# Stock Market and Demand for Skill

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November 18, 2021

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**ABSTRACT**

Stock price movements, even when driven by non-fundamental factors, can have pronounced effects on firms' investment decisions. We use detailed job posting data to examine changes in demand for skills around the 2015 A-share stock market crash in China, which was caused by deleveraging fire sales from speculative investors. Firms affected by these adverse shocks shift skill composition downward and replace high-skilled workers with low-skilled workers. The effect is stronger for financially constrained firms. The downward shift in skill composition coincides with an increase in wage premium demanded by high-skilled workers. The increase in skill premium is more substantial in locations that labor supply is lower and high-skilled workers have more bargaining power. Firms that are more adversely affected by the stock market crash also cut their technology investments and have worse performance in productivity and sales growth. Our results are robust when we adopt a fuzzy regression discontinuity design (RDD) in an instrumental variable approach to address the potential endogeneity concern. Our findings suggest that the stock market has real impacts on firm decisions and is far from a sideshow.

Keywords: Skill, Labor Composition, Technology Investment, Stock Market

# 1 Introduction

Understanding whether and how equity markets affect firms' investments, and, ultimately, productivity and long-term growth are among the most important questions in corporate finance. The literature provides a somewhat mixed answer (see the recent survey by Bond, Edmans, and Goldstein (2012)). Many papers show that stock market shocks significantly affect corporate investment decisions, while others have long argued that secondary stock market transactions are mostly a "sideshow" to the real economy.

The question is inherently challenging because stock prices are forward-looking and reflect future growth opportunities. A firm that expects changes in opportunities may respond by adjusting its labor force or investments. Therefore, linking firms' investment decisions with stock price movements can be subject to reverse causality. Also, both firm decisions and market prices can correlate with some omitted variables. For example, technology advancements can lead to higher market value and more hiring and technology adoption. To pin down the effect of stock prices on firm action, we need first to disentangle fluctuations in the stock price from variation in the underlying economic conditions that influence firm value.

In this paper, we use the stock market crash in the Chinese A-share market in 2015 to examine the role of non-fundamental shocks to stock prices on firms' decisions to hire and invest in technology. It is widely accepted that this crash was primarily driven by fire sales when the government decided to clean up the excessive use of financial leverage by speculative investors and did not reflect the prospect of the economy or firms' fundamental value. Thus, the crash provides a quasi-exogenous shock on stock prices that had little to do with the firms' fundamental value.

To examine changes in skill demand following the crash, we use a proprietary dataset that contains detailed job posting data from a large online job site in China. Based on regulations, employers in China must provide a wage range for each job post, together with job descriptions and skill requirements. We first use textual analysis to collect information on skill requirements for each job in a set of dimensions (including computer skills, cognitive skills, management skills, education, and experience). Then, we construct a comprehensive skill index at the job level using the estimated wage premium for each skill category (prior to the crash) as weights. The skill index allows us to compare changes in skill demand following the crash while controlling for occupation, location, and firm characteristics. To supplement the job-level evidence, we construct a firm-level skill index using the distribution of occupations and skill proxies for each occupation. China Securities Regulatory Commission (CSRC, the counterpart of the U.S. SEC) requires all firms publicly listed in the Chinese A-share stock market to report the number of employees by occupation in the annual reports. To examine the effect of stock prices on technology adoption and investments, we take advantage of China's disclosure regulation, requiring all publicly listed firms to provide detailed information by asset type on an annual basis. Specifically, we measure technology-related investments in three categories – R&D spending, investments in high-tech tangibles (computers, electronic equipment, R&D-related equipment, etc.), and investments in high-tech intangibles (computer software, technology with or without patents, patents, information management system, etc.).

We use a difference-in-differences (DiD) method to evaluate the effect of stock prices on firms' demand for skill and investments in technology. We compare changes before and after the stock market crash across firms disproportionally affected by the price shock. For job-level regressions, we control for a battery of fixed effects, including city–month, occupation–month, city–occupation, and firm fixed effects. The full panel of fixed effects helps eliminate potential trends in investment opportunities or labor market conditions so that we can measure the time-varying relative difference within each employer. For firm-level regressions, we control for year and firm fixed effects.

Using the job posting data, we find that firms that are more affected by the stock market crash have a 5.6% higher drop in skill index than less affected firms. We find similar results using the firm-level skill index. More affected firms significantly decrease the number of high-skilled workers employed and pay a lower average wage. At the same time, more affected firms also increase the number of low-skilled workers employed. One standard deviation increase in price drop during the crash relates to an 11.1% drop in high-skilled works, a 12.5% increase in low-skilled workers, and a 2.5% drop in the average wage. It suggests that firms with bigger drops in stock prices choose to substitute high-skilled workers with low-skilled workers, rendering to a less-sophisticated workforce. Correspondingly, firms with bigger drops in stock prices also cut more technology spending, in both R&D and high-tech investments, with a more substantial effect on the former. Acquisition of equipment decreases by 1.95% with a one-standard-deviation drop in stock price, while a one-standard-deviation drop in stock price is related to a 12.28% cut in R&D spending. Following firms over time, we find that more affected firms fare worse in productivity, sales growth, and market share, although most of the effect (other than productivity) only lasts for one year.

Taken together, our results suggest that firms that experienced more severe drops in stock price during the 2015 stock market crash respond by lowering their demand for skill and technology. What motivates these changes? One potential explanation is that substantial declines in stock prices increase the cost of external financing. Share pledge, where lenders hold pledged shares as collateral, is a popular way for equity holders, especially large controlling shareholders, to obtain funding in China. As stock prices drop, the amount a shareholder can borrow falls accordingly. Consistent with this hypothesis, we find that more constrained firms(young firms and firms that have participated in the share pledge market) exhibit more substantial declines in skill demand following the crash. It is also possible that declines in stock prices and the accompanying financial constraints increase the skill premium firms need to pay to hire talents. Indeed, the wage gap widened following the stock crash between high- and low-skilled workers in firms with bigger price drops. Our results are consistent with findings in Brown and Matsa (2016), who show that job seekers are reluctant to work in firms with poor financial conditions, and distressed firms face higher costs in recruiting for skilled positions.

We investigate two channels for the increase in the skill premium around the stock market crash. First, we show that high-skilled workers face higher transition costs from longer unemployment spell in the case of job separation. Second, high-skilled workers may have greater bargaining power compared to low-skilled workers. We show that the increase in the skill premium around the stock market crash is more substantial for firms located in provinces where labor supply is low and high-skilled workers have more bargaining power.

Although the 2015 stock market crash provides a useful setting to study the effect of stock prices on firm decisions, we still cannot fully rule out the endogeneity concerns. Firms that lose more value in stock may have other characteristics that make them more sensitive to the overall economic conditions. To address the remaining endogeneity concerns, we employ two empirical strategies. First, we perform the propensity score matching (PSM) to reduce heterogeneity along many dimensions. Specifically, we perform a one-to-one nearness neighbor matching based on the propensity score of price changes (above- or below-median) from a logit regression using firm characteristics measured at the end of 2014, the year prior to the crash. We find similar results as those from the OLS regressions.

Second, we combine the fuzzy regression discontinuity design (RDD) and the instrumental variable (IV) method to capture the local (close to the cutoff) exogenous variation. It is well accepted that the main driving force behind the Chinese stock market crash in 2015 was speculative investors' deleveraging-induced fire sales, and the most crucial root cause for the unforeseen amount of leverage in Chinese stock markets prior to the crash was the sharp rise in margin financing in 2014. In three rounds from 2010 to 2014, the Chinese government announced a series of criteria to qualify for margin trading and selected a fixed number of stocks according to these criteria. In the first stage, we compute an inclusion index based on the government's criteria to find potential candidates that qualify for margin trading. It is essentially a value-weighted average of a stock's market value and trading volume. We rank all candidate stocks based on the inclusion index and choose the same number of firms from the top of the list as in the actual number selected by the government. In the second stage, we predict the probability of having margin trading among the top candidates chosen and identify the fuzzy RDD threshold. We use the fuzzy RDD method in our context because although margin trading eligibility is closely related to the selection criteria, the assignment near the threshold is difficult to control precisely. For example, the government only provides the formula for inclusion index, but not the details on how relevant variables are calculated. In the last step, we perform a two-stage least square (2SLS) analysis using firms within the bandwidth of the threshold of the estimated marginablity. For 2SLS, we first use the predicted marginablity as an instrumental variable to predict the actual price drop during the crash. As expected, margin eligibility strongly predicts the extent to which a firm's stock price will be affected during the crash. Then, in the second stage, we use the instrumented stock price drop to estimate the relation between stock price drops and firms' actions. Consistently with our OLS setting, we find that firms with large price drop during the crash cut more in high-skilled labor, hire more low-skilled labor and invest less in high-tech investments.

We performed several tests to check the robustness of our findings. We eliminate firms with price changes in similar magnitudes but opposite directions before and after the crash to avoid the reversal effect. We use abnormal returns to measure firms' exposure to the stock market crash. We control for the confounding effects of two concurrent events: the implementation of Shanghai–Hong Kong Connection and the direct purchase plan by the national team during the stock market crash. We use the fraction (rather than the number) of high-skilled employees and use alternative occupation categories to define high- and low-skilled workers. Moreover, we construct alternative samples to exclude crash periods or only include firms that show up in the job posting data. We find qualitatively similar results in all of the tests.

Our paper contributes to the literature that examines the effect of stock prices on firm behaviors (see Bond, Edmans, and Goldstein (2012) for a recent survey). It provides new evidence that shocks, even unrelated to firms' fundamentals, may still lead to real changes in hiring and investment decisions. Our work is closely related to Hau and Lai (2013), who document the impact of extremely negative market conditions on total investment and total employment. We find consistent results using our data and provide new insights on how firms react to stock market crash through changes in skill demand, employee composition, technology-related investment, and R&D expenditures.

This paper is related to the empirical literature that studies the effect of financial shocks on skill premiums, most of which focus on the side of labor supply. Brown and Matsa (2016) find that distressed firms face more costs in recruiting for skilled positions as job seekers are reluctant to work in firms with poor financial conditions. Baghai et al. (2020) find that talented employees are more likely to abandon the firm when it suffers from financial distress. Consistent with their work, Gortmaker, Jeffers, and Lee (2020) find that high-skilled workers increase their networking effort when the firm faces credit deterioration. Our paper complements the existing literature by exploring responses to financial distress from the demand side and show that firms cut their demand for high-skilled labor in the presence of financial shocks.

Finally, our paper relates to concurrent literature that examines the 2015 Chinese stock market crash. Most of the existing work focuses on the cause of the stock market crash and its implications for market efficiency and asset pricing. Bian et al. (2018) use individual trading data to show that leverage-induced fire sales contribute to a major stock market crash. An, Bian, Lou, and Shi (2020) argue that the crash leads to a rise in wealth inequality among Chinese investors. Our study complements the literature by examining the effect of the crash on firm decisions.

The rest of this paper is organized as follows. Section 2 presents the institutional background. Section 3 presents the data and variable construction. Section 4 presents the regression specifications. Section 5 shows the main results, and Section 6 presents the evidence on exploring the mechanisms. Section 7 addresses endogeneity concerns, Section 8 presents robustness tests, and Section 9 concludes.

## 2 Institutional Background

In this section, we provide the institutional backgrounds on the Chinese stock market crash starting in the middle of 2015. China's stock market has experienced dramatic growth during the last 20 years, becoming the second-largest stock market around the world. Unlike developed stock markets, it is well known for its speculative nature manipulated by speculators (Carpenter and Whitelaw, 2017). According to the Shanghai Stock Exchange Annual Statistics 2015, trading volume from unsophisticated retail investors account for around 85% of the total volume. China's stock market has allowed investors to buy some stocks on margin via brokerage firms starting from March 2010. An investor needs to meet several requirements to obtain margin financing, so some investors use leverage in the off-exchange margin system and keep a much higher leverage ratio, leading to a market crash in 2015.

In the summer of 2014, the Chinese A-share stock market ended the bear market since the global financial crisis in 2008 and started to experience a bull market from mid-2014 to mid-2015. As shown in Panel A of Figure 1, the solid red line shows that the Shanghai Security Exchange Composite Index (SSECI) closed at 2,048 on Jun. 30th of 2014 and skyrocketed to 5,166 on June 12th of 2015, a 152% increase. It is widely believed that the super bull market is attributed to four factors (Huang, Miao, and Wang, 2016). First, the Third Plenum of the 18th Communist Party of China Conference announced that the government would deepen economic and social reforms, especially for sluggish state-owned firms. This is a good sign for the long-term economic growth and the stock market because many state-owned firms are publicly listed firms. Next, the Chinese central bank (People's Bank of China, PBC for short) started to release monetary policy after years of tightening. PBC implemented a series of monetary policies from November 22, 2014, to March 1, 2015. Third, numerous new trading accounts were opened by Chinese retail investors. From June 30th, 2014 to May 29th, 2015, 38.08 million investors entered the Chinese A-share market, carrying a large amount of money that became a driving force for the hot stock market. The new entrants are unsophisticated and inexperienced in investing in stocks and prefer radical investment strategies, contributing to the speculative bubble. The last driving force is considered as the most important one, the rising margin financing activities in China (Bian, He, Shue, and Zhou, 2018; Song and Xiong, 2018).

[Insert Figure 1 here]

Margin trading and short-selling were introduced in the Chinese A-share stock market on January 8th, 2010, on a small scale to enhance market efficiency. As the stock market kept rising in 2014–2015, the demand for margin financing thrived because an increasing number of retail investors used the margin financing as a new tool to borrow money and wager on the rising of share prices.

Two types of margin accounts exist - brokerage-financed and shadow-financed margin accounts. Both grew rapidly in popularity in early 2015, while only the brokerage-financed margin trading system is regulated by the China Securities Regulatory Commission (CSRC, the counterpart of the U.S. SEC). For example, an investor was supposed to own at least RMB 0.5 million in stocks and cash and experienced enough to pass an exam. In addition, investors could borrow no more than twice their own capital from securities brokers. The blue dotted line in Panel A of Figure 1 shows that the total margin trading balance standardized by the total market value rose from around 0.02 in the middle of 2014 to the peak of 0.05, suggesting the popularity of investment with margin finance.

Different from brokerage-financed margin accounts, shadow-financed margin accounts are not subject to regulations by CSRC and lenders. Their funding came from a broader set of sources related to China's shadow banking system, and investors usually do not require borrowers to obey the same strict wealth and investment experience requirement. Also, the leverage of shadow-financed margin accounts does not have a unified limit. Instead, it is set through the negotiation between borrowers and shadow lenders. We could conjecture that shadow accounts have even higher leverage levels than brokerage accounts and are preferred by individual investors in their speculative investments. According to the statistics provided by the 2015 Chinese Money Matching Industry Conference, at the end of 2014, more than 10 thousand fund-matching firms existed, and they provided more than RMB 100 billion. The scale of shadow-financed margin accounts at the peak of the bull market in 2015 is estimated at RMB 1.0–1.4 trillion by Bian et al. (2018) and China Securities Daily on June 12, 2015.

CSRC was aware of the potential and high risk involved in the unregulated development of shadow-financed margin accounts. From June 13, 2015, the CSRC announced a series of regulations to restrict shadow-financed margin trading and prohibited all security companies from providing the facility for shadow margin lending. Then, the bull market turned to the stock market collapse overnight. On June 15, 2015, the market unintendedly started to fall from the next trading day, and the SSECI lost 13.1% in one week, the largest weekly loss since 2008. Some investors with high leverage ratios reached the Pingcang Line and were forced to sell stocks after the first wave of drops. Meanwhile, forward-looking investors sell as the account's leverage approaches its Pingcang Line due to precautionary motives. Consequently, individual fire sales accelerate the decline of the market. Bian et al. (2018) use account-level trading data and prove that the main driving force behind the collapse of the Chinese stock market in the summer of 2015 is deleveraging-induced trading.

From June 12, 2015, to January 29, 2016, the SSECI dropped from 5166.35 to 2737.60, wiping up about 48% of the market value. During this period, the daily limits (10%) on stock trading exacerbated the dry-up of liquidity and the collapse of the whole market. "A thousand Stocks on Lower Limit" happened several times. As shown in Panel B of Figure 1, on the darkest date, June 26, 2015, SSECI dropped 7.4%, and 2049 stocks closed at the lower limit. Inconsistent with the general view that the stock market bubble and the following crash is driven by economic fluctuations, the Chinese A-share stock market crash in 2015 was not supported by the real economy. The annual GDP growth of China in 2015 is nearly 7%, slightly lower than in 2014 and 2016, suggesting that the economy has not experienced a significant drop or rise around 2015. Thus, this boom-bust episode showed almost entirely speculative patterns without shocks to economic fundamentals.

## 3 Data and Variables

This paper uses two separate samples: (1) unique microdata from more than 30 thousand job postings in China collected by an online job posting platform: Lagou.com, and (2) the full set of A-share companies listed in the Chinese public exchanges. In this section, we describe the data and our variable construction.

### 3.1 Data

Lagou (https://www.lagou.com/) is a leading online platform for job seekers in China that started in July 2013. The job posting data provide rich information about the characteristics of vacancies. First, each job ad shows codified information, including a firm identifier, occupation title, education requirement, working experience requirement, geographical location, and posting period. More importantly, most job ads in our sample post the range of monthly wage offered, which allows us to study the relationship between skill demands and wages for individual job vacancies. Second, each posting ad provides texts to describe occupation responsibility and detailed job requirements.

However, it also has a few limitations. First, the distribution of vacancies posted on

Lagou.com over-represents firms in the information technology industry. Second, online postings are not prevalent for every type of job. For example, unskilled jobs such as production workers and staff are less likely to be posted online. In Appendix B, we compare the distribution of firms that post vacancies in Lagou relative to the entire sample of A-share listed firms. To mitigate the problem, we conduct several robustness tests later in the paper. Another limitation is that job vacancies show the labor demand but do not indicate whether the vacancies are filled or not. Thus, we also provide analysis based on the employment outcomes using the firm panel data.

The initial job posting sample contains more than 50,000 job advertisements by 833 A-share firms listed on Shanghai and Shenzhen Stock Exchanges from 2014 through 2016. We restrict our job posting sample to ads of full-time jobs and then remove the repetition of job ads with the same contents, which are re-posted by firms to attract attention. We only keep firms that have posted at least two ads during the period and were listed before the end of 2014. The final sample includes 532 unique firms and 33,108 job posting ads between 2014 and 2016. We summarize the distribution of job postings used in the paper in Table 1 Panel A.

[Insert Table 1 Here]

Our second sample consists of all A-share firms publicly listed at the beginning of the stock market crash in June 2015 and traded in the Shanghai and Shenzhen stock exchanges from 2013 to 2018. We obtain trading and financial data from the two leading Chinese financial and economic data providers, The China Securities Markets and Accounting Research Database (CSMAR) and Wind Financial Terminal (WIND) database. In addition, we obtain firm-level labor information, including the number of employees by occupation, from RESSET (www.resset.cn).

We drop financial firms classified by the CSRC as these firms are regulated and use different accounting standards in their financial reporting. We also exclude firms that were traded for less than 30 trading days during the stock market crash period. Our final sample includes 2,493 unique Chinese A-share stocks and 14,667 firm-year observations. The distribution of the number of firms in our panel sample is presented in Panel B of

Table 1. We also drop observations in 2015 in the baseline regressions to eliminate the potential effect of the crash year.

We construct a firm-level measure using the buy-and-hold returns during the stock market crash period, from June 12, 2015, to February 1, 2016. During the stock market crash, the average price loss reaches 47.1%, a sharp drop consistent with what's documented in recent papers (e.g., Bian et al., 2018). Figure 2 shows histograms of the changes in the stock price over the period from June 15, 2015, to February 01, 2016. We define a variable, $Affected$, as the negative of the buy-and-hold return.

[Insert Figure 2 Here]

## 3.2 Constructing Skill Index using Job Posting Data

We construct our skill measure based on the codified requirements (working experience and education) and the text of each posting. It is well documented in the literature that workers with higher education or greater working experience exhibit better skills (Deming and Kahn, 2018). Thus, we incorporate the working experience and education requirements as components to measure skill requirements. We map the requirement of working experience into a categorical variable, with one for no requirement, 2 for at least one year, 3 for at least three years, and 4 for at least five years. Table 2 Panel A summarizes the experience data for the sample. Around 85 percent of ads require at least one year of experience. Job vacancies that require working experience of at least one, three, five years account for 37 percent, 37 percent, and 11 percent, respectively. We construct a dummy variable indicating that the job requires at least a bachelor's degree to capture the education requirements. Around 71 percent of ads require at least a bachelor's degree, suggesting that most of the job vacancies in this sample require high-skilled workers.

[Insert Table 2 Here]

Second, we use textual analysis to construct measures of job skills in three categories, including computer, cognitive, and management skills, by searching for the keywords and phrases coded from the text of job posting ads. Panel A in Table 3 lists the three types of skills and provides the corresponding words and phrases that fall into each category in both languages. For example, job vacancies that require computer skills ask for keywords and phrases such as “computer,” “programming,” “development,” and “coding.” The second skill, “cognitive skills,” is an umbrella term for keywords and phrases such as “research,” “statistics,” and “analyzing.” These skills are matched with the “non-routine analytical” job tasks described in Autor, Levy, and Murnane (2003). Third, “management” is a category of skill commonly listed and generally applicable to many types of jobs. Previous studies show that managerial skills are an important determinant of innovation and productivity (see, for example, Custódio, Ferreira, and Matos, 2019). The approach to constructing the three skill components is similar to Deming and Kahn (2018), Hershbein and Kahn (2018), and Kim, Li, Lu, and Shi (2020). For each skill, we count the number of times relevant words appear in the posting. In our sample, more than 93% of ads have at least one such skill requirement. Table 3, Panel C summarizes the three skill components for our sample. The average number of counts of computer, cognitive, and management skills are 1.735, 0.830, and 0.727, respectively.

[Insert Table 3 Here]

We construct a skill index based on the five skill components, including computer skills, cognitive skills, management skills, experience requirements, and education requirements. The correlation among these five components is low, indicating that they capture different dimensions for skills.

Specifically, we run the following regression to estimate the contribution of each component to wage:

$$\begin{aligned} LnSalaryMean_{ijlot} = {} & \beta_1 LnComputer_{ijlot} + \beta_2 LnCognitive_{ijlot} \\ & + \beta_3 LnManagement_{ijlot} + \beta_4 LnExp_{ijlot} + \beta_5 Above\_BA_{ijlot} \\ & + \lambda_i + \alpha_{lt} + \mu_{ot} + \delta_{lo} + \epsilon_{ijlot} \end{aligned} \tag{1}$$

where the dependent variable is the average wage for firm $i$ for occupation $o$ in city $l$ in year-month $m$. *LnComputer*, *LnCognitive*, and *LnManagement* are the logarithm of one plus the number of mentions for computer skills, cognitive skills, and management skills, respectively. *LnExp* is the logarithm of the categorical experience requirements, and

$Above\_BA$ is an indicator variable for education requirements of at least bachelor's degree. Each skill component is normalized by their respective mean and standard deviation calculated across all observations of job ads to have zero mean and unit variance. We also control for various fixed effects, including firm ($\lambda_i$), city–year-month ($\alpha_{lt}$), occupation–year-month ($\mu_{ot}$), and city–occupation ($\delta_{lo}$) to account for alternative explanations for the positive correlation between skill demands and wages. We use the posting data before the shock in 2014 for the regression.

Table 3, Panel B presents the estimated coefficients. All five components are positively related to wage, significant at 1% level. The magnitude of the coefficient implies a one-standard-deviation increase in the computer skill, the cognitive skill, the management skill, and the working experience increases wages by 5.8%, 1.4%, 2.8%, and 17.5%, respectively. In addition, having a bachelor's degree increases wages by 3.2%. The five components of skill, together with fixed effects, explain 57.9% of the wage variation, with 25.8% of the variation explained by the five components of the skill only.

We then construct our skill index using estimates from Table 3 as weights:

$$\begin{aligned} Skill\_Index = {} & 0.058 \times LnComputer + 0.014 \times LnCognitive \\ & + 0.028 \times LnManagement + 0.175 \times LnExp + 0.032 \times Above\_BA \end{aligned} \tag{2}$$

### 3.3 Firm-level Information

We supplement our job-level analysis with firm-level information on labor composition. To do so, we rely on occupation information from the Resset Database, which collects the number of employees in different occupation categories for public listed firms from annual reports. Firms do not follow a unified standard in their reporting of occupation categories, so we manually reviewed the data and standardized the occupation classifications for all firms in the sample. Following Kim et al. (2020), our employee occupation categories include production workers, R&D staff, technicians, finance staff, and sales and marketing staff. We further divided occupations into two groups: high-skilled and low-skilled. High-skilled workers include R&D staff, technicians, finance staff, and sales and marketing staff. These are professionals who possess specialized skills. In contrast, production workers, mainly blue-collar production workers who perform repetitive physical work, are defined as low-skilled workers. For each firm, we calculate the number of high-skilled workers (*HSemp*) and low-skilled workers (*LSemp*). On average, firms in the sample have 5,433 employees, with 1,658 high-skilled employees and 2,498 low-skilled employees. The average wage is about 73,000 RMB (about $11,600), and the logarithm of yearly average wages (*Ln_AWAGE*) is about 11.20.

[Insert Table 4 about here]

The CSRC requires publicly listed firms to announce detailed information about tangible and intangible capital expenditure. The information allows us to extract firms' behaviors of purchasing newly added investments in technology-related assets. In general, technology investments include two categories: acquiring external technologies and cultivating internal innovation. Acquisition of external technologies is measured as the logarithm of the cost of newly acquired high-tech tangibles and intangibles (*Ln_HighTechInv*). High-tech tangibles include high-tech machines and equipment, such as computers, electronic equipment, and R&D-related equipment, and high-tech intangibles include computer software, technology with or without patents, patents, and information management systems. Internal innovation is measured as the logarithm of R&D expenditure (*Ln_RDexpense*).

Table 4 report the summary statistics for a set of key variables that we use in the firm panel data, including the firm-level stock crash measure, the total number of employees, two continuous variables for the employee composition by skill, one continuous variable for an average wage, and two continuous variables for high-tech investment. We winsorize continuous variables by year at the 1% level and normalize financial variables to the RMB in 2000. Appendix A provides detailed descriptions of the data source and definitions of all these variables.

# 4 Main Results

## 4.1 Job-level Regressions: Demand for Skill

Our first goal is to estimate how the stock market crash affected the demand for skill. Figure 3 Panel A plots the skill demand for all firms in the quarters around the stock market crash using our main variable, *Skill_Index*. We average the skill index across the job postings by quarter and then over the previous four quarters. We find that the skill index experiences a drop during the crash period and rise slowly after the crash. In Panel B, we plot the average demand for skill separately for the treatment (firms with the price change during the stock market crash less than -30%) and control (those with the price change not less than -30%) firm samples. The evidence is striking. Before the stock market crash, the skill index of treatment and control firms moves in tandem, supporting the parallel trends assumption. After the crash, the skill index of treatment firms exhibits a significant downward trend (relative to control firms).

[Insert Figure 3 here]

[Insert Table 5 here]

To pin down the change in skill demand for the same firm for similar jobs, We employ a difference-in-differences specification based on the following model:

$$Skill\_Index_{ijlot} = \beta \times Affected_i \times Post_t + \lambda_i + \alpha_{lt} + \mu_{ot} + \delta_{lo} + \epsilon_{ijlot} \quad (3)$$

in which each observation is measured at job posting ($j$), firm ($i$), city ($l$), occupation ($o$), and month ($t$) levels. The dependent variable, $Skill\_Index_{ijlot}$ is the skill index (constructed using five skill components) for job j in firm i, month t, city l, occupation o, and constructed in Section 3. The (continuous) treatment variable Affected_i is the negative firm-level buy-and-hold return during the stock market crash period (from 6/12/2015 to 02/01/2016), capturing the severity of the price crashes. Dummy variable Post_t equals 1 for job posting advertisement posted after the start of the crash, and 0 otherwise. We also control for a full set of fixed effects: $\alpha_{lt}$ represents city–year-month fixed effects to control for some unobservable time-varying demand shocks that are common to jobs in the same geographical location; $\mu_{ot}$ represents occupation–year-month fixed effects and allow us to control for occupation-specific time trends in demand for skill; $\delta_{lo}$ represents city–occupation fixed effects to address the concern that skill requirements vary across locations and occupations; $\lambda_i$ is firm fixed effect, controlling for other time-invariant firm heterogeneity not captured by the price change. We cluster standard errors by firms to address possible serial correlation within a firm.

The primary coefficient of interest is the coefficient $\beta$ on the interaction term, *Affected* $\times$ *Post*, which compares the difference in the demand for skill around the stock market crash between firms that experience more severe and their peers that experience less severe drops in stock price. Essentially, $\beta$ captures the DiD estimate of the impact of the stock market crash on jobs' demand for skill. The validity of the DiD design in producing causal estimates depends on the assumption that absent from the stock market crash, the skill requirement of jobs posted by treatment and control firms exhibits parallel trends. We later conduct several tests to assess the plausibility of the assumption.

Table 5 reports the estimates of the effects of firms' stock price changes during the stock market crash on jobs' skill demands. Column (1) shows that the coefficient estimate of *Affected* $\times$ *Post* is negative and statistically significant, implying that the more-affected firms reduce the demand for skill by more, compared to their less-affected peers. Specifically, a one-standard-deviation increase in the price change (21.7% for our sample) decreases jobs' demand for skill advertised by the firm by 0.95 percentage points (= 21.7% $\times$ 0.044). Column (2) to (3) in Table 5 show that our findings are robust to alternative samples. In Column (2), we remove the job posting from the crash period (from Jun. 15, 2015, to Feb. 1, 2016) to rule out the possibility that the decrease in the demand for skill happens only during the crash period but recover afterward. In Column (3), we exclude the sample of State-Owned Enterprises (SOEs), which may be subject to government initiatives, and focus on non-SOE firms.

To summarize, the job-level analyses allow us to investigate how the demand for skill evolves following the stock market crash. We find that firms with more severe price drops during the stock market crash lower their demand for skill more than those experiencing less severe price drops.

### 4.2 Firm-Level Regressions: Skill Composition and Technology Investments

So far, the job-level analyses show that the skill demands within occupations decrease by more for the firms that are more affected by the 2015 stock market crash, relative to their less-affected peers. In this section, we focus on firm-level analyses and examine the effect of the stock market crash on skill composition in the labor force and technology investments.

To identify the effect of the stock market crash, we run standard difference-in-differences regressions on firm-year observations of sample firms from two years before to three years after the year of the stock market crash. Because the stock market crash started in the mid of 2015, we drop observations for 2015 that partially span periods both before and after the crash. Specifically, we estimate the following equation:

$$Y_{i,t} = \beta \times Affected_i \times Post_t + \gamma_t + \lambda_i + \epsilon_{i,t} \tag{4}$$

where $Y_{i,t}$ is any of several measures of the outcome variables (discussed in more detail below) including the number of employees, employee composition, wages, and technology investments, in firm $i$ and year $t$ ($2013 \leq t \leq 2018$). $Affected_i$ is the negative price change generated during the stock market crash, and fixed at the firm-level for our entire sample period, and $Post_t$ indicates the year after the stock market crash. The specification includes year fixed effects, $\gamma_t$ and firm fixed effects, $\lambda_i$. We cluster the standard errors at the firm level to address possible serial correlation within a firm.

The primary coefficient of interest in the specification above is the coefficient, $\beta$, on the interaction term *Affected* $\times$ *Post*, which compares the more-affected firms' outcome variables before the crash relative to the post-crash times (first difference), relative to those that are less affected by the stock market crash (second difference). Essentially, coefficient $\beta$ captures the difference-in-differences estimate of the impact of the stock market crash on firms' real decisions of employment and investment. The results are presented in Table 6.

[Insert Table 6 here]

Columns (1)–(3) in Table 6 show the effect of the stock market crash on firm-level total employment and the number of employees by skill level. Column (1) uses the log of the number of workers ($Ln\_EMP$) as the dependent variable. The coefficient on the main variables of interest, the interaction of *Affected* $\times$ *Post*, is negative and significant at 5%. This finding is consistent with previous studies examining the effect of financial shocks on aggregate employment at the firm or state level (see, for example, Berton, Mocetti, Presbitero, and Richiardi, 2018; and Benmelech, Frydman, Papanikolaou, 2019).

More importantly, Table 6 presents the effect of the stock market crash on firm-level employment by skill level. We focus on the number of high-skilled (Column (2)) and low-skilled (Column (3)) workers, respectively. Low-skilled workers are defined as production workers who do routine and physical tasks that require low skills, and high-skilled workers specialize in particular fields, such as finance, technology, and marketing. For high-skill workers (Column (2)), the coefficient estimates for the interaction term, *Affected* $\times$ *Post*, is negative, significant at 1%. It suggests that firms that were hit harder during the stock market crash experienced a larger decline in the number of high-skilled workers employed following the crash in 2015 than their less hard-hit peers. The decrease in the number of high-skilled workers is also economically meaningful: the coefficient estimate implies that the average firm whose price loss is higher by one standard deviation (21.7% for our sample) hires 11.05% ($= -0.509 \times 21.7\%$) fewer high skill workers following the crash. In contrast, for low-skill workers (Column 3), the point estimate of the specification with dependent variable *Ln_LSemp* suggests that with a one-standard-deviation drop in stock price, the number of low-skilled workers increases by 12.50% ($= 0.576 \times 21.7\%$). Taken together, results in Columns (1) to (3) suggest that a decline in stock price leads to the change in the employee composition by skill.

Next, we use wage as a proxy for employee talent (Baghai, Silva, Thell, and Vig, 2020) and examine how wages change following the stock market crash. Column (4) uses the log of average wage per employee (*Ln_Awage*) as the dependent variable. The coefficient on $Affected \times Post$ is negative and significant at 1%, indicating that the average wage per employee for the harder-hit firms relatively decrease after the stock market crash, compared to the less hard-hit firms.

So far, we document that firms that experience a more considerable decline in stock price decrease the demand for high-skilled workers. Since human capital is crucial for technology adoption, do firms with a larger decline in stock prices also cut their technology-related investments? Next, we explore the effect of the stock market crash on technology investment.

Firms could adopt advanced technologies through external acquisitions or internal R&D

activities. External acquisitions can occur through purchasing physical assets such as technology-related machines and equipment or intangible inputs, including the information required to employ new technologies, such as software applications, patents, and copyrights. We construct a variable *Ln_HighTechInv* to measure the amount of technology-related spending, which is defined as the logarithm of one plus the cost of newly acquired, high-tech tangibles and intangibles. High-tech tangibles include computers, electronic equipment, and R&D-related equipment, and high-tech intangibles cover items such as computer software, technology with or without patents, patents, information management systems, and the like. We measure internal innovation as the logarithm of R&D expenditure (*Ln_RDexpense*). We use inputs rather than innovation outputs to measure innovation because the patent information is not available for years 2018–2020, and the post-crash observations are insufficient.

The results are reported in Columns (5) and (6) of Table 6. In Column (5), the dependent variable is *Ln_HighTechInv*, the acquisition costs of newly added high-tech tangibles and intangibles, and the coefficient estimate of $Affected \times Post$, is negative and significant at 1% level. With a one-standard-deviation drop in stock price, the investment in the acquisition of newly added machines and equipment decreases by 1.95% . Regarding expenditures on R&D activities, Column (6) shows a negative impact of the stock market crash on innovative activities. The interaction variable's coefficient is $-0.566$, significant at 1% level. The effect's economic magnitude is also substantial - the differential decrease experienced by the more-affected firms is about 12.28% ($= -0.566 \times 21.7\%$), with a one-standard-deviation drop in stock price.

We show that drops in stock price during the stock market crash lead to substantial changes in production inputs: lower total employment, less skilled workforce, and lower technology investments and R&D expenditures. Both human capital and technology investments and R&D expenditures are directly related to firm productivity. Thus, it is natural to ask whether changes led by shocks from the stock market ultimately affect firm performance.

To answer this question, we explore three measures – labor productivity using sales per employee (*Sales/Emp*), sales growth over the last three years (*Sales_Growth*), and firm's market share (*Market_Share*) within the industry .

[Insert Table 7 around here]

Table 7 reports the estimation results. We use the three measures of firm productivity and competitiveness in year $t + 1$ and year $t + 2$ as dependent variables, respectively. Most of the coefficient estimates on the interaction term are significantly negative, and the magnitudes are substantial. For example, as shown in Column (1) of Table 7, a one-standard-deviation drop in stock price leads to reduced worker productivity by 6.34% ($= -0.292 \times 21.7\%$) in year $t+1$. Therefore, the results show that the more-affected firms experience a relatively more severe decline in firm performance after the stock market crash.

## 5 Exploring the Mechanisms

Thus far, we have documented a significant negative effect of the stock market crash on skill demand. In this subsection, we turn to the task of identifying possible underlying mechanisms.

### 5.1 Skill Premium

Previous studies document that firms hit by financial shocks may face a higher skill premium. Brown and Matsa (2016) find that job seekers are reluctant to work in firms with poor financial conditions, and distressed firms face more costs in recruiting for skilled positions. Baghai et al. (2020) find that talented employees are more likely to voluntarily abandon the firm that suffers financial distress driven by financial shocks. Similarly, the high-skilled applicants may require a higher wage premium due to firms' price losses during the stock market crash. Therefore, one mechanism through which the stock market crash reduces skill demand may be increased skill premiums for firms experiencing large price collapses.

To test the skill premium channel, we compare the gap for skill premium (of high- and low-skilled workers) before and after the crash between the treatment and control groups.

Specifically, in the job-level regression specification, we use the following form:

$$\begin{aligned} Salary_{ijlot} = {} & \beta_1 \times Affected_i \times Skill\_Index_{ijlot} + \beta_2 \times Skill\_Index_{ijlot} \\ & + \lambda_i + \alpha_{lt} + \mu_{ot} + \delta_{lo} + \epsilon_{ijlot} \end{aligned} \tag{5}$$

The dependent variable $Salary_{ijlot}$ is a proxy for the monthly wage offered in a job advertisement posted on the Lagou website by firm $i$ in month $t$, city $l$, and occupation $o$. $Affected_i$ is a firm-level measure of the severity of the price crash during the stock market crash period, defined as in Equation (3). $Skill\_Index_{ijlot}$ is the measure of job $j$'s demand for skill in firm $i$, month $t$, city $l$, occupation $o$, and constructed in Section 3.2. The fixed effects are defined as in Equation (3). Thus, the coefficient estimate on $Affected \times Skill\_Index$ captures the differential wage returns to the demand for skill between the treatment and control groups.

[Insert Table 8 here]

We first divide the whole sample of job vacancy advertisements into two periods, with the stock market crash as the cut-off point, and show the results in Table 8. The *Before* columns (Columns (1), (3), and (5)) include the job advertisements posted before the stock market crash, and the *After* columns (Columns (2), (4), and (6)) include the job advertisements posted after the end of the stock market crash in February 2016. The dependent variables are the log of the mean (Columns (1) and (2)), minimum (Columns (3) and (4)), and maximum (Columns (5) and (6)) values of the wage range that is offered in a job description, respectively. The results show that $\beta_1$ is insignificant for the subsamples before the onset of the stock market crash in Column (1), indicating no significant difference in skill premiums across firms experiencing different price changes during the stock market crash. In contrast, during the post-crash period, $\beta_1$ becomes significantly positive in Column (2). Specifically, a one-standard-deviation increase in price changes during the stock market crash (0.217) leads to a higher wage return to a one-standard-deviation increase in the skill index (0.203) by 1.62% (= 0.217 × 0.203 × 0.367). The equality test between the two coefficients between Columns (1) and (2) is significant at the less than 1% level. We find similar patterns using two other wage proxies.

Column (6) shows that the post-crash difference in skill premium is only marginally significant between the treatment and control groups when we use the upper bound of wage offered. The possible reason is that for job applicants, the upper bound provided in the advertisement is often not realistic. To validate, we compare the wage ranges provided in the job advertisements with the average annual wage of non-executives reported by the same set of firms. In our sample, the average annual non-executive wage is about 89,000 RMB. In comparison, the lower and upper bound from the job posting data are about 123,000 RMB and 72,000 RMB, respectively, with an average of 95,000 RMB. That is, the lower bound and the mean level of the wage range in the job postings are closer to the reasonable wage than the upper bound.

What drives the higher wage premium for firms with sharper declines in stock prices? We propose two potential channels, and our results are reported in Tables 9 and 10.

The first possible mechanism is that high-skilled workers may expect to bear greater costs of involuntary job mobility due to firms' financial distress or bankruptcy because high-skilled workers face higher cost of job searching and matching. In that case, the firms need to offer a higher wage premium as compensation to attract potential high-skilled employees. When the stock market crash intensifies firms' exposure to financial distress risk, the skill premium driven by the higher cost of job mobility in turn increases.

To test the validity of this mechanism, we examine the relationship between the posting-level vacancy duration and the skill level. Long delays before reemployment is one of key components of unemployment or job mobility cost (Katz and Meyer, 1990; Agrawal and Matsa, 2013). To proxy for such cost, we construct posting-level vacancy duration (*Days-to-Fill*) to measure how long the firm has to search until the vacancy is filled. Longer vacancy duration reflects longer delays for job seekers to match specific job opportunities. Specifically, *Days-to-Fill* measures the number of days for which a given job posting is active online. In Table 9, the dependent variables are *Days-to-Fill* in Column (1) and *log(Days-to-Fill)* in Column (2). We document a significantly positive correlation between the posting-level vacancy duration and the skill level, suggesting that workers with higher skill levels need a longer period of job searching and matching. This finding align with Connolly and Gottchalk (2006)'s finding that highly educated workers bear particularly large unemployment costs. Thus, the first mechanism is supported by the evidence in Table 9.

[Insert Table 9 here]

The second possible channel is that high-skilled workers have higher bargaining power than low-skilled workers and thus require higher wage premiums when the firms' risk of financial distress and bankruptcy increases. If the mechanism is valid, then firms would suffer a higher increase in skill premiums through the stock market crash where workers have greater bargaining power versus firms.

We provide a test of the bargaining power mechanism using heterogeneous analyses of the evolution of skill premiums around the stock market crash. We use the province-level index of human resources supply condition in 2014, constructed by Wang, Fan, and Hu (2019), to capture the province-level bargaining power between workers and firms before the stock market crash. A higher value indicates a better local condition of human resources supply and in turn lower employee bargaining power. We split the sample of job postings into two groups by the index of local human resources supply conditions and re-conduct the regressions in Table 8 based on the two subsamples, respectively. We find that the increase in skill premium is more substantial for firms located in the provinces with lower human resources supply conditions. The evidence aligns with the idea that high-skilled employees' bargaining power is one explanation for the increase in the skill premium through the 2015 stock market crash.

[Insert Table 10 here]

## 5.2 Financial Frictions

When stock prices fall dramatically, external financing such as seasoned equity offerings or share pledges become increasingly costly. Firms, especially those that are more financially constrained, may reduce their spending on labor and technology. This section examines the role of financial constraints on firms' reaction to the stock market crash.

Focusing on the job-level data, we proceed by dividing our sample based on proxies of financial constraints and estimate our main specifications separately for each group. We choose two proxies - firm age and the status of share pledge. Compared with old firms, young firms are more likely to face higher information asymmetry and lack of collateral. The second proxy is well-rooted in the Chinese institutional context (Li, Qian, Wang, and Zhu, 2019). When the stock price drops significantly, the borrowers/shareholders are required to increase margins or forced to sell stocks to cover the lenders' losses. Therefore, in a downtrend market, firms with more stock pledged loans are more likely to suffer from financial constraints.

[Insert Table 11 here]

Table 11 reports our results. Firm age is measured as the number of years between the firm was established and the year prior to the onset of the crash. We split our sample into two groups: young firms with firm age no more than 15 years and old firm with firm age greater than 15 years. Table 10 Columns (1) and (2) show that the average treatment effect of the stock market crash on skill demands for young firms is almost seven times as large as that for old firms.

In Columns (3) and (4), we split the sample based on whether the firm's ownership is pledged as collateral to raise financing at the beginning of the stock market crash and compare the firms with and without pledged ownership. The estimated results indicate that the decline in the demand for skill in job advertisements is significantly greater for firms with pledged ownership ($p$-value $< 0.001$). There is a negative effect between shock price drops and skill demand for firms with share pledges, significant at 1%. In contrast, for firms without pledged ownership, the coefficient estimate is insignificant from zero.

Table 12 reports the firm-level analyses. We use three measures of financial constraints to partition samples, including firm age, share pledge status, and state ownership, and re-run the regression in Equation (4) for each subsample. Table 12 presents the results. Based on firm age in Panel A and share pledge status in Panel B, the subgroups are partitioned similarly as those in Table 11.

[Insert Table 12 here]

Similar to what we find using the job posting data, the coefficients of $Affected \times Post$

are larger for young firms and firms with share pledges, consistently with the hypothesis that firms cut demand for skill and technology investment following the stock crash due to financial constraints.

We also performed a similar analysis for subsamples of SOE and non-SOE firms. Compared to non-SOE firms, SOEs in China possess government support and thus enjoy lower financing costs (Allen, Qian, and Qian, 2005; Cai and Liu, 2009). Panel C presents our findings. Consistent with the other two partition results, we find that the stock market crash effects are significant only for non-SOE firms.

To verify the financial friction mechanism, we further document the real effect of the stock market crash on firms' financing behaviors. Specifically, we examine the effect on three financing behaviors: seasoned equity offerings, share pledges, and long-term debt. In the Chinese capital market, seasoned equity offerings and share pledges are important tools of equity financing for listed firms. The cost of the two financing channels are directly related to firms' stock prices. Generally, firms will time the seasoned equity offerings according to the stock prices to maximize the financing funds. Before the stock market crash, many firms published the letters of intent for seasoned equity offerings. However, the unexpected stock market crash delayed or cancelled the seasoned equity offering plans. From the view of share pledges, as capital providers, banks faced stock pledging risks driven by the stock market crash. Thus, many banks stopped accepting share pledges or largely reduced the share pledging ratios. These measures in turn increased firms' cost of capital financed through share pledges.

Table 13 report our findings. In Columns (1) and (2), we use the indicator of SEO and the SEO amount (normalized by total assets) for a given year as dependent variables. In Columns (3) and (4), we use the indicator of *SharePledge* (one if any shares of the firm are pledged), and *SharePledge_Ratio* (the amount of pledged shares divided by the total shares), as dependent variables. In all four cases, we find a negative coefficient for $Affected \times Post$, which suggests that the harder-hit firms relatively reduce their financing behaviors such as seasoned equity offerings and share pledges, compared to the less hard-hit firms. Moreover, we find similar result using long-term debt. Table 13 Column 5 shows that more-affected firms experience a larger decline in long-term debt.

[Insert Table 13 here]

# 6 Addressing Endogeneity Concerns

Although the 2015 stock market crash provides a useful setting to study stock prices' effect on firm decisions, we still cannot fully rule out the endogeneity concerns. Firms that lose more value in stock may have other characteristics that make them more sensitive to the overall economic conditions, which affect demand for skill, leading to a spurious correlation. By controlling for firm, Month–City, Month–Occupation, and City–Occupation fixed effects in our baseline regressions, we can limit potential bias due to firm heterogeneity, city-level time trends, occupation-level time trends, and City–Occupation heterogeneity. However, the price collapses may reflect these shocks controlled by the fixed effects and other economic shocks that simultaneously affect price changes and firm behaviors. We address these endogeneity concerns through two different strategies.

## 6.1 Propensity Score Matching

In this section, we perform a propensity score matching (PSM) analysis and create a matched sample to further control for observable differences in firm characteristics. We match firms with above-median price changes with firms with below-median price changes using a one-to-one nearest neighbor matching (without replacement). The matching is based on the propensity score generated from a logit regression, in which the dependent variable is the dummy for being a firm with an above-median price change during the crash. We regress this indicator variable on a set of firm characteristics measured at the end of 2014, the year prior to the crash. We include the following matching variables: three-digit CSRC (2012) industry FE, the log of sales income ($LnSales$), the log of turnover ($LnTurnover$), the proportion of shares owned by state-owned entities ($State\_own$), the log of the number of years between the firm's listed year and 2014 ($Ln\_Nyear\_listed$), net income divided by total assets ($ROA$), log of the number of employees ($Ln\_EMP$), the proportion of the high-skilled workers over the total employees ($HEmp\_ratio$), the log of average wage per employee ($Ln\_Awage$), and the book value of property, plant, and equipment divided by the total assets ($PPE\_TA$). For each firm with above-median price change during the crash, we find the firm with the closest propensity score that belongs to the below-median group and operates in the same three-digit CSRC (2012) industry, imposing a 0.05 caliper.

For the online job posting data, we merge it with the firm panel data to obtain the covariates in 2014. The first-stage logit model is estimated with 325 firms (with 166 above-median and 159 below-median) with no missing data for all covariates in 2014 to ensure that the covariates capture the determinants of the price changes. The logit model results are presented in Column (1) of Table D.1 in Appendix D, showing that the model captures a significant variation in the selection variables, as indicated by a p-value less than 1% from the Chi-square test of the overall model fitness. Table D.1 Column 1 shows that firms with larger sizes, lower turnover rates, fewer employees, higher profitability, and higher asset tangibility are more likely to be hit harder by the stock market crash. The one-to-one matching procedure gives us a sample of 102 firms with above-median price change during the crash and 102 matched firms. After the matching, there exist no discernible differences in all dimensions, as indicated in Panel A of Table D.2.

For the firm panel data, the first-stage logit model is estimated with 1,694 firms (with 850 above-median and 844 below-median) with no missing data for all covariates in 2014. Column (2) of Table D.1 in Appendix D shows that firms with higher turnover rates, listed year, lower profitability, a higher proportion of high-skilled workers, and higher average wage per employee are more likely to be hit harder by the stock market crash. The one-to-one matching procedure gives us a sample of 655 pairs of firms with no discernible differences in all dimensions, as indicated in Panel B of Table D.2.

[Insert Table 14 here]

Overall, the comparisons of firm characteristics suggest that the propensity-score matched group of firms is more comparable to firms with above-median price change during the crash. Using the PSM sample, we conduct the DiD regressions shown in Equations (3) and (4) to gauge the impact of stock price crash on firms' skill demands, employee composition by skill, technology investments, and R&D expenditures. Results presented in Table 14 are consistent with our baseline results.

### 6.2 Fuzzy Regression Discontinuity Design

As stated in Section 2, the boom and bust in 2015 were fueled by excessive margin lending. In contrast to the illegal, shadow-financed margin trading, the brokerage-regulated margin trading provides a lower cost of margin trading. We hypothesize that firms that are qualified for brokerage-financed margin accounts attract more speculative investors, and thus experience a larger price decline during the crash period.

Unlike in developed countries, margin trading and short selling were prohibited in the Chinese stock markets until 2010. Since March 31, 2010, the CSRC started introducing several rounds of pilot programs of margin trading and short selling in a staggered manner.

In the first stage, stocks included in market indices were selected to have margin trading accounts. For example, on March 31, 2010, regulators allowed "qualified" investors to buy 90 blue-chip stocks on margin and/or to short sell those stocks. The 90 stocks belonged to two major stock market indices, the Shanghai 50 Index (50 stocks) and the Shenzhen Component index (40 stocks). Similarly, on November 25, 2011, the list was expanded to include 278 stocks with 180 from the Shanghai 180 Index and 98 from the Shenzhen 100 Index.

In the second stage, stocks were added to or removed from the list based on an inclusion index. Three major revisions and several minor revisions of the qualification list occurred in this stage. The set of stocks in the first revision was announced on January 25, 2013, and implemented on January 31, 2013. Similarly, the second revision was announced on September 6, 2013, and implemented on September 16, 2013; and the third revision was announced on September 12, 2014, and implemented on September 22, 2014.

Our identification design of fuzzy regression discontinuity will focus on the stocks close to the inclusion index criteria in the three major revisions. For each revision, stocks are selected from the previous qualified list (but have not been approved) and from the newly added list following a screening-and-ranking rule. First, the stocks that fail to satisfy some requirements were removed from the list to eliminate small, volatile, illiquid, and newly listed firms. Second, for stock $i$ in revision $k$ ($k = 1$, 2, or 3) that satisfies the criteria in the first step, an inclusion index is constructed according to the following formula:

$$Inclusion_i^k = 2 \times \frac{AverageMarketValue_i^k}{(AverageMarketValueofAllStocksinSH/SZ} + \frac{AverageTradingVolume_i^k}{AverageTradingVolumeofAllStocksinSH/SZ} \quad (6)$$

The inclusion index is essentially a value-weighted average of a stock's market value and trading volume during the three months before the announcement date. All candidate stocks were ranked based on their inclusion indices, and a certain number of top candidates in the Shanghai (SH) and Shenzhen (SZ) Stock Exchanges were selected separately. Thus, there exists a threshold $C_E^k$ for revision k in stock exchange E.

We use a fuzzy regression discontinuity design to predict the probability of becoming marginable stocks. The basic premise of fuzzy RDD in our context is that the assignment of margin eligibility near the threshold $C_E^k$ is difficult to control precisely, resulting in a discontinuous jump in the probability of margin eligibility at the threshold. The variable, $Inclusion\_Index_i^k$ is normalized to have a value of zero at the threshold $C_E^k$ for vintage k in exchange E, following Hansman, Hong, Jiang, Liu, and Meng (2019). If a stock appears in the sample for more than one time, only the most recent one is included.

First, we need to show that the threshold $C_E^k$ performs a discontinuity in the probability that a given stock is selected in the marginable stock list. In Appendix E.1, we show how the inclusion index determines marginability. In Figure E.1, we include vintage 3 and all exchanges. The $x$-axis represents the inclusion index (normalized to have a value of zero at the threshold $C_E^k$ and the $y$-axis is the probability that a stock becomes marginable. The scatter plot shows averages within bins of width 0.00005 in the index. Lines show local linear fits with 95% confidence intervals on either side of the threshold. We see there exists an evident sharp jump at the threshold.

Our analysis focuses on the "local" sample of stocks, defined as those stocks whose screening rule is satisfied and inclusion indexes lie close to the cutoff of 0.0003. We predict the probability that a stock becomes marginable using the local linear regression specification:

$$Marginable_i^k = \alpha[I_i^k(Index_i^k \geq C_E^k)] + \beta(Index_i^k - C_E^k) + \theta_k + \epsilon_i^k \tag{7}$$

where the $Marginable_i^k$ variable is a dummy variable indicating that firm i becomes marginable in vintage k; The dummy variable $I_i^k$ $(Index_i^k \geq C_E^k)$ is equal to one if the firm has an inclusion index $Index_i^k$ no less than the threshold $C_E^k$ and thus is expected to be more likely to become marginable. $\theta_k$) captures a vintage fixed effect. The coefficient $\alpha$ represents the discontinuous change in the probability of margin eligibility. We cluster standard errors at the firm level. For the regression estimation, we have the predicted probability of becoming marginable, *Predicted Marginability*.

Finally, we use a two-stage least squares (2SLS) approach to estimate the effect of price drops on firm decisions within a bandwidth of 0.0003 around the threshold of the estimated marginability. $Affected \times Post$ is instrumented by the interaction between the probability of becoming marginable (*Predicted Marginability*) and the *Post* indicator. The first-stage regression estimates

$$Affected \times Post = Predicted\, Marginability \times Post + FEs + \epsilon \tag{8}$$

We estimate this first stage separately for the job-level analysis and the firm-level analysis. Fixed effects (FEs) are firm fixed effects and year fixed effects for the firm panel data and firm fixed effects, Month-City fixed effects, Month-Occupation fixed effects, and City-Occupation fixed effects for the job posting data. For the second stage, we estimate the equation for each outcome of interest

$$Y = \widehat{Affected} \times Post + FEs + \epsilon \tag{9}$$

The outcome variables Y include the skill demand (*Skill_Index*), the log of the number of total employees (*Ln_EMP*), the log of the number of high skill workers (*Ln_HSemp*), the log of the number of low skill workers (*Ln_LSemp*), and the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets ($Ln\_HTechAsset$). If the conditions for a valid instrumental variable are met, the coefficient on $Affected \times Post$ captures the causal effect of the stock market crash on the firm outcome.

[Insert Table 15 here]

The results of these two-stage regressions are reported in Table 15. Panel A presents the results based on the job posting data, in which Column (1) reports the first-stage result with the dependent variable Affected×Post, and Columns (2) reports the second-stage result. We find that in the local sample, the coefficient on Predicted Marginability is significantly positive, suggesting that the firms that are more likely to become marginable experienced a larger price decline during the period of the 2015 stock market crash. In Panel B, we show the relationship between marginability and firm-level changes in technology decisions around the stock market crash in 2015. The dependent variable is $Affected \times Post$ in Column (1). In Columns (2) to (5), we present the second-stage results based on the firm panel data and find that the signs of coefficients of instrumented $Affected \times Post$ for *Ln_EMP*, *Ln_HSemp*, and *Ln_HTechAsset* go in the expected direction: firms that experience more severe price crashes decrease the total employment, the number of high-skilled employees, and technology-related investments by more, compared to firms that experience less severe price crashes. The exception is *Ln_LSemp*, but the coefficient is insignificant. We do not include the R&D expenditures in this local test due to too many missing data.

# 7 Robustness Checks

In this section, we conduct several robustness tests. We first test the pre-existing time trends to justify our empirical identification. We then eliminate the potential effect of the bubble period on our baseline results. We also control for the effects of two concurrent events including the implementation of Shanghai–Hong Kong Connection and the direct purchase plan by the national team during the stock market crash.. Finally, we use alternative measures and samples to eliminate potential biases.

## 7.1 Pre-existing Time Trends

The validity of a DiD estimation requires the pre-assumption that the difference in time trends of outcomes between the treatment and control groups should be the same without the 2015 stock market crash. Thus, in this subsection, we try to capture the dynamic effect of the price change during the 2015 stock market crash on each of the six firm outcomes of interest over the sample period.

[Insert Figure 4 about here]

We report the results in Figure 4. Panel (a) plots the estimated coefficients based on a job-regression of the skill index on a set of interactions between Affected (which is the minus Price_Change) and half-year dummies (excluding the first half-year of 2014). Firm fixed effects, Month–City fixed effects, Month–Occupation fixed effects, and City–Occupation fixed effects are controlled. The omitted time category is the first half-year of 2014, indicating that the estimated effect is relative to the first half-year. The $x$ axis represents the half-year relative to the first half-year of 2014, and the $y$ axis is the estimated coefficient of $Affected \times HalfYear_t$. Panels (b) to (f) plot the estimated coefficients based on firm-level regressions of firm outcomes on a set of interactions between *Affected* and year dummies (excluding 2014). Firm fixed effects and year fixed effects are controlled. The $x$ axis represents the year relative to 2014, and the $y$ axis is the estimated coefficient of $Affected \times Year_t$. The omitted time category is 2014. Hence, the estimated effect is relative to 2014. The dashed lines in all panels represent the 90% confidence interval, adjusted for clustering at the firm level.

Panel (a) shows no significant difference between the treatment and control groups during the pre-crash period. The reform effect becomes significant at the 10% level during the post-crash period. The post-period (the first and second half years of 2016) coefficients are jointly different than zero and statistically significant at the 10% level ($p$-value $= 0.057$). This result indicates the nonexistence of pre-existing time trends, providing evidence that the pre-assumption of the DiD strategy holds. Panels for the other outcomes exhibit similar patterns.

## 7.2 Eliminating the Effect of the Run-up Period

In the baseline results, we use the buy-and-hold raw returns to measure the price change during the stock market crash period from Jun. 12, 2015, to Feb. 1, 2016 and define the Affected variable as minus price change. However, this measure, based on the raw returns, may lead to potential biases. As mentioned in the institutional background, the stock market experienced a bubble period before the crash. High-beta stocks that experienced price increases during the bubble period are more likely to have disproportionately lower returns during the crash. Indeed, we find that the price increase during the bubble period and the price drop during the crash period are positively correlated for the same firm. Figure F1 in the Appendix shows the binned scatter plots with linear fitted lines for the price change during the bubble period versus the bust period in the same firm, using 20 quantiles. Next, we independently double sort stocks into 3×3 subgroups by their bubble returns and then by their crash returns. As shown in Panel A of Table F1, the counter-diagonal groups are more likely than off- counter-diagonal groups.

We conduct two tests to address the concern. First, we conduct difference-in-differences analyses of skill requirements, employee composition by skill, technology investments, and R&D expenditures based on a sample of stocks that are off the counter-diagonal subgroups. Panel B of Table F1 reports the results. Our results are robust, suggesting that our findings are not merely driven by stocks that experience large price increases during the boom period and substantial price crashes during the crash period.

Second, to remove the confounding effect of firms' market betas, we use abnormal returns rather than raw returns to measure firms' price changes during the crash period. Unlike the original price changes, we construct the cumulative abnormal return during the 2015 stock market crash as the measure of price fluctuations to remove the impact of the whole market. The abnormal return is estimated based on the CAPM model as follows:

$$Abnormal\,Return = Price\,Change - \beta \times (R_m - R_f) \tag{10}$$

where PriceChange is the buy-and-hold returns during the stock market crash period; the market betas are estimated from daily stock prices over one year prior to the onset of the 2015 stock market crash; the market return is the cumulative return of the value-weighted average of market returns minus the cumulative return of risk-free assets (one-year Chinese Treasury rate) over the same period.

We replace Affected with minus AbnormalReturn and repeat our main analyses in Section 5. The results are reported in Table F2. They again strongly support our hypotheses that the substantial decrease in stock price during the stock market crash reduces the firms' demand for skilled labor and technology investment.

## 7.3 Confounding Events

Our empirical results can be attributed to other reasons. In this section, we provide evidence that these alternative explanations cannot rationalize our results. The following important events have also occurred approximately the same time as the stock market crash, thereby introducing possible bias in our estimations.

### 7.3.1 Shanghai–Hong Kong Connection

The Shanghai–Hong Kong Stock Connect program implemented on November 17, 2014, allows qualified investors in mainland China and Hong Kong investors to trade and settle on an eligible list of stocks listed on the other market through the exchange and clearing houses in their home markets, contributing to the openness of Chinese capital market . On the one hand, the program improves the informativeness of the market by introducing sophisticated investors from developed markets, and thus increases firms' fixed investment and R&D inputs. On the other hand, this program reduces the stock crash risk of the pilot firms, contributing to the stability of the firm's stock price. If pilot firms in the program are less affected during the stock market crash and spend more on innovation, then our estimates would be overestimated.

To address this concern, we include firm-level time-variant $SH\_HK \times Post\_SH\_HK$ in our baseline regression. The sample period ranges from 2013 to 2016 to eliminate the effect of the Shenzhen-Hong Kong Stock Connect program implemented on December 5, 2016. We also remove the sample firms that was once added to but then removed from the pilot list of the program. $SH\_HK$ is a dummy variable that equals one for once connected stocks and zero for other stocks. $Post\_SH\_HK$ is a dummy variable indicating the post-connect period. The regression results are presented in Panel A of Table F3. The coefficient estimate on the key variable Affected×Post are similar to our main results, thereby suggesting that the Shanghai–Hong Kong Stock Connect program does not pose a concern in this study.

### 7.3.2 Government Purchase

To stabilize the stock market from the tumbling down, the Chinese government undertook a series of actions. The most direct one is a direct purchase plan by the "national team", which consists of China Securities Finance Corporation Limited (CSF), China Central Huijin Investment Limited (CCH), to mitigate the crash. At the beginning of July, 2015, the spokesman of CSRC Xiaojun Zhang stated that the CSF will increase its capital from 24 billion Yuan to 100 billion to enlarge the business scale and provide sufficient fund support for brokerage firms' margin trading and short selling trading ; the CCH will purchase the stocks to rescue the market under the support by the central bank; and 25 mutual fund corporations announced to actively purchase stocks . This direct purchase plan started from the beginning of July and ended in the mid of August, 2015.

The large-scale direct purchase plan affected a large proportion of stocks in the A-share market. According to the estimation by Goldman Sachs' analysis, the capital amount spent by the national team was at least 1,500 billion RMB in 2015Q3 . According to the WIND's statistics, the national team had become the shareholders of 1,411 stocks until September 30. 1,365 firms directly owned by the CSF and the CCH, accounting for 49% of all A-share stock market. The purchased shares account for 7% of the total outstanding market value in the market.

Existing studies examine the effect of the direct purchase plan by the "national team" from both the long-term and the short-term view. In the short run, the government purchase plan during the stock market crash directly increases the demand for outstanding shares in the market and provides liquidity, effectively stabilizing the investors and the market (e.g., Huang et al., 2019). For example, Huang et al. (2019) estimated that the national team saved the non-financial firms' market value by 206 billion RMB. However, the implementation of the government purchase plan has negative effects on firm fundamentals in the long run. For example, after being rescued, the firms' long-term stock volatility increased, liquidity decreased, and pricing efficiency decreased. Even the operating performance was negatively affected by the program (Liu, Xu, and Zhang, 2019). Therefore, the government purchase plan could release the rescued firms' crash pressure, but reduce their following operating performance. In that case, we check whether our main results are driven by the direct purchase plan during the sampling period.

To verify whether our results are driven by this plan, we include an additional control variable that measures the effect of the national team's direct purchase plan, GovRes×Post, where GovRes is the share percentage purchased by the national team (including the CSF, the CCH, and other funds representing the central government) in the third quarter of 2015 , and the dummy variable Post takes the value of one if it is in the post-rescue period, i.e., after 2016. The results reported in Panel B of Table F3 show that our main results are unchanged when the effect of the national team's direct purchase plan is controlled.

### 7.4 Alternative Employee Composition Measures

Our baseline results are based on regressions using specific measures of employee composition. In this section, we repeat our regressions in Section 5.2 using alternative measures for employee skill composition.

To directly compare the relative change in the number of the two groups of workers, we construct the fraction of high-skilled employees, defined as the number of high-skilled workers divided by the total number of employees (% HSemp), as an alternative employee composition measure. Table F4, Column (1) restates our baseline regression in Equation (4) using the fraction of high-skilled employees as the dependent variable. We document that after the stock market crash, the proportion of high-skilled employees increases by more for firms that experience a more-severe decline in stock price, relative to the firms that experience a less-severe decline in stock price.

Besides, as we discuss in Section 3.4, the high-skilled workers include several categories of occupations: (1) R&D or technicians with research abilities, (2) finance staff with accounting and financial skills, and (3) sales and marketing staff with sales abilities. To check whether some specific categories of workers drive our main finding, we run the regressions separately for each of the three detailed occupation categories. The results are shown in Columns (2)–(4) of Table F4. The dependent variables are the log of the number of specific types of employees, including R&D or technicians in Column (2), finance staff in Column (3), and sales and marketing staff in Column (4). We find that all the three categories of workers show a similar pattern with the high-skilled workers, suggesting that our baseline results are not driven by some specific detailed occupations.

## 7.5 Alternative Samples

### 7.5.1 Eliminating the Period of the Run-ups

In this subsection, we partial out the potential bias is driven by the market bubble prior to the market crash. Our main analyses document that the skill premium gap between the treatment and control groups significantly increases through the 2015 stock market crash. The pre-crash period is widely considered a bubble period (An, Bian, Lou, and Shi, 2020) . The Chinese stock market experienced a roller coaster ride from the beginning of July 2014 to the onset of the market crash. Figure 1 shows that the SSECI skyrocketed by 152.22% during the period (from 2048.33 on Jun. 30th of 2014 to 5166.35 on Jun. 12th of 2015). Suppose a firm's skill premium is affected by its stock price. In that case, the jobs posted during the bubble period may overpay, especially for firms with larger stock price increases during the bubble episode. Besides, the firms with larger price bubbles are more likely to drop dramatically during the crash period, as shown in Section 8.2. In that case, the increase in the skill premium gap between the treatment and control groups would be driven by the negative gap of the skill premium during the bubble period. That is, the post-crash skill premium gap is not larger than that in the average time. Thus, the effects that we document in the main section are biased upwards.

To rule out this possibility, we eliminate the period of the bubble-crash episodes from Jul. 1st of 2014 to Feb. 1st of 2016 in the job posting data and exclude 2014 to 2015 in the firm panel data. The results shown in Table F5 are similar to our main results.

### 7.5.2 Merging the Online Job Posting data with the Firm Panel Data

The online job posting data do not cover the entire firm sample listed on the A-share market. We expect to obtain consistent patterns in firm-level analyses using a subsample of firms that show up in the online job posting data. If there exist large differences between results based on the entire firm sample and the online job posting sample, the online job posting sample seems not as representative as expected. Table F6 reports the firm-level estimation results using a subsample of firms from the online job posting data. The results are consistent with our baseline results.

# 8 Conclusion

We use detailed job-posting data from a large online job site in China to study how stock price shocks unrelated to fundamental factors affect firms' hiring and investment decisions. We use the Chinese A-share stock market crash in 2015, which was prompted by fire sales following the government's regulatory actions towards extensive margin trading, unrelated to firms' fundamental value. It enables us to abstract from addressing the endogeneity of investment opportunities and stock market performances and examine whether and how fluctuations in financial markets lead to real consequences for firms.

We find a significant and economic effect. Firms that experience more severe declines in stock price during the stock market crash reduce demand for high-skilled workers, invest less in technology-related assets, and spend less in and R&D, compared to less-affected firms. One standard deviation increase in price drop during the cash period is related to an 11.1% drop in high-skilled workers, a 12.5% increase in low-skilled workers, a 2.5% drop in the average wage, and a 12.3% drop in R&D activities. Ultimately, harder-hit firms performed worse in productivity, sales growth, and market share after the crash.

Two potential mechanisms may explain our findings. First, a substantial price decline renders firms pay a compensating wage premium for high-skilled workers, thus lowering the demand. Second, the price crash makes external financing more costly, especially for more financially constrained ones, forcing firms to reduce technology-related inputs. We find empirical results consistent with both explanations. Using the job-posting data, we show that jobs requiring a higher level of skill take a significantly longer duration to fill, suggesting that high-skilled workers face higher transaction costs from unemployment spell in the case of job separation. The increase in the skill premium is also more substantial for firms located in provinces where labor supply is low, and high-skilled workers have more bargaining power. Consistent with the financial friction channel, we find that the effect is more significant for younger firms and firms are that rely more on share pledges (and use stock as collater), which are likely to be more financially constrained.

We address the potential endogeneity concerns using two approaches - the propensity score matching and a combination of fuzzy RDD and an IV approach. Given that excessive margin trading is the main driving force of the crash, we estimate the margin trading eligibility using inclusion criteria posted by the government and compare firms that fall within a narrow band of the predicted eligibility. Both approaches offer qualitatively similar results.

Our findings suggest a tight connection between stock markets and firm decisions. Given frictions in the capital market, financial shocks unrelated to the underlying economic factors can force firms to deviate from first-best actions, resulting in sub-optimal choices for technology adoption. Our paper also highlights the cost of the stock market crash for the real economy. Following the 2015 stock market crash, the collapse of external financing channels makes it more difficult for firms to invest in technology and develop complementary skills.

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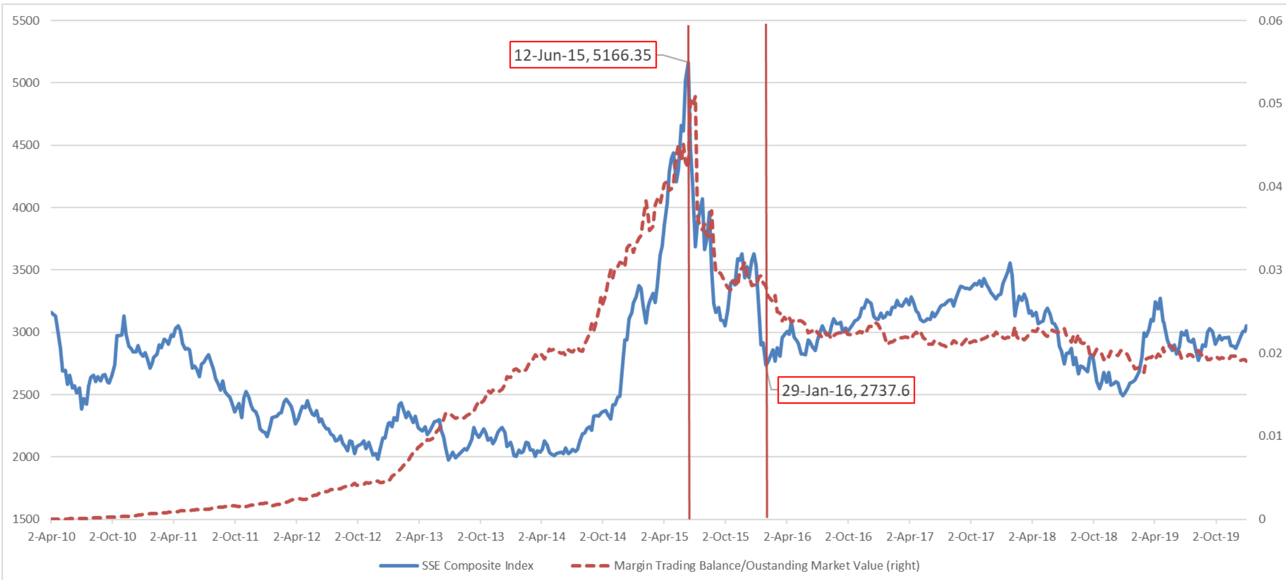
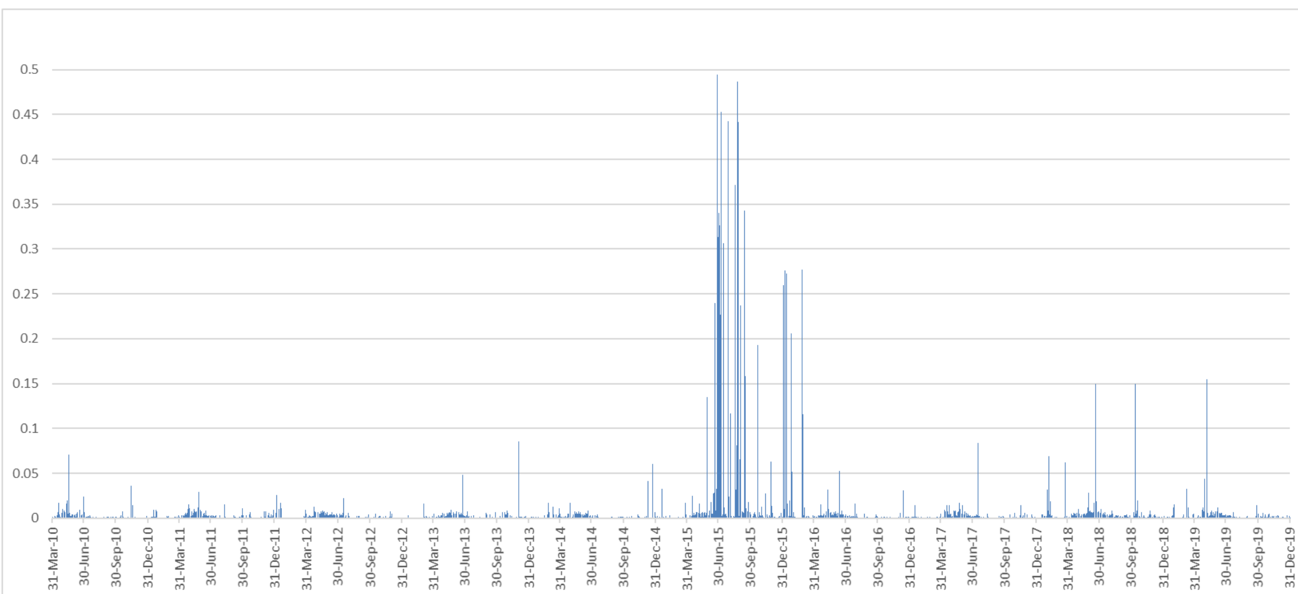
**Figure 1. 2015 Stock Market Crash in China**

Panel A: Shanghai Stock Exchange Composite Index and Margin Trading Balance.



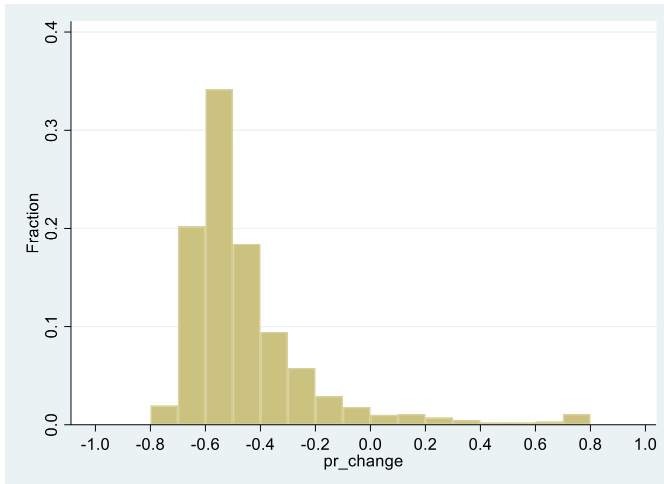

Panel B: % of Stocks Hitting Lower Price Limit.



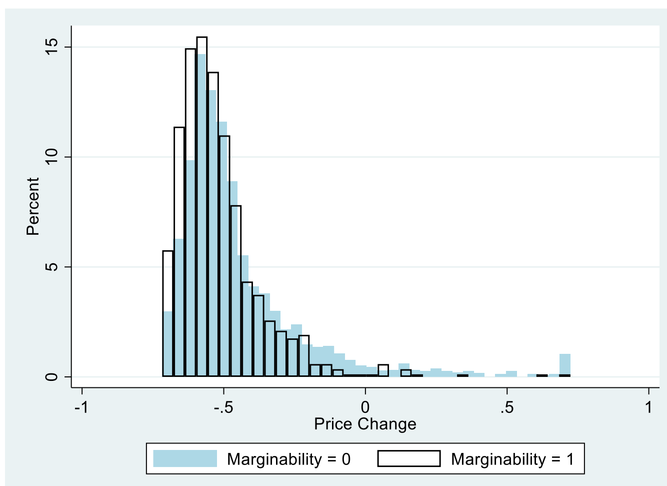
Panel A depicts the Shanghai Stock Exchange (SSE) composite index (the solid red line) and the margin trading balance standardized by the total market value (the blue dotted line) from April 2nd, 2010 to December 31st, 2019. Panel B presents the proportion of stocks that hit the lower price limit during the same period from April 2nd, 2010 to December 31st, 2019.

**Figure 2. Histograms of Price Changes during the 2015 Stock Market Crash**

Panel A: Total Sample



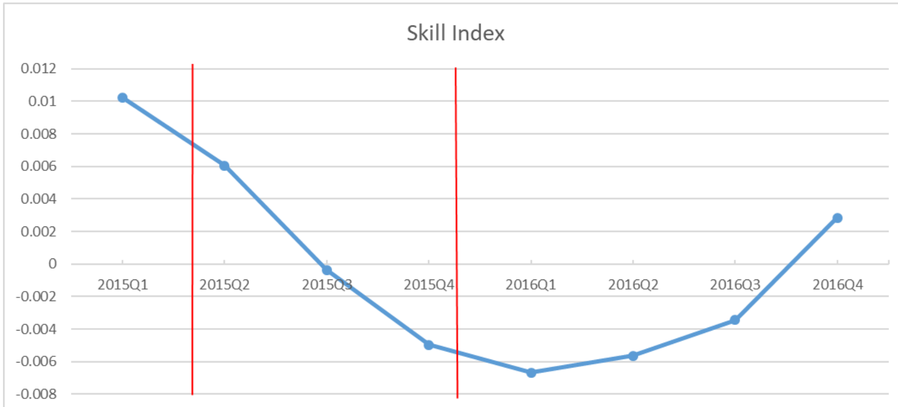

Panel B: Sub-groups divided by marginability



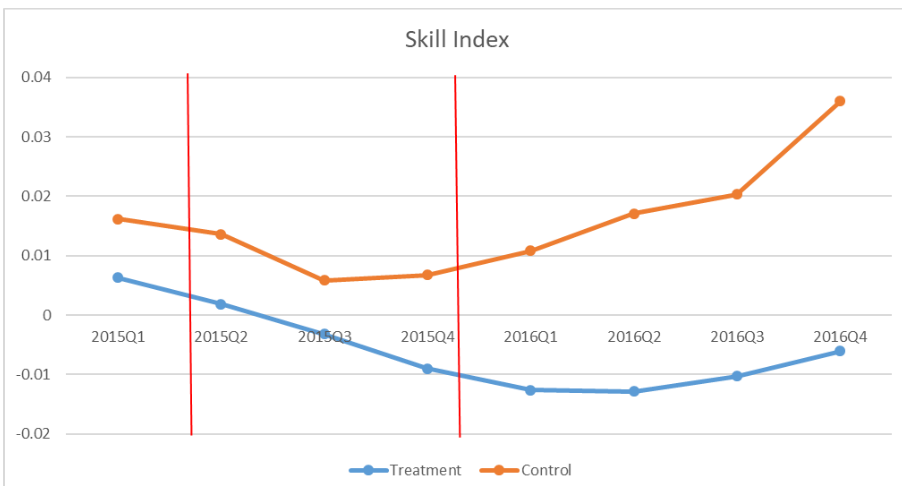

The figures show histograms of firms' price changes over the period from Jun. 15, 2015, to Feb. 01, 2016. Panel A includes the full sample and shows the proportions of stocks in each price change bin (of size 0.1). The distribution has been winsorized at the top and bottom 1%. Panel B shows the histogram of the price changes during the crash period for sub-groups divided by marginability. We compare the distribution of price changes for firms that are marginable against those that are not.

**Figure 3. Skill Index during the pre- and post- crash periods**

Panel A: All firms

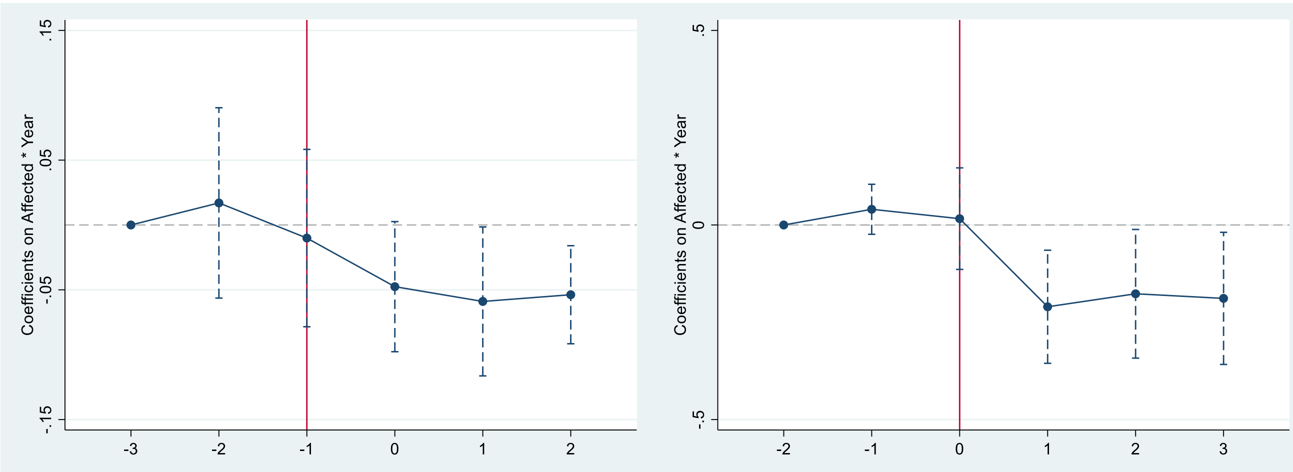



Panel B: Treatment versus control firms

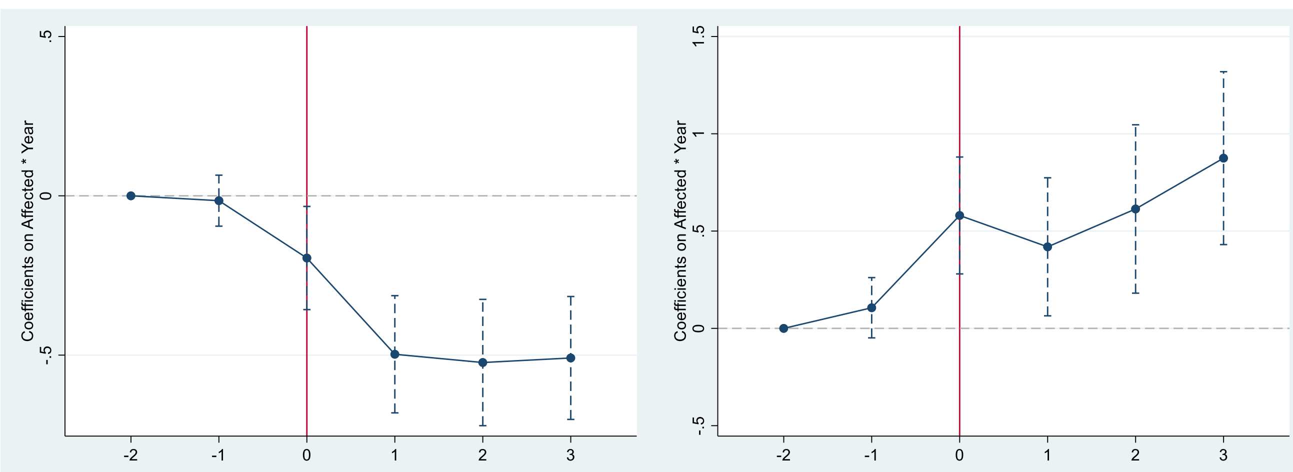



The figure depicts the average skill index (the dashed blue line) around the stock market crash. We aggregate skill index across job postings by quarter and then by year. Panel A plots the demand for skill for all firms, and Panel B plots the series separately for firms in the treatment (firms with the price change during the period of the stock market crash less than −30%) and control (firms with the price change during the period of the stock market crash not less than −30%) groups.

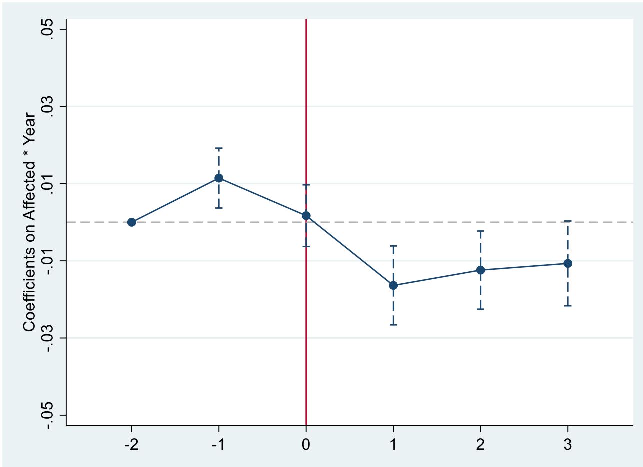
**Figure 4. Pre-existing Trends**



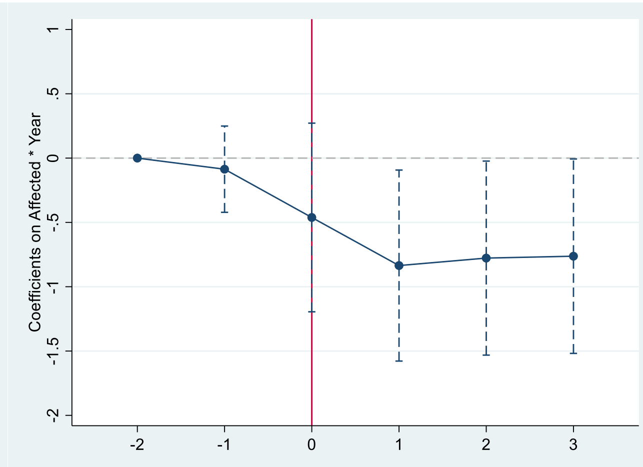

**(a) Skill index** **(b) Ln_Emp**




**(c) Ln_HSemp** **(d) Ln_LSemp**




**(e) Ln_HighTechInv**




**(f) Ln_RDexpense**

In Panels (a) to (f), this figure shows the dynamic impact of the price change during the 2015 stock market crash on each of the six firm outcomes of interest over the sample period. Panel (a) plots the estimated coefficients based on a job-regression of the skill index on a set of interactions between $Affected$ (which is the negative value of $Price\_Change$) and half-year dummies (excluding the first half-year of 2014). Firm fixed effects, Month–City fixed effects, Month–Occupation fixed effects, and City–Occupation fixed effects are included. The omitted time category is the first half-year of 2014. The $x$ axis represents the half-year relative to the first half-year of 2014, and the $y$ axis is the estimated coefficient of $Affected \times HalfYear_t$. Panels (b) to (f) plot the estimated coefficients based on a firm-level regression of firm outcomes on a set of interactions between $Affected$ (which is the negative value of $Price\_Change$) and year dummies (excluding 2014). Firm fixed effects and year fixed effects are included. The omitted time category is 2014. The $x$ axis represents the year relative to 2014, and the $y$ axis is the estimated coefficient of $Affected \times Year_t$. The vertical dashed lines in all panels represent the 90% confidence interval, adjusted for clustering at the firm level.

## Table 1. Summary Distribution

This table reports the yearly distribution of the number of job advertisements in the online job posting data and the number of firms in the overall sample. Panel A reports the overview of unique full-time job advertisements posted by firms listed in Shanghai and Shenzhen Stock Exchanges in Lagou.com (https://www.lagou.com) between 2014 and 2016. Three types of observations are removed: (1) The repetition of job ads with the same contents; (2) firms that have posted less than two ads in total; and (3) firms listed after the end of 2014. The final sample includes 532 unique firms and 33,108 job posting ads for the years 2014–2016. Our overall sample in Panel B consists of all A-share firms publicly listed for at least one year as of the beginning of the stock market crash, Jun. 15, 2015, and traded in the Shanghai and Shenzhen stock exchanges from 2013 to 2018. We drop the firms that traded on less than 30 trading days during the stock market crash period from Jun. 15, 2015, to Feb. 01, 2016, firms with total employment less than 100, and ST and *ST firms. In the baseline analyses, we drop the observations in 2015 to eliminate the potential effect of the crash year. Column (1) presents the number of sample firms by year. Columns (2) presents the percentage of firms.

**Panel A: Online Job Posting Data**

| Year | Number of Unique Job Advertisements | Percent |
|---|---|---|
| 2014 | 4,311 | 13.03 |
| 2015 | 11,745 | 35.50 |
| 2016 | 17,032 | 51.47 |
| Total | 33,108 | 100.00 |

**Panel B: Firm Panel Data**

| Year | Number of Unique Firms | Percent |
|---|---|---|
| 2013 | 2,364 | 16.12 |
| 2014 | 2,491 | 16.98 |
| 2015 | 2,451 | 16.71 |
| 2016 | 2,453 | 16.72 |
| 2017 | 2,458 | 16.76 |
| 2018 | 2,450 | 16.70 |
| Total | 14,667 | 100.00 |

## Table 2. Summary Statistics (Job Posting Data)

This table provides information on online job vacancy posting data. Panel A shows the summary statistics of the main job requirement variables used in the following analysis. Panel B reports the summary statistics of other variables. Appendix A provides detailed variable definitions and data sources. Panel C presents the distribution of firms and job postings by city across time. Cities are classified into two groups: first-tier cities (Beijing, Shenzhen, Shanghai, and Guangzhou) and other cities. The first tier includes the four cities with the largest population and economic importance in China.

**Panel A: Working Experience and Education Requirements**

| Job Requirement | Categorical Variables | Freq. | Percent |
|---|---|---|---|
| **Experience** | | | |
| Any | 1 | 4,869 | 14.72 |
| 1 Year | 2 | 12,340 | 37.29 |
| 3 Year | 3 | 12,169 | 36.78 |
| 5 Year | 4 | 3710 | 11.21 |
| **Education** | | | |
| Any or Junior Colleges | 0 | 9545 | 28.85 |
| > Bachelor | 1 | 23543 | 71.15 |
| **Total** | | **33,108** | **100** |

**Panel B: Other Job characteristics**

| Variable | N | Mean | SD | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| ln_SalaryMean | 33,088 | 2.096 | 0.539 | -1.043 | 1.729 | 2.135 | 2.437 | 4.255 |
| ln_SalaryMin | 33,079 | 1.807 | 0.523 | -0.370 | 1.442 | 1.847 | 2.149 | 4.255 |
| ln_SalaryMax | 32,689 | 2.334 | 0.540 | 0.323 | 1.952 | 2.358 | 2.646 | 4.269 |
| Price Change | 33,088 | -0.445 | 0.243 | -0.717 | -0.597 | -0.517 | -0.337 | 0.723 |
| % of young firms | 31,955 | 0.339 | 0.473 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| % of firms with share pledge | 33,088 | 0.711 | 0.453 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 |
| % of SOE | 30,613 | 0.083 | 0.276 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |

**Panel C: Distribution by City**

| | | | Before Crash (2014.01.01–2015.06.15) | | After Crash (2015.06.15–2016.12.31) | |
|---|---|---|---|---|---|---|
| | City | Number of firms | # of postings | proportion (%) | # of postings | proportion (%) |
| First-tier City | Beijing | 143 | 4,567 | 50.48 | 9,857 | 41.00 |
| | Shenzhen | 83 | 977 | 10.80 | 3,748 | 15.59 |
| | Shanghai | 79 | 1,066 | 11.78 | 2,919 | 12.14 |
| | Guangzhou | 43 | 426 | 4.71 | 1,354 | 5.63 |
| Other Cities | | 184 | 2,012 | 22.24 | 6,162 | 25.63 |
| | Total | 532 | 9,048 | | 24,040 | |

## Table 3. Constructing the Skill Index

This table shows how to identify different skill requirements and construct the skill index. Panel A reports the list of the words or phrases in both Chinese and English versions to identify the requirements for computer skills, cognitive skills, and management skills, respectively. Panel B presents the estimation results of regressions of the wage offered in the job posting advertisements on the five skill component variables including the computer skills, cognitive skills, management skills, working experience requirements, and education requirements, using the 2014 observations (Column (1)) and post-crash observations (Column (2)), respectively. The dependent variable, $LnSalaryMean$, is the log of the mean of salary (in 2000 RMB) provided in a job description. The independent variables include the log of the number of words indicating computer skills ($LnComputer$), cognitive skills ($LnCognitive$), management skills ($LnManagement$) required in a job description, the log of experience in a job posting ($LnExp$), and a dummy variable indicating that the job requires at least a bachelor's degree ($Above\_BA$), all of which are standardized by their respective mean and standard deviation calculated across all observations of job ads, to have zero mean and unit variance. The full set of fixed effects (FE), including firm FE, city–year-month FE, occupation–year-month FE, and city–occupation FE are included in all models. Standard errors clustered at the firm level are presented in parentheses below coefficient estimates. Panel C reports summary statistics of skill index and the number of words indicating computer skills, cognitive skills, and management skills, respectively. Appendix A provides detailed variable definitions and data sources.

**Panel A: Key Words and Phrases Used to Identify Different Skill Requirements**

| **Job Skills** | **Keywords and Phrases** |
|---|---|
| Computer Skills | computer, programming, development, coding, testing, framework, machine learning.<br>(in Chinese) 计算机，编程，开发，编写，测试，架构，机器学习，电脑 |
| Cognitive Skills | research, statistics, analyzing, math, improvement, thinking.<br>(in Chinese) 研究，分析，统计，改进，思考，数学 |
| Management Skills | management, guide, negotiation, strategy, leadership, supervisory, client.<br>(in Chinese) 管理，指导，谈判，战略，领导力，监督，客户 |

**Table 3**
**Continued**

**Panel B: Constructing the Skill Index**

| | (1) | (2) |
|---|---|---|
| VARIABLES | ln_SalaryMean | |
| | Before | After |
| LnComputer | 0.058*** | 0.084*** |
| | (0.009) | (0.006) |
| LnCognitive | 0.014 | 0.027*** |
| | (0.009) | (0.006) |
| LnManagement | 0.028*** | 0.004 |
| | (0.007) | (0.005) |
| LnExp | 0.175*** | 0.208*** |
| | (0.032) | (0.012) |
| Above_BA | 0.032*** | 0.050*** |
| | (0.011) | (0.007) |
| Observations | 4,273 | 16,062 |
| Firm FE | Yes | Yes |
| Month*City FE | Yes | Yes |
| Month*Occupation FE | Yes | Yes |
| City*Occupation FE | Yes | Yes |
| Adjusted R-squared | 0.579 | 0.588 |

**Panel C: Summary Statistics**

| **Variable** | **N** | **Mean** | **SD** | **Min** | **P25** | **P50** | **P75** | **Max** |
|---|---|---|---|---|---|---|---|---|
| Skill index | 33,088 | 0.000 | 0.203 | −0.504 | −0.105 | 0.030 | 0.164 | 0.427 |
| Computer Skills | 33,088 | 1.735 | 1.482 | 0.000 | 0.000 | 2.000 | 3.000 | 6.000 |
| Cognitive Skills | 33,088 | 0.830 | 0.920 | 0.000 | 0.000 | 1.000 | 1.000 | 6.000 |
| Management Skills | 33,088 | 0.727 | 0.833 | 0.000 | 0.000 | 1.000 | 1.000 | 6.000 |

## Table 4. Summary Statistics (Firm Panel Data)

This table reports summary statistics for the key variables used in our baseline research. Appendix A provides detailed definitions and sources of these variables.

| Variable | N | Mean | SD | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| Price Change | 2,493 | −0.471 | 0.217 | −0.717 | −0.596 | −0.529 | −0.425 | 0.723 |
| Post | 12,216 | 0.603 | 0.489 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 |
| Ln_Emp | 12,067 | 7.764 | 1.229 | 5.094 | 6.933 | 7.692 | 8.515 | 11.179 |
| Ln_HSemp | 10,927 | 6.496 | 1.278 | 3.091 | 5.663 | 6.444 | 7.298 | 9.856 |
| Ln_LSemp | 12,216 | 5.978 | 2.795 | 0.000 | 5.352 | 6.714 | 7.763 | 10.408 |
| Ln_AWAGE | 11,950 | 11.204 | 0.479 | 10.170 | 10.877 | 11.158 | 11.486 | 12.612 |
| Ln_HighTechInv | 10,646 | 0.025 | 0.059 | -0.015 | 0.000 | 0.004 | 0.021 | 0.392 |
| Ln_RDexpense | 9,787 | 0.093 | 0.166 | 0.000 | 0.016 | 0.039 | 0.092 | 1.098 |
| Sales/Emp (t+1) | 9,604 | 13.836 | 0.890 | 11.838 | 13.238 | 13.741 | 14.334 | 16.470 |
| Sales/Emp (t+2) | 7,185 | 13.837 | 0.889 | 11.838 | 13.246 | 13.739 | 14.335 | 16.470 |
| Sales Growth (t+1) | 9,352 | 0.857 | 2.159 | -0.768 | 0.007 | 0.342 | 0.893 | 16.781 |
| Sales Growth (t+2) | 7,043 | 0.848 | 2.113 | -0.768 | -0.016 | 0.336 | 0.902 | 16.781 |
| Market Share (t+1) | 9,689 | 0.028 | 0.062 | 0.000 | 0.002 | 0.006 | 0.021 | 0.397 |
| Market Share (t+2) | 7,199 | 0.028 | 0.062 | 0.000 | 0.002 | 0.006 | 0.021 | 0.397 |

## Table 5. Skill Requirement in Online Job Postings

This table relates the 2015 stock market crash to the ad-level skill requirements in online job posting descriptions for the full sample and subsamples. The sample period covers 2014–2016. The dependent variable is $Skill\ index$, the weighted average of the five normalized skill components including computer skills, cognitive skills, management skills, experience requirements, and education requirements. $Affected$ is the firm-level negative buy-and-hold return during the stock market crash period through Jun. 12, 2015, to Feb. 01, 2016, capturing the severity of the price crash during the stock market crash period. Dummy variable $Post$ equals 1 for every job posting advertisement posted after the start of the crash, Jun. 12, 2015, and 0 otherwise. Column (1) uses the total sample in the online job posting data; Column (2) deletes the job posting advertisements posted from the crash period, and Column (3) keeps only a sample of non-state-owned enterprises. The definitions of these variables can be found in Appendix A. Firm fixed effects, Month–City fixed effects, Month–Occupation fixed effects, and City–Occupation fixed effects are included in all regressions. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| Dep Var: | Skill index | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Entire Sample | Delete Crash Period | non-SOE |
| Affected × Post | −0.044** | −0.056** | −0.047** |
| | (0.019) | (0.023) | (0.019) |
| Observations | 33,088 | 25,122 | 28,032 |
| Firm FE | Yes | Yes | Yes |
| Month*City | Yes | Yes | Yes |
| Month*Occupation | Yes | Yes | Yes |
| City*Occupation | Yes | Yes | Yes |
| Adjusted R-squared | 0.224 | 0.225 | 0.222 |

## Table 6. The Effect on Employment and Technology Investments

This table reports difference-in-differences analyses of employee numbers by occupation, average wages, technology investments, and R&D expenditures for the entire sample using the firm panel data. The dependent variables are the log of the number of total employees (*Ln_EMP*) in Column (1), the log of the number of high skill workers (*Ln_HSemp*) in Column (2), the log of the number of low skill workers (*Ln_LSemp*) in Column (3), the log of average wage per employee (*Ln_Awage*) in Column (4), the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets (Unit: billion) in 2000 RMB (*Ln_HighTechInv*) in Column (5), and the log of one plus total R&D expenditures in 2000 RMB (*Ln_RDexpense*) in Column (6). *Affected* is the negative value of buy-and-hold returns generated during the stock market crash, from Jun. 12, 2015, to Feb. 01, 2016. *Post* indicates the year after the stock market crash. Year fixed effects and firm fixed effects are both controlled. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_Awage | Ln_HighTechInv | Ln_RDexpense |
| Affected × Post | −0.211** | −0.509*** | 0.576** | −0.116*** | −0.019*** | −0.566*** |
| | (0.086) | (0.106) | (0.231) | (0.039) | (0.005) | (0.113) |
| Observations | 12,061 | 10,905 | 12,215 | 11,943 | 10,589 | 9,675 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.900 | 0.844 | 0.782 | 0.788 | 0.496 | 0.816 |

## Table 7. The Effect on Firm Performance

This table presents the impact of stock price crashes on firm performance for the overall sample. The dependent variables are sales per employee (*Sales/Emp*) in columns (1)–(2), sales growth rate over the last three years (*Sales Growth*) in columns (3)–(4), and market share in the three-digit CSRC (2012) industry (*Market Share*) in columns (5)–(6). Year fixed effects and firm fixed effects are both controlled in all columns. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Sales/Emp | | Sales Growth | | Market Share | |
| | t+1 | t+2 | t+1 | t+2 | t+1 | t+2 |
| Affected × Post | −0.292*** | −0.125** | −1.685*** | −0.213 | −0.007* | −0.001 |
| | (0.073) | (0.061) | (0.409) | (0.362) | (0.004) | (0.002) |
| Observations | 9,585 | 7,168 | 9,316 | 6,900 | 5,898 | 4,689 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.830 | 0.849 | 0.284 | 0.344 | 0.950 | 0.961 |

## Table 8. Evolution of Skill Premiums around the Stock Market Crash

This table shows the skill premium gap between the treatment group and the control group during the pre-crash period and that during the post-crash period, respectively. The whole sample of job vacancy advertisements are split into two periods, with the stock market crash as the cut-off point and show the results. The "Before" columns (Columns (1), (3), and (5)) include the job vacancy advertisements posted before the onset of the stock market crash, June 15, 2015, and the "After" columns (Columns (2), (4), and (6)) include the job vacancy advertisements posted after the end of the stock market crash, February 1, 2016. The dependent variables are the log of the mean (Columns (1) and (2)), minimum (Columns (3) and (4)), and maximum (Columns (5) and (6)) values of the wage range that is offered in a job description, respectively. The independent variable $Skill\ index$ is the weighted average of the five normalized skill components, including computer skills, cognitive skills, management skills, experience requirements, and education requirements. $Affected$ is the firm-level opposite number of buy-and-hold return during the stock market crash period through Jun. 12, 2015, to Feb. 01, 2016, capturing the severity of the price crash during the stock market crash period. The empirical $p$-values for equality tests are computed using the simulation procedure described in Cleary (1999). The definitions of all variables can be found in Appendix A. Firm fixed effects, Month–City fixed effects, Month–Occupation fixed effects, and City–Occupation fixed effects are controlled in all regressions. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | LnSalaryMean | | LnSalaryMin | | LnSalaryMax | |
| | Before | After | Before | After | Before | After |
| Affected × Skill_index | 0.138 | 0.367* | 0.126 | 0.403** | 0.146 | 0.343 |
| | (0.267) | (0.192) | (0.256) | (0.158) | (0.275) | (0.215) |
| Skill_index | 0.991*** | 1.030*** | 0.993*** | 1.013*** | 0.990*** | 1.041*** |
| | (0.167) | (0.110) | (0.155) | (0.091) | (0.174) | (0.122) |
| Equality test | $P$=0.000 | | $P$=0.000 | | $P$=0.009 | |
| Observations | 8,821 | 15,946 | 8,816 | 15,942 | 8,821 | 15,946 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*Occupation | Yes | Yes | Yes | Yes | Yes | Yes |
| City*Occupation | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.574 | 0.593 | 0.561 | 0.584 | 0.570 | 0.586 |

## Table 9. Vacancy Duration and the Skill Level

This table tests the relationship between the posting-level vacancy duration and the skill level. Days-to-Fill measures the number of days for which a given job posting is active online. The dependent variables are Days-to-Fill in Column (1) and the logarithm of Days-to-Fill in Column (2). The definitions of all variables can be found in Appendix A. Firm fixed effects, Month–City fixed effects, Month–Occupation fixed effects, and City–Occupation fixed effects are controlled in all regressions. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) |
|---|---|---|
| | **Duration of Postings** | |
| VARIABLES | Days-to-Fill | log(Days-to-Fill) |
| Skill | 26.949*** | 0.367*** |
| | (5.501) | (0.105) |
| Firm FE | Yes | Yes |
| Month*City | Yes | Yes |
| Month*Occupation | Yes | Yes |
| City*Occupation | Yes | Yes |
| Adjusted R-squared | 0.247 | 0.203 |
| Observations | 32,851 | 32,851 |

## Table 10. The Evolution of Skill Premiums by Employee Bargaining Power

This table presents estimates from the regressions explaining the ad-level skill requirements in online job posting descriptions for firms located in provinces with different levels of employee bargaining power. The regressions in Table 8 are estimated separately for subsamples of firms formed on the basis of the bargaining power measure. The province-level index of human resources supply condition in 2014, constructed by Wang, Fan, and Hu (2019), captures the province-level bargaining power between workers and firms before the stock market crash. The empirical *p*-values for equality tests are determined using the simulation procedure described in Cleary (1999). The definitions of all variables can be found in Appendix A. Firm fixed effects, Month–City fixed effects, Month–Occupation fixed effects, and City–Occupation fixed effects are controlled in all regressions. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Low Bargaining Power (Labor supply condition > Median)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | LnSalaryMean | | LnSalaryMin | | LnSalaryMax | |
| | Before | After | Before | After | Before | After |
| Affected × Skill_index | 0.735 | 0.705* | 0.637 | 0.655** | 0.790 | 0.731 |
| | (0.597) | (0.399) | (0.569) | (0.319) | (0.616) | (0.451) |
| Skill_index | 0.587** | 0.824*** | 0.627** | 0.857*** | 0.565* | 0.805*** |
| | (0.291) | (0.209) | (0.272) | (0.171) | (0.304) | (0.232) |
| Equality test | *P*=0.451 | | *P*=0.423 | | *P*=0.396 | |
| Observations | 4,287 | 7,351 | 4,287 | 7,349 | 4,287 | 7,351 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*Occupation | Yes | Yes | Yes | Yes | Yes | Yes |
| City*Occupation | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.529 | 0.618 | 0.510 | 0.604 | 0.530 | 0.614 |

**Panel B: High Bargaining Power (Labor supply condition < Median)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | LnSalaryMean | | LnSalaryMin | | LnSalaryMax | |
| | Before | After | Before | After | Before | After |
| Affected × Skill_index | 0.091 | 0.255** | 0.111 | 0.307*** | 0.080 | 0.224* |
| | (0.151) | (0.115) | (0.162) | (0.111) | (0.147) | (0.120) |
| Skill_index | 1.130*** | 1.100*** | 1.117*** | 1.076*** | 1.137*** | 1.115*** |
| | (0.072) | (0.069) | (0.077) | (0.065) | (0.071) | (0.072) |
| Equality test | *P*=0.052 | | *P*=0.020 | | *P*=0.091 | |
| Observations | 4,452 | 8,516 | 4,447 | 8,514 | 4,452 | 8,516 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |

| | | | | | | |
|---|---|---|---|---|---|---|
| Month*City | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*Occupation | Yes | Yes | Yes | Yes | Yes | Yes |
| City*Occupation | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.623 | 0.578 | 0.611 | 0.570 | 0.617 | 0.570 |

## Table 11. The Heterogeneous Effects on Skill Demands by Financial Constraints

This table presents estimates from the regressions explaining the ad-level skill requirements in online job posting descriptions for firms with different levels of financial constraints. The regressions are estimated separately for subsamples of firms formed on the basis of financial constraint measures, including firm age and the share pledge status. Firm age is measured as the number of years between the firm is established and the year prior to the onset of the crash, and the subsamples comprise firms with firm age below and above the entire sample median. For the share pledge status, the subsamples are split based on whether the firm's ownership is pledged as collateral to raise financing at the beginning of the stock market crash. The empirical *p*-values for equality tests are determined using the simulation procedure described in Cleary (1999). The definitions of all variables can be found in Appendix A. Firm fixed effects, Month–City fixed effects, Month–Occupation fixed effects, and City–Occupation fixed effects are controlled in all regressions. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| DEPVAR = | Skill index | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Young | Old | SharePledge Yes | SharePledge No |
| Affected × Post | −0.073*** | −0.011 | −0.063*** | 0.046 |
| | (0.025) | (0.015) | (0.021) | (0.042) |
| Equality test | *P*=0.000 | | *P*=0.000 | |
| Observations | 21,032 | 10,726 | 23,458 | 9,446 |
| Firm FE | Yes | Yes | Yes | Yes |
| Month*City | Yes | Yes | Yes | Yes |
| Month*Occupation | Yes | Yes | Yes | Yes |
| City*Occupation | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.217 | 0.273 | 0.228 | 0.254 |

## Table 12. The Heterogeneous Effects on Technology by Financial Constraints

This table reports difference-in-differences analyses in Table 9 for subsamples formed on the basis of financial constraint measures, including firm age (Panel A), share pledge status (Panel B), and state ownership (Panel C), respectively. In Panel A, firm age is measured as the number of years between the firm is established and the year prior to the onset of the crash, and the subsamples comprise firms with firm age below and above the entire sample median. For the share pledge status in Panel B, the subsamples are split based on whether the firm's ownership is pledged as collateral to raise financing at the beginning of the stock market crash. In Panel C, the full sample is divided into two subsamples: SOE firms and non-SOE firms. Following prior literature (e.g., Allen, Qian and Qian, 2005; Li et al., 2017), a company is defined as state-owned if the ultimate controlling shareholder is a government agency. The empirical *p*-values for equality tests are determined using the simulation procedure described in Cleary (1999). The definitions of all variables can be found in Appendix A. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Panel A: Firm Age**

| **Young** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_AWAGE | Ln_HighTechInv | Ln_RDexpense |
| Affected × Post | −0.426*** | −0.661*** | 0.593* | −0.117** | −0.025*** | −0.633*** |
| | (0.115) | (0.152) | (0.306) | (0.059) | (0.008) | (0.134) |
| Observations | 5,942 | 5,235 | 5,979 | 5,873 | 5,333 | 5,405 |
| Adjusted R2 | 0.898 | 0.830 | 0.785 | 0.766 | 0.503 | 0.823 |
| **Old** | (7) | (8) | (9) | (10) | (11) | (12) |
| Affected × Post | −0.001 | −0.402*** | 0.558* | −0.115** | −0.013** | −0.476** |
| | (0.120) | (0.143) | (0.336) | (0.052) | (0.006) | (0.189) |
| Observations | 6,119 | 5,670 | 6,236 | 6,070 | 5,256 | 4,270 |
| Adjusted R2 | 0.904 | 0.855 | 0.780 | 0.804 | 0.487 | 0.809 |
| Equality test | 0.000 | 0.012 | 0.422 | 0.478 | 0.049 | 0.102 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 12**
**Continued**

**Panel B: Share Pledge Status**

| **SP = Y** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_AWAGE | Ln_HighTechInv | Ln_RDexpense |
| Affected × Post | −0.222* | −0.634*** | 0.770** | −0.148*** | −0.022*** | −0.667*** |
| | (0.116) | (0.129) | (0.307) | (0.049) | (0.006) | (0.129) |
| Observations | 6,840 | 6,294 | 6,943 | 6,787 | 6,033 | 5,615 |
| Adjusted R2 | 0.867 | 0.819 | 0.775 | 0.758 | 0.465 | 0.805 |
| **SP= N** | (7) | (8) | (9) | (10) | (11) | (12) |
| Affected × Post | −0.139 | −0.242 | 0.329 | −0.031 | −0.013 | −0.259 |
| | (0.122) | (0.173) | (0.324) | (0.067) | (0.009) | (0.202) |
| Observations | 5,221 | 4,611 | 5,272 | 5,156 | 4,556 | 4,060 |
| Adjusted R2 | 0.932 | 0.873 | 0.790 | 0.810 | 0.523 | 0.823 |
| Equality test | 0.000 | 0.000 | 0.000 | 0.008 | 0.047 | 0.001 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Panel C: State Ownership**

| **Non-SOE** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_AWAGE | Ln_HighTechInv | Ln_RDexpense |
| Affected × Post | −0.240** | −0.565*** | 0.823*** | −0.076* | −0.028*** | −0.651*** |
| | (0.116) | (0.138) | (0.290) | (0.045) | (0.006) | (0.147) |
| Observations | 6,771 | 6,118 | 6,844 | 6,744 | 5,999 | 5,879 |
| Adjusted R2 | 0.879 | 0.825 | 0.785 | 0.777 | 0.495 | 0.780 |
| **SOE** | (7) | (8) | (9) | (10) | (11) | (12) |
| Affected × Post | 0.012 | −0.079 | 0.320 | −0.010 | −0.011 | −0.291 |
| | (0.176) | (0.186) | (0.409) | (0.066) | (0.013) | (0.311) |
| Observations | 4,008 | 3,587 | 4,044 | 3,996 | 3,495 | 2,791 |
| Adjusted R2 | 0.925 | 0.875 | 0.802 | 0.802 | 0.491 | 0.873 |
| Equality test | 0.104 | 0.000 | 0.003 | 0.000 | 0.000 | 0.000 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 13. The Effect on Financing Behaviors

This table presents the impact of stock price crashes on firm financing behaviors for the overall sample. The dependent variables are the SEO dummy (*SEO*) in column (1), the amount of SEO divided by the total assets (*SEO_amount*) in column (2), the share pledge dummy (*SharePledge*) in column (3), the ratio of pledged shares over total shares (*SharePledge Ratio*) in column (4), and the long-term debt divided by the total assets (*LongtermDebt*) in column (5). Year fixed effects and firm fixed effects are both controlled in all columns. Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | SEO | SEO_amount | SharePledge | SharePledge Ratio | LongtermDebt |
| Affected × Post | −0.145*** | −0.049*** | −0.168*** | −0.019* | −0.018*** |
| | (0.026) | (0.008) | (0.042) | (0.011) | (0.007) |
| Observations | 12,215 | 12,202 | 12,215 | 12,215 | 12,215 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.0316 | 0.0301 | 0.433 | 0.357 | −0.0153 |

## Table 14. Propensity Score Matching

This table shows difference-in-differences analyses of skill requirements (Column (1)) and employee composition by skill (Columns (2)–(4)), technology investments (Column (5)), and R&D expenditures (Column (6)) using the propensity score-matched sample. Firms with above-median price change during the crash with those with below-median price change during the crash using a one-to-one nearest neighbor matching (without replacement) of the propensity score matching approach. Column (1) reports the results based on the job posting data, where the dependent variable is $Skill\ index$, the weighted average of the five normalized skill components including computer skills, cognitive skills, management skills, experience requirements, and education requirements. Columns (2)–(6) report the results based on the firm panel data, where the dependent variables are the log of the number of total employees ($Ln\_EMP$) in Column (1), the log of the number of high skill workers ($Ln\_HSemp$) in Column (2), the log of the number of low skill workers ($Ln\_LSemp$) in Column (3), the log of average wage per employee ($Ln\_Awage$) in Column (4), the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets (Unit: billion) in 2000 RMB ($Ln\_HTechAsset$) in Column (5), and the log of one plus total R&D expenditures in 2000 RMB ($Ln\_RDexpense$) in Column (6). $Affected$ is the firm-level negative buy-and-hold return during the stock market crash period through Jun. 12, 2015, to Feb. 01, 2016, capturing the severity of the price crash during the stock market crash period. Dummy variable $Post$ in Column (1) equals 1 for every job posting advertisement posted after the start of the crash, Jun. 12, 2015, and 0 otherwise. $Post$ in Columns (2)–(6) indicates the year after the stock market crash. Detailed variable definitions can be found in the Appendix. Firm fixed effects, Month*City fixed effects, Month*Occupation fixed effects, and City*Occupation fixed effects are controlled in Column (1). Year fixed effects and firm fixed effects are both controlled in Columns (2) to (6). Standard errors are shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Skill_index | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_HighTechInv | Ln_RDexpense |
| Affected × Post | -0.025** | -0.398*** | -0.376*** | 0.152 | -0.026*** | -0.746*** |
| | (0.012) | (0.121) | (0.137) | (0.281) | (0.008) | (0.172) |
| Observations | 9,237 | 6,488 | 6,437 | 6,514 | 5,656 | 5,222 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | No | No | No | No | No |
| Month*Occ | Yes | No | No | No | No | No |
| City*Occ | Yes | No | No | No | No | No |
| Adjusted R2 | 0.269 | 0.902 | 0.836 | 0.790 | 0.522 | 0.785 |

## Table 15. Fuzzy Regression Discontinuity and Instrumental Variable Approach

This table reports the results of the fuzzy RD estimation based upon crossing the vintage-specific threshold of the index used to determine marginability. Panel A presents the results of skill requirements based on the online job posting data and Panel B presents the results of employee numbers by occupation based on the firm panel data. We construct the running variable for stock $i$ in vintage $k$ as follows:

$$Inclusion\ index_i^k = 2 * \frac{Avearge\ Market\ Value_i^k}{Avearge\ Market\ Value\ of\ All\ Stocks\ in\ SH/SZ} + \frac{Avearge\ Trading\ Volume_i^k}{Avearge\ Trading\ Volume\ of\ All\ Stocks\ in\ SH/SZ}.$$

For each vintage, all not previously marginable stocks in the primary sample. The regulatory agency published a screening-and-ranking rule to determine the list of marginable stocks for two steps. First, screen out stocks that did not satisfy criteria to eliminate particularly small, volatile, illiquid, and newly listed stocks; second, rank the remaining stocks according to the inclusion index shown in the equation above and select the top candidates in the Shanghai (SH) and Shenzhen (SZ) Stock Exchanges, separately. The running variable $Inclusion\ index_i^k$ is normalized to have a value of zero at the threshold for each vintage. If a stock appears in the sample more than one time, only the most recent one is included. The analysis focuses on the "local" sample of stocks, defined as those stocks whose screening rule is satisfied and inclusion indexes lie close to the cutoff of 0.0003. We predict the probability that a stock becomes marginable using the local linear regression specification:

$$Marginable_i^k = \alpha\left[I_i^k(Index_i^k \geq C_E^k)\right] + \beta\left(Index_i^k - C_E^k\right) + \theta_k + \varepsilon_i^k,$$

where the $Marginable_i^k$ variable is a dummy variable indicating that firm $i$ becomes marginable in vintage $k$; The dummy variable $I_i^k(Index_i^k \geq C_E^k)$ is equal to one if the firm has an inclusion index $Index_i^k$ no less than the threshold $C_E^k$ and thus is expected to be more likely to become marginable. $\theta_k$ captures a vintage fixed effect. Standard errors are clustered at the firm level. For the regression estimation, we have the predicted probability of becoming marginable, $Predicted\ Marginability$. The two-stage least squares (2SLS) approach is used within the specified bandwidth (0.0003) of the threshold at the time marginability was determined. $Affected \times Post$ is instrumented by the interaction between the probability of becoming marginable ($Predicted\ Marginability$) and the *Post* indicator. The first-stage regression estimates

$$Affected \times Post = Predicted\ Marginability \times Post + FEs + \varepsilon.$$

The first stage is estimated separately for the job-level analysis in Panel A and the firm-level analysis in Panel B. Fixed effects ($FEs$) are firm fixed effects and year fixed effects when the firm panel data is used, and firm fixed effects, Month−City fixed effects, Month−Occupation fixed effects, and City−Occupation fixed effects when the job posting data is used.

For the second stage, the equation for each outcome of interest is estimated:

$$Y = \widehat{Affected} \times Post + FEs + \varepsilon.$$

The outcome variables $Y$ include the skill demand ($Skill\_index$) in Column (2) of Panel A, the log of the number of total employees ($Ln\_EMP$) in Column (2) of Panel B, the log of the number of high skill workers ($Ln\_HSemp$) in Column (3) of Panel B, the log of the number of low skill workers ($Ln\_LSemp$) in Column (4) of Panel B, and the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets (Unit: billion) in 2000 RMB ($Ln\_HTechAsset$) in Column (5) of Panel B. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 15**
**Continued**

**Panel A. Job Posting Data**

| VARIABLES | (1)<br>First-stage<br>Affected × Post | (2)<br>Second-stage<br>Skill_index |
|---|---|---|
| Predicted Marginability × Post | 0.551*** | |
| | (0.109) | |
| Affected × Post | | −0.165** |
| | | (0.075) |
| Observations | 1,324 | 1,324 |
| Firm FE | Yes | Yes |
| Month*City FE | Yes | Yes |
| Month*Occupation FE | Yes | Yes |
| City*Occupation FE | Yes | Yes |
| Adjusted R2 | 0.970 | 0.426 |

**Panel B. Firm Panel Data**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | First-stage | Second-stage | | | |
| | Affected × Post | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_HighTechInv |
| Predicted Marginability × Post | 0.070** | | | | |
| | (0.027) | | | | |
| Affected × Post | | −2.251 | −3.867** | −5.563 | −0.199* |
| | | (1.517) | (1.828) | (4.079) | (0.113) |
| Observations | 1,374 | 1,366 | 1,240 | 1,374 | 1,240 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.899 | 0.882 | 0.861 | 0.824 | 0.861 |

## Appendix

### A Variable Definition and Data Source

**Table A1. Variable Definition**

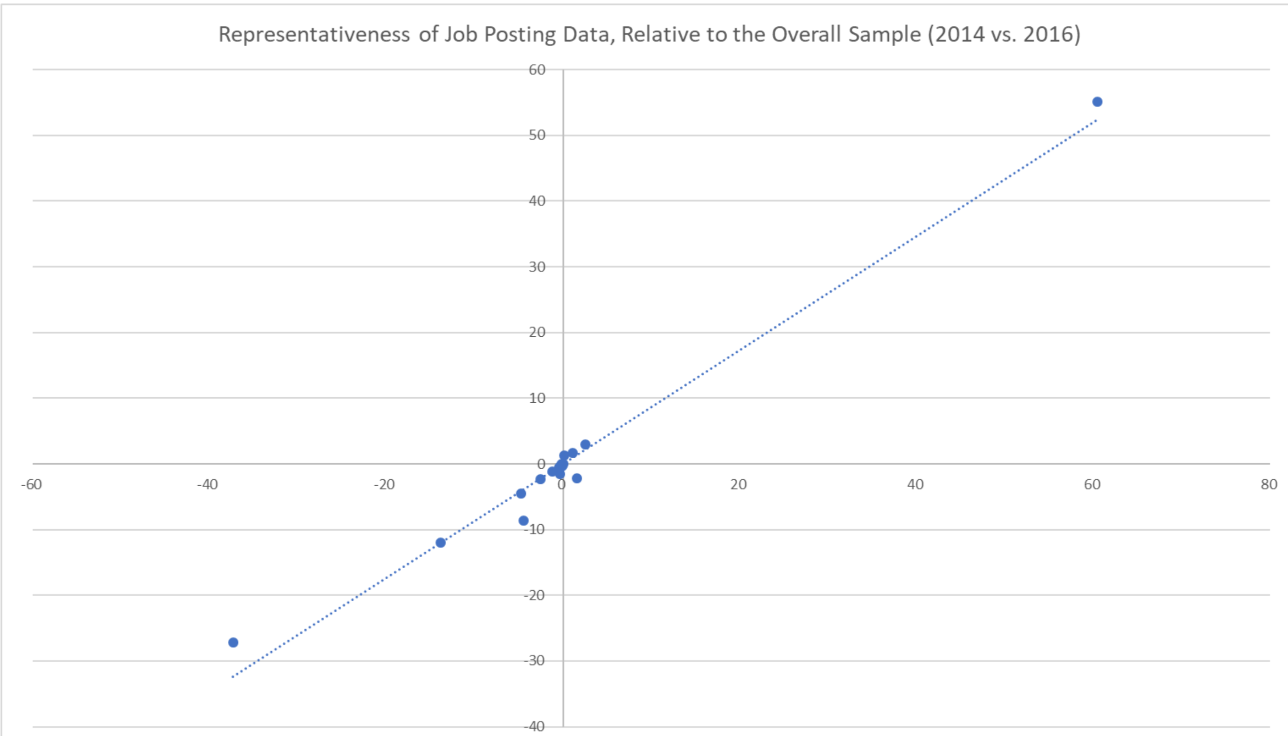
| Variables | **Definition** | **Data Sources** |
|---|---|---|
| Stock price-related Variables | | |
| Price_Change | The buy-and-hold returns during the stock market crash period, from Jun. 12, 2015, to Feb. 01, 2016 | CSMAR |
| Affected | The negative value of *Price_Change* | CSMAR |
| Affected_Dum | Dummy variable indicating that *Price_Change* is lower than -30% | CSMAR |
| **Variables in the Firm Panel Data** | | |
| EMP | Total number of employees. | Resset |
| HSemp | Number of high skill workers, which is the sum of *RD_Tech*, *fin*, and *mkt.* | Resset |
| LSemp | Number of production workers. | Resset |
| RD_Tech | Number of technicians and R&D personnel. | Resset |
| Ln_Payroll | Log of the total wage to all employees in 2000 RMB. | Resset |
| Ln_Awage | Log of the average wage per employee in 2000 RMB. | Resset |
| Ln_HighTechInv | Log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets in 2000 RMB (Unit: billion). | CSMAR |
| Ln_RDexpense | Log of one plus total R&D expenditures in 2000 RMB. | CSMAR |
| Sales Growth (t) | Sales growth rate from year t-3 to year t. | CSMAR |
| Sales/Emp | Sales per employee | CSMAR |
| Market Share | Market share in the three-digit CSRC (2012) industry, only for firms in competitive industries | CSMAR |
| Young/Old firms | Firms with below versus above median age, the number of years between the firm is established and 2014. | CSMAR |
| SharePledge | Dummy variable indicating that the firm's stocks are pledged as collateral to raise financing at the beginning of the stock market crash. | CSMAR |
| SOE | State-owned firms, which is controlled by state-owned entities in 2014 | CSMAR |
| Leverage | Total debt/total assets | CSMAR |
| LnSales | Log of sales income in 2014 | CSMAR |
| LnTurnover | Log of turnover in 2014 | CSMAR |
| State_own | The proportion of shares owned by state-owned entities in 2014 | CSMAR |
| Ln_Nyear_listed | Log of the number of years between the firm's listed year and 2014 | CSMAR |
| ROA | Net income divided by total assets in 2014 | CSMAR |
| Ln_EMP | Log of the number of employees in 2014 | CSMAR |
| HEmp_ratio | The proportion of the high-skilled workers in 2014 | CSMAR |
| **Variables in the Job Posting Data** | | |

| | | |
|---|---|---|
| Skill_index | Weighted average of experience, education, cognitive skills, computer skills, and management skills. | Lagou.com |
| Experience | Categorical variable based on the number of working years required in a job description. | Lagou.com |
| ln_exp | Log of *Experience* in a job posting. | |
| Above_BA | Dummy variable indicating that the job requires at least a bachelor's degree. | Lagou.com |
| Computer Skills | Number of words indicating computer skills required in a job description. | Lagou.com |
| Cognitive Skills | Number of words indicating cognitive skills required in a job description. | Lagou.com |
| Management Skills | Number of words indicating management skills required in a job description. | Lagou.com |
| ln_computer_skill | Log of *Computer Skills* | Lagou.com |
| ln_cognitive_skill | Log of *Cognitive Skills* | Lagou.com |
| ln_management_skill | Log of *Management Skills* | Lagou.com |
| ln_SalaryMean | Log of the mean of salary (in 2000 RMB) provided in a job description. | Lagou.com |
| ln_SalaryMin | Log of the minimum of salary (in 2000 RMB) provided in a job description. | Lagou.com |
| ln_SalaryMax | Log of the maximum of salary (in 2000 RMB) provided in a job description. | Lagou.com |
| Occupation | Categorical variable based on the type of job postings including production workers, support staff, technicians and R&D staff, sales and marketing forces, finance staff, and others. | Lagou.com |
| Days-to-Fill | The number of days for which a given job posting is active online | Lagou.com |

## B Job Posting Data versus Firm Panel Data

### B.1 Representativeness of Job Posting Data over Time

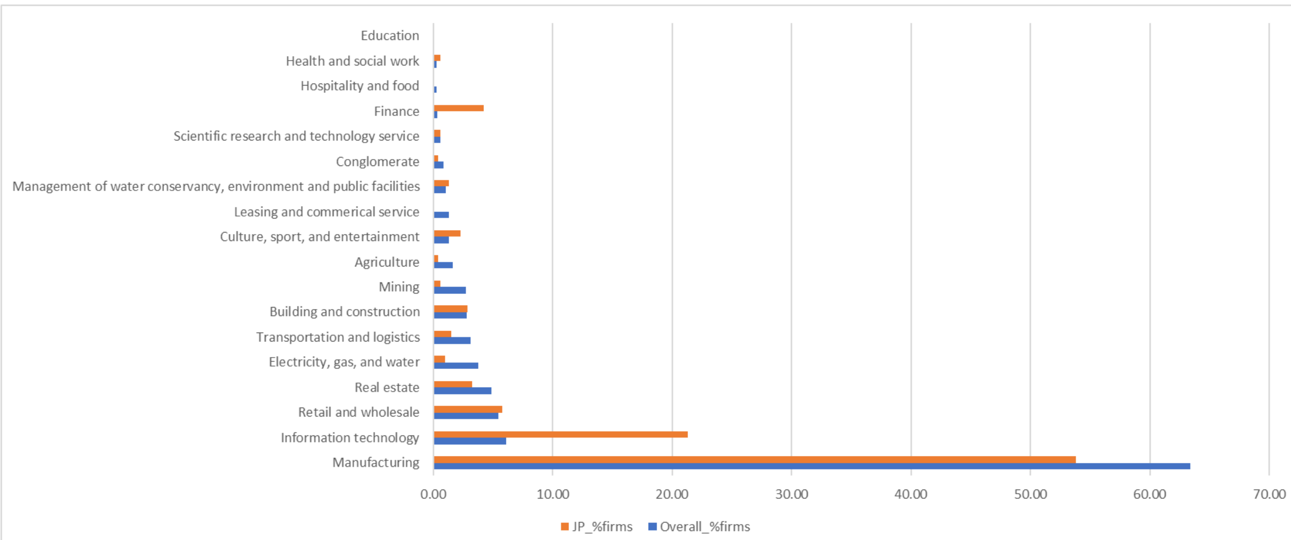
The $x$-axis is the job vacancy share in an industry from the job posting data in 2014 minus the employee share in the same industry from the firm panel data in 2014. The $y$-axis is these differences in 2016. The dotted line is the fitted line of these points, which is nearly a 45-degree line, indicating that representation in the job posting data, relative to the overall sample, did not change from 2014 to 2016.



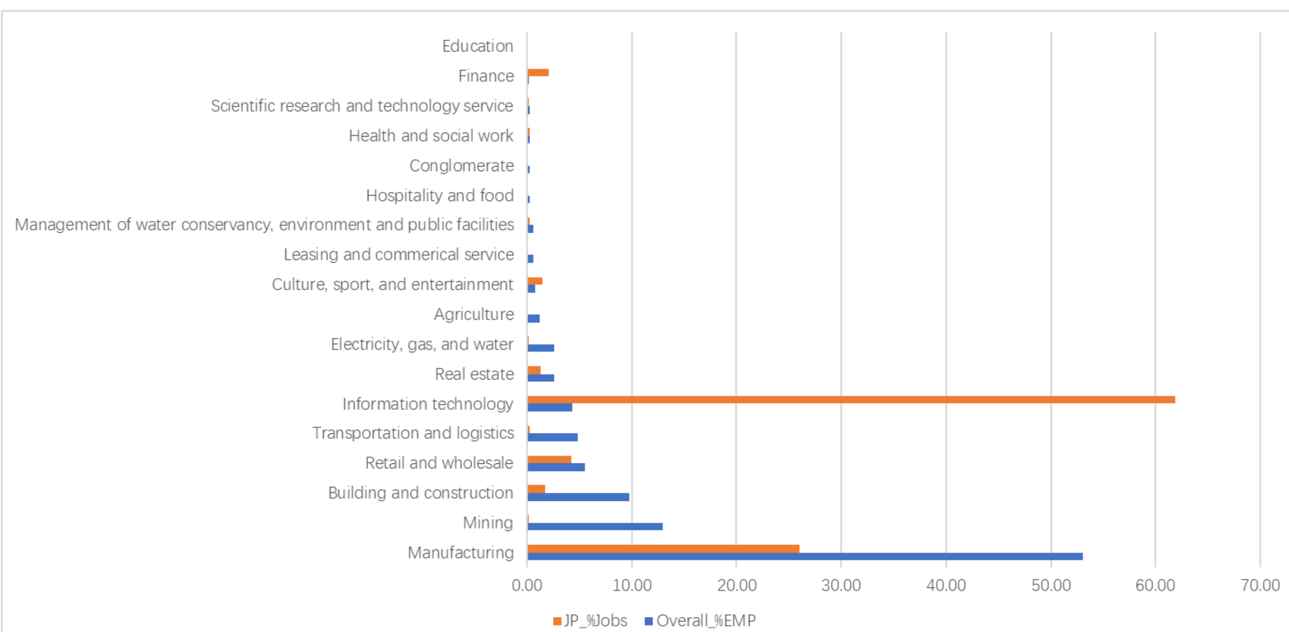
### B.2 Industry Distributions (Job Posting Data vs. Firm Panel Data

This figure plots the distribution of overall samples across industry groups (blue bars), sorted from largest to smallest, as well as the distribution of job vacancies in the job posting data (orange bars). The classification of industries is based on the official industry classification of the China Securities Regulatory Commission (CSRC, the counterpart of the U.S. SEC) (2012). Panel A presents the distribution of the sample of firms; Panel B shows the distribution of the job vacancies in the job posting data and the distribution of the number of employees in the overall sample. In Appendix B, we further show that the representativeness of job posting data does not change over time.

**Panel A: The Distributions of Firms Across Industries.**



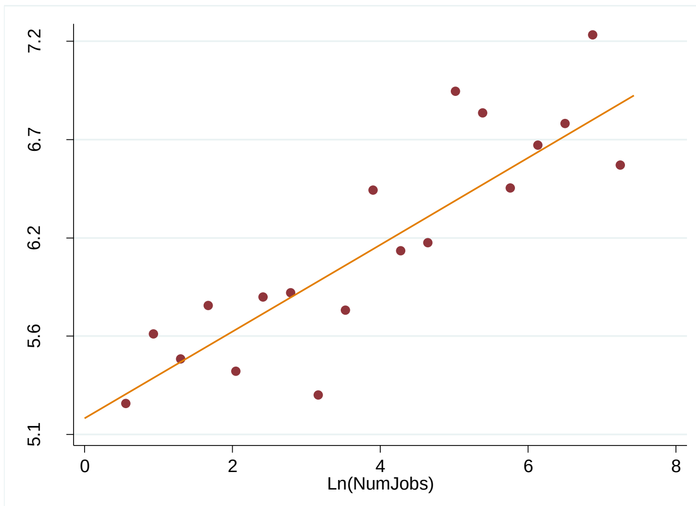

**Panel B: The Distributions of Job Vacancies/Employees Across Industries.**



### B.3 Binned scatters of Number of Job Postings and the Growth of Employees

The figure shows the binned scatter plots with linear fitted lines for the growth of employees versus the number of job postings in the same firm, using 20 quantiles. For each panel, we plot the logarithm of the number of jobs postings on the y-axis against the logarithm of the change in the number of employees in Panel A, the logarithm of the change in the number of high skill workers in Panel B, and the logarithm of the change in the number of low skill workers in Panel C, respectively, on the x-axis.

**Panel A: Ln(# of Jobs) and Ln (Employment Growth)**




**Panel B: Ln(# of Jobs) and Ln (Growth of High skill Workers)**

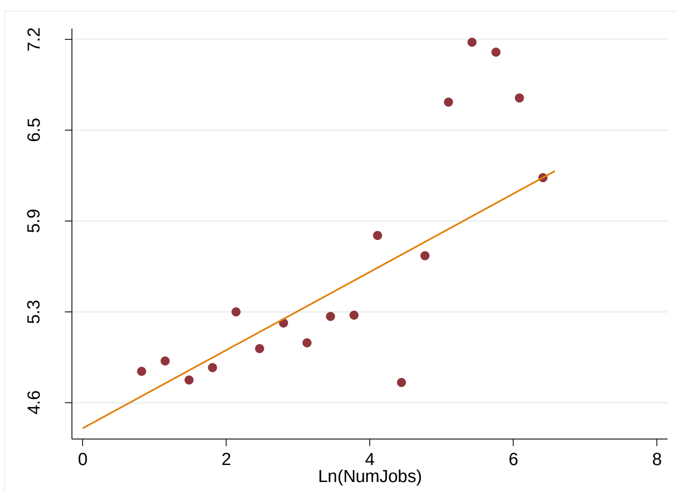
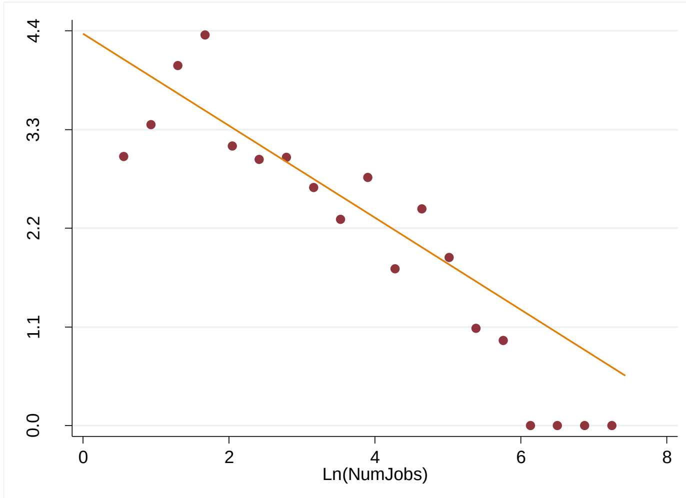


**Figure 4**
**Continued**

**Panel C: Ln(# of Jobs) and Ln(Growth of Low skill Workers)**




**B.4 Pairwise Correlations between the Number of Job Vacancies and the Growth of Employees**

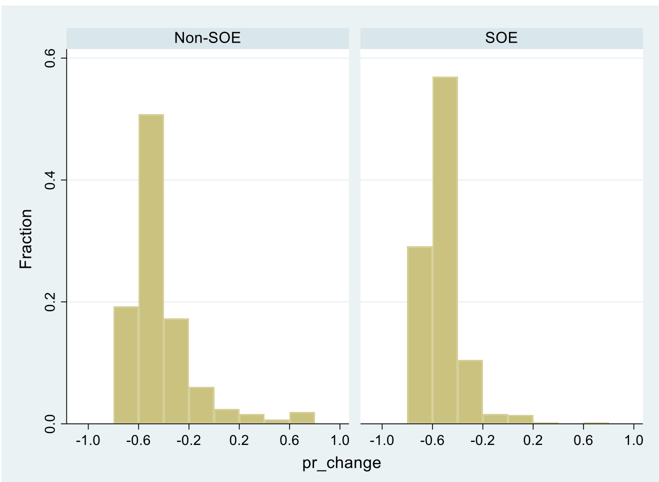
This table reports the correlation matrix of the number job vacancies in the job posting data and the corresponding firms' growth of numbers of employees in the firm panel data. * shows significance at the 0.05 level.

| | | Job Posting Data | | | |
|---|---|---|---|---|---|
| | | NumJobs | ComputerJobs | CognitiveJobs | ManagerJobs |
| Firm Panel Data | Growth of emp | 0.183* | 0.180* | 0.185* | 0.183* |
| | Growth of LSemp | -0.227* | -0.237* | -0.221* | -0.210* |
| | Growth HSemp | 0.215* | 0.203* | 0.207* | 0.215* |
| | Growth RD_Tech | 0.198* | 0.222* | 0.188* | 0.181* |
| | Growth grad_BA | 0.299* | 0.304* | 0.283* | 0.284* |

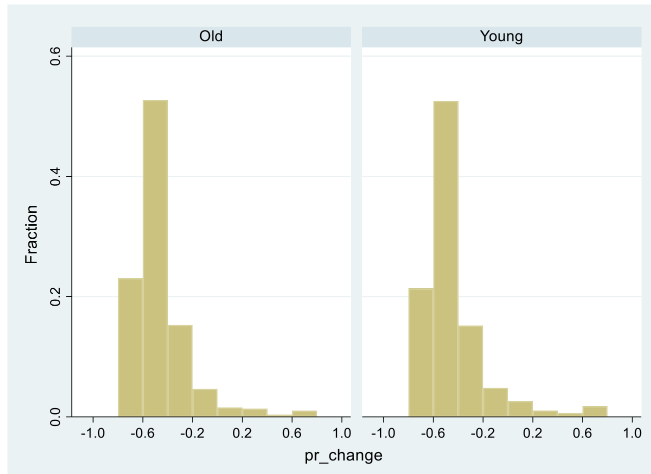
## C Histograms of Changes in Stock Price by Group

This figure shows histograms of the changes in stock price over the period from Jun. 15, 2015 to Feb. 01, 2016. In Panels A to D, we show the proportions of stocks in each price change bin (of size 0.2) for the subsamples based on firm ownership, firm age, share pledge status, and IT (information technology) industry, respectively.

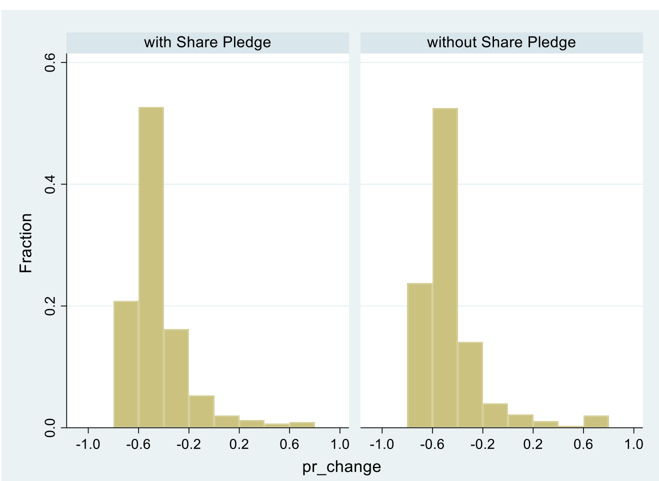
**Panel A: Non-SOE firms vs. SOE firms**



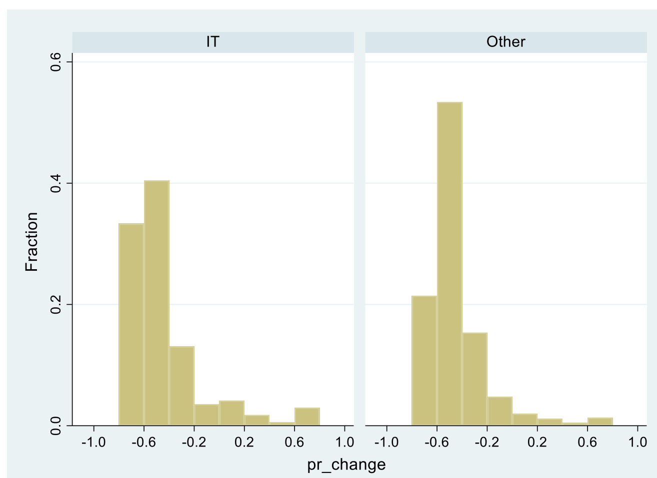

**Panel B: Old Firms vs. Young Firms**




**Panel C: Firms with share pledge vs. without share pledge**




**Panel D: IT firms vs. other firms**



## D Propensity Score Matching

### D.1 Logit for Propensity Score Matching

This table presents the major determinants of the effects of the 2015 stock market crash on price change using a logit model. We present the results based on the firm panel data in column (1) and the results based on the online job posting data in column (2), respectively. In each panel, we sort firms into two groups based on the price change during the crash and define the top group (less affected) as the treatment group. The dependent variable is a dummy variable, which equal to one if the firm is in the treatment group, and zero otherwise. The logit regressions are run at the firm level and all covariates included in the regression are the value of the firm characteristics in 2014. The models are used to generate the propensity scores for matching. All variables are defined in Appendix A. Robust standard errors are clustered at the firm level and reported in brackets.

| | (1) | (2) |
|---|---|---|
| | **Dependent Variable: Dummy = 1 in the above-median group** | |
| | Online Job Posting Data | Firm Panel Data |
| Ln_Sales | −0.3590** | −0.0709 |
| | (0.1785) | (0.0714) |
| LnTurnover | 0.5217*** | −0.4409*** |
| | (0.1957) | (0.0843) |
| State_own | 1.7679 | −0.4734 |
| | (1.2567) | (0.4948) |
| Ln_Nyear_listed | 0.2364 | −0.2062*** |
| | (0.1790) | (0.0785) |
| Ln_EMP | 0.4493** | −0.1064 |
| | (0.2096) | (0.0818) |
| ROA | −6.1022** | 3.7103*** |
| | (2.5837) | (1.0988) |
| HEmp_ratio | 0.3866 | −0.4662* |
| | (0.5616) | (0.2767) |
| Ln_Awage | 0.5162 | −0.2725* |
| | (0.3409) | (0.1397) |
| PPE_TA | −2.0723* | 0.4667 |
| | (1.0644) | (0.3563) |
| Observations | 325 | 1,694 |
| Pseudo R-squared | 0.0806 | 0.0325 |
| p-value for Chi2 | 0.0005 | 0.0000 |

### D.2 Balanced Tests for Propensity Score Matching

This table summarizes firm characteristics before and after matching. All firms with non-missing firm characteristics are used to construct the matched sample. Using propensity-score matching, for each firm with above-median price change during the crash, we find one firm with the closest propensity score that belongs to the below-median group and operates in the same three-digit CSRC (2012) industry. It presents the summary statistics of before-matching and after-matching firm characteristics based on the online job posting data (in Panel A) and the firm panel data (in Panel B), respectively. It reports the mean before matching in Columns (1)–(3) and after matching in Columns (4)–(6), respectively, and provide the corresponding difference between firms with above-median price changes during the crash and matched firms with below-median price changes in Columns (3) and (6). All variables are defined in Appendix A. ***, **, * indicate significance of student t-test at the 1%, 5% and 10% levels, respectively.

**Panel A. Online Job Posting Data**

| | Before matching | | | After matching | | |
|---|---|---|---|---|---|---|
| | Price Change < median | Price Change > median | Difference | Price Change < median | Price Change > median | Difference |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln_Sales | 21.52 | 21.7 | −0.18 | 21.6 | 21.47 | 0.13 |
| LnTurnover | 7.46 | 7.18 | 0.28*** | 7.37 | 7.43 | −0.06 |
| State_own | 0.04 | 0.02 | 0.02* | 0.02 | 0.03 | 0.00 |
| Ln_Nyear_listed | 2.16 | 2.11 | 0.05 | 2.08 | 2.10 | −0.02 |
| Ln_EMP | 7.94 | 8.01 | −0.07 | 8.03 | 7.90 | 0.13 |
| ROA | 0.05 | 0.06 | −0.01*** | 0.05 | 0.05 | 0.00 |
| Hemp_ratio | 0.48 | 0.42 | 0.06** | 0.47 | 0.47 | 0.00 |
| Ln_Awage | 11.21 | 11.13 | 0.08* | 11.19 | 11.16 | 0.03 |
| PPE_TA | 0.15 | 0.19 | −0.04** | 0.18 | 0.16 | 0.02 |

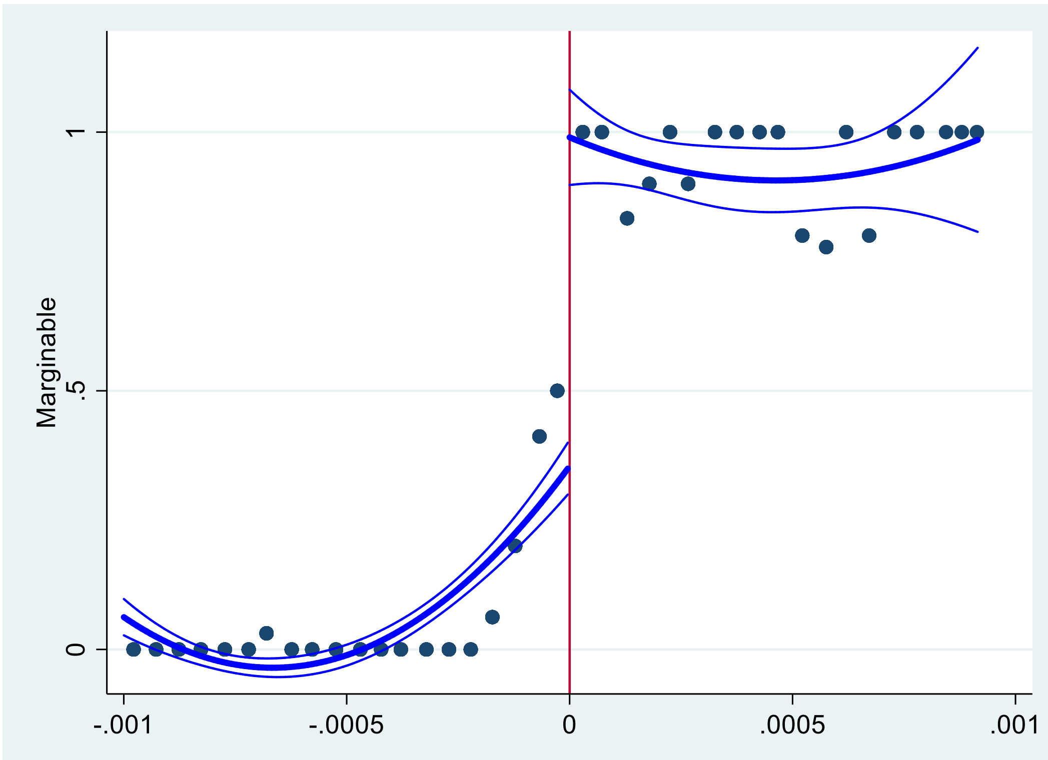
**Panel B. Firm Panel Data**

| | Before matching | | | After matching | | |
|---|---|---|---|---|---|---|
| | Price Change < median | Price Change >median | Difference | Price Change < median | Price Change > median | Difference |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln_Sales | 21.60 | 21.38 | 0.23*** | 21.45 | 21.49 | −0.04 |
| LnTurnover | 7.33 | 7.19 | 0.14*** | 7.27 | 7.32 | −0.05 |
| State_own | 0.04 | 0.03 | 0.01*** | 0.03 | 0.03 | 0.00 |
| Ln_Nyear_listed | 2.33 | 2.21 | 0.12*** | 2.27 | 2.29 | −0.02 |
| Ln_EMP | 7.84 | 7.71 | 0.13** | 7.77 | 7.77 | 0.00 |
| ROA | 0.03 | 0.04 | −0.01*** | 0.03 | 0.03 | 0.00 |
| Hemp_ratio | 0.34 | 0.32 | 0.02 | 0.33 | 0.33 | 0.00 |
| Ln_Awage | 11.10 | 11.04 | 0.07*** | 11.05 | 11.06 | −0.01 |
| PPE_TA | 0.23 | 0.24 | −0.01 | 0.24 | 0.23 | 0.01 |

## E Regression Discontinuity Design

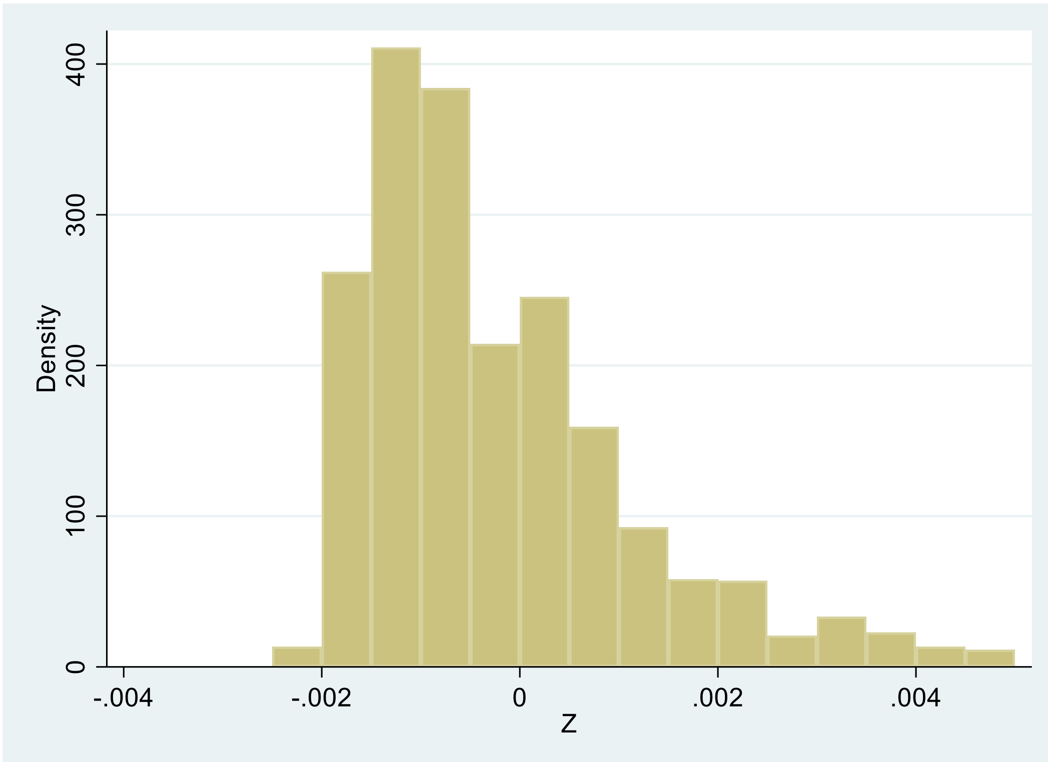
### E.1 Inclusion Index Determines Marginability

This figure plots the marginability against inclusion index for vintage 3. Inclusion index normalized to set vintage specific threshold equal to 0. For vintage 3, all not-yet marginable stocks with inclusion index within 0.001 at the time marginability was determined are included. Marginability is measured in the third calendar month following the start of the vintage. The $x$-axis is the inclusion index. The $y$-axis is the probability that a stock becomes marginable. Points show averages within bins of width 0.00005 in the index. Lines shows local linear fits with 95% confidence intervals on either side of the threshold.



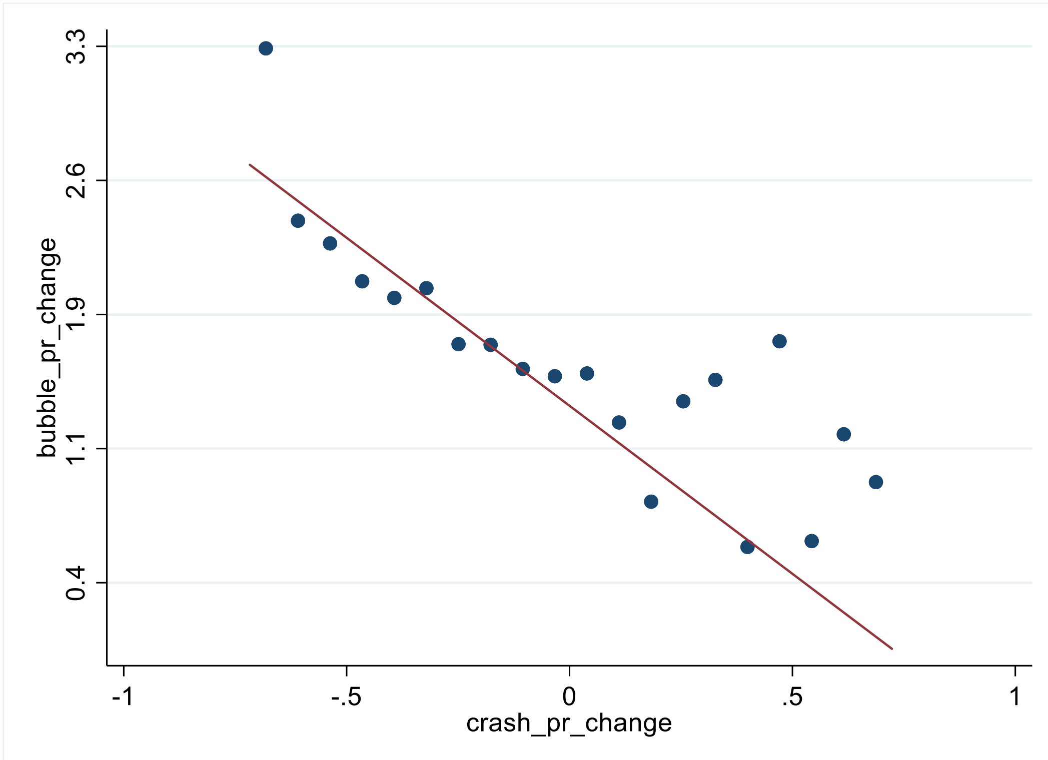
### E.2 No Evidence of Bunching at Threshold

This figure shows the histogram of the value of the inclusion index, normalized to the vintage specific threshold. The sample is restricted to show only the stocks that have the absolute value of the inclusion index less than 0.005 in magnitude.



### F Robustness Checks

**Figure F1. Binned scatters of the price change during the bubble versus the bust period**




The figure shows the binned scatter plots with linear fitted lines for the price change during the bubble versus the bust period in the same firm, using 20 quantiles. We plot the raw cumulative price changes during the bubble period (from July 1, 2014 to June 12, 2015) on the *y*-axis against the raw cumulative price changes during the bust period (from June 12, 2015 to February 1, 2016) on the *x*-axis.

**Table F1. Eliminating the Effect of the Run-up Period**

This table eliminate the confounding effect of the run-up period. Panel A explores the correlation of the price changes between the bubble period and the bust period. The entire firm sample is independently double-sorted in to $3 \times 3$ subgroups first by their bubble returns and then by their crash returns. Panel A presents the number of stocks across the double sorts. Panel B shows difference-in-differences analyses of skill requirements (Column (1)) and employee composition by skill (Columns (2)–(4)), technology investments (Column (5)), and R&D expenditures (Column (6)) using a sample of stocks that are off the subdiagonal subgroups. The dependent variable is $Skill\ index$, the weighted average of the five normalized skill components including computer skills, cognitive skills, management skills, experience requirements, and education requirements. Columns (2)–(6) report the results based on the firm panel data during the pre-bubble (2013) and post-crash years (2016–2018). The dependent variables are the log of the number of total employees ($Ln\_EMP$) in Column (2), the log of the number of high skill workers ($Ln\_HSemp$) in Column (3), the log of the number of low skill workers ($Ln\_LSemp$) in Column (4), the log of average wage per employee ($Ln\_Awage$) in Column (5), the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets (Unit: billion) in 2000 RMB ($Ln\_HTechAsset$) in Column (6), and the log of one plus total R&D expenditures in 2000 RMB ($Ln\_RDexpense$) in Column (7). $Affected$ is the firm-level negative buy-and-hold return during the stock market crash period through Jun. 12, 2015, to Feb. 01, 2016, capturing the severity of the price crash during the period of the 2015 stock market crash. Dummy variable $Post$ in Column (1) equals 1 for every job posting advertisement posted after the start of the crash, Jun. 12, 2015, and 0 otherwise. $Post$ in Columns (2)–(6) indicates the year after the stock market crash. Detailed variable definitions can be found in the Appendix. Firm fixed effects, Month*City fixed effects, Month*Occupation fixed effects, and City*Occupation fixed effects are controlled in Column (1). Year fixed effects and firm fixed effects are both controlled in Columns (2) to (6). Standard errors shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A

| | | Price change during the bubble period (2014.07.01–2015.06.12) | | |
|---|---|---|---|---|
| | | Low | Medium | High |
| Price change during the crash period (2015.06.15–2016.02.01) | Low | 187 | 278 | 411 |
| | Medium | 263 | 320 | 264 |
| | High | 385 | 238 | 161 |

**Table F1**
**Continued**

Panel B

| | Skill index | LnEMP | LnHSemp | LnLSemp | LnAWAGE | LnHighTechInv | LnRDexpense |
|---|---|---|---|---|---|---|---|
| Affected × Post | -0.062** | -0.356** | -0.515*** | 0.331 | -0.150** | -0.026*** | -0.701** |
| | (0.026) | (0.161) | (0.174) | (0.398) | (0.062) | (0.009) | (0.342) |
| Observations | 16,163 | 6,862 | 6,221 | 6,939 | 6,755 | 6,038 | 4,485 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | No | No | No | No | No | No |
| Month*Occ | Yes | No | No | No | No | No | No |
| City*Occ | Yes | No | No | No | No | No | No |
| Adjusted R2 | 0.153 | 0.896 | 0.829 | 0.778 | 0.781 | 0.449 | 0.749 |

**Table F2. Abnormal Returns**

This table shows difference-in-differences analyses of skill requirements (Column (1)) and employee composition by skill (Columns (2)–(4)), technology investments (Column (5)), and R&D expenditures (Column (6)) using abnormal returns to measure the price changes during the stock market crash. The dependent variable is $Skill\ index$, the weighted average of the five normalized skill components including computer skills, cognitive skills, management skills, experience requirements, and education requirements. Columns (2)–(6) report the results based on the firm panel data during the pre-bubble (2013) and post-crash years (2016–2018). The dependent variables are the log of the number of total employees ($Ln\_EMP$) in Column (2), the log of the number of high skill workers ($Ln\_HSemp$) in Column (3), the log of the number of low skill workers ($Ln\_LSemp$) in Column (4), the log of average wage per employee ($Ln\_Awage$) in Column (5), the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets (Unit: billion) in 2000 RMB ($Ln\_HTechAsset$) in Column (6), and the log of one plus total R&D expenditures in 2000 RMB ($Ln\_RDexpense$) in Column (7). The abnormal return ($Ad\_ret$) is estimated based on the CAPM model as follows: $AbnormalReturn = PriceChange - \hat{\beta} \times (R_m - R_f)$ , where $Price\_Change$ is the buy-and-hold returns during the stock market crash period, from Jun. 12, 2015, to Feb. 1, 2016; the market betas are estimated from daily stock prices over one year prior to the onset of the 2015 stock market crash (from Jun. 13, 2014, to Jun. 12, 2015)[1]; the market return is the cumulative return of the value-weighted average of market returns minus the cumulative return of risk-free assets (one-year Chinese Treasury rate) over the same period. Dummy variable $Post$ in Column (1) equals 1 for every job posting advertisement posted after the start of the crash, Jun. 12, 2015, and 0 otherwise. $Post$ in Columns (2)–(6) indicates the year after the stock market crash. Detailed variable definitions can be found in the Appendix. Firm fixed effects, Month*City fixed effects, Month*Occupation fixed effects, and City*Occupation fixed effects are controlled in Column (1). Year fixed effects and firm fixed effects are both controlled in Columns (2) to (6). Standard errors shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Skill index | LnEMP | LnHSemp | LnLSemp | LnAWAGE | LnHighTechInv | LnRDexpense |
| (−Ad_ret) × Post | -0.045** | -0.078 | -0.310*** | 0.590*** | -0.091*** | -0.015*** | -0.429*** |
| | (0.021) | (0.073) | (0.093) | (0.202) | (0.033) | (0.005) | (0.100) |
| Observations | 33,088 | 12,026 | 10,870 | 12,178 | 11,910 | 10,561 | 9,653 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | No | No | No | No | No | No |
| Month*Occ | Yes | No | No | No | No | No | No |
| City*Occ | Yes | No | No | No | No | No | No |
| Adjusted R2 | 0.224 | 0.899 | 0.843 | 0.781 | 0.788 | 0.495 | 0.815 |

[1] Using the alternative length of estimation window, such as 18 months or two years prior to the onset of the stock market crash, will obtain consistent results.

**Table F3. Confounding Events**

This table controls for two confounding events: the implementation of Shanghai–Hong Kong Connection (Panel A) and the direct purchase plan by the "national team" during the stock market crash (Panel B). Panel A includes firm-level time-variant $SH\_HK \times Post\_SH\_HK$ in our baseline regression. The sample period ranges from 2013 to 2016. We also remove the sample firms that was once added to but then removed from the pilot list of the program. $SH\_HK$ is a dummy variable that equals one for once connected stocks and zero for other stocks. $Post\_SH\_HK$ is a dummy variable indicating the post-connect period. Panel B includes an additional control variable that measures the effect of the national team's direct purchase plan, $GovRes \times Post$, where $GovRes$ is the share percentage purchased by the national team (including the CSF, the CCH, and other funds representing the central government) in the third quarter of 2015, and the dummy variable $Post$ takes the value of one if it is in the post-rescue period, i.e., after 2016. Detailed variable definitions can be found in the Appendix. Firm fixed effects, Month*City fixed effects, Month*Occupation fixed effects, and City*Occupation fixed effects are controlled in Column (1). Year fixed effects and firm fixed effects are both controlled in Columns (2) to (6). Standard errors shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Skill index | LnEMP | LnHSemp | LnLSemp | LnAWAGE | LnHighTechInv | LnRDexpense |
| Affected × Post | −0.047** | -0.190** | -0.492*** | 0.699*** | -0.119*** | -0.020*** | -0.547*** |
| | (0.019) | (0.089) | (0.109) | (0.235) | (0.041) | (0.005) | (0.111) |
| SH_HK × | 0.016 | -0.078*** | -0.081** | -0.472*** | 0.014 | 0.012*** | 0.005 |
| Post_SH_HK | (0.015) | (0.026) | (0.033) | (0.092) | (0.015) | (0.003) | (0.050) |
| Observations | 32,839 | 11,329 | 10,204 | 11,472 | 11,217 | 9,943 | 9,184 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | No | No | No | No | No | No |
| Month*Occ | Yes | No | No | No | No | No | No |
| City*Occ | Yes | No | No | No | No | No | No |
| Adjusted R2 | 0.223 | 0.899 | 0.845 | 0.780 | 0.786 | 0.503 | 0.822 |

Panel B

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| VARIABLES | Skill index | LnEMP | LnHSemp | LnLSemp | LnAWAGE | LnHighTechInv | LnRDexpense |
| Affected × Post | −0.045** | -0.194** | -0.493*** | 0.651*** | -0.109*** | -0.020*** | -0.525*** |
| | (0.019) | (0.089) | (0.109) | (0.235) | (0.041) | (0.005) | (0.112) |
| GovRes × | 0.085 | -0.826 | -1.027 | -2.598 | -0.588** | 0.228*** | -1.877** |
| Post_GovRes | (0.121) | (0.506) | (0.737) | (1.766) | (0.285) | (0.078) | (0.931) |
| Observations | 33,088 | 11,329 | 10,204 | 11,472 | 11,217 | 9,943 | 9,184 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | No | No | No | No | No | No |
| Month*Occ | Yes | No | No | No | No | No | No |
| City*Occ | Yes | No | No | No | No | No | No |
| Adjusted R2 | 0.224 | 0.898 | 0.845 | 0.779 | 0.786 | 0.503 | 0.822 |

**Table F4. Alternative Measures of Outcome Variables**

This tables presents the results using alternative measures of employee composition variables. In Column (1), the dependent variable is the number of high-skilled workers divided by the total number of employees (*%HSemp*). In Columns (2)–(4), the dependent variables are the log of the number of specific types of employees, including R&D or technicians in Column (2), finance staff in Column (3), and sales and marketing staff in Column (4). Detailed variable definitions can be found in the Appendix. Both year fixed effects and firm fixed effects are controlled. Standard errors shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | %HSemp | Ln_RD_Tech | Ln_fin | Ln_mkt |
| Affected × Post | −0.075*** | −0.565*** | −0.520*** | −0.410*** |
| | (0.021) | (0.163) | (0.100) | (0.117) |
| Observations | 10,809 | 12,215 | 11,222 | 11,591 |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.829 | 0.685 | 0.801 | 0.816 |

**Table F5. Eliminating the Bubble Period**

This table shows difference-in-differences analyses of skill requirements (Column (1)) and employee composition by skill (Columns (2)–(4)), technology investments (Column (5)), and R&D expenditures (Column (6)) using a sample eliminating the bubble period. Specifically, Column (1) reports the results based on the job advertisements posted during the pre-bubble period (from January to June 2014) and post-crash period (from June 15, 2015 to December 2016). The dependent variable is $Skill\ index$, the weighted average of the five normalized skill components including computer skills, cognitive skills, management skills, experience requirements, and education requirements. Columns (2)–(6) report the results based on the firm panel data during the pre-bubble (2013) and post-crash years (2016–2018). The dependent variables are the log of the number of total employees ($Ln\_EMP$) in Column (1), the log of the number of high skill workers ($Ln\_HSemp$) in Column (2), the log of the number of low skill workers ($Ln\_LSemp$) in Column (3), the log of average wage per employee ($Ln\_Awage$) in Column (4), the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets (Unit: billion) in 2000 RMB ($Ln\_HTechAsset$) in Column (5), and the log of one plus total R&D expenditures in 2000 RMB ($Ln\_RDexpense$) in Column (6). $Affected$ is the firm-level negative buy-and-hold return during the stock market crash period through Jun. 12, 2015, to Feb. 01, 2016, capturing the severity of the price crash during the period of the 2015 stock market crash. Dummy variable $Post$ in Column (1) equals 1 for every job posting advertisement posted after the start of the crash, Jun. 12, 2015, and 0 otherwise. $Post$ in Columns (2)–(6) indicates the year after the stock market crash. Detailed variable definitions can be found in the Appendix. Firm fixed effects, Month*City fixed effects, Month*Occupation fixed effects, and City*Occupation fixed effects are controlled in Column (1). Year fixed effects and firm fixed effects are both controlled in Columns (2) to (6). Standard errors shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Skill index | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_HighTechInv | Ln_RDexpense |
| Affected × Post | -0.065** | -0.154 | -0.507*** | 0.652*** | -0.013** | -0.479*** |
| | (0.028) | (0.097) | (0.118) | (0.241) | (0.006) | (0.126) |
| Observations | 17,412 | 9,793 | 9,043 | 9,867 | 8,760 | 7,731 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes | Yes |
| Month*City | Yes | No | No | No | No | No |
| Month*Occupation | Yes | No | No | No | No | No |
| City*Occupation | Yes | No | No | No | No | No |
| Adjusted R-squared | 0.245 | 0.899 | 0.850 | 0.797 | 0.502 | 0.808 |

**Table F6. Alternative Samples**

This table reports the firm-level estimation results using a sample of firms that appear in the online job posting data. The dependent variables are the log of the number of total employees ($Ln\_EMP$) in Column (1), the log of the number of high skill workers ($Ln\_HSemp$) in Column (2), the log of the number of low skill workers ($Ln\_LSemp$) in Column (3), the log of average wage per employee ($Ln\_Awage$) in Column (4), the log of one plus the cost of the sum of newly acquired technology-related tangible assets and intangible assets (Unit: billion) in 2000 RMB ($Ln\_HTechAsset$) in Column (5), and the log of one plus total R&D expenditures in 2000 RMB ($Ln\_RDexpense$) in Column (6). $Affected$ is the firm-level negative buy-and-hold return during the stock market crash period through Jun. 12, 2015, to Feb. 01, 2016, capturing the severity of the price crash during the period of the 2015 stock market crash. Dummy variable $Post$ indicates the year after the stock market crash. Detailed variable definitions can be found in the Appendix. Year fixed effects and firm fixed effects are both controlled. Standard errors shown in parentheses adjusted for heteroscedasticity and firm-level clustering. In all columns, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|
| VARIABLES | Ln_EMP | Ln_HSemp | Ln_LSemp | Ln_AWAGE | Ln_HighTechInv | Ln_RDexpense |
| Affected × Post | -0.219 | -0.683*** | 0.891 | -0.199** | -0.034** | -0.828*** |
| | (0.181) | (0.213) | (0.585) | (0.082) | (0.015) | (0.211) |
| Observations | 2,479 | 2,144 | 2,497 | 2,468 | 2,217 | 2,192 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.918 | 0.856 | 0.820 | 0.805 | 0.544 | 0.818 |