How Seasoned Equity Offerings Affect Firms: Evidence on Technology, Employment, and Performance

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Abstract

Using regulatory shocks on the eligibility to issue seasoned equity offerings in China, we find that over the two-to-three years following SEOs, expenditures on technology-related tangible- and intangible assets increase, and low (high) skill workers decrease (increase). The decrease of low skill workers outnumbers the increase of high skill workers, resulting in a net decline in firm-level employment. The decline in employment is more extensive among firms investing more in technology after SEOs and among firms more financially constrained before SEOs. Within-firm average wages increase because of the higher skill composition of employees, but total wages remain unchanged because of the fewer remaining employees. Finally, SEOs substantially increase firm profitability and productivity, suggesting the changes to the inputs of production—a smaller and higher skilled workforce using newer technology, and with no increase in total wages—enhance firm performance. These findings illustrate how access to external financing can affect employment and firm performance by facilitating the adoption of productivity-improving technologies.

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1. INTRODUCTION

Much research has been devoted to study how access to stock and debt markets affects employment.[1] Notably absent in that literature is an analysis of how access to external capital facilitate the adoption of new technologies, which the labor literature shows have significant impacts on employment (see Acemoglu and Autor (2011) for a survey). Media news stories also abound about the effects of new technologies on workers. Under the catchy title, "Will robots displace humans as motorized vehicles ousted horses?" *The Economist* (April 1, 2017) warns that robots might replace humans and depress wages. In this paper, we investigate how access to stock markets facilitates technology adoption and affects firm-level employment, wages, and firm performance.

How external capital affects employment depends on its use. If it is invested in a purely scale-expanding project—e.g., building a second plant producing the same product using the current technology—employment will increase due to the scale effect. However, if the capital is used to adopt new technologies automating tasks previously performed by humans, it may lead to a loss of jobs.[2] While the literature provides ample support for the scale effect, few studies document a pure substitution effect—the substitution effect dominating the scale effect. The lack of evidence may reflect frictions against implementing automation. The substitution effect often is a source of controversy between firms wanting to adopt automation technology for efficiency gains, and stakeholders concerned about the job loss. Resistance from unions and the local community, state and federal regulations on laying off employees, and other socio-political forces may delay the technology adoption and raise barriers against firms from making optimal choices on technology. Such delays and barriers weaken the substitution effect external capital can bring about through the facilitation of new technology adoption.

Would the substitution effect of external capital more prevalent if adopting new automation technology faces lower barriers? Studying the Chinese economy helps answer the question. During our

[1] An incomplete survey of recent papers studying how access to financing affects employment include Beck, Levine, and Levkov (2010), Benmelech, Bergman, and Seru (2011), Hau and Lai (2013), Chodorow-Reich (2014), Carvalho (2014), Almeida, Fos, and Kronlund (2016), Cingano, Manaresi, and Sette (2016), Falato and Liang (2016), Brown and Earle (2017), Acharya et al. (2018), Bentolila, Jansen, and Jimenez (2018), Bai, Carvalho, and Phillips (2018), Luck and Zimmermann (forthcoming), Borisov, Ellul, and Sevilir (2019). See Matsa (2018) for a comprehensive survey of the labor and finance literature.

[2] New technologies may also create new tasks in which humans have comparative advantage over machines, increasing demand for workers. (Autor and Salomons, 2017; Acemoglu and Restrepo, 2018). This complementary effect offsets the substitution effect. We examine both the substitution and commentary effects on employment.

sample period, the Chinese government had friendly policies toward automation technology, and labor showed little resistance against the technology amid double-digit annual economic growth rates, allowing rapid adoption of automation technologies. [3]

We investigate how access to external capital through seasoned equity offerings affects technology adoption, firm-level employment, and performance. Studying SEOs in China provides two advantages: identification and firm-level data on technology investments and employee skills. The China Securities Regulatory Commission (CSRC) mandated in 2006 that for listed firms to issue public SEOs, their cumulative distributed profits in cash or stocks during the most recent past three years must be no less than 20% of the average annual distributable profits over the same period. The 20% in these regulatory terms is equivalent to about seven percent annual dividend-to-earnings payout ratio. In 2008, the RSRC raised the threshold to 30%, counting only cash payouts, which is about a 10% annual cash dividend-to-earnings payout ratio. We use these regulatory shocks to construct an instrument to estimate the causal effects of issuing SEOs.[4] Firms affected by the shocks cannot circumvent the regulations because their past actions determine the eligibility, so the instrument is devoid of issues arising from the possibility that a particular group of firms (e.g., firms needing capital more) might circumvent the regulations. Also, the shocks did not directly affect how firms use SEO proceeds.

We are mindful of other issues regarding the validity of the instrument. First, different past payout ratios may reflect differences between the treated and untreated firms. To help satisfy the exclusion restriction that the instrument is uncorrelated with the error term in the second-stage regressions, we control for the most recent past three-year payout ratio. Second, outcome variables of treated and untreated firms may have different trends in the absence of the shocks. We test for differences in outcome variables between treated and untreated firms during the years leading up to the first shock and find no difference. Third, though unlikely, some firms may have anticipated the regulatory changes and circumvented them by paying higher dividends before the regulations than they

[3] For example, Cheng et al. (2019) point out that the operational stock of industrial robots in China increased at an annual average rate of 38 percent between 2005 and 2016. They explain the rapid rise by relating the supply and demand for robots to favorable government policies and relatively docile labor.

[4] We do not use the regression discontinuity design because observations around the cutoff points are too few for RD analyses. See Section 2.

would otherwise. Such maneuvers, if any, are likely to manifest as a jump in payout ratios just above the thresholds required by the regulations. We find no such discontinuity using the McCrary (2008) test. Finally, we conduct a battery of tests to check robustness to alternative ways to construct the IV. The results are robust.

The second advantage of studying the Chinese experience is the availability of firm-level data on technology investments and employee occupation and education. Listed firms in China are required to disclose by type the value of assets based on the purchase price and the number of employees by occupation and education in annual filings. These disclosure requirements allow construction of panel data on firm-level technology investments and employee skills, which are difficult, if not impossible, to construct with U.S. public data.

SEOs are an essential means to raise external capital in China. Listed firms, if eligible to issue equity, tend to rely more on the stock market than on debt financing vis-a-vis American firms (Ni and Yu, 2008; Yuan, 2018). The heavy reliance on equity offerings is partly attributable to the relative underdevelopment of the Chinese corporate bond market (see Online Appendix 1). Bank loans, as in other countries, are also commonly used to raise external capital. However, when a firm's equity base is considered inadequate to support incremental debt, banks often demand the firm to raise new equity, and it is not unusual for firms to use shares as collateral to obtain bank loans.[5] Online Appendix 1 explains why China's stock market is well suited to study SEOs and provides background information on both the financial and the labor markets.

Our sample contains 557 public SEOs over the period 2000 through 2012, which spans the two regulation changes. Through these SEOs, firms raised over 404 billion in 2000 RMB or, on average, 726 million RMB (about US$88 million based on the exchange rate in 2000) per SEO. Using an instrumental variable approach, we find SEOs lead to a 9.1% decline in firm-level employment over the two-to-three years following the receipts of SEO proceeds.[6] For the 557 SEOs, the 9.1% decline

[5] The shares pledged for bank loans often belong to major shareholders, who can increase their shareholding via SEOs (e.g., rights offerings). The Guarantee Law came into effect in 1995, establishing the pledge system, which was further clarified for equity pledge by the Property Law that came into effect in 2007.

[6] The decline in employment at the firm level does not imply lower employment at the economy-wide level because our sample does not include private firms. Autor and Salomons (2017) argue that as aggregate productivity rises, employment at the country level, especially in the tertiary sector, tends to grow.

implies 236,048 fewer employees remaining with the firms, or 424 fewer employees per SEO.

To provide a conceptual framework for the dynamics underlying the data, we offer a simple model wherein a firm facing an opportunity to upgrade technology has access to external capital. We follow Acemoglu and Autor (2011) and assume the production of final goods is a constant elasticity of substitution (CES) aggregation of two intermediate inputs: an input produced by high skill workers with machines and the other input produced by low skill workers. The model predicts that if the technology is sufficiently productivity-improving, the firm will raise the necessary capital to adopt the technology, which changes the firm's optimal choice of inputs: fewer low skill workers and more high skill workers. Furthermore, if the level of productivity improvement exceeds a certain threshold, the decline of low skill workers will outnumber the addition of high skill workers.[7]

To investigate the employee skill channel through which access to external capital affects employment, we begin by estimating the effect of SEOs on the skill composition of employees. We classify production workers and support staff as low skilled and technicians, R&D employees, and sales and marketing forces as highly skilled. We also classify those with four-year university bachelor's degrees and above as highly skilled and those without four-year university bachelor's degrees as low skilled. Our estimates indicate that SEOs lead to 25%, 46%, and 17% reduction in production workers, support staff, and employees without a four-year university bachelor's degree, respectively. In contrast, SEOs lead to a 13%, 10%, and 11% increase in technicians and R&D employees, sales and marketing forces, and employees with post-graduate degrees, respectively.

The higher skill composition leads to higher within-firm average wages (total payroll/total number of employees) because higher-skilled and more educated employees are paid more (Card, 1999; Zhang et al., 2005). We find the average wage of non-executive employees increases by 9% following SEOs. However, we find no change in total wages, which represent the bulk of labor costs. Average wages increase because of the higher skill composition, but the higher average wage applies to a smaller

[7] These predictions require that the elasticity of substitution between high- and low skill workers is greater than one. Prior estimates of the elasticity are well above one. (Katz and Murphy, 1992); Heckman, Lochner, and Taber, 1998; Card and DiNardo, 2002; Acemoglu and Autor, 2011; and Card and Lemieux, 2002). In Appendix B, we estimate the elasticity for our sample firms. Our estimates are slightly above two when the level of education classifies high- and low skill workers are.

number of employees due to the reduction in firm-level employment.

We also investigate the technology channel through which our model suggests leads to the above changes. We find expenditures on technology-related assets increase significantly following SEOs. The assets consist of tangible assets—computers and technology-related electronic machines and equipment—and intangible assets—computer software, technology with or without patents, patents, and information management systems. Expenditures on technology-related tangible assets increase by 27%, or by 40.4 million in 2000 RMB. Expenditures on intangible technology assets increase by 36%, or by 3.5 million RMB.

If these increases in technology investments augment high skill workers as our model assumes, firms' demand for skills will increase after SEOs. To check the validity of the assumption, we investigate the relation between SEOs and demand for skills using data provided by a major job posting company in China. The data are available only for 2014 - 2016, which does not overlap with the regulatory shocks used for identification. We find a significant increase in the advertisement of job vacancies requiring basic and advanced computer skills and non-routine analytical and interactive skills when firms receive SEO proceeds. Although this does not establish causation, SEOs seem to facilitate investments in technology that requires high skills, consistent with our prediction.

In addition, we find the decline in employment following SEOs is related to the intensity of technology investments. The decline is more substantial and significant among firms investing more in technology after SEOs. The effects of SEOs are also stronger on both technology investments and employment among firms more financially constrained before SEOs. These findings, taken together, suggest that technology investment plays a vital role in how SEOs impact firm-level employment.

How do the changes in inputs of production—a smaller, higher-skilled workforce using newer technology, and with no higher total wage bill—affect firm performance? We find SEOs significantly increase profits, sales growth, and labor and total factor productivity. Return on assets increases by 1.8 percentage points, sales growth rate increases by 21 percentage points, annual sales per employee increases by 847,000 RMB, and total factor productivity (TFP) improve by 0.094. All these improvements are quite substantial in comparison to their respective sample means.

This paper encompasses a broad range of topics covering financing, labor, and the link between finance and labor. Beck, Levine, and Levkov (2010), Benmelech, Bergman, and Seru (2011), Carvalho (2014), Bai, Carvalho, and Phillips (2018), and Luck and Zimmermann (forthcoming) study the effects of positive shocks on the accessibility to debt financing on employment in the local economy. Hau and Lai (2013), Chodorow-Reich (2014), Almeida, Fos, and Kronlund (2016), Cingano, Manaresi, and Sette (2016), Falato and Liang (2016), Brown and Earle (2017), Acharya et al. (2018), and Bentolila, Jansen, and Jimenez (2018) study the effects of reduced access to debt or equity financing on firm-level employment. Mitton (2006), Butler and Cornaggia (2011), and Berger and Bouwman (2013) study how access to capital affects firm performance and productivity. Agrawal and Tambe (2016), Olsson and Tag (2017), and Antoni, Maug, and Obernberger (2019) examine how private equity buyouts affect target firms' employee skills, employment by job tasks, and wages. Baghai et al. (2018) and Ghaly, Dang, and Stathopoulos (2017) relate the employment of skilled workers to financial distress and precautionary cash.

Although some of the papers on employee skills relate their findings to information and computer technology, none of the above studies explicitly analyze how accessibility to external financing affects technology investments. By exploring the technology channel, we add new evidence on how the infusion of capital through SEOs differentially impacts the employment of high- vs. low skill workers and improves firm performance when there are opportunities to adopt productivity-improving technologies.

Perhaps most surprising, we find SEOs lead to a reduction in firm-level employment. This is somewhat at odds with some of the findings in the above studies on how the accessibility to external capital affects firm-level employment. The difference is likely due to differences in the sample. As mentioned at the outset of the paper, during our sample period, the Chinese government had friendly policies toward automation technology, and labor showed little resistance amid the rapidly growing economy. In that regard, our evidence is more about the potential impact that SEOs can have when firms face little (no) obstacles against laying off low skill workers that can be substituted by technology.

Prior studies document sporadic incidents of investments coinciding with declines in employment. Letterie, Pfann, and Polder (2004) observe that when there is an investment spike, some Dutch firms decrease employment. Hawkins, Michaels, and Oh (2015) show that Korean plants undertaking large investments sometimes reduce employment. Acemoglu and Restrepo (2017) report that a commuting zone's exposure to robots is negatively related to employment. Tuzel and Zhang (2018) find investment tax incentives in the U.S. have adverse, though insignificant, effects on firm-level employment over three years.[8] These findings illustrate that some investments lead to the displacement of workers, but do not link the loss of jobs to access to external capital. The novelty of our evidence is that external financing through SEOs leads to a substantial, significant decline in *average* firm-level employment when firms face little barriers to adopting automation technologies.

This paper also adds to the literature on equity offerings. Prior studies suggest that equity offerings reduce leverage (Pagano, Panetta, and Zingales, 1998; Eckbo, Masulis, and Norli, 2000; Gustafson and Iliev, 2017), replenish cash balances (DeAngelo, DeAngelo, and Stulz, 2010; McLean, 2011), increase investments (Kim and Weisbach, 2008; Gustafson and Iliev, 2017); change innovation strategies (Bernstein, 2015); and improve the ability to acquire other firms and make strategic shifts toward commercialization (Borisov et al., 2019). We contribute to this literature by adding evidence on the effects of SEOs on technology adoption, firm-level employment, and performance.

Finally, we add to the labor literature on the capital-technology-skill complementarity. Lewis (2011) and Akerman, Gaarder, and Mogstad (2015) provide identification using exogenous shocks, but their findings apply only to the technology-skill complementarity, without linking financial capital (as opposed to physical capital) to technology or skills. Our identification begins from financial capital, identifying its impacts on technology adoption, employment, the skill composition of employees, and firm performance. Acemoglu and Finkelstein (2008) find a decrease in the price of capital relative to labor for hospitals leads to more adoption of new health care technology, decreases total labor input, and upgrades the skill composition of hospital nurses. We add to their contribution by expanding the scope of the investigation: capital-technology-skill complementarity holds for a broad range of sectors and occupations. We also show the capital skill complementary process triggered by SEOs affects wages and improves firm productivity.

[8] The negative sign is consistent with our evidence that SEOs reduce firm-level employment. Investment tax credits reduce the cost of fixed-asset investments, allowing the firm to allocate more money to other input factors, with an effect similar to increasing capital budgets. We find a more significant and stronger negative effect on employment because SEOs have more direct and stronger impacts on relaxing budgets than investment tax credits.

The next section describes our empirical strategy and data; Section 3 provides evidence on how SEOs affect firm-level employment; Section 4 provides a theoretical framework to help interpret the data; Section 5 presents evidence on technology, demand for skills, financial constraints, wages, and firm performance; Section 6 conducts robustness tests; and Section 7 concludes.

2. EMPIRICAL STRATEGY AND DATA

We employ an IV approach using shocks on the eligibility to issue SEOs. We do not use a difference-in-differences (DID) approach because it provides estimates of the effects of regulatory changes, not the direct effects of SEOs.[9] Observations in the neighborhood around the thresholds in 2006 and 2008 shocks are too few to conduct meaningful regression discontinuity analyses.[10]

2.1. Regulatory Changes on the Eligibility to Issue SEOs

On May 6, 2006, the CSRC issued Decree No.30 requiring that to conduct a public SEO, a firm's payout ratio as defined by $(D_{t-1} + D_{t-2} + D_{t-3}) / [(I_{t-1} + I_{t-2} + I_{t-3}) / 3]$ must be no less than 20%, where D_t is the amount of cash and stock dividends paid in year t, and I_t is the distributable profits in year t.[11] Because of the way the formula defines the denominator, the payout ratio is roughly three times the average annual payout to earnings ratio over the past three years. Before this regulation, the eligibility requirement was a positive dividend during the past three years.

What triggered the new regulation was the dramatic increase in the supply of tradeable shares following the Split Share Structure Reform of 2005 that made non-tradable shares tradable in stock

[9] Let $y = \alpha + \beta * \mathrm{SEO} + \varepsilon$, where β captures effects of SEOs. We construct an IV from a regulatory shock, and the relation between SEO and IV is $\mathrm{SEO} = \gamma + \delta * \mathrm{IV} + v$. The DID approach estimates $y = \alpha + \beta * (\gamma + \delta * \mathrm{IV} + v) + \varepsilon = \alpha + \beta * \gamma + \beta * \delta * \mathrm{IV} + \beta * v + \varepsilon$. That is, the coefficient we get from the DID approach is $\beta * \delta$, not β that we hope to estimate using the IV approach.

[10] For the 2006 regulation cutoff, there are no eligible firms conducting SEOs and four ineligible firms not conducting SEOs in the neighborhood of [19%, 21%]. For the broader neighborhoods of [17%, 23%] and [15%, 25%], there are one and four eligible firms conducting SEOs and 7 and 11 ineligible firms not conducting SEOs, respectively. For the 2008 regulation cutoff, for the neighborhoods of [29%, 31%], [27%, 33%], and [25%, 35%], the number of eligible firms conducting SEOs is 2, 11, and 22; the number of ineligible firms not conducting SEOs is 7, 13, and 22. For the neighborhood containing the most observations ([25%, 35%]), the calculated power of the RD strategy for the estimated effect of SEOs on total employment by the IV strategy in the paper (i.e., the coefficient of $\widehat{\mathrm{SEO}}$ in Table 3, Panel B, Column 1) is only 0.060, substantially lower than the conventional threshold 0.8. Stata code "rdpower" is used for this calculation.

[11] For consolidated financial statements, I_t is the parent's net income. For firms listed for less than three years, the same formula (with fewer years) applies to the years they have been listed. See http://www.csrc.gov.cn/zjhpublic/zjh/200804/t20080418_14487.htm, http://www.csrc.gov.cn/pub/newsite/gszqjgb/fwzn/201603/t20160329_294910.htm, and the CSRC internal publication, *BaoJianYeWuTongXun (Investment Banking Practice Letters)* 2, 2010, p.24).

markets.[12] Before the Reform, about two-thirds of listed firms' shares were non-tradable, so the Reform tripled the number of tradeable shares in stock markets, which the regulators thought would hurt the stock price. The 2006 regulation was intended to reduce the supply of new shares through SEOs. For that purpose, the regulators targeted low-payout firms, which might appear odd because firms paying out a small portion of their earnings tend to be in a greater need for external capital. It appears the regulators chose to prevent low-payout firms from issuing SEOs based on the belief that firms paying out less free cash flows are less likely to waste financial resources more and hurt investors.[13]

The CSRC further tightened the requirement when it issued Decree No.57 in 2008, raising the threshold to 30% and counting only cash payments as distributed profits. A stock market crash triggered this change in regulation. The Shanghai Stock Exchange Composite Index reached its peak on October 16, 2007, then fell precipitously, dropping more than 50% by June 2008. The CSRC raised the bar in an attempt to prevent further decline in stock prices by reducing the supply of newly issued shares. It issued a draft of the 2008 regulation on August 22, 2008, and the official announcement on October 9, 2008.

2.2. The SEO Variable and the Instrument

2.2.1. The SEO Variable

We follow prior studies on equity offerings (e.g., Kim and Weisbach, 2008; DeAngelo et al., 2010) and define the SEO variable, *SEO,* as the "SEO years" in which proceeds from SEOs are most likely to affect outcome variables of interest. Some firms receive SEO proceeds very late in the year, and it takes time for the capital to be invested and affect employment and firm performance; therefore, we define *SEO* as the year of receiving SEO proceeds and two years afterward.

2.2.2. Construction of the Instrument

The instrument for *SEO, SEOIneligible,* is an indicator for firms that became ineligible to receive SEO proceeds during the SEO years. The indicator has a two-year lag from the year of the shock;

[12] The Reform has been considered the milestone of the new era of Chinese financial markets. It made the stock price more informative by increasing liquidity of publicly-listed firms' shares and strengthened corporate governance by exposing controlling shareholders to the external pressure for good governance that arises with takeover threats. See Kim, Lu, Shi, and Zheng (2019) for more details.

[13] Go to http://www.csrc.gov.cn/pub/newsite/hdjl/zxft/lsonlyft/200710/t20071021_95210.html for a press conference on the 2006 regulation. For more details, see *Regulation for Issuing Stocks*, 2006, China's Securities Regulatory Commission.

that is, had a firm been eligible, it would have taken two years from the year of getting an approval to issue SEOs to receive SEO proceeds. Consider the 2006 regulation. This regulation treats firms if their average payout ratios over 2003 – 2005 are less than 20% as defined by the regulation. Starting an SEO process in 2006 is unlikely to provide the firm with the proceeds in 2006. The average time elapsed from the initial SEO announcement to the receipt of the proceeds is 337 calendar days in our sample,. Hence, if a firm received SEO proceeds in 2006, it is likely that the SEO was approved before the 2006 regulation took effect. So we use a two-year lag to match the SEO variable *SEO* with the applicable instrumentation: if the 2006 regulation treated a firm in 2006, we assume it prevented the firm from receiving SEO proceeds in 2008, and turn on *SEOIneligible* in 2008, 2009, and 2010. (We use a two-year lag because the shocks occurred in May 2006 and October 2008. The results are robust to using a one-year lag.) We also allow the 2006 regulation to treat firms in 2007 because it may be difficult to circumvent the regulation in 2007 by increasing dividends in 2006 alone. So if a firm has less than 20% payout ratio over 2004 – 2006, we turn on the instrument in 2009, 2010, and 2011. Results are robust to turning off the instrument for firms affected by the 2006 regulation in 2007.

We follow the same procedure for firms treated by the 2008 regulation. *SEOIneligible* is equal to one in 2010, 2011, and 2012 for firms with average payout ratios less than 30% over 2005 – 2007, and in 2011 and 2012 for firms with average payout ratios less than 30% over 2006 – 2008. Online Appendix 2 illustrates the construction of the instrument.

2.2.3. The Validity of the Instrument

The exclusion restriction condition requires the instrument to be uncorrelated with the error term in the second stage. In this regard, we are concerned with two potential issues. First, treated and untreated firms may differ to the extent that past dividend payouts reflect firm characteristics. For example, firms may pay out more of their earnings when management anticipates positive shocks to cash flows in the future. As the anticipated positive shocks realize, firms make more investments in technology, leading to changes in outcome variables of interest. For this reason, all regressions containing time-varying control variables control for the most recent past three-year payout ratio, *P3_PR*. We also examine, in Section 6.1, whether treated and untreated firms would have had different time trends in outcome variables had there been no shock. Using data before 2006, we find no different pre-trends in outcome variables between treated firms and untreated firms before the first shock.

It is unlikely that firms circumvented the regulations. For low payout firms to avoid treatment require anticipation well ahead (about two years ahead) of the announcement of the regulations and then payout more than they otherwise would. Even if they were able to anticipate, anticipation is subject to uncertainty, reducing the present value of benefits from the maneuvers. The uncertainty is not only about future regulations; there is also the uncertainty of approval. SEOs require the CSRC's approval, which adds uncertainty over whether and how much capital an SEO can raise. The cost of maneuvering dividends in anticipation of the 2008 regulation is likely to be economically significant because it counts only cash dividends.[14] Maneuvering dividend payouts in anticipation of the 2006 regulation can be less costly because it counts stock dividends as payouts. If low-payout firms anticipated this aspect of the forthcoming regulation, they could have satisfied the dividend requirement by issuing sufficient stock dividends during 2003 - 2005. Data show otherwise. Stock dividends were relatively rare in China during that period. Among 600 dividend cases in 2005, for example, only 41 included stock dividends. Over the 2003-2005 period, 94% of all the dividend cases did not include any stock dividends.

Despite all these facts, if some firms somehow manipulated payout ratios to meet the eligibility requirements, the average payout ratios for the most recent past three years are likely to be just above 20% in 2006 and 30% in 2008. They are unlikely to exceed the thresholds by much because the maneuvers would force the firm to pay out more than it would otherwise. To check whether there are discontinuities in the most recent past three-year payout ratios at 20% for 2006 and 30% for 2008, we use the method proposed in McCrary (2008). Using Stata command "DCdensity," which chooses bin size and bandwidth, yields a discontinuity estimate of 0.724 for 2006, with standard error and P-value of 0.708 and 0.306, respectively. For 2008, the discontinuity estimate is 0.179, with standard error and

[14] To circumvent the 2008 regulation, a firm would have to guess the higher required payout ratio, pay more dividends in 2005 through 2007 than it would otherwise, then gross up the size of the SEO to make up for the difference. Such maneuvers are costly due to financing frictions. Firms wishing to issue SEOs tend to be cash-constrained (DeAngelo et al., 2010), so paying out more cash would further exacerbate the constraint, subjecting the firm to higher costs associated with financial constraints, such as forego value-enhancing investments.

P-value of 0.274 and 0.514. Although the McCrary test is only about the necessary condition, the results support the validity of our instrument.

2.3. Baseline Specifications

We use two baseline specifications to cross-check the robustness of estimation results. The first controls for year- and firm fixed effects and firm-specific time trend. Year fixed effects control for economy-wide shocks, such as changes in labor policy or stock market crashes, while firm fixed effects control for time-invariant firm characteristics. Firm-specific time trend controls for a firm-specific time trend, such as lifecycle, in outcome variables. DeAngelo et al. (2010) show that dividend payout is related to the stage of the lifecycle. Firms in a different stage of the lifecycle may have different opportunities to upgrade technology and different employment policies.

The second specification adds the following time-varying control variables:

Legal Variables: (1) The minimum wage required in the province or provincial-level city of a firm's headquarter location, *Ln(MIN_WAGE)*. Minimum wages, which are adjusted every two or three years, may affect not only employment but also the skill composition of employees by imposing a lower limit on what firms can pay unskilled workers. (2) Effects of the Labor Law of the People's Republic of China on employment and wages. The labor law, which became effective on January 1, 2008, effects higher labor intensity firms more. We measure the law's effect, *Labor_Law_Effect,* by the interaction of the labor intensity, as measured by each industry's average ratio of the total number of employees to total fixed assets in 2007, with a post-regulation indicator equal to one for 2008 through 2012. We use industry classifications as defined by the CSRC. (3) Local legal environment, *LAWSCORE.* A higher score indicates that the location of a firm is in a region with more developed legal institutions and stronger law enforcement. We include this variable because the law and finance literature suggests firms located in countries with stronger investor protections tend to have stronger corporate governance and suffer from fewer agency problems, which may affect dividend payouts, investments, employment, and performance[15]

[15] The National Economic Research Institute (NERI) constructs the index for each province or provincial-level region. The index changes, reflecting changes in the number of lawyers as a percentage of the population, the efficiency of the local courts, and the protection of property rights (Wang, Wong, and Xia, 2008).

Firm Characteristics: (1) Firm size, the log of sales, *Ln(SALES).* (2) The percentage of shares held by the local or central government, *%_STATE_OWN*. State share ownership varies substantially over time and across firms. (3) The most recent past three-year payout ratio, *P3_PR*. Some firm-years show negative *P3_PR* because some firms with negative average annual distributable profit over the past three years paid dividends when they had a profitable year over the same period. We avoid losing these observations by replacing a negative *P3_PR* by one.[16] We distinguish those observations by adding a dummy, *P3_PR_D,* for a negative ratio. (4) The current dividend payout ratio, *DIV_PR.* Higher dividends may reduce the misuse of free cash flows (Jensen, 1986), influencing the outcome variables of interest. Since dividends are serially correlated, current dividends may be related to the past dividend payouts used to construct the instrument. (5) Strength of corporate governance. Strong governance reduces misuse of SEO proceeds (Jung, Kim, and Stulz, 1996; Kim and Purnanandam, 2014), influencing investments, employment and wages (Jensen, 1986; Bertrand and Mullainathan, 2003; Atanassov and Kim, 2009; Cronqvist et al., 2009; Kim and Ouimet, 2014). Proxies for governance include the *LAWSCORE* mentioned above; ownership concentration as measured by the percentage of shares held by the largest shareholder, *%_LARGST_SH;* board independence, the percentage of independent directors on the board, *%_IND_DIR.* (6) Asset tangibility, property, plants, and equipment over total assets, *PPE/TA*. High-tech firms tend to have fewer fixed assets and fewer production workers. (7) Financial leverage, *Leverage*, to partial out the leverage channel through which SEOs may affect outcome variables. SEOs reduce leverage (Pagano, Panetta, and Zingales, 1998; Eckbo et al., 2000; Gustafson and Iliev, 2017), and a number of studies argue leverage affects employment and wages (Bronars and Deer, 1991; Perotti and Spier, 1993; Berk, Stanton, and Zechner, 2010; Chemmanur, Cheng, and Zhang, 2013; and Michaels, Page, and Whited, 2019). (8) Percentage of non-tradable shares, *%_NONTRD_SH,* to control for the potential confounding effects of the Split Share Structure Reform, which triggered the 2006 regulatory change on the eligibility to issue SEOs.

2.4. Data and Summary Statistics

[16] We assign one to negative *P3_PR* because the dividend payout ratio in the year a firm pays dividends while having negative average profits over the three-years is likely to be very high. None of our sample firms paid dividends when they reported a loss.

2.4.1. Sample Construction and Data Sources

The sample period covers 2000 through 2012 to span the regulatory shocks. China first allowed underwritten offerings in 2000, and data for many key variables are available only after 2000. The sample includes all A-share firms listed on the Shanghai and Shenzhen Stock Exchanges.[17] We exclude financial firms as defined by the CSRC (e.g., banks, insurance firms, and brokerage firms); firms with fewer than 100 employees; and ST (special treatment) and *ST firms, which have had two (ST) or three (*ST) consecutive years of negative net profit.

Table 1 lists the sample distribution by year. The sample contains 17,838 firm-year observations associated with 2,341 unique firms. In total, our sample contains 557 public SEOs. We do not include privately placed equity offerings because the 2006 and 2008 shocks apply only to public offerings. The table shows a surge of public SEOs when underwritten offerings were first allowed in 2000. The small number of SEOs in 2005 and 2006 is due to the suspension of all public equity offerings during the Split Share Structure Reform. (The suspension began in April 2005 and ended in May 2006.) SEO activities recovered in 2007 and increased in 2008, but the stock market crash mentioned above and the 2008 regulation appear to have dampened SEOs: the number of SEOs dropped in 2009 and remained low until the end of the sample period.

The primary source of data for labor, financial, and corporate governance variables is Resset (http://www.resset.cn/en/). Although similar to Compustat, Resset provides reliable data on wages and employment that we can link to our sample firms. The data is reliable because disclosures of employment and payroll information in company filings and financial statements are mandatory for listed firms in China. For data on SEOs and expenditures on technology-related assets, we rely on CSMAR (http://www.gtarsc.com/). We hand-collect minimum wages from provincial government webpages. Online Appendix 3 lists the data source for each variable.

2.4.2. Skill Variables

Acemoglu and Autor (2011: p. 1045) define skills as "a worker's endowment of capabilities for

[17] Stock markets in China offer two types of stocks: A and B shares. We restrict our sample to the A-share market because the total market capitalization of the A-share market is about 122 times that of the B-share market as of the end of 2013, and most firms listed in the B-share market are also listed in the A-share market.

performing various tasks," where a task is "a unit of work activity that produces output." The labor literature classifies tasks into three broad categories: abstract, routine, and manual (Autor, Katz, and Kearney, 2006; Autor and Dorn, 2013). Abstract tasks, such as research and legal writing, tend to require high skills. Routine tasks, such as picking/sorting, repetitive assembling, and record-keeping, are codifiable manual and cognitive tasks following specific procedures, which tend to require low skills. Non-routine manual tasks, such as janitorial service and driving, are tasks requiring physical adaptability, which also tend to require low skills (Autor and Handel, 2013).

We proxy the level of skills by occupation and education. Each occupation may comprise multiple tasks at different levels of intensity, but the variation is higher across occupations than within an occupation (Autor and Handel, 2013). The intensity of routine tasks is higher in occupations such as production workers, assemblers, and support staff than occupations such as engineers, R&D staff, and sales and marketing forces. Thus, we classify production workers and support staff as low skill workers and engineers, R&D staff, and sales and marketing forces as high skill workers. We also use education as a proxy for skill and classify employees with at least bachelor's degrees from four-year universities and above as high skill workers and the rest as low skill workers.

Because of the required disclosure of workforce composition, all firms report the number of employees by occupation or job type, and most firms report the number of employees by education. Resset collects the information and constructs firm-level panel data on the number of employees by occupation and education. It also provides written descriptions of each job type coded from the company filings for each firm-year.

The regulation does not specify how to classify occupation and education level; consequently, firms vary in the definition of occupations, reflecting differences in the business, operation, and organizational structure. Consequently, occupation data in Resset show some inconsistencies between occupation variable names and textual descriptions of occupation or job type. We manually clean the occupation data by cross-checking with textual descriptions in the filings. We also find some jobs classified as "others" by Resset classifiable into a specific occupation group using the written descriptions.

We define six occupation-based categories. *Production* is production workers. It includes mainly blue-collar workers performing assembly line work, sorting, moving, and other routine physical tasks. Most firms report this category quite clearly. Some high-tech and non-manufacturing firms do not have employees in this category.

The second, *Staff*, stands for support staff. This category is not as clear-cut as the production worker category. Some firms breakdown the number of employees into different categories, such as office support staff and HR staff, while others aggregate them into one category of staff. Support staff may include both office staff (receptionists, secretaries, customer service providers, and office administrators) and non-office staff (employees for warehouse maintenance, security, and logistics support, including their supervisors). Some firms report office and non-office staff separately, while others lump them together. To make the data comparable across firms, we manually check written descriptions for each firm-year and aggregate the number of employees in all staff positions. The majority of employees in this group perform routine clerical or non-routine low-skill manual tasks. However, this group also includes managerial positions (e.g., HR manager, logistics supervisor, office managers), which require non-routine abstract skills.

The third, *Tech_R&D*, includes technicians and R&D staff. Technicians include engineers and IT staff, who tend to possess technical skills for non-routine tasks. R&D staff includes scientists, researchers, and designers working on creative tasks and the development of new products. We group technicians and R&D staff into one category because only about 20% of our sample firms have a separate category for R&D employees.

The fourth, *S&M,* is the sales and marketing force, which includes salespersons and employees for marketing, advertising, and brand management. Most of these employees perform non-routine tasks requiring communication and analytical skills.

The fifth, *Finance,* includes record keepers, accountants, and financial managers for capital budgeting, investment, and asset management. Recordkeepers and low-level accountants perform routine tasks, while high-level accountants and finance staff tend to perform non-routine abstract tasks. We cannot tell whether the majority in this category perform routine or non-routine abstract tasks.

The last category, *Others,* includes those reported as "others" by sample firms and job categories such as "operating" that cannot be put into one of the above categories. Some firms put sales force in the same group with technicians or with financial accountants. Since we cannot separate them, we treat them as *Others*. We do the same when some firms report the number of managers. We do not make a separate category for managers because only about 25% of sample firms report the number of managers, which cannot mean the rest of the sample firms do not have managers.

To separate employees by education, we construct three education groups: holders of post-graduate degrees, *Grad*; holders of four-year university bachelor's degrees and above, *BA*; and those with no four-year university bachelor's degree, *NBA*. *Grad* includes all master's and doctorate degrees (e.g., MS, MA, MBA, EMBA, Ph.D., MD, and JD). Only about 50% of sample firms separately report the number of employees with post-graduate degrees, while others lump those with four-year university bachelor's degrees and post-graduate degrees into one category. So our definition of *BA* includes both post-graduate degree holders and four-year university bachelor's degree holders.[18]

2.4.3. Descriptive Statistics

Table 2 provides summary statistics for all key variables. Online Appendix 3 provides variable definitions and the data source for each variable. To mitigate outlier problems, we winsorize all financial variables at 1% and 99% level and replace them with the value at 1% or 99%. We normalize all monetary variables to the RMB in the year 2000.

The indicator for SEO years, *SEO*, shows that 9% of firm-year observations are in SEO years. The instrument, *SEOIneligible,* indicates that the regulatory shocks treated 16% of observations. The average fractions of production workers, support staff, technicians and R&D staff, sales and marketing forces, finance staff, and others are 48%, 9%, 18%, 13%, 3%, and 17%, respectively.[19] The very high percentage of production workers reflects the fact that China was the manufacturing hub of the world during the sample period and the exclusion of the financial services sector. The average number of employees is 4,592, and about 20% of employees have bachelor's degrees and above, and 3% have

[18] Not all four-year university bachelor's degree holders are included in *BA* because we do not include cases in which firms lump non-four-year college (e.g., junior college) degree holders together with four-year university degree holders into one group.
[19] The percentages do not sum to 100% because of missing observations.

post-graduate degrees.[20] The average past three-year payout ratio, *P3_PR,* is about three times the average annual dividend payout ratio, *DIV_PR*,[21] because of the unique way the regulators define *P3_PR.* The average wage for all employees, *AWAGE*, is slightly lower than the average wage for all non-executive employees, *AWAGE_NonExe,* because *AWAGE* is calculated over 2000-2012*,* while *AWAGE_NonExe* is over 2001-2012 (firms did not separately disclose payroll information for executives until 2001).

3. EMPLOYMENT AND EMPLOYEE SKILL COMPOSITION

We begin our investigation by estimating how SEOs affect firm-level employment and the skill composition of employees.

3.1. Firm-level Employment

The first stage of the 2SLS estimation relies on the firm-level conditional (fixed-effects) logistic regression because the endogenous variable *SEO* is an indicator. Under the assumption that the instrument has predictive power over the endogenous variable, IV estimators using the logit model in the first stage are asymptotically efficient; i.e., coefficients of the model can be more precisely estimated (Wooldridge, 2010, p. 939). Standard errors of the first-stage regression are clustered at the firm level, and those of the second-stage regression are corrected by bootstrapping. Online Appendix 4, Columns (1) and (2) report the first-stage results. The coefficients on *SEOIneligible* are negative and highly significant, indicating that the instrument has strong predictive power for *SEO*. We do not report F-statistics because of the conditional logit, a non-linear estimation. When the first-stage is estimated using the OLS, the F-statistics are 11.89 and 14.06, depending on whether we add control variables.

Table 3 reports the second-stage results for employment level: Panel A with year- and firm fixed effects and firm-specific time trend; Panel B adds control variables. The results are similar. When we include control variables, the estimated coefficient indicates a 9.1% decline in total employment follows SEOs. Our sample contains 557 SEOs. The total number of people employed by these firms at

[20] The sum of mean BA and mean NBA is higher than the mean EMP, the total number of employees. Many small firms do not separately report the number of employees with four-year university bachelor's degrees and above, often lumping them together with those with junior college and vocational school degrees. As mentioned earlier, we do not include those small firms when we calculate the number of employees with BA or NBA. When we calculate the mean EMP, we include all firms in the sample

[21] The minimum *DIV_PR* is zero because no firm in our sample paid dividends in a year of negative profits.

the time of issuing SEOs was 2,593,934. Thus, the 9.1% decline implies 236,048 fewer employees remain with these firms following SEOs or 424 fewer employees per SEO.

Coefficients of control variables suggest that there are more employees when firms are larger and have a higher state share of ownership, more tangible assets, and higher leverage. Firms located in regions with higher minimum wage and stronger legal environments tend to have fewer employees.

We do not rely on the OLS estimate because of bias due to unobservable time-varying factors correlated with employment and SEOs. For example, steady employment growth to maintain social stability is a high priority of the Chinese government.[22] Since the central government internalizes all the external effects of social stability (Bai, Lu, and Tao, 2006), the CSRC might be more inclined to approve an SEO if the applying firm has a large workforce and needs to raise money to keep them employed. Without accounting for this unobservable factor, OLS estimates of how SEOs affect employment will contain an upward bias. For the record, we report OLS estimates with time-varying control variables in Online Appendix 5. Column (1) indicates that SEOs are associated with a 3% decline in total employment, a smaller decline than the IV estimate.

3.2. Composition of Employee Occupation and Education

The remaining columns in Table 3 break down employees by occupation or education, where the dependent variable is the log of one plus the number of employees (some firm-years show no employees in some occupation and education categories.) Estimation results with control variables indicate the number of technicians and R&D employees, the sales and marketing force, and post-graduate degree holders increased by 13%, 10%, and 11%, respectively.[23] In contrast, the number of production workers, support staff, and employees without a four-year university bachelor's degree decreased by 25%, 46%, and 17%, respectively. Because there are more employees in the latter group than in the former group, these results imply SEOs led to more displacement of low skill workers than to adding high skill workers.

[22] Premier Wen Jiabao states in the 2010 Government Work Report, "the government promises to do everything in our power to increase employment" (Wen, Jiabao, 2010 年政府工作报告 http://www.gov.cn/2010lh/content_1555767.htm.)

[23] When *Grad* is the dependent variable, the number of observations falls sharply because only about 50% of sample firms separately report the number of employees with post-graduate degrees.

The changes in the level of high- and low skill workers should lead to a higher skill composition of employees. That is what we find in Table 4, which shows similar results regardless of whether we include control variables. Results with control variables indicate SEOs significantly increase the fractions of technicians and R&D employees, the sales and marketing force, and finance staff. The fractions of employees with four-year university bachelor's degrees and above and with post-graduate degrees also significantly increase. In contrast, significant decreases in the fractions of production workers, support staff, and employees without a four-year university bachelor's degree follow SEOs.[24] The skill composition of employees becomes significantly higher following SEOs.

4. THEORETICAL EXPLANATION

The net decline in firm-level employment following SEOs is surprising because one usually associates infusion of new capital with an increase in the scale of operation, necessitating more employees. In a typical Cobb-Douglas production function of labor and capital, for example, relaxing the budget constraint would increase the optimal levels of both. However, the data indicate that the decline in employment is due to the decrease of low skill workers outnumbering the increase of high skill workers. To provide a conceptual framework to interpret these findings, we offer a simple static model wherein a firm adopts a new technology by raising external capital. Although our empirical identification relies on SEOs, the model is not specific to SEOs and applies to other methods of external financing.

4.1. A Simple Model

We consider the optimal choice of production inputs for a profit-maximizing firm that has an opportunity to adopt new technology. The firm can continue to operate with the technology that it currently uses, or alter its production process by adopting new technology. The firm's current cash balance, K, is given. It can only pay for the inputs of production using old technology. Adopting the new technology requires raising external capital ΔK, which can be accomplished by an SEO issuance and additional debt that the new equity capital can support. We compare the optimal inputs of production before and after the SEO.

[24] Table 4 does not report the estimation result on the fraction of *NBA*, because *%_NBA* is equal to 1 - *%_BA*; hence, the coefficients on *%_NBA* are the same as those on *%_BA* with the signs reversed.

We follow Acemoglu and Autor (2011) and assume the production of final goods is a constant elasticity of substitution (CES) aggregation of two intermediate inputs. One intermediate input is produced by H high skill workers with A machines, using a Cobb-Douglas production function, $\varepsilon A^{\alpha} H^{1-\alpha}$, where ε denotes the productivity of high skill workers with machines, and α measures the share of machines in the production. The production of the other intermediate input only uses L low skill workers. Therefore, the production function of final goods takes the form of $\left[(\varepsilon A^{\alpha} H^{1-\alpha})^{\frac{\sigma-1}{\sigma}} + L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, where σ is the elasticity of substitution between the two intermediate inputs. This production function assumes constant returns to scale, which makes the optimal scale undetermined. However, in our model, the scale is bounded by budget constraints.

Note that the production function does not assume Hicks-neutral technological progress. Instead, we follow Kahn and Lim (1998) and Acemoglu (2002) and assume that each production input factor experiences its specific technological progress. That is, skilled labor-augmenting technological progress improves the productivity of high skill workers much more than that of low skill workers. Advancement of computer software is an example: it impacts the productivity of high skill workers much more than that of low skill workers. For simplicity, we assume the productivity of low skill workers remains constant at one when technological advances improve high skill workers' productivity.

Payments for the inputs of production are made at the beginning of the period, subject to a budget constraint K. Production outputs generate revenue at the end of the period. The firm is a price taker for both inputs and outputs. The cost of using a machine is r, the wage of a high skill worker is w, and the wage of a low skill worker is 1; and w > 1 because of the skill premium. The present value of revenue at the end of the period is p, the present value of price per unit of output, times outputs. With these assumptions, the firm's profit maximization problem with the old technology without an SEO is:

$$V(K, \varepsilon) \equiv \underset{\{A,H,L\}}{Max}\, p\left[(\varepsilon A^{\alpha} H^{1-\alpha})^{\frac{\sigma-1}{\sigma}} + L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - rA - wH - L$$

$$\text{s.t. } rA + wH + L = K$$

The profit maximization problem changes if the firm adopts the new technology. This part of the model borrows heavily from Midrigan and Xu (2014): Adoption of the new technology increases the capital-augmenting productivity by $\phi \geq 0$ such that the productivity of high-skilled production becomes $\varepsilon + \phi$. The technology requires one-time investment in sunk cost, $C(\phi)$, which is higher the more productivity improvement it can generate. Both ϕ and $C(\phi)$are exogenous. The firm's choice is binary—it either adopts the new technology or does not. If the firm decides to adopt the technology, it needs to raise $\Delta K \geq C(\phi)$. The firm's profit maximization problem then becomes:

$$V(K + \Delta K - C(\phi), \varepsilon + \phi) \equiv \underset{\{A,H,L\}}{Max}\, p\left[\left((\varepsilon + \phi)A^{\alpha}H^{1-\alpha}\right)^{\frac{\sigma-1}{\sigma}} + L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - rA - wH - L$$

$$\text{s.t.} \quad rA + wH + L = K + \Delta K - C(\phi)$$

Appendix A provides solutions to both profit maximization problems. We denote the optimal level of machines, high skill workers, and low skill workers before an SEO as A_1^* , H_1^*, and L_1^* , respectively. If the firm upgrades its technology, these optimal levels change to A_2^*, H_2^*, and L_2^*. Let $m = \left(\frac{1-\alpha}{w}\right)^{1-\alpha}\left(\frac{\alpha}{r}\right)^{\alpha}$, then the optimal level of inputs are:

$$A_1^* = \frac{\alpha K}{r}\left(1 - \frac{1}{1+[m\varepsilon]^{\sigma-1}}\right) \tag{1}$$

$$H_1^* = \frac{(1-\alpha)K}{w}\left(1 - \frac{1}{1+[m\varepsilon]^{\sigma-1}}\right) \tag{2}$$

$$L_1^* = \frac{K}{1+[m\varepsilon]^{\sigma-1}} \tag{3}$$

$$A_2^* = \frac{\alpha}{r}\left(K + \Delta K - C(\phi)\right)\left(1 - \frac{1}{1+[m(\varepsilon+\phi)]^{\sigma-1}}\right) \tag{4}$$

$$H_2^* = \frac{1-\alpha}{w}\left(K + \Delta K - C(\phi)\right)\left(1 - \frac{1}{1+[m(\varepsilon+\phi)]^{\sigma-1}}\right) \tag{5}$$

$$L_2^* = \frac{K+\Delta K - C(\phi)}{1+[m(\varepsilon+\phi)]^{\sigma-1}} \tag{6}$$

Lemma. Infusion of external capital can increase profits regardless of whether or not the capital is deployed to upgrade the technology. But if $K + \Delta K > K^*$, where $K^* \equiv \frac{C(\phi)\left[p\left[\left(m(\varepsilon+\phi)\right)^{\sigma-1}+1\right]^{\frac{1}{\sigma-1}}-1\right]}{p\left(\left[\left(m(\varepsilon+\phi)\right)^{\sigma-1}+1\right]^{\frac{1}{\sigma-1}}-[(m\varepsilon)^{\sigma-1}+1]^{\frac{1}{\sigma-1}}\right)}$, then profits will increase more with the upgrade of technology than with simply expanding the scale of operation with the old technology.

*Proof**:*** See Appendix A

The Lemma establishes that if a firm can raise sufficient funds such that $K + \Delta K > K^*$, it will upgrade its technology. The threshold point, K^*, is the capital level at which the firm is indifferent between keeping the old technology and upgrading technology. When $K + \Delta K > K^*$, the productivity improvement with the new technology is worth more than the cost of adopting the technology, leading to a higher profit than the profit the firm can achieve by expanding the scale of operation using the old technology.

Proposition. If a firm upgrades technology and $\sigma > 1$, $A_2^* > A_1^*$ and $H_2^* > H_1^*$. And if $\phi \in [0, C^{-1}(\Delta K)]$, there exists a $\bar{\phi}$, such that when $\phi > \bar{\phi}$, $L_1^* > L_2^*$. Furthermore, there also exists a $\phi^* > \bar{\phi}$, such that when $\phi > \phi^*$, $H_1^* + L_1^* > H_2^* + L_2^*$.

Proof: See Appendix A.[25]

The Proposition specifies the conditions under which the number of low skill workers and total employment decline following an SEO. Specifically, $\sigma > 1$ means that high skill production and low skill production are substitutes. Note that $\frac{L_1^*}{L_2^*} = \frac{K}{K+\Delta K - C(\phi)} \frac{1+[m(\varepsilon+\phi)]^{\sigma-1}}{1+(m\varepsilon)^{\sigma-1}}$. The first component $\frac{K}{K+\Delta K - C(\phi)}$ can be interpreted as the scale effect on low skill workers. If the external capital raised through an SEO exceeds the cost of technology upgrade, this component increases L_2^* relative to L_1^*. The second component $\frac{1+[m(\varepsilon+\phi)]^{\sigma-1}}{1+(m\varepsilon)^{\sigma-1}}$ can be interpreted as the substitution effect. An increase in the productivity of high skill production replaces low skill production if the elasticity of substitution (σ) is greater than one. If the productivity of high skill production increases sufficiently such that $\phi > \bar{\phi}$, then the substitution effect dominates the scale effect, resulting in $\frac{L_1^*}{L_2^*} > 1$: the number of low skill workers declines after an SEO. Furthermore, if the increase in productivity of high skill production is so high that ϕ exceeds $\phi^* > \bar{\phi}$, the decline of low skill workers will outnumber the increase of high skilled workers, leading to a reduction in the total number of employees.

The prediction with $\phi > \phi^*$ explains the decline in firm-level employment: Infusion of external capital through SEOs allowed firms to adopt new technologies that improved the productivity

[25] Note that the proposition specifies an upper bound $C^{-1}(\Delta K)$ for ϕ. This condition excludes situations where ΔK is so large that the scale effect dominates all other effects.

of high skill production so much that the firms ended up laying off more low skill workers than adding new high skill workers.

4.2. Elasticity of Substitution

A critical condition for the Proposition is that the elasticity of substitution between machine-augmented high skill tasks and low skill tasks is greater than one. All prior estimates of the elasticity of substitution between high- and low skill workers rely on U.S. and U.K. data. Although there are variations across time, all estimates are well above one.[26] To check whether the condition is satisfied for our sample, we estimate the elasticity using our sample in Appendix B. When we use education to classify high- and low skill workers, the elasticity estimates are 2.13 and 2.10 if we assume linear and non-linear time trend in technology development, respectively. They are well within the range of prior estimates based on education. Our elasticity estimates based on occupation are about 4.89, which are also comparable to existing estimates based on occupation.[27]

5. TECHNOLOGY ADOPTION, WAGES, AND FIRM PERFORMANCE

5.1. Technology Adoption

In our model, a key channel through which SEOs affect firm-level employment is technology adoption. We use expenditures on technology-related assets to proxy technology adoption. Technology-related assets consist of tangible- and intangible assets. For tangible assets, we include only technology-related machines and equipment such as computers and electronic equipment, and exclude assets not directly related to technology such as transportation equipment (e.g., cars and trucks) and real estate assets (e.g., lands and buildings). Data on expenditures for machines and equipment are available from 2003 when the CSRC started to require listed firms to breakdown by type the value of fixed assets based

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[26] Katz and Murphy (1992) assume that technology has a log-linear increasing time trend, and obtain an estimate of 1.41 for the elasticity of substitution between college and high school graduates using US data from 1963 to 1987. Heckman, Lochner, and Taber (1998) show an estimate of 1.441 for the elasticity over 1963-1993 using a similar production function as in Katz and Murphy (1992). Extending the sample period to more recent years yields higher estimates. Card and DiNardo (2002)'s estimate of the elasticity is 1.56 when they use US data from 1967 to 1990, but when they extend the sample period to 1999, the elasticity estimate more than doubles to 3.3. Acemoglu and Autor (2011) obtain an estimate of 2.9 for the elasticity over a sample period of 1963 to 2008, but their estimates become smaller (1.6 to 1.8) when they substitute the linear time trend with quadratic or cubic trends. As for international evidence, Card and Lemieux (2002) use UK data from 1974 to 1996 and obtain estimates of the elasticity ranging from 2 to 2.5.

[27] Card (2001) reports that the implied estimate of the elasticity of substitution between occupations ranges from 5 to 10, which is much larger than the estimates based on education.

on the purchase price. For intangible assets, we include computer software, technology with or without patents, patents, and information management systems. We exclude intangible assets not directly related to technology, such as goodwill, rights to land use, and franchising. Data on intangible assets are available only from 2007 because the CSRC did not require the breakdown of intangible assets by type until 2007. For each firm-year, we separate tangible and intangible assets into technology-related and technology-unrelated and sum up the values of all technology-related tangible and intangible assets. The CSMAR is the data source.

Table 5 reports the second-stage estimation results. The results in both panels imply that raising external capital through SEOs significantly increase expenditures on technology-related assets. The estimated coefficients with control variables imply that SEOs increase expenditures on technology-related machines and equipment by 27%, or by 40.2 million 2000 RMB (.27 x 148.9M in Table 2); and expenditures on technology-related intangible assets by 36%, or by 3.5 million 2000 RMB (0.36 x 9.8M in Table 2).[28]

Given our definition of technology-related intangible assets, it is reasonable to assume that the increases in expenditures are for new technology or upgraded versions of technology currently in use. The same can be said about expenditures on technology-related machines and equipment, but some of the increases can be to purchase more machines and equipment currently in use. However, if a sufficient portion of the expenditures on technology-related assets in our sample is made to adopt productivity-improving technologies, they will impact employee and firm profitability, which we investigate in Section 5.6.

The last column of Table 5 confirms previous findings that SEOs increase capital expenditures (e.g., Kim and Weisbach, 2008; Gustafson and Iliev, 2017). Because capital expenditures include investments unrelated to technology, we cannot draw inferences on technology adoption from this result; however, it illustrates that our sample firms are not unique.

5.2. Demand for Skills

[28] The second column does not contain LAWSCORE as a control variable because it does not have variation over the sample period for the intangible assets: the data for the intangible assets begins in 2007 and the National Economic Research Institute updates LAWSCORE only up to 2009.

If the increases in technology investments following SEOs are indeed skill-related, as we assume, firms will recruit more high skill workers to utilize the technology. In this section, we relate SEOs to firms' demand for skills using online job-posting data provided by Lagou.com (https://www.lagou.com), a major job posting company in China. The company started the job posting business in 2013, so our data covers only 2014 through 2016, which does not overlap with the regulatory shocks. As such, the results presented here are only suggestive, as we relate endogenous variables without exogenous variation. Nevertheless, they serve as a robustness test, because finding no relation between SEOs and demand for skills will cast doubt on our hypothesis on the role technology plays in firm-level employment.

The job posting sample contains 45,585 unique full-time job advertisements by 790 A-share firms listed on Shanghai and Shenzhen Stock Exchanges over 2014 – 2016. We exclude the repetition of the same advertisements that firms re-post to attract more attention. Online Appendix 7, Panel A, shows that of 45,585 new job postings, 7,791 are from firms receiving SEO proceeds. Because the estimation in this section does not rely on the shocks to the eligibility to issue public SEOs, we include both public and private placements.

Our approach to constructing skill variables is similar to Hershbein and Kahn (2018). For each job advertisement, we machine-search for the keywords indicating four types of skills: (1) advanced computer skills, (2) basic computer skills, (3) non-routine analytical task skills, and (4) non-routine interactive task skills. Online Appendix 7, Panel B lists the English translation of Chinese keywords used to identify each skill.

All estimations are at the job advertisement level, relating skills mentioned in each job posting to whether the posting occurred during the year in which a company receives SEO proceeds.[29] The dependent variable is either an indicator for the presence of a keyword indicating a specific skill or the log of one plus the number of keywords associated with each skill type to capture the intensity of the skill requirement. The variable of interest is the SEO indicator, *JP_SEO*, which equals to one only in

[29] We cannot conduct firm-level analyses because firms may advertise job openings with other job posting companies and through other recruiting channels.

the year of receiving SEO proceeds.[30] All regressions control for year- and firm dummies to control for heterogeneity in demand for skills and jobs across time and firm. We also control for location dummies at the county level because many firms operate in multiple locations and job skill requirements vary across different locations (R&D centers requiring advanced computer skills and non-routine analytical skills are mostly located in metropolitan areas, while the location of sales offices is in both countryside and metropolitan areas.)

Table 6, Panel A reports the results relating advanced computer skills to the SEO indicator. Columns (1) and (3) show positive and significant coefficients, which suggest firms receiving SEO proceeds are more likely to specify advanced computer skills in their job posting. Hershbein and Kahn (2018) point out that online job postings tend to target white-collar employees more than blue-collar workers. So we control for job-related omitted variables by adding job dummies in Columns (2) and (4) using job titles mentioned in the postings. Reestimation results continue to show significant positive coefficients on the SEO indicator, suggesting that when firms receive SEO proceeds, their demand for advanced computer skills increases even for the same type of jobs. Panel B repeats the same exercise for basic computer skills. Coefficients on the SEO indicator are again positive and significant, indicating the likelihood of specifying basic computer skills in job advertisements is higher when firms receive SEO proceeds.

In Table 7, we relate the SEO indicator to non-routine analytical and interactive task skills. Again, the coefficients are all positive, and six of the eight coefficients are significant. In sum, firms obtaining new capital through SEOs exhibit increased demand for computer and non-routine task skills, consistent with our hypothesis that technology is a channel through which SEOs affect firm-level employment.

5.3.Technology Investments and Firm-level Employment

If the adoption of skill augmenting technology is a key channel through which SEOs lead to the decline in employment, we would expect the more firms to invest in technology following SEOs,

[30] We turn on the indicator only in the year a firm receives SEO proceeds because the sample period covers only three years. If a firm fills newly-advertised positions in the year of the posting, the advertisement is unlikely to appear in the following year unless the newly hired employees leave the firm.

the larger the reduction in employment. To test this prediction, we construct two subsamples. The first includes firms that issued SEOs and invested in technology-related tangible assets during the SEO years more than the SEO sample median and firms that never issued an SEO. The second subsample includes firms that issued SEOs and invested in technology-related tangible assets during the SEO years less than the SEO sample median and firms that never issued an SEO. We use only technology-related tangible assets to construct high- and low technology investment subsamples because data on technology-related intangible assets are available only after 2007. We measure changes in technology-related tangible assets by the differences between their average value during SEO years and the value in the year before the SEO years divided by total assets in the year before the SEO years.

We reestimate the baseline regressions for firm-level employment, Ln(EMP), for each subsample. Table 8 reports the results. The effect of SEOs on firm-level employment is more negative with higher statistical significance for the high technology investment subsample than for the low technology investment subsample. It appears that firm-level employment declines more when SEOs lead to more technology investments.

5.4. Financial Constraints

Some firms issuing SEOs may have financial constraints before SEOs. If such firms had opportunities to upgrade technology but were unable to do so due to financial constraints, SEOs might impact their technology investments and employment more. To explore possible heterogeneous effects across financial constraints, we separate SEO firms into two subsamples based on the level of financial constraints the year before the SEO years. Financial constraints are proxied by the widely-used Kaplan and Zingales (1997) index.[31] We classify firms as highly constrained when the index is above the SEO sample median; otherwise, lowly constrained. For each SEO, we include the observations in SEO years (the year when firms receive SEO proceeds and the following two years) and the three years before SEO years. The high (low) constraint subsample includes observations associated with SEOs issued by

[31] The KZ index has been questioned, and other measures have been offered. It is not our intent to take a stand on which measures are better; instead, our choice reflects that the KZ index is widely used and that our Chinese data allow its construction.

firms with high (low) financial constraints. Both subsamples include observations of firms that never issue SEOs.

We re-estimate the baseline regressions for each subsample, with technology-related tangible assets or firm-level employment as the dependent variable. Table 9 reports the results. The SEO coefficient is larger in absolute magnitude with higher statistical significance for firms more financially constrained, for both technology investments and employment. It appears that the effects of SEOs on both technology and employment are stronger when firms are under more financial constraints.

5.5. Wages

The higher skill composition following SEOs (shown in Section 3.2.) will increase within-firm average wages because of the skill premium. The China Urban Household Survey shows that Chinese workers with more education are paid more, and technicians are paid substantially more than production, staff, and service or agricultural workers (see Online Appendix 8). Table 10 reports the second-stage results, which show significantly higher average wages following SEOs. Non-executive employees drive the increase in average wages. Estimates with control variables indicate that the average wage of non-executive employees increases by 9%. We observe no significant changes in the average wage of executives (classified as such in financial statements).[32]

How do changes in employment and skill composition affect total wages? Because the total number of employees declines, the higher average wage does not necessarily imply a higher total wage. Table 11 reports the second-stage results for total wages. SEOs show no significant impact on total wages regardless of how we stratify employee groups and whether we include control variables.

5.6. Firm Performance

Our estimation results so far indicate that SEOs lead to significant changes in inputs to production: smaller but more skilled employees working with more technology, and with no increase

[32] The executive wage results do not reflect the value of equity incentives, which are an essential component of executive compensation in the U.S. In China, wages constitute most of the executive compensation, with executive stock options playing no, or a minor role in the compensation during our sample period. Bryson, Forth, and Zhou (2014) reports, "Fewer than 1% of top executives were granted options in any given year between 2006 and 2010 and, for these few cases, at the median they were worth 30% of CEO cash compensation and 21% of non-CEO top executive cash compensation." Chinese firms were unable to offer stock options until 2006 when equity incentives were formally introduced in the form of employee stock options and discounted share purchase programs. These equity incentives are issued to both non-executive employees and executives.

in the total wage bill. How do these changes in inputs to production affect firm performance? To answer this question, we measure profitability by return on assets, *ROA*. For productivity, we use three different yet related measures: sales growth, *SALES_GR* for output growth rate, sales per employee, *SALES/Employees* for worker productivity, and total factor productivity, *TFP*.

Table 12 reports the second-stage estimation results. SEOs significantly improve all four measures of performance. The magnitude of improvement in each measure is substantial in comparison to the sample mean. Estimates with time-varying control variables indicate that ROA increases by 1.8 percentage points (sample mean = 3.5%). Sales growth rate increases by 21 percentage points (sample mean = 23%). Sales per employee increases by 847,000 RMB (sample mean = 1,105,000 RMB). TFP increases by 0.094 (sample mean = 0.003.)[33]

6. ROBUSTNESS TESTS

In this section, we examine pre-trends before the first shock and test whether our evidence is robust to alternative ways to construct the instrument and excluding small SEOs. To save space, we only report the results with control variables.

6.1. Pre-Trends

WE construct the instrument using the variation in the impacts that regulatory shocks have on firms' eligibility to issue SEOs. Its validity requires that if there were no shock, affected and unaffected firms would not show different time trends in the outcome variables. To test the parallel trend assumption, we conduct a placebo test using the 2000-2005 sample before the 2006 shock. We do not use the post-2006 shock sample for two reasons: (1) the presence of the second shock in 2008 and (2) starting in 2007, the composition of treated and untreated firms changes from year to year because the variable determining the treatment, *P3_PR*, is a moving average over the most recent past three years.

[33]The TFP estimates may contain biases; they are residuals of an OLS estimation of the production function, which regresses the log of total output value on the log of total assets and the log of the total number of employees. We include firm- and year fixed effects to control for any time-invariant firm-specific shocks and economy-wide time-specific shocks. However, the correlations between input levels and unobservable time-varying firm-specific shocks could bias estimates (Levinsohn and Petrin (2003) suggest using intermediate inputs to control for the correlation between input levels and unobservable time-varying firm-specific shocks; however, data on intermediate inputs are not available for our sample firms.) We re-estimate the production function by replacing the total number of employees with the total number of production workers and with the total payroll. The results, reported in Online Appendix 9, are robust. However, these alternative measures of TFP may still be biased.

We construct an indicator for firms affected by the 2006 regulation, *Affected*. Then we test whether there is any difference between the outcome variables of shock-affected and shock-unaffected firms during the years before 2006 using 2000 as the base year. We define five placebo shock indicators, *Year01,..., Year05,* which equates to one in 2001,…, 2005, respectively. We then estimate the baseline regression for all key outcome variables with the interactions of *Affected* and the year indicators.

Table 13 reports the coefficients on the interaction terms, which are insignificant for all but one at the ten percent level, suggesting no different time trends in the outcome variables between affected and unaffected firms before the 2006 shock.[34]

6.2. Alternative Ways to Construct the Instrument and Definition of the SEO Variable

Since the instrument is the key to our identification, we test the robustness to three alternative ways to construct the instrument. First, some firms may circumvent the 2006 and 2008 regulations in 2007 and 2009, respectively, by increasing dividends in 2006 and 2008. To guard against such possibilities, we turn on the instrument only for firms treated by the 2006 regulation in 2006 and firms treated by the 2008 regulation in 2008. Second, we shorten the time elapsed from the beginning of the SEO process to the receipt of proceeds from two years to one year. Third, we rely only on the 2006 shock because some firms may have anticipated the 2008 shock. We also exclude small SEOs in the bottom decile in the size of proceeds. Firms conducting these small SEOs are typically small-cap firms with highly volatile performance. Table 14 reports the second-stage results for all outcome variables. All results are robust. Online Appendix 4, Columns (3) – (6) report the first-stage estimation results.

7. SUMMARY AND IMPLICATIONS

This paper presents evidence on how access to external capital through SEOs affects technology adoption, firm-level employment, employee skill composition, wages, and firm performance. To identify causal effects, we rely on external shocks that cut off access to public SEOs as a means to raise external capital. We find SEOs facilitate the adoption of productivity-improving technologies, and displace more low skill workers than adding high skill workers, leading to lower firm-level employment.

[34] Placebo shock indicators for *Ln(Tangible_Tech)* cover only 2004 and 2005 with 2003 as the base year because *Ln(Tangible_Tech)* is avaiable only from 2003. We cannot conduct the placebo test on technology-related intangible assets because the data are available only from 2007.

The decline in employment is more significant among firms investing more in technology and among firms more financially constrained. The higher skill composition following SEOs increases within-firm average wages because of the skill premium, but total wages remain unchanged because of the reduction in total employment. These changes in the inputs to production—better technology, employment of fewer but higher-skilled workers, and without increasing the total wage bill—result in higher profits, more outputs, and improvement in worker and total factor productivity. These findings demonstrate the impacts that SEOs can have on employees and firm performance when firms facing opportunities to adopt productivity-improving technologies have access to stock markets to fund investments in the technology.

Our findings shed light on how accessibility to stock markets affects labor markets by altering the demand for high- vs. low skill workers. Easier access to capital may not only increase demand for high skill workers but also stimulate their supply as the demand for, and the supply of skills is endogenous to each other and dynamically moves together. If the supply of high skill workers increases in response to increased demand, it may lead to further development of skill complementary technologies, which is likely to enhance economic growth.

The highly developed, sophisticated, global financial markets of recent years have opened more access to external capital, which can lead to the displacement of low skilled and less-educated workers. Unless other employers are absorbing displaced low skill workers, demand for their skills will decline. Retraining to upgrade skills requires financial resources, time, and effort; thus, many low skill workers may not be able to leave the shrinking market for their services, at least not in the short run. The ensuing imbalance between the supply of and the demand for low skilled and less-educated workers is likely to keep their income low. High skilled and more-educated employees, on the other hand, will enjoy increasing demand for their services as frictions to accessing external capital decline and capital skill complementarity kicks in. The result might be further widening income inequality.

However, the reduction in firm-level employment we document is a rather short-term effect over two-to-three years following SEOs. In the long-run, the ensuing increases in firm profits and productivity, also documented in the paper, are likely to increase the scale and scope of the business, which may offset the short-run decline in employment. Also, the positive spillovers of technology advances to the tertiary sector might offset the negative employment effect on low skill workers (Autor and Salomons, 2017). When low skill workers undergo proper retraining, the aggregate employment opportunities will grow, as capital markets facilitate the development of complementary technologies and processes to harness the recent technological advances to yield their full economic benefits.

APPENDIX A: Equations (1) through (6) and Proofs of the Lemma and the Proposition

Derivations of Equations (1) through (6) in Section 4.1.

The firm faces an output price, p, and a series of input prices; r is the rent to use a machine, w is the wage of a high skilled worker. The wage of a low skill worker is one such that other prices are relative to the low skill worker wage. Because of the skill premium, w > 1. K is the budget to pay for the usage of machines and the employment of high- and low skill workers. The production function is of a simple CES form, $\left[(\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{\sigma-1}{\sigma}}+L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, $\sigma\in[0,\infty)$. It is similar to the production function in Autor, Katz, and Krueger (1998), except we allow the technology to augment only high skill workers. The profit maximization problem faced by the firm before an SEO is:

$$\underset{\{A,H,L\}}{Max}\; p\left[(\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{\sigma-1}{\sigma}}+L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}-rA-wH-L$$

$$\text{s.t. }\; rA+wH+L=K \tag{A1}$$

The Lagrangian function for solving (A1) is

$$L(A,H,L,\lambda)=p\left[(\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{\sigma-1}{\sigma}}+L^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}-rA-wH-L+\lambda(K-rA-wH-L).$$

Let $M=(\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{\sigma-1}{\sigma}}+L^{\frac{\sigma-1}{\sigma}}$. Then, the first-order necessary conditions for this maximization problem are as follows:

$$L_A=pM^{\frac{\sigma}{\sigma-1}-1}\alpha\varepsilon^{\frac{\sigma-1}{\sigma}}A^{\alpha\frac{\sigma-1}{\sigma}-1}H^{(1-\alpha)\frac{\sigma-1}{\sigma}}-(1+\lambda)r=0 \tag{A2}$$

$$L_H=pM^{\frac{\sigma}{\sigma-1}-1}(1-\alpha)\varepsilon^{\frac{\sigma-1}{\sigma}}A^{\alpha\frac{\sigma-1}{\sigma}}H^{(1-\alpha)\frac{\sigma-1}{\sigma}-1}-(1+\lambda)w=0 \tag{A3}$$

$$L_L=pM^{\frac{\sigma}{\sigma-1}-1}L^{\frac{\sigma-1}{\sigma}-1}-(1+\lambda)=0 \tag{A4}$$

$$L_\lambda=-rA-wH-L+K=0 \tag{A5}$$

Combining equations (A2) and (A3) yields

$$\frac{\alpha H}{(1-\alpha)A}=\frac{r}{w} \tag{A6}$$

Combining equations (A2) and (A4) yields

$$\frac{\alpha\varepsilon^{\frac{\sigma-1}{\sigma}}A^{\alpha\frac{\sigma-1}{\sigma}-1}H^{(1-\alpha)\frac{\sigma-1}{\sigma}}}{L^{\frac{\sigma-1}{\sigma}-1}}=r \tag{A7}$$

Combining equations (A5), (A6) and (A7) and defining $m = \left(\frac{1-\alpha}{w}\right)^{1-\alpha}\left(\frac{\alpha}{r}\right)^{\alpha}$, we derive the optimal choice of machines, high skill workers, and low skill workers before an SEO as:

$$A_1^* = \frac{\alpha K}{r}\left(1 - \frac{1}{1+[m\varepsilon]^{\sigma-1}}\right)$$

$$H_1^* = \frac{(1-\alpha)K}{w}\left(1 - \frac{1}{1+[m\varepsilon]^{\sigma-1}}\right)$$

$$L_1^* = \frac{K}{1+[m\varepsilon]^{\sigma-1}}$$

Following the same procedure, we derive the optimal choice of machines, high skill workers, and low skill workers if the firm upgrades technology after an SEO:

$$A_2^* = \frac{\alpha}{r}\left(K + \Delta K - C(\phi)\right)\left(1 - \frac{1}{1+[m(\varepsilon+\phi)]^{\sigma-1}}\right)$$

$$H_2^* = \frac{1-\alpha}{w}\left(K + \Delta K - C(\phi)\right)\left(1 - \frac{1}{1+[m(\varepsilon+\phi)]^{\sigma-1}}\right)$$

$$L_2^* = \frac{K+\Delta K - C(\phi)}{1+[m(\varepsilon+\phi)]^{\sigma-1}}$$

Proof of Lemma

The firm's maximum profit is:

$\pi_0 = pK\left\{[(m\varepsilon)^{\sigma-1}+1]^{\frac{1}{\sigma-1}} - 1\right\}$, with the old technology and a budget of K.

$\pi_1 = p(K+\Delta K)\left\{[(m\varepsilon)^{\sigma-1}+1]^{\frac{1}{\sigma-1}} - 1\right\}$, with the old technology and a budget of $K + \Delta K$.

$\pi_2 = p\big(K + \Delta K - C(\phi)\big)\{\left[(m(\varepsilon+\phi))^{\sigma-1}+1\right]^{\frac{1}{\sigma-1}} - 1\big\}$, with the new technology and a budget of $K + \Delta K$.

It is easy to see that $\frac{\pi_1}{\pi_0} > 1$ and $\frac{\pi_2}{\pi_0} > 1$. Therefore, profits are higher with the infusion of capital through an SEO regardless of whether the firm upgrades the technology.

The firm will upgrade the technology if $\pi_2 > \pi_1$; that is, if

$$\pi_2 - \pi_1 = p(K+\Delta K)\left([(m(\varepsilon+\phi))^{\sigma-1}+1]^{\frac{1}{\sigma-1}} - [(m\varepsilon)^{\sigma-1}+1]^{\frac{1}{\sigma-1}}\right)$$
$$- C(\phi)\left[p[(m(\varepsilon+\phi))^{\sigma-1}+1]^{\frac{1}{\sigma-1}} - 1\right] \geq 0$$

Writing $\pi_2 - \pi_1$ as a function of $K + \Delta K$, or $f(K + \Delta K)$, it follows that f increases monotonically with $K + \Delta K$. Thus, we derive K^* that satisfies $f(K^*) = 0$

$$f(K^*) = 0 \Rightarrow K^* = \frac{C(\phi)\left[p[(m(\varepsilon + \phi))^{\sigma-1} + 1]^{\frac{1}{\sigma-1}} - 1\right]}{p([(m(\varepsilon + \phi))^{\sigma-1} + 1]^{\frac{1}{\sigma-1}} - [(m\varepsilon)^{\sigma-1} + 1]^{\frac{1}{\sigma-1}})}$$

Therefore, if $K + \Delta K > K^*$, the firm will upgrade its technology to maximize its profit.

Rewriting $K^* = \frac{C(\phi)\left[p[(m(\varepsilon+\phi))^{\sigma-1}+1]^{\frac{1}{\sigma-1}}-1\right]}{p(([(m(\varepsilon+\phi))^{\sigma-1}+1]^{\frac{1}{\sigma-1}}-1)-([(m\varepsilon)^{\sigma-1}+1]^{\frac{1}{\sigma-1}}-1))}$ and rearranging, we obtain:

$$\left(K^* - C(\phi)\right)\left[p[(m(\varepsilon + \phi))^{\sigma-1} + 1]^{\frac{1}{\sigma-1}} - 1\right] = K^*\left\{p\left([(m\varepsilon)^{\sigma-1} + 1]^{\frac{1}{\sigma-1}} - 1\right)\right\}.$$

That is, $V(K^* - C(\phi), \varepsilon + \phi) = V(K^*, \varepsilon)$. Since $V(K^* - C(\phi), \varepsilon + \phi)$ is the profit with the technology upgrade and $V(K^*, \varepsilon)$ is the profit without the technology upgrade, K^* is the capital level at which the firm is indifferent between upgrading its technology and keeping the old technology.

Proof of Proposition.

First, we prove that if $\sigma > 1$, then $A_2^* > A_1^*$ and $H_2^* > H_1^*$. The intuition is the scale effect. Because $\Delta K \geq C(\phi)$, $K + \Delta K - C(\phi) \geq K$. Further, because $\phi \geq 0$, $\varepsilon + \phi \geq \varepsilon$. And if $\sigma > 1$, we can easily check from the above optimal solutions that $A_2^* > A_1^*$ and $H_2^* > H_1^*$.

To compare L_1^* with L_2^*, we define $f(\phi) = \frac{L_1^*}{L_2^*} = \frac{K}{K+\Delta K - C(\phi)} \frac{1+[m(\varepsilon+\phi)]^{\sigma-1}}{1+(m\varepsilon)^{\sigma-1}}$. Note $f(\phi)$ is a continuous and increasing function of ϕ. If we assume that $\phi \in [0, C^{-1}(\Delta K)]$, then we can calculate $f(0) = \frac{K}{K+\Delta K}$ and $f\left(C^{-1}(\Delta K)\right) = \frac{1+\left[m\left(\varepsilon+C^{-1}(\Delta K)\right)\right]^{\sigma-1}}{1+(m\varepsilon)^{\sigma-1}}$. When $\sigma > 1$, $f(0) < 1 < f(C^{-1}(K))$. Based on the monotonicity of $f(\phi)$, we know that there must exist a $\bar{\phi}$ such that $f(\bar{\phi}) = 1$. Therefore for $\phi > \bar{\phi}$, we have $f(\phi) = \frac{L_1^*}{L_2^*} > f(\bar{\phi}) = 1$; that is, $L_1^* > L_2^*$.

To show how the total number of employees differs between before and after an SEO, we similarly define $g(\phi) = \frac{H_1^* + L_1^*}{H_2^* + L_2^*} = \frac{K}{K+\Delta K - C(\phi)} \frac{1-\alpha+\frac{w+\alpha-1}{1+(m\varepsilon)^{\sigma-1}}}{1-\alpha+\frac{w+\alpha-1}{1+[m(\varepsilon+\phi)]^{\sigma-1}}}$. $g(\phi)$ is a continuous and increasing function of ϕ. As noted above, when $\phi = \bar{\phi}$, $L_1^* = L_2^*$. Since $H_2^* > H_1^*$, $H_2^* + L_2^* > H_1^* + L_1^*$, which means $g(\bar{\phi}) < 1$. When $\phi = C^{-1}(\Delta K)$, $g(\phi) = \frac{1-\alpha+\frac{w+\alpha-1}{1+(m\varepsilon)^{\sigma-1}}}{1-\alpha+\frac{w+\alpha-1}{1+\left[m\left(\varepsilon+C^{-1}(\Delta K)\right)\right]^{\sigma-1}}} > 1$. As a result, there exists $\phi^* \in [\bar{\phi}, C^{-1}(\Delta K)]$, such that $g(\phi^*) = 1$. Therefore, when $\phi > \phi^*$, we have $g(\phi) > 1$, indicating $\frac{H_1^*+L_1^*}{H_2^*+L_2^*} > 1$; that is, $H_1^* + L_1^* > H_2^* + L_2^*$.

APPENDIX B: Elasticity of Substitution between High and Low Skill Workers

To estimate the elasticity of substitution between high- and low skill workers for our sample firms, we use a procedure widely used in the wage inequality literature (e.g., Katz and Murphy, 1992; Hechman, Lochner, and Taber, 1998; Card and DiNardo, 2002; Acemoglu and Autor, 2011). Rewriting the maximization problem (A1) in Appendix A, we obtain:

$$\underset{\{A,H\}}{Max}\, p\left[(\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{\sigma-1}{\sigma}} + (K - rA - wH)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - K \tag{B1}$$

Let $M = (\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{\sigma-1}{\sigma}} + L^{\frac{\sigma-1}{\sigma}}$ and $L = K - rA - wH$, then the first-order condition with respect to H can be written as:

$$p\frac{\sigma}{\sigma-1}M^{\frac{1}{\sigma-1}}\left[\frac{\sigma-1}{\sigma}(1-\alpha)H^{-\alpha}(\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{-1}{\sigma}} - \frac{\sigma-1}{\sigma}wL^{\frac{-1}{\sigma}}\right] = 0 \tag{B2}$$

Hence, $$\frac{\sigma-1}{\sigma}(1-\alpha)H^{-\alpha}(\varepsilon A^{\alpha}H^{1-\alpha})^{\frac{-1}{\sigma}} = \frac{\sigma-1}{\sigma}wL^{\frac{-1}{\sigma}} \tag{B3}$$

Taking natural logarithm on both sides of (B3) and re-arranging, we obtain:

$$lnw = [ln(1-\alpha) - \frac{1}{\sigma}ln\varepsilon] - \frac{\alpha}{\sigma}lnA + (\frac{\alpha}{\sigma} - \alpha)lnH - \frac{1}{\sigma}ln\frac{H}{L} \tag{B4}$$

For the technology term, A, our initial specification follows Katz and Murphy (1992) and Card and DiNardo (2002) and assumes it follows a log-linear form and increases over time:

$$ln\, A_t = \gamma_0 + \gamma_1 t \tag{B5}$$

Substituting (B5) into (B4), we obtain

$$lnw = [ln(1-\alpha) - \frac{1}{\sigma}ln\varepsilon - \frac{\alpha}{\sigma}\gamma_0] - \frac{\alpha}{\sigma}\gamma_1 t + (\frac{\alpha}{\sigma} - \alpha)lnH - \frac{1}{\sigma}ln\frac{H}{L} \tag{B6}$$

To estimate the elasticity of substitution (σ) for our sample firms, we convert (B6) to the following panel regression:

$$lnw_{it} = constant + \alpha_1 Time_{jt} + \beta \ln\left(\frac{H_{it}}{L_{it}}\right) + \zeta \ln(H_{it}) + \lambda_t + \lambda_i + \varepsilon_{it} \tag{B7}$$

Where λ_t and λ_i are year- and firm fixed effects. $Time_{jt}$ is the time trend for industry *j,* which allows for different time trends in technology development across industries. We use industry classification defined by the CSRC. (B7) does not include a general time trend because year fixed effects absorb it.

The coefficient of interest is β; the negative value of its reciprocal (i.e., $\beta = -\frac{1}{\sigma}$) is σ. We estimate two specifications: (B7) and (B7) with a square term, $\alpha_2 Time^2_{jt}$, to allow for non-linear time trends as in Acemoglu and Autor (2011).

$\text{Ln}\left(\frac{H_{it}}{L_{it}}\right)$ is the log of firm *i*'s ratio of high skill to low skill workers in year *t*. We proxy high and low skill workers by education or occupation. Education-based classification treats those with at least bachelor degrees from four-year universities as high skill workers, and those without four-year university degrees as low skill workers. Occupation-based classification treats technicians and R&D staff, sales and marketing forces as high skill workers, and production workers and support staff as low skill workers. We do not include finance staff and "others" in the occupation-based classification because of the ambiguity in the routineness of their tasks (see Section 2.4.2).

The dependent variable, $\text{Ln}w_{it}$, is the log of high to low skill worker average wage ratio for each firm-year. There are no data to calculate the ratio because firms do not disclose payroll information broken down by education or occupation. Thus, we rely on implied average wages obtained by running an OLS regression relating firm average wages to the fractions of employees by education or by occupation without a constant term.[35] Then the estimated coefficient on each fraction can be interpreted as the implied wage for its respective education level or occupation category because average wages are the weighted averages of employees with different education levels or occupation categories, and the fractions are the weights used in calculating weighted averages.

To estimate implied wages by education, we form five education groups: (1) *Grad,* employees with post-graduate degrees; (2) *BAOnly,* employees with only bachelor degrees from four-year universities; (3) *JBAOnly,* employees with only degrees from three-year junior colleges; (4) *HighSchoolOnly,* employees with only high school equivalent education including technical and

[35] We do not use data from China Urban Household Survey in Online Appendix 7 because wages of publicly listed firms are different from wages of those covered in the Survey.

vocational schools; and (5) *Below,* employees without high school equivalent education. Not all firms separate employees into five groups. Some firms separate employees into four or fewer education groups. To avoid losing observations, we do the following: For each year during 2000-2012, we calculate the average fraction of employees in each of the five education groups using only the subsample of firms reporting the number of employees in all five groups. Then, we use these fractions to disaggregate the aggregated number of employees overlapping two or more education groups and assign the disaggregated numbers into their corresponding groups.[36] We use these implied wages to calculate the ratios of high- to low skill worker wages. Wages for high skill workers are the weighted average of implied wages of *BAOnly* and *Grad;* wages for low skill are the weighted average of implied wages of the three lower education groups. For occupation, we use the categories defined in Section 2.4.2. Online Appendix 9 reports implied wages by education and occupation during our sample period.[37]

We estimate the panel regression (B7) with these $\text{Ln}\, w_{it}$ and $\text{Ln}\left(\frac{H_{it}}{L_{it}}\right)$, yielding the following four estimates of σ; two for each classification of high and low skill workers with linear and non-linear time trends. The elasticity estimates are about 2.1 when we classify high and low skill workers by education and are about 4.8 when we classify high and low skill workers by occupation.

	$\hat{\sigma}$	
	Linear Time Trend	**Non-Linear Time Trend**
Low Skill: Without a four-year university bachelor' degree High Skill: With at least four-year university bachelor's degree	2.127	2.097
Low Skill: Production workers and support staff High Skill: Technicians, R&D staff, and sales and marketing personnel	4.794	4.787

[36] To illustrate, consider a firm reporting 100 of its employees have college degrees without separating them into four-year university bachelor degrees and three-year junior college degrees. We calculate the average fraction of employees in each of the five education groups using the sub-sample of firms that report the number of employees in all the five groups in the same year. If this calculation shows 15% of employees have bachelor's degrees from four-year universities, and 10% of employees have junior college degrees, we assume this firm has 60 (100*(15%/(15%+10%))) employees with four-year university bachelor's degrees and 40 (100*(10%/(15%+10%))) employees with junior college degrees.

[37] As expected, implied wages are higher when the level of education is higher. As for occupation categories, the implied wage is the lowest for production workers, but the implied wage for *Staff* is about the same as *Tech_ R&D*. *Staff* includes some high-pay administrators, and *Tech_ R&D* includes some low-pay technicians. The meager implied wage for the *S&M* category is misleading because their wages do not include sales commissions, which are the primary source of their income.

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Table 1: Sample and SEOs by Year.

The sample includes Chinese firms listed on Shanghai and Shenzhen Stock Exchanges over 2000 - 2012. Financial firms, firms with fewer than 100 employees, ST (special treatment), and *ST firms are excluded. Firms are classified as ST or *ST if they have two (ST) or three (*ST) consecutive years of negative net profits. Column (1) shows the number of firms in the full sample by year. Column (2) shows the number of public offerings by year of receiving SEO proceeds.

Year	**Full**	**Number of SEOs**
	(1)	**(2)**
2000	885	154
2001	951	131
2002	1,002	44
2003	1,059	38
2004	1,153	32
2005	1,172	7
2006	1,204	7
2007	1,323	28
2008	1,395	43
2009	1,485	18
2010	1,830	20
2011	2,120	23
2012	2,259	12
Total	17,838	557

Table 2: Summary Statistics.

This table reports summary statistics for variables used in the panel regressions. Online Appendix 3 provides variable definitions and data sources.

VARIABLES	Mean	Std. Dev.	Min	Max
SEO	0.088	0.283	0.000	1.000
SEO_Proceed (1,000,000)	725.902	1595.407	34.656	23947.61
SEOIneligible	0.155	0.362	0.000	1.000
EMP (100)	45.916	176.742	1.000	5528.100
Production	2228.760	9157.168	0.000	337036.000
Staff	320.840	1822.266	10.000	85228.000
Tech_R&D	650.142	3731.857	0.000	199531.000
S&M	503.142	2862.225	0.000	94476.000
Finance	95.998	472.648	0.000	14445.000
Others	861.889	5531.349	0.000	226361.000
Grad	124.597	767.276	0.000	24642.000
BA	868.775	4826.496	0.000	152840.000
NBA	4205.349	16702.3	8.000	427676.000
%_Production	0.483	0.284	0.000	0.997
%_Staff	0.093	0.109	0.001	0.998
%_Tech_R&D	0.175	0.158	0.000	0.987
%_S&M	0.130	0.162	0.000	0.996
%_Finance	0.034	0.035	0.000	0.788
%_Others	0.173	0.259	0.000	1.000
%_Grad	0.031	0.043	0.000	0.237
%_BA	0.202	0.178	0.000	0.959
Tangible_Tech (1,000,000)	148.853	1475.197	0.000	91309.090
Intangible_Tech (10,000)	978.125	6733.577	0.000	197295.200
Capx (1,000,000)	479.913	4753.238	0.001	247650.400
AWAGE (10,000)	6.928	11.691	0.013	658.944
AWAGE_NonExe (10,000)	7.054	12.352	0.011	723.361
AEXEPAY (10,000)	20.192	20.009	0.360	506.227
Payroll (1,000,000)	296.153	1908.561	0.039	108031.000
Payroll_NonExe (1,000,000)	306.816	1964.043	0.019	108015.900
Payroll_Exe (1,000,000)	2.876	3.534	0.022	111.370
ROA	0.035	0.111	-4.051	6.109
Sales_GR	0.228	0.497	-0.609	3.379
Sales/Employees (1,000,000)	1.105	2.878	0.000	130.867
TFP	0.003	0.336	-1.217	0.976
P3_PR	0.766	0.827	0.000	4.085
P3_PR_D	0.027	0.161	0.000	1.000
Ln(MIN_WAGE)	640.329	207.828	208.540	1085.329
LAWSCORE	7.784	3.916	0.000	16.610
Labor_Law_Effect	3.689	3.850	0.000	13.312
SALES (1,000,000)	4517.473	39862.920	0.003	2085363.000
%_LARGEST_SH	0.390	0.163	0.022	0.894
DIV_PR	0.259	0.306	0.000	1.500
%_STATE_OWN	0.215	0.252	0.000	0.886
%_IND_DIR	0.306	0.127	0.000	0.833
%_NONTRD_SH	0.212	0.296	0.000	0.913
LEVERAGE	0.456	0.201	0.047	0.889
PPE/TA	0.320	0.201	0.000	0.975

Table 3: Firm-level Employment: Total Employment and by Occupation or Education.

This table reports the second-stage estimation of the impacts that SEOs have on firm-level employment. Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. The dependent variable is the number of all employees in Column (1), production workers in Column (2), support staff in Column (3), technicians and R&D employees in Column (4), sales and marketing forces in Column (5), finance staff in Column (6), employees in uncategorized occupations in Column (7), employees with post-graduate degrees in Column (8), employees with four-year university bachelor's degrees and above in Column (9), and employees without four-year university bachelor's degrees in Column (10). All dependent variables, except Column (1), are the log of one plus the number of employees. Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012. Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A										
	Ln (EMP)	**Ln (Production)**	**Ln (Staff)**	**Ln (Tech_R&D)**	**Ln (S&M)**	**Ln (Finance)**	**Ln (Others)**	**Ln (Grad)**	**Ln (BA)**	**Ln (NBA)**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widehat{SEO}$	-0.080*	-0.208*	-0.497***	0.239***	0.162**	-0.002	-0.277	0.033	0.115*	-0.149***
	(0.047)	(0.124)	(0.129)	(0.082)	(0.076)	(0.055)	(0.297)	(0.084)	(0.061)	(0.048)
Constant	2.589***	6.004***	3.671***	5.262***	4.757***	3.481***	3.154***	2.378***	4.837***	6.899***
	(0.026)	(0.058)	(0.053)	(0.036)	(0.045)	(0.028)	(0.119)	(0.057)	(0.044)	(0.068)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	17,597	17,597	17,597	14,438	15,064	13,840	17,597	8,345	12,020	12,020
Panel B										
	Ln (EMP)	**Ln (Production)**	**Ln (Staff)**	**Ln (Tech_R&D)**	**Ln (S&M)**	**Ln (Finance)**	**Ln (Others)**	**Ln (Grad)**	**Ln (BA)**	**Ln (NBA)**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\widehat{SEO}$	-0.091**	-0.252**	-0.463***	0.133**	0.103*	0.008	-0.070	0.111*	0.004	-0.174***
	(0.043)	(0.102)	(0.097)	(0.056)	(0.062)	(0.052)	(0.218)	(0.065)	(0.061)	(0.053)
P3_PR	0.011*	0.045***	0.038**	0.002	0.016	-0.004	-0.030	-0.021*	0.018	0.014*
	(0.006)	(0.014)	(0.015)	(0.010)	(0.015)	(0.008)	(0.031)	(0.011)	(0.012)	(0.007)
P3_PR_D	-0.017	-0.025	0.063	-0.063*	0.035	-0.035	0.052	-0.075	-0.079**	0.002
	(0.024)	(0.056)	(0.073)	(0.033)	(0.033)	(0.024)	(0.129)	(0.053)	(0.034)	(0.030)
Ln(MIN_WAGE)	-0.265***	-0.175	-0.213*	-0.227***	-0.106	-0.160***	0.036	0.255**	-0.002	-0.432***
	(0.058)	(0.117)	(0.116)	(0.075)	(0.086)	(0.058)	(0.239)	(0.121)	(0.091)	(0.084)
LAWSCORE	-0.012**	0.011	0.005	0.003	0.014*	-0.011**	-0.069***	-0.022*	-0.009	-0.023***
	(0.005)	(0.011)	(0.012)	(0.007)	(0.008)	(0.005)	(0.022)	(0.013)	(0.008)	(0.009)
Labor_Law_Effect	-0.004	-0.041***	0.011	0.006	-0.025**	0.002	0.050***	-0.037***	-0.020***	0.012**
	(0.003)	(0.008)	(0.011)	(0.006)	(0.012)	(0.005)	(0.017)	(0.005)	(0.005)	(0.005)
Ln(SALES)	0.421***	0.326***	0.259***	0.396***	0.415***	0.319***	0.325***	0.393***	0.421***	0.446***
	(0.012)	(0.027)	(0.016)	(0.016)	(0.016)	(0.012)	(0.036)	(0.020)	(0.015)	(0.016)
%_LARGEST_SH	-0.094	-0.273*	0.242**	0.023	0.082	0.131*	0.084	-0.092	0.074	-0.346**
	(0.075)	(0.163)	(0.123)	(0.109)	(0.136)	(0.074)	(0.316)	(0.138)	(0.110)	(0.142)
DIV_PR	0.005	0.008	0.008	0.002	-0.002	0.003	-0.004	-0.002	0.005	0.006
	(0.010)	(0.013)	(0.021)	(0.012)	(0.013)	(0.010)	(0.019)	(0.016)	(0.013)	(0.009)
%_STATE_OWN	0.125***	0.007	0.074	0.076	-0.007	0.060*	0.221*	0.023	0.148***	0.143***
	(0.028)	(0.076)	(0.084)	(0.054)	(0.091)	(0.035)	(0.123)	(0.055)	(0.050)	(0.045)
%_IND_DIR	0.039	-0.190*	-0.042	0.227***	0.192**	0.079	0.150	0.034	0.023	0.063
	(0.043)	(0.112)	(0.116)	(0.081)	(0.085)	(0.049)	(0.186)	(0.097)	(0.084)	(0.075)
%_NONTRD_SH	0.040	0.046	-0.102	-0.077	-0.056	-0.012	0.027	-0.016	-0.034	0.037
	(0.044)	(0.092)	(0.105)	(0.062)	(0.048)	(0.041)	(0.167)	(0.090)	(0.058)	(0.062)
Leverage	0.261***	-0.130	0.276***	0.208***	0.202**	0.429***	0.581***	0.228**	0.267***	0.239***
	(0.041)	(0.115)	(0.105)	(0.059)	(0.098)	(0.051)	(0.223)	(0.110)	(0.066)	(0.064)
PPE/TA	0.530***	0.963***	0.451***	0.272***	-0.236**	-0.078	-0.501**	-0.056	0.178**	0.702***
	(0.050)	(0.114)	(0.094)	(0.073)	(0.114)	(0.049)	(0.213)	(0.118)	(0.085)	(0.089)
Constant	1.455***	4.976***	3.113***	4.067***	2.770***	2.387***	1.118	-1.390*	2.148***	6.701***
	(0.348)	(0.728)	(0.703)	(0.474)	(0.527)	(0.359)	(1.532)	(0.771)	(0.555)	(0.520)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm-sepcific Time Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,964	16,964	16,964	13,916	10,576	13,326	16,964	8,109	11,650	11,650

Table 4: Employee Composition by Occupation or Education.

This table reports the second-stage estimation of the impacts that SEOs have on the employee composition by occupation or education. Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. The dependent variable is the percentage of production workers in Column (1), support staff in Column (2), technicians and R&D employees in Column (3), sales and marketing forces in Column (4), finance staff in Column (5), employees in uncategorized occupations in Column (6), employees with post-graduate degrees in Column (7), and employees with four-year university Bachelor's degrees and above in Column (8). Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012. Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A								
	%_Production	**%_Staff**	**%_Tech_R&D**	**%_S&M**	**%_Finance**	**%_Others**	**%_Grad**	**%_BA**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\widehat{\text{SEO}}$	-0.031**	-0.020***	0.052***	0.022**	0.002	-0.007	0.003	0.019**
	(0.016)	(0.006)	(0.011)	(0.010)	(0.003)	(0.020)	(0.003)	(0.009)
Constant	0.498***	0.062***	0.183***	0.135***	0.030***	0.177***	0.030***	0.165***
	(0.009)	(0.004)	(0.006)	(0.005)	(0.001)	(0.011)	(0.002)	(0.006)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y	Y	Y	Y	Y
Observations	17,597	17,597	14,438	15,064	13,840	17,597	8,345	12,020

Panel B								
	%_Production	**%_Staff**	**%_Tech_R&D**	**%_S&M**	**%_Finance**	**%_Others**	**%_Grad**	**%_BA**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\widehat{\text{SEO}}$	-0.037***	-0.011*	0.038***	0.023***	0.004*	0.007	0.006**	0.018**
	(0.014)	(0.007)	(0.010)	(0.005)	(0.002)	(0.018)	(0.003)	(0.007)
P3_PR	0.005**	0.002*	-0.001	0.000	-0.001***	-0.008***	-0.000	0.001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.003)	(0.000)	(0.001)
P3_PR_D	0.001	0.002	-0.010**	0.001	-0.002**	0.002	0.000	-0.010**
	(0.009)	(0.004)	(0.004)	(0.003)	(0.001)	(0.010)	(0.001)	(0.004)
Ln(MIN_WAGE)	0.004	0.006	-0.003	-0.002	0.001	0.008	0.005	0.038***
	(0.019)	(0.008)	(0.013)	(0.012)	(0.002)	(0.025)	(0.003)	(0.011)
LAWSCORE	0.003*	-0.000	0.002**	0.000	-0.000	-0.007***	-0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)
Labor_Law_Effect	-0.006***	0.002***	0.001	-0.003***	0.001	0.004**	-0.001***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)
Ln(SALES)	0.003	-0.006***	-0.004**	0.002	-0.002***	0.004	-0.001	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.001)	(0.002)
%_LARGEST_SH	-0.055**	0.036***	0.027	0.024*	0.018***	0.012	0.007*	0.067***
	(0.025)	(0.011)	(0.018)	(0.014)	(0.003)	(0.027)	(0.004)	(0.017)
DIV_PR	0.001	0.000	-0.001	-0.000	-0.000	0.000	-0.000	-0.000
	(0.003)	(0.001)	(0.002)	(0.001)	(0.000)	(0.004)	(0.001)	(0.001)
%_STATE_OWN	-0.003	-0.013***	-0.008	-0.023***	-0.002	0.019*	-0.003	0.002
	(0.011)	(0.005)	(0.005)	(0.005)	(0.001)	(0.011)	(0.002)	(0.007)
%_IND_DIR	-0.054***	0.013*	0.029***	0.034***	-0.002	0.010	-0.003	-0.014
	(0.019)	(0.008)	(0.010)	(0.012)	(0.003)	(0.024)	(0.003)	(0.012)
%_NONTRD_SH	-0.001	0.004	-0.006	-0.006	0.000	0.008	0.005	-0.011
	(0.018)	(0.008)	(0.008)	(0.011)	(0.002)	(0.017)	(0.003)	(0.010)
Leverage	-0.081***	0.016*	-0.001	0.003	0.009***	0.049***	0.004	0.009
	(0.015)	(0.010)	(0.012)	(0.007)	(0.002)	(0.019)	(0.003)	(0.010)
PPE/TA	0.168***	-0.012	-0.030**	-0.054***	-0.024***	-0.113***	-0.015***	-0.084***
	(0.018)	(0.009)	(0.012)	(0.017)	(0.002)	(0.023)	(0.003)	(0.013)
Constant	0.464***	0.047	0.214**	0.146**	0.033***	0.129	0.006	-0.048
	(0.112)	(0.047)	(0.086)	(0.067)	(0.013)	(0.148)	(0.022)	(0.070)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,964	16,964	13,916	10,576	13,326	16,964	8,109	11,650

Table 5: Technology Investments.

This table reports the second-stage estimation of the effects of SEOs on expenditures on technology-related tangible- and intangible assets and total capital expenditures. Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. The dependent variable is expenditures on technology-related machines and equipment (Column 1), expenditures on technology-related intangible assets (Columns 2), and total capital expenditures (Column 3). Online Appendix 3 provides variable definitions and data sources. The sample period covers 2003-2012 for Column (1), 2007-2012 for Column (2), and 2000-2012 for Column (3). Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A

	Ln(Tangible_Tech)	**Ln(Intangible_Tech)**	**Ln(Capx)**
VARIABLES	**(1)**	**(2)**	**(3)**
$\widehat{SEO}$	0.537***	0.447*	0.580***
	(0.127)	(0.262)	(0.092)
Constant	1.968***	12.614***	3.720***
	(0.069)	(0.241)	(0.067)
Firm & Year FE	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y
Observations	14,967	6,255	17,728

Panel B

	Ln(Tangible_Tech)	**Ln(Intangible_Tech)**	**Ln(Capx)**
VARIABLES	**(1)**	**(2)**	**(3)**
$\widehat{SEO}$	0.272***	0.363*	0.265***
	(0.094)	(0.188)	(0.091)
P3_PR	0.005	-0.031	0.050***
	(0.019)	(0.050)	(0.014)
P3_PR_D	-0.149***	0.315	-0.399***
	(0.057)	(0.252)	(0.060)
Ln(MIN_WAGE)	0.029	-0.087	0.013
	(0.183)	(0.556)	(0.118)
LAWSCORE	-0.030		-0.006
	(0.020)		(0.010)
Labor_Law_Effect	-0.030***	0.004	-0.041***
	(0.011)	(0.034)	(0.009)
Ln(SALES)	0.552***	0.443***	0.801***
	(0.025)	(0.091)	(0.024)
%_LARGEST_SH	0.237	0.340	0.476***
	(0.167)	(0.746)	(0.169)
DIV_PR	0.001	0.003	0.008
	(0.024)	(0.044)	(0.019)
%_STATE_OWN	0.128*	0.316	0.085
	(0.066)	(0.200)	(0.053)
%_IND_DIR	-0.044	-0.221	0.199
	(0.186)	(0.417)	(0.132)
%_NONTRD_SH	-0.148*	-0.765	-0.655***
	(0.085)	(1.364)	(0.104)
Leverage	0.693***	0.103	0.044
	(0.128)	(0.412)	(0.111)
PPE/TA	2.225***	0.658	2.862***
	(0.154)	(0.408)	(0.117)
Constant	-2.332**	0.825	-1.788***
	(1.166)	(3.413)	(0.692)
Firm & Year FE	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y
Observations	14,453	6,187	17,099

Table 6: Demand for Computer Skills.

This table relates SEOs to computer skills mentioned in online job postings. Panels A and B report the results for advanced and basic computer skills, respectively. Online Appendix 8, Panel B lists keywords used to identify advanced and basic computer skills. The dependent variable in Columns (1) and (2) is an indicator equal to one if any of the keywords related to advanced and basic computer skills, respectively, appear in a job description. The dependent variable in Columns (3) and (4) is the log of one plus the number of the relevant keywords appearing in the job description. Columns (1) and (2) are estimated by logit regressions; Columns (3) and (4), the OLS regressions. The sample period covers 2014 – 2016. Regressions in Columns (1) and (3) control for year-, firm-, and location dummies, and regressions in Columns (2) and (4) add job dummies. Standard errors (in parentheses) are clustered at the firm-job pair level in all regressions. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Advanced Computer Skills				
	Adv_Computer_Dum		**Ln(Adv_Computer)**	
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
JP_SEO	0.183***	0.153**	0.059***	0.042***
	(0.060)	(0.063)	(0.017)	(0.012)
Constant	2.033***	1.122**	1.855***	1.215***
	(0.779)	(0.481)	(0.293)	(0.115)
Year Dummies	Y	Y	Y	Y
Firm Dummies	Y	Y	Y	Y
Location Dummies	Y	Y	Y	Y
Job Dummies	N	Y	N	Y
Observations	44,767	44,767	45,582	45,582
Pseudo-R^2	0.078	0.297		
Adjusted R^2			0.101	0.398
Panel B: Basic Computer Skills				
VARIABLES	**Basic_Computer_Dum**		**Ln(Basic_Computer)**	
JP_SEO	0.370**	0.381***	0.008**	0.008**
	(0.148)	(0.146)	(0.004)	(0.003)
Constant	-4.514***	-3.880***	0.018	0.048**
	(1.196)	(1.183)	(0.015)	(0.019)
Year Dummies	Y	Y	Y	Y
Firm Dummies	Y	Y	Y	Y
Location Dummies	Y	Y	Y	Y
Job Dummies	N	Y	N	Y
Observations	40,218	40,218	45,582	45,582
Pseudo-R^2	0.085	0.120		
Adjusted R^2			0.032	0.045

Table 7: Demand for Non-routine Analytical and Interactive Task Skills.

This table relates SEOs to non-routine task skills mentioned in online job postings. Panels A and B report the results for non-routine analytical and interactive task skills, respectively. Online Appendix 8, Panel B lists keywords used to identify non-routine task skills. The dependent variable in Columns (1) and (2) is an indicator equal to one if any of the keywords related to non-routine analytical and interactive task skills appear in a job description. The dependent variable in Columns (3) and (4) is the log of one plus the number of relevant keywords appearing in a job description. Columns (1) and (2) are estimated by logit regressions; Columns (3) and (4), the OLS regressions. The sample period covers 2014 – 2016. Regressions in Columns (1) and (3) control for year-, firm-, and location dummies, and regressions in Columns (2) and (4) add job dummies. Standard errors (in parentheses) are clustered at the firm-job pair level in all regressions. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A: Non-routine Analytic Task Skills				
	Non-routine Analytical Task Skills_Dum		**Ln(Non-routine Analytical Task Skills)**	
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
JP_SEO	0.166***	0.169***	0.022*	0.022
	(0.057)	(0.058)	(0.013)	(0.013)
Constant	0.578	0.373	0.524***	0.419**
	(0.365)	(0.380)	(0.125)	(0.164)
Year Dummies	Y	Y	Y	Y
Firm Dummies	Y	Y	Y	Y
Location Dummies	Y	Y	Y	Y
Job Dummies	N	Y	N	Y
Observations	44,992	44,992	45,582	45,582
Pseudo-R^2	0.072	0.090		
Adjusted R^2			0.082	0.115
Panel B: Non-routine Interactive Task Skills				
VARIABLES	**Non-routine Interactive Task Skills_Dum**		**Ln(Non-routine Interactive Task Skills)**	
JP_SEO	0.110*	0.143**	0.015	0.024**
	(0.061)	(0.063)	(0.011)	(0.011)
Constant	2.490***	3.030***	0.959***	1.215***
	(0.545)	(0.608)	(0.158)	(0.205)
Year Dummies	Y	Y	Y	Y
Firm Dummies	Y	Y	Y	Y
Location Dummies	Y	Y	Y	Y
Job Dummies	N	Y	N	Y
Observations	44,214	44,214	45,582	45,582
Pseudo-R^2	0.052	0.096		
Adjusted R^2			0.069	0.156

Table 8: Technologe Investments and Firm-level Employment

This table relates the effect of SEOs on firm-level employment to changes in technology-related tangible assets following SEOs. The dependent variable is the total number of employees. Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. Columns (1) and (3) report the estimation results for SEOs followed by changes in technology-related tangible assets greater than the SEO sample median. Columns (2) and (4) report the estimation results for SEOs followed by changes in technology-related tangible assets less than the SEO sample median. Changes in technology-related tangible assets are measured by changes in the average value of technology-related machines and equipment during SEO years relative to the year before SEO years, divided by total assets in the year before SEO years. Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012. Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	Panel A		**Panel B**	
	Ln(EMP)			
	High Changes in Ln(Tangible_Tech)	**Low Changes in Ln(Tangible_Tech)**	**High Changes in Ln(Tangible_Tech)**	**Low Changes in Ln(Tangible_Tech)**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
$\widehat{SEO}$	-0.113***	-0.099*	-0.118***	-0.093
	(0.042)	(0.055)	(0.044)	(0.057)
Control Variables	N	N	Y	Y
Firm & Year FE	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y
Observations	12,514	12,494	12,077	12,043

Table 9: Financial Constraints, Technologe Investments, and Firm-level Employment

This table relates the effect of SEOs on technology investments and firm-level employment to the level of financial constraints of equity issuing firms. The dependent variable in Columns (1), (2), (5) and (6) is the value of technology-related tangible assets; in Columns (3), (4), (7) and (8), the total number of employees. Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. Columns (1), (3), (5) and (7) report the estimation results for SEO firms more financially constrained than the SEO sample median. Columns (2), (4), (6) and (8) report the estimation results for SEO firms less financially constrained than the SEO sample median. Financial constraints are measured by the KZ index (Kaplan and Zingales, 1998) in the year before the year in which firms receive SEO proceeds. Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012. Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	Panel A				**Panel B**			
	Ln(Tangible_Tech)		**Ln(EMP)**		**Ln(Tangible_Tech)**		**Ln(EMP)**	
	High Financial Constraints	**Low Financial Constraints**	**High Financial Constraints**	**Low Financial Constraints**	**High Financial Constraints**	**Low Financial Constraints**	**High Financial Constraints**	**Low Financial Constraints**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\widehat{SEO}$	0.586***	0.524***	-0.123***	-0.099*	0.335***	0.259*	-0.118***	-0.094*
	(0.120)	(0.140)	(0.046)	(0.051)	(0.121)	(0.138)	(0.042)	(0.049)
Control Variables	N	N	N	N	Y	Y	Y	Y
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm-sepcific Time Trend	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,292	11,162	13,082	13,016	10,919	10,785	12,616	12,551

Table 10: Average Wages.

This table reports the second-stage estimation of the impacts that SEOs have on average wages (total payroll/total number of employees). Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. The dependent variable is the log of the average wage of all employees in Column (1), all non-executive employees in Column (2), all executives in Column (3). Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012 for Column (1) and 2001 – 2012 for Columns (2) – (3). Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A

	Ln(AWAGE)	**Ln(AWAGE_NonExe)**	**Ln(AEXEPAY)**
VARIABLES	**(1)**	**(2)**	**(3)**
$\widehat{SEO}$	0.102***	0.135***	-0.018
	(0.039)	(0.040)	(0.036)
Constant	0.611***	0.737***	1.819***
	(0.022)	(0.023)	(0.022)
Firm & Year FE	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y
Observations	17,593	16,599	16,599

Panel B

	Ln(AWAGE)	**Ln(AWAGE_NonExe)**	**Ln(AEXEPAY)**
VARIABLES	**(1)**	**(2)**	**(3)**
$\widehat{SEO}$	0.065*	0.089**	0.025
	(0.037)	(0.044)	(0.032)
P3_PR	0.015***	0.011**	0.014***
	(0.006)	(0.005)	(0.005)
P3_PR_D	0.031	0.028	-0.078***
	(0.025)	(0.020)	(0.022)
Ln(MIN_WAGE)	0.296***	0.295***	0.176***
	(0.047)	(0.051)	(0.050)
LAWSCORE	-0.007*	-0.006	-0.030***
	(0.004)	(0.006)	(0.005)
Labor_Law_Effect	0.003	0.001	0.014***
	(0.003)	(0.004)	(0.003)
Ln(SALES)	0.120***	0.124***	0.196***
	(0.011)	(0.010)	(0.008)
%_LARGEST_SH	0.220***	0.257***	0.011
	(0.055)	(0.064)	(0.051)
DIV_PR	0.001	0.001	0.005
	(0.012)	(0.011)	(0.006)
%_STATE_OWN	0.079***	0.069***	-0.019
	(0.024)	(0.020)	(0.027)
%_IND_DIR	-0.017	-0.022	-0.028
	(0.045)	(0.046)	(0.042)
%_NONTRD_SH	-0.058	-0.034	-0.030
	(0.044)	(0.047)	(0.034)
Leverage	-0.111***	-0.119***	-0.176***
	(0.037)	(0.043)	(0.035)
PPE/TA	-0.128***	-0.085	-0.193***
	(0.042)	(0.060)	(0.040)
Constant	-1.836***	-1.781***	-0.116
	(0.288)	(0.317)	(0.310)
Firm & Year FE	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y
Observations	16,960	16,026	16,026

Table 11: Total Wages.

This table reports the second-stage estimation of the impacts that SEOs have on total wages. Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. The dependent variable is the log of total wages to all employees in Column (1), all non-executive employees in Column (2), all executives in Column (3). Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012 for Column (1) and 2001 – 2012 for Columns (2) – (3). Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A			
	Ln(Payroll)	**Ln(Payroll_NonExe)**	**Ln(Payroll_Exe)**
VARIABLES	**(1)**	**(2)**	**(3)**
$\widehat{SEO}$	0.021	0.044	-0.020
	(0.051)	(0.041)	(0.040)
Constant	3.198***	3.238***	-0.486***
	(0.026)	(0.024)	(0.024)
Firm & Year FE	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y
Observations	17,792	16,747	16,747

Panel B			
	Ln(Payroll)	**Ln(Payroll_NonExe)**	**Ln(Payroll_Exe)**
VARIABLES	**(1)**	**(2)**	**(3)**
$\widehat{SEO}$	-0.035	-0.033	0.011
	(0.035)	(0.034)	(0.033)
P3_PR	0.027***	0.022***	0.020***
	(0.004)	(0.005)	(0.006)
P3_PR_D	0.017	0.021	-0.134***
	(0.019)	(0.018)	(0.025)
Ln(MIN_WAGE)	0.021	0.001	0.116**
	(0.047)	(0.042)	(0.051)
LAWSCORE	-0.020***	-0.021***	-0.022***
	(0.003)	(0.004)	(0.004)
Labor_Law_Effect	-0.001	0.000	0.015***
	(0.003)	(0.003)	(0.004)
Ln(SALES)	0.538***	0.545***	0.226***
	(0.011)	(0.011)	(0.011)
%_LARGEST_SH	0.165**	0.191***	0.011
	(0.064)	(0.064)	(0.077)
DIV_PR	0.006	0.006*	0.006
	(0.004)	(0.003)	(0.007)
%_STATE_OWN	0.192***	0.197***	-0.014
	(0.022)	(0.023)	(0.025)
%_IND_DIR	0.012	-0.002	0.072
	(0.034)	(0.036)	(0.048)
%_NONTRD_SH	-0.024	-0.011	-0.117***
	(0.042)	(0.034)	(0.043)
Leverage	0.164***	0.190***	-0.085*
	(0.035)	(0.041)	(0.047)
PPE/TA	0.413***	0.444***	-0.152***
	(0.043)	(0.054)	(0.036)
Constant	-0.323	-0.236	-2.285***
	(0.287)	(0.271)	(0.313)
Firm & Year FE	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y
Observations	17,131	16,152	16,152

Table 12: Firm Performance.

This table reports the second-stage estimation of the impacts that SEOs have on firm performance. Panel A includes only year- and firm fixed effects and firm-specific time trends; Panel B adds time-varying control variables. The dependent variable is ROA in Column (1), the sales growth rate in Column (2), sales per employee in Column (3), and total factor productivity in Column (4). Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000-2012. Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A				
	ROA	**SALES_GR**	**Sales/Emp**	**TFP**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
$\widehat{SEO}$	0.009**	0.089*	0.713*	0.066**
	(0.004)	(0.049)	(0.386)	(0.028)
Constant	0.064***	0.275***	0.470***	0.018
	(0.003)	(0.017)	(0.073)	(0.017)
Firm & Year FE	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y
Observations	17,481	17,797	17,597	17,383

Panel B				
	ROA	**SALES_GR**	**Sales/Emp**	**TFP**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
$\widehat{SEO}$	0.018***	0.213***	0.847**	0.094***
	(0.007)	(0.041)	(0.425)	(0.027)
P3_PR	-0.002***	-0.024***	-0.023	-0.001
	(0.000)	(0.005)	(0.024)	(0.004)
P3_PR_D	-0.014**	0.026	0.052	-0.027*
	(0.006)	(0.026)	(0.063)	(0.015)
Ln(MIN_WAGE)	0.008	-0.104*	0.111	0.044
	(0.007)	(0.056)	(0.154)	(0.033)
LAWSCORE	-0.002***	-0.010**	0.158***	-0.006**
	(0.001)	(0.004)	(0.029)	(0.003)
Labor_Law_Effect	0.002***	0.005	0.003	-0.002
	(0.000)	(0.004)	(0.011)	(0.002)
Ln(SALES)	0.018***	0.231***	0.698***	0.374***
	(0.003)	(0.011)	(0.051)	(0.008)
%_LARGEST_SH	0.052***	0.459***	0.563***	-0.007
	(0.010)	(0.077)	(0.207)	(0.044)
DIV_PR	-0.000	-0.004	-0.007	-0.004
	(0.001)	(0.008)	(0.027)	(0.007)
%_STATE_OWN	-0.005	0.077**	-0.315**	-0.101***
	(0.004)	(0.033)	(0.134)	(0.018)
%_IND_DIR	-0.007	-0.020	-0.131	-0.042
	(0.008)	(0.047)	(0.205)	(0.033)
%_NONTRD_SH	-0.005	-0.142***	-0.064	0.021
	(0.009)	(0.040)	(0.229)	(0.031)
Leverage	-0.159***	0.153***	0.107	-0.275***
	(0.007)	(0.053)	(0.203)	(0.034)
PPE/TA	-0.049***	-0.087*	-1.178***	-0.185***
	(0.009)	(0.051)	(0.237)	(0.040)
Constant	-0.042	-0.579*	-4.781***	-2.244***
	(0.048)	(0.339)	(0.934)	(0.203)
Firm & Year FE	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y
Observations	16,916	17,136	16,964	16,827

Table 13: Results of Pre-trend Placebo Tests.

This table reports the results of placebo tests for pre-trends. Dependent variables in Columns (2) – (11) are the log of one plus the number of the relevant variables. Online Appendix 3 provides variable definitions and data sources. Robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	Ln (EMP)	Ln (Production)	Ln (Staff)	Ln (Tech_R&D)	Ln (S&M)	Ln (Finance)	Ln (Others)	Ln (Grad)	Ln (BA)	Ln (NBA)	Ln (Fixed_ Tech)	ROA	SALES _GR	Sales /Emp	TFP	Ln (AWAGE)	Ln (Payroll)
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**
Affected*Year01	0.015	0.071	-0.132	-0.002	-0.000	0.056	-0.380	0.110	0.032	0.029		-0.008	0.028	-0.060	-0.018	-0.058	-0.027
	(0.034)	(0.100)	(0.107)	(0.055)	(0.063)	(0.041)	(0.239)	(0.160)	(0.091)	(0.070)		(0.006)	(0.052)	(0.093)	(0.026)	(0.038)	(0.031)
Affected*Year02	-0.017	0.001	-0.130	-0.012	-0.102	0.021	-0.305	0.098	0.023	0.005		-0.010	0.021	-0.107	-0.006	-0.034	-0.038
	(0.040)	(0.112)	(0.124)	(0.064)	(0.073)	(0.049)	(0.266)	(0.176)	(0.102)	(0.087)		(0.006)	(0.058)	(0.130)	(0.029)	(0.040)	(0.035)
Affected*Year03	-0.011	-0.024	-0.132	-0.102	-0.114	0.052	-0.449	0.001	-0.064	0.018		-0.010	0.053	-0.263	0.032	-0.062	-0.060
	(0.044)	(0.119)	(0.130)	(0.072)	(0.081)	(0.054)	(0.275)	(0.185)	(0.106)	(0.095)		(0.007)	(0.061)	(0.220)	(0.031)	(0.042)	(0.037)
Affected*Year04	-0.025	-0.081	-0.105	-0.043	-0.132	0.025	-0.379	-0.079	-0.175	0.026	-0.007	-0.010	0.102	-0.220	0.053	-0.069	-0.080*
	(0.050)	(0.129)	(0.138)	(0.076)	(0.084)	(0.060)	(0.297)	(0.192)	(0.115)	(0.107)	(0.143)	(0.008)	(0.065)	(0.141)	(0.033)	(0.048)	(0.044)
Affected*Year05	-0.009	-0.015	-0.161	-0.075	-0.132	0.049	-0.261	-0.044	-0.189	0.011	-0.150	-0.012	0.104	-0.229	0.046	-0.059	-0.055
	(0.053)	(0.139)	(0.155)	(0.081)	(0.096)	(0.063)	(0.316)	(0.204)	(0.117)	(0.114)	(0.158)	(0.008)	(0.065)	(0.155)	(0.034)	(0.051)	(0.047)
Firm FE/YearFE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,683	5,683	5,683	4,787	4,642	4,799	5,683	2,043	2,936	2,936	3,084	5,636	5,767	5,683	5,609	5,680	5,763
Adjusted R^2	0.922	0.807	0.603	0.813	0.876	0.872	0.574	0.891	0.907	0.956	0.739	0.470	0.185	0.817	0.696	0.855	0.944

Table 14: Alternative Ways to Construct the Instrument and Definition of SEOs.

This table reports the second-stage estimation results using alternative instruments and the definition of SEOs. Column (1) lists the dependent variables. Only coefficients on the predicted SEO, standard errors, and sample sizes are reported for each robustness test. Column (2) turns on the instrument only for the firms treated by the 2006 regulation in 2006 and the firms treated by the 2008 regulation in 2008. Column (3) uses a one-year lag between the beginning of an SEO process and the availability of SEO proceeds. Column (4) relies only on the 2006 regulation to construct the instrument. Column (5) excludes small SEOs whose proceeds are in the bottom decile. Online Appendix 3 provides variable definitions and data sources. Online Appendix 4 reports the first-stage estimation results. All regressions include firm- and year-fixed effects, firm-specific time trends, and time-varying control variables. Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

DEPENDENT VARIABLES	**IV based on treatments only in 2006 and 2008**	**Using one-year lag**	**IV based only on the 2006 regulation**	**Excluding small SEOs**
(1)	(2)	(3)	(4)	(5)
Ln(EMP)	-0.081**	-0.094**	-0.092**	-0.095**
	(0.038)	(0.047)	(0.046)	(0.048)
N	16,964	16,964	16,964	16,964
Ln(Production)	-0.232**	-0.279**	-0.092**	-0.254**
	(0.098)	(0.109)	(0.046)	(0.102)
N	16,964	16,964	16,964	16,964
Ln(Staff)	-0.456***	-0.509***	-0.467***	-0.478***
	(0.105)	(0.108)	(0.121)	(0.109)
N	16,964	16,964	16,964	16,964
Ln(Tech_R&D)	0.111*	0.116*	0.077	0.127**
	(0.060)	(0.067)	(0.057)	(0.060)
N	13,916	13,916	13,916	13,916
Ln(S&M)	0.103*	0.077	0.074	0.104*
	(0.059)	(0.081)	(0.069)	(0.061)
N	10,576	10,576	10,576	10,576
Ln(Finance)	0.003	0.007	0.006	0.006
	(0.053)	(0.057)	(0.056)	(0.048)
N	13,326	13,326	13,326	13,326
Ln(Others)	-0.075	-0.016	-0.055	-0.056
	(0.183)	(0.225)	(0.203)	(0.211)
N	16,964	16,964	16,964	16,964
Ln(Grad)	0.108*	0.117*	0.117*	0.109*
	(0.058)	(0.064)	(0.067)	(0.057)
N	8,109	8,109	8,109	8,109
Ln(BA)	-0.023	-0.036	-0.038	0.002
	(0.056)	(0.056)	(0.062)	(0.065)
N	11,650	11,650	11,650	11,650
Ln(NBA)	-0.163***	-0.171***	-0.164***	-0.183***
	(0.047)	(0.063)	(0.050)	(0.043)
N	11,650	11,650	11,650	11,650
Ln(Tangible_Tech)	0.272**	0.245**	0.240**	0.286**
	(0.115)	(0.106)	(0.122)	(0.133)
N	14,453	14,453	14,453	14,453
Ln(Intangible_Tech)	0.353*	0.334	0.432	0.387
	(0.199)	(0.283)	(0.269)	(0.237)
N	6,187	6,187	6,187	6,187
Ln(AWAGE)	0.062	0.066*	0.065*	0.064*
	(0.040)	(0.040)	(0.037)	(0.037)
N	16,960	16,960	16,960	16,960
Ln(Payroll)	-0.026	-0.040	-0.037	-0.041
	(0.037)	(0.028)	(0.037)	(0.034)
N	17,131	17,131	17,131	17,131
ROA	0.018**	0.018***	0.022***	0.019***
	(0.007)	(0.006)	(0.005)	(0.006)
N	16,916	16,916	16,916	16,916
Sales_GR	0.206***	0.233***	0.240***	0.220***
	(0.049)	(0.047)	(0.041)	(0.042)
N	17,136	17,136	17,136	17,136
Sales/Employees	0.841*	0.894*	0.909*	0.857*
	(0.441)	(0.533)	(0.549)	(0.489)
N	16,964	16,964	16,964	16,964
TFP	0.085***	0.091**	0.104***	0.100***
	(0.028)	(0.035)	(0.033)	(0.026)
N	16,827	16,827	16,827	16,827

Online Appendices to:

How Seasoned Equity Offerings Can Affect Firms: Evidence on Technology, Employees, and Performance

E. Han Kim, Yuan Li, Yao Lu, and Xinzheng Shi

Appendix 1: Institutional Backgrounds on Chinese Labor and Capital Markets

1. Economic Reforms and Labor Markets

China's labor market has undergone several major changes. In the early years of Communist China (1952-1978), the state sector dominated employment in the urban area, and management did not have the authority to hire or fire workers without government approval (Lin, Cai, and Li, 1996). Firms set wages according to a grid determined by the government; wages barely reflected differences in productivity (Cai, Park, and Zhao, 2008).

China embarked on economic reforms in 1978, leading to a new, floating wage system by the mid-1980s. The reforms allowed an enterprise's total payroll to reflect its performance in the previous three years. (Before this reform, central and local planners had determined the total payroll for each enterprise (Yueh, 2004)). At the same time, the State Council formally introduced the concept of labor contracts, giving management the flexibility to adjust employment in response to market competition (Meng, 2000). The labor contract system gave firms the freedom to hire suitable workers; however, the dismissal of workers remained under the government's tight control.

In 1992 state-owned enterprises (SOEs) were given more autonomy, enabling them to link the total payroll more closely to firm performance and set their internal wage structures (Li and Zhao, 2003; Yueh, 2004). More reforms followed in 1994-1995, allowing listed SOEs to set their wages and encouraging enterprises to consider skills and productivity in addition to occupation and rank in determining wages (Yueh, 2004). Some SOEs began to lay off workers, as the labor law issued in 1994 permitted no-fault dismissal of workers in response to changing economic conditions (Ho, 2006). A major state-sector restructuring followed, closing down or privatizing more than 80% of SOEs (Hsieh and Song, 2015). When restructuring-affected employees left SOEs, they faced a more market-driven re-employment process, and the previously inflexible labor market became one in which supply and demand affected employment and wages. By the mid-2000s, China's labor market had become similar to those of other countries based on capitalism; labor is mobile, and enterprises consider market conditions in making employment decisions and in setting wages (Cai, Park, and Zhao, 2008).

During our sample period, China had well-established legal provisions for hours of work, payment of wages, and employment. The standard workweek is 40 hours (eight hours per day, five days per week). Overtime must be paid for any work exceeding the standard working hours and cannot exceed three hours a day or 36 hours per month (Labor Law Article 41). Wages are paid monthly, and may not be delayed without reason (Labor Law Article 50). Employees can be fired in the middle of two fixed-term contracts (or ten years of employment),[1] after which contracts must be made open-ended. Open-ended contracts can be terminated only for causes (Gallagher et al., 2015).

A consequence of these reforms particularly relevant to our study is the increase in returns to education. Li et al. (2012) show that the return to an additional year of schooling increased from 2.3 percent in 1988 to about 9 percent in 2000, and the return to college education increased from 7.4 percent in 1988 to 49.2 percent in 2009. These dramatic increases in returns to education are attributable to the labor reforms and the fast-growing demand for skills (Zhang et al., 2005).

2. Capital Markets and SEOs in China

The modernization of Chinese capital markets began when former Premier Rongji Zhu, who led China to join the World Trade Organization (WTO), spearheaded a series of reforms during his tenure as vice premier and a premier in 1993 – 2003. The reforms included restructuring state-owned enterprises (SOEs) and the banking industry.[2] A major theme of the reforms was to modernize capital markets and corporate governance practices of SOEs. The modernization process sped up in 2001 when China officially joined the WTO. In January 2004, the State Council issued "Opinions on Promoting the Reform, Opening and Steady Growth of Capital Markets," which sets the importance of developing capital markets as a high-priority national strategy.[3] In response to the guiding principles from the State Council, the CSRC implemented several new regulations to modernize stock markets and improve corporate governance (http://www.china.com.cn/chinese/FI-c/723240.htm). According to the World Bank, the modernization of stock markets, together with the rapid growth of China's economy, have helped stock markets in mainland China to become the second-largest in the world in both market cap and the total value of shares traded in 2009.[4]

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[1] Contracts are subject to negotiation after the first term.
[2] Economist, March 6th, 2003. http://www.economist.com/node/1623179
[3] OECD report: Corporate Governance of Listed Companies in China. https://www.oecd.org/corporate/ca/corporategovernanceprinciples/48444985.pdf
[4]http://data.worldbank.org/indicator/CM.MKT.LCAP.CD?end=2016&locations=CN-JP-US-HK-FR-GB-DE&name_desc=false&page=5&start=2003&view=chart.

In China, the stock market has been a more important source of external financing than the corporate bond market, which has been growing at a much slower pace than the stock market. Although a regulated bond market for enterprises began in 1996, regulators have allowed only very large and stable companies to issue bonds because of the strict approval process required for issuing bonds. Over the period 2010 through 2012, for example, China-listed firms raised 2,147.5 billion RMB through stock markets (via SEOs and IPOs), while bond markets helped raise only 429.5 billion RMB. Over the same period, adjusted for differences in stock market capitalization, non-financial Chinese firms issued SEOs three times more than their U.S. counterparts did.[5]

The Chinese stock market is well suited to study SEOs. The types of SEOs available and the underwriting procedures in China are similar to those in the U.S. There are three types of SEOs: rights offerings, underwritten offerings, and private placements to no more than ten qualified investors. As in the U.S., there are two types of underwriting contracts, best efforts and firm commitments.

In comparison to U.S. SEOs, Chinese SEOs provide a cleaner sample to study how firms use the proceeds from SEOs because virtually all Chinese SEOs are primary shares.[6] SEOs in the U.S. often include secondary offerings, sale of shares held by insiders and block holders. Proceeds of secondary offerings do not go to the firm and hence cannot affect investment and employment decisions. Thus, if one studies the effects of deploying U.S. SEO proceeds without carefully screening out secondary offerings, the results will be noisy.

[5] Over the period of 2010 through 2012, the average total Chinese stock market capitalization is 3,949.77 billion USD and non-financial Chinese listed firms raised 86.09 billion USD through SEOs, or 2.18% of total market capitalization. This is more than three times of the ratio for US counterparts. During the same period, the average market capitalization of the US stock market is 17,149.34 billion USD and non-financial US listed firms raised 102.75 billion USD through SEOs, or 0.6% of the total market cap. Total stock market capitalization excludes financial firms. Capital raised through SEOs is taken from SDC Platinum. The market capitalization data are taken from the data on the World Bank website (http://data.worldbank.org/). Capital raised through SEOs includes proceeds only from primary offerings.

[6] There were only three mixed offerings containing secondary offerings of state-owned shares, all of which occurred in 2001. At that time, the CSRC required that if a firm plans to issue N new shares through an underwritten offering and has state-owned shares, then the offering must contain 10% of N state-owned shares. The regulation lasted only four months, and there have been no mixed offerings since 2001.

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Appendix 2: Construction of the Instrumental Variable.

This table illustrates how the instrument, *SEOIneligible*, is constructed. "Conditions" specify the past three-year period during which the minimum payout ratio applies to make a firm ineligible to issue a public SEO. For example, 2003 – 2005 < 20% means that if the payout ratio over 2003 – 2005 is less than 20%, the firm is ineligible to issue a public SEO in 2006. In this table, we assume it takes two years to complete an SEO. Since SEO years include the SEO year and two post-SEO years, we turn on the instrument in 2008, 2009, and 2010 for firms affected by the 2006 regulation in 2006. We follow the same procedure for firms affected by the 2006 regulation in 2007, and for firms affected by the 2008 regulation in 2008 and 2009.

Year	**SEOIneligible**	**Conditions**
2000	0	NA
2001	0	NA
2002	0	NA
2003	0	NA
2004	0	NA
2005	0	NA
2006	0	NA
2007	0	NA
2008	1	If 2003 – 2005 < 20%
2009	1	If 2004 – 2006 < 20% or 2003 – 2005 < 20%
2010	1	If 2005 – 2007 < 30%, 2004 – 2006 < 20%, or 2003 – 2005 < 20%
2011	1	If 2006 – 2008 < 30%, 2005 – 2007 < 30%, or 2004 – 2006 < 20%
2012	1	If 2006 – 2008 < 30% or 2005 – 2007 < 30%

Appendix 3: Variable Definitions and Data Sources.

Variables	Definition	Data Sources
SEO-related Variables		
SEO	An indicator equal to one in SEO years (the year in which SEO proceeds are received and the two years after), and zero otherwise. It applies to only public offerings.	CSMAR
SEOIneligible	The instrument for SEO years. Online Appendix 2 illustrates how it is constructed.	Wind
JP_SEO	An indicator equal to one in the year in which a firm receives SEO (public or private placement) proceeds, and zero otherwise.	CSMAR
Outcome Variables		
EMP	The total number of employees at the firm-level Unit: 100.	Resset
Production	The number of production workers.	Resset
Staff	The number of support staff.	Resset
Tech_R&D	The number of technicians (including engineers and IT staff) and R&D employees.	Resset
S&M	The number of employees in sales and marketing.	Resset
Finance	The number of accounting and finance staff.	Resset
Others	The number of employees with unidentified occupations.	Resset
BA	The number of employees with four-year university bachelor's degrees and above.	Resset
Grad	The number of employees with post-graduate degrees.	Resset
Tangible_Tech	Expenditures on machines and equipment in 2000 RMB. Unit: 1,000,000.	CSMAR
Intangible_Tech	Expenditures on technology-related intangible assets in 2000 RMB. Unit: 10,000.	CSMAR
Capex	Total capital expenditures in 2000 RMB. Unit: 1,000,000.	Resset
ROA	Return on assets: Net income divided by total assets.	Resset
SALES_GR	Sales growth rate from year t-1 to year t.	Resset
SALES/Employees	Total sales in 2000 RMB (Unit: 1,000,000) divided by the total number of employees.	Resset
TFP	The residuals of $\ln(Y) = a_i + a_t + \ln(\text{total assets}) + \ln(EMP) + e_{it}$. Y is s total output, as measured by prime operating revenue + changes in inventory* the cost profit margin, where the cost profit margin = prime operating revenue /cost of goods sold. a_i is firm fixed effects and a_t is year fixed effects.	Resset
AWAGE	Total annual cash salary and bonuses to all employees in 2000 RMB divided by total number of employees. Unit: 10,000.	Resset
AWAGE_NonEXE	AWAGE for all non-executive employees. Unit: 10,000.	Resset
AEXEPAY	AWAGE for all executives. Unit: 10,000.	Resset
Payroll	Total annual cash salary and bonuses to all employees in 2000 RMB. Unit: 1,000,000.	Resset
Payroll_NonExe	Payroll to all non-executive employees in 2000 RMB. Unit: 1,000,000.	Resset
Payroll_Exe	Payroll to all executives in 2000 RMB. Unit: 1,000,000.	Resset

Adv_Computer_Dum	An indicator of the presence of words indicating advanced computer skills in a job advertisement.	Lagou.com
Outcome Variables	**Definition**	**Data Sources**
Adv_Computer	The number of words indicating advanced computer skills in a job advertisement.	Lagou.com
Basic_Computer_Dum	An indicator of the presence of words indicating basic computer skills in a job advertisement.	Lagou.com
Basic_Computer	The number of words indicating advanced computer skills in a job advertisement.	Lagou.com
Non-routine Analytical Task Skill_Dum	An indicator of the presence of words indicating non-routine analytical task skills in a job advertisement.	Lagou.com
Non-routine Analytical Task Skills	The number of words indicating non-routine analytical task skills in a job advertisement.	Lagou.com
Non-routine Interactive Task Skill_Dum	An indicator of the presence of words indicating non-routine interactive task skills in a job advertisement.	Lagou.com
Non-routine Interactive Task Skills	The number of words indicating non-routine interactive task skills in a job advertisement.	Lagou.com
Control Variables		
P3_PR	The average payout ratio over the most recent past three years as defined by the CSRC. See Section 3.2.3. If it is negative, we replace it with one.	Resset
P3_PR_D	Indicator equal to one if the payout ratio during the most recent past three years as defined by the CSRC is negative, zero otherwise.	Resset
MIN_WAGE	The minimum monthly wage in the province or provincial city of the firm's headquarters location in 2000 RMB.	Government Websites
LAWSCORE	An index for the strength of the legal environment described in Section 3.2.3. The National Economic Research Institute updated by the index up to 2009. For years after 2009, we use the 2009 index.	National Economic Research Institute
Labor_Law_Effect	The degree to which the 2008 Labor Law of the People's Republic of China affects a firm. See Section 3.2.3.	CSMAR
SALES	Total sales in 2000 RMB. Unit: 1,000,000.	Resset
%_LARGEST_SH	The percentage of shares held by the largest shareholder.	Resset
DIV_PR	Dividend payout ratio, equal to the total dividend paid over net income.	Resset
%_STATE_OWN	The percentage of shares held by the local or central government.	Resset
%_IND_DIR	The percentage of independent directors on the board.	Resset
%_NONTRD_SH	The percentage of non-tradable shares.	Resset
Leverage	Total liability divided by total assets.	Resset
PPE/TA	The property, plants, and equipment divided by total assets.	Resset
Affected	An indicator for firms affected by the 2006 regulation.	Resset

Appendix 4: The First-stage Regression Results.

This table reports the first-stage estimation results: Columns (1)-(2) is for the second-stage results reported in Panels A and B of Tables 3 – 9 and Online Appendix 8. Columns (3) - (6) are for the second-stage results reported in Table 11, Columns (2) - (5), respectively. The first-stage is estimated by the firm-level conditional logistic regression. Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012. Robust standard errors clustered at the firm level are in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	SEO					
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SEOIneligible	-1.794***	-1.434***	-1.616***	-1.067***	-1.352***	-1.370***
	(0.390)	(0.371)	(0.404)	(0.350)	(0.471)	(0.364)
P3_PR		0.120	0.126	0.093	0.108	0.091
		(0.089)	(0.089)	(0.089)	(0.089)	(0.088)
P3_PR_D		-1.003***	-0.999***	-0.993***	-0.976***	-0.911***
		(0.362)	(0.363)	(0.358)	(0.359)	(0.340)
Ln(SALES)		1.033***	1.041***	1.018***	1.010***	1.022***
		(0.170)	(0.170)	(0.169)	(0.166)	(0.163)
Leverage		-5.225***	-5.275***	-5.142***	-5.026***	-5.000***
		(0.810)	(0.809)	(0.810)	(0.794)	(0.788)
PPE/TA		1.287	1.309	1.293	1.281	1.370
		(0.941)	(0.944)	(0.935)	(0.918)	(0.918)
%_IND_DIR		-0.792	-0.821	-0.828	-0.786	-0.825
		(0.636)	(0.635)	(0.634)	(0.640)	(0.639)
%_STATE_OWN		0.254	0.256	0.218	0.167	0.196
		(0.523)	(0.522)	(0.520)	(0.519)	(0.514)
%_LARGEST_SH		-2.308**	-2.303**	-2.325**	-2.342**	-1.926*
		(1.137)	(1.146)	(1.131)	(1.120)	(1.095)
%_NONTRD_SH		-1.552***	-1.561***	-1.522**	-1.551***	-1.353**
		(0.601)	(0.601)	(0.601)	(0.601)	(0.589)
DIV_PR		0.108	0.107	0.100	0.100	0.107
		(0.075)	(0.073)	(0.074)	(0.075)	(0.074)
Ln(MIN_WAGE)		1.690**	1.734**	1.605**	1.604**	1.574**
		(0.677)	(0.676)	(0.673)	(0.670)	(0.683)
LAWSCORE		0.064	0.064	0.069	0.069	0.062
		(0.068)	(0.068)	(0.068)	(0.068)	(0.069)
Labor_Law_Effect		0.115	0.119	0.102	0.107	0.111
		(0.084)	(0.085)	(0.082)	(0.082)	(0.081)
Firm & Year FE	Y	Y	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y	Y	Y
Observations	5,480	5,251	5,251	5,251	5,251	5,251
Pseudo R2	0.3695	0.4153	0.4167	0.4127	0.4126	0.397
Wald	577.9	635.3	633.3	643.7	646.4	602.3

Appendix 5: OLS Estimation on Firm-level Employment.

This table reports the OLS estimates of the impacts that SEOs have on firm-level employment. The dependent variable in Column (1) is the log of the total number of employees; dependent variables in the remaining columns are the log of one plus the number of employees in each occupation or education category. All dependent variables, except Column (1), are the log of one plus the number of employees. All regressions include firm- and year fixed effects. Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012. Robust standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	Ln(EMP)	Ln (Production)	Ln (Staff)	Ln (Tech_R&D)	Ln (S&M)	Ln (Finance)	Ln (Others)	Ln (Grad)	Ln (BA)
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SEO	-0.028*	-0.069*	0.010	0.022	-0.012	-0.012	-0.116	-0.009	0.028
	(0.017)	(0.037)	(0.042)	(0.023)	(0.028)	(0.017)	(0.082)	(0.034)	(0.023)
P3_PR	0.010*	0.041***	0.032**	0.004	0.018	-0.004	-0.031	-0.020	0.018**
	(0.006)	(0.013)	(0.015)	(0.008)	(0.011)	(0.007)	(0.030)	(0.012)	(0.009)
P3_PR_D	-0.013	-0.016	0.087	-0.069**	0.028	-0.036	0.050	-0.080*	-0.078**
	(0.024)	(0.055)	(0.060)	(0.033)	(0.041)	(0.026)	(0.120)	(0.046)	(0.033)
Ln(MIN_WAGE)	-0.272***	-0.194*	-0.249**	-0.217***	-0.096	-0.159***	0.032	0.263**	-0.002
	(0.051)	(0.116)	(0.125)	(0.075)	(0.094)	(0.056)	(0.248)	(0.112)	(0.082)
LAWSCORE	-0.013***	0.009	0.001	0.004	0.015	-0.011**	-0.069***	-0.021**	-0.009
	(0.005)	(0.011)	(0.011)	(0.007)	(0.009)	(0.005)	(0.021)	(0.010)	(0.007)
Labor_Law_Effect	-0.004	-0.042***	0.010	0.006	-0.024**	0.002	0.051***	-0.036***	-0.020***
	(0.004)	(0.008)	(0.009)	(0.006)	(0.010)	(0.004)	(0.016)	(0.006)	(0.005)
Ln(SALES)	0.418***	0.317***	0.239***	0.401***	0.420***	0.320***	0.325***	0.397***	0.420***
	(0.011)	(0.022)	(0.021)	(0.016)	(0.022)	(0.011)	(0.040)	(0.020)	(0.016)
%_LARGEST_SH	-0.083	-0.241	0.303**	0.006	0.069	0.129*	0.090	-0.107	0.074
	(0.075)	(0.156)	(0.148)	(0.108)	(0.138)	(0.078)	(0.295)	(0.143)	(0.107)
DIV_PR	0.004***	0.008***	0.006***	0.002**	-0.002**	0.003***	-0.004	-0.001	0.005***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.015)	(0.001)
%_STATE_OWN	0.123***	0.003	0.066	0.077	-0.006	0.061*	0.220	0.025	0.149***
	(0.030)	(0.069)	(0.074)	(0.050)	(0.064)	(0.033)	(0.136)	(0.050)	(0.045)
%_IND_DIR	0.040	-0.187	-0.017	0.223***	0.188**	0.077	0.138	0.026	0.028
	(0.051)	(0.116)	(0.128)	(0.072)	(0.094)	(0.054)	(0.243)	(0.109)	(0.080)
%_NONTRD_SH	0.038	0.042	-0.091	-0.078	-0.059	-0.014	0.013	-0.018	-0.033
	(0.043)	(0.090)	(0.096)	(0.058)	(0.073)	(0.042)	(0.198)	(0.084)	(0.061)
Leverage	0.277***	-0.084	0.394***	0.180***	0.171*	0.424***	0.571***	0.199**	0.273***
	(0.048)	(0.098)	(0.100)	(0.067)	(0.095)	(0.048)	(0.194)	(0.093)	(0.068)
PPE/TA	0.523***	0.944***	0.413***	0.281***	-0.225**	-0.077	-0.504**	-0.049	0.177**
	(0.057)	(0.111)	(0.112)	(0.080)	(0.112)	(0.058)	(0.218)	(0.110)	(0.081)
Constant	1.517***	5.148***	3.431***	3.977***	2.685***	2.381***	1.165	-1.456**	2.147***
	(0.319)	(0.712)	(0.759)	(0.460)	(0.588)	(0.341)	(1.502)	(0.694)	(0.504)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm-specific Time Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,964	16,964	16,964	13,916	10,576	13,326	16,964	8,109	11,650
R-squared	0.884	0.747	0.552	0.803	0.843	0.842	0.518	0.896	0.873

Appendix 6: Implied Wages by Education and Occupation.

This table reports the OLS estimation results for implied wages by education or occupation. The sample period covers 2000 – 2012. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	AWAGE	
VARIABLES	**(1)**	**(2)**
%_Grad	44.750***	
	(3.610)	
%_BAOnly	19.124***	
	(0.892)	
%_JBAOnly	5.489***	
	(1.048)	
%_HighSchoolOnly	2.641***	
	(0.526)	
%_Below	2.644***	
	(0.390)	
%_Production		1.613***
		(0.185)
%_Staff		12.737***
		(0.744)
%_Tech_R&D		11.606***
		(0.482)
%_S&M		0.616
		(0.573)
%_Finance		69.489***
		(2.537)
%_Others		8.129***
		(0.286)
Observations	17,635	17,635
Adjusted R^2	0.305	0.319

Appendix 7: Online Job Posting Sample and Words Related to Skills.

This table provides information obtained from job posting data. Panel A reports the number of full-time job advertisements in Lagou.com (https://www.lagou.com) posted by firms listed on Shanghai and Shenzhen Stock Exchanges over 2014 - 2016. Panel A, Column (1) shows the number of all new full-time job advertisements by year, and Column (2) shows the number of new full-time job advertisements in the year in which firms issued seasoned equity offerings (including underwritten offerings, rights offerings, and private placements). Panel B provides the list of the English translation of Chinese words used to identify the requirements for the different types of skills.

Panel A: Sample Distribution

Year	**Number of Unique Job Advertisements**	**JP_SEO=1**
	(1)	**(2)**
2014	5,702	1,410
2015	15,041	3,591
2016	24,842	2,790
Total	45,585	7,791

Panel B: Key Words Used to Identify Different Skill Requirements

Skills	**Key Words**
Advanced computer	Programming, Java, SQL, Python, developing, server, artificial intelligence, big data, machine learning, html, and software
Basic computer	Diannao (an unofficial name for computer), PPT, presentation slides, Excel, spreadsheets, Microsoft Office, Windows, and Word.
Non-routine analytical task skills	Research, analysis, problem-solving, analytical critical thinking, math, statistics, learning, thinking, changing, improving, professional writing, and reporting.
Non-routine interactive task skills	Communication, cooperation, negotiation, services, clients, persuading, selling, management, monitoring, supervisory, leadership, mentoring, guidance, and making a deal.

Appendix 8: Average Annual Wages in China by Education and Occupation.

This table reports average annual wages in China by education or occupation. The data is from China Urban Household Survey (2000-2009), which provides access to nine provinces; Beijing, Liaoning, Zhejiang, Anhui, Hubei, Guangdong, Sichuan, Shaanxi, and Gansu. Annual wage is deflated using provincial CPI with 2000 as the base year. The unit is Chinese RMB.

	Education			Occupation				
Year	College or above	High School	Middle School or below	Technician	Production Workers	Staff or Service Workers	Agricultural Workers	Others
2000	11084.013	8944.776	5139.363	15239.261	9258.860	11053.963	8566.029	7946.278
2001	11976.958	9554.838	5438.288	16852.991	9864.254	11841.001	9827.922	8882.542
2002	15822.367	10409.411	5757.975	18404.414	10912.095	13807.288	9452.208	9661.626
2003	17728.367	11346.542	5975.318	20489.257	12303.120	15216.043	10937.459	11118.318
2004	19451.303	12139.160	6495.877	23086.913	13622.273	16191.782	12360.412	12257.059
2005	21261.428	13013.126	7123.790	25598.902	14743.270	18072.238	15012.060	14361.187
2006	23030.351	14092.422	7931.302	27949.907	16697.195	19682.444	16756.711	15198.924
2007	24665.948	15261.617	8603.666	29624.443	17833.485	21563.516	18206.153	17030.791
2008	27924.529	16415.125	9329.643	32551.162	20094.639	23523.721	19247.500	20093.954
2009	30928.259	18155.407	10323.152	35799.283	22402.561	26124.442	23231.018	20988.433

Appendix 9: Alternative Measures of TFP.

This table reports the second-stage estimation of the impacts that SEOs have on the alternative measures of TFPs. TFP_A1 is the residuals from ln(Y) = $a_i + a_t$ + ln(total assets) + ln(total payrolls) + e_{it}. TFP_A2 is the residuals from ln(Y) = $a_i + a_t$ + ln(total assets) + ln(total number of production workers) + e_{it}. Y is total output, as measured by prime operating revenue + changes in inventory* the cost profit margin, where the cost profit margin = prime operating revenue / cost of goods sold. a_i is firm fixed effects and a_t is year fixed effects. Online Appendix 3 provides variable definitions and data sources. The sample period covers 2000 – 2012. Bootstrapped standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

	TFP_A1	**TFP_A2**
VARIABLES	**(1)**	**(2)**
$\widehat{SEO}$	0.049*	0.096***
	(0.028)	(0.026)
P3_PR	-0.010***	-0.001
	(0.004)	(0.003)
P3_PR_D	-0.044***	-0.026
	(0.012)	(0.019)
Ln(MIN_WAGE)	-0.006	-0.004
	(0.032)	(0.030)
LAWSCORE	0.003	-0.010***
	(0.003)	(0.003)
Labor_Law_Effect	0.000	-0.003
	(0.002)	(0.003)
Ln(SALES)	0.308***	0.402***
	(0.008)	(0.008)
%_LARGEST_SH	-0.013	-0.040
	(0.045)	(0.054)
DIV_PR	-0.004	-0.003
	(0.007)	(0.009)
%_STATE_OWN	-0.144***	-0.090***
	(0.018)	(0.017)
%_IND_DIR	-0.051	-0.029
	(0.032)	(0.032)
%_NONTRD_SH	-0.003	0.037
	(0.030)	(0.032)
Leverage	-0.159***	-0.288***
	(0.040)	(0.039)
PPE/TA	-0.283***	-0.110***
	(0.037)	(0.038)
Constant	-1.539***	-2.143***
	(0.198)	(0.187)
Firm & Year FE	Y	Y
Firm-specific Time Trend	Y	Y
Observations	16,981	16,827