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

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Abstract

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JEL codes: G30, G32, L14

Keywords: Social capital; Social networks; Labor and finance

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We show that the social capital embedded in employees' networks contributes to firm value and provide evidence on the mechanisms. Using novel, individual-level network data, we measure a firm's social capital derived from employees' connections with external stakeholders. The directed nature of connections allows for identifying whether one party in a connection is a more valued contact. Results show that firms with more employee social capital perform better; the positive effect stems primarily from employees being valued by others. We provide causal evidence exploiting the enactment of a government regulation that imparted a negative shock to networking with specific sectors.

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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 of the relationships that a firm and its employees have built with economically related agents outside the firm (see, e.g., Servaes and Tamayo, 2017). Social capital is a broad concept that can be understood as the norms of reciprocity and trustworthiness within social networks (Putnam, 2000). A large literature shows that the social capital of individuals—such as the size of their Rolodex—provides access to resources and enables them to reap benefits from interactions with others (Bourdieu, 1986; Coleman, 1988; Lin, 2002; Glaeser et al., 2002).[1] At the firm level, individual social capital is important since employees, including both management and rank and file, interact directly with business partners, clients, and other stakeholders. Yet, due to the latent nature of social networks, how the social capital embodied in employees' connections contributes to firm value and performance remains an open question.[2]

The goal of this paper is twofold. First, we aim to establish a causal link between the social capital embedded in employee networks and firm performance. To this end, we construct a novel firm-level measure of employee social capital using professional connections that a firm's employees, across all job levels, have built with business contacts outside the firm.[3] Second, we identify the types of employee connections that are valuable to firms, thus contributing to a more granular understanding of social capital in corporations.

To measure employee social capital, we exploit a unique cultural practice in Asia: the exchange of business cards when people make connections. We obtain full access to novel data from the professional networking app "Remember," to which users upload business cards they have collected from others.

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[1] A complementary approach defines social capital at the country or regional level and relies on measures such as the civic engagement of the population or civic norms and trust. These studies find that regions with more social capital experience better economic outcomes (e.g., Knack and Keefer, 1997; La Porta et al., 1997; Guiso et al., 2004, 2008) and that firms operating in these regions suffer less from agency problems (Hasan et al., 2017; Hoi et al., 2019).
[2] Limited by data availability on networks, the finance literature that uses 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 et al., 2012; Larcker et al., 2013).
[3] Our construction of employee social capital distinguishes it from relationships *within* the firm (see, e.g., Jeffers and Lee, 2019) or norms and values that are shared within the firm, also referred to as corporate culture (see, e.g., Guiso et al., 2015; Grennan, 2020; Graham et al., 2021).

Remember has a near-monopoly of business card management in Korea. We obtain the business card collections of each user and screen out individuals who are not employees of firms. The data allow us to directly identify the professional networks of individual employees and quantify the connections each employee has built with people outside of their firm. We further map the connections of public firm employees to the financial variables of their employers to obtain a matched employer-employee dataset.

Several aspects of our data are novel and noteworthy. First, our final sample consists of 2.4 million employees, with 12.4 million professional connections between them. The data's broad coverage of employees across ranks, including managers and rank-and-file employees, allows us to quantify employee social capital at the firm level. Second, because in Asian culture business cards are typically exchanged in face-to-face meetings (it is not the norm to pass on cards on behalf of others), our data depict real-world professional connections more reliably than those from online networking platforms, such as LinkedIn where people can connect even though they have never met. Third, while card exchanges are mutual between the two parties, uploading cards to the app is not necessarily mutual because users are more likely to upload the cards of contacts that they value and thus want to remember (apropos the name of the app). Using language from the network literature, we refer to the network as *directed*: each connection is directed from the employee who uploads the card to the employee whose card is uploaded. This directed feature allows us to determine whether one of the two connected parties is a more valued contact.

We calculate several connection measures at the individual employee level—*In-degree* (the number of others who have uploaded the employee as a contact), *Out-degree* (the number of business contacts uploaded by the employee), and *Total degree* (the sum of *In-degree* and *Out-degree)*. In other words, *In-degree* counts the people who remember or value the employee by uploading the employee's card on the app, which we refer to as "who knows you"; *Out-degree* counts the contacts the employee remembers or values by uploading their cards, which we refer to as "who you know." [4] As we discuss below, the directed

[4] Although none are perfect descriptors, we use "who knows you," "who remembers you," and "who values you" interchangeably throughout the paper to describe an employee's *In-degree* connections. Similar descriptors are used to describe *Out-degree* connections. A reciprocal connection where both parties upload each other's cards ("know each other") counts toward both the *In-degree* and *Out-degree* for each party.

nature of our network data enables us to move beyond "who knows who" and analyze the extent to which social capital—as distinguished by "who knows you" versus "who you know"—matters for the firm.

We begin by constructing firm-level measures of employee social capital (ESC) by appropriately averaging the employee-level degree measures (*In-degree*, *Out-degree*, *Total degree*) within a firm. Drawn from a comprehensive sample of Korean public firms in the OSIRIS Industrials database from 2014 to 2018, our initial analysis examines the average *Total degree* of a firm's employees without regard to the direction of connections; baseline regressions show that firms with more employee social capital have significantly higher profitability and sales growth in the following year.

We then investigate whether the direction of connections matters in the relation between employee social capital and firm performance. We re-estimate the model when firm-level employee social capital takes the value of *ESC in-degree* ("who knows you") and *ESC out-degree* ("who you know"). Results show that the positive association with future performance arises mainly from *ESC in-degree*, which captures the extent to which a firm's employees are remembered or valued by their external contacts. In sharp contrast, the coefficient estimates on *ESC out-degree* are largely insignificant. While the social capital literature argues that networks endow employees with access to resources, our findings suggest that the extent to which employees can mobilize these benefits for their employers depends on whether their business contacts value them. In this sense, having a broad network of business contacts who know you appears more valuable to your employer than having a broad network of contacts whom you know.[5]

We perform a range of robustness checks to allay concerns with omitted variable bias, measurement error, and selection bias. A firm's employee social capital may proxy for other variables that are positively linked to firm performance. For example, sales personnel who serve as customer touchpoints are, by nature, active in exchanging cards, such that the observed relation between employee connections and sales growth might simply reflect firms' sales activities. Our results, however, are robust to excluding the connections

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

of a firm's customer-facing employees or excluding the connections with external contacts working in the customer industries. Another possibility is that firms with well-connected employees might also have high employee technical skills or high employee satisfaction, both associated with superior firm performance. Following the strategy in Cohen et al. (2010), we exclude subsamples of firms that are popular employers among skilled employees and find the results continue to hold. Finally, we conduct a battery of tests to show the robustness of our results against potential measurement error and selection bias in constructing firm-level employee social capital caused by differential app usage among a firm's employees.

Establishing a causal link between employee social capital and firm performance requires a careful account of the endogeneity of networks. Despite our extensive robustness tests, concerns remain, such as reverse causality whereby better firm performance leads to the formation of professional connections. To address the endogeneity of employee social capital and reinforce its causal effect on firm performance, we exploit the 2016 enactment of the Kim Young-ran Act (the Act) as a plausibly exogenous negative shock to professional networking in Korea. The Act makes it illegal for media professionals (such as journalists) and public sector employees (such as public servants, lawmakers, and teachers), and their spouses to accept gifts or meals exceeding a specified limit, regardless of whether they are in exchange for favors. The Act is a suitable identification tool because of the uncertainty in the legislative process and its aggressive enforcement. Evidence suggests that the Act caused significant precautions among businesses, creating a chilling effect on social events and meetings with contacts employed in the media and the public sector. By limiting employees' ability to extract benefits from their existing connections to these affected sectors, the Act constituted a negative shock to a firm's employee social capital.

We use a difference-in-differences framework surrounding the enactment of the Act and set the treatment intensity as the fraction of a firm's preexisting employee social capital derived from its employees' connections with the media and the public sector. Since some firms have employee social capital that is more exposed to the Act than others, we can estimate differences in performance before and after the Act between firms with differential exposure. We find that firms with ESC more exposed to the Act experience a significant decline in performance after the Act relative to those less exposed. For instance, a one standard deviation increase in treatment intensity yields an increase in *Tobin's q* by 17.5% relative to the sample mean before the Act, but only by 4.4% after. This differential effect does not appear in pre-treatment years and persists over the years following the enactment. 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 sectors directly affected by the Act, such as customers and suppliers of the media and the public sector.

Using an event study approach, we examine stock price reactions around the court ruling date to provide corroborating evidence. Consistent with the value of firms' employee social capital being destroyed by the limits on social interactions imposed by the Act, we find a significantly negative cumulative abnormal return of −0.61% (*p*-value = 0.017) for firms with ESC more exposed to the Act over the [−3, 3] event window, and a differential cumulative abnormal return of −1.02% (*p*-value = 0.019) relative to firms with ESC less exposed to the Act.

To shed light on the mechanisms through which employee social capital contributes to firm value, we consider the benefits that firms can derive from their employees' connections with the sectors affected by the Act—the media and the public sector. Motivated by the literature on media coverage and firm value (e.g., Gurun and Butler, 2012; Solomon, 2012; Ahern and Sosyura, 2014), we predict that employees' media connections will foster reciprocity and information sharing with journalists, which in turn promotes news coverage of the firm, and news stories with a positive tone. Indeed, we find that firms with more employee media connections have substantially more news articles and a greater fraction of positive coverage. Moreover, the positive effects diminish after the enactment of the Act, reinforcing our causal inference.[6]

We then turn to the benefits of employee connections with the public sector. Drawing on evidence that public officers allocate more procurement contracts to firms with a connected CEO (Schoenherr, 2019), we expect that employees with public sector connections may also help their firms secure procurement

[6] A possible channel through which employees' media connections achieve favorable media coverage is by facilitating favor exchanges with journalists (which may include bribery). Although bribery reflects a dark side from a societal perspective, it represents a favor exchange facilitated through employee networks that benefits the firm. We elaborate on this point in Section 4.4.

contracts. Our evidence is consistent with this prediction. For example, a one standard deviation increase in the fraction of employee social capital accumulated from public sector connections leads to a 6.8% increase in the number of newly signed contracts before the Act and to only a 3.4% increase after.

Finally, our data's coverage of employees across job levels allows us to study employee social capital beyond the executive team—an aspect less explored in the literature. We find that employee connections across all job levels, including the rank and file, are valuable. The positive contribution of rank-and-file employee social capital is noteworthy and novel to the literature. A plausible channel through which rank-and-file employee social capital improves firm outcomes is that their connections with external contacts facilitate information sharing. To provide evidence on this channel, we examine employees' connections to the investment banking industry, where information acquisition is central to capital raising. Our results show that firms with more investment banking connections incur lower at-issue bond spreads, highlighting reduced financing cost as a benefit that adds to firm value. Notably, connections between investment bankers and rank-and-file employees contribute substantially to lower bond spreads. Since rank-and-file employees are not the decision makers for corporate bond issuance, a likely motivation for investment bankers to remember them is to acquire information in due diligence investigations. Hence, our evidence highlights information sharing with related entities as an important channel through which employee social capital enhances firm performance.

Our study adds to the burgeoning literature on the role of social capital in corporations. Because relationships of a firm are difficult to observe and measure, existing metrics for firm social capital largely rely on corporate social responsibility efforts or secular norms and social interactions in local areas surrounding corporate headquarters, such as voter turnout, census response rate, density of sports clubs, and friendship links on Facebook. This literature finds that firms that entered a financial crisis with more social capital perform better (Lins et al., 2017; Servaes and Tamayo, 2017) and that firms operating in regions with higher social capital have better access to capital (Hasan et al., 2017; Kuchler et al., 2021), suffer less from agency problems (Hoi et al., 2019), and have earnings news more rapidly incorporated into their stock prices (Hirshleifer et al., 2021). For example, using Bailey et al. (2018) social connectedness index based on Facebook friendships, Kuchler et al. (2021) find that firms in counties with stronger social ties to the headquarters locations of institutional investors are more likely to obtain capital. Contributing to this line of research, we develop a novel measure of a firm's social capital using the professional connections of its employees, and show that otherwise similar firms with more employee social capital perform better. By exploiting the directed feature of our network data, we uniquely show that the value of employee social capital to a firm comes mainly from employees being valued by their external contacts.

Our study also complements prior work that identifies the benefits of managerial networks, such as high announcement returns in mergers and acquisitions (Cai and Sevilir, 2012), better firm performance (Larcker et al., 2013; Cai and Szeidl, 2017; Dass et al., 2014), favorable lending terms (Engelberg et al., 2012; Haselmann et al., 2018; Karolyi, 2018), and survival during a financial crisis (Acemoglu et al., 2016).[7] We present novel evidence that executives are not the only group that possesses beneficial connections for their firms; employee connections (when valued by their external contacts) across all job ranks matter for firm outcomes.

Finally, our study leverages the Asian cultural practice of exchanging business cards, which provides a unique institutional setting for identifying interpersonal networks. Although our evidence draws from Korean firms, the effects of social ties on business outcomes have been documented in diverse business cultures, such as the US (Hochberg et al., 2007; Shue, 2013), China (Cai and Szeidl, 2017), Germany (Haselmann et al., 2018), the UK (Rossi et al., 2018), and the global setting (Houston et al., 2018), suggesting that the insights are general and broadly contribute to our understanding of social capital.

2. Data and summary statistics

2.1. Remember, a professional networking app

We exploit a unique dataset extracted from a professional networking app, Remember, which was developed by the Korean mobile and web service provider Drama & Company. Since its launch in January

[7] Other studies point out potential downside to the firm associated with executives being well networked: connections could weaken effective monitoring of board members, increase the entrenchment of CEOs, and lead to rent-seeking coalitions (Hwang and Kim, 2009; Fracassi and Tate, 2012; Ishii and Xuan, 2014; Khanna et al., 2015; Gompers et al., 2016).

2014, Remember has become the single most popular professional business card management app in Korea, with virtually no domestic competitors.[8] As of December 2018, the total number of users was around 2.5 million, which is approximately 18.1% of the total number of full-time employees in Korea.

To keep a record of their professional network, users of the app upload the business cards they have collected in face-to-face meetings, either scanning the cards by themselves or having the app developer scan the cards in bulk for a small fee. Professional typists hired by the app developer hand-type the scanned cards into the database, which renders the network data virtually free of automatic recognition errors. The app allows users to keep track of their professional networks, to use search criteria to connect to calls, texts, emails, and addresses, and to add updates about promotions or new job titles. Unlike online networking platforms (e.g., LinkedIn, Facebook, or Twitter), the network of an app-user is not visible to others.

2.2. Business card data and individual employee-level connections

The cultural background of Korea strongly supports the notion that tracking business card exchanges is a useful way to identify employees' professional networks. As in most other Asian countries, in Korea, exchanging business cards in face-to-face meetings is more than an exchange of personal details; it is an important ritual for building professional connections. It is widely believed that, besides being an ice breaker, the exchange of business cards can help establish a positive first impression and boost professional credibility. Business cards are also a physical reminder that one has met the contact rather than simply googled them. In addition, exchanging cards helps the two parties bond and build trust by encouraging follow-up social events.[9]

Tracing the exchange of business cards using our dataset is thus a relatively feasible and reasonable way to identify Koreans' professional networks. From each card uploaded by each app-user by December

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[8] The Remember app won the Google Play Awards in 2015 and 2016 and received the Brand of the Year Korea for four consecutive years, from 2015 through 2018. The app is accessible at rememberapp.co.kr, and is available free of charge from Google Play and the App Store. Figure IA.1 in the Internet Appendix illustrates how the app appears in the App Store, the app's user interface, and how to upload business cards.

[9] As discussed extensively in the *Economist* (May 2015), "business cards are doubly useful. They can be a quick way of establishing connections, particularly in Asia, where they are something of an obsession . . . exchanging business cards still seems to be an excellent way to initiate a lasting relationship. The ritual swapping of paper rectangles may be old-fashioned but on it will go." Also see "Why Business Cards Still Matter," *BBC*, September 2016, www.bbc.com/worklife/article/20160914-how-a-small-yet-mighty-bit-of-paper-can-still-get-you-a-job.

2018, we obtain detailed information about the business contact, including an individual identifier (uniquely defined by a coded name and coded mobile phone number to comply with user privacy laws), email domain, firm name, job position, and timestamp of card upload. The unit of observation in the raw data is the *connection level*—that is, a pair consisting of the app-user and the business contact whose card is uploaded. Since our goal is to count connections among employees, we exclude connections that involve individuals who do not have a firm name on their card, whose listed email domain is inconsistent with their firm, or whose firm does not have a Korea Investors Service (KIS) firm identifier (a corporate registration number for both listed and unlisted firms). To focus on interfirm connections, we select connections between employees with different KIS identifiers. Accordingly, each connection involves two employees of different firms: the app-user who uploads the business card and the contact to whom the card belongs. The Internet Appendix provides more details on our data and an illustrative example.

In general, cards are mutually exchanged between two parties, but the upload of exchanged cards is not necessarily mutual. For example, after Aaron and Bob meet and exchange cards, Aaron uploads Bob's card, but Bob does not upload Aaron's card. Borrowing terminology from the network literature (e.g., Jackson, 2008; Newman, 2010), this feature implies our connection-level data are directed. More specifically, in social networks, individuals, also called nodes, form links (connections) to other individuals; the nodes and links constitute the network. If the links have a specified direction and are not necessarily mutual, we say the network is directed.[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 uploads the card to the contact whose card is uploaded. The example of Aaron uploading Bob's card is represented graphically by an arrow from Aaron pointing to Bob. This connection counts as an *out-degree* for Aaron,

[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 be a directed network. By contrast, professional connections on LinkedIn and friendship networks on Facebook are undirected.

and an *in-degree* for Bob. Because users are most likely to upload only the cards they value and intend to "remember"—as suggested by the name of the app—Bob is more likely a valued contact when his card is uploaded by others as opposed to when Bob uploads others' cards. To capture this distinction more generally, we define the degree measures at the employee-year level as follows. *In-degree* is the number of employees of other firms who have uploaded the employee as a business contact by a given year ("who knows you"). *Out-degree* is the number of external business contacts uploaded by the employee by a given year ("who you know"). *Total degree* is the sum of *In-degree* and *Out-degree*. A reciprocal relationship, which occurs when both parties upload each other's cards, counts toward both the *In-degree* and *Out-degree* for each party, thereby increasing the *Total degree* of each party by two.

Since our interest is in the performance of publicly listed firms, we keep only the connections in which at least one of the two individuals is a public firm employee. This network consists of 12.4 million connections between 2.4 million employees. Among these employees, 17.4% are app-users and 43.0% work for public firms. There are 126,987 firms with KIS identifiers; among them, 1,866 are public firms. To analyze the performance of Korean public firms, we use the OSIRIS Industrials database compiled by Bureau van Dijk, which contains financial information on publicly listed industrial firms worldwide. Our network data cover firms in a wide array of sectors, as shown in Table IA.1 in the Internet Appendix.

Panel A of Table 1 presents summary statistics of employee-level connections as of December 2018 for the public firms' employees in our sample. We begin by summarizing the connections of the 119,423 app-user employees. *In-degree* shows that an average app-user employee has been uploaded as a contact by 26 app-users outside the firm. *Out-degree* shows that the average app-user has uploaded 57 contacts from other firms. The sum of the two degrees, *Total degree*, has a mean of 83. All degree measures have a median much lower than the mean, suggesting that the distributions are highly right skewed. In the network, there are 896,600 non-app-users working for public firms. Non-app-users enter the network when their cards are uploaded by app-users and thus, by definition, only have links pointing inward.[11] On average, a

[11] We discuss potential measurement error and selection bias caused by not observing the *Out-degree* of non-app-users in Section 3.3.2.

non-app-user, whose *In-degree* (which also equals *Total degree*) is around five, is uploaded as a contact by five app-users outside the firm. Pooling the app-users and non-app-users together, an average public firm employee in the network is uploaded by seven others as a business contact and has a total degree of 14.

[Table 1 about here]

Our data have several advantages in identifying employees' professional networks. First, the data's broad coverage of individual employees (including management and rank and file) allows us to map employee-level connections to their employers to construct a matched employer-employee dataset. This feature overcomes a limitation of the corporate finance literature that has focused primarily on managerial networks. Second, because business cards are typically exchanged in a face-to-face meeting, our data depict real-world professional relationships more reliably than online professional networks such as LinkedIn. An uploaded card is a physical imprint that the two people indeed met rather than simply connected via an online invitation. Moreover, since the connections of an employee are not publicly visible, one's *In-degree* and *Out-degree* are unlikely to strategically influence each other. Third, the directed nature of the data allows us to move beyond "who knows who" and analyze the extent to which social capital—as distinguished by "who knows you" versus "who you know"—matters for firm outcomes.

2.3. Firm-level employee social capital (ESC)

To examine the extent to which resources inherent in an employee's professional connections contribute to the employer's performance, we construct measures of firm-level employee social capital (ESC) based on the employee-level degree measures. Our strategy is to average across the employee-level degrees to obtain a proxy for the connectedness of the representative employee of each firm. We utilize the direction of connections to decompose firm-level employee social capital into *ESC in-degree* and *ESC out-degree*. *ESC in-degree* is the average *In-degree* across a firm's employees in the network; it quantifies the number of times a firm's employees have been uploaded as business contacts. As noted earlier, non-app-users enter the network when their cards are uploaded by others and thus, do not have *Out-degree*. Accordingly, *ESC out-degree* is the average *Out-degree* across the app-user employees of a firm; it quantifies the number of external business contacts that a firm's app-user employees have uploaded. Finally, *ESC total degree* is the average *Total degree* across a firm's employees in the network.[12]

2.4. Sample construction and summary statistics

To construct our sample, we start with Korean public firms from the annual OSIRIS Industrials database from 2014 through 2018. We match the 1,866 public firms in the network data with OSIRIS Industrials using firm 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 lagged total assets;[13] *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.

Panel B of Table 1 reports summary statistics for our firm-year sample. *ESC in-degree* has a mean of 3.7 and a median of 3.1; *ESC total degree* has a mean of 6.8 and a median of 5.3. These numbers show that employees of a firm, on average, have 6.8 connections with employees of other firms and that in 3.7 of those connections, they are uploaded as a business contact by others. In comparison, *ESC out-degree* has a mean of 31.0 and a median of 24.2, suggesting that app-user employees of a firm, on average, upload 31.0 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 reported in Panel A of Table 1.[14] The financial variables are comparable in magnitude to those of US firms during the same period; Korean firms have relatively less skewed *Tobin's q*, larger *ROA*, smaller *Sales Growth*, and lower *Book Leverage*. Summary statistics of firm-level ESC measures by sector are reported in Table IA.1. Aside

[12] To reduce measurement error when taking averages, we restrict our sample to firm-year observations with at least ten employees observed in the network. Our results are robust to using alternative thresholds for the minimum number of employees who appear in the network; see further discussions in Section 3.3.2 on potential measurement error and selection bias.
[13] Using EBIT instead of EBITDA to measure *ROA* does not change our results.
[14] 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 do not have app-user employees and thus are missing *ESC out-degree*.

from the mining and quarrying sector, which has only three public firms, firms in the financial sector (SIC codes 61, 62, 65, 67) have the highest ESC, suggesting that they tend to be central in the network.[15]

3. Employee social capital and firm performance: baseline analysis

This section provides baseline estimates of the relation between employee social capital, as variously measured by employee professional connections, and firm performance. In Section 3.1, we examine the importance of *ESC total degree,* which represents the average total connections across employees of a firm, without accounting for the direction of 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 the direction of connections matters. Section 3.3 provides a variety of robustness tests to address concerns with omitted variable bias, measurement error, and selection bias.

3.1. Employee social capital measured by total degree

The social capital literature suggests that social ties are associated with valuable resources (Bourdieu, 1986; Coleman, 1988; Putnam, 2000; Lin, 2002; Glaeser et al., 2002; Granovetter, 2005). For instance, Bourdieu (1986) considers social capital as "the actual or potential resources which are linked to possession of a durable network"; Putnam (2000) notes that social connections lead to reciprocity, trust, and better sharing of information; and Lin (2002) defines social capital as resources embedded in one's social networks, resources that can be accessed or mobilized through ties in the networks. Motivated by this literature, we examine the empirical relation between employee social capital and future firm performance, by estimating the following ordinary least squares (OLS) specification:

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

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

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

measured at 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 (see, e.g., Anderson and Reeb, 2003), and $\alpha_{j,t}$ is a full set of two-digit Standard Industrial Classification (SIC) industry-by-year fixed effects. As our data have a short time span, much of the variation in firm-level ESC is in the cross section; hence, we rely on specifications that include industry-by-year fixed effects to mitigate identification concerns by controlling for unobserved time-varying heterogeneity across industries in, for example, business performance or employee app usage. Since our ESC measures are right skewed, we take the log transformation to reduce the effects of outliers; our results are qualitatively robust to using ln(ESC) and robust to not taking the log transformation.

[Table 2 about here]

The estimation results are presented in Panel A of Table 2. The coefficient estimates of employee social capital are positive across all firm performance measures. The estimated effect is statistically significant for *ROA* and *Sales Growth*, but not for *Tobin's q*. The coefficient estimates on ln(1+*ESC*) in columns (2)–(3) imply that a one standard deviation increase in *ESC* from its mean is associated with an increase in *ROA* of 0.4 percentage points (=0.008×(ln(1+6.836+5.844) −ln(1+6.836))) and *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 over the sample period.[16] These baseline regressions suggest a positive relation between a firm's future performance and its employee social capital based on employees' total professional connections.

3.2. Does direction of employee connections matter? In-degree versus out-degree

The results above are based on employees' *Total degree*, namely the total number of connections, without regard to the direction of those connections. To shed more light on the economic value of

[16] 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.

employees' professional connections, we exploit the directed nature of our data which allows us to differentiate the direction of connections to assess 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 direction of connections matters.

Panel B of Table 2 reports the results where we re-estimate equation (1) separately for *ESC in-degree* and *ESC out-degree.* The results provide strong evidence suggesting that the direction of connections plays a significant role in firm performance. All coefficient estimates on *ESC in-degree*, reported in columns (1)–(3), are positive and statistically significant at the 1% level. The estimated effects are also economically meaningful: 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. By contrast, the coefficient estimates on *ESC out-degree* in columns (4)–(6) are insignificant or borderline significant at the 10% level. The estimated coefficients for *ESC out-degree* and the economic significance are an order of magnitude smaller than those for *ESC in-degree*, which is also confirmed by the one-tailed tests (with *p*-value < 1%). For example, in comparison with the 9.4% increase in *Tobin's q* for *ESC in-degree* noted 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*.[17]

These findings suggest that the positive relation between employee social capital and firm performance comes mainly from employees' connections with external contacts who remember or value the firm's employees. While social ties can provide resources, the extent to which employees can leverage these benefits for their employers depends on whether the employees are valued by their business contacts. Although out-degree business contacts are less useful to their employers, individuals can derive personal

[17] In Table IA.2 in the Internet Appendix, we perform a propensity score matching analysis to mitigate the potential effects of heterogeneous selection by matching each above-median ESC firm with a below-median firm on year, industry, and the controls in our baseline regression. Results confirm that firms with above-median *ESC in-degree* experience significantly better performance than their matched firms, whereas no significant difference is found for firms with different *ESC out-degree*. In addition, to evaluate whether the effects of *ESC in-degree* are evident for both firms with high performance and firms with low performance, we run quantile regressions and find that the estimated effect is equally strong among firms in different deciles of the performance distribution (shown in Figure IA.2).

benefits from these connections. For example, studies show that social networks are a useful resource for individuals seeking outside job opportunities (e.g., Lin et al., 1981; Granovetter, 1973, 1995; Hacamo and Kleiner, 2021). If employees uploading contacts from other firms—as measured by *ESC out-degree*—reflects employees' desire and efforts to switch employers,[18] the resources mobilized through these connections do not accrue to their employer. Overall, our baseline regressions show that firms with more employee social capital have significantly better performance in the next year; however, compared with remembering and valuing others, being remembered and valued by others is a more robust indicator of employee social capital that can benefit firms.

3.3. Robustness tests

We conduct robustness tests to show that potential omitted factors, measurement error, or selection bias in constructing firm-level employee social capital are unlikely to drive the results that "who knows you" matters more than "who you know."

3.3.1. Omitted variables

One concern with our empirical analysis is that omitted variables that are correlated with both employee social capital and firm performance may be driving our findings. Although including industry-by-year fixed effects mitigates such concerns by controlling for any unobservable industry-specific trend, we perform tests in Panel A of Table 3 to further address this issue.

One possibility is that the observed positive association between *ESC in-degree* and sales growth might merely reflect a firm's sales activities. Employees in sales departments serve as customer touchpoints and are particularly active in exchanging business cards, such that firms with more sales employees mechanically have both greater sales and more employee connections. To alleviate this concern, we calculate *ESC: Excl. Sales* by excluding the connections of a firm's customer-facing employees who

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

perform sales functions.[19] In addition, while connections with customer industries are clearly important to firms, to provide further evidence that our results are not a byproduct of sales activities, we also calculate *ESC: Excl. Customers* by excluding a firm's employee connections with the individuals working in its customer industries.[20] As shown in Panel A of Table 3, the coefficients on *ESC in-degree* continue to be positive and statistically significant for both alternative measures, while those for *ESC out-degree* are not.

[Table 3 about here]

Another possibility is that firms with well-connected employees might also have high employee technical skills or high employee satisfaction, and it is the employees' skill or job satisfaction rather than their connections that drives superior firm performance. To alleviate this concern, we use a similar strategy as Cohen et al. (2010) and conduct subsample analyses. We first exclude firms that were ranked at least once in the "top 20 most wanted employers by university students" in the period 2015–2018 according to the Job Korea Survey, such as Samsung Electronics and Hyundai Motor, because these firms tend to have high employee satisfaction and attract some of the most talented university graduates. We then drop financial firms (SIC codes 61, 62, 65, 67) and firms that are in the top three percentile of the asset size distribution, which are both competitive in the market for talented employees. The results, in Panel A of Table 3, show that *ESC in-degree* remains positively related to firm performance, whereas the coefficient estimates of *ESC out-degree* largely remain insignificant, indicating that our results are not an artifact of a selected sample of employees with good technical skills or job satisfaction that drive firm performance.

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

[20] To identify customer industries, we follow Frésard et al. (2020) and measure vertical relatedness using detailed Make-and-Use tables obtained from the Bank of Korea Economic Statistics System. Specifically, we use the 2014 Make-and-Use tables to construct a 328-by-328 industry flow matrix in which each cell indicates the dollar flows from an upstream industry to a downstream industry. We define industry *j* as a customer industry of industry *i* if the fraction of industry *i*'s total production used by industry *j* exceeds a threshold of 3%.

3.3.2. Measurement error and selection bias

Although our network data have comprehensive coverage for employees in a wide array of firms and industries, we do not observe the universe of employee connections. Thus, we investigate the robustness of our results against potential measurement error and selection bias caused by (i) differential app usage among a firm's employees, (ii) potential differences between app-users and non-app-users, and (iii) our aggregation approach to measuring firm-level employee social capital.

First, the fact that our network data are based on the business card collections of app-users might introduce measurement error and selection bias. As discussed in Section 2, the *In-degree* connections of a firm's employees ("who knows you") can only be seen when their cards are uploaded by app-users of other firms. Thus, *ESC in-degree* likely underestimates "who knows you" because it does not reflect external employees that value or know the firm's employees but do not use the app. To the extent that measurement error biases our estimates toward zero, partially observing employees' *In-degree* biases against finding a significant effect of *ESC in-degree*. On the other hand, because we do not observe the *Out-degree* of non-app-user employees, *ESC out-degree* might also contain noise as it is measured on a smaller sample than *ESC in-degree*. To address this issue, we randomly assign *Out-degree* to non-app-users by drawing from the *Out-degree* distribution of app-users in the same firm with replacement; we then construct a bootstrapped *ESC out-degree* using the actual *Out-degree* of app-users and the bootstrapped *Out-degree* of non-app-users. Results based on the bootstrapped data show that the coefficient estimate of *ESC out-degree* is robustly small in magnitude and insignificant (see Figure IA.3 in the Internet Appendix), suggesting that the insignificance of *ESC out-degree* to firm performance is unlikely an outcome of measurement error.[21]

Second, app-users, by nature, are more likely to be tech-savvy and socially active than non-app-users. Since *In-degree* is observed for both app- and non-app-users, whereas *Out-degree* is observed only for app-users, a concern is that our decomposition of employee social capital by the direction of connections may pick up these or other differences between app- and non-app-users. To address this concern, in Panel

[21] We repeat this procedure 500 times and find that none of the coefficient estimates based on the bootstrapped data are significant at the 5% level. Results are similar when we multiply the bootstrapped *Out-degree* of non-app-users with a scaler from 0.5 to 1.5 to account for potential differences between app-users and non-app-users.

B of Table 3, we examine *ESC in-degree* of non-app-user employees of a firm to compare with our baseline estimates for *ESC in-degree* (measured for both app- and non-app-user employees). If app-user employees drive our results, we should expect *ESC in-degree* of non-app-user employees to lose significance; however, our results show that the coefficients on *ESC in-degree* continue to be positive and statistically significant. Similarly, we examine *ESC out-degree* to only those external contacts who are app-users to compare with our baseline estimates for *ESC out-degree* (to external contacts including app- and non-app-users), and still find similar results. Moreover, to directly compare the effects of *ESC in-degree* and *ESC out-degree*, we include both measures in the same regression; and, since we observe a more complete picture of connections by app-users, we also run the same regression when we construct both measures using only app-user employees of a firm. As summarized in Panel B of Table 3, our findings are robust in both cases. These tests suggest that our findings concerning the direction of connections are not an artifact of the asymmetry between app- and non-app-users.

Third, errors could arise in measuring firm-level ESC since we average across the individual-level degree measures among the employees that appear in the app. To reduce error when taking averages, we restrict our sample to observations with at least ten employees observed in the network. Panel B of Table IA.2 in the Internet Appendix shows that our results are unchanged when we apply alternative thresholds for the minimum number of employees or a minimum percentage of firm employees who appear in the network. Relatedly, employees' connections might *collectively* contribute to firm performance; hence, in lieu of averaging across employees, we calculate *ESC: Sum* as the sum of *In-degree* (or *Out-degree*) aggregated across the firm's employees and find qualitatively similar results. These tests suggest that our results are robust to alternative sample selection and aggregation methods at the firm level.

4. Establishing a causal relation between employee social capital and firm performance

Although we have conducted a battery of tests to mitigate concerns with omitted variable bias and measurement error (and to some extent reverse causality by using lagged ESC measures), the results of our analysis may still be subject to endogeneity concerns. To establish a causal relation between employee connections and firm performance, it is important to identify exogenous variation in employee social capital. In this section, we establish causality by exploiting a quasi-natural experiment that imparted a negative shock to professional networking in Korea.

4.1. Exogenous shock to employee social capital: the 2016 Kim Young-ran Act

We exploit the enactment of the Kim Young-ran Act (the Act) in September 2016 as an exogenous shock to social interactions with employees in specific sectors. Named after the former head of the Anticorruption and Civil Rights Commission, the Act makes it illegal for media professionals (such as journalists) and public sector employees (such as civil servants, lawmakers, and teachers), and their spouses to accept gifts of more than 50,000 Korean won (about 45 USD) or 100,000 won at events such as weddings and funerals; it also limits meal expenditures to 30,000 won per person.[22] Violations of the Act are subject to aggressive penalties, including imprisonment.[23]

Although the Act was intended to prevent corruption, the gift and meal limits also resulted in fewer social events and meetings with contacts employed in the media and the public sector, thereby restricting firms' ability to leverage their employee social capital with these sectors. As a culturally ingrained business practice in Korea, corporate employees would regularly treat clients, business partners, and public employees to dinners, drinks, and other entertainment as part of normal networking activity (Choi and Storr, 2019). Through engagement in these networking activities, professionals invest in their social capital, enhance trust, and share information. However, anecdotal evidence suggests that the Act has caused significant precautions among businesses in their interactions with the media and the public sector due to the severity of its penalties, as well as its somewhat abstract and vague provisions and the lack of precedents.[24] For example, 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

[22] The upper limits were adjusted in January 2018 to 100,000 won for non-cash gifts and to 50,000 won for cash gifts.
[23] The Act imposes a punishment of imprisonment for up to three years, or a fine of up to 30 million Korean won on persons convicted of accepting money or goods valued at more than one million won from one person in one installment, regardless of whether such compensation was in exchange for favors or related to the recipient's work. If the money or goods are worth less than one million won, a fine of up to five times the gift's value is imposed.
[24] See, for example, "Corporate Korea Braces for Change over Anti-Graft Law," *Korea Herald*, September 27, 2016, www.koreaherald.com/view.php?ud=20160927000851; "Companies Still Need to be Cautious of Kim Young-ran Act," *Korea Herald*, September 24, 2017, www.koreaherald.com/view.php?ud=20170922000818.

of those related to work is ambiguous…as it excludes socializing as part of business formality." This concern by firms is consistent with the observations that "reservation rates of restaurants in Seoul's financial and legal districts and those near government complexes in Sejong and Daejeon, have rapidly dropped" and that Korean reporters were intentionally left out of the invitation list in a launch event for Apple's iPhone X.

To provide more systematic evidence that the Act resulted in an exogenous shock to employee social capital with the media and the public sector, we examine changes in the formation of connections with these sectors around the Act. Specifically, we examine the fraction of a firm's employee social capital (*ESC in-degree*) that is derived from connections with employees in the industries affected by the Act ($ESC\ in\text{-}degree^{Act}$), as identified using industry codes listed in Appendix A.[25] Figure IA.4 in the Internet Appendix compares the networks before the Act in 2015 and after the Act in 2018 and illustrates a sharp decline in this fraction. Our estimation results in Table IA.3 further show that the fraction dropped by 7.7% after the enactment relative to its sample mean. Hence, the evidence is consistent with the Act discouraging the formation of new connections with personnel in the media and the public sector.

Another aspect of the Act that makes it a useful identification tool is the uncertainty around whether the Act would be ruled constitutional. Right after bipartisan approval of the Act in 2015, the Korean Bar Association and the Korean Journalists Association filed a court petition questioning the law's constitutionality on the grounds that it threatened freedom of speech. The Constitutional Court upheld the law on July 28, 2016, rejecting the petition. This series of unforeseen events lends credibility to our identifying assumption of orthogonality between the enactment and unobservable covariates that affect corporate performance.

4.2. Evidence for causality

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

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

We test the predictions of our hypothesis by estimating the following regression model:

$$Y_{i,t} = \beta_0 + \beta_1 \times \mathit{Act\ Exposure}_i + \beta_2 \times \mathit{Act\ Exposure}_i \times \mathit{Post}_t + \gamma' X_{i,t\text{-}1} + \alpha_{j,t} + \varepsilon_{i,t} \qquad (2)$$

where $Y_{i,t}$ measures firm performance and *Act Exposure*$_i$, the treatment intensity, is calculated as the ratio $\mathit{ESC\ in\text{-}degree}^{Act}_{i,2015} / \mathit{ESC\ in\text{-}degree}_{i,2015}$, where $\mathit{ESC\ in\text{-}degree}^{Act}_{i,2015}$ is *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Act.[26] We measure the treatment intensity in 2015, before the enactment, to isolate it from the dynamic response of a firm's employee social capital to the Act. *Post* is a dummy variable for the years during and after the enactment (2016–2018). *X* is the same set of lagged control variables as in Table 2; $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. Our coefficient of interest is β_2, the coefficient of the interaction term, *Act Exposure*×*Post*. If employee social capital indeed has a causal effect on firm performance, we expect firms with ESC more exposed to the Act to derive less value from their employee social capital after the Act than firms that are less exposed, i.e., we expect β_2 to be negative.

[Table 4 about here]

Table 4 summarizes the results of estimating equation (2). The regression in column (1) excludes observations during the enactment year because the Act only became effective in the latter half of 2016.

[26] We focus on *Tobin's q* as our measure of firm performance in testing for causality since, as shown in Table IA.4 in the Internet Appendix, connections to industries affected by the Act have a significant and positive impact on firm performance, with the effect concentrated in *Tobin's q*.

Consistent with our prediction, the estimate of β_2 is negative and significant at the 1% level. Based on the positive and significant β_1 estimate, employee connections to the media and the public sector contribute positively to a firm's *Tobin's q* before the Act; however, the negative β_2 estimate shows that the positive impact declines substantially after the Act. For instance, a one standard deviation increase in *Act Exposure* (0.038) leads to an increase in *Tobin's q* by 17.5% (=0.038×6.578/1.432) relative to the sample mean before the Act, but only by 4.4% after. Our estimate is essentially unchanged when we control for *Act Exposure* measured by *ESC out-degree* in the regressions (reported in Panel A of Table IA.6 in the Internet Appendix); this robustness result reinforces our earlier finding on the value of in-degree connections to firms as opposed to out-degree connections. Panel A of Table IA.6 also shows that the results are robust to alternative thresholds for the minimum number of employees or a minimum percentage of firm employees who appear in the network. Finally, we include observations in 2016 in column (2) of Table 4 and find little change in the magnitude and significance of our β_2 estimate.

To test for the presence of pre-trends, in columns (3)–(4) we estimate an augmented version of equation (2) where we interact *Act Exposure* with an indicator variable for each year *t*.[27] Consistent with *Act Exposure* capturing an adverse shock to employee social capital, the decline in firm performance does not occur prior to the enactment. Starting from the enactment year of 2016, the estimate becomes negative and remains negative and significant at the 1% level. The finding is visualized in Figure IA.5 in the Internet Appendix. Our results suggest no preexisting trend in firm performance before the enactment, reinforcing that the Act negatively affects firm performance by reducing employee social capital.

To further assess the reliability of our identification strategy, we perform a placebo test. We randomly assign a *Pseudo Exposure* to each firm by maintaining the true distribution of *Act Exposure* and re-estimate column (1) in Table 4. By randomizing *Act Exposure* but holding all other variables fixed, we break the true link between employee social capital and firm performance, thereby imposing the null

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

hypothesis on the data. We repeat this procedure 1,000 times and obtain the empirical distribution of the coefficient estimate on the interaction term. The true coefficient estimate (−4.930) falls well below the 1% threshold of this distribution, as reported in Table IA.5 in the Internet Appendix. This placebo test gives confidence that the negative estimate of β_2 is not a statistical artifact.

The exposure of a firm's employee social capital to the Act is not randomly assigned. Firms with ESC more exposed to the Act tend to be larger in asset size and number of employees. It is likely they also had more frequent business interactions with the media and the public sector by 2015. We perform robustness checks to address the issue of covariate balance. First, we use propensity score matching to generate a group of control firms similar to the treated firms and conduct the tests within this matched sample. We use a probit model to estimate the probability of being a treated firm (those with above-median exposure in 2015). Then we match each treated firm to a control firm with replacement, using nearest neighbor matching with a maximum difference of 0.01. Panel A of Table 5 shows that the treated and control firms in the matched sample display indistinguishable observable differences. Columns (1)–(4) estimate the same specifications as in Table 4 for the matched sample, and we find consistent estimates with those in Table 4. As a second robustness test addressing covariate balance, we use the full sample and interact firm-level control variables with the *Post* dummy to control for any observable differences in characteristics related to the treatment that could lead to differences in performance around the enactment. We find the results continue to hold, as reported in Panel B of Table IA.6.

[Table 5 about here]

To alleviate concerns that adverse sectoral shocks to the industries directly affected by the Act could spill over to treated firms through economic linkages rather than employee connections, we conduct subsample analyses in Panel B of Table 5. Firms in the media and the public sector may be highly connected among themselves, thereby mechanically having a high *Act Exposure*; therefore, we drop firms that belong to the industries directly affected by the Act (26 firms) in column (1) and also drop firms that more broadly belong to the media and the publishing activities sectors (KSIC 58, 59) in column (2). In column (3), we further drop firms in the supplier and customer industries of the media and the public sector.[28] To examine whether our results are driven by firms that have no employee connections to the affected industries, in column (4), we focus on the subsample with positive exposure of employee social capital to the Act. Across all these subsamples, the coefficient estimates on the interaction term remain negative and significant at the 1% level. These tests help rule out alternative explanations for our results due to potential differences between the treated and control firms and economic spillovers.

4.3. Stock market reaction to the court ruling on the Kim Young-ran Act

To reinforce a causal interpretation of our findings, we conduct an event study analysis of the stock market response to the Act. We focus on event days surrounding the date (day 0) the court ruled that the Act was constitutional. After bipartisan approval, the Act faced a lengthy petition challenging its scope and constitutionality. The Korean Bar Association and the Korean Journalists Association argued that applying the law to journalists and private school teachers (and their spouses) infringed on freedom of the press and on the rights of private schools. However, the petition was eventually rejected at 2pm on July 28, 2016 when seven out of the nine Constitutional Court justices ruled that the Act was constitutional. We examine stock price reactions around the court ruling for firms differentially exposed to the Act. A negative market reaction for firms with ESC more exposed to the Act would buttress support for the causal effect of employee social capital on firm performance.

[Table 6 about here]

We divide firms into above-median and below-median subgroups based on *Act Exposure*, which is the fraction of *ESC in-degree* in 2015 derived from employees' connections with sectors subject to the Act ($\textit{ESC in-degree}^{Act}_{i,2015}/\textit{ESC in-degree}_{i,2015}$). We calculate average cumulative abnormal returns for each subgroup, both CAPM-adjusted and size-adjusted, for various windows around the court ruling date. As

[28] We use the same method described in footnote 20 to identify the customer industries and a similar method to identify the supplier industries. Examples of supplier industries include manufacturers of newsprint, printing and reproduction of recorded media, infrastructure suppliers, and restaurants; examples of customer industries include the wholesale and retail sectors and sellers of motor vehicles and parts (with significant advertising expenses).

reported in Table 6, we find evidence of a negative market reaction to firms with ESC more exposed to the Act. For example, the average cumulative abnormal return over the [−3, 3] event window is −0.61% (*p*-value = 0.017) for firms with ESC more exposed to the Act and 0.41% for firms with ESC that is less exposed. The difference between the two groups is statistically significant with a *p*-value of 0.019.[29] We also examine the cross-sectional pairwise correlation between *Act Exposure* and the cumulative abnormal returns and find that greater exposure to the Act is significantly associated with more negative stock price reactions. Taken together, the event study evidence supports the notion that employee social capital positively contributes to firm value.

4.4. Mechanisms: economic benefits of employee connections with the media and the public sector

To provide additional confidence in our causality tests and to shed light on the mechanisms through which employee social capital contributes to firm value, we proceed to identify economic benefits that a firm may be able to extract from its employee connections to the sectors affected by the Act—the media and the public sector.

We start by showing that the negative effect of the Act on the value of employee social capital that we demonstrate in Table 4 (where *Act Exposure* is measured using the *sum* of the connections to both affected sectors) is also observed *separately* in each of the affected sectors. We define $\textit{Act Exposure}^{\textit{Media}}$ as the fraction of *ESC in-degree* in 2015 that is due to connections to employees in the media ($\textit{ESC in-degree}_{2015}^{\textit{Media}}/\textit{ESC in-degree}_{2015}$); $\textit{Act Exposure}^{\textit{Public}}$ is defined similarly. As shown in Panel A of Table 7, when we re-estimate equation (2) by setting the treatment intensity separately as $\textit{Act Exposure}^{\textit{Media}}$ and $\textit{Act Exposure}^{\textit{Public}}$, we find results similar to what we find for the combined effect as captured by *Act Exposure*. Before the Act, employee connections to both the media and the public sector have a significant positive impact on firm *Tobin's q*, and the impact declines for both sectors after the Act.

[Table 7 about here]

[29] 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.

Given the positive value of employee social capital documented for each sector, we can now consider some specific benefits that firms can derive from their employee connections with these sectors. With respect to our analysis of media connections, a large body of literature suggests that media coverage influences stock returns (Tetlock et al., 2008; Dougal et al., 2012; Gurun and Butler, 2012; Ahern and Sosyura, 2014). In particular, Gurun and Butler (2012) document that local media tend to display a "positive slant" toward local firms by using fewer negative words in news articles and that the positive slant strongly relates to firms' equity value. Relatedly, Ahern and Sosyura (2014) find that firms actively manage media coverage to influence their stock prices. Like the positive slant observed when media covers local firms, media connections of a firm's employees may lead to a positive slant in news coverage and an associated positive effect on firm value. For instance, reporters who are well connected to a firm's employees may have developed trust in those employees and therefore be more likely to report positive news about the firm. Media connections might also facilitate active media management by allowing firms to influence the timing and content of media coverage. We thus expect that all else equal, employee connections with the media foster more news coverage of the firm, and more news stories with a positive tone.

To test these predictions, we examine the effect of a firm's employee social capital—derived from connections with the media—on media coverage of the firm before and after the Act; the results are reported in columns (1)–(2) in Panel B of Table 7. The dependent variable in column (1) is the log of the weighted count of news articles from RavenPack News Analytics covering a firm in a given year. To measure positive slant by media, we calculate the fraction of news articles covering a firm each year that are associated with a positive sentiment (according to the BMQ sentiment series of RavenPack) and use this measure as the dependent variable in column (2).[30]

Consistent with the notion that media connections promote news coverage, we obtain a significant and positive coefficient on $Act\,Exposure^{Media}$. Moreover, consistent with the idea that reduced social interactions due to the Act undermine the benefits of media connections, the estimated coefficient for

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

Act Exposure^{Media}×*Post* is significantly negative for both the number and the tone of news articles. For example, a one standard deviation increase in *Act Exposure*^{Media} increases the number of news articles by 13.0% (=0.029×4.495) and positive media coverage by 49.1% before the Act, but only increases news articles by 4.3% and positive media coverage by 14.8% after the Act. Taken together, these findings suggest that connections to the media lead to more frequent media coverage and a greater fraction of media coverage with positive sentiment, enhancing firm performance. After the adoption of the Act, the positive impact of media coverage declines substantially, consistent with the diminished contribution to *Tobin's q* in Panel A as well as the event study results showing negative valuation effects.

We now turn to investigating the benefits of employee social capital due to connections with the public sector. A nontrivial responsibility of public sector employees is public procurement, which accounts for 10–20% of GDP in developed countries (OECD, 2015). Schoenherr (2019) documents that Korean public officers who control the distribution of government contracts allocate significantly more procurement contracts to firms with connected CEOs. Similarly, we expect that firms with employees (including non-executive employees) who are better connected with the public sector may obtain more government contracts, thereby resulting in superior performance.

To assess this prediction, we examine the effect of a firm's employee connections with the public sector on public procurement contracting outcomes using data from the Korea online e-Procurement Service. Consistent with our prediction, findings in columns (3)–(5) in Panel B of Table 7 show that firms highly connected to public sector employees obtain more public procurement contracts, in terms of the number of newly signed contracts, their value in Korean won, and their value scaled by firm assets, respectively. The estimated effect is reduced by about half after the Act. For example, column (3) shows that a one standard deviation increase in *Act Exposure*^{Public} leads to a 6.8% increase in the number of newly signed contracts before the Act and only 3.4% after.

We also conduct a falsification test to ensure our results are not driven by unobserved firm characteristics that are associated with exposure to the Act. Specifically, we switch the Act exposure variables and instead regress the media coverage outcomes on *Act Exposure*^{Public} and regress the procurement contracting outcomes on *Act Exposure*^{Media}. If our findings in Panel B indeed reflect a causal effect of media connections in promoting media coverage and of public sector connections in obtaining procurement contracts, rather than unobserved firm characteristics, we should not expect significant effects in this falsification test. The results reported in Panel C of Table 7 confirm this prediction, thus supporting a causal interpretation of the economic benefits in Panel B.

In summary, Tables 4–7 provide evidence that a firm's employee social capital tied to the media or the public sector contributes to its performance by promoting media coverage of the firm or by enhancing its ability to obtain public procurement contracts. Given the intention of the Act, a natural question is to what extent our results are due to the Act's success in reducing the ability of firms to obtain resources (favorable news stories and procurement contracts) by bribing their connections in the media and the public sector. Several points are worth considering in this context.

First, the social capital literature (e.g., Bourdieu, 1986) highlights favor exchanges and reciprocity as important channels through which social relations increase the ability of individuals to advance their economic interests. Despite the negative connotation (and negative welfare effects more broadly), bribery for resources is a perfect example of a favor exchange that can be more easily obtained when employees are more connected.[31] For example, it is hard to offer bribes to people who do not know or trust you. Hence, employees' connections with journalists or public officials facilitating bribery for resources is consistent with the notion that employee social capital improves firm outcomes (although not necessarily social welfare).

Second, our evidence suggests that a reduction in bribery is unlikely the only channel driving our results in Table 7. While bribery is not directly observable, a firm's entertainment expenses are shown to include a significant bribe component (Cai et al., 2011; Kang et al., 2020). Using a firm's entertainment expenses scaled by total assets as a proxy for bribery activities, we find that its correlation with *Act*

[31] This "dark-side" view of social connections is consistent with the evidence of crony lending documented in Haselmann et al. (2018) and the distortive allocation of government resources to politically connected firms (Schoenherr, 2019). While these rent-seeking activities are not allocatively efficient, they do benefit the connected borrowers and firms.

Exposure is only 0.043, suggesting that firms with employees well connected with the media and the public sector do not seem to coincide with those that actively pay bribes. In addition, when we decompose Panel B of Table 7 according to employee job ranks in Table IA.7, we find that the connections by non-executive employees are also significantly valuable in bringing benefits to their firm. Hence, to the extent that bribing for resources for their firm is mostly carried out by executives, bribery does not appear as the only driver.

5. Employee social capital by job level

Our baseline regression results in Section 3 show a robust positive relation between employee social capital and firm performance. Using a negative shock to employee social capital in the context of the Kim Young-ran Act, our difference-in-differences analysis provides evidence of causality in Section 4. In this section, we leverage our data's coverage of employees across ranks and investigate the value of employee social capital by job level.

5.1. Does job level matter?

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

[Table 8 about here]

Table 8 presents results on the effects of employee social capital on firm performance across employees of various ranks. We start in the upper panel by examining a firm's employee social capital derived from connections by executives and non-executive employees.[32] Results show that *ESC in-degree* is positively associated with all firm performance measures for both executives and non-executives. While our findings echo existing studies on the value of executive networks (e.g., Cai and Sevilir, 2012; Engelberg et al., 2012; Larcker et al., 2013), they also suggest that non-executive employees have beneficial connections that contribute to their employers' performance.

One third of our sample is rank-and-file employees without a managerial title. In the lower panel of Table 8, we alternatively divide a firm's employees into managerial employees (those with a managerial title, such as vice president and department head) and rank-and-file employees; we find that the connections of both groups significantly add to firm performance. The economic significance to *ROA* and *Sales Growth* is comparable for the two groups. For example, a one standard deviation increase in *ESC in-degree* of managerial employees is associated with an increase in *ROA* of 0.9 percentage points, and the same increase for rank-and-file employees is associated with an increase in *ROA* of 0.8 percentage points.[33] Our results on the managerial employees are consistent with the idea that managers—executives, vice presidents, department heads, section heads—are on the front line interacting with external stakeholders and responsible for steering the firm's business activities. While the contributions of managerial employees' connections to firm value are perhaps expected, the finding that rank-and-file employee social capital translates to better firm performance is noteworthy and novel to the literature. Thus, we dig deeper and explore the economic channels through which the connections of rank-and-file employees add to firm value in the next section.

5.2. Information sharing and rank-and-file employee social capital

The social capital literature has identified a number of channels through which individuals or groups can derive benefits from their network connections, such as information sharing (Durlauf and

[32] Job levels classified as executives include chairman, vice chairman, president, deputy president, executive vice president, and senior vice president; about 9.7% of the observed employees are executives. Non-executive employees include all other employees.

[33] The number of observations varies slightly across regressions because a small number of firm-years do not have executives or rank-and-file employees. Results are similar when we run the regressions on the same set of observations.

Fafchamps, 2005), reciprocity (Putnam, 1993, 2000), and favor exchanges (Bourdieu, 1986). A plausible underlying channel through which rank-and-file employee social capital improves firm outcomes is that their connections with external contacts catalyze information sharing, i.e., it seems unlikely that rank-and-file employees are in a position to do favor exchanges or to provide access to resources other than information. To provide evidence on the information-sharing channel, we examine employee connections to the investment banking industry, where acquisition of information is a quintessential business activity.

The availability of detailed bond issuance terms and information about employee connections to the investment banking industry provide a unique opportunity to analyze the information-sharing channel.[34] Financial intermediation theories suggest that investment banks play an integral role in acquiring issuer-specific information such as employee productivity and operational efficiency, and any inside information that may affect security prices (Leland and Pyle, 1977; Campbell and Kracaw, 1980). Hence, based on the theoretical model by Easley and O'Hara (2004) and the empirical findings in Francis et al. (2005), all else equal, effective information sharing between the underwriter and the issuer reduces information risk, resulting in a lower cost of capital as reflected in bond spreads at issuance. Like the way that geographic proximity facilitates monitoring and access to information (e.g., Coval and Moskowitz, 2001; Sufi, 2007; Bernstein et al., 2016), social proximity achieved by interpersonal ties may also improve information flow (Cohen et al., 2008). More specifically, if employee connections with the investment banking industry bridge the information gap between the issuer and bond investors, we expect firms with more investment banking connections to incur lower bond spreads when issuing public bonds.

To test this prediction, we calculate $\textit{ESC in-degree}^{\textit{I-bank}}$ broken out by employee job level. $\textit{ESC in-degree}^{\textit{I-bank}}$ is defined as the employee social capital accumulated by in-degree connections with

[34] Whereas the literature has examined connections with bankers and bank lending terms, we focus on connections with the investment banking industry and the corporate bond market for several reasons. First, public bonds, not bank loans, constitute the primary source of financing for Korean listed firms in our sample period. The dollar amount of corporate bonds outstanding is about five times that of bank loans in 2018, according to data from Korea Financial Investment Association. Second, detailed data on bond issuance terms allow us to assess the effect on the cost of public bond issuance, whereas comparable data on bank loan contracting terms are scant. Third, bond investors are more sensitive than banks when pricing borrower information (Bharath et al., 2008), making the bond market a more relevant setting for analyzing the information sharing channel.

the investment banking industry (KSIC 6612), which consists of investment banks and security brokerage firms.[35] In Panel A of Table 9, we start by examining the relation between firm performance and *ESC in-degree*$^{I\text{-}bank}$ by employee job level. Consistent with the idea that connections with the investment banking industry make bond issuance less costly, we find that, across all employee job levels, *ESC in-degree*$^{I\text{-}bank}$ is positively associated with firm performance for all performance measures. For the connections of rank-and-file employees, for example, a one standard deviation increase in *ESC in-degree*$^{I\text{-}bank}$ from its mean is associated with a 6.0% increase in *Tobin's q* relative to the sample mean, and an increase of 0.4 percentage points in *ROA*.

[Table 9 about here]

We proceed to explore the relation between *ESC in-degree*$^{I\text{-}bank}$ and at-issue bond spreads using a comprehensive sample of 480 bond issues in our sample period. The outcome variable, *At-Issue Bond Spread*, is defined as the difference between the bond's yield at issuance and the mark-to-market benchmark yield of a corporate bond portfolio with the same maturity and credit rating. To provide evidence supporting the channel of information sharing through connections with rank-and-file employees, we also separately examine *ESC in-degree*$^{I\text{-}bank}$ for managerial employees and for rank-and-file employees.

Our regression results in Panel B of Table 9 show a significant and negative relation between *ESC in-degree*$^{I\text{-}bank}$ and at-issue bond spreads. In column (1), we observe a negative coefficient of *ESC in-degree*$^{I\text{-}bank}$ which is statistically significant at the 5% level. A one standard deviation increase in *ESC in-degree*$^{I\text{-}bank}$ from its mean is associated with a reduction of 7.29 basis points (bps) in at-issue bond spreads, relative to the sample average benchmark corporate bond yield of 2.7%. This estimate is comparable to that in Hasan et al. (2017), who find that firms headquartered in high-social-capital counties obtain at-issue bond spreads that are, on average, 7.98 bps lower.

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

Columns (2)–(3) of Panel B provide evidence for the managerial and the rank-and-file employees. Of particular interest, the in-degree connections with the investment banking industry of the issuer's rank-and-file employees contribute substantially to the reduction in the at-issue bond spreads. A one standard deviation increase in *ESC in-degree*$^{I\text{-}bank}$ of rank-and-file employees from its mean is associated with a reduction of 7.67 bps in the at-issue bond spreads (column 3).[36] These results are noteworthy because the rank and file are not likely to be the decision makers about corporate bond issuance, or to be relevant to investment bankers for access to resources other than information or for expectations of favor exchanges. Hence, a more likely motivation for investment bankers to remember (upload the cards of) the issuer's rank-and-file employees is to reduce the information costs associated with due diligence. Although investment bankers can obtain information from executives and managers about the issuer firm, they often talk with rank-and-file employees during on-site visits to gain additional perspective on employee productivity and operational efficiency. In this sense, personal connections with the investment banking industry by a firm's assembly line workers, salespeople, and analysts could help channel useful information about their employers, enhance transparency, and lead to lower financing costs. Altogether, our results on connections with the investment banking industry suggest that enhancing information sharing with economically related entities is an essential mechanism through which employee social capital boosts firm performance.

6. Conclusion

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

[36] While an upcoming bond issuance may be expected to lead to more employee connections with the investment banking industry, there is no reason to expect that lower at-issue bond spreads generate more connections with rank-and-file employees.

to investigate whether the direction of connection matters. Our results show that the positive effect on firm performance is primarily the result of external stakeholders remembering and valuing a firm's employees.

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

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

Appendix A: Variable definitions

Variable name	Description
<u>*Measures of employee social capital (ESC)*</u>	
ESC in-degree	The average *In-degree*—the number of employees of other firms who have uploaded the employee as a business contact ("who knows you") by the end of year *t*—across employees of firm *i* who are in the network in year *t*
ESC out-degree	The average *Out-degree*—the number of business contacts of other firms uploaded by the corresponding employee ("who you know") by the end of year *t*—across app-user employees of firm *i* in year *t*
ESC total degree	The average *Total degree*—the sum of *In-degree* and *Out-degree*—across employees of firm *i* who are in the network in year *t*
ESC in-degree of non-app-user employees	The average *In-degree*—the number of employees of other firms who have uploaded the employee as a business contact ("who knows you") by the end of year *t*—across non-app-user employees of firm *i* who are in the network in year *t*
ESC out-degree to app-users	The average *Out-degree* to app-users—the number of app-user business contacts of other firms uploaded by the corresponding employee ("who you know") by the end of year *t* —across app-user employees of firm *i* in year *t*
ESC: Excl. Sales	*ESC* in which we exclude connections of a firm's customer-facing employees who perform sales functions
ESC: Excl. Customers	*ESC* in which we exclude connections with individuals working in a firm's customer industries
ESC: Sum	The sum of *In-degree* (or *Out-degree)* aggregated across employees of firm *i* who are in the network in year *t*
ESC in-degree^{Act}	*ESC in-degree* using only the connections to employees in the industries subject to the Kim Young-ran Act according to the industry codes in Appendix A
ESC in-degree^{Media} (*ESC in-degree^{Public}*)	*ESC in-degree* using only the connections to employees in the media (public) sector according to the industry codes in Appendix A
ESC in-degree$^{I\text{-}bank}$	*ESC in-degree* using only the connections to employees in the investment banking industry (KSIC 6612, Securities and commodity contracts brokerage), which consists of investment banks and security brokerage firms
<u>*Other variables*</u>	
Tobin's q	Market value of assets divided by book value of assets, in which market value of assets is the sum of market value of equity (common shares outstanding times fiscal-year closing price) and book value of assets minus book value of equity
ROA	Return on assets, calculated as EBITDA divided by the lagged total assets
Sales Growth	Log growth rate of sales
R&D	The ratio of R&D expenses to sales; the ratio is set equal to zero when R&D expenses are missing
Book Leverage	Total debt (sum of total long-term interest-bearing debt and current long-term debt) divided by total assets
ln(1+*Assets*)	Log of one plus total assets (in million Korean won)
Volatility	Stock return volatility of a firm during the past 24 months

Firm Age	Current year minus year of incorporation
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	$ESC\ in\text{-}degree_{2015}^{Act}/ESC\ in\text{-}degree_{2015}$, that is, the fraction of *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Act (we use the industry codes listed in Appendix A to identify these connections)
Act Exposure$^{Media\ (Public)}$	$ESC\ in\text{-}degree_{2015}^{Media\ (Public)}/ESC\ in\text{-}degree_{2015}$, that is, the fraction of *ESC in-degree* in 2015 that is due to connections to employees in the media (public) sector subject to the Act (we use the industry codes listed in Appendix A to identify these connections)
ln(1+*Media Coverage*)	Log of one plus the weighted count of news articles from RavenPack News Analytics covering a firm over a year in which the weight is the relevance score of each article which ranges from 0 to 100%. We only include news articles with relevance scores greater than or equal to 75%.
Positive Media Coverage Ratio	The ratio of positive media coverage to media coverage. Positive media coverage is the weighted count of news articles with BMQ sentiment scores of 100 from RavenPack News Analytics covering a firm over a year. The BMQ sentiment score represents the news sentiment of a given story according to the BMQ classifier, which specializes in short commentary and editorials. We only include news articles with relevance scores greater than or equal to 75%.
ln(1+*# of Proc. Contracts*)	Log of one plus the total number of newly signed procurement contracts of firm *i* in year *t*, from the Korea online e-Procurement Service, which is managed by the Public Procurement Service, Ministry of Economy and Finance
ln(1+*Tot Amt. of Proc. Contracts*)	Log of one plus the total amount of newly signed procurement contracts of firm *i* in year *t*, from the Korea online e-Procurement Service
ln(1+*Tot Amt. of Proc. Contracts / Assets*)	Log of one plus the total amount of newly signed procurement contracts normalized by total assets of firm *i* in year *t*, from the Korea online e-Procurement Service
ln(1+*Sales*)	Log of one plus sales
At-Issue Bond Spread	The difference, in percentage, between the bond's yield at issuance and the mark-to-market benchmark yield of a corporate bond portfolio for the same maturity and credit rating from the Korea Financial Investment Association
PPENT	Net property, plant, and equipment normalized by total assets
Modified Z-Score	Modified Altman's z-score according to Campello et al. (2010) = 3.3 × (earnings before interest and tax / total assets) + 1.0 × (sales / total assets) + 1.4 × (retained earnings / total assets) + 1.2 × (working capital / total assets)
Capital Expenditure	Capital expenditure normalized by total assets
Current Ratio	The ratio of current assets to current liabilities
ln(1+ *Maturity*)	Log of one plus the maturity of the bond (in years)
ln(1+ *Issue Amount*)	Log of one plus the bond issue amount (in billion Korean won)

List of industries subject to the Kim Young-ran Act

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

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Table 1. Summary statistics: employee-level connections and firm-year sample

This table provides summary statistics for our data. Panel A presents summary statistics of the employee-level connections as of December 2018, based on the 1,016,023 public firm employees of our sample. *In-degree,* which measures "who knows you," is the number of employees of other firms who have uploaded the corresponding employee as a business contact as of December 2018. *Out-degree,* which measures "who you know," is the number of business contacts of other firms uploaded by the focal app-user employee as of December 2018; 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*. Panel B presents summary statistics of the main variables for our firm-year sample. *ESC in-degree* is the average *In-degree* across employees of firm *i* who are in the network in year *t*. *ESC out-degree* is the average *Out-degree* across app-user employees of firm *i* in year *t*. *ESC total degree* is the average *Total degree* across employees of firm *i* who are in the network in year *t*. The sample period is 2014–2018. The definitions of all variables are provided in Appendix A.

Panel A. 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

Panel B. Firm-level employee social capital (ESC) measures and other main variables

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

Table 2. Employee social capital and firm performance

This table reports OLS regression estimates on the relation between employee social capital and firm performance in the following year. 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 $Y_{i,t}$ is one of the performance measures (*Tobin's q*, *ROA*, or *Sales Growth*), $ESC_{i,t\text{-}1}$ is the one-year lagged firm-level employee social capital of firm i in year t-1; $X_{i,t\text{-}1}$ is a set of lagged firm-specific control variables commonly included in the literature (Anderson and Reeb, 2003); $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. Panel A reports results when measuring employee social capital by *ESC total degree*, without accounting for the direction of connections. Panel B reports results when we measure employee social capital by *ESC in-degree* and *ESC out-degree* to differentiate the direction of connections. H_0: *ESC in-degree – ESC out-degree* = 0 is based on a one-tailed test on the coefficient estimates of *ESC in-degree* and *ESC out-degree* with *p*-values in square brackets. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. Total degree

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

Panel B. "Who knows you" versus "who you know"

Dep. var.	*ESC in-degree* ("who knows you")			*ESC out-degree* ("who you know")		
	Tobin's q	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
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)
Firm 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)
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
H_0: *ESC in-degree* – *ESC out-degree* = 0	0.288	0.017	0.094			
[*p*-value]	[0.000]	[0.004]	[0.000]			

Table 3. Robustness analyses: omitted variables bias and measurement error

This table presents robustness checks for Panel B of Table 2. Panel A addresses omitted variables bias related to firm sales activities and employee technical skills/job satisfaction. We measure employee social capital by excluding connections of a firm's customer-facing employees who perform sales functions (*ESC: Excl. Sales*) and by excluding connections with individuals working in a firm's customer industries (*ESC: Excl. Customers*). We also repeat the analysis in Panel B of Table 2 using subsamples, which exclude, respectively, firms rated at least once in the "top 20 most wanted employers by university students" in 2015–2018, or financial firms (SIC codes 61, 62, 65, 67) and firms in the top three percentile of asset size distribution. Panel B addresses measurement error issues in *ESC in-degree* and *ESC out-degree*. In the upper panel, *ESC* is measured as *ESC in-degree of non-app-user employees* in columns (1)–(3) and *ESC out-degree to app-users* in columns (4)–(6). In the lower panel, we include both *ESC in-degree* and *ESC out-degree* in the same regression in columns (1)–(3). In columns (4)–(6), we focus on connections of app-users in measuring both *ESC in-degree* and *ESC out-degree* and require the firm-year observations to have at least ten app-user employees to reduce measurement errors. In both panels, we include the same set of lagged firm-level control variables and industry-by-year fixed effects as in Table 2. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. Omitted variables: sales activities and employee technical skills/job satisfaction

	ESC in-degree ("who knows you")			*ESC out-degree* ("who you know")		
Dep. var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
[Excluding connections of employees who perform sales functions]						
ln(1+ *ESC: Excl. Sales*)	0.389***	0.020***	0.093***	0.050*	0.003	0.002
	(0.084)	(0.007)	(0.024)	(0.028)	(0.002)	(0.006)
Observations	5,340	5,340	5,340	4,860	4,860	4,860
Adjusted R^2	0.254	0.150	0.037	0.252	0.139	0.038
[Excluding connections with the customer industries]						
ln(1+ *ESC: Excl. Customers*)	0.309***	0.014*	0.082***	0.044	0.003	0.005
	(0.083)	(0.007)	(0.025)	(0.029)	(0.002)	(0.007)
Observations	5,340	5,340	5,340	4,994	4,994	4,994
Adjusted R^2	0.251	0.148	0.036	0.252	0.141	0.035
[Excluding top 20 most wanted employers 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)
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 and top 3% firms based on total assets]						
ln(1+*ESC*)	0.342***	0.019**	0.081***	0.044	0.004*	0.002
	(0.093)	(0.008)	(0.022)	(0.031)	(0.002)	(0.007)
Observations	5,056	5,056	5,056	4,715	4,715	4,715
Adjusted R^2	0.258	0.146	0.041	0.258	0.137	0.040
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year

Panel B. Measurement errors in ESC in-degree and ESC out-degree

Dep. var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
[Differences in characteristics between app- and non-app-users]						
	ESC in-degree of non-app-user employees			*ESC out-degree to app-users*		
ln(1+*ESC*)	0.427***	0.029***	0.135***	0.089*	0.005*	0.006
	(0.110)	(0.009)	(0.029)	(0.047)	(0.003)	(0.010)
Observations	5,340	5,340	5,340	4,994	4,994	4,994
Adjusted R^2	0.252	0.151	0.039	0.253	0.142	0.035
[*ESC in-degree* and *ESC out-degree* in the same regression]						
	Based on app-users and non-app-users			Based on app-users		
ln(1+*ESC in-degree*)	0.371***	0.020**	0.118***	0.416***	0.023**	0.062**
	(0.103)	(0.008)	(0.028)	(0.119)	(0.010)	(0.031)
ln(1+*ESC out-degree*)	-0.015	0.001	-0.014*	-0.158	-0.004	-0.015
	(0.032)	(0.002)	(0.007)	(0.097)	(0.008)	(0.026)
Observations	4,994	4,994	4,994	2,322	2,322	2,322
Adjusted R^2	0.257	0.144	0.041	0.249	0.136	0.067
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year

Table 4. Causal evidence: the 2016 Kim Young-ran Act as an exogenous shock to employee social capital

This table provides evidence on the causal effect of employee social capital on firm performance. We estimate the following difference-in-differences model surrounding the enactment of the Kim Young-ran Act:

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

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

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

Table 5. Causal evidence: robustness analyses

Panel A uses a propensity score matched sample to estimate the specifications in Table 4. 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 Table 4. Each treated firm is matched to a control firm using nearest neighbor with replacement within each two-digit SIC industry, where the maximum absolute difference in propensity scores between the matched observations is 0.01. We first tabulate the means of the matched variables for the treated group (those with above-median exposure) and the control group (those with below-median exposure) in the year 2015. We also report the mean differences between the two groups and their corresponding *p*-values based on heteroskedasticity-consistent standard errors. We next present the results estimating the specifications in Table 4 using the matched sample, and including the same set of lagged control variables and industry-by-year fixed effects as in Table 4. In Panel B, we re-estimate the specification of column (1) in Table 4 using subsamples. Column (1) drops firms that belong to the industries directly affected by the Act (26 unique firms identified according to the industry codes in Appendix A); column (2) additionally drops firms that belong more broadly to the media and the publishing activities sectors (KSIC 58, 59); column (3) further drops firms that belong to the supplier and customer industries of the media and the public sector using detailed Make-and-Use tables; column (4) focuses on a subsample with positive exposure of employee social capital to the Act. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A. Propensity score matched sample

	Above median (Obs. = 635)	Below median (Obs. = 635)	Above − Below	*p*-value
R&D	0.021	0.023	-0.002	0.587
Book Leverage	0.107	0.109	-0.002	0.679
ln(1+*Assets*)	12.347	12.304	0.043	0.574
Volatility	0.142	0.148	-0.006	0.189
Firm Age	29.191	30.710	-1.519	0.117
ln(1+*Emp*)	5.572	5.565	0.007	0.917
Dep. var.	*Tobin's q*			
	(1)	(2)	(3)	(4)
Act Exposure	6.507***	6.531***	6.531***	5.521***
	(1.356)	(1.353)	(1.353)	(1.177)
Act Exposure × *Post*	-4.651***	-4.409***		
	(1.232)	(1.140)		
Act Exposure × d_{2015}				0.964
				(0.878)
Act Exposure × d_{2016}			-3.957***	-2.997***
			(1.050)	(1.002)
Act Exposure × d_{2017}			-4.064***	-3.102***
			(1.218)	(1.099)
Act Exposure × d_{2018}			-5.237***	-4.272***
			(1.306)	(1.150)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including year 2016	No	Yes	Yes	Yes
Observations	3,541	4,811	4,811	5,721
Adjusted R^2	0.266	0.265	0.265	0.264

Panel B. Subsamples

Dep. var.	*Tobin's q*			
	(1)	(2)	(3)	(4)
Act Exposure	8.010***	8.350***	8.190***	6.362***
	(1.419)	(1.535)	(2.232)	(1.363)
Act Exposure × *Post*	-5.884***	-6.211***	-6.376***	-4.760***
	(1.304)	(1.407)	(2.046)	(1.196)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including year 2016	No	No	No	No
Observations	3,708	3,464	2,686	3,344
Adjusted R^2	0.247	0.251	0.222	0.234

Table 6. 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 Kim Young-ran Act is constitutional. In the upper panel, 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 the lower panel, 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 benchmark portfolio equally weighted 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 $Act\ Exposure = ESC\ in\text{-}degree^{Act}_{2015} / ESC\ in\text{-}degree_{2015}$. Column (3) reports the mean difference between the above-median and the below-median subgroup; column (4) reports the cross-sectional pairwise correlation coefficient between *Act Exposure* and the cumulative abnormal returns. The *p*-values in square brackets are based on one-tailed tests for positive returns in column (1), for negative returns in columns (2)–(3), and for negative correlations in column (4), with the standard errors clustered at the industry (two-digit SIC) level. We exclude penny stocks with stock prices less than 1,000 Korean won (about 0.9 USD) as of June 28, 2016, one month prior to the court ruling.

	$Act\ Exposure = ESC\ in\text{-}degree^{Act}_{2015}/ESC\ in\text{-}degree_{2015}$			
	Below median	Above median	Diff Above − Below	Correlation coefficient
	(1)	(2)	(3)	(4)
[Cumulative CAPM-adjusted abnormal returns]				
[-1, 1]	0.07%	-0.27%	-0.34%	-0.009
	[0.325]	[0.080]	[0.083]	[0.363]
[-3, 3]	0.41%	-0.61%	-1.02%	-0.076
	[0.173]	[0.017]	[0.019]	[0.020]
[-5, 5]	0.62%	-1.04%	-1.66%	-0.086
	[0.131]	[0.007]	[0.008]	[0.014]
Observations	751	751		
[Cumulative size-adjusted abnormal returns]				
[-1, 1]	0.16%	-0.11%	-0.27%	-0.004
	[0.182]	[0.207]	[0.098]	[0.440]
[-3, 3]	0.52%	-0.43%	-0.95%	-0.065
	[0.119]	[0.041]	[0.014]	[0.035]
[-5, 5]	0.65%	-0.69%	-1.33%	-0.071
	[0.128]	[0.009]	[0.013]	[0.034]
Observations	788	782		

Table 7. Mechanisms: economic benefits of employee connections with the media and the public sector

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

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

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

Panel A. The value of connections with the media and the public sector: before and after the Act

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

Panel B. The value of connections with the media and the public sector: economic benefits

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

Panel C. The value of connections with the media and the public sector: falsification test

Dep. var.	*Act Exposure*^{Public}		*Act Exposure*^{Media}		
	ln(1+*Media Coverage*)	*Positive Media Coverage Ratio*	ln(1+*# of Proc. Contracts*)	ln(1+*Tot Amt of Proc. Contracts*)	ln(1+*Tot Amt of Proc. Contracts / Assets*)
	(1)	(2)	(3)	(4)	(5)
Act Exposure$^{Public\ (Media)}$	3.357*	0.320	-0.428	-2.443	-0.022**
	(1.889)	(0.239)	(0.495)	(2.617)	(0.011)
Act Exposure$^{Public\ (Media)}$ × *Post*	-2.868	-0.263	0.390	3.245	0.011
	(1.748)	(0.236)	(0.403)	(2.483)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes
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	0.339	0.162	0.231	0.255	0.186

Table 8. Employee social capital and firm performance: by employee job level

This table reports OLS regression estimates on the relation between employee social capital and firm performance in the following year when we differentiate the connections of employees by their job level. In the upper panel, we group a firm's employees who are in the network into executives (chairman, vice chairman, president, deputy president, executive vice president, and senior vice president) and non-executive employees (all other employees). Firm-level employee social capital takes the lagged value of *ESC in-degree* averaged across executives in columns (1)–(3) and averaged across non-executive employees in columns (4)–(6). In the lower panel, we group a firm's employees who are in the network into managerial employees (those with a managerial title, such as vice president and department head) and rank-and-file employees (those without a managerial title). Firm-level employee social capital takes the lagged value of *ESC in-degree* averaged across managerial employees in columns (1)–(3) and averaged across rank-and-file employees in columns (4)–(6). We include the same set of lagged control variables and industry-by-year fixed effects as in Table 2. The dependent variable is *Tobin's q* in columns (1) and (4), *ROA* in columns (2) and (5), and *Sales Growth* in columns (3) and (6). Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Dep. var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
[Executives versus non-executive employees]						
	ESC in-degree of executives			*ESC in-degree* of non-executive employees		
ln(1+ *ESC in-degree*)	0.190***	0.013***	0.050***	0.207**	0.032***	0.090***
	(0.056)	(0.004)	(0.013)	(0.100)	(0.008)	(0.025)
Observations	5,321	5,321	5,321	5,340	5,340	5,340
Adjusted R^2	0.251	0.151	0.036	0.249	0.154	0.037
[Managerial employees versus rank-and-file employees]						
	ESC in-degree of managerial employees			*ESC in-degree* of rank-and-file employees		
ln(1+ *ESC in-degree*)	0.307***	0.021***	0.083***	0.136	0.024***	0.084***
	(0.082)	(0.007)	(0.022)	(0.108)	(0.007)	(0.022)
Observations	5,340	5,340	5,340	5,290	5,290	5,290
Adjusted R^2	0.252	0.151	0.037	0.250	0.150	0.036
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year

Table 9. Employee social capital with the investment banking industry

Panel A repeats the analyses in Table 8 by replacing *ESC in-degree* with *ESC in-degree*$^{I\text{-}bank}$, a firm's *ESC in-degree* with the investment banking industry (KSIC 6612). In the upper panel, firm-level employee social capital takes the lagged value of *ESC in-degree*$^{I\text{-}bank}$ averaged across executives in columns (1)–(3) and averaged across non-executive employees in columns (4)–(6). In the lower panel, firm-level employee social capital takes the lagged value of *ESC in-degree*$^{I\text{-}bank}$ averaged across managerial employees in columns (1)–(3) and averaged across rank-and-file employees in columns (4)–(6). We include the same set of lagged control variables and industry-by-year fixed effects as in Table 2. 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 in-degree*$^{I\text{-}bank}$ relates to the bond spreads at issuance. The dependent variable is bond yield spreads at issuance (in percentage), defined as the difference between the bond's yield at issuance and the mark-to-market benchmark yield of a portfolio of corporate bonds with the same maturity and credit rating. Data on bond issuance are from the Korea Financial Investment Association. The firm-level and issuance-level controls largely follow Bharath et al. (2011) and Hasan et al. (2017); we only include industry fixed effects because the mark-to-market benchmark yields already control for potential economy-wide shocks. In columns (2)–(3), we re-estimate column (1) by differentiating *ESC in-degree*$^{I\text{-}bank}$ of managerial employees and of rank-and-file employees. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. ESC in-degree with the investment banking industry and firm performance: by employee job level

Dep. var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
[Executives versus non-executive employees]						
		ESC in-degree$^{I\text{-}bank}$ of executives			*ESC in-degree*$^{I\text{-}bank}$ of non-executive employees	
ln(1+*ESC in-degree*$^{I\text{-}bank}$)	0.533***	0.027***	0.076***	1.358***	0.061***	0.084*
	(0.112)	(0.008)	(0.021)	(0.268)	(0.015)	(0.043)
Observations	5,321	5,321	5,321	5,340	5,340	5,340
Adjusted R^2	0.258	0.152	0.035	0.263	0.152	0.033
[Managerial employees versus rank-and-file employees]						
		ESC in-degree$^{I\text{-}bank}$ of managerial employees			*ESC in-degree*$^{I\text{-}bank}$ of rank-and-file employees	
ln(1+*ESC in-degree*$^{I\text{-}bank}$)	1.246***	0.049***	0.104***	0.868***	0.042**	0.073
	(0.209)	(0.012)	(0.033)	(0.290)	(0.018)	(0.051)
Observations	5,340	5,340	5,340	5,290	5,290	5,290
Adjusted R^2	0.270	0.152	0.035	0.253	0.147	0.033
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year

Panel B. At-issue bond spread

	All employees	Managerial employees	Rank-and-file employees
Dep. var.		*At-Issue Bond Spread*	
	(1)	(2)	(3)
ln(1+*ESC in-degree*$^{I\text{-}bank}$)	-0.454**	-0.365*	-0.710**
	(0.216)	(0.185)	(0.299)
PPENT	-0.543***	-0.544***	-0.567***
	(0.165)	(0.168)	(0.162)
ln(1+Sales)	0.026	0.022	0.036
	(0.027)	(0.026)	(0.027)
ROA	0.675	0.672	0.679
	(0.517)	(0.511)	(0.527)
Volatility	1.614	1.605	1.637
	(1.196)	(1.191)	(1.181)
Firm Age	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
ln(1+*Emp*)	-0.043*	-0.036	-0.046**
	(0.023)	(0.022)	(0.023)
Tobin's q	-0.162*	-0.164*	-0.165*
	(0.089)	(0.088)	(0.086)
Modified Z-Score	0.020	0.022	0.017
	(0.039)	(0.039)	(0.040)
R&D	1.234	1.248	1.197
	(1.083)	(1.096)	(1.065)
Capital Expenditure	-0.940**	-0.928**	-0.944*
	(0.470)	(0.468)	(0.482)
Current Ratio	-0.090*	-0.092*	-0.078
	(0.049)	(0.049)	(0.049)
ln(1+ *Maturity*)	0.043	0.042	0.040
	(0.050)	(0.050)	(0.051)
ln(1+ *Issue Amount*)	0.003	0.002	0.001
	(0.033)	(0.033)	(0.034)
Fixed effects	Ind	Ind	Ind
Observations	480	480	480
Adjusted R^2	0.314	0.313	0.318

Internet Appendix

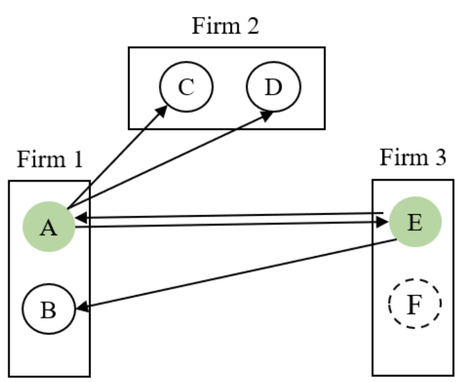
Internet Appendix I: Data on business card exchange network and an example

This Appendix provides descriptive statistics for the business card exchange network data based on all business cards uploaded as of December 31, 2018.

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

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

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



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

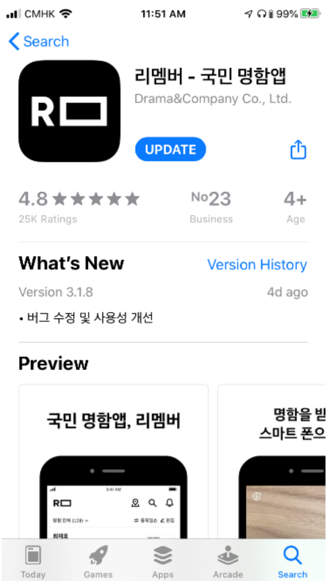
degree across the firm's app-user employees. Firm 1 has only one app-user employee, A, so its *ESC out-degree* equals the out-degree of employee A, which is three. Finally, *ESC total degree* is the average *Total degree* across the firm's employees who are in the network. The total degree is four for employee A and one for employee B, so its *ESC total degree* = 2.5(=5/2). Firm 2 does not have *ESC out-degree* because we can only observe the out-degree of app-users.

Firm_ID	Number of employees in the network	Number of app-user employees in the network	*ESC in-degree*	*ESC out-degree*	*ESC total degree*
1	2	1	1	3	2.5
2	2	0	1	-	1
3	1	1	1	2	3

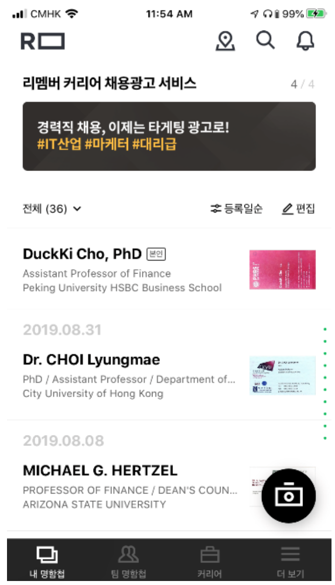
Internet Appendix II: additional figures and tables

Figure IA.1. Remember, the professional business card management app

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



Panel A. Remember on App Store



Panel B. User interface

Panel C. Uploading a card

Figure IA.2. Employee social capital and firm performance: quantile regressions

This figure plots quantile regression estimates on the relation between employee social capital and firm performance based on the specification in Panel B of Table 2. Firm-level employee social capital takes the lagged value of *ESC in-degree* ("Who Knows You"). In each panel, the solid red line represents the estimated coefficients on ln(1+ *ESC in-degree*) from quantile regressions, and the solid black line represents those from OLS estimates. The shaded area indicates the 95% confidence interval of quantile regression estimates, and the dotted line indicates that of OLS estimates.

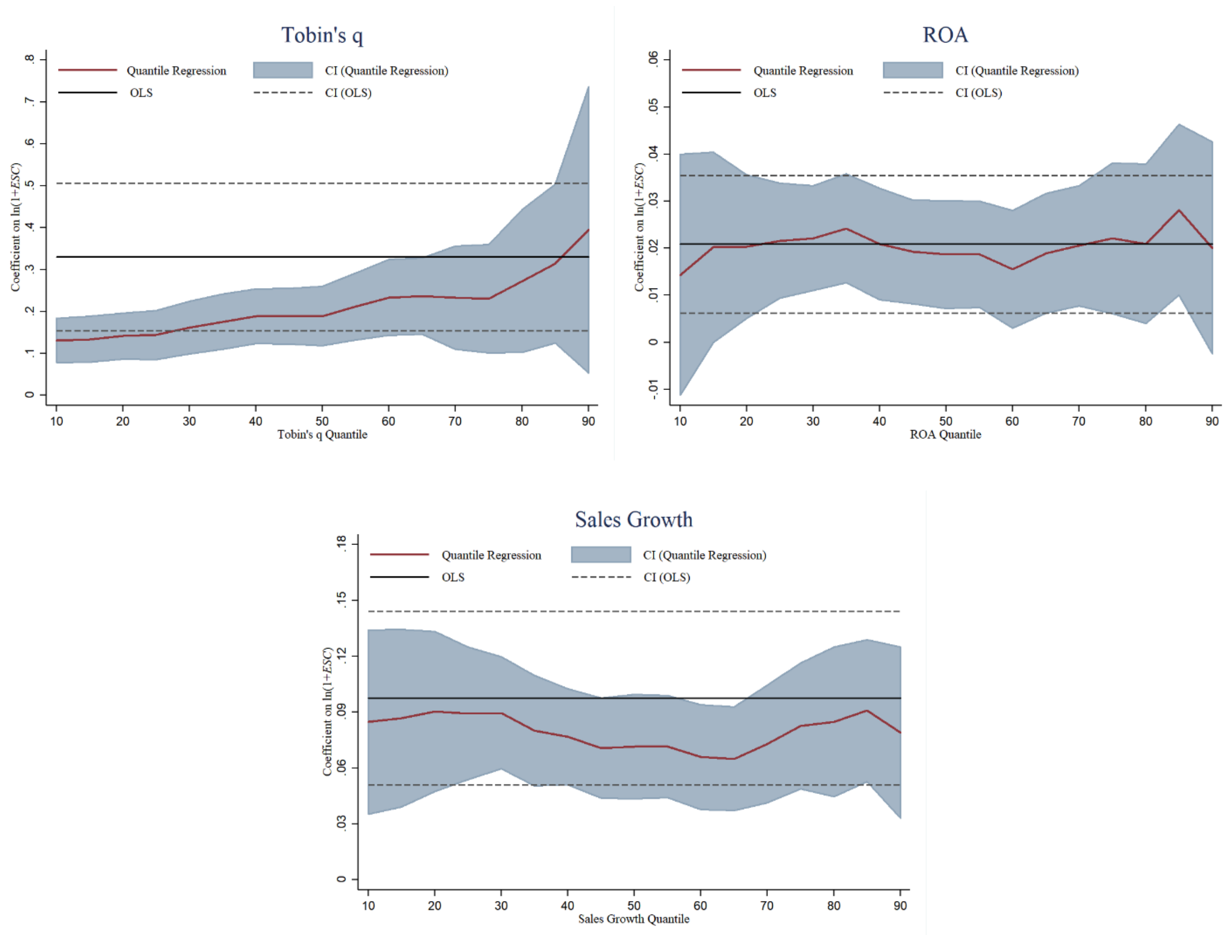


Figure IA.3. Employee social capital and firm performance: measurement error in *ESC out-degree*

To address the potential measurement error in constructing *ESC out-degree* because the *Out-degree* of non-app-users is unobservable, we randomly draw *Out-degree* for non-app-users from the distribution of app-users' *Out-degree* in the same firm with replacement. We then reconstruct *ESC out-degree* using users' actual *Out-degree* and non-app-users' bootstrapped *Out-degree* and rerun the analyses in Panel B of Table 2. We repeat this procedure 500 times to generate a distribution of the estimated coefficients. This figure plots the kernel density of the coefficient distribution, with a vertical line indicating the actual coefficient estimates in columns (4)–(6) in Panel B of Table 2.

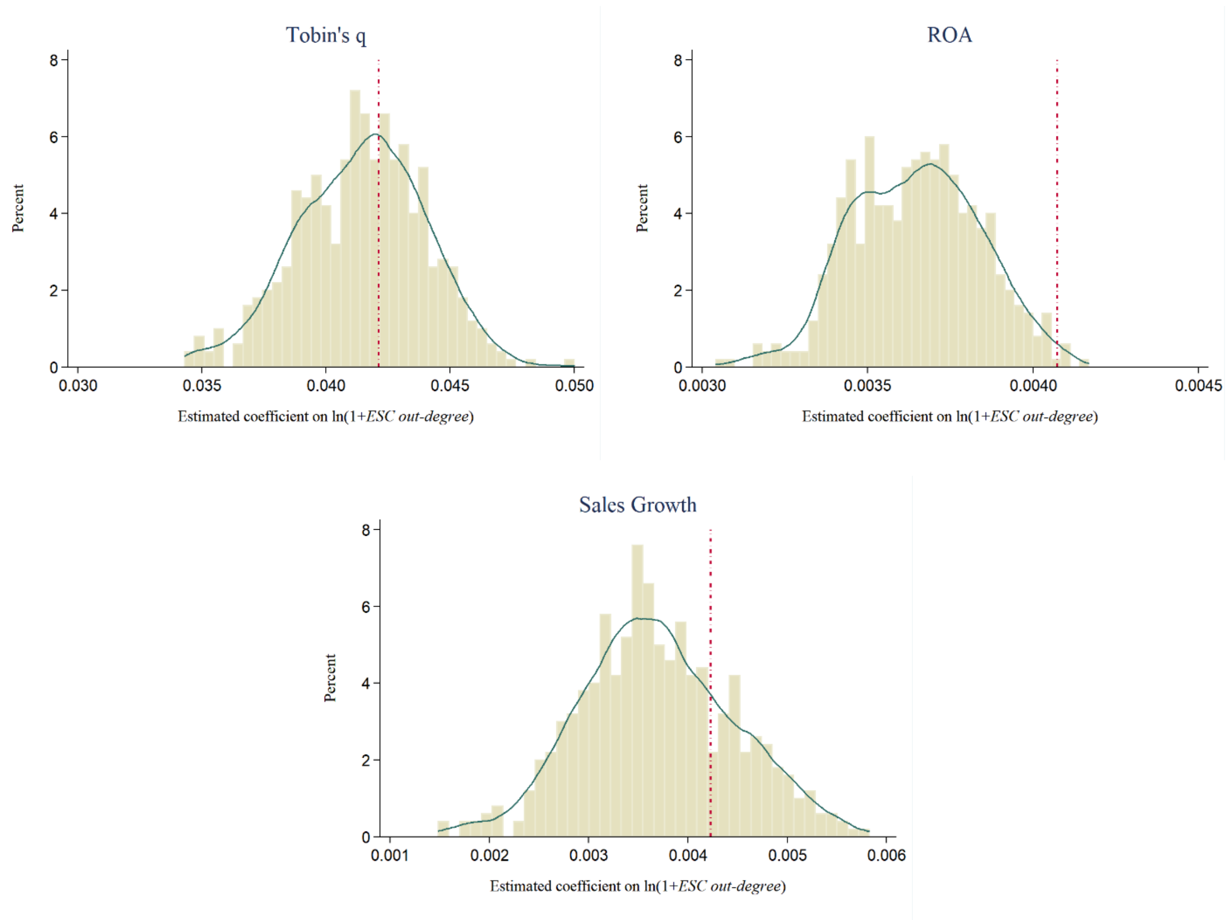
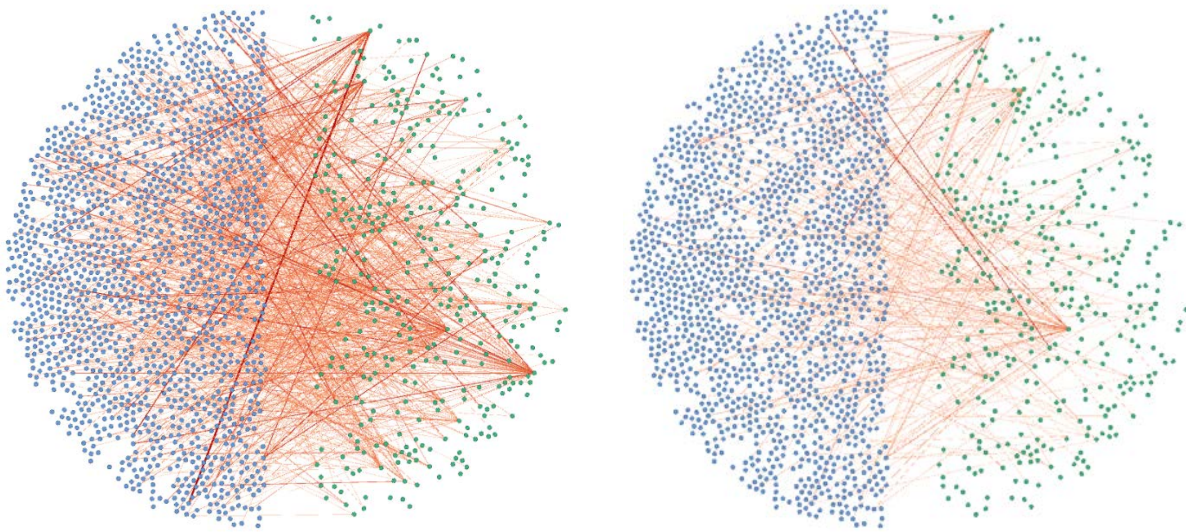


Figure IA.4. Employee social capital before and after the Kim Young-ran Act

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



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

Figure IA.5. Effect of the exposure of employee social capital to the Act on firm performance year by year

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

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

where $Y_{i,t}$ is *Tobin's q*, $Act\ Exposure_i = ESC\ in\text{-}degree_{i,2015}^{Act} / ESC\ in\text{-}degree_{i,2015}$, and $ESC\ in\text{-}degree_{i,2015}^{Act}$ 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 the year 2014 and set 2014 as the baseline year, omitting the 2014 interaction term. The vertical bars correspond to the 95% confidence intervals based on standard errors clustered by firm.

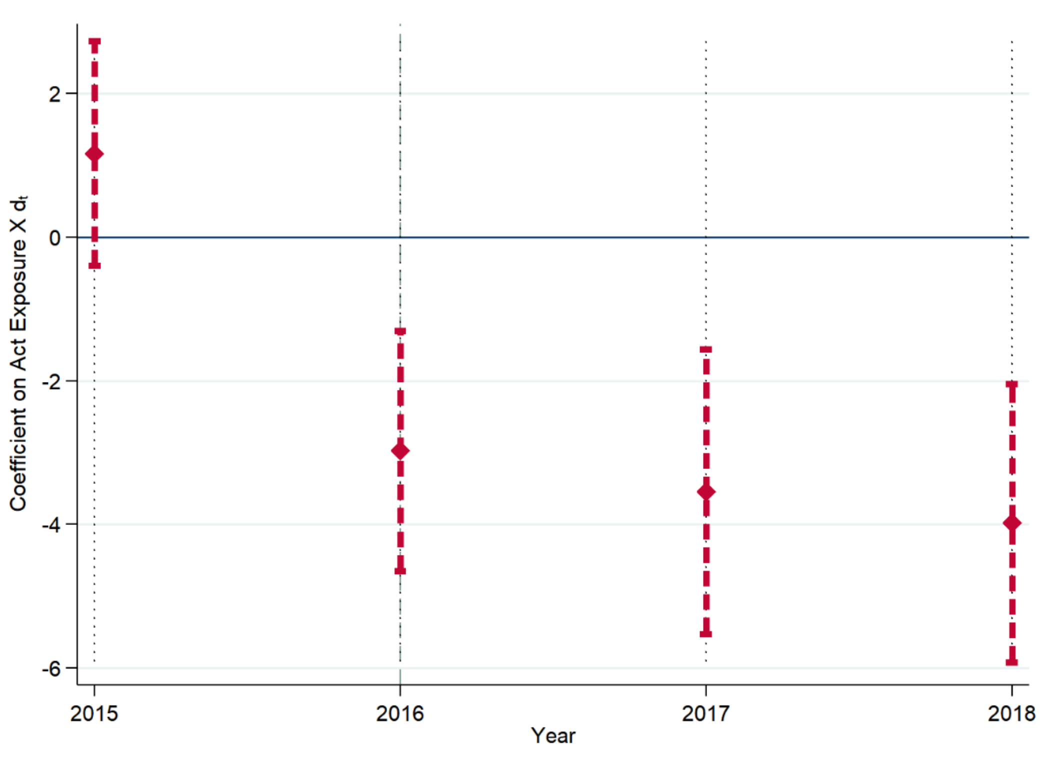


Table IA.1. Descriptive statistics of the business card exchange network by sector

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

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

Table IA.2. Additional robustness results: "who knows you" versus "who you know"

This table reports a battery of robustness tests for Panel B of Table 2. Panel A 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 2, using the nearest-neighbor-matching algorithm with a caliper of 0.01, and with replacement. Standard errors in parentheses are bootstrapped based on five hundred replications with replacement. Panel B repeats the analysis in Panel B of Table 2 with alternative sample selection criteria where we restrict our sample to firm-year observations where at least 20 employees are observed in the network or at least 20% of the firm's employees are observed in the network. We also present an alternative aggregation method of employee social capital: *ESC: Sum* is the sum of *In-degree* (or *Out-degree*) aggregated across employees of firm *i* in the network that year. We include an additional control, the number of employees of firm *i* in the network that year. In both panels, we include the same set of lagged control variables (unless specified) and industry-by-year fixed effects as in Table 2. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2015–2018 for output variables. The definitions of all variables are provided in Appendix A.

Panel A. 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)	

Panel B. Alternative sample selection criteria and measures of employee social capital

	ESC in-degree ("who knows you")			*ESC out-degree* ("who you know")		
Dep. var.	*Tobin's q*	*ROA*	*Sales Growth*	*Tobin's q*	*ROA*	*Sales Growth*
	(1)	(2)	(3)	(4)	(5)	(6)
[At least 20 individuals]						
ln(1+*ESC*)	0.353***	0.026***	0.128***	0.047	0.003	0.007
	(0.097)	(0.008)	(0.025)	(0.032)	(0.002)	(0.007)
Observations	4,842	4,842	4,842	4,680	4,680	4,680
Adjusted R^2	0.259	0.147	0.048	0.257	0.140	0.040
[At least 20% of employees]						
ln(1+*ESC*)	0.289***	0.024***	0.105***	0.035	0.005*	0.007
	(0.098)	(0.008)	(0.027)	(0.040)	(0.003)	(0.008)
Observations	4,209	4,209	4,209	4,014	4,014	4,014
Adjusted R^2	0.263	0.170	0.043	0.267	0.154	0.039
[Sum of *In-degree* (*Out-degree*) across employees]						
ln(1+*ESC: Sum*)	0.251***	0.016***	0.067***	-0.004	0.002	0.007
	(0.070)	(0.006)	(0.017)	(0.022)	(0.002)	(0.005)
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
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year

Table IA.3. Kim Young-ran Act and employee social capital

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

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

where $\frac{ESC\ in\text{-}degree_{i,t}^{Act}}{ESC\ in\text{-}degree_{i,t}}$ measures the fraction of a firm's employee social capital that is derived from connections with employees in the industries affected by the Act. $Post_t$ is an indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. $X_{i,t\text{-}1}$ is the same set of lagged firm-level control variables as in Table 2; α_j is a full set of two-digit SIC industry fixed effects. We no longer include year fixed effects in the regressions due to the collinearity with the dummy variable *Post*. Since the Act became effective in the latter half of 2016, we report results excluding the enactment year of 2016 in column (1) and results including the year 2016 in column (2) for robustness; the sample period is 2015–2018 for output variables. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Dep. var.	*ESC in-degree*^{Act}/ *ESC in-degree (%)*	
	(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)
Firm Age	0.000	0.001
	(0.005)	(0.005)
ln(1+*Emp*)	-0.201*	-0.178
	(0.113)	(0.112)
Fixed effects	Ind	Ind
Including year 2016	No	Yes
Observations	4,017	5,340
Adjusted R^2	0.274	0.277

Table IA.4. 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 Kim Young-ran 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 4, we estimate the following difference-in-differences model surrounding the enactment of the Act:

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

where $Y_{i,t}$ is *Tobin's q*, *ROA*, and *Sales Growth*. $Act\ Exposure_i = ESC\ in\text{-}degree^{Act}_{i,2015} / ESC\ in\text{-}degree_{i,2015}$, where $ESC\ in\text{-}degree^{Act}_{i,2015}$ is *ESC in-degree* in 2015 that is due to connections to employees in industries subject to the Act. $Post_t$ is an indicator variable that takes the value of one during and after the enactment year (2016–2018) and zero otherwise. $X_{i,t\text{-}1}$ is the same set of lagged controls as in Table 2; $\alpha_{j,t}$ is a full set of industry-by-year fixed effects. Columns (1)–(3) report results excluding the enactment year (2016), whereas columns (4)–(6) report results when we include the year 2016. The sample period is 2015–2018 for output variables. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

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

Table IA.5. Placebo test: randomization of the exposure to the Act

This table reports the empirical distribution of the coefficient estimate on *Pseudo Exposure* × *Post* when re-estimating column (1) in Table 4 for 1,000 times using the bootstrapped sample. To obtain the bootstrapped sample, we randomly assign a false treatment intensity, *Pseudo Exposure*, to each firm by maintaining the true distribution of *Act Exposure*. We also plot the kernel density of the coefficient estimate distribution and draw a vertical line to indicate the actual coefficient of -4.930.

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

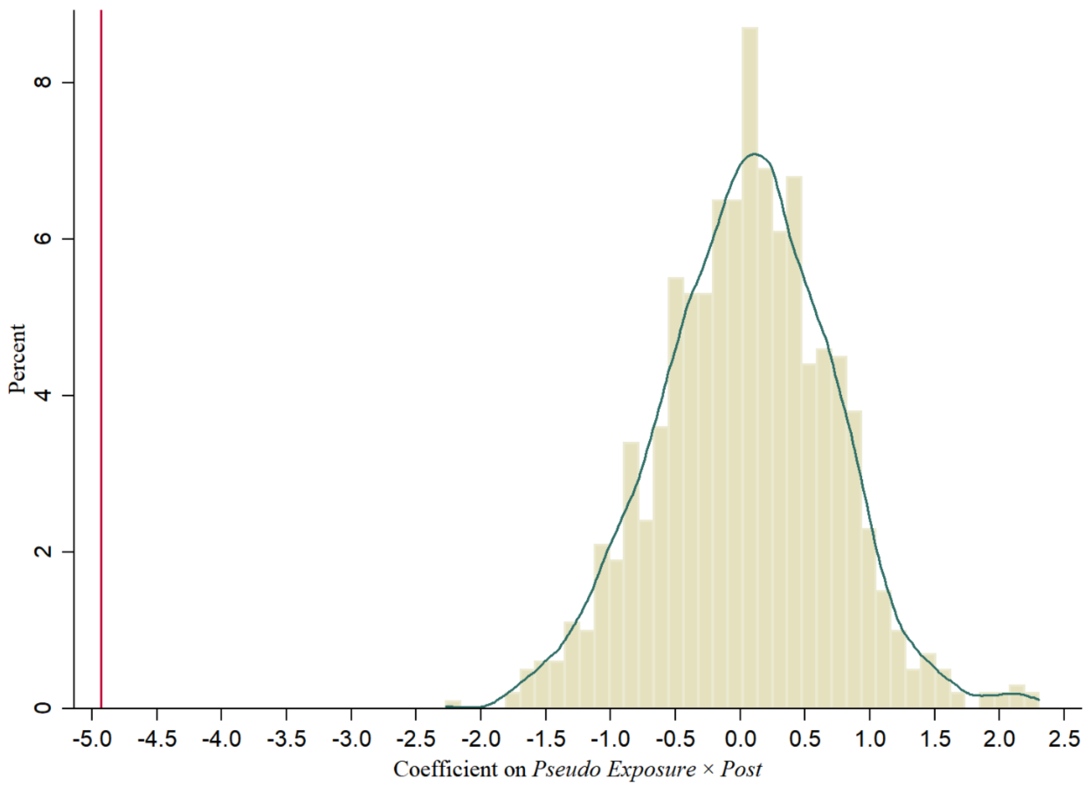


Table IA.6. Robustness results for the difference-in-differences estimation

This table presents robustness checks for the results in Table 4. Panel A considers alternative measures of *Act Exposure* and alternative sample selection criteria. In column (1), we additionally include *Act Exposure out-degree* and *Act Exposure out-degree* × *Post* to the estimation of equation (2). Here, $\textit{Act Exposure out-degree}_i = \textit{ESC out-degree}^{Act}_{i,2015} / \textit{ESC out-degree}_{i,2015}$, and $\textit{ESC out-degree}^{Act}_{i,2015}$ is *ESC out-degree* in 2015 that is due to connections to employees in industries subject to the Act. In columns (2) and (3), we repeat the analysis in column (1) of Table 4 with alternative sample selection criteria: we restrict our sample to firm-year observations where at least 20 employees are observed in the network in column (2), and to those where at least 20% of the firm's employees are observed in the network in column (3). In panel B, we include the interaction terms between the firm-level control variables and the dummy variable $Post_t$ to the estimation of equation (2). Column (1) reports results excluding the enactment year of 2016; column (2) reports results including the year 2016. The sample period is 2015–2018 for output variables. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

Panel A. Alternative measures of Act Exposure and alternative sample selection criteria

Dep. var.	*Tobin's q*		
	(1)	(2)	(3)
Act Exposure	6.338***	6.068***	4.828***
	(1.465)	(1.266)	(1.700)
Act Exposure × *Post*	-4.165***	-3.530***	-2.600*
	(1.315)	(1.214)	(1.543)
Act Exposure out-degree	0.408		
	(0.772)		
Act Exposure out-degree × *Post*	-0.782		
	(0.764)		
R&D	5.179***	5.550***	5.286***
	(0.705)	(0.693)	(0.733)
Book Leverage	0.026	0.124	0.054
	(0.183)	(0.188)	(0.217)
ln(1+*Assets*)	-0.141***	-0.141***	-0.137***
	(0.026)	(0.025)	(0.028)
Volatility	3.585***	3.420***	3.690***
	(0.491)	(0.479)	(0.509)
Firm Age	-0.005***	-0.005***	-0.004**
	(0.002)	(0.002)	(0.002)
ln(1+*Emp*)	0.094***	0.094***	0.083***
	(0.027)	(0.027)	(0.025)
Fixed effects	Ind × Year	Ind × Year	Ind × Year
Including year 2016	No	No	No
Observations	3,577	3,390	2,895
Adjusted R^2	0.249	0.245	0.245

Panel B. Including the control variables interacted with the dummy variable Post

Dep. var.	*Tobin's q*	
	(1)	(2)
Act Exposure	7.380***	7.380***
	(1.319)	(1.318)
Act Exposure × *Post*	-5.847***	-5.544***
	(1.175)	(1.100)
R&D	1.997***	1.997***
	(0.712)	(0.711)
Book Leverage	0.564*	0.564*
	(0.314)	(0.314)
ln(1+*Assets*)	-0.249***	-0.249***
	(0.034)	(0.034)
Volatility	3.742***	3.742***
	(0.666)	(0.666)
Firm 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)
Firm Age × *Post*	0.008***	0.007***
	(0.002)	(0.002)
ln(1+*Emp*) × *Post*	-0.070*	-0.081**
	(0.036)	(0.034)
Fixed effects	Ind × Year	Ind × Year
Including year 2016	No	Yes
Observations	3,778	5,101
Adjusted R^2	0.253	0.252

Table IA.7. Connections with the media and the public sector: by employee job level

This table reports results on the economic benefits of connections with the media and the public sector when we differentiate the connections of employees by their job level. We group a firm's employees who are in the network into executives (chairman, vice chairman, president, deputy president, executive vice president, and senior vice president) and non-executive employees (all other employees). $Act\ Exposure_i^{Media}$ is $ESC\ in\text{-}degree_{i,2015}^{Media}/ESC\ in\text{-}degree_{i,2015}$ for columns (1)–(2) and $Act\ Exposure_i^{Public}$ is $ESC\ in\text{-}degree_{i,2015}^{Public}/ESC\ in\text{-}degree_{i,2015}$ for columns (3)–(5). Dependent variables in columns (1)–(2) are *Media Coverage*, the weighted count of news articles from RavenPack News Analytics covering a firm in a given year (the weight is the relevance score of each article provided by RavenPack; we only include articles with relevance scores greater than or equal to 75%), and *Positive Media Coverage Ratio*, the fraction of news articles with a 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 logarithm of one plus the number of newly signed procurement contracts, the amount of newly signed procurement contracts in Korean won, and the amount of newly signed procurement contracts in Korean won scaled by the firm's total assets. Standard errors in parentheses are clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are provided in Appendix A.

	$Act\ Exposure^{Media}$		$Act\ Exposure^{Public}$		
Dep. var.	ln(1+*Media Coverage*)	*Positive Media Coverage Ratio*	ln(1+*# of Proc. Contracts*)	ln(1+*Tot Amt of Proc. Contracts*)	ln(1+*Tot Amt of Proc. Contracts / Assets*)
	(1)	(2)	(3)	(4)	(5)
[Executives]					
$Act\ Exposure^{Media(Public)}$	2.667***	0.269***	1.491***	7.535***	0.023**
	(0.744)	(0.094)	(0.438)	(2.284)	(0.010)
$Act\ Exposure^{Media(Public)} \times Post$	-2.013***	-0.182**	-0.703**	-2.660	-0.004
	(0.707)	(0.080)	(0.297)	(1.745)	(0.009)
Observations	3,748	3,748	3,748	3,748	3,748
Adjusted R^2	0.351	0.168	0.241	0.264	0.190
[Non-executive employees]					
$Act\ Exposure^{Media(Public)}$	5.317***	0.502***	3.015***	16.979***	0.081***
	(1.707)	(0.180)	(1.117)	(5.243)	(0.026)
$Act\ Exposure^{Media(Public)} \times Post$	-3.654**	-0.393**	-1.498*	-8.627**	-0.039*
	(1.548)	(0.193)	(0.822)	(4.366)	(0.021)
Observations	3,770	3,770	3,770	3,770	3,770
Adjusted R^2	0.343	0.164	0.236	0.260	0.191
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Ind × Year	Ind × Year	Ind × Year	Ind × Year	Ind × Year
Including year 2016	No	No	No	No	No