Equity Financing, Skill Composition, and Firm Wages

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

Abstract

We examine whether and how equity financing affects employment and wages. Job descriptions posted online suggest demands for computer and non-routine analytical and interactive task skills increase when firms receive proceeds from seasoned equity offerings (SEOs). To draw causal inference, we rely on exogenous shocks on the eligibility to issue SEOs in China. We find capital infusion through SEOs increases innovation and the relative proportion of skilled employees. Unskilled employees displaced following SEOs outnumber skilled employees added, resulting in a net loss of total employment. The change in the skill composition leads to higher average wages, but total wages remain unchanged, implying the capital infusion enables firms to upgrade employee skills without incurring higher labor costs. These findings illustrate channels through which financial markets affect labor markets.

First Draft: September 5, 2017

Keywords: Capital Skill Complementarity, Equity Issuance, Employment, Wages, Innovations.

JEL Classifications: G32, J24, J31

---

†E. Han Kim is Everett E. Berg Professor of Finance at the University of Michigan, Ross School of Business, Ann Arbor, Michigan 48109: ehkim@umich.edu. Heuijung Kim is an instructor at Sungkyunkwan University, SKK Business School, Seoul, Korea: heuikim@skku.edu. Yuan Li is a doctoral student at University of Southern California: yuan.li.2019@marshall.use.edu. Yao Lu is Associate Professor of Finance at Tsinghua University School of Economics and Management, Beijing, China: luyao@sem.tsinghua.edu.cn. Xinzheng Shi is Associate Professor of Economics at Tsinghua University School of Economics and Management, Beijing, China: shixzh@sem.tsinghua.edu. We are grateful to Jagadeesh Sivadasan, Stefan Zeume, and seminar participants at University of Michigan, UNLV, and Korea University for helpful suggestions, and Pend Zhang and Yeqing Zhang for excellent research assistance. This project received generous financial support from Mitsui Life Financial Research Center at the University of Michigan. Yao Lu acknowledges support from Project 71202020 and Project 71722001 of National Natural Science Foundation of China. Xinzheng Shi acknowledges support from Project 71673155 of National Natural Science Foundation of China.

1. INTRODUCTION

The finance literature offers numerous studies on how external equity financing is related to shareholder value, financial policies, investments, and agency costs, but mostly from the shareholder perspective.[1] This focus on capital providers leaves out an equally important stakeholder—employees, who are also likely to be affected by equity financing. Equity financing is often required for technology-advancing investments (Hall and Lerner, 2010). Technology advances, in turn, complement workers in performing non-routine abstract tasks and substitute workers in performing routine tasks (Autor, Levy, and Murnane, 2003).[2] Such complementary and substitution effects are likely to change the skill composition of employees, the size of employment, and the wage structure.

In this paper, we investigate how equity financing affects employment and wages. Specifically, does equity financing alter the skill composition of employee through its differential effects on skilled vs. unskilled employees? Are sufficient skilled employees added through the complementary effect to offset unskilled employees displaced by the substitution effect? If equity financing leads to a higher skill composition, average wages will increase due to the skill premium (Card, 1999), but what happens to total wages, which represent the bulk of labor costs? These closely interrelated questions raise important welfare and policy implications.

Investigating these issues faces two main obstacles: (1) endogeneity in decisions to raise

---

[1] Studies relating external equity financing to shareholder value include Asquith and Mullins (1986); Masulis and Korwar (1986); Korajczyk, Lucas, and McDonald (1990); Eckbo and Masulis (1995); Bayless and Chaplinsky (1996); and Eckbo, Panetta, and Luigi Zingales (2000). Studies relating to financial policies include Pagano, Panetta and Luigi Zingales (1998); DeAngelo, DeAngelo, and Stulz (2010); McLean (2011); and Gustafson and Iliev (2017). Studies relating to corporate investments include Kim and Weisbach (2008) and Gustafson and Iliev (2017). Studies relating to agency costs include Jung, Kim, and Stulz (1996) and Kim and Purnanandam (2014).

[2] See also Griliches (1969); Hamermesh (1993); Fallon and Layard (1975); Berman, Bound, and Griliches (1994); Goldin and Katz (1996, 1998); Doms, Dunne, and Troske (1997); Autor, Katz and Krueger (1998); Machin and Van Reenen (1998); Krusell, et al. (2000); Caroli and Van Reenen (2001); Bresnahan, Brynjolfsson, and Hitt (2002); Duffy, Papageorgiou, and Perez-Sebastian (2004); Lindquist (2004); Acemoglu and Finkelstein (2008); Yasar and Paul (2008); Ben-Gad (2008); Lewis (2011); Parro (2013); and Akerman, Gaarder and Mogstad (2015); Kasahara, Liang, and Rodrigue (2016); Hershbein and Kahn (2016); and Acemoglu and Restrepo (2017b).

external equity and (2) the scarcity of data on employee skills. We address endogeneity issues by constructing an instrument using the 2006 and 2008 regulatory shocks on the eligibility to issue seasoned equity offerings (SEOs) in China. Eligibility was based on the *past* three years' dividend payout ratio, making it difficult for treated firms (those that became ineligible to issue SEOs) to circumvent the regulations. Relying on the Chinese experiments also helps solve the data problem. The China Securities Regulatory Commission (the CSRC, equivalent to the SEC in the U.S.) requires publicly listed firms to disclose yearly the number of employees by occupation and education in company filings. Since the general level of employee skills is related to occupation and education, these employment data allow us to infer how SEOs affect the skill composition. Additionally, Chinese accounting rules require publicly listed firms to disclose payroll information in financial statements, providing access to reliable wage data.

Our sample period is 2000 through 2012, covering the exogenous shocks on the eligibility to issues SEOs. The Chinese data over our sample period are representative enough to render generalization. China undertook a number of major economic reforms during the 1980s and 1990s, making its labor market during the sample period similar to those of other countries based on capitalism. China's manufacturing and production processes during our sample period are comparable to those of the US during the twentieth century. This is important because Goldin and Katz (1998) show that capital and skill became relative complements when production processes in the US shifted from factories to continuous-process and batch methods early in the twentieth century, but not during the more distant period when the artisanal shop transited to the factory. In addition, the Chinese stock market became the second largest in the world during our sample period,[3] and its stock market has been a more important source of external financing than the corporate bond market.

Our investigation begins by relating SEOs to demand for skills as manifested in job

[3] 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.

advertisements by a major online job posting company in China. The data show job advertisements posted by firms receiving SEO proceeds are significantly more likely to contain words indicating requirements of (1) advanced computer skills, (2) basic computer skills, (3) non-routine analytical task skills, and (4) non-routine interactive task skills. We obtain these relations while controlling for firm-, year-, location-, and occupation dummies, suggesting capital infusion through SEOs is associated with higher demand for technical and non-routine task skills even within the same occupation. However, they are correlations between endogenous variables without exogenous variations, preventing us from drawing casual inferences on how SEOs affect demand for skills. For example, firms under competitive pressure to upgrade their employee skills may issue SEOs to finance hiring new employees possessing higher skills.

To identify causal relations we estimate 2SLS regressions on panel data of publicly listed Chinese firms with an instrument constructed using the exogenous shocks. We find SEOs lead to significantly higher fractions of technicians, R&D scientists, managers, and holders of post-graduate degrees, who tend to possess higher technical and non-routine abstract task skills. Conversely, the relative proportion declines significantly for production workers and clerical staff (assembly and factory workers, secretaries and other administrative staff), who work on routine tasks requiring low-skills. Importantly, SEOs lead to a reduction in total employment. The displacement effect of the capital infusion on low-skilled workers is larger than the complementary effect on high-skilled workers, resulting in a net loss of employment.

The intermediate step in capital skill complementarity is technology-advancing investments, which complement high-technical and non-routine abstract task skills and substitute low-technical and routine-task skills. Kim and Weisbach (2008) and Gustafson and Iliev (2017) find SEOs increase corporate investments in general, which may contain scale-expanding and/or structural investments that may not be technology advancing. To isolate the effects of SEOs on technology-advancing investments, we focus on one of the possible outcomes—innovations. We proxy innovations by the number of patents, and find SEOs increase the number of patents granted by about 13%. Moreover, the increase in patents is significant only for the categories of patents considered more technologically innovative.

The higher skill composition of employees should increase average firm wages, because higher skilled and more educated employees are paid more (see Card (1999) for a survey and Zhang et. al (2005) for the Chinese evidence). Implied wage calculation for our sample firms suggests that production workers are paid the least, followed by staff, technicians, R&D scientists, and managers, in that order. In terms of education, holders of post-graduate degrees are paid the most. Thus, we are not surprised to find SEOs lead to significantly higher average wages. For all non-executive employees, the average wage increases by 12% more than firms that do not issue SEOs during the year of SEO and two years after (SEO years, hereafter). The average executive wages, by contrast, show little difference between firms issuing SEOs and not issuing SEOs.

We find higher average wages do not lead to higher total wages because of a reduction in total employment. Average wages increase because of the higher skill composition, but the higher wages apply to a smaller number of employees. SEOs enable firms to upgrade employee skills without incurring higher labor costs.

This paper contributes to the emerging finance and labor literature by demonstrating how stock markets affect labor markets. Our evidence shows that capital infusion through SEOs increases the relative proportion of skilled employees, leading to higher average wages. However, total wages do not increase because investments made with the capital reduce unskilled workers. To our knowledge, this is the first study on equity issuance that documents these important phenomena linking access to capital markets to firm employment and wages.

We also add to a debate on how financial leverage affects wages. Bronars and Deer (1991), Perotti and Spier (1993), and Michaels, Page, and Whited (2016) argue a decrease in financial leverage increases wages by weakening employers' bargaining power against workers. In contrast, Berk, Stanton, and Zechner (2010) and Chemmanur, Cheng, and Zhang (2013) argue a decrease in financial leverage decreases wages by reducing ex-ante employment risk at the time of wage negotiation. The evidence used in this debate is based on average wages, which our evidence shows depends on the skill composition. It is possible for firms with different financial leverage to have different skill composition; for example, firms with low financial leverage may be less capital constrained, allowing more investments in technology, which lead to a higher skill composition and a higher average wage. Thus, a more thorough investigation of how financial leverage affects wages requires a proper accounting for differences in the skill composition.

This paper is closely related to the literature on capital-technology-skill complementarity: capital increases investments leading to skill-biased technological changes, whereby the new technologies substitute for low-skill and routine-task jobs and complement high-skill and non-routine abstract task jobs. As noted at the outset of the paper, a large body of important studies on capital skill complementarity exists. However, identification is difficult because capital infusion, technology, and skill composition are all endogenous choices for firms. Three recent studies examine the complementarity hypothesis with cleaner identification using exogenous shocks. Lewis (2011) employs variation in the growth of the relative supply of low-skilled workers stemming from an immigration wave and new immigrants' tendency to cluster geographically to show the technology and skilled worker complementary relation. Akerman, Gaarder, and Mogstad (2015) exploit the variation in the availability of broadband internet across municipalities in Norway to demonstrate skill complementarity of broadband internet. These findings, however, are about technology-skill complementary, and do not directly test the relation with capital. Our study provides evidence directly linking capital to technology advances, skill composition, and a net loss in total employment. Our results are similar to those in Acemoglu and Finkelstein (2008), who employ a shock decreasing the relative price of capital for hospitals. They find that the shock is associated with an increase in new health care technology adoptions, a decline in labor input, and an increase in the skill composition of hospital nurses. We add to their contribution by using a direct shock on the access to capital and identify capital-technology-skill complementarity for all sectors of publicly listed firms (except financial services) and for broader categories of occupations.

The next section reviews the relevant literature to develop empirical predictions. Section 3 provides institutional backgrounds on China's capital and labor markets. Section 4 analyzes online job posting data. Section 5 provides the main results; how SEOs affect the skill composition, the level of employment, innovations, and wages. Section 6 contains a battery of robustness tests. Section 7 concludes.

2. CONCEPTUAL FRAMEWORK AND PREDICTIONS

In this section, we review the related literature to develop predictions on how capital infusion through SEOs affects technology-advancing investments, the skill composition, employment level, and firm wages.

Firms can obtain a new infusion of capital by issuing equity or debt. To link capital to technology and skill, we focus on equity financing because technology-advancing investments, such as R&D activities and acquisitions of new business models, provide firm-specific intangible knowledge assets. These assets are not readily "re-deployable" by others and hence are not attractive collaterals for raising debt, which makes equity financing a viable alternative (Hall and Lerner, 2010). Consistent with this conjecture, Kim and Weisbach (2008) find significant correlations between R&D expenditures and equity offerings.

To predict how a new infusion of equity capital through SEOs[4] affects technology advances, demand for skills, and employment, we invoke capital skill complementarity. Griliches (1969) was the first to document the complementary relation. Goldin and Katz (1996, 1998) develop a conceptual framework to analyze the origins of such complementarity. They point out that whether capital and skilled workers are relative complements or substitutes depends on the nature of technological change. For the more recent past characterized by "batch and continuous-process methods of production," they show that capital and skilled labor are relative complements.

[4] There are various ways to raise new equity, such as venture capital, private equity, initial public offerings, and so on. Our choice of SEOs over other means of equity financing is purely for identification purposes, namely, the external shocks on the eligibility to issue SEOs and the availability of relevant data.

They consider two distinct stages of manufacturing: (1) a machine-installation and machine-maintenance segment and (2) a production or assembly portion. Capital can be used to acquire machines or assets. Installing new machinery and make it run in the first stage requires skilled labor. In the second stage, the workable capital created by skilled labor plus raw capital is then used by unskilled labor to create the final product in the production or assembly segment of manufacturing. China's manufacturing and production processes during our sample period can be characterized by what Goldin and Katz describe as the batch and continuous-process method of production. Thus, we expect that our sample of Chinese firms also exhibit the relative complementary relation.

Acemoglu and Finkelstein (2008) argue that technology is always embodied in capital, and that technology requires a capital outlay. They develop a model and provide evidence of how a shock in the US health care sector lowering the relative price of capital increases new technology adoption by hospitals, enhances the skill composition of nurses and decreases total labor input. The capital skill complementarity is also evident in cross-country data at both the aggregate and the sectorial levels (Fallon and Layard, 1975; Duffy, Pagageorigiou, and Perez-Sebastian, 2004; and Parro, 2013). Therefore, our first prediction is that capital infusion through SEOs will increase the demand for skills by increasing investments in technology.

Testing this prediction requires proxies for skills, which Acemoglu and Autor (2011) define as "a worker's endowment of capabilities for performing various tasks," where a task is defined as "a unit of work activity that produces output (goods and services)." (p. 1045) Tasks can be classified into three broad categories: abstract, routine, and manual (Autor, Katz, and Kearney, 2006; Autor and Dorn, 2013).[5] Abstract tasks, such as research, legal writing, and managing, are referred to as problem solving, creative, organizational, and managerial tasks, which tend to require high skills. Routine tasks, such as picking/sorting, repetitive assembly, and

[5] Autor, Levy, and Murnane (2003) list five task categories: non-routine analytic tasks, non-routine interactive tasks, cognitive tasks, manual tasks, and non-routine manual tasks. But more recent studies collapse these five measures to the three task aggregates.

record keeping are referred to codifiable manual and cognitive tasks that follow explicit procedures, which tend to be performed by workers with low skills. Non-routine manual tasks, such as janitorial service and driving, are referred to as tasks requiring physical adaptability, which also tend to be performed by workers with low skills (Autor and Handel, 2013).[6]

Autor, Levy, and Murnane (2003) provide the conceptual framework and evidence that technological advances replace routine tasks and therefore substitutes for workers in performing routine tasks, but complements workers in performing non-routine abstract tasks.[7] Accordingly, we predict that investments in technology reduce labor input for routine tasks and increase labor input for non-routine abstract tasks. To test this prediction, we use occupation to proxy for routine vs. non-routine abstract tasks. Each occupation category may comprise multiple tasks at different levels of intensity. However, the variation is greater across occupation groups than within an occupation (Autor and Handel, 2013). The intensity of routine tasks is greater in occupations such as production workers, assemblers, and office and administration support staff than occupations such as technicians, engineers, R&D scientists, and managers, which tend to require higher intensity of non-routine abstract tasks. Thus, we predict that capital infusion through SEOs leads to a reduction in the relative proportion of workers in the routine task-intensive occupations and an increase in the non-routine abstract task-intensive occupations.

Another useful proxy for skills is the level of education; hence, we make a parallel prediction that SEOs lead to an increase in the relative proportion of employees with a higher education level.

SEOs may also change the total number of employees. When technological improvement embodied in capital substitutes low skilled employees and complements high skilled employees, the substitution and complementary effects may not be one-to-one. Technological improvement may substitute more low-skill employees than adding high-skill employees through the

[6] Many of the examples of different tasks are from Autor, Levy, and Murnane's (2003) Table 1.

[7] Acemoglu and Restrepo (2017a) show automation technology reduces employment and wages but creation of new tasks has the opposite effect.

complementary effect (Acemoglu and Restrepo, 2017b).

The predicted increase in the skill composition of employees implies a higher average wage. Skill premiums, namely skilled employees being paid more than unskilled workers, have been widely documented around the world during the past two decades (Card, 1999), and it is also true in China (Zhang et.al, 2005). However, the total firm wage, which represents the bulk of firms' total labor costs, may not increase if the reduction in total employment is sufficient to offset the higher average wage.

3. INSTITUTIONAL BACKGROUND

3.1. China's SEOs and Capital Markets

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

In comparison to US SEOs, Chinese SEOs provide a cleaner sample to study how the proceeds from SEOs affect firm investments, employment, and wages because virtually all Chinese SEOs are primary shares.[8] SEOs in the US 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.

In China, the stock market has been a more important source of external financing than its corporate bond market, which has been growing at a much slower pace than the stock market.[9] Over the period 2010 through 2012, for example, Chinese listed firms raised 2,147.5 billion RMB through stock markets (via SEOs and initial public offerings), while bond markets helped raise

[8] 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 for only four months, and there have been no mixed offerings since 2001.

[9] A regulated bond market for enterprises began in 1996, but the strict approval process required for issuing bonds has led to a situation where only very large and stable companies can issue bonds.

only 429.5 billion RMB. Over the same period, adjusted for differences in stock market capitalization, non-financial Chinese firms issued SEOs more than three times those issued by US counterparts.[10]

3.2. China's Labor Market

China has undergone several major changes in its labor market. 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, and wages hardly 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. (Prior to 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 levels in response to market competition (Meng, 2000). However, the labor contract system gave firms the freedom to hire suitable workers, but 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 own 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

[10] Over the period 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, 2.18% of total market capitalization. This is more than three times the ratio for US counterparts. During the same period, the average market capitalization of US stock market is 17,149.34 billion USD and non-financial US listed firms raised 102.75 billion USD through SEOs, 0.6% of 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 data on the World Bank website (http://data.worldbank.org/). Capital raised through SEOs includes only proceeds from primary offerings.

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 was transformed into one in which supply and demand affect 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 on working hours, payment of wages, and employment. The standard workweek is 40 hours (eight hours per day, five days per week). Overtime has to be paid for any work exceeding standard working hours and cannot exceed three hours a day or 36 hours per month (Labor Law Article 41). Wages are paid on a monthly basis, 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),[11] after which contracts must be made open-ended. Open-ended contracts can be terminated only for cause (Gallagher et al., 2015).

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

4. Correlation between SEOs and Demand for Skills: Job Posting Data Analyses

We begin by examining online job posting data obtained from one of the major job posting companies in China, Lagou.com (https://www.lagou.com). If capital infusion through SEOs increases the demand for skills, job advertisements by firms receiving SEO proceeds are

[11] Contracts are subject to negotiation after the first term.

more likely to specify technical or non-routine task skills. Lagou.com started the job posting business in 2013, so our data covers only 2014 through 2016. The evidence provided in this section is only suggestive because there was no exogenous event during 2014 – 2016 that we could use to identify a causal relation.

Our sample contains 45,585 unique full-time job advertisements posted by 790 A-share firms listed on Shanghai and Shenzhen Stock Exchanges.[12] We exclude all repetition of the same advertisements some firms re-post to attract more attention. When a job advertisement remains posted online longer than a year, we include only the job advertisement in the year of new posting. Table 1, Panel A reports the number of new job postings by year. Of the 45,585 unique job advertisements, 7,791 are posted by firms during the year in which they received proceeds from publicly or privately placed SEOs. To relate SEOs to skills mentioned in job advertisements, we turn on the SEO indicator, *JP_SEO*, only in the year SEO proceeds are received.[13]

We follow an approach similar to that of Hershbein and Kahn (2016) to construct skill variables. For each job advertisement, we machine-search for 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. Table 1, Panel B lists the English version of Chinese keywords used to identify each type of skill.[14]

---

[12] China has two types of stocks: A- and B-shares. Originally, the A-share market was designed for domestic investors to trade with RMB, and the B-share market was designed for foreign investors to trade with US dollars. The B-share market was opened to domestic investors in 2001, and qualified foreign institutional investors (QFII) were also allowed to trade in the A-share market beginning in 2006. A firm can issue both A-shares and B-shares, and these shares have identical rights. 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. In addition, most of firms listed in the B-share market are also listed in the A-share market.

[13] We do not turn on the indicator in the year following the year SEO proceeds are received for two reasons: (1) If a newly advertised position is filled in the year of the posting, it will not be posted again in the following year; however, if the newly hired person leaves in the following year, a new posting will appear again, which will result in a double counting. (2) The sample period covers only three years.

[14] One of the words used to identify non-routine interactive task skills is "services," which may be associated non-routine manual tasks such as restaurant waiters, janitors, and taxi drivers. However, none of our sample firms are involved in restaurant, building maintenance, or personal transportation business.

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. We cannot conduct firm level analyses because firms may advertise job openings with other job posting companies and/or through other recruiting channels. The dependent variable is either an indicator for, or log of one plus the number of key words associated with each skill type. The indicator variable captures the presence of a keyword indicating a specific skill, while the logged value is to capture the intensity of the skill requirement.

Table 2, Panel A reports regression results relating advanced computer skills to the SEO indicator. 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 may vary across location (e.g., R&D centers requiring advanced computer and non-routine analytical skills tend to be located in metropolitan areas, while sales offices tend to be located in both countryside and metropolitan areas.) Columns (1) and (3) show positive and significant coefficients on the SEO indicator, suggesting that firms receiving SEO proceeds are more likely to require advanced computer skills in job specifications.

Online job postings tend to target white-collar employees more than blue-collar workers (Hershbein and Kahn, 2016). To control for the potential bias, we add occupation dummies to examine variation within an occupation. Reestimation results in Columns (2) and (4) continue to show significantly positive coefficients on the SEO indicator, suggesting that when firms receive SEO proceeds, they are more likely to require advanced computer skills in job descriptions even within the same occupation.

Panel B of Table 2 repeats the same estimations for basic computer skills. Coefficients on the SEO indicator remain positive and significant; indicating the probability of specifying basic computer skills is higher when firms receive SEO proceeds. In Table 3, we relate the SEO indicator to non-routine analytical and interactive task skills. Again, the coefficients are all positive and six out of eight are significant. In sum, when firms have new capital infusion through SEOs, they are more likely to demand technical and non-routine task skills from job applicants.

These job posting data analysis results, though informative, do not establish a causal relation, because they are about association between two endogenous variables. Furthermore, because of multiple channels available for job advertisement, our analysis is confined to job advertisement level variation, which indicates only whether the probability of requiring specific skills changes given a job posting. Because the number of job postings at the firm level may also change, a more complete analysis requires a firm level analysis.

5. Causal Relations

In this section, we attempt to identify causal effects capital infusion through SEOs has on skill composition, employment, innovations, and wages by conducting firm-level analyses using the external shocks on the eligibility to issue SEOs.

5.1. Empirical Design

We estimate the two-stage least square regressions using an instrument based on the regulatory shocks. We use the IV approach rather than a difference-in-differences (DID) approach because the 2SLS estimation provides direct estimates of impacts SEOs have on outcome variables.[15] The key explanatory variable is an indicator for the years in which SEO proceeds are likely to be deployed, *SEO*. It is equal to one during the year an SEO is issued and two years afterward—the SEO years—to fully capture the effects of SEOs on outcome variables and to reduce noise arising from conducting SEOs at different points in a year (e.g., February vs. November). The results are robust to defining the SEO year as only the year following an issuance of SEO (see Section 6).

[15] If we use a DID approach, the estimates may include the impacts of the shock through other channels besides its impact through SEOs. Let $y = \alpha + \beta * SEO + \varepsilon$, where β captures effects of SEOs. We construct an IV, SEO_IV from a regulatory shock, and the relation between SEO and SEO_IV is $SEO = \gamma + \delta * SEO\_IV + v$. The DID approach implies that we estimate $y = \alpha + \beta * (\gamma + \delta * SEO\_IV + v) + \varepsilon = \alpha + \beta * \gamma + \beta * \delta * SEO\_IV + \beta * v + \varepsilon$. That is, the coefficient we get is $\beta * \delta$, which is different from β; hence, the estimate may include impacts of the shock through other channels.

5.2. Regulatory Changes on the Eligibility to Issue SEOs

Prior to 2006, a listed firm could issue equities as long as it issued a dividend in the past three years. On May 6, 2006, the CSRC issued Decree No.30, requiring that to be eligible to conduct a public SEO, a firm's cumulative distributed profits in cash or stocks during the past three years must be no less than 20% of the average annual distributable profits realized over the same period. The CSRC further tightened the requirement on October 9, 2008, when it issued Decree No. 57, which states the cumulative distributed profit in the past three years shall be no less than 30% of the average annual distributable profits realized over the same period counting only cash payments as distributed profits. These 20% and 30% thresholds raise the possibility of a regression discontinuity (RD) design, i.e., comparing firms with just above the thresholds with those just below them. However, there are too few observations in the neighborhood around the thresholds to conduct a meaningful RD analysis.[16]

The catalyst for the 2006 regulation was the Split Share Structure Reform of 2005, which made non-tradable controlling shares tradable in stock markets beginning 2005. The reform led to a large increase in the supply of stocks traded, which CSRC deemed adversely impacted stock price. The 2006 regulation was to limit the supply of new shares to help stabilize stock prices by raising the bar for new share issuers.[17] After two years in force, the consensus was that a higher bar would benefit long-term investors through higher dividends and more stable stock prices.[18] The Shanghai Stock Exchange Composite Index reached its peak on October 16, 2007, and then entered a free fall, dropping by more than 50% by June 2008. The regulatory response was an

[16] For the 2006 regulation cutoff, there are only 2 eligible firms conducting SEO and 5 ineligible firms not conducting SEO in the neighborhood of [19%, 21%]. For wider neighborhoods of [17%, 23%] and [15%, 25%], there are 3 and 5 eligible firms conducting SEO and 7 and 11 ineligible firms not conducting SEO, respectively. For the 2008 regulation cutoff, for the neighborhoods of [29%, 31%], [27%, 33%], and [25%, 35%], the number of eligible firms conducting SEO is 4, 10, and 17; the number of ineligible firms not conducting SEO is 5, 12, and 22. For the neighborhood containing the most observations ([25%, 35%]), the calculated power of the RD strategy for the estimated effect of SEO on the proportion of production workers by the IV strategy in the paper (i.e., the coefficient of $\widehat{SEO}$ in Table 6, Panel A, Column 1) is only 0.102, lower than the conventional threshold 0.8. Stata code "rdpower" is used for this calculation.

[17] *Regulation for Issuing Stocks*, 2006, China's Securities Regulator Commission.

[18] A news report by *First Financial Daily* on October 9, 2008.

issuance of a draft of the 2008 regulation on August 22, 2008, followed by an official announcement on October 9, 2008. Although the 2006 and 2008 regulations limit the ability to issue public SEOs, they do not directly affect how SEO proceeds are used.

5.3. Instruments

We use the 2006 and 2008 regulations to construct instruments for the availability of SEO proceeds, *IV_SEO*. We consider firms affected by the 2008 regulation if the dividend payout ratio over the past three years[19] as of 2008 and 2009 (2005 – 2007 and 2006 – 2008, respectively) is less than 30%. *IV_SEO* takes a value equal to one in 2010 (2011) for all firms affected by the regulation; firms that became ineligible to issue SEOs because their past three-year dividend payout ratios as of 2008 (2009) are less than 30%. The two-year lag between 2008 and 2010 (2009 and 2011) allows for time elapsed from starting the process, to obtain an approval to issue SEO, and to the deployment of the proceeds. In our sample, the average time from the initial announcement of an SEO to the receipt of the proceeds is 242 days.[20] We allow for an extra year because the shock occurred in October 2008. We turn on the instrument also in 2011 if the dividend payout ratio over 2006 - 2008 is less than 30%. Because the regulation is based on the past three years' dividend payments, it is difficult to circumvent it by increasing dividend payments in only 2008 (especially because the shock occurred in October 2008). We do not turn on the instrument in 2012, because firms affected by the 2008 regulation can become eligible to issue an SEO in 2010 by increasing their payout ratio in both 2008 and 2009. For firms affected by the 2006 regulation, we follow the same procedure and set *IV_ SEO* equal to one in 2008 and 2009 based on dividend payout ratios over the past three years as of 2006 and 2007.

Since the two-year lag is somewhat arbitrary, we test the sensitivity to reducing the time lag between shocks and the availability of SEO proceeds to one year (i.e., *IV_SEO* is turned on

[19] The ratio in year t is $(D_{t-1} + D_{t-2} + D_{t-3}) / [(I_{t-1} + I_{t-2} + I_{t-3}) / 3]$, where D is the amount of dividends paid and I is the amount of distributable profits.
[20] Firms often announce their intention to issue an SEO then seek approval from the board, shareholders, and the CSRC.

2009 and 2010 for firms affected by the 2008 regulation, and in 2007 and 2008 for firms affected by the 2006 regulation.) We also set *IV_SEO* equal to one only in 2010 and 2008 to guard against the possibility of some firms increasing dividends in 2009 and 2007, respectively, to circumvent the 2008 and 2006 regulations. In addition, we test the sensitivity to relying only on the 2006 shock because some firms may have anticipated the 2008 shock. The results, reported in Section 6, are robust to all three alternative constructions of the instrument.

The relevancy condition is likely to be satisfied because it is difficult for affected firms to circumvent regulations based on past three years' dividend payouts.[21] The exclusion restriction requires that the instrument is not correlated with the error term in the second-stage regression; that is, the instrument should not be correlated with the dependent variable after controlling for relevant variables. One concern is that higher dividends may reduce free cash flows, affecting firm behavior and outcome variables (Jensen, 1986). However, the regulations used to construct our instruments are based on past dividend payout ratios, not current or future dividend payout ratios. Nevertheless, dividend payout ratios may be serially correlated due to persistency in corporate financial policies (Lemmon, Roberts, and Zender, 2008). Inclusion of firm fixed effects in all regressions helps control for the persistency in corporate policies. As a further precautionary measure, we include the current dividend ratio as an additional control variable.

[21] To circumvent the regulation, otherwise low dividend-paying firms have to anticipate the regulatory changes and increase dividends prior to the regulation. Anticipation is subject to uncertainty, which makes the benefits from dividend maneuvers uncertain, reducing the present value of the benefits. The uncertainty is not just about future regulations. There is also the approval uncertainty. SEOs in China and the amount that can be raised require the CSRC's approval, which adds further uncertainty over whether and how much capital can be raised through an SEO. The cost of maneuvering dividends in anticipation of the 2008 regulation is likely to be economically significant because it requires paying higher cash dividends and then grossing up the size of SEO to make up for the cash used to pay the higher dividends prior to the SEO. Such maneuvers impose costs. Firms wishing to issue SEOs tend to be cash constrained (DeAngelo et al., 2010). Paying out extra cash dividends may lead to foregoing value-enhancing investments. If the firm takes on more borrowing to meet the cash needs, the financial leverage will exceed the optimal level. The cost of dividend maneuvers in anticipation of the 2006 regulation is likely to be lower because it counts stock dividends towards meeting the dividend requirement. If low dividend-paying 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 period 2003-2005, 94% of all the dividend cases did not issue any stock dividends.

We also control for a number of proxies for the strength of corporate governance, because the instruments may be related to the strength of corporate governance. Governance may have direct impacts on firm investment (Jensen, 1986) and labor policies (Bertrand and Mullainathan, 2003; Atanassov and Kim, 2009; Cronqvist et. al., 2009; Kim and Ouimet, 2014).

We are also concerned with whether the outcome variables of shock affected and unaffected firms have different the time trends. We examine pre-trends in Section 6 and find no significant differences in the outcome variables between affected and unaffected firms prior to the 2006, suggesting no different time trends.

5.4. Data and Summary Statistics

5.4.1. Sample Construction and Data Sources

As in the job posting data analyses, we construct the sample using all A-share firms listed on the Shanghai and Shenzhen Stock Exchanges. We exclude financial firms as defined by the CSRC (e.g., banks, insurance firms, and brokerage firms) and firms with total employment less than 100. We also exclude ST (special treatment) and *ST firms, which have had two (ST) or three (*ST) consecutive years of negative net profit. These are often financially distressed firms undergoing restructuring.

Resset (http://www.resset.cn/en/) is the data source for labor, financial and corporate governance variables. It is similar to US Compustat but provides comprehensive and reliable data on wages and employment, which Compustat does not. In China, accounting rules require publicly listed firms to disclose payroll information in their financial statements. Importantly, the CSRC requires publicly listed firms to disclose the number of employees by occupation and education in their filings each year. The CSRC website posts the information, providing the data source to Resset. For SEO data, we rely on CSMAR (http://www.gtarsc.com/) because it provides more detailed information on SEOs than Resset. For dividend ratios required by the 2006 and 2008 regulations, we rely on Wind Information (http://www.wind.com.cn/En/Default.aspx.). We hand-collect minimum wages from provincial government webpages. To mitigate outlier problems, we winsorize accounting variables at the 1% and 99% level by replacing the extreme values with the value at 1% or 99%. All monetary variables are normalized to 2000 RMB.

Our sample period covers 2000 through 2012 to span the two regulatory shocks. It starts in 2000 because underwritten offerings were first allowed in 2000. Some corporate governance variables, such as board information, are also available only after 2000. It ends in 2012 because according to our design, it is the last of SEO years affected by the 2008 regulatory shock.

Table 4 lists the sample distribution by year. The sample contains 18,417 firm-year observations associated with 2,342 unique firms. Column (1) reports the number of firms in the full sample. Column (2) shows the number of public SEOs by the offering year. Unlike the job posting data analyses, for 2SLS estimations we include only rights and underwritten offerings and exclude private offerings, because the regulatory shocks used to construct the instrument apply only to public offerings. In total, our sample contains 557 public SEOs. Table 4 shows a surge of SEOs when underwritten offerings were first allowed in 2000, then a steady decline in the number of SEOs. There were very few SEOs in 2005 and 2006 because during the Split Share Structure Reform in April 2005 the CSRC stopped approving any equity offering proposals until May 2006. The sharp increase in SEOs in 2007 and 2008 reflects the release of pent-up demand to issue SEOs during 2005 and 2006. The Chinese stock market also reached its peak in 2007.

5.4.2. Employment Variables

Key labor variables in our conceptual framework are employee skills. We do not have data on specific skills for the 2SLS estimation. Instead, we use occupation and education to proxy for skills. As noted earlier, the variation in the intensity of different tasks requiring routine vs. non-routine abstract task skills is much greater across occupations than within an occupation (Autor and Handel, 2013), and more educated employees are likely to possess higher skills.

Resset provides firm level panel data on the number of employees classified as production workers, administrative staff, technicians, R&D scientists, managers, salespersons, financial accountants, and others. The production worker category covers mainly blue-collar workers, such as assembly line workers doing routine physical work. The administrative staff category includes mostly clerical jobs doing routine work, such as secretaries and receptionists. Technicians include engineers and IT staff. R&D scientists include employees involved in new product development and researchers. Managers include all top, middle, and low level managers. The salesperson category includes all the marketing force. Financial accountants include accounting and finance staff.

Resset also provides the number of employees with different levels of education for each firm-year. We use the information to separate employees into three education groups: (1) no four-year university bachelor's degree; (2) four-year university bachelor's degree and above; and (3) post-graduate degrees (all masters and doctorate degrees, including MS, MA, MBA, EMBA, PhD, MD, and JD).

5.4.3. Descriptive Statistics

Table 5 provides summary statistics for all key variables. Appendix 1 provides variable definitions and data sources. The SEO indicator, *SEO*, shows 9% of firm-year observations are in SEO years. The instrument, *IV_SEO,* indicates 10% of observations are treated by the regulatory shocks. The average fractions of production workers, managers, administrative staff, sales force, R&D scientists, technicians, financial accountants, and others are 49%, 3%, 4%, 8%, 1%, 20%, 3% and 9%, respectively. The large percentage of production workers and technicians reflects overrepresentation by manufacturing firms in our sample due to the exclusion of financial services firms and the fact that many large Chinese internet-based firms, such as Alibaba and Baidu.com, are not in our sample because they are listed overseas during our sample period. About 19% of employees have bachelors' degree and above, and 3% have post-graduate degrees. The average number of employees is about 4,600.

5.5. Skill Composition and Employment

Our job posting data analyses suggest that demand for skills and receipt of SEO proceeds are correlated. If SEOs increase demand for skills and the demand is met, SEOs will lead to an increase in the relative proportion of skilled employees in the work force. In this section, we test this prediction by estimating 2SLS regressions on how SEOs change the fraction of employees by occupation and education. We also estimate the effects SEOs have on total employment, as well as the level of employment by occupation and education.

For robustness, we use two specifications throughout the paper. The first controls only for firm- and year fixed effects and four exogenous variables; firm age and three legal variables. Firm age is measured by the log of the number of years a firm has been listed, *ln(NYEAR_LISTED).* Legal variables include: (1) The log of minimum wage required in the province or provincial level city of a firm's headquarters location, *ln(MIN_WAGE)*.[22] Higher minimum wages may affect the skill composition of employees by imposing a lower limit on what firms can pay unskilled workers. (2) The degree to which the Labor Law of People's Republic, effective January 1, 2008, affects a firm's employment and wages. The law's effect, *Labor_Law_Effect*, is likely to be greater when a firm belongs to an industry with greater labor intensity. *Labor_Law_Effect* is equal to the industry average ratio of the total number of employees to the value of all fixed assets in 2007 multiplied by a post-2008 indicator, which is one for 2008 through 2012 and zero otherwise. We use industry classification as defined by the CSRC. (3) Legal environment index, *LAWSCORE.* Higher *LAWSCORE* indicates more developed legal institutions and stronger law enforcement.[23] We include this variable because the law and finance literature (e.g., La Porta et al., 1998) suggests firms located in countries with stronger investor protection tend to have better corporate governance and suffer from fewer agency problems, which may affect firms' investment and labor policies.

In the second specification we control for time-varying firm characteristics that may be related to the decision to issue SEOs, the deployment of SEO proceeds, and the outcome

[22] Provinces and provincial level cities adjust minimum wages every two or three years. In China, there are four provincial level cities: Beijing, Shanghai, Tianjin, and Chongqing.

[23] The National Economic Research Institute (NERI) constructs the index for each province or provincial level region. The index changes over time, 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. For a more in-depth description, see Wang, Wong, and Xia (2008).

variables—innovations, employment, and wages. They include firm size as measured by the log of sales, *ln(SALES)*; firm performance as measured by return on equity, *ROE*; and firm growth rate as measured by sales growth rate, *SALES_GR*.[24] We also include financial leverage to partial out the leverage channels through which SEOs can affect wages. The finance literature suggests SEOs reduce leverage (e.g., Pagano, Panetta, and Zingales, 1998; Eckbo, Masulis, and Norli, 2000; Gustafson and Iliev, 2017). As noted earlier, a number of studies argue financial leverage affects wages, although the direction of the effect is controversial. The corporate governance literature suggests the strength of governance affects firms' investment and labor policies.[25] To control for differences in the strength of governance, we include the percentage of shares held by the local or central government, *%_STATE_OWN*; the percentage of shares held by the biggest shareholder, *%_LARGEST_SH;* and the percentage of independent directors on the board, *%_IND_DIR*. To control for the potential confounding effects of the Stock Split Reform, we include the percentage of non-tradable shares, *NONTRDPCT*. We also control for concurrent dividend payout ratio, *DIVPRT*, because our instruments are based on past dividend payouts, which may be related to the current dividend payout; and an indicator for private equity offerings, *D_PRIVATE_PLACE,* because the proceeds may affect our outcome variables.

The first-stage is estimated by the conditional (fixed-effects) logistic regression because the endogenous variable 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; 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.

Appendix 2, Columns (1) and (2) report the first-stage estimation result for each specification. The coefficients on *IV_SEO* are negative and significant at the 1% level for both

[24] Hanka (1998) points out that firms' employment is affected by profitability and growth opportunities.
[25] See, for example, Jensen (1986), Bertrand and Mullainathan (2003), and Atanassov and Kim (2009).

specifications, implying that the shocks significantly reduced the likelihood of SEOs. It also suggests that the instrument has strong predictive power over the endogenous variable. F-statistics are not reported because the first-stage regression is conditional logit, a non-linear estimation. When the first stage is estimated using the OLS, F-statistics are 30.46 and 27.64.

Table 6 reports the second-stage estimation results for the occupation composition of employees. Regardless of which specification is used, we find SEOs significantly increase proportions of technicians, R&D scientists, managers, and post-graduate degree holders.[26] Technicians and R&D scientists tend to possess technical skills required for non-routine analytical tasks. Managers tend to possess problem-solving and complex communication skills required for non-routine interactive tasks. These employees are also more likely to possess post-graduate degrees—masters and doctorates in engineering, science, business, economics, and law. The post-graduate degree holders may possess higher non-routine abstract task skills.

In contrast, SEOs significantly decrease the proportions of production workers and staff that mostly perform routine physical and clerical tasks requiring fewer skills and less education. From these results, we infer SEOs change the skill composition of employees; SEOs increase (decrease) the relative proportion of skilled (unskilled) employees.

Table 7 reports the second-stage estimation result for the level of employment. The dependent variable in the first column is the log of the total number of employees. Both specifications yield negative coefficients of $\widehat{SEO}$, and the specification with the full set of control variables (Panel B) shows a significant negative coefficient implying SEOs leads to, on average, a 10% reduction in the total number of employees. The remaining columns break down the number of employees by occupation and education. The results show significant increases in the number of R&D scientists and managers, and significant decreases in the number of production workers

[26] The CSRC requires publicly listed firms to disclosure the number of employees by level of education but does not provide clear instruction on how precisely it should be disclosed. Consequently, some firms fail to report the number of employees who hold post-graduate degrees, resulting in substantially fewer observations for regressions on the education variables in Tables 6 and 7.

and staff. Technicians show a decrease in numbers, although their relative proportion increases (Table 6). The other occupations (sales, financial accountants, and others) all show a decline in the number of employees, although their relative proportions do not.

In sum, capital infusion through SEOs increases the relative proportion of employees in occupations requiring technical and managerial skills required for non-routine abstract tasks, and decreases the relative proportion of employees performing routine physical and clerical tasks. The displacement of unskilled workers outnumbers additions of skilled workers, resulting in a net decline in total employment.

5.6. Investments in Technology and Innovations

The process of capital infusion leading to changes in the skill composition and employment has an intermediate step: investments and advances in technology, which complement high-technical and non-routine abstract task skills and substitute low-technical and routine-task skills. Kim and Weisbach (2008) and Gustafson and Iliev (2017) provide evidence that SEOs increase investments in general, which include both non-technology-advancing investments (e.g., scale-expanding and structural investments) and technology-advancing investments. To isolate the effects of SEOs on technology-advancing investments, we focus on one of the possible outcomes—innovations, which we measure by the number of patents.[27] Although many patents could be useless, the number of patents reflects the effort and resources devoted to advance technology. We relate SEOs to the number of patents granted in year t + 2 to allow time for SEO proceeds to be invested, for the investment to yield innovations, and for the innovations to be granted patents. Results are robust to using a three-year lag.

[27] Another proxy for technology-advancing investments is research and development expenditures. However, the Chinese accounting rule did not require disclosure of R&D expenditure until 2007and thus we do not have adequate data for R&D. The R&D data available from 2007 show R&D expenditures are positively and significantly correlated to the total number of patents. The correlation between R&D expenditures and the total number of patents in year t+2 over 2007 - 2012 is 0.13, significant at the one percent level.

Patent data is obtained from Baiten (http://www.baiten.cn/). The State Intellectual Property Office (SIPO) (http://www.sipo.gov.cn/), a Chinese government agency in charge of patent applications, classifies patents into three types: invention patents, utility model patents, and design patents. According to the Guidelines for Patent Examination 2010 on the SIPO website, invention (design) patents are considered most (least) innovative among the three, requiring the longest (shortest) evaluation period with the longest (shortest) protection period.

Table 8 reports the second-stage estimation results with the log of one plus the number of patents as the dependent variable. The first two columns show the total number of patents increases significantly following SEOs. The estimated coefficient with the full set of control variables suggests that, on average, SEOs increase the total number of patents by 13%. When we separately examine patents by type, we find invention patents and utility model patents significantly increase following SEOs, while design patents do not. Because the level of innovativeness is higher for invention and utility model patents than design patents, these results further buttress our prediction that SEOs lead to more technology-advancing investments.

5.7. Firm Wages

The empirical results presented so far support our hypothesis that capital infusion through SEOs leads to more technology-advancing investments, increasing (decreasing) the relative proportion of skilled (unskilled) workers. This change in the skill composition should lead to higher firm average wages because skilled workers are paid more.

Table 9 reports the second-stage estimation results with firm average wage as the dependent variable. The predicted SEO is the same as before. The first two columns show significant and positive increases in average wages of all employees. Column (3) reports a separate estimate for all non-executive employees using the full set of control variables. The estimated coefficient indicates that average wages of all non-executive employees increase by 12% during the SEO years.

In contrast, average wages of executives (those classified as executives in financial statements) are unaffected by the capital infusion. The difference between non-executive and executive employees can be explained by capital skill complementarity: Capital infusion leads to changes in the skill composition of employees, increasing their average wages, but there is no compelling reason to expect a change in the skill composition within the executive group.[28]

Our prediction of higher average wages based on the observed changes in the occupation composition presumes that wages are higher in occupations requiring higher skills. To validate this presumption, we estimate implied average wages by occupation or education by estimating the OLS regression relating firm average wages to the fractions of employees by occupation or by education without constant terms. The coefficient on each fraction can then be interpreted as the implied average wage for the occupation or the level of education, because average wages are weighted averages of employees with different occupation or education such that the fractions are the weights in calculating the weighted averages.

Table 10 reports the estimated implied wages. The production worker implied wage is the lowest (16,950 RMB or 2,047 USD in 2000), much lower than the average wage of all employees (58,500 RMB or 7,065 USD).[29] The second lowest paid are staff, followed by technicians, R&D scientists, and managers, in that order.[30] For the education level, post-graduate degree holders are paid the most, followed by four-year university graduates[31] and those without four-year college

[28] The wage results do not reflect the value of equity incentives, which are an important component of compensation in the U.S. In China, equity incentives were formally introduced in 2006 in the form of employee stock options and discounted share purchase programs. Stock options are granted and vested shortly after they are approved by shareholders. They can be exercised according to a fixed schedule when certain performance targets are met. Discounted share purchase programs allow stock purchases at a discount but the stocks cannot be sold until a performance target is achieved. These equity incentives are issued to both non-executive employees and executives, and are difficult to price because of the vesting requirements and sales restrictions. As a consequence, examining how SEOs affect employee compensation through equity incentives is beyond the scope of this paper.

[29] RMB is deflated using 2000 as the base year, so conversion of RMB to USD is based on the average exchange rate of 8.28 in 2000.

[30] The very low implied wage for sales force is misleading because the wage data do not include sales commissions, which represent the main source of income for a sales force.

[31] %_Undergrad is different from BA in Tables 6 and 7. %_Undergrad includes those with only a bachelor's degree.

degrees.[32] These implied wages confirm our assertion that the higher average wage following SEOs is due to changes in skill composition; more precisely, due to the decrease in the proportion of employees in the two lowest paid occupations and the increase in the proportion of employees in the three higher paid occupations.

How do the changes in the skill composition and employment affect total wages? The total wage represents the bulk of labor costs and hence is an important factor determining firm profitability. The higher average wages do not necessarily lead to a higher total wage because of a decline in the total number of employees following SEOs. Table 11 reports the second-stage estimation results on total wages. Regardless of which specification is used and how we stratify employee groups, SEOs have no significant impact on total wages. Capital infusions through SEOs enable firms to upgrade their employee skills without incurring higher labor costs.

6. ROBUSTNESS

The key to our identification is the instrument for SEOs. In this section, we examine whether pre-trends violate the exclusion restriction and whether main results are robust to alternative definitions of SEOs and alternative ways to construct the instrument.

6.1. Pre-Trends

We construct the instrumental variable based on the variation in the impacts of the shocks on the eligibility to issue SEOs. One presumption for the validity of the IV is that if there were no shock, affected and unaffected firms would have no different time trends in the outcome variables (occupation composition, employment, innovations, and wages); otherwise, the exclusion restriction will not be satisfied.

To test whether this presumption holds, we conduct a placebo test using the 2000-2005 samples prior to the 2006 regulatory shock to simulate the situation with no shock. We do not use

[32] These implied average wages are consistent with the China Urban Household Survey, which shows Chinese workers with more education are paid more and technicians are paid substantially more than production workers and staff (see Appendix 3).

post-2006 shock samples because of the presence of the second shock in 2008.[33] We construct an indicator for firms affected by the regulation in 2006, *Affected*. Then we test whether there is any differnce between the outcome varables of shock affected and shock unaffected firms during the period prior to 2006 using 2000 as the base year. We define five placebo shock indicators, *Year01, Year02, Year03, Year04 and Year05*, which are equal to one for years 2001 through 2005. We then estimate the baseline regressions with the full set of control variables for all key outcome variables with the interactions of *Affected* and placebo indicators as variables of interest.

Table 12 reports the results, which show none of the coefficients of interaction terms is statistically significant for any of the outcome variables, implying that the outcome variables of affected and unaffected firms prior to the 2006 shock are not different. These results suggest no different time trends in the outcome variables between affected and unaffected firms had there been no shock, alleviating our concerns of violating the exclusion restriction.

6.2. Alternative Definitions of SEOs

In our baseline regressions, we turn on the SEO indicator for all completed underwritten offerings and rights offerings. We experiment with two alternative definitions for the SEO indicator. First, we exclude small SEOs in the bottom decile in terms of proceeds. Firms with small market caps and highly volatile performances typically make these small SEOs. Appendix 2, Column (3) reports the first-stage result with the full set of control variables. Table 13, Column (2) reports the second-stage results for the fraction of employees by occupation and education, total employment, patents, average wages, and total wages. All results are robust.

We also experiment with alternative SEO years, setting the SEO indicator equal to one only in the year following the year of SEO as in Kim and Weisbach (2008). Although this approach avoids noise due to different timing within the year of SEO (e.g., February vs. October

[33] In the baseline regressions, we assume a two-year lag between the year of SEO announcements and the first year in which SEO proceed are deployed. However, some firms announcing SEOs in 2006 may complete the process in 2006 or 2007, affecting outcome variables in 2006 or 2007. Thus, we focus only on years before 2006.

in the same year), it may not capture the full effects by omitting the year of SEO and the second year following the year of SEO. The results, reported in Column (3) of Table 13, are robust. Appendix 2, Column (4) reports the first-stage results.

6.3. Alternative Ways to Construct the Instrument

In constructing the instrumental variable, we assume a two-year elapsed time from the beginning of an SEO process to the deployment of the proceeds, defining 2008 and 2009 as years affected by the 2006 regulation and 2010 and 2011 as years affected by the 2008 regulation. To ensure our sample is uncontaminated by firms which circumvent the 2006 and 2008 regulations by increasing dividends sufficiently in 2007 and 2009, respectively, we exclude 2009 and 2011 and define only 2008 and 2010 as the regulation affected years. The second-stage results are reported in Column (4). We also shorten the time lag from the beginning of the SEO process to the availability of the proceeds from two years to one year and report the second-stage results in Column (5). Finally, because the first shock may have led some firms to anticipate the second shock we reestimate the results relying only on the 2006 shock and report the second-stage results in Column (6). All results are robust. Appendix 2, Columns (5) - (7) report the first-stage estimation results.

7. CONCLUDING REMARKS

This paper studies how equity financing affects employee skills, employment, and wages. We begin by analyzing job descriptions in online job posting data, which suggest demand for computer, and non-routine analytical and interactive task skills increase when firms receive SEO proceeds. To identify causal effects, we rely on external shocks cutting off assess to external financing through SEOs. We find capital infusion through SEOs increases innovations and the proportion of high-skilled employees relative to low-skilled workers. Importantly, displaced low-skilled workers outnumber newly hired high-skilled workers, resulting in a net reduction in employment. The higher proportion of high-skilled workers, in turn, increases firm average wages because they are paid more, but total wages remain unchanged due to the reduction in total employment. It appears SEOs enable firms to upgrade the skill composition of employees without increasing labor costs.

These findings shed light on how differential access to stock markets affects labor markets by altering demand for high- vs. low-skilled workers. Easier access to capital may not only increase demand for high-skilled workers but also stimulate their supply, as the demand and supply of skills are endogenous to each other and dynamically move together. If the supply of high-skilled workers indeed increases in response to increased demand, it will also induce greater development of skill complementary technologies, which may enhance long-term economic growth.

The implications are not all positive, however. The highly developed and sophisticated financial markets of recent years have allowed less costly access to external capital, which we show can lead to displacement of a low-skilled and less-educated work force. Retraining to upgrade skills to meet changing demands requires financial resources, time, and effort; thus, many displaced 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 and demand for low-skilled and less-educated workers is likely to keep their income low. Highly skilled and highly educated employees, on the other hand, will enjoy increasing demand for their services as frictions to assessing external capital decline and capital skill complementarity kicks in. The end results might be further widening income inequality.

References

Acemoglu, Daron and Amy Finkelstein, 2008, Input and Technology Choices in Regulated Industries: Evidence from the Health Care Sector, *Journal of Political Economy* 116, 837-880.

Acemoglu, Daron and David Autor, 2011, Skills, Tasks and Technologies: Implications for Employment and Earnings, In: David Card and Orley Ashenfelter (Ed.), *Handbook of Labor Economics*, Vol. 4b, Elsevier/North-Holland, Amsterdam, Chapter 12, 1043-1171.

Acemoglu, Daron and Pascual Restrepo, 2017a, The Race between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment, NBER Working Paper No. 22252.

Acemoglu, Daron and Pascual Restrepo, 2017b, Robots and Jobs: Evidence from US Labor Markets, Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2940245.

Akerman, Anders, Ingvil Gaarder and Magne Mogstad, 2015, The Skill Complementarity of Broadband Internet, *Quarterly Journal of Economics* 130, 1781-1824.

Asquith, Paul and David W. Mullins, 1986, Equity Issues and Offering Dilution, *Journal of Financial Economics* 15, 61-89.

Atanassov, Julian and E. Han Kim, 2009, Labor and Corporate Governance: International Evidence from Restructuring Decisions, *Journal of Finance* 64, 341-374.

Autor, David H. and Michael J. Handel, 2013, Putting Tasks to the Test: Human Capital, Job Tasks, and Wages, *Journal of Labor Economics* 31, 59-96.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney, 2006, The Polarization of the U.S. Labor Market, *American Economics Review* 96, 189-194.

Autor, David H., Lawrence F. Katz and Alan B. Krueger, 1998, Computing Inequality: Have Computers Changed the Labor Market? *Quarterly Journal of Economics* 113, 1169-1213.

Autor, David. H., Frank Levy and Richard J. Murnane, 2003, The Skill Content of Recent Technological Change: An Empirical Exploration, *Quarterly Journal of Economics* 118, 1279-1333.

Bayless, Mark and Susan Chaplinsky, 1996, Is There a Window of Opportunity for Seasoned Equity Issuance? *Journal of Finance* 51, 253-278.

Ben-Gad, Michael, 2008, Capital-Skill Complementarity and the Immigration Surplus, *Review of Economic Dynamics*, 11, 335-365.

Berk, Jonathan B., Richard Stanton and Josef Zechner, 2010, Human Capital, Bankruptcy, and Capital Structure, *Journal of Finance* 65, 891-926.

Berman, Eli, John Bound and Zvi Griliches, 1994, Changes in the Demand for Skilled Labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufacturing, *Quarterly Journal of Economics* 109, 367-397.

Bertrand, Marianne and Sendhi Mullainathan, 2003, Enjoying the Quiet Life? Corporate Governance and Managerial Preferences, *Journal of Political Economy* 111, 1043-1075.

Bresnahan, Timothy F., Erik Brynjolfsson and Lorin M. Hitt, 2002, Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence, *Quarterly Journal of Economics* 117, 339-376.

Bronars, Stephen G. and Donald R. Deere, 1991, The Threat of Unionization, the Use of Debt, and the Preservation of Shareholder Wealth, *Quarterly Journal of Economics* 106, 231-254.

Brown, Charles and James L. Medoff, 1989, The Employer Size-Wage Effect, *Journal of Political Economy* 97, 1027-1059.

Card, David, 1999, The Causal Effect of Education on Earnings, In: David Card and Orley Ashenfelter (Ed.), *Handbook of Labor Economics*, Vol. 3a, Elsevier/North-Holland, Amsterdam, Chapter 30, 1801-1863.

Caroli, Eve and John Van Reenen, 2001, Skill Biased Organizational Change? Evidence from a Panel of British and French Establishments, *Quarterly Journal of Economics* 116, 1449-

1492.
Chemmanur, Thomas, Yingmei Cheng and Tianming Zhang, 2013, Human Capital, Capital Structure, and Employee Pay: An Empirical Analysis, *Journal of Financial Economics* 110, 478-502.
Cronqvist, Henrik, Fredrik Heyman, Mattias Nilsson, Helena Svaleryd, and Jonas Vlachos, 2009, Do Entrenched Managers Pay Their Workers More? *Journal of Finance* 64, 309-339.
Currie, Janet and Sheena McConnell, 1992, Firm-Specific Determinants of the Real Wage, *Review of Economics and Statistics* 74, 297-304.
DeAngelo, Harry, Linda DeAngelo and René Stulz, 2010, Seasoned Equity Offerings, Market Timing, and the Corporate Lifecycle, *Journal of Financial Economics* 95, 275-295.
Doms, Mark, Timothy Dunne and Kenneth R. Troske, 1997, Workers, Wages, and Technology, *Quarterly Journal of Economics* 62, 253-290.
Duffy, John, Chris Pagageorgiou and Fidel Perez-Sebastian, 2004, Capital-Skill Complementarity? Evidence from a Panel of Countries, *Review of Economics and Statistics* 86, 327-344.
Eckbo, B. Espen and Ronald W. Masulis, 1995, Seasoned Equity Offerings: A Survey, In: John R. Birge and Vadim Linetsky (Ed.), *Handbooks in Operations Research and Management Science*, Vol. 9, Elsevier/North-Holland, Amsterdam, Chapter 31, 1017-1072.
Eckbo, B. Espen, Ronald W. Masulis and Øyvind Norli, 2000, Seasoned Public Offerings: Resolution of the 'New Issues Puzzle', *Journal of Financial Economics* 56, 251-291.
Fallon, P. R. and Richard Layard, 1975, Capital-Skill Complementarity, Income Distribution, and Output Accounting, *Journal of Political Economy* 83, 279-302.
Gallagher, Mary, John Giles, Albert Park, and Meiyan Wang, 2015, China's 2008 Labor Contract Law: Implementation and Impacts on Workers, *Human Relations*, 68(2), 197-235.
Goldin, Claudia and Lawrence F. Katz, 1996, Technology, Skill, and the Wage Structure: Insights from the Past, *American Economic Review* 86, 252-257.
Goldin, Claudia and Lawrence F. Katz, 1998, The Origins of Technology-Skill Complementarity, *Quarterly Journal of Economics* 113, 693-732.
Griliches, Zvi, 1969, Capital-Skill Complementarity, *Review of Economics and Statistics* 51, 465-468.
Gustafson, Matthew T. and Peter Iliev, 2017, The Effects of Removing Barriers to Equity Issuance, *Journal of Financial Economics* 124, 580-598.
Hall, Brownyn H. and Josh Lerner, 2010, The Financing of R&D and Innovation, In: Brownyn H. Hall and Nathan Rosenberg (Ed.), *Handbooks in Economics of Innovation,* Vol. 1, Elsevier/North-Holland, Amsterdam, Chapter 14, 609-639.
Hamermesh, Daniel S., 1993, *Labor Demand,* Princeton, Princeton University Press.
Hanka, Gordon, 1998, Debt and the Terms of Employment, *Journal of Financial Economics* 48, 245-282.
Hershbein, Brad and Lisa Kahn, 2016, Do Recessions Accelerate Routine-Biased Technology Change? Evidence from Vacancy Postings, http://www.nber.org/papers/w22762.
Ho, Virginia, 2006, Labor Law in China's Reform Era: The Evolving Legal Framework for Labor Rights. In: Mary Gallagher, Ching Kwan Lee, and Albert Park (Ed.), *The Labor of Reform in China*, Unpublished Edited Vol.
Hsieh, Chang-Tai and Zheng (Michael) Song, 2015, Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China, *Brookings Papers on Economic Activity* Spring, 295-346.
Jensen, Michael C., 1986, Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers, *American Economic Review* 76, 323-329.
Jung, Kooyul, Yong-Cheol Kim and René M. Stulz, 1996, Timing, Investment Opportunities, Managerial Discretion, and the Security Issue Decision, *Journal of Financial Economics* 42, 159-185.

Kasahara, Hiroyuki, Yawen Liang and Joel Rodrigue, 2016, Does Importing Intermediates Increase the Demand for Skilled Workers? Plant-Level Evidence from Indonesia, *Journal of International Economics* 102, 242-261.

Kim, E. Han and Paige Ouimet, 2014, Broad-Based Employee Stock Ownership: Motives and Outcomes, *Journal of Finance* 69, 1273-1319.

Kim, E. Han and Amiyatosh Purnanandam, 2014, Seasoned Equity Offerings, Corporate Governance, and Investments, *Review of Finance* 18, 1023-1057.

Kim, Woojin and Michael S. Weisbach, 2008, Motivations for Public Equity Offers: An International Perspective, *Journal of Financial Economics* 87, 281-307.

Korajczyk, Robert A., Deborah Lucas and Robert L. McDonald, 1990, Understanding Stock Price Behavior around the Time of Equity Issues, In: Hubbard, R. Glenn (Ed.), *Asymmetric Information, Corporate Finance and Investment*, University of Chicago Press, Chicago.

Krusell, Per, Lee E. Ohanian, José-Victor Ríos-Rull and Givanni L. Violante, 2000, Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis, *Econometrica* 68, 1029-1053.

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer and Robert W. Vishny, 1998, Law and Finance, *Journal of Political Economy* 106, 1113-1155.

Lee, David S. and Thomas Lemieux, 2010, Regression Discontinuity Designs in Economics, *Journal of Economic Literature* 48, 281-355.

Lemmon, Michael L., Michael R. Roberts, and Jaime F. Zender, 2008, Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure, *Journal of Finance* 63, 1575-1608.

Lewis, Ethan, 2011, Immigration, Skill Mix, and Capital-Skill Complementarity, *Quarterly Journal of Economics* 126, 1029-1069.

Li, Hongbin, Lei Li, Binzhen Wu, and Yanyan Xiong, 2012, The End of Cheap Chinese Labor, *Journal of Economic Perspectives*, 26(4), 57-74.

Li, Shi and Yaohui Zhao, 2003, The Decline of In-kind Wage Payments in Urban China, *Journal of Chinese Economics and Business Studies* 1, 245-258.

Lin, Justin, Fang Cai, and Zhou Li, 1996, *The China Miracle: Development Strategy and Economic Reform,* Hong Kong, Chinese University of Hong Kong Press.

Lindquist, Matthew J., 2004, Capital-Skill Complementarity and Inequality over the Business Cycle, *Review of Economic Dynamics* 7, 519-540.

Machin, Stephen and John Van Reenen, 1998, Technology and Changes in Skill Structure: Evidence from Seven OECD Countries, *Quarterly Journal of Economics* 113, 1215-1244.

Masulis, Ronald W. and Ashok N. Korwar, 1986, Seasoned Equity Offerings: An Empirical Investigation, *Journal of Financial Economics* 15, 91-118.

McLean, R. David, 2011, Share Issuance and Cash Savings, *Journal of Financial Economics* 99, 693-715.

Meng, Xin, 2000, *Labor Market Reform in China*. Cambridge and New York: Cambridge University Press.

Michaels, Ryan, T. Beau Page and Toni Whited, 2016, Labor and Capital Dynamics under Financing Frictions. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2850790.

Moore, Henry Ludwell, 1911, Laws of Wages: An Essay in Statistical Economics, New York, the Macmillan Company.

Pagano, Marco, Fabio Panetta and Luigi Zingales, 1998, Why Do Companies Go Public? An Empirical Analysis, *Journal of Finance* 53, 27-64.

Pagano, Marco and Paolo F. Volpin, 2005, Managers, Workers, and Corporate Control, *Journal of Finance* 60, 841-868.

Parro, Fernando, 2013, Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade, *American Economic Journal: Macroeconomics* 5, 72-117.

Perotti, Enrico C. and Kathlyn E. Spier, 1993, Capital Structure as a Bargaining Tool: The Role

of Leverage in Contract Renegotiation, *American Economic Review* 83, 1131-1141.
Rauh, Joshua, D., 2006, Own Company Stock in Defined Contribution Pension Plans: A Takeover Defense? *Journal of Financial Economics* 81, 379-410.
Wang, Qian, T. J. Wong and Lijun Xia, 2008, State Ownership, the Institutional Environment, and Auditor Choice: Evidence from China, *Journal of Accounting and Economics* 46. 112-134.
Wooldridge, Jeffrey, 2010, Econometric Analysis of Cross Section and Panel Data, Cambridge, the MIT Press.
Yasar, Mahmut and Catherine J. Morrison Paul, 2008, Capital-Skill Complementarity, Productivity and Wages: Evidence from Plant-Level Data for a Developing Country, *Labor Economics* 15, 1-17.
Yueh, Linda, 2004, Wage Reforms in China during the 1990s, *Asian Economic Journal* 18, 149-164.
Zhang, Junsen, Yaohui Zhao, Albert Park, and Xiaoqing Song, 2005, Economic Returns to Schooling in Urban China, 1988 to 2001, *Journal of Comparative Economics* 33, 730-752.

Table 1: Skill Requirements Mentioned in Online Job Postings.

This table provides information on job posting data. Panel A reports the number of full-time job advertisements posted in Lagou.com (https://www.lagou.com) by firms listed in Shanghai and Shenzhen Stock Exchanges from 2014-2016. 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 firms issued seasoned equity offerings (including underwritten offerings, right offerings, and private placements). Repetition of the same advertisements is excluded. Panel B provides the list of key words used to identify four different types of skill requirements specified in each job advertisement. The key words are English version of Chinese words used in the advertisements.

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 of 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.

Table 2: SEOs and Computer Skills Mentioned in Job Descriptions.

This table relates SEOs to computer skills mentioned in job descriptions. Panels A and B report the results for advanced and basic computer skills, respectively. Key words used to identify advanced and basic computer skills are listed in Table 1, Panel B. The dependent variable in Columns (1) and (2) is an indicator equal to one if any of the key words used to identify advanced or basic computer skill appear in a job description. The dependent variable in Columns (3) and (4) is the log of one plus the number of words appearing in a job description related to advanced or basic computer skills. 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 occupation dummies. Standard errors (in parentheses) are clustered at the firm-occupation 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
Occupation Dummies	N	Y	N	Y
Observations	44,767	44,767	45,582	45,582
Pseudo-R-squared	0.078	0.297		
Adjusted R-squared			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
Occupation Dummies	N	Y	N	Y
Observations	40,218	40,218	45,582	45,582
Pseudo-R-squared	0.085	0.120		
Adjusted R-squared			0.032	0.045

Table 3: SEOs and Non-routine Task Skills Mentioned in Job Descriptions.

This table relates SEOs to non-routine task skills mentioned in job descriptions. Panels A and B report the results for non-routine analytic task skills and non-routine interactive task skills, respectively. Key words used to identify non-routine analytic task skills and non-routine interactive task skills are listed in Table 1, Panel B. The dependent variable in Columns (1) and (2) is an indicator equal to one if any of the key words used to identify non-routine analytic task skills or non-routine interactive task skills appear in a job description. The dependent variable in Columns (3) and (4) is log of one plus the number of words appearing in a job description related to non-routine analytic task or non-routine interactive task skills. 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 occupation dummies. Standard errors (in parentheses) are clustered at the firm-occupation 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
Occupation Dummies	N	Y	N	Y
Observations	44,992	44,992	45,582	45,582
Pseudo-R-squared	0.072	0.090		
Adjusted R-squared			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
Occupation Dummies	N	Y	N	Y
Observations	44,214	44,214	45,582	45,582
Pseudo-R-squared	0.052	0.096		
Adjusted R-squared			0.069	0.156

Table 4: Sample for Panel Data Analyses.

This table reports the number of firms in the total sample and in the seasoned equity offering sample for the panel data analyses. The sample includes Chinese firms listed on Shanghai and Shenzhen Stock Exchanges from 2000 to 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 (underwritten offerings and rights offerings) by offering year.

Year	Full	Number of SEOs
	(1)	(2)
2000	901	154
2001	980	131
2002	1,040	44
2003	1,108	38
2004	1,205	32
2005	1,217	7
2006	1,248	7
2007	1,374	28
2008	1,451	43
2009	1,541	18
2010	1,892	20
2011	2,170	23
2012	2,290	12
Total	18,417	557

Table 5: Summary Statistics of Variables Used in the Panel Data Analyses.

This table reports summary statistics for variables used in the panel data regressions. Variable definitions are provided in Appendix 1.

	Mean	Std. Dev.	Min	Max
Key Variables	**(1)**	**(2)**	**(3)**	**(4)**
SEO	0.088	0.283	0.000	1.000
IV_SEO	0.102	0.303	0.000	1.000
%_Production	0.486	0.293	0.000	0.956
%_Managers	0.032	0.069	0.000	0.868
%_Staff	0.043	0.069	0.000	0.785
%_Sales	0.076	0.129	0.000	0.928
%_R&D	0.014	0.067	0.000	0.885
%_Technician	0.195	0.199	0.000	0.882
%_Financel	0.026	0.031	0.000	0.672
%_Others	0.089	0.190	0.000	1.000
%_BA	0.188	0.170	0.003	0.771
%_Grad	0.031	0.043	0.000	0.237
Ln(EMP)	7.513	1.200	4.605	13.223
Ln(Production)	5.717	2.972	0.000	12.728
Ln(Managers)	2.136	2.594	0.000	10.491
Ln(Staff)	0.382	1.400	0.000	10.315
Ln(Sales)	5.109	2.015	0.000	12.204
Lu(R&D)	1.350	2.341	0.000	11.227
Ln(Technician)	3.041	2.576	0.000	11.456
Ln(Finance)	3.078	1.731	0.000	9.578
Ln(Others)	2.185	2.868	0.000	12.395
Ln(BA)	5.396	1.391	0.000	11.842
Ln(Grad)	3.336	1.401	0.000	10.112
AWAGE	5.725	8.592	0.012	285.293
AWAGE_NonExe	5.786	8.847	0.010	233.738
AEXEPAY	0.167	0.158	0.003	3.995
Payroll	252.083	1548.080	0.203	80861.520
Payroll_NonExe	260.224	1592.241	0.016	80850.260
Payroll_Exe	2.361	2.735	0.020	51.937
Total_Patent	4.615	18.767	0.000	445.000
Invention	1.789	8.366	0.000	231.000
Utility_Model	2.028	9.948	0.000	371.000
Design	0.799	5.879	0.000	220.000
NYEAR_LISTED	7.011	5.013	0.000	22.000
SALES	4504.244	39792.610	0.003	2085363.000
ROE	0.058	0.141	-0.817	0.339
LEVERAGE	0.321	0.201	0.000	0.975
PPE/TA	0.227	0.494	-0.603	3.353

Table 5: Summary Statistics of Variables Used in the Panel Data Analyses. (Continued)

Other Variables				
SALES_GR	0.305	0.127	0.000	0.833
%_IND_DIR	0.194	0.246	0.000	0.944
%_STATE_OWN	0.390	0.163	0.022	0.894
%_LARGEST_SH	0.211	0.296	0.000	0.913
NONTRDPCT	0.046	0.210	0.000	1.000
D_PRIVATE_PLACE	0.288	1.851	0.000	240.000
DIVPRT	640.446	207.807	208.540	1085.329
MIN_WAGE	7.786	3.916	0.000	16.610
LAWSCORE	3.575	3.931	0.000	13.273
Labor_Law_Effect	7.011	5.013	0.000	22.000

Table 6: SEOs and Employee Composition by Occupation and Education.

This table reports the second-stage estimation of the impact SEOs have on the employee composition by occupation and education. The dependent variables are the percentages of production workers in Column (1), administration staff in Column (2), R&D staff in Column (3), technicians in Column (4), managers in Column (5), sales persons in Column (6), finance staff in Column (7), employees in other occupations in Column (8), employees with bachelor degree or above in Column (9), and employees with post-graduate degrees in Column (10). All regressions include firm- and year- fixed effects. Regressions in Panel A control for firm age and legal environments. Regressions in Panel B add the full set of time-varying firm characteristic variables. Variable definitions are provided in Appendix 1. The first-stage regression results are reported in Appendix 2. The sample period covers 2000 – 2012. Bootstrapping standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5% and 1%, respectively.

Panel A

	%_Production	**%_Staff**	**%_R&D**	**%_Technician**	**%_Managers**	**%_Sales**	**%_Finance**	**%_Others**	**%_BA**	**%_Grad**
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\widehat{SEO}$	-0.039***	-0.025***	0.012**	0.023**	0.015***	0.008	-0.002	-0.005	-0.008	0.006**
	(0.012)	(0.007)	(0.005)	(0.012)	(0.006)	(0.008)	(0.002)	(0.019)	(0.009)	(0.003)
ln(NYEAR_LISTED)	0.013**	0.002	-0.005***	-0.016***	-0.005*	-0.009**	0.000	0.024***	0.002	-0.003**
	(0.005)	(0.003)	(0.002)	(0.006)	(0.003)	(0.004)	(0.001)	(0.008)	(0.004)	(0.001)
ln(MIN_WAGE)	-0.009	0.012**	-0.012***	0.035**	-0.003	0.021**	0.004*	-0.048***	0.037***	0.007*
	(0.021)	(0.005)	(0.003)	(0.017)	(0.005)	(0.010)	(0.002)	(0.014)	(0.012)	(0.004)
LAWSCORE	-0.001	0.000	-0.001***	0.007***	-0.001*	-0.001	0.000**	-0.004**	0.004***	0.000
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Labor_Law_Effect	-0.011***	-0.001	0.001**	0.005***	-0.000	-0.003***	0.001**	0.007***	-0.005***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Constant	0.616***	0.013	0.102***	-0.128	0.066*	0.010	-0.008	0.314***	-0.036	-0.009
	(0.144)	(0.040)	(0.022)	(0.116)	(0.040)	(0.072)	(0.017)	(0.099)	(0.089)	(0.024)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,934	14,934	14,934	14,934	14,934	14,934	14,934	14,934	12,040	8,310

Panel B

VARIABLES	%_Production (1)	%_Staff (2)	%_R&D (3)	%_Technician (4)	%_Managers (5)	%_Sales (6)	%_Finance (7)	%_Others (8)	%_BA (9)	%_Grad (10)
$\widehat{SEO}$	-0.042***	-0.024***	0.010**	0.026**	0.018***	0.001	0.000	-0.001	0.002	0.006**
	(0.014)	(0.007)	(0.004)	(0.013)	(0.005)	(0.009)	(0.002)	(0.015)	(0.010)	(0.003)
ln(NYEAR_LISTED)	0.004	0.003	-0.005***	-0.013**	-0.006***	-0.005	0.001	0.023***	0.003	-0.001
	(0.006)	(0.003)	(0.002)	(0.006)	(0.002)	(0.004)	(0.001)	(0.007)	(0.004)	(0.001)
ln(SALES)	0.007*	-0.003**	0.001	-0.001	-0.000	0.003	-0.002***	-0.001	-0.001	-0.001
	(0.004)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.000)	(0.005)	(0.002)	(0.001)
ROE	-0.028**	0.001	0.004*	0.011	-0.002	0.010	0.007***	-0.004	0.014*	0.003
	(0.012)	(0.004)	(0.002)	(0.011)	(0.004)	(0.007)	(0.002)	(0.014)	(0.008)	(0.002)
Leverage	-0.059***	0.004	0.002	-0.020	0.010*	-0.003	0.005	0.067***	0.013	-0.002
	(0.018)	(0.006)	(0.003)	(0.013)	(0.005)	(0.009)	(0.003)	(0.020)	(0.012)	(0.003)
PPE/TA	0.173***	-0.009	0.001	-0.026	-0.015***	-0.034***	-0.020***	-0.051**	-0.074***	-0.018***
	(0.024)	(0.006)	(0.003)	(0.017)	(0.006)	(0.009)	(0.002)	(0.021)	(0.015)	(0.004)
SALES_GR	-0.009**	0.003***	-0.001	0.005*	0.000	-0.004***	0.002***	0.003	-0.001	0.000
	(0.004)	(0.001)	(0.000)	(0.003)	(0.001)	(0.002)	(0.000)	(0.004)	(0.002)	(0.001)
%_IND_DIR	-0.050**	0.003	-0.002	0.050***	-0.006	0.031***	0.001	-0.024	-0.012	-0.001
	(0.020)	(0.006)	(0.003)	(0.015)	(0.005)	(0.010)	(0.002)	(0.016)	(0.010)	(0.003)
%_STATE_OWN	0.020*	0.004	0.001	-0.040***	0.001	0.005	-0.001	0.015	-0.013**	-0.005***
	(0.011)	(0.004)	(0.002)	(0.007)	(0.003)	(0.006)	(0.001)	(0.010)	(0.006)	(0.002)
%_LARGEST_SH	-0.096***	-0.017**	0.003	0.012	-0.001	-0.029***	0.012***	0.092***	0.033**	0.005
	(0.033)	(0.007)	(0.005)	(0.016)	(0.009)	(0.010)	(0.004)	(0.020)	(0.016)	(0.005)
NONTRDPCT	-0.002	-0.001	-0.005**	0.022**	0.005	-0.011	0.002	-0.015	-0.018**	0.004
	(0.014)	(0.005)	(0.002)	(0.011)	(0.006)	(0.008)	(0.002)	(0.013)	(0.008)	(0.003)
D_PRIVATE_PLACE	-0.001	-0.003	0.003	0.009	0.002	-0.001	-0.000	-0.008*	0.001	0.001
	(0.008)	(0.002)	(0.002)	(0.006)	(0.002)	(0.004)	(0.001)	(0.005)	(0.004)	(0.001)
DIVPRT	0.001	0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
ln(MIN_WAGE)	-0.008	0.013**	-0.012***	0.034**	-0.003	0.021**	0.005**	-0.049***	0.038***	0.007**
	(0.015)	(0.006)	(0.004)	(0.016)	(0.004)	(0.009)	(0.002)	(0.018)	(0.011)	(0.003)
LAWSCORE	0.000	0.000	-0.001**	0.007***	-0.001**	-0.000	0.000	-0.005***	0.004***	-0.000
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Labor_Law_Effect	-0.010***	-0.001	0.001*	0.004***	-0.000	-0.003***	0.000	0.007***	-0.005***	-0.001***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Constant	0.575***	0.028	0.099***	-0.128	0.076**	-0.009	0.007	0.321**	-0.024	-0.002
	(0.111)	(0.044)	(0.029)	(0.111)	(0.034)	(0.063)	(0.016)	(0.133)	(0.081)	(0.024)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,910	14,910	14,910	14,910	14,910	14,910	14,910	14,910	12,026	8,303

Table 7: SEOs and the Number of Employees

This table reports the second-stage estimation of the impact SEOs have on the number of employees. The dependent variables are the total number of employees in Column (1), production workers in Column (2), administration staff in Column (3), R&D staff in Column (4), technicians in Column (5), managers in Column (6), sales persons in Column (7), finance staff in Column (8), employees in other occupations in Column (9), employees with bachelor degree or above in Column (10), and employees with post-graduate degrees in Column (11). All dependent variables are logged, and all regressions include firm- and year- fixed effects. Regressions in Panel A control for firm age and legal environments. Regressions in Panel B add the full set of time-varying firm characteristic variables. Variable definitions are provided in Appendix 1. The first-stage regression results are reported in Appendix 2. The sample period covers 2000 – 2012. Bootstrapping 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(R&D)	Ln(Technician)	Ln(Managers)	Ln(Sales)	Ln(Finance)	Ln(Others)	Ln(BA)	Ln(Grad)
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
$\widehat{SEO}$	-0.053	-0.570***	-1.553***	0.337***	-0.301*	0.729***	-0.334**	-0.274*	-0.296	-0.026	0.057
	(0.044)	(0.146)	(0.218)	(0.110)	(0.172)	(0.217)	(0.162)	(0.151)	(0.184)	(0.060)	(0.076)
Ln(NYEAR_LISTED)	0.248***	0.375***	0.534***	-0.121***	0.290***	-0.218**	0.087	0.298***	0.589***	0.136***	0.171***
	(0.022)	(0.081)	(0.082)	(0.047)	(0.066)	(0.093)	(0.074)	(0.060)	(0.099)	(0.038)	(0.036)
Ln(MIN_WAGE)	-0.123**	-0.093	0.376	-0.361***	0.336*	-0.036	0.245*	0.183	-0.428	0.173*	0.320***
	(0.055)	(0.188)	(0.240)	(0.068)	(0.196)	(0.216)	(0.146)	(0.121)	(0.274)	(0.097)	(0.112)
LAWSCORE	-0.022***	-0.018	0.033*	-0.020***	0.034**	-0.021	0.043**	-0.001	-0.037	0.002	-0.027**
	(0.006)	(0.018)	(0.018)	(0.007)	(0.014)	(0.020)	(0.019)	(0.012)	(0.024)	(0.010)	(0.011)
Labor_Law_Effect	-0.005	-0.120***	-0.035**	0.013*	0.007	0.013	-0.042***	0.016*	0.061***	-0.038***	-0.037***
	(0.005)	(0.018)	(0.015)	(0.007)	(0.013)	(0.015)	(0.012)	(0.009)	(0.015)	(0.005)	(0.007)
Constant	8.289***	6.949***	0.559	3.085***	2.058	1.939	2.667**	1.736**	3.139	4.753***	1.790**
	(0.377)	(1.360)	(1.722)	(0.504)	(1.415)	(1.499)	(1.065)	(0.881)	(1.975)	(0.718)	(0.798)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	17,398	14,934	14,934	14,934	14,934	14,934	14,934	14,934	14,934	12,077	8,313

Panel B

VARIABLES	Ln(EMP) (1)	Ln(Production) (2)	Ln(Staff) (3)	Ln(R&D) (4)	Ln(Technician) (5)	Ln(Managers) (6)	Ln(Sales) (7)	Ln(Finance) (8)	Ln(Others) (9)	Ln(BA) (10)	Ln(Grad) (11)
$\widehat{SEO}$	-0.098**	-0.633***	-1.498***	0.303***	-0.286*	0.764***	-0.364***	-0.216*	-0.338*	-0.014	0.065
	(0.041)	(0.130)	(0.223)	(0.107)	(0.162)	(0.210)	(0.130)	(0.114)	(0.197)	(0.073)	(0.069)
Ln(NYEAR_LISTED)	0.116***	0.222***	0.430***	-0.134***	0.158**	-0.278***	0.022	0.203***	0.505***	-0.006	0.034
	(0.019)	(0.076)	(0.106)	(0.039)	(0.064)	(0.092)	(0.067)	(0.057)	(0.100)	(0.043)	(0.041)
Ln(SALES)	0.417***	0.341***	0.158***	0.029*	0.421***	0.180***	0.284***	0.243***	0.230***	0.412***	0.397***
	(0.019)	(0.041)	(0.034)	(0.017)	(0.028)	(0.034)	(0.031)	(0.021)	(0.052)	(0.017)	(0.020)
ROE	-0.298***	-0.437***	-0.126	0.088	-0.213**	-0.115	-0.117	-0.134*	-0.435***	-0.176***	-0.245***
	(0.039)	(0.139)	(0.136)	(0.061)	(0.084)	(0.133)	(0.103)	(0.080)	(0.149)	(0.061)	(0.057)
Leverage	0.319***	-0.234	-0.079	0.134*	0.194	0.267	0.162	0.341***	0.662***	0.457***	0.293***
	(0.062)	(0.193)	(0.174)	(0.070)	(0.130)	(0.193)	(0.130)	(0.095)	(0.220)	(0.101)	(0.105)
PPE/TA	0.486***	1.329***	0.645***	0.150***	0.299*	-0.212	-0.177	-0.146	-0.183	0.240***	-0.105
	(0.054)	(0.180)	(0.165)	(0.047)	(0.167)	(0.155)	(0.142)	(0.114)	(0.226)	(0.083)	(0.119)
SALES_GR	-0.096***	-0.131***	0.001	-0.016	-0.079***	-0.063**	-0.134***	-0.039*	-0.022	-0.061***	-0.051***
	(0.013)	(0.035)	(0.037)	(0.016)	(0.027)	(0.032)	(0.026)	(0.021)	(0.037)	(0.014)	(0.017)
%_IND_DIR	0.018	-0.256	-0.348	0.043	0.303**	-0.082	0.146	0.053	-0.116	0.084	0.055
	(0.053)	(0.219)	(0.235)	(0.102)	(0.138)	(0.186)	(0.171)	(0.116)	(0.249)	(0.090)	(0.113)
%_STATE_OWN	0.118***	0.160	0.115	0.086*	-0.065	0.011	0.117	0.134**	0.344**	0.063	0.023
	(0.026)	(0.112)	(0.096)	(0.047)	(0.076)	(0.096)	(0.103)	(0.059)	(0.135)	(0.041)	(0.043)
%_LARGEST_SH	0.114*	-0.895***	0.127	-0.169	0.024	-0.306	0.005	0.198	1.013***	0.221*	-0.038
	(0.065)	(0.273)	(0.245)	(0.126)	(0.190)	(0.226)	(0.178)	(0.161)	(0.320)	(0.118)	(0.120)
NONTRDPCT	0.027	0.040	-0.490***	-0.022	0.108	0.091	-0.343***	-0.162*	-0.341*	-0.076	-0.024
	(0.049)	(0.120)	(0.182)	(0.070)	(0.126)	(0.170)	(0.107)	(0.089)	(0.192)	(0.076)	(0.068)
D_PRIVATE_PLACE	0.096***	0.114	-0.102	0.049	0.166**	0.109	-0.012	0.068	-0.067	0.066*	0.089***
	(0.021)	(0.076)	(0.072)	(0.049)	(0.066)	(0.101)	(0.063)	(0.053)	(0.083)	(0.036)	(0.034)
DIVPRT	0.005	0.009	0.018	-0.002	0.006	-0.009	-0.001	0.008	-0.008	0.005	-0.003
	(0.012)	(0.021)	(0.018)	(0.013)	(0.020)	(0.023)	(0.021)	(0.018)	(0.023)	(0.007)	(0.015)
Ln(MIN_WAGE)	-0.265***	-0.168	0.348*	-0.373***	0.219	-0.104	0.175	0.107	-0.504**	0.020	0.235**
	(0.043)	(0.189)	(0.201)	(0.100)	(0.184)	(0.201)	(0.180)	(0.128)	(0.250)	(0.089)	(0.091)
LAWSCORE	-0.013***	-0.000	0.038**	-0.017**	0.044***	-0.018	0.049***	0.002	-0.040	0.025***	-0.014
	(0.005)	(0.018)	(0.017)	(0.008)	(0.014)	(0.018)	(0.015)	(0.012)	(0.026)	(0.009)	(0.010)
Labor_Law_Effect	-0.001	-0.107***	-0.033**	0.015**	0.011	0.016	-0.043***	0.016*	0.062***	-0.037***	-0.032***
	(0.003)	(0.016)	(0.014)	(0.006)	(0.013)	(0.011)	(0.014)	(0.009)	(0.015)	(0.006)	(0.007)
Constant	6.131***	5.144***	-0.339	2.915***	-0.294	1.308	1.152	0.519	1.812	2.590***	-0.441
	(0.313)	(1.369)	(1.446)	(0.719)	(1.292)	(1.427)	(1.299)	(0.920)	(1.887)	(0.653)	(0.597)
Firm & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	17,366	14,910	14,910	14,910	14,910	14,910	14,910	14,910	14,910	12,063	8,306

Table 8: SEOs and Innovations.

This table reports the second-stage estimation of the impact SEOs have on corporate innovations. The dependent variable is the log of total patents granted in t+2 in Columns (1) and (2), invention patents, utility model patents, and design patents granted in t+2 in Columns (3) - (5), respectively. Variable definitions are provided in Appendix 1. The first-stage regression results are reported in Appendix 2. The sample period covers 2000 – 2012. All regressions include firm- and year- fixed effects. Bootstrapping standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5% and 1%, respectively.

	Ln(Total_Patent)$_{t+2}$		**Ln(Invention)$_{t+2}$**	**Ln(Utility Model)$_{t+2}$**	**Ln(Design)$_{t+2}$**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
$\widehat{SEO}$	0.324***	0.125*	0.117**	0.131**	-0.009
	(0.122)	(0.075)	(0.058)	(0.062)	(0.039)
Ln(NYEAR_LISTED)	0.161***	0.191***	0.159***	0.145***	-0.004
	(0.031)	(0.031)	(0.024)	(0.028)	(0.014)
Ln(SALES)		0.030***	0.028***	0.021***	0.002
		(0.010)	(0.006)	(0.007)	(0.004)
ROE		0.009	0.024	-0.017	0.001
		(0.023)	(0.018)	(0.024)	(0.014)
Leverage		0.035	0.002	0.034	0.019
		(0.050)	(0.041)	(0.041)	(0.034)
PPE/TA		-0.086	0.010	-0.136***	-0.040
		(0.064)	(0.029)	(0.031)	(0.028)
SALES_GR		-0.012*	-0.016***	-0.008	-0.001
		(0.007)	(0.006)	(0.006)	(0.004)
%_IND_DIR		-0.074	-0.124**	-0.017	-0.022
		(0.086)	(0.059)	(0.052)	(0.040)
%_STATE_OWN		-0.063	-0.055	-0.067**	-0.022
		(0.040)	(0.035)	(0.031)	(0.020)
%_LARGEST_SH		-0.114	-0.105**	-0.086*	0.024
		(0.076)	(0.049)	(0.052)	(0.039)
NONTRDPCT		-0.106**	-0.041	-0.067**	-0.041
		(0.047)	(0.033)	(0.029)	(0.030)
D_PRIVATE_PLACE		0.045	0.060**	0.043	-0.006
		(0.033)	(0.030)	(0.031)	(0.019)
DIVPRT		-0.021**	-0.023*	-0.007	0.002
		(0.011)	(0.012)	(0.010)	(0.006)
Ln(MIN_WAGE)	0.139*	0.137**	0.030	0.091	0.101***
	(0.077)	(0.066)	(0.048)	(0.061)	(0.037)
LAWSCORE	-0.001	0.001	0.004	-0.004	0.001
	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)
Labor_Law_Effect	-0.008**	-0.007**	-0.001	-0.005*	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
Constant	-0.501	-0.691	-0.200	-0.468	-0.501**
	(0.519)	(0.468)	(0.343)	(0.416)	(0.254)
Firm & Year FE	Y	Y	Y	Y	Y
Observations	13,075	13,046	13,046	13,046	13,046

Table 9: SEOs and Average Wages.

This table reports the second-stage estimation of the impact SEOs have on firm average wages. The dependent variable is the log of average wages of all employees in Columns (1) and (2); the log of average wages of non-executive employees in Column (3); the log of average wages of executives in Column (4). Variable definitions are provided in Appendix 1. The first-stage estimation results are reported in Appendix 2. The sample period covers 2000 – 2012. All regressions include firm- and year- fixed effects. Bootstrapping standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5% and 1%, respectively.

	Ln(AWAGE)		**Ln(AWAGE_NonExe)**	**Ln(AEXEPAY)**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
$\widehat{SEO}$	0.091**	0.094**	0.118***	0.037
	(0.037)	(0.039)	(0.045)	(0.058)
Ln(NYEAR_LISTED)	-0.010	-0.012	-0.022	-0.071***
	(0.018)	(0.017)	(0.024)	(0.022)
Ln(SALES)		0.120***	0.122***	0.176***
		(0.012)	(0.015)	(0.009)
ROE		0.116***	0.094**	0.304***
		(0.040)	(0.037)	(0.032)
Leverage		-0.172***	-0.164***	-0.053
		(0.043)	(0.058)	(0.034)
PPE/TA		-0.116**	-0.080	-0.176***
		(0.052)	(0.050)	(0.046)
SALES_GR		-0.006	-0.006	-0.033***
		(0.009)	(0.011)	(0.009)
%_IND_DIR		0.001	-0.008	0.001
		(0.043)	(0.051)	(0.043)
%_STATE_OWN		0.035*	0.034	-0.025
		(0.021)	(0.027)	(0.022)
%_LARGEST_SH		0.212***	0.244***	0.047
		(0.063)	(0.057)	(0.058)
NONTRDPCT		-0.075**	-0.048	-0.028
		(0.031)	(0.037)	(0.028)
D_PRIVATE_PLACE		-0.020	-0.014	0.006
		(0.016)	(0.016)	(0.015)
DIVPRT		0.001	0.000	0.005
		(0.010)	(0.010)	(0.004)
Ln(MIN_WAGE)	0.330***	0.302***	0.288***	0.141***
	(0.042)	(0.043)	(0.040)	(0.046)
LAWSCORE	-0.010**	-0.009**	-0.012**	-0.027***
	(0.005)	(0.005)	(0.005)	(0.004)
Labor_Law_Effect	0.008**	0.001	-0.001	0.011***
	(0.004)	(0.003)	(0.003)	(0.002)
Constant	-0.433	-1.109***	-1.007***	-3.563***
	(0.300)	(0.362)	(0.310)	(0.334)
Firm & Year FE	Y	Y	Y	Y
Observations	17,384	17,352	16,301	15,442

Table 10: Implied Wages by Occupation and Education.

This table estimates implied average wages for each occupation and education level. Coefficients in Column (1) are implied average wages for each occupation. Coefficients in Column (2) are implied average wages for each educational level. The regressions are the OLS estimations without constant. Variable definitions are provided in Appendix 1. The sample period covers 2000 – 2012. Standard errors clustered at firm level are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5% and 1%, respectively.

	AWAGE	
VARIABLES	**(1)**	**(2)**
%_Production	1.695***	
	(0.335)	
%_Staff	7.513***	
	(2.884)	
%_R&D	9.588***	
	(1.108)	
%_Technician	8.831***	
	(1.071)	
%_Managers	13.763***	
	(2.748)	
%_Sales	0.504	
	(1.274)	
%_Financial	64.909***	
	(13.502)	
%_Others	5.292***	
	(0.665)	
%_Grad		55.584***
		(12.908)
%_UnderGrad		9.794***
		(1.883)
%_Below_UnderGrad		3.903***
		(0.232)
Observations	15,035	7,667
Adjusted R-squared	0.359	0.429

Table 11: SEOs and Total Wages.

This table reports the second-stage estimation of the impact SEOs have on total wages. The dependent variable is the log of total wages to all employees in Columns (1) and (2); the log of total wages to all non-executive employees in Column (3); the log of total wages to all executives in Column (4). Variable definitions are provided in Appendix 1. The first-stage estimation results are reported in Appendix 2. The sample period covers 2000 – 2012. All regressions include firm- and year fixed effects. Bootstrapping standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5% and 1%, respectively.

	Ln(Payroll)		**Ln(Payroll_NonExe)**	**Ln(Payroll_Exe)**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
$\widehat{SEO}$	0.021	-0.013	-0.006	0.001
	(0.046)	(0.036)	(0.038)	(0.044)
Ln(NYEAR_LISTED)	0.245***	0.107***	0.103***	-0.045**
	(0.023)	(0.019)	(0.019)	(0.021)
Ln(SALES)		0.538***	0.551***	0.214***
		(0.015)	(0.017)	(0.014)
ROE		-0.182***	-0.207***	0.271***
		(0.030)	(0.041)	(0.037)
Leverage		0.152***	0.178***	0.021
		(0.041)	(0.049)	(0.051)
PPE/TA		0.374***	0.403***	-0.143***
		(0.047)	(0.037)	(0.048)
SALES_GR		-0.099***	-0.096***	-0.039***
		(0.010)	(0.012)	(0.010)
%_IND_DIR		0.016	-0.004	0.088*
		(0.040)	(0.044)	(0.051)
%_STATE_OWN		0.154***	0.151***	-0.015
		(0.021)	(0.021)	(0.023)
%_LARGEST_SH		0.336***	0.353***	0.044
		(0.062)	(0.073)	(0.069)
NONTRDPCT		-0.050	-0.031	-0.101***
		(0.035)	(0.035)	(0.033)
D_PRIVATE_PLACE		0.076***	0.078***	0.007
		(0.017)	(0.019)	(0.016)
DIVPRT		0.006*	0.006	0.006
		(0.004)	(0.004)	(0.006)
Ln(MIN_WAGE)	0.205***	0.034	0.021	0.092*
	(0.053)	(0.042)	(0.043)	(0.055)
LAWSCORE	-0.030***	-0.020***	-0.022***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.004)
Labor_Law_Effect	0.002	0.001	0.003	0.013***
	(0.003)	(0.003)	(0.003)	(0.004)
Constant	3.242***	0.408	0.377	-1.010***
	(0.395)	(0.316)	(0.289)	(0.388)
Firm & Year FE	Y	Y	Y	Y
Observations	17,485	17,453	16,464	15,511

Table 12: Pre-Trends.

This table reports the results of placebo tests for pre-trends with the full set of control variables. The sample period covers 2000 – 2005.Variable definitions are provided in Appendix 1. Robust standard errors clustered at the firm level are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5% and 1%, respectively.

	%_Production	%_Staffs	%_R&D	%_Technician	%_Managers	%_Sales	%_Financial	%_Others	%_BA	%_Grad	Ln(EMP)	Ln(Total_Patent)$_{t+2}$	Ln(AWAGE)	Ln(Payroll)
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**
Affected*Year01	0.002	-0.009	-0.002	0.002	0.007	0.005	-0.002	-0.004	0.003	0.003	0.007	-0.002	-0.027	-0.002
	(0.018)	(0.006)	(0.002)	(0.014)	(0.005)	(0.010)	(0.002)	(0.017)	(0.013)	(0.005)	(0.036)	(0.032)	(0.041)	(0.031)
Affected*Year02	-0.019	-0.004	-0.003	0.015	-0.001	0.010	-0.001	0.006	0.006	0.005	-0.030	-0.024	-0.032	-0.046
	(0.020)	(0.007)	(0.003)	(0.016)	(0.006)	(0.012)	(0.002)	(0.018)	(0.014)	(0.005)	(0.044)	(0.038)	(0.045)	(0.035)
Affected*Year03	-0.026	-0.008	-0.003	0.017	0.003	0.014	-0.000	0.004	-0.007	-0.000	-0.020	-0.065	-0.054	-0.056
	(0.021)	(0.007)	(0.003)	(0.017)	(0.006)	(0.012)	(0.002)	(0.018)	(0.014)	(0.006)	(0.049)	(0.040)	(0.049)	(0.036)
Affected*Year04	-0.024	-0.000	-0.005	0.020	-0.001	0.008	-0.002	-0.001	-0.010	-0.003	-0.047	-0.046	-0.025	-0.052
	(0.023)	(0.008)	(0.004)	(0.018)	(0.007)	(0.013)	(0.002)	(0.019)	(0.016)	(0.006)	(0.055)	(0.046)	(0.055)	(0.042)
Affected*Year05	-0.016	-0.000	-0.005	0.018	-0.006	0.005	0.000	-0.002	-0.012	-0.001	-0.051	-0.075	-0.040	-0.071
	(0.024)	(0.008)	(0.003)	(0.019)	(0.007)	(0.014)	(0.003)	(0.021)	(0.017)	(0.005)	(0.060)	(0.050)	(0.057)	(0.044)
Constant	0.493**	0.013	0.022	0.317*	0.079	-0.023	0.046**	0.026	0.147	0.036	5.517***	-0.113	-0.784	0.165
	(0.196)	(0.072)	(0.022)	(0.176)	(0.057)	(0.127)	(0.022)	(0.176)	(0.102)	(0.044)	(0.487)	(0.596)	(0.504)	(0.425)
Firm FE, Year FE, and other controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,129	5,129	5,129	5,129	5,129	5,129	5,129	5,129	3,202	2,149	5,903	5,872	5,896	5,959
Adjusted R-squared	0.817	0.565	0.753	0.721	0.580	0.758	0.705	0.517	0.891	0.874	0.911	0.741	0.827	0.939

Table 13: Other Robustness Tests.

This table reports second-stage estimation results using alternative definitions of SEO and alternative instruments for SEO. Column (1) shows dependent variables for each alternative definition. The remaining columns report the coefficients on the predicted SEO with the full set of control variables. Column (2) excludes small SEOs with proceeds in the bottom decile; Column (3) defines only the year following SEO as the SEO year; Column (4) defines only 2008 and 2010 as years affected by the 2006 and 2008 regulation, respectively; Column (5) uses one-year lag between shocks and the availability of SEO proceeds, e.g., *IV_SEO* turns on 2009 and 2010 for firms affected by the 2008 regulation; Column (6) relies only on the 2006 regulation to construct an instrument. Variable definitions are provided in Appendix 1. The sample period covers 2000 – 2012. Bootstrapping standard errors are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5% and 1%, respectively.

	Independent Variable: SEO^				
DEP VARIABLES	**Exclude small SEOs**	**Only the Year after an SEO as the SEO Year**	**Only 2008 and 2010 as Years a Affected by the 2006 and 2008 Regulations**	**Using One-Year Lag**	**IV is Based Only on the 2006 Regulation**
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
%_Production	-0.043***	-0.043***	-0.048***	-0.044***	-0.047***
	(0.014)	(0.012)	(0.013)	(0.014)	(0.015)
N	14,910	14,910	14,910	14,910	14,910
%_Staff	-0.024***	-0.022***	-0.025***	-0.025***	-0.026***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
N	14,910	14,910	14,910	14,910	14,910
%_R&D	0.010*	0.007*	0.009*	0.012**	0.011**
	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)
N	14,910	14,910	14,910	14,910	14,910
%_Technician	0.026**	0.028**	0.028**	0.020*	0.025*
	(0.012)	(0.011)	(0.013)	(0.012)	(0.015)
N	14,910	14,910	14,910	14,910	14,910
%_Managers	0.018***	0.017***	0.021***	0.021***	0.021***
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)
N	14,910	14,910	14,910	14,910	14,910
%_Sales	0.002	0.001	0.002	0.003	0.002
	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)
N	14,910	14,910	14,910	14,910	14,910
%_Financial	0.001	0.000	0.000	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
N	14,910	14,910	14,910	14,910	14,910
%_Others	-0.001	0.003	0.000	0.001	0.001
	(0.017)	(0.011)	(0.016)	(0.015)	(0.017)
N	14,910	14,910	14,910	14,910	14,910
%_BA	0.002	-0.003	0.003	-0.002	0.001
	(0.009)	(0.006)	(0.008)	(0.008)	(0.008)
N	12,026	12,026	12,026	12,026	12,026
%_Grad	0.006*	0.005**	0.005**	0.005**	0.005**
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
N	8,303	8,303	8,303	8,303	8,303
Ln(EMP)	-0.100**	-0.094**	-0.130***	-0.091*	-0.130***
	(0.051)	(0.038)	(0.041)	(0.048)	(0.046)
N	17,366	17,366	17,366	17,366	17,366
Ln(Total_Patent)$_{t+2}$	0.199*	0.289***	0.139*	0.161**	0.173**
	(0.111)	(0.074)	(0.079)	(0.081)	(0.077)
N	11,087	11,185	11,185	11,185	11,185
Ln(AWAGE)	0.093**	0.095***	0.104***	0.101***	0.110***
	(0.037)	(0.030)	(0.030)	(0.036)	(0.035)
N	17,352	17,352	17,352	17,352	17,352
Ln(Payroll)	-0.017	0.003	-0.034	0.002	-0.028
	(0.039)	(0.029)	(0.032)	(0.033)	(0.039)
N	17,453	17,453	17,453	17,453	17,453

Appendices

Appendix 1: Variable definitions.

Variables	Definition	Sources
SEO-related Variables		
JP_SEO	An indicator variable equal to one in the year in which an SEO (public or private placement) proceeds are received), and zero otherwise.	CSMAR
SEO	An indicator equal to one in SEO (only public offerings) years (the year in which SEO proceeds are received and two years after), and zero otherwise.	CSMAR
IV_SEO	It is equal to one in 2010 (or 2011) for all firms affected (i.e., became ineligible to issue SEOs) by the 2008 regulation in 2008 (or in 2009). For all firms affected (became ineligible to issue SEOs) by the 2006 regulation in 2006 (or in 2007), it is equal to one in 2008 (or in 2009). Firms were affected by the 2008 regulation if the ratio of total dividends over the past three years to the average annual distributable profits over the past three years was less than 30%. Firms were affected by the 2006 regulation if the ratio of total dividends over the past three years to the average annual distributable profits over the past three years was less than 20%.	Wind
Key Dependent Variables		
Adv_Computer_Dum	The indicator of the presence of words indicating advanced computer skills in the job description.	Lagou.com
Ln(Adv_Computer)	The log of one plus the number of words indicating advanced computer skills in the job description.	Lagou.com
Basic_Computer_Dum	The indicator of the presence of words indicating basic computer skills in the job description.	Lagou.com
Ln(Basic_Computer)	The log of one plus the number of words indicating advanced computer skills in the job description.	Lagou.com
Non-routine Analytical Task Skill_Dum	The indicator of the presence of words indicating non-routine analytical task skills in the job description.	Lagou.com
Ln(Non-routine Analytical Task Skills)	The log of one plus the number of words indicating non-routine analytical task skills in the job description.	Lagou.com
Non-routine Interactive Task Skill_Dum	The indicator of the presence of words indicating non-routine interactive task skills in the job description.	Lagou.com
Ln(Non-routine Interactive Task Skills)	The log of one plus the number of words indicating non-routine interactive task skills in the job description.	Lagou.com
%_BA	The fraction of employees with four-year university undergraduate degree or above.	Resset
%_Grad	Fraction of employees with post-graduate degrees.	Resset
%_Production	Fraction of production workers.	Resset
%_Managers	Fraction of managers.	Resset
%_Staff	Fraction of administration staff.	Resset
%_Marketing	Fraction of sales persons.	Resset
%_R&D	Fraction of employees working on R&D.	Resset
%_Technician	Fraction of technicians (including engineers and IT staffs).	Resset

Appendix 1: Variable definitions (Continued)

Variables	Definition	Variables
%_Finance	Fraction of staff working on accounting and financial issues.	Resset
%_Others	Fraction of employees with unidentified occupation.	Resset
Ln(EMP)	Log of total number of employees.	Resset
Ln(BA)	Log of one plus the number of employees with four-year university undergraduate degree or above.	Resset
Ln(Grad)	Log of one plus the number of employees with post-graduate degrees.	Resset
Ln(Production)	Log of one plus the number of production workers.	Resset
Ln(Managers)	Log of one plus the number of managers.	Resset
Ln(Staff)	Log of one plus the number of administration staff.	Resset
Ln(Sales)	Log of one plus the number of sales persons.	Resset
Ln(R&D)	Log of one plus the number of employees working on R&D.	Resset
Ln(Technician)	Log of one plus the number of technicians (including engineers and IT staffs).	Resset
Ln(Financial)	Log of one plus the number of employees working on accounting and financial issues.	Resset
Ln(Others)	Log of one plus the number of employees with unidentified occupation.	Resset
AWAGE	Average cash compensation for all employees, deflated using 2000 as the base year. Unit: 10,000 RMB.	Resset
AWAGE_NonEXE	Average cash compensation for all non-top-executive employees, deflated using 2000 as the base year. Unit: 10,000 RMB.	Resset
AEXEPAY	Average cash compensation of all top executives, deflated using 2000 as the base year. Unit: 1,000,000 RMB.	Resset
Ln(Payroll)	Log of total wage to all employees, deflated using 2000 as the base year. Unit: 1,000,000 RMB.	Resset
Ln(Payroll_NonExe)	Log of total wage to non-executive employees, deflated using 2000 as the base year. Unit: 1,000,000 RMB.	Resset
Ln(Payroll_Exe)	Log of total wage to top executives, deflated using 2000 as the base year. Unit: 1,000,000 RMB.	Resset
Ln(Total_Patent)	Log of one plus the number of patents granted.	Baiten
Ln(Invention)	Log of one plus the number of invention patents granted.	Baiten
Ln(Utility_Model)	Log of one plus the number of utility model patents granted.	Baiten
Ln(Design)	Log of one plus the number of design patents granted.	Baiten
NYEAR_LISTED	The number of years a firm is listed since its IPO.	Resset
SALES	Total sales, deflated using 2000 as the base year. Unit: 10,000 RMB.	Resset
LEVERAGE	Ratio of total debts (short term debt + long term debt) to total assets.	Resset
ROE	Return on equity: the ratio of net income to the book value of equity.	Resset
PPE/TA	Ratio of tangible asset (properties, plants, and equipment) to total assets.	Resset
SALES_GR	Sales growth rate from year t-1 to year t.	Resset
%_IND_DIR	Percentage of independent directors on the board.	Resset

Appendix 1: Variable definitions (Continued)

Variables	Definition	Sources
%_STATE_OWN	Percentage of shares held by the government.	Resset
%_LARGEST_SH	Percentage of shares held by the largest shareholder.	Resset
NONTRDPCT	Percentage of non-tradable shares.	Resset
D_PRIVATE_PLACE	An indicator variable equal to one if the firm conducted private placement in a given year.	CSMAR
DIVPRT	Dividend payout ratio, equal to total dividend paid over net income.	Resset
MIN_WAGE	The minimum wage of the province where the firm's headquarters is located in a given year, deflated using 2000 as the base year. Unit: Yuan RMB.	Provincial Governme nt Webpage
LAWSCORE	An index for the strength of legal environment, as measured by the number of lawyers as a percentage of the population, the efficiency of the local courts and protection of property rights, for each province or provincial level region. Higher scores indicate more developed legal institutions and stronger law enforcement. The index has been updated by the National Economic Research Institute up to 2009, so for years after 2009, we use the 2009 index.	The National Economic Research Institute
Labor_Law_Effect	The degree to which the Labor Law of People's Republic, effective January 1, 2008, affects a firm's employment and wages. It is equal to the industry average ratio of the total number of employees to the value of all fixed assets in 2007 multiplied by a post-2008 indicator, which is one for 2008 through 2012 and zero otherwise..	CSMAR
Affected	An indicator equal to one for firms affected by the 2006 regulation; zero otherwise	WIND

Appendix 2: First-stage Regressions.

This table reports the first stage regression results. Column (1) reports the first stage results for Panel A of Table 6, Panel A of Table 7, Column (1) of Tables 8, 10, and 11. Column (2) reports the first stage results for Panel B of Table 6, Panel B of Table 7, Columns (2)-(5) of Table 8, Columns (2)-(4) of Table 10, and Columns (2)-(4) of Table 11. Columns (3)-(7) report the first-stage results for Columns (2)-(6) of Table 13, respectively. 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)**	**(7)**
IV_SEO	-1.707***	-1.377***	-1.348***	-1.410***	-1.481***	-1.439***	-0.963**
	(0.387)	(0.404)	(0.401)	(0.457)	(0.548)	(0.459)	(0.429)
ln(NYEAR_LISTED)	4.515***	4.313***	4.147***	5.013***	4.343***	4.311***	4.361***
	(0.427)	(0.441)	(0.435)	(0.531)	(0.442)	(0.441)	(0.444)
ln(SALES)		0.888***	0.885***	0.718***	0.928***	0.874***	0.922***
		(0.164)	(0.158)	(0.152)	(0.162)	(0.162)	(0.161)
ROE		-1.475***	-1.466***	-1.053***	-1.530***	-1.516***	-1.500***
		(0.400)	(0.389)	(0.356)	(0.395)	(0.403)	(0.390)
Leverage		-2.236***	-2.094***	-0.023	-2.173***	-2.239***	-2.167***
		(0.783)	(0.772)	(0.714)	(0.780)	(0.785)	(0.782)
PPE/TA		1.064	1.159	2.330***	1.087	1.146	1.078
		(0.805)	(0.802)	(0.768)	(0.805)	(0.800)	(0.806)
SALES_GR		-0.352***	-0.364***	-0.388***	-0.379***	-0.357***	-0.366***
		(0.113)	(0.111)	(0.117)	(0.112)	(0.113)	(0.112)
%_IND_DIR		-0.963	-0.999	-1.054*	-0.953	-0.950	-0.945
		(0.609)	(0.610)	(0.602)	(0.609)	(0.609)	(0.612)
%_STATE_OWN		-0.244	-0.324	-0.121	-0.231	-0.231	-0.230
		(0.417)	(0.412)	(0.400)	(0.413)	(0.419)	(0.415)
%_LARGEST_SH		-1.679	-1.349	0.273	-1.660	-1.730	-1.667
		(1.076)	(1.059)	(0.899)	(1.054)	(1.067)	(1.050)
NONTRDPCT		-1.862***	-1.666***	-0.678	-1.854***	-1.861***	-1.839***
		(0.581)	(0.577)	(0.550)	(0.582)	(0.582)	(0.583)
D_PRIVATE_PLACE		-0.964***	-0.954***	-0.317	-1.018***	-0.944***	-0.973***
		(0.266)	(0.264)	(0.276)	(0.269)	(0.278)	(0.270)
DIVPRT		0.146*	0.141*	0.159**	0.140*	0.147*	0.143*
		(0.079)	(0.078)	(0.074)	(0.077)	(0.080)	(0.079)
ln(MIN_WAGE)	0.997	1.111*	1.026	0.283	1.083*	1.061	1.060
	(0.630)	(0.656)	(0.662)	(0.619)	(0.656)	(0.656)	(0.653)
LAWSCORE	0.037	0.066	0.063	0.066	0.073	0.068	0.074
	(0.058)	(0.063)	(0.064)	(0.074)	(0.063)	(0.063)	(0.064)
Labor_Law_Effect	0.094	0.069	0.066	0.121*	0.062	0.067	0.062
	(0.067)	(0.073)	(0.071)	(0.073)	(0.072)	(0.074)	(0.073)
Year Dummy	Y	Y	Y	Y	Y	Y	Y
Observations	5,436	5,431	5,431	5,345	5,431	5,431	5,431
Pseudo R^2	0.360	0.391	0.376	0.376	0.389	0.391	0.391
Wald	579.3	604.6	577.2	46024	599.1	592.3	603.7

Appendix 3: Average Annual Wages by Education and Occupation.

This table reports average annual wage by education and 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 and the unit is Chinese RMB.

	Education			Occupation				
Year	College or above	High School	Middle School or below	Technician	Production Worker	Staff or Service Workers	Agricultural Workers	Other
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