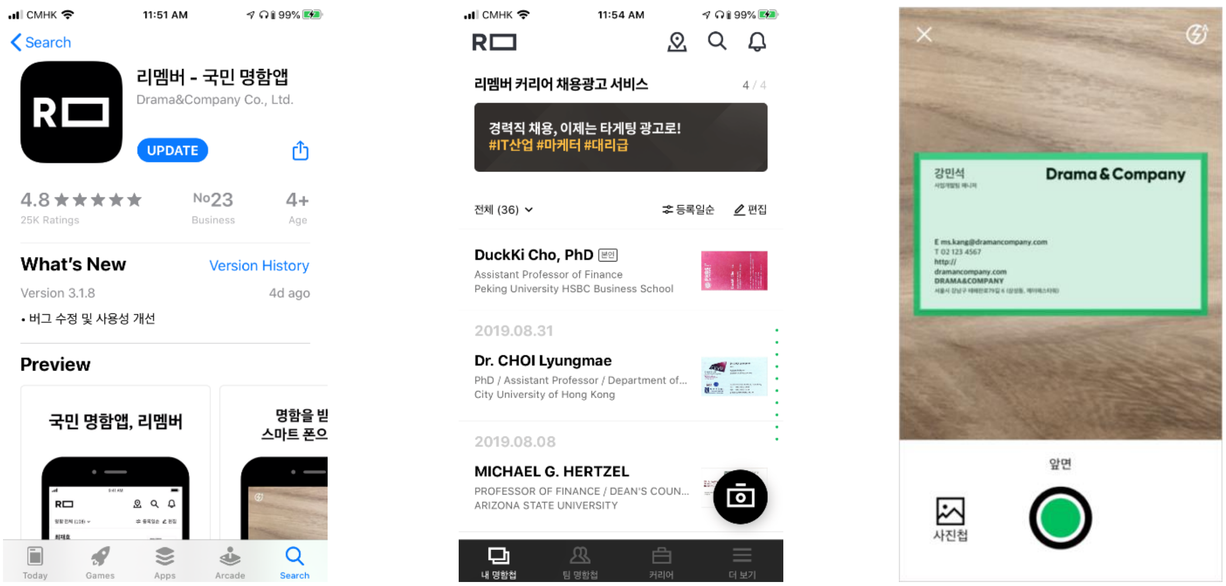


Figure 2. Construction of Firm-level ESC from Employee-level Network Measures

This figure illustrates the construction of firm-level *ESC in-degree* and *ESC out-degree*. Since not all of the firm's employees are part of the business card exchange network, our strategy to identify firm-level ESC is to use averages of the employee-level degrees as representative of the typical public firm employee. To measure firm-level *ESC in-degree*, we average over the *In-degree* of the users and non-users in the network, because they are all capable of being registered 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 over the *Out-degree* of app-users, since these are the only employees we can observe as registering 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.

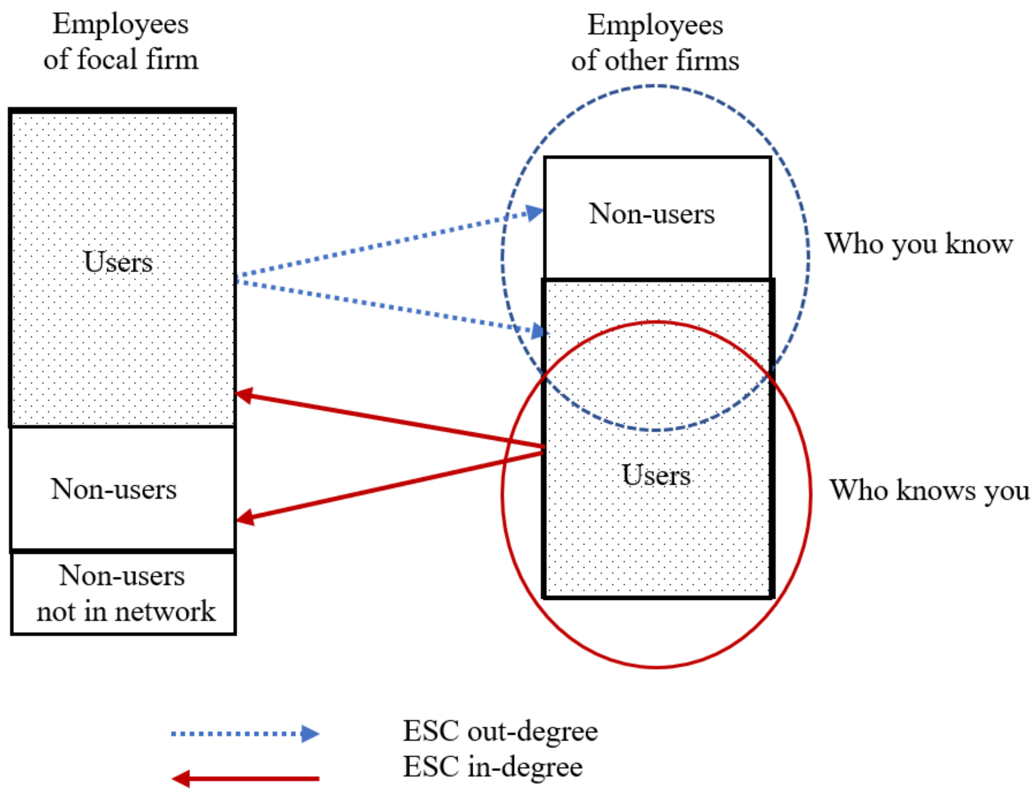


Figure 3. Effect of the Exposure of Employee Social Capital to the Act on Firm Performance Year by Year

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

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

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.

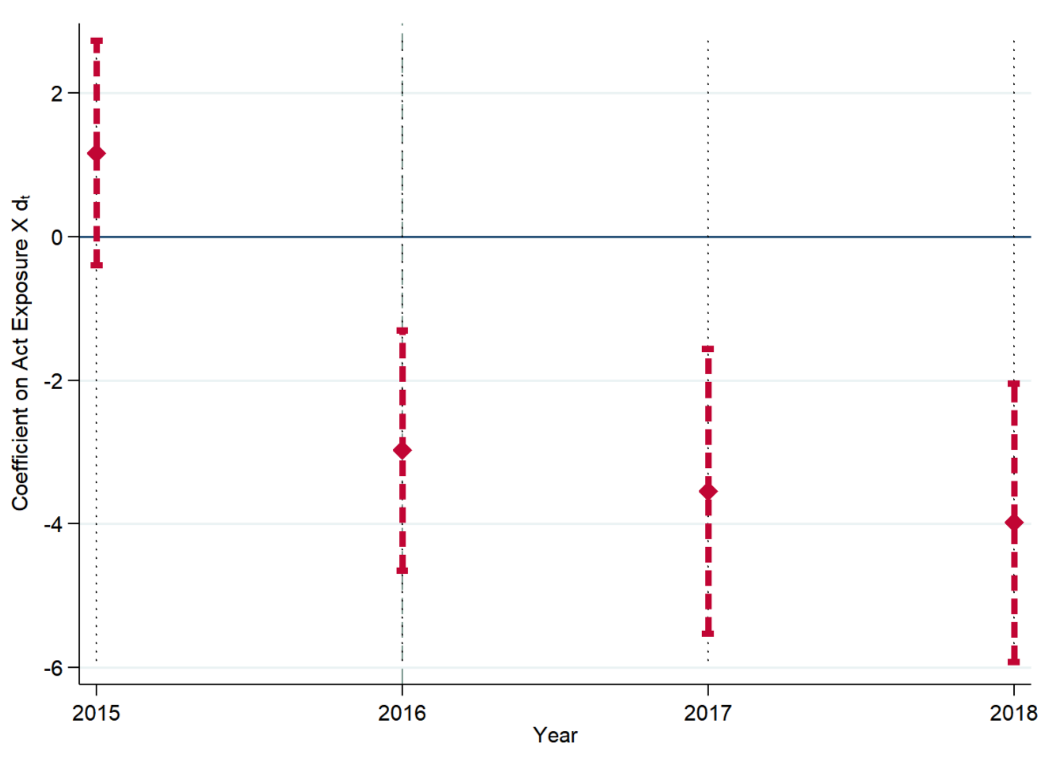


Table 1. Descriptive Statistics: Business Card Exchange Network and Employee-level Connections

Panel A provides detailed information for our business card exchange network data obtained from a professional networking app, Remember. We obtain de-identified data on all business cards registered as of December 31, 2018. From the raw data, we exclude connections that involve any individual who does not have a company name on their cards, or whose listed email domain is inconsistent with their company, or whose company does not have a Korea Investors Service (KIS) firm identifier. We include only connections between employees with different KIS firm identifiers. Since our research focuses on the outcomes of public firms, we obtain our main sample by keeping only the connections in which at least one of the two individuals involved 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 main sample. *In-degree,* which measures "who knows you," is the number of employees of other firms who have registered the corresponding employee as a business contact. *Out-degree,* which measures "who you know," is the number of business contacts of other firms registered 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 levels 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 in KIS	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 levels						
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 employees	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. To reduce noise in our firm-level ESC measures, we restrict our sample to firm-year observations with at least 10 employees observed in the network. 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. The symbols ***, **, 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 KRW million)	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*) (in KRW million)	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 directions of connections. We estimate the following specification:

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

where $ESC_{i,t\text{-}1}$ is the measure of one-year lagged firm-level employee social capital using *ESC total degree* of firm i in year $t\text{-}1$; $X_{i,t\text{-}1}$ is a set of lagged firm-level control variables commonly included in the literature (see, e.g., 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		
Dependent Variable =	*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)
Constant	2.005***	-0.131***	-1.500***
	(0.286)	(0.020)	(0.111)
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 directions 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 with p-values in square brackets. Panel B presents robustness checks. We exclude reciprocal connections by considering only nonreciprocal connections in calculating *ESC nonreciprocal in-degree* and *ESC nonreciprocal out-degree*. We also focus separately on the nonreciprocal in-degree among app-user employees and non-app-user employees. 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. The symbols ***, **, 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")		
Dependent Variable =	*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)
Constant	1.811***	-0.141***	-1.548***	1.834***	-0.129***	-1.447***
	(0.290)	(0.021)	(0.108)	(0.286)	(0.021)	(0.122)
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

Dependent Variable =	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
	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
H_0: *ESC in-degree – ESC out-degree* = 0	0.491	0.027	0.123			
[p-value]	[0.000]	[0.001]	[0.000]			

	ESC nonreciprocal in-degree of App-User Employees			*ESC nonreciprocal in-degree of Non-App-User Employees*		
ln(1+*ESC*)	0.126**	0.014***	0.018	0.427***	0.029***	0.135***
	(0.063)	(0.005)	(0.015)	(0.110)	(0.009)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	4,994	4,994	4,994	5,340	5,340	5,340
Adjusted R^2	0.253	0.143	0.035	0.252	0.151	0.039

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

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 levels. In Panel A, we divide a firm's employees in the network based on whether they belong to the executive management into Executives (chairman, vice chairman, president, deputy president, executive and senior vice president) and Non-Executive Employees (the 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 further divide Non-Executive Employees based on whether they have a managerial title into Non-Executive Managers (vice president, general manager, department head, deputy general manager, manager, section head) and 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. The symbols ***, **, 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.

Dependent Variable =	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Dividing all Employees into Executives or Not						
	Executives			*Non-Executive Employees*		
ln(1+*ESC*)	0.191***	0.013***	0.051***	0.201**	0.032***	0.093***
	(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	5,320	5,320	5,320	5,340	5,340	5,340
Adjusted R^2	0.251	0.151	0.037	0.248	0.154	0.037
Panel B. Dividing Non-Executive Employees into Managers or Not						
	Non-Executive Managers			*Rank and File Employees*		
ln(1+*ESC*)	0.160*	0.029***	0.070***	0.114	0.025***	0.086***
	(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	5,287	5,287	5,287
Adjusted R^2	0.248	0.154	0.036	0.249	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:

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

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 takes the value of one during and after the enactment year (2016–2018) and zero otherwise. d_t is an indicator variable for year t. $X_{i,t-1}$ 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. The symbols ***, **, 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

Dependent Variable =	*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)
Constant	1.372***	1.554***	1.557***	2.157***
	(0.314)	(0.298)	(0.298)	(0.252)
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 2-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 (with above-median exposure) and the control group (with below-median exposure) in year 2015. We also report the mean difference between the two groups and their differences with 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. The symbols ***, **, 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

Dependent Variable =	*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 industries (KSIC 58, 59); column (3) further drops firms that belong to the supplier and customer industries of the media and public sectors using the detailed Make-and-Use tables and an algorithm we will describe in detail in Section 5.1; column (4) focuses on a subsample with positive exposure of employee social capital to the Act. Standard errors in parentheses are clustered at the firm level. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel C: Subsamples

Dependent Variable =	*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)
Book Leverage	0.192	0.204	0.521**	0.146
	(0.187)	(0.193)	(0.211)	(0.206)
ln(1+*Assets*)	-0.139***	-0.128***	-0.140***	-0.142***
	(0.025)	(0.025)	(0.032)	(0.027)
Volatility	3.369***	3.303***	3.201***	3.533***
	(0.456)	(0.478)	(0.555)	(0.541)
Age	-0.005***	-0.005***	-0.003*	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(1+*Emp*)	0.074***	0.062**	0.076**	0.094***
	(0.025)	(0.026)	(0.034)	(0.027)
Constant	1.266***	1.101***	1.116***	1.349***
	(0.318)	(0.324)	(0.397)	(0.346)
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

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. The symbols ***, **, 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 (2-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 (2-digit SIC) level. We exclude penny stocks with stock price less than 1,000 KRW (about 0.9 USD) as of June 28, 2016, one month prior to the court ruling date.

	$Act\ Exposure = ESC_{2015}^{Act}/ESC_{2015}$					
	Below Median	Above Median	Diff Above − Below	P-value	Correlation Coefficient	P-value
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Cumulative CAPM-adjusted Abnormal Returns						
[-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						
[-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:

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

where $Y_{i,t}$ is *Tobin's q*, *Act Exposure* is $ESC^{Media}_{i,2015}/ESC_{i,2015}$ for columns (1)–(2) and $ESC^{Public}_{i,2015}/ESC_{i,2015}$ for columns (3)–(4); $ESC_{i,2015}$ is *ESC in-degree* in 2015; $ESC^{Media}_{i,2015}$ and $ESC^{Public}_{i,2015}$ are *ESC in-degree* in 2015 due to connections to the media and the public sector. $Post_t$ is an indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. $X_{i,t-1}$ 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 economic channels behind the value of connections with the media and the public sector. *Act Exposure* is $ESC^{Media}_{i,2015}/ESC_{i,2015}$ for columns (1)–(2) and $ESC^{Public}_{i,2015}/ESC_{i,2015}$ for columns (3)–(5). Dependent variables are measures of media coverage in columns (1)–(2). *Media Coverage* in column (1) is 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%. *Positive Media Coverage Ratio* in column (2) is 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 new 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. The symbols ***, **, 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 = $ESC^{Media}_{i,2015}/ESC_{i,2015}$		*Act Exposure* = $ESC^{Public}_{i,2015}/ESC_{i,2015}$	
Dependent Variable =	*Tobin's q*			
	(1)	(2)	(3)	(4)
Act Exposure	8.016***	8.070***	6.181**	6.303***
	(1.591)	(1.588)	(2.414)	(2.407)
Act Exposure × *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)
Constant	1.735***	1.919***	1.460***	1.647***
	(0.306)	(0.288)	(0.334)	(0.317)
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 Channels

	Act Exposure = $ESC_{2015}^{Media}/ESC_{2015}$		*Act Exposure* = $ESC_{2015}^{Public}/ESC_{2015}$		
Dependent Variable =	ln(1+*Media Coverage*)	ln(1+*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	4.495***	0.363**	3.756***	19.837***	0.091***
	(1.564)	(0.144)	(1.111)	(5.295)	(0.027)
Act Exposure × *Post*	-2.991**	-0.263*	-1.878**	-9.700**	-0.040*
	(1.445)	(0.139)	(0.839)	(4.443)	(0.022)
Tobin's q	0.116***	0.010***	-0.003	-0.015	-0.000*
	(0.017)	(0.003)	(0.008)	(0.041)	(0.000)
Book Leverage	0.131	-0.001	0.094	0.442	-0.003
	(0.158)	(0.019)	(0.125)	(0.538)	(0.002)
ROA	-0.931***	-0.084***	-0.191*	-1.668***	-0.005**
	(0.195)	(0.021)	(0.105)	(0.521)	(0.002)
R&D	0.611**	0.018	-0.367**	-1.883**	-0.013***
	(0.245)	(0.030)	(0.159)	(0.772)	(0.005)
ln(1+*Sales*)	0.267***	0.016***	0.030***	0.229***	-0.000
	(0.025)	(0.002)	(0.011)	(0.055)	(0.000)
Volatility	-0.204	-0.013	0.143	1.049*	0.005
	(0.181)	(0.024)	(0.104)	(0.596)	(0.003)
Age	0.009***	0.000**	0.001	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.004)	(0.000)
ln(1+*Emp*)	0.069***	0.007***	0.107***	0.576***	0.002***
	(0.024)	(0.002)	(0.014)	(0.066)	(0.000)
Constant	-3.992***	-0.258***	-1.146***	-6.855***	-0.011***
	(0.278)	(0.028)	(0.150)	(0.736)	(0.003)
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	0.177	0.241	0.264	0.194

Table 9. Employee Social Capital with Customer and Supplier Industries

Panel A reports OLS regression estimates on the relation between a firm's ESC measured by connections with customer and supplier industries and its performance in the following year. Firm-level employee social capital takes the value of *ESC in-degree with Customers* in columns (1)–(3) and *ESC in-degree with Suppliers* in columns (4)–(6). We calculate *ESC in-degree with Customers* using only the connections to employees in customer industries, weighted by the fraction of an upstream industry's total production used by a downstream industry. *ESC in-degree with Suppliers* is computed similarly. 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 columns (1) and (4), *ROA* in columns (2) and (5), and *Sales Growth* in columns (3) and (6). Panel B reports economic channels through which employee social capital with customer industries is valuable to firms. Firm-level employee social capital takes the value of *ESC in-degree with Customers*. Dependent variables are cash conversion cycle (*CCC*), days in account receivable (*Days in AR*), days in inventory (*Days in Inventory*), and days in account payable (*Days in AP*). Standard errors in parentheses are clustered at the firm level. The symbols ***, **, 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 Customers vs. ESC in-degree with Suppliers

	ESC in-degree with Customers			*ESC in-degree with Suppliers*		
Dependent Variable =	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	l(1)	(2)	(3)	(4)	(5)	(6)
ln(1+*ESC*)	0.286	0.144***	0.366***	1.433	0.103	0.176
	(0.673)	(0.053)	(0.122)	(1.359)	(0.105)	(0.246)
R&D	4.663***	-0.181***	0.430***	4.678***	-0.178***	0.437***
	(0.575)	(0.034)	(0.125)	(0.576)	(0.033)	(0.124)
Book Leverage	0.178	-0.136***	0.081	0.181	-0.137***	0.079
	(0.178)	(0.016)	(0.054)	(0.179)	(0.016)	(0.054)
ln(1+*Assets*)	-0.130***	0.010***	-0.007	-0.132***	0.010***	-0.008
	(0.023)	(0.002)	(0.008)	(0.023)	(0.002)	(0.008)
Volatility	3.516***	-0.100***	0.062	3.510***	-0.103***	0.056
	(0.389)	(0.026)	(0.079)	(0.389)	(0.026)	(0.079)
Age	-0.006***	-0.000***	0.000	-0.006***	-0.000***	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ln(1+*Emp*)	0.060***	0.009***	-0.010*	0.062***	0.009***	-0.008
	(0.023)	(0.002)	(0.006)	(0.023)	(0.002)	(0.006)
Constant	2.062***	-0.124***	-1.472***	2.063***	-0.125***	-1.474***
	(0.276)	(0.020)	(0.114)	(0.276)	(0.020)	(0.115)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340	5,340	5,340	5,340
Adjusted R^2	0.247	0.149	0.034	0.247	0.147	0.033

Panel B: ESC in-degree with Customers and Cash Conversion Cycle

Dependent Variable =	*CCC*	*Days in AR*	*Days in Inventory*	*Days in AP*
	(1)	(2)	(3)	(4)
ln(1+$ESC^{Customer}$)	-314.322***	-86.867**	-167.665***	67.576**
	(67.290)	(37.963)	(45.210)	(32.103)
R&D	300.699***	94.854***	229.746***	51.795***
	(76.767)	(31.004)	(53.030)	(19.046)
Book Leverage	77.012***	63.944***	18.152	-6.616
	(23.859)	(15.403)	(13.810)	(7.848)
ln(1+*Assets*)	-9.115***	-1.382	-4.425**	3.733***
	(2.948)	(1.765)	(1.788)	(1.163)
Volatility	49.445	76.726***	-8.217	13.318
	(45.734)	(27.996)	(21.721)	(12.077)
Age	0.049	0.210*	-0.159	-0.059
	(0.176)	(0.110)	(0.106)	(0.057)
ln(1+*Emp*)	-0.148	-7.484***	4.008**	-3.428***
	(2.680)	(1.718)	(1.640)	(1.202)
Constant	836.218***	560.559***	512.919***	379.605***
	(34.827)	(19.455)	(22.634)	(11.589)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	4,973	5,325	5,023	5,125
Adjusted R^2	0.173	0.113	0.222	0.072

Table 10. Employee Social Capital with the Investment Banking Industry

Panel A reports OLS regression estimates on the relation between $ESC^{I\text{-}banks}$, 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 columns (1) and (4), *ROA* in columns (2) and (5), and *Sales Growth* in columns (3) and (6). Panel B reports how $ESC^{I\text{-}banks}$ relates to access to the public bond market and the bond spread at issuance. The dependent variable in column (1) is bond yield spread 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). The dependent variable in column (2) is a dummy variable if a firm has positive bond issuance in that year. In the conditional logit regression, we condition the likelihood on the number of bond issues in each industry-year pair; hence, only industry-year pairs with at least one bond issue during the sample period are included in the conditional logit estimation. The dependent variable in column (3) is the natural logarithm of one plus the amount of bond issuance of a firm in that year. The dependent variables in columns (4) and (5) are the natural logarithm of one plus the total debt, and book leverage. Standard errors in parentheses are clustered at the firm level, except for column (2) which is clustered at the industry level. The symbols ***, **, 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

	ESC in-degree with the Investment Banking Industry		
Dependent Variable =	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)
ln(1+$ESC^{I\text{-}banks}$)	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)
Constant	1.903***	-0.131***	-1.488***
	(0.274)	(0.020)	(0.113)
Fixed Effects	Ind × Year	Ind × Year	Ind × Year
Observations	5,340	5,340	5,340
Adjusted R^2	0.270	0.151	0.035

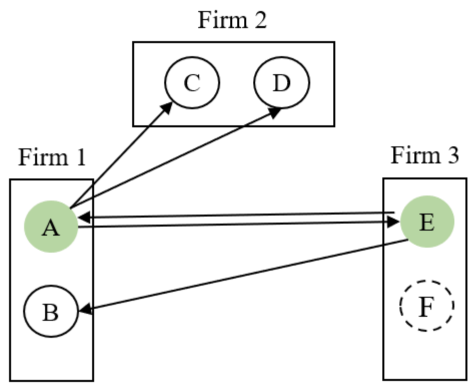
Panel B: ESC in-degree with the Investment Banking Industry, Bond Spreads, and Access to Public Bond Market

Dependent Variable =	*At-issue Bond Spreads*	*Bond Issue*	ln(1+*Total Issue Amount*)	ln(1+*Total Debt*)	*Book Leverage*
	(1)	(2)	(3)	(4)	(5)
ln(1+$ESC^{I\text{-}banks}$)	-0.454**	3.016***	0.563*	2.277***	0.061***
	(0.216)	(0.695)	(0.313)	(0.690)	(0.017)
PPENT	-0.543***	0.085	-0.225	3.409***	0.100***
	(0.165)	(1.227)	(0.261)	(0.537)	(0.016)
ln(1+Sales)	0.026	1.077***	0.616***	1.554***	0.017***
	(0.027)	(0.150)	(0.075)	(0.081)	(0.002)
ROA	0.675	3.694**	0.262	3.001***	-0.024
	(0.517)	(1.744)	(0.471)	(1.132)	(0.033)
Volatility	1.614	-5.521*	0.051	6.530***	0.151***
	(1.196)	(3.313)	(0.357)	(1.307)	(0.036)
Age	0.002**	-0.008	-0.008***	-0.020***	-0.001***
	(0.001)	(0.006)	(0.003)	(0.006)	(0.000)
ln(1+Emp)	-0.043*	0.434***	0.157**	-0.066	0.002
	(0.023)	(0.167)	(0.069)	(0.106)	(0.003)
Tobin's q	-0.162*	-0.365***	0.033	-0.276***	-0.002
	(0.089)	(0.138)	(0.028)	(0.088)	(0.002)
Modified Z-Score	0.020	-0.353*	-0.283***	-1.750***	-0.042***
	(0.039)	(0.208)	(0.042)	(0.106)	(0.003)
R&D	1.234	2.927	1.608***	1.055	-0.012
	(1.083)	(6.004)	(0.397)	(1.235)	(0.031)
Capital Expenditure	-0.940**				
	(0.470)				
Current Ratio	-0.090*				
	(0.049)				
ln(1+ *Maturity*)	0.043				
	(0.050)				
ln(1+ *Issue Amount*)	0.003				
	(0.033)				
Constant	-0.024		-7.451***	-15.553***	-0.162***
	(0.403)		(0.819)	(0.842)	(0.024)
Fixed Effects	Ind	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Observations	480	3,718	5,330	5,330	5,330
Adjusted/Pseudo R^2	0.314	0.493	0.261	0.379	0.294

Internet Appendix I: An Example for the Network Analysis

We use an example to illustrate the data structure of our business card exchange network and the method for constructing the firm-level employee social capital measures. 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 registers the card to the employee (Employee_ID_To) whose card is registered. For example, the first entry shows that employee A, a staff of firm 1, has registered a card of employee C, a staff of firm 2. This link counts toward the out-degree for A and in-degree for C. Based on the connection-level data, we construct the firm-level employee social capital (ESC) measures. *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 has *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, which gives *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. 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 figure, 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 link 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*

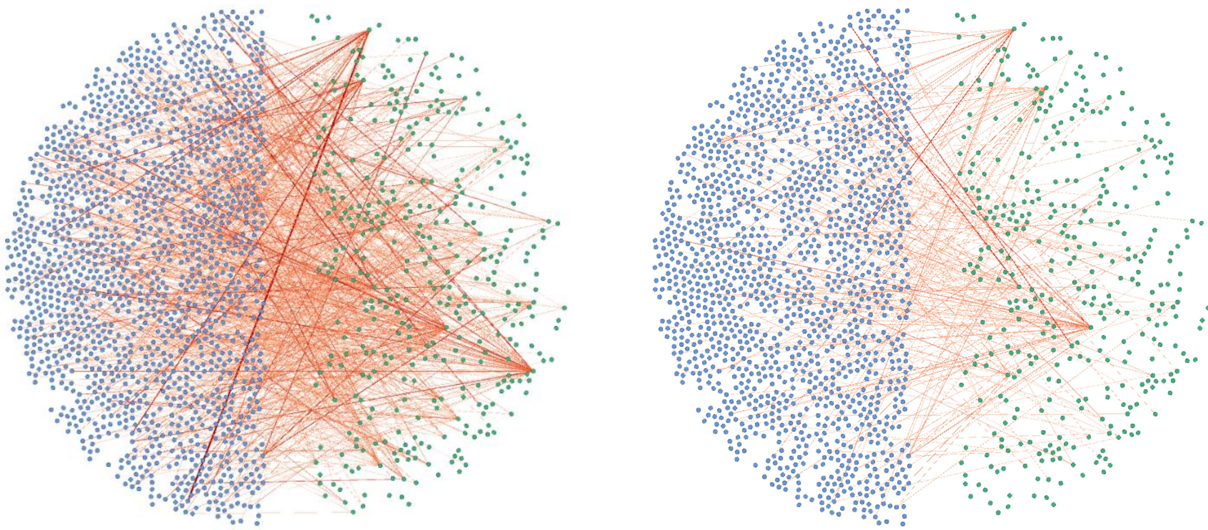


Table IA.1. Descriptive Statistics of the Business Card Exchange Network by Sector

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*
Total	1,016,023	119,423	1,866	3.676	30.953	6.836
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: Total* 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, firms in the financial sector (SIC codes 61, 62, 65, 67), or firms in the top three percentile of total assets distribution. In both Panels A and B, 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 and common support. Standard errors in parentheses are bootstrapped based on 500 replications with replacement. The symbols ***, **, 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")		
Dependent Variable =	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
ln(1+*ESC: Excl. Sales*)	0.385***	0.020***	0.094***	0.050*	0.003	0.001
	(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	0.038	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: Total*)	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

Dependent Variable =	*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 Differences in the Role of Labor

This table shows cross-sectional analyses of employer performance sensitivity to employee social capital across firms with heterogeneous labor-related characteristics. Firm-level employee social capital takes the lagged value of *ESC in-degree*. In Panel A, we split 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 split 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%. H_0: Above − Below = 0 is based on a one-tailed test with p-values in square brackets. Standard errors in parentheses are clustered at the firm level. The symbols ***, **, 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.

Dependent Variable =	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. by Labor Intensity						
	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						
	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]			

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

We examine the impact of the Anti-Graft Act on the composition of firm-level employee social capital by estimating changes in the fraction of ESC subject to the Act around the enactment as follows:

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

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 ($ESC_{i,t}^{Act}$). We use *ESC in-degree* to measure $ESC_{i,t}$ and calculate $ESC_{i,t}^{Act}$ using only the connections to employees in the industries subject to Act (we use the industry codes in Appendix A to identify these connections). $Post_t$ is an indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. $X_{i,t-1}$ 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. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Dependent Variable =	*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)
Constant	3.619***	3.360***
	(0.943)	(0.935)
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 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 Anti-Graft Act:

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

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. $X_{i,t-1}$ 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 of 2016. The sample period is 2015–2018 for output variables. Standard errors in parentheses are clustered at the firm level. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Dependent Variable =	*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)
Constant	1.372***	-0.141***	-1.513***	1.554***	-0.139***	-1.511***
	(0.314)	(0.022)	(0.126)	(0.298)	(0.021)	(0.124)
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*$_i$ × *Post*$_t$ 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*$_i$, to each firm by maintaining the true distribution of *Act Exposure*$_i$. We also plot the kernel density of the coefficient estimate distribution and draw a vertical line in red to indicate the actual coefficient of -4.930.

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

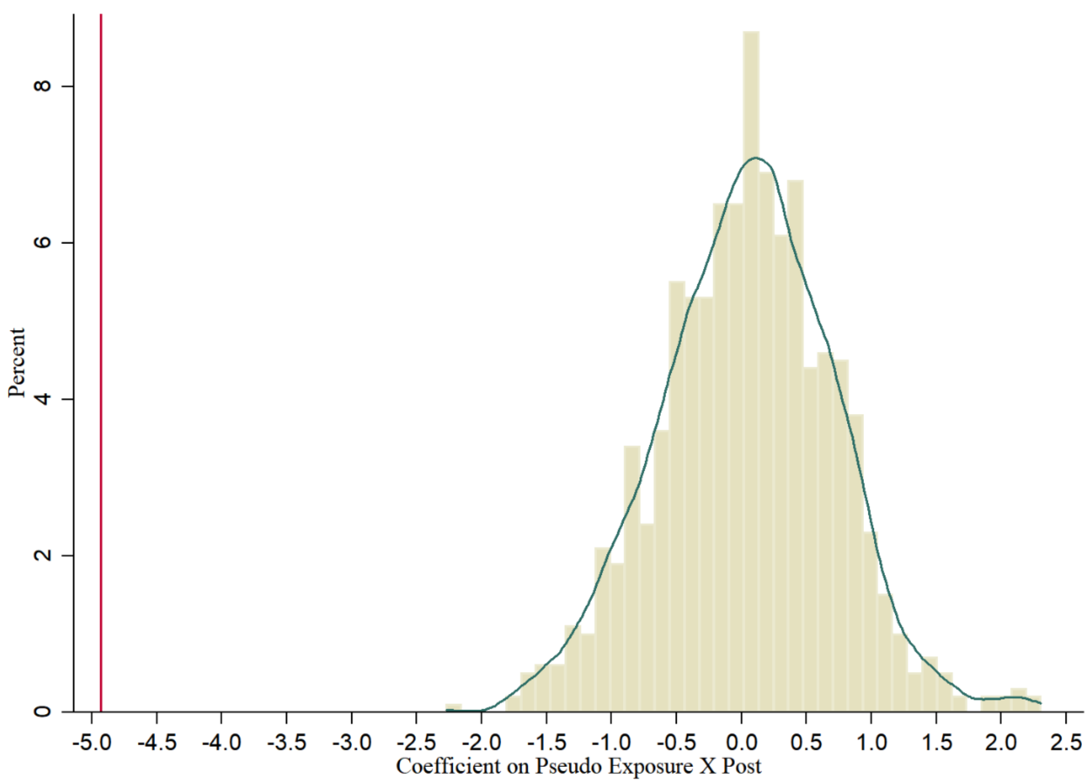


Table IA.7. Robustness Results for the Difference-in-Differences Estimation

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 post period 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. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Dependent Variable =	*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)
Constant	2.802***	2.802***
	(0.406)	(0.405)
Fixed Effects	Ind × Year	Ind × Year
Including Year 2016	No	Yes
Observations	3,778	5,101
Adjusted R^2	0.253	0.252