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Essays on corporate finance

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ESSAYS ON CORPORATE FINANCE

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by
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I hereby declare that this PhD dissertation is my original work
and it has been written by me in its entirety.
I have duly acknowledged all the sources of information
which have been used in this dissertation.
This PhD dissertation has also not been submitted for any degree
in any university previously.

Shuyu Xue
31 May 2020

ABSTRACT

Essays on Corporate Finance

Shuyu Xue

This dissertation has two essays on corporate finance. In the first chapter, I investigate the dual-class structure. The dual-class structure is often regarded as poor corporate governance and the source of agency problems. However, I find that, for companies with high information asymmetry and long investment horizon, dual-class structure delivers higher operating performance and valuation ratios. These performing dual-class companies tend to have a higher investment in intangibles, more innovations, less pay-out, and less CEO compensation. The findings suggest that dual-class structure could be optimal in empowering information-advantageous inside shareholders and ensuring corporate long-term goals.

In the second chapter of my dissertation, we study how air pollution influences firm performance. Air pollution is a growing hazard to human health. This study examines whether air pollution affects the formation of corporate human capital and thereby performance. We find that people exhibit an intention to look for jobs in less polluted areas on days when air pollution occurs in the area where they are located, suggesting that an individual's sort in response to air pollution. Consistent with this sorting prediction, we find that the level of firms' skilled executives and employees significantly drops when pollution information becomes real-time accessible and when the pollution level increases in their locations, especially in places where concerns for health is more sensitive to air pollution. Moreover, parallel reductions in firm productivity and value are found and become more salient when firms have a greater dependence on human capital.

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Chapter 1

The Bright Side of Dual-Class Structure

1.1 Introduction

Recently, the dual-class shares structure raised a lot of attention. In the first half of 2018, both Hong Kong Exchange (HKEX) and Singapore Exchange (SGX) amended their listing rules to allow dual-class share IPOs. A pipeline of dual-class IPO is already in the works, Xiaomi Corporation, the world's fourth-largest smartphone maker by shipment, became the first dual-class share IPO in Hong Kong with a value of US$54 billion [1]. Reportedly, companies from various markets have asked for more information about the revised listing regime, indicating their interests in listing with dual-class structures. However, in the U.S., voices against dual-class shares have increased over time. In January 2017, a coalition of institutional investors, Investor Stewardship Group (ISG), overseeing $22 trillion in assets, demands total elimination of dual-class stock.[2] Also, the Council of Institutional Investors (CII), representing managers of $25 trillion assets, demanded to limit any company's dual-class share structure to seven years.[3] Corporate governance confers equitable voting rights to shareholders. Common shareholders usually enjoy the one share, one vote right to influence a company's operations. Dual-class structure gives differential voting rights to various sets of shareholders and is a potential roadblock to shareholder democracy. However, many established companies——including Nike, Comcast, Berkshire Hathaway, The New York Times Company, and Ford——have had dual-class

[1] CNBC News, "China's Xiaomi raises $4.72 billion after pricing Hong Kong IPO", is available at https://www.cnbc.com/2018/06/29/xiaomi-prices-hk-ipo-at-bottom-of-range-raises-4point72-billion-report.html
[2] ISG's manifesto, "Corporate governance principles for U.S. listed companies," is available at https://isgframework.org/corporate-governance-principles/
[3] Harvard Business Review, "Should Dual-Class Shares Be Banned?" is available at https://hbr.org/2018/12/should-dual-class-shares-be-banned

stock for decades. The practice of dual-class stock has escalated in the 21st century; recent IPOs of commonly recognized companies include Facebook, Google, Alibaba, LinkedIn, Zillow, Groupon, Fitbit, GoDaddy, Planet Fitness, Orbitz, Shake Shack, RE/MAX, WebMD, DreamWorks, Animation, and Yelp. Thus, is the dual-class structure a combination of entrenchment and low equity holdings to ruin corporate governance or an efficient way for the modern capital market? The previous academic findings are mixed on the merits of dual-class structures.

In this paper, by using a new dataset of dual-class companies from 1994 to 2014, I want to show that in some certain scenarios, dual-class companies are performing better. The dual-class stock structure can provide benefits to shareholders for some specific types of companies. Although the majority of past literature (Gompers, Ishii, and Metrick, 2010; Masulis, Wang, and Xie, 2009; Smart, Thirumalai, and Zutter, 2008) consider the dual-class structure as the agency problem to lower the firm value and a signal of poor corporate governance; this paper has a further exploration on the specific attributes of dual-class companies and presents the bright side of the dual-class structure. My hypothesis is that the dual-class structure has a positive effect on the high-information asymmetry companies with long-term investment goals. For the companies relying on insider information advantage and having long term investment focus, the dual-class structure can help them perform better than the single-class companies. With the empirical results of the new dataset, I find that dual-class companies with high information asymmetry and long-term investment horizon perform better in ROA, sales growth, and Tobin's Q than their single-class counterparts. In addition, I find these special dual-class firms have a higher investment in intangibles, more innovation, less payout, and less CEO compensation, suggesting that for these specific types of companies, the dual-class structure can help them improve the operation and provide benefit to firm values. In this paper, to capture the specific features of information asymmetry and long term investment focus, I use seven measures from different dimensions: 1. Companies in the high technology industry; 2. Companies with high R&D expenses; 3. Companies with high idiosyncratic volatility; 4. Companies with larger analyst forecast dispersion; 5. Companies without any analyst cover; 6. Companies with low institution investor ownership; 7. Companies with a long-term investment horizon. By using these measures interacted with the dual-class indicator, I find that in the pooled OLS regression, dual-class companies with high information asymmetry and long-term investment goals have higher ROA, higher sales growth, and higher Tobin's Q than both other dual-class companies and single-class companies. The empirical results show that companies with high information asymmetry and long-term investment horizons are more favorable to the dual-class structure. For these companies, insiders possess proprietary information and expertise on variables such as product lifecycle and future product pipeline, which can neither be easily explained to common investors nor fully revealed to the market for risk of competitors' advance knowledge so that these companies are facing high information asymmetry. Besides, these companies are inclined to have larger intangible assets that have long gestation periods; so, without the dual-class structure, these companies are more vulnerable to the short-term market pressure and investor myopia. A dual-class structure offers immunity against the misleading decisions made by short-term investors so that these companies can focus on long-term value creation.

In fact, the dual-class stock is a trade-off between ownership and control. In the world of corporate governance, a modern corporation usually owned by two different groups of shareholders: (1) original founders and (2) multiple atomistic shareholders (Shleifer and Vishny,1986). The first group continues to manage the company. These shareholders do not hold diversified investments, and their fortunes and personal prestige are linked to the success of the company. The second group holds diversified investments and seeks to earn dividends and capital gains. The objectives and horizons of the two shareholder groups clearly differ. The founders want to maintain control but have to opt for wider ownership in order to access capital markets and to provide liquidity to stock options owned by rank-and-file employees. Many of these companies compete in technology markets, wherein innovations often have long gestation periods. Here, founders and key executives have more advantage in information and expertise, which can neither be easily explained to common investors nor fully revealed to the market. Hence, outside investors are unable to make informed choices about the company's strategic initiatives. In such scenarios, insiders might better be left alone to plan investments and run company affairs rather than be questioned by outside investors regarding each strategic move. In those specific circumstances, managers might need more voting power to maintain control so as to better exploit their private information for the benefit of all shareholders. The dual-class structure provides an optimal balance here because external investors can help in financing for these companies but cannot influence any operating decision.

Because of the special demand for these companies, the dual-class structure becomes more and more popular in exchanges over the world. Although dual-class structures are not new—having first came into existence in the late 19th century—such structures have also become increasingly commonplace in recent times on the back of a wave of high-profile IPOs of technology companies. In 2004, Google. Inc was the first technology company that went to IPO by dual-class structure.[4] Before Google IPO, the majority of dual-class IPOs are concentrated in

[4] The Wall Street Journal, "Google's Multi-Class Stock Structure Made Alphabet Move Unique" is available at https://blogs.wsj.com/cfo/2015/08/12/googles-multi-class-stock-structure-made-alphabet-move-unique/

the media industry and family firms. (Gompers, Ishii, and Metrick (2010); Anderson, Ottolenghi, and Reeb (2017)); but now these high information asymmetry companies become a culmination of the growing trend of dual-class shares. Govindarajan and Srivastava (2018) come up with three economic trends to explain the increasing of dual-class stock: the growing importance of intangible investments, the rise of activist investors, and the decline of staggered boards and poison pills. Based on these three trends for the dual-class stock, I believe the high information asymmetry companies with long-term investment horizons are more fit to the dual-class structure following three reasons.

First, creative destruction in U.S. corporations is occurring at an increasingly rapid rate (Gao, Ritter, and Zhu (2013)). Firms die more quickly but also reach large market capitalization faster than ever before. Hence, intangible investments such as R&D, digital services, and human capital play an ever more important role in shaping and sustaining companies' competitive advantages. While these investments often produce benefits in years beyond the current reporting period, they hurt profits in the short run. Accounting regulations require that R&D investments be reported as expenses and not as assets. So, the firms with high R&D investment become high information asymmetry and have more uncertainty since they cannot use financial reports to prove the benefit of R&D and long-term investment. For these firms in the high-tech industry and with high R&D investment, the dual-class structure can be the optimal immunity against the wrong operating decision from common shareholders and short-term focus investors.

Second, activist investors seeking to boost short-term earnings (Semuels, 2016) are on the rise. The first economic trend helps activist shareholders because cutting intangible investments could boost the bottom line, though such actions hurt companies' long-term health. For example, Blockbuster director Carl Icahn forced the company to abandon its digital plans[5]. As co-founder of an activist investing firm, Nelson Peltz pursued a merger of Dow Chemicals and Dupont and caused the closure of a corporate research center responsible for the invention of nylon, Kevlar, Teflon, and solar cells[6]. Thus, activists' intervention might boost short-term profits or even stock prices but could destroy shareholder value in the long term. Activist shareholders' demands often run contrary to the desires of long-term investors who want higher R&D investments (David, Hitt, and Gimeno, 2001). Thus, the firms with lower institutional investors, long-term investment horizon, and without analyst coverage can escape from the short-term activist shareholders and have more chances to focus on the long-term and risky project. In this circumstance, the dual-class structure provides an optimal, transparent balance to give these long-term focus companies access to the capital market and avoid these companies surrendering to the market fluctuations and market pressures to drop out the potential long-term investment.

Third, the practices of the staggered board and poison pills——which serve as powerful antitakeover devices and ensure corporate control——are in decline (Matheson, 1999; Solomon, 2012). While this trend makes managers more responsive to the discipline imposed by the market for corporate control, it also makes managers more susceptible to shareholder pressures for short-term profits even when they come at the expense of long-term profits. However, if founders and key executives have more advantage in information and expertise, which cannot be easily explained to external investors, the high uncertainty and high information asymmetry firms will easily become the targets for market control. Thus, for companies with high uncertainty (for example, high idiosyncratic volatility and high analyst forecast dispersion), they

[5] Harvard Business Review, "How I Did It: Blockbuster's Former CEO on Sparring with an Activist Shareholder" is available at https://hbr.org/2011/04/how-i-did-it-blockbusters-former-ceo-on-sparring-with-an-activist-shareholder.
[6] The Wall Street Journal, "Dow, DuPont Deal Cements Activists' Rise" is available at https://www.wsj.com/articles/dow-dupont-deal-cements-activists-rise-1449882586.

can escape from the market control by adopting the dual-class structure. The managers in these high information asymmetry firms do not need to give in the long-term profit to maintain the short-term stable stock price and protect themselves from acquisitions. These managers and founders can feel more secure in the position and focus more on firm operations and performance improvement.

Arguably, these three trends and reasons could explain why the dual-class structure provides benefits to companies with high information asymmetry and long-term focus. The dual-class structure provides immunity against proxy contests initiated by short-term investors and enables managers to ignore capital market pressures (Jordan, Kim, and Liu, 2016). Thus, managers do not have to take myopic actions that might please activist investors but destroy long-term value. For example, Berkshire Hathaway's Warren Buffet is known for its focus on long-term value creation; this would not be possible if they measured their performance solely on the basis of quarterly profits or if activist investors controlled them. The New York Times Company has weathered the economic storms faced by many print media firms while maintaining high editorial standards, foreign reporting, and print editions. Alphabet has extended beyond web search business by investing in self-driving cars, delivery drones, wind turbines, genomics, and healthcare, none of which have earned profits, but which nonetheless have enhanced shareholder value. Facebook, which has access to a network of customers and vast amounts of confidential consumer data, has warded off an activist investor's demand to capitalize on those assets to boost short-term profits. Alibaba has committed to setting a strategic course without being influenced by fluctuating capital market attitudes.

Therefore, I believe in those specific circumstances, the dual-class structure can provide benefits to shareholders. In this paper, I want to provide the empirical evidence to support that for companies with high information asymmetry and long-term focus, the dual-class structure may be another defense mechanism to myopic market pressure and increase the firm values. In Section 2, I show how this paper can contribute to the literature. In Section 3, I present the data construction method and constitution of measures on high information asymmetry and long-term focus. Section 4 shows the characteristics of dual-class firms when IPO. Section 5 and Section 6 presents the baseline results of how dual-class firms with high information asymmetry and long-term focus would have better performance. Then, I conclude in Section 7.

1.2 Literature review

Academic findings are mixed on the merits of the dual-class structure. One set of studies shows that, on average, shareholders dislike dual-class stock. Examining data from 1994 to 2002, Gompers, Ishii, and Metrick (2010) found lower stock returns for dual-class firms as compared to single-class firms. Smart, Thirumalai, and Zutter (2008) established that, relative to fundamentals, dual-class firms trade at lower prices than single-class firms, both at the time of IPO and for at least 5 years subsequent. Management entrenchment among dual-class firms is evident, with less-frequent CEO turnover. Masulis, Wang, and Xie (2009) found that CEOs receive higher compensation, managers make acquisitions that destroy shareholder value more often, and capital expenditures contribute less to shareholder value. Other studies show that dual-class firms have opaque financial reporting, lower credibility of earnings information, and more tax avoidance (Fan and Wong, 2002; Francis, Schipper, and Vincent, 2005; McGuire, Wang, and Wilson, 2014). In this paper, I replicate the results of dual class's effect on firm valuation and I also receive similar results with the past literature. However, when the dual-class structure interacting with the measures of high information asymmetry and long-term investment horizon, the effect of the dual-class becomes different. The dual-class structure has a positive effect on the firm's valuation for firms with high information asymmetry and long-term goals. Aligned with the past literature, this paper explores further in dual-class companies and contributes to the literature by finding out the bright side of dual-class firms.

Another set of studies concludes that the dual-class structure is optimal in certain scenarios (Demsetz and Lehn, 1985). Lehn, Netter, and Poulsen (1990) found that firms that convert from single-class to dual-class structure have higher sales growth, research, and development (R&D) and advertising expenditures, secondary equity offerings, market-to-book ratios, and undistributed profits. These findings indicate growth opportunities as well as the need for external equity financing, but without passing control to external stakeholders. Dimitrov and Jain (2006) showed that superior, long-term shareholder returns are associated with aggressive-growth dual-class companies. In addition, some recent working papers uncover the decline in the relative valuation of dual-class firms as they mature (Cremers, Lauterbach, and Pajuste (2018), Kim and Michaely (2019), Bebchuk and Kastiel (2017)). These papers focus on the dynamic life cycle of dual-class firms and have substantial concerns about dual-class structures that provide perpetual or lifetime control; they suggest implying the sunset provision in the dual-class IPO.

Different from this past literature, I used a new dataset from 1994 to 2014 to provide new empirical evidence showing that under certain circumstance, where the firm has high information asymmetry and is more focus on long-term investment, the dual-class structure can provide a defense mechanism to market pressure and increase the shareholders' value. Since after 2004, the attribution of the dual-class firm has changed from media firms or family firms to high technology firms. New evidence is needed to show whether the effect of the dual-class structure has changed. Even if the dual-class structure is banned in the future, we still need to know whether the dual-class structure has favorable attributes that we can mimic in the future corporate governance environment.

1.3 Data and measures

1.3.1 Dual-class measure

To develop our sample of dual-class companies, I begin with the sample in Gompers, Ishii, and Metrick (2010) (GIM sample). The GIM sample was constructed from the universe of U.S. public firms from 1994 to 2002. It is the most comprehensive of all readily available datasets on dual-class firms with lots of past literature used. I expand the GIM sample period from 1994-2002 to 1994-2014 by drawing relevant dual-class data from the same primary sources that they used: Securities Data Company (SDC), S&P's COMPUSTAT, and the Center for Research in Security Prices (CRSP). The SDC's Global New Issues Database not only tracks corporate new issue activity from 1970 but flags those that have a separate class of common stock. In the CRSP database, I identify dual-class firms by their Committee on Uniform Security Identification Procedures (CUSIP) numbers. Following GIM (2010), those having the same 6-digit CUSIP number with different 2-digit extensions are considered to have dual-class share structures (Gompers et al., 2010). Firms having a letter (A, B, C…) as part of their "share class" in the CRSP monthly database in any month of a year are also defined as dual-class firms in that year. Finally, because the CRSP data reports one specific stock issue of a firm while COMPUSTAT contains all shares of all classes of a firm's stock, I compare "shares outstanding" in CRSP with "common shares outstanding" in COMPUSTAT. When the difference is more than 1%, I identify that firm as dual-class. Merging all of the above data together produces the final 1994-2014 list of dual-class firms.

Finally, I find that from 1994 to 2014, there are 939 unique dual-class firms. Table 1.1 presents the summary statistics for all the main variable difference between dual-class and single-class companies. The dual-class firms usually have larger total assets and higher firm age. Also, Figure 1 presents the number of dual-class from 1994 to 2014. In 1998, the number of dual-class reaches its peak as more than 500 firms are dual-class in the total capital market. For the industry distribution, most dual-class companies are concentrated in the communications and business services industry according to the SIC 2-digit code (Table 1.1). This result is aligned with the past literature that dual-class companies are concentrated in the media industry. (Gompers, Ishii, and Metrick's (2010)).

1.3.2 Measure for information asymmetry and long-term investment focus

For the key variable, to measure the information asymmetry and long-term investment focus, I review different kinds of literature and develop seven measures to capture the feature of information asymmetry and long-term investment focus from different dimensions:

1. High Tech Industry: Following Ouimet and Zarutskie (2014), "High-tech" industries include Computers, Electronics, Biotech, and Telecom. A firm is in the "Biotech" industry if its primary SIC code is 2830 2839, 3826, 3841 3851, 5047, 5048, 5122, 6324, 7352, 8000 8099, or 8730 8739 excluding 8732. A firm is in the "Telecom" industry if its primary SIC code is 3660 3669 or 4810 4899. A firm is in the "Computers" industry if its primary SIC code is 3570 5379, 5044, 5045, 5734, or 7370 7379. A firm is in the "Electronics" industry if its primary SIC code is 3600 3629, 3643, 3644, 3670 3699, 3825, 5065, or 5063. As Holmstrom (1989) points out, the whole innovation process is not only long, idiosyncratic, and unpredictable, but also involves a very high probability of failure. Thus, firms in the

high tech industry, which has more intensive innovation, face more information asymmetry, and focus more on long-term investment.

2. High R&D Companies: The companies having higher R&D expenses above the median within their SIC code industries. The potential benefit of an R&D increase reflects intangible information about future cash flows and the market is slow to recognize the extent of this benefit. So, R&D expense is considered as an intangible investment that has high uncertainty in return and may hurt the profit in the short-term. Thus, high R&D companies also mean high information asymmetry and need to focus on long-term development (Eberhart, Maxwell, and Siddique (2004); Eng, and Shackell (2001)).
3. High Idiosyncratic Volatility: I calculated the idiosyncratic volatility annually by using the standard deviation of daily excess stock returns within one year. Excess return is defined using a CAPM market model estimated over the prior year. Following the literature (Chen, Huang, and Jha (2012); Irvine, and Pontiff (2008)), there is a relation between idiosyncratic stock-return volatility and fundamental volatility; opaque information deters a country's product-market competition, affects stock trading and affects firms' fundamental volatility. Thus, high idiosyncratic volatility also means high information asymmetry.
4. High Analyst Dispersion: The firm's analyst forecast dispersion is above the median of its industry (SIC code). Dispersion is the standard deviation of analysts' forecasts deflated by the stock price five days before the earnings announcement date. According to the literature in accounting (Thomas (2002); Brown and Hillegeist (2007)), this variable is a measure of disagreement among analysts. The disagreement could result from a lack of available information about a firm. Thus, greater disagreement among analysts' forecasts could imply

a larger information gap. Larger analyst dispersion means more information asymmetry to the market.

5. Low Institutional Ownership: The firm's institutional ownership is above the median of its industry (SIC code) in year t. Institutional ownership is measured by the percentage of shares holding by mutual fund investors (13f investors). Institutional ownership can provide a monitor effect on public firms. Less institutional ownership, less monitoring effect, and more information asymmetry (Boone and White (2015); Baik, Kang, and Kim (2010)).
6. No Analyst Cover: The firms are not covered by any sell-side analyst in year t. Companies without analyst cover have less attention from the market and suffer less from short-term market pressure, which increases the information asymmetry in the firms and is more focused on the long-term investment.
7. Long-term Investment Horizon: Following Gaspar, Massa, and Matos (2005), the firm with long-term investment horizon has the investor turnover rate lower than the top third of the distribution of the entire universe in year t. According to Yan and Zhang (2007), I can measure the investor's investment horizon by calculating the weighted investor turnover (churn rate). Firms having investors with long-term investment horizons focus more on long-term investment.

By calculating these seven measures, I have comprehensive measures on information asymmetry and long-term investment. I identify firms with high information asymmetry and more focus on long-term investment and provide the evidence that these firms with high information asymmetry and long-term investment focus are more favorable for dual-class structures. They can perform better under the dual-class structures.

For the control variables, I follow the past literature which studies the dual-class structure and includes log assets, market leverage, dividend, R&D expense, tangibility, etc. The detailed information for all the control variables is included in Table IA.1.

1.3.3 Sample

The whole sample consists of 26,867 single-class firms and 939 dual-class firms from 1994-2014. In Table 1.1, I present the summary statistics for both dual-class and single-class firms and show the mean values for dual-class firms and single-class firms. Dual-class firms exhibit substantial differences from single-class firms. Notably, I observe that dual-class firms are larger (higher total assets), older (larger firm age), and substantially more levered (higher market leverage ratio) than their single-class counterparts. However, these firms' operating performance is mixed comparing single-class firms. From the univariate test, dual-class firms have higher ROA but lower sales growth and lower Tobin's Q than single-class firms, which is also consistent with the past literature (Gompers, Ishii, and Metrick's (2010); Smart, Thirumalai, and Zutter (2008); Masulis, Wang, and Xie (2009)).

In Figure 1, I present the number of dual-class firms from 1994 to 2014. In 1998, the number of dual-class firms reaches a peak at 504. The number of dual-class firms is higher in the 1990s while most of past literature (Gompers, Ishii, and Metrick's (2010); Masulis, Wang, and Xie (2009); Jordan, Liu, and Wu (2014)) is using the sample from 1992 to 2004 to study dual-class structures. However, in 2004, Google became the first high-tech firm that went IPO by issuing dual-class shares[7]. Although the number of dual-class firms is only around 200, more and more high-tech firms went IPO by issuing dual-class shares, such as Google LLC (now Alphabet

[7] This statement excerpts from Google's IPO prospectus in 2004.

Inc., 2004), LinkedIn Corporation (2011), Facebook, Inc. (2012), Alibaba Group Holding Limited (2014), and Snap Inc. (2017). I also found that most of the dual-class firms concentrate on the communication and business services industry (SIC 48 and SIC 73) while the number of dual-class companies is also not small for the electronic industry. According to past studies (DeAngelo and DeAngelo (1985); Field and Karpoff (2002); Smart and Zutter (2003)), in the 1990s, majority dual-class firms focus in the media industry, for example, Comcast, Liberty Media and The New York Times Company; however, in 2000s, more and more high-tech companies choose the dual-class IPO. The different environment changes the attitude of the company to choose dual-class or single-class. Thus, in the next session, I present evidence about the characteristics of dual-class IPO firms.

1.4 Characteristic of dual-class firm

Using the dual-class firm sample, I can analyze the characteristic of the dual-class firm. This exercise is useful since I can show what kinds of firms are more likely to go IPO with a dual-class structure. In Section 1.5, I will show that the firms with high information asymmetry and long-term goals have better performance for dual-class structures. Thus, in this section, I want to analyze whether these firms with high information asymmetry and long-term goals are more likely to go IPO with dual-class structure. However, before the IPO, companies are lack of data to measure the information asymmetry and long-term investment goal. So, for the measure of information asymmetry and long-term investment goals, I need to use the after-IPO data.

As suggested, I use seven measures to identify firms with high information asymmetry. To check whether these characteristics influence the probability of dual-class IPO, I create seven dummy variables: high-tech, high R&D, high ivol, high analyst dispersion, low io, no analyst cover, and low investor turnover. These dummy variables equal to 1 if the firm has ever been in the high tech industry, with high R&D, with high idiosyncratic volatility, with high analyst forecast dispersion, with low institutional ownership, out of analyst coverage, and with long term investor horizon in 1994 to 2014; otherwise the dummy variables equal to 0. For the control variables, I follow Smart, Thirumalai, and Zutter (2008) and use the IPO data from 1980 to 2014 from the SDC platform. Are these firms with high information asymmetry and long-term goals more likely to join the dual-class share structure? To answer this question, for each company which went IPO in 1980-2014, I estimate a probit regression of

$$Dual_i = Info\ Asymmetry_i + Control_i + \varepsilon_i \qquad (1)$$

where Dual is a dummy variable equal to 1 if firm i is a dual-class firm and 0 otherwise. Info asymmetry is the dummy variable equal to 1 if firm i is high information asymmetric and long-term focus in the seven measures after IPO. I include control variables: log of offer value, market return after IPO year, the dummy for Nasdaq listed, percentage of underwriting fee, the dummy for private equity backed, the dummy for venture capital backed, percentage of institutional ownership at the time of IPO, the dummy for equity-spinoff, and log of IPO proceeds.

The results of the probit estimations of equation (1) are listed in Table 1.2. In column 1, I only include the measures for high information asymmetry and long-term investment goals, which is designed to predict how these after IPO characteristics influence the probability of dual-class IPO. In column 2, I also include the control variables, which are variables at the time of IPO, and is used to capture the status of the firms at the time of IPO.

In the pooled regression, I find four positive significant coefficients in column 2. The coefficient for the high tech industry is positive and significant at 5% level, and the coefficients for high idiosyncratic volatility, high analyst forecast dispersion, and no analyst cover are positive and significant at 1% level. The results are consistent with the intuition. Companies facing high information asymmetry and targeting long-term goals are more likely to choose dual-class status because the dual-class structures give these companies more flexibility to make investment and operating.

1.5 Baseline results: firm performance

To examine whether the firms with specific characteristics, such as high information asymmetry and long-term focus, are more favorable to the dual-class structure. I first examine the results of operating performance, market valuation, sales growth by using the seven measures of high information asymmetry, and long-term focus.

1.5.1 Operating performance

Using this sample, I examine whether the firm performance and valuation increase for dual-class relative to single-class when the information asymmetry is high by estimating the following regression equation:

$$ROA_{i,t+1} = \alpha_{it} + Info\ Asymmetry_{it} * DUAL_{it} + DUAL_{it} + Info\ Asymmetry_{it} + Controls_{it} + \varepsilon_{it} \qquad (2)$$

where ROA is the operating income divided by total assets. For different results, the dependent variables include ROA, Tobin's Q, sales growth, intangible investment, innovation, payout, and CEO compensation. The information asymmetry measures are the seven measures I search from past literature to capture the feature of information asymmetry and long-term investment focus from different dimensions: high tech industry, high R&D, high idiosyncratic volatility, high analyst forecast dispersion, low institutional ownership, out of analyst coverage, and long-term investment horizon. The control variables include log assets, sale growth rate, market leverage, tangibility, R&D expense, payout, interest expense, net financing, and firm age. I also control for industry fixed effect using SIC 2 digit and year fixed effect.

With these measures of information asymmetry, I can divide the dual-class firms into two samples and the results show that the dual-class firms with high information asymmetry and long-term goals perform better than both dual-class companies with lower information asymmetry and single-class companies. Panel A of Table 1.3 presents the result for operating performance. I find that the coefficients for the interaction of high information asymmetry and dual ($Info\ Asymmetry_{it} * DUAL_{it}$) are positive, suggesting that dual-class firms with high information asymmetry and long-term goals have higher operating income. In terms of magnitude, the high tech industry and high analyst forecast dispersion dual-class companies have the strongest effects on ROA. A dual-class firm in the high tech industry or having high analyst forecast dispersion would have 2.9% higher in ROA than the single-class firm in the low tech industry or having low analyst forecast dispersion. The coefficients for the dual-class dummy is also positive but without significance, which is consistent with the past literature. In Panel B and Panel C in Table 1.3, I divide the ROA into gross margin (operating income/sales) and asset turnover (sales/assets). I find that the positive effect of the dual-class firm with high information asymmetry and long-term goals is still significant for gross margin while the results are insignificant for asset turnover. Thus, the effect on operating performance may come from efficient operating income management rather than a large scale of sales and assets.

1.5.2 Valuation

Now, I examine the valuation of the dual-class firm with high information asymmetry and long-term goals. Using the full sample of firms, I repeat the same OLS regression with Equation (2) by changing the dependent variable to Tobin's Q.

$$Q_{i,t+1} = \alpha_{it} + \ Info\ Asymmetry_{it} * DUAL_{it} + \ DUAL_{it} + Info\ Asymmetry_{it} + Controls_{it} + \varepsilon_{it} \qquad (3)$$

where $Q_{i,t}$ = [$BV_{i,t}$ Assets + $MV_{i,t}$ of Common Stock – $BV_{i,t}$ of Common Stock – Deferred $Taxes_{i,t}$] / $BV_{i,t}$ Assets (Gompers, Ishii and Metrick (2009)). The information asymmetry measures are the seven measures I search from past literature to capture the feature of high information asymmetry and long-term investment focus from different dimensions: high tech industry, high R&D, high idiosyncratic volatility, high analyst forecast dispersion, low institutional ownership, out of analyst coverage, and long-term investment horizon. The control variables include log assets, R&D expense, ROA, market leverage, firm risk, cash flow, and firm age. I also control for industry fixed effect using SIC 2 digit and year fixed effect.

Table 1.4 gives the results of estimating equation (3) using a variety of specifications. In Panel A, I present the results for general Tobin's Q measure while Panel B presents the industry-adjusted Tobin's Q (=Q_i minus industry average Q). Following the Gompers, Ishii, and Metrick (2009), I also construct the different variations of Tobin's Q measures (In Q- In industry Q; – [1/Q – 1/ (industry Q)]) and the results are similar.[8] I find that dual-class firms in the high-tech industry, having high R&D expenses, having high idiosyncratic volatility, and having high

[8] The tables for the results are not included because of the limited space and can be presented by request.

analyst forecast dispersion can have a greater valuation in terms of Tobin's Q. The coefficients for the interaction terms of high information asymmetry and dual ($Info\ Asymmetry_{it} * DUAL_{it}$) are almost positive, suggesting that dual-class firms with high information asymmetry and long-term goals have a higher valuation. The coefficients for dual-class in the high-tech industry, having high R&D expense, having high idiosyncratic volatility, and having high analyst forecast dispersion are all positive and significant at 5% level. The coefficients for interaction of dual dummy and low institutional ownership, out of analyst coverage remain positive but without significance. Although the coefficient for long term investment horizon and the dual dummy is negative without significance, the insignificant result may be driven by the strong negative effect of low institutional ownership, out of analyst coverage, and long-term investor horizon on Tobin's Q. Since the firms with low institutional ownership, out of analyst coverage, and long-term investor horizon always have a lower stock return on the market (Asquith, Pathak, and Ritter (2005); Hong, Lim, and Stein (2000); Yan and Zhang (2007)), which influence the forward-looking value of the company (the numerator of Tobin's Q).

In sum, consistent with the literature, dual-class firms have a lower valuation on the market comparing with the single-class firm while the coefficient for dual dummy in Column 1 is negative. However, dual-class firms with high information asymmetry and long-term goals have higher valuation comparing with single-class firms with low information asymmetry. Thus, for firms with high information asymmetry and long-term focus, the dual-class structure can improve the confidence of investors and increase the valuation.

1.5.3 Sales growth

In this section, I analyze the sales growth of dual-class firms with high information asymmetry and long-term focus. Sales growth usually serves as a key proxy for profitability and always plays an important role for managers (Batt (2002); Brush, Bromiley, and Hendrick (2000)). After analyzing ROA, I use the analysis of the sales growth to ensure the positive effect of dual-class firms with high information asymmetry and long-term focus on profitability.

Using the full sample of firms, I repeat the OLS regression with Equation (3) by changing the dependent variable to the annual sales growth rate. The sales growth rate in year t is measured by ($Sale_{i,t}$ – $Sale_{i,t-1}$)/ $Sale_{i,t-1}$. The control variables include log assets, capital expenditure, R&D expense, interest expense, ROA, cost of capital, payout ratio, cash flow, and firm age. Table 1.5 presents the results for different measures of information asymmetry and long-term focus. Similar to the results in Table 1.3, the coefficients of the interaction terms of the dual-class dummy and information asymmetry measures are all positive and almost significant. Dual-class firms in the high tech industry, with high idiosyncratic volatility, high analyst forecast dispersion, low institutional ownership, out of analyst coverage have significantly higher sale growth rates than their single-class counterpart. Thus, dual-class firms with high information asymmetry and long-term focus have better profitability.

In sum, these results show that when considering the whole sample of dual-class firms, the dual-class structure seems to have no help on the firm performance. However, when identifying specific types of dual-class firms, dual-class firms with high information asymmetry and long-term focus would have better operating performance than their single-class counterparts in terms of higher ROA, higher Tobin’s Q and higher sale growth rate. For firms with high information asymmetry and long-term focus, they have more investment in intangible assets and always prefer long-term investments with high uncertainty; thus, with dual-class structures, these firms can immune from the short-term market pressure and investors myopic and make the right decision to improve the operating performance. The results are consistent with the main hypothesis that dual-class firms with high information asymmetry and long-term focus can have better operating performance. In Section 1.7, I check out economic outcomes to show how these dual-class firms improve operating performance.

1.6 Tests for endogeneity concerns

For the hypothesis that dual-class firms with high information asymmetry and long-term focus can have better performance, it is hard to prove the causality since whether the firms go IPO with dual-class structure is endogenous and the high information asymmetry and long-term focus is also endogenous. Demsetz and Lehn (1985) pointed out that since ownership structure is one of many governance variables that are endogenously determined with firm value and performance, it will always be difficult to uncover the underlying relationships with empirical analysis. Thus, this paper cannot prove the causality between good performance and dual-class structure, but in this section, I try to solve the omitted variable concerns and show that the correlation between good performance and specific types of dual-class structure.

1.6.1 Results for propensity-matched firms

One concern for the results is the omitted variables, such as size, leverage, and tangibility to cause a good performance instead of the special dual-class structure. Thus, to mitigate this concern, I use the propensity score match to restrict the sample to firms that have similar control variables. In Panel A of Table 1.6, within the matched sample, the dual-class firms and the single-class firms are insignificantly different in Log (Asset), sales growth, leverage, payout ratio, interest expense, net financing, and firm age.

Then, I re-estimate the Equation (2) and Equation (3) by using the propensity matched sample. The results are presented in Panel B to Panel D in Table 1.6. I find that the results are similar to Table 1.3, Table 1.4, and Table 1.5. In Panel B, dual-class firms in the high-tech industry, having high R&D expenses, high idiosyncratic volatility, high analyst forecast dispersion, low institutional ownership, have significantly positive ROA than the matched single-class firms. Although with the restricted sample, the coefficients for the dual-class firm with no analyst cover and long-term investment horizon are insignificant; they remain positive. Also, in this propensity matched sample, the dual-class firms have higher ROA than their single-class peers.

In Panel C and Panel D, the results also mirror from Table 1.4 and Table 1.5. The dual-class firms in the high-tech industry, having high R&D, high idiosyncratic volatility, high analyst forecast dispersion, low institutional ownership, out of analyst coverage, and long-term investment horizon, have higher Tobin's Q and higher sales growth, comparing with the propensity matched single-class firms. Restricting the sample by propensity score match doesn't change the results so that the firms with high information asymmetry and long-term focus are favorable to dual-class structure and can have better performance.

1.6.2 CAR for allowing dual-class issuance in Hong Kong exchange

As known, most of the dual-class decision is made at the time of IPO; so, it is difficult to identify the causality because of the lack of companies' pre-IPO data. Kim and Michaely (2019) use the CAR of recapitalization and unification to show partial causality. However, recapitalizations and unifications are also endogenous.

In this session, by applying the sudden change of regulation of Hong Kong Exchange (HKEX), I try to show the influence of dual-class structure on the firms with high information asymmetry and long-term focus. On December 15, 2017, in the New Board Concept Paper

Conclusions, the HKEX stated that it would proceed to expand the existing listing regime by introducing changes to the Rules to allow the listing of innovative and high growth issuers that have WVR (weighted voting rights) structures. On April 24, 2018, HKEX announced to allow the companies to go IPO in the dual-class share structure[9]. Although this regulation has been discussed by the market consultation of HKEX since 2014 in response to Alibaba's listing demand, the announcement of taking effect of new rules was sudden and became influential to the stock markets. If dual-class share structure benefits for firms in the high-tech industry and high R&D companies, the cumulative abnormal return (CAR) should be lower for these firms which have listed in HKEX in the past. By examining the different CAR for different types of firms, I can suggest that the dual-class is favorable to the specific types of firms. Since the announcement of this regulation is sudden, the results are exogenous of the firms' fundamental characteristics, which can help to prove my hypothesis that firms with specific characteristics are more favorable to the dual-class structure.

By using the data from DataStream, I divide the listed companies in HKEX into high-tech firms and low-tech firms. I also use the data in past one year before the announcement of the regulation to identify the high R&D firms and low R&D firms. Firms which have higher R&D expense than the median R&D expense in the market, are identified as high R&D firms, similar to the definition in section 3.2. Then, I calculate the 5-days CAR of different types of companies. In Figure 2, Panel A shows that the high-tech firms have a continuously lower return than the low-tech firms while Panel B shows that the high R&D firms also experience a lower return than low R&D firms responding to the announcement of allowing dual-class IPO. The results suggest

[9] November 2018, "LISTING REGIME REFORMS FOR DUAL-CLASS SHARE STRUCTURE AND BIOTECH INDUSTRY"; available at https://www.hkex.com.hk/News/Research-Reports/HKEX-Research-Papers/2018?sc_lang=en

that the investors in the market think the dual-class structure is favorable to high-tech and high R&D firms. So, when HKEX allows dual-class structure, the existing high-tech and high R&D firms, which cannot change their shares to dual-class structure, suffer from the market, and have a lower CAR. Thus, the results support my hypothesis that firms with specific characteristics are more favorable to the dual-class structure.

1.7 Other results and possible channels

With the dual-class structure, some firms benefit from higher ROA, higher valuation, and higher sales growth. In this section, I examine how they retain these benefits; the dual-class firms with high information asymmetry and long-term focus have better performance by having a higher intangible investment, more innovation, lower CEO compensation, and lower payout.

1.7.1 Intangible investment

As I suggested, the firms with high information asymmetry and long-term focus are more suitable for dual-class structures because these companies have more investment in intangible assets, which is difficult to show the value through financial reports and have a higher risk in long run. Thus, first, I want to show the results that dual-class firms with high information asymmetry and long-term focus do have more investment in the intangible investment.

Using the same sample, I still run the OLS regression following Equation (3) by changing the dependent variable to intangible investment. I measure the intangible investment by using R&D /(R&D+CAPEX) since R&D expense is the most important investment in intangible assets and capital expenditure is the main factor of tangible assets. This ratio can help to understand how much the firm invest in intangible assets. Table 1.7 presents the results. The high R&D expense measure is not included since the dependent variable highly correlates with R&D

expenses. As I suggest, all the coefficients for the interaction term of the dual dummy and high information asymmetry and long-term focus measures are positive and the majority of them are significant at least 10% level. Dual-class firms in the high tech industry, with high analyst forecast dispersion, with low institutional ownership, out of analyst coverage, and with long term investment horizon have a significantly higher investment in R&D.

The coefficient of the dual-class dummy in column 1 is significantly negative, which means dual-class firms generally have a lower intangible investment. However, when interacting with high information asymmetry measures, the coefficients turn to significantly positive. For firms with high information asymmetry and long-term focus, the dual-class structure can help them invest more in intangible assets because using the dual-class structure can avoid short-term market pressure and have more expense on R&D investment.

1.7.2 Innovation

After analyzing the effect of dual-class firms with high information asymmetry and long-term focus on intangible investment, I want to examine whether these R&D investments would influence the outcome -- corporate innovation. Following Hall, Jaffe, and Trajtenberg (2001), I use the number of patents and the number of citations to measure corporate innovation. The data set provides the number of patents granted and citations for each firm from 1926 to 2010 (Kogan, Papanikolaou, Seru, and Stoffman (2017)). Since the main sample data is from 1994 to 2014, in this section, the data only cover firms from 1994 to 2009.

Table 1.8 presents the result. I repeat the regression of Equation (3) by changing the dependent variable to log(1+Citation/Patents). Using the citation/patent can measure both the quantity and quality of innovation. The result is similar to others. The coefficient of the interaction term of the dual-class dummy and high information asymmetry measures are almost positive and significant. The coefficients of interactions between the dual dummy and high analyst forecast dispersion, low institutional ownership, out of analyst coverage, and long-term investor horizon are all positive and significant at 5% level, which means the dual-class firm with high analyst forecast dispersion, with low institutional ownership, out of analyst coverage, and with long term investment horizon have more innovation than single-class firms. The results are consistent with the intangible investment. More investment in intangible assets helps the firm create more innovation. For interaction terms between dual-class dummy and high-tech industry, high R&D, high idiosyncratic volatility, although the coefficients are negative, the coefficients for the solo term of high-tech industry, high R&D, high idiosyncratic volatility are significantly positive. I believe it is because firms with the high tech industry, high R&D, high idiosyncratic volatility have already had more innovation than normal companies so that it is more difficult for dual-class firms in the high tech industry, with high R&D and with high idiosyncratic volatility have differentially higher innovation.

Panel B presents the results using the number of patents as the measure of innovation, which only consider the quantity of innovation. The results are similar. Most of the coefficients of the interaction term between the dual dummy and high information asymmetry measures are positive while the coefficient of the dual dummy in column 1 is negative. Although only the dual-class firms with high idiosyncratic volatility and with high analyst forecast dispersion have a significant positive effect on the number of patents, the coefficients for other interaction terms are all positive. Thus, the results are still consistent with Panel A.

Overall, when considering the whole sample of dual-class firms, the dual-class firms even have less innovation comparing with single-class firms. However, after identifying the dual-class firms with high information asymmetry and long-term focus, these dual-class firms can have more innovation than their sing-class counterpart. For firms with high information asymmetry and long-term focus, the dual-class structure can help them bear more risk in long-term projects and have more innovation. In addition, the dual-class structure can stimulate the managers to take riskier and long-term project since the market control cannot easily change the managers, which is good for nurturing innovation. Thus, the dual-class structure is more favorable to firms with high information asymmetry and long-term focus.

1.7.3 CEO compensation

The dual-class structure can protect companies from capital market pressure and fixation on short-term earnings so that companies can invest in long-term, innovative projects that external shareholders may not fully appreciate. However, if the dual-class helps the firms loosen the control from external shareholders, how this structure influences the CEO compensation? Past literature (Masulis, Wang, and Xie (2009)) find that managers facing a larger separation of ownership and control enjoy more benefits in the form of higher compensation. But for firms with more information asymmetry and long-term focus, they are more vulnerable to the market control and management team are easily influenced by the fixation on short-term earnings thus CEO compensation should be higher than normal companies. In this case, the dual-class structure provides protection of CEO from external shareholder and short-term investors; thus, I suggest that the CEO of dual-class firms with high information asymmetry and long-term focus would have less compensation.

To test this hypothesis, I match the dual-class sample with the ExecuComp database, which provides information on CEO compensation. I exclude firm-year observations in which CEOs have been in office for less than one year since the compensation to these CEOs is for only part of a fiscal year. Following prior studies such as Aggarwal and Samwick (1999), Core, Holthausen, and Larcker (1999), and Bertrand and Mullainathan (1999), I use the level of CEO total compensation (ExecuComp variable: TDC1) as the dependent variable and run the regression of Equation (3). The key explanatory variable is still the interactions between the dual dummy and high information measures. The control variables include the determinants of CEO compensation previously found in the literature. They include log assets, leverage, Tobin's Q, R&D expense/sales, interest expense, capital expenditures, advertising expenses, industry-adjusted ROA, market-adjusted abnormal stock return, stock return volatility, firm age, CEO tenure, and CEO ownership. The detailed definition of each variable is included in Table IA.1.

Table 1.9 presents the results. I find that the coefficients for interaction terms between dual dummy and high-tech industry, high idiosyncratic volatility, low institutional ownership, and out of analyst coverage are significantly negative while the coefficients for other measures are still positive without significance. These results are consistent with the hypothesis that dual-class firms with high information asymmetry and long-term focus pay less to the CEOs since the CEO is facing less pressure and risk from the capital market. I think this is also one reason that these special dual-class firms can have a better operating performance by reducing the cost of the CEO payments.

There is still another explanation that the less CEO compensation may result from the low stock price for the dual-class shares in the equity part of compensation. Panel B in Table 1.9 shows the result for the ratio of equity pay in total compensation. The results of coefficients are mixed, which means that the dual-class firm with high information asymmetry and long-term focus is not paying more equity to CEOs. Thus, the effect of less CEO compensation is coming from the reduced total payments and does not result from the restricted stock paid by the dual-class shares. Also, by using this sample, I find that the coefficient of the dual-class dummy (column1) is significantly negative, which gives the contradicting results of prior studies. I think this is because of the different sample period; past studies use the sample from GIM (2009) and only covers firms over 1994-2002 while my sample is longer from 1994 to 2014. So, there is still limited convincing evidence for how the dual-class structure affects the CEO compensation.

Overall, the dual-class firms with high information asymmetry and long-term focus pay less to CEOs. I believe this effect is because the dual-class structure reduces CEOs' pressure from market control and short-term investors. For firms with high information asymmetry and long-term focus, managers are more willing to sacrifice the payment to have more stability so that these dual-class firms can benefit from the lower payment of CEOs.

1.7.4 Payout

Firms with high information asymmetry and long-term focus can use the dual-class structure to mitigate managerial myopia and to take risky and long-term projects. In this section, I examine the effect of dual-class firms with high information asymmetry and long-term focus on the corporate payout. I assume the corporate payout should be also lower for firms with high information asymmetry and long-term focus. The cost of paying out dividends to investors is high for firms with long-term focus because firms may have to forgo valuable investment opportunities. However, firms with high information asymmetry and long-term focus may have to pay high dividends to give good signals and pre-commitment to investors. With the dual-class structure, these companies do not need to sacrifice the investment opportunities to pay the dividend so that these firms may pay lower dividends.

To test this hypothesis, I use three measures to compare the payout policies, the level of total payout, payout yields, and cash dividend yields. The total payout includes the cash dividend and stock repurchase. The total payout yield is the ratio of the sum of cash dividends and stock repurchases to the total market value of the stock. The cash dividend yield is defined as the ratio of cash dividends on the common stock to the total market value of the stock. The key explanatory variables are still the interaction between the dual dummy and high information asymmetry measures. The control variables include log assets, sale growth rate, leverage, Tobin's Q, R&D expense, ROA, firm age, capital expenditures, advertising expense, cash, and tangibility. The industry fixed effect and year fixed effect are also included.

Table 1.10 presents the results. In Panel A, the total payout is less for dual-class firms in the high tech industry, with high analyst forecast dispersion, with low institutional ownership, out of analyst coverage, and with long term investment horizon. The coefficients for these interaction terms are negative and significant. In Panel B, I present the results for payout yields. The results are similar. The coefficients of the interaction terms between the dual dummy and high-tech industry, high R&D, high analyst forecast dispersion, low institutional ownership, out of analyst coverage, and long-term investor horizon are all negative and three coefficients (interactions between the dual dummy and low institutional ownership, out of analyst coverage, and long-term investor horizon) are significant at 10% level. Panel C presents the results for cash dividend yields and finds similar results. For most measures of firms with high information asymmetry and long-term focus, the dual-class firms have less payout yield and cash dividend yields.

Interestingly, the coefficients for dual-class dummy in column 1 in Panel A, Panel B, and Panel C maintain significantly negative. Thus, from 1994 to 2014, comparing with single-class companies, dual-class firms have fewer corporate payouts. Also, the coefficients of the interaction term between the dual dummy and high idiosyncratic volatility are positive without significance. I believe this effect is because firms with high idiosyncratic volatility have already had less payout comparing firms with low idiosyncratic volatility as the coefficient for high idiosyncratic volatility dummy is significantly negative, so having dual-class structure does not reduce the already low payout. Overall, considering the consistent results for other high information asymmetry and long-term focus measures, I find that the dual-class firms with high information asymmetry and long-term focus pay less dividend and have less repurchase because by using dual-class structure, these firms do not need to provide the short-term signal to outside investors so that they can use the cash and earnings to develop more risky and long-term projects.

In conclusion, in this section, besides the profitability and firm valuation, I find that dual-class firms with high information asymmetry and long-term focus also have better performance on other financial outcomes, which help to explain how these special dual-class firms can have better profitability and valuation. By applying the dual-class structure, the firms with high information asymmetry and long-term focus can have more investment in intangibles assets, such as R&D expense, so that these firms have more innovations both in quantity and in quality. Besides, dual-class firms with high information asymmetry and long-term focus have less CEO compensation and less dividend payout, which can save the operating cost and results in better profitability. Even in the past literature, dual-class firms perform worse due to the agency problem, I still can find that after identifying the dual-class firms with high information asymmetry and long-term focus, the dual-class structure would also bring some good economic outcomes.

1.8 Conclusion

In this paper, by examining the different performances of different attributed dual-class firms, I want to explain the increasing prominence of dual-class stock. The dual-class structure has become increasingly commonplace on the back of a wave of high-profile IPOs of technology companies, such as Google LLC (now Alphabet Inc., 2004), LinkedIn Corporation (2011), Facebook, Inc. (2012), Alibaba Group Holding Limited (2014), and Snap Inc. (2017). According to the data in Loughran and Ritter (2004), between 2006 and 2015, there were a total of 150 dual-class IPOs in the United States. The popularity of dual-class IPOs has renewed the debate on how these structures affect corporate governance and investor protection. Thus, through this paper, I want to provide empirical evidence that because of some specific features, the dual-class can provide some benefits to shareholders and can help the success of the companies with high information asymmetry and long-term investment goals.

Using the sample from 1994 to 2014, I find that dual-class firms with high information asymmetry and long-term focus can have better operating performance and higher firm valuation. These results may come from higher investment in intangible assets, more innovations, less CEO compensation, and less dividend payout. By using different measures (high tech industry, high R&D, high idiosyncratic volatility, high analyst forecast dispersion, low institutional ownership, out of analyst coverage, and long-term investor horizon) to identify the firms with high information asymmetry and long-term focus, I find the bright side of the dual-class structure. These results also help to explain why the dual-class structures become more and more popular in recent years. The dual-class structure can protect firms from capital market pressure and short-term investors' myopia, so for firms with high information asymmetry and long-term focus, the dual-class structure provides the flexibility to grow and invest in long-term projects. Thus, when dual-class do bring the agency problems to the firms, the benefits of the dual-class structure should also be admitted.

Chapter 2

Brain Drain: The Impact of Air Pollution on Firm Performance

2.1 Introduction

"The last few years of living in such a singular environment [in Beijing] have taken a huge toll on my life and started affecting my health," Hugo Barra, the former vice president of Xiaomi's international business, wrote in a Facebook post announcing his departure in January 2017, hinting that a factor in his decision to move was Beijing's air pollution.[10] Air pollution is acute and becoming a growing hazard to human health. For example, the World Health Organization reveals that 90% of the world's population breathe polluted air in 2018.[11] The worsening air quality in recent years, especially in developing countries, has provoked great public concern, which may drive talents and skilled workers to leave and thereby hurt economic growth. Hugo Barra's post raises the question of whether his case is merely anecdotal or the tip of the iceberg. In this paper, we try to answer this question.

Ambient air pollution is known to harm human physical and mental health.[12] Financial economists recognize that participants in financial markets are not immune to unhealthy air quality. For example, recent studies show that air pollution intensifies investors' and financial analysts' behavioral biases (Chang, Huang and Wang, 2018; Dong *et al.*, 2019; Huang, Xu and Yu, 2019;

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[10] "Ex-Android executive quits Chinese smartphone maker Xiaomi," *Financial Times*, January 23, 2017. Available at: https://www.ft.com/content/2d8be270-e148-11e6-8405-9e5580d6e5fb

[11] "9 out of 10 people worldwide breathe polluted air, but more countries are taking action," World Health Organization, May 2, 2018. Available at: https://www.who.int/news-room/detail/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-countries-are-taking-action

[12] An extensive scholarly literature finds that ambient air pollution may cause adverse impacts on human health, such as premature death and shortened lives (Chen *et al.*, 2013; Tanaka, 2015); it is listed as the single largest environmental health risk (see, European Environment Agency, 2015).

Li *et al.*, 2019). Thus far, most studies focus on the *short-term* costs of air pollution, and there is little evidence regarding the *long-term* impact of air pollution on firms. Given the essential role of corporate human capital for value creation and the success of firms, we study whether and how air pollution affects the accumulation of corporate human capital and firm performance.

Our intuition rests on Tiebout's (1956) model, which proposes that individuals have heterogeneous preferences for public goods and sort themselves into localities that most closely match those preferences. People facing poor air quality can adopt defensive behaviors to prevent exposure to air pollution. If these provisional defensive behaviors cannot assure health or are too costly in the long run, people will ultimately seek to settle in areas with better air quality. Nevertheless, not everyone has the flexibility to "vote with their feet." We expect air pollution to have a more acute effect on skilled individuals.

Skilled people tend to have higher incomes and greater demand for quality of life. They also have more knowledge and a better understanding of the harmful effects of air pollution, and thus are more sensitive to air pollution (Arntz, 2010). With more career opportunities, skilled people can sort themselves into locations where better air quality is capitalized into housing prices (Chay and Greenstone, 2005). As a result, firms located in more polluted areas are less able to recruit and retain high-quality individuals, leading to the loss of corporate human capital. We call this view *the brain drain hypothesis*. We test the brain drain effect of air pollution in China and examine how such an effect eventually impacts firm performance. To the best of our knowledge, this paper is the first to assess the effect of environmental pollution on corporate human capital.

To illuminate the influence of individuals' sorting response to air pollution on corporate human capital, we start by examining how people decide on their intended places of work when air pollution occurs. We use the Search Volume Index of Baidu, the largest search engine in China, to measure people's intended places of work. We find that, when air pollution occurs in a region (e.g., Chengdu, the provincial capital of Sichuan), people located in the region exhibit an increased intention to work in less polluted areas (e.g., Shenzhen) but a reduced intention to work in more polluted areas (e.g., Beijing). Moreover, the tendency is stronger in regions where people's concern for health is more sensitive to air pollution. This finding suggests that the concern of air pollution induces people to choose relatively less polluted areas as their intended workplace.

We then study how such an air pollution effect on people's sorting decisions is compounded into firms' human capital formation. Empirical tests at the firm level tend to be challenging because ambient air pollution is associated with local business activities, which in turn affect labor market opportunities and the labor supply to an individual firm. To deal with potential endogeneity problems, we use three empirical settings to test our prediction. First, we use a difference-in-differences (DID) strategy that exploits the exogenous increase in public access to air pollution information as a result of the implementation of the air pollution monitoring and disclosure program in China (hereafter the monitoring program) (Barwick *et al.*, 2019). From 2012 to 2014, China launched a nationwide program that rolls out in three waves of cities to establish a comprehensive monitoring network to monitor and publish air quality information in real time. The program has no direct impact on air pollution, but rather significantly increases public access to pollution information and individuals' awareness about air pollution. We test whether brain drain occurs in the post period of the monitoring program.

Second, we use a regression discontinuity design (RDD) that exploits discontinuous variation in air pollution created by an arbitrary policy at the Qinling-Huai River (hereafter QH) boundary in China (Almond *et al.*, 2009). The Chinese government established a free coal-based central heating system in the 1950s–1980s. Due to budgetary constraints, free heating is only provided to households living in regions on the north side of the QH boundary. Because the combustion of coal releases massive particulate matter and other pollutants, the areas where the policy applies have a significantly higher level of air pollution (Almond *et al.*, 2009; Chen *et al.*, 2013). Therefore, air pollution has discontinuous variation in areas across the QH boundary. We test the difference in corporate human capital and performance across the two sides of the QH boundary.

Third, we use a two-stage least squares (2SLS) regression that exploits the extensive variation in air pollution as a result of thermal inversions (Chen, Oliva and Zhang, 2017). Thermal inversions are a meteorological phenomenon. Given that air moves from hot to cold areas, when the above-ground temperature is higher than the ground temperature, air pollutants are trapped near the ground, leading to a higher level of air pollution. As a result, the strength of thermal inversions can be used as an instrument variable to capture the variation in air pollution that is independent of human activities. We test whether the level of instrumented air quality is related to the level of firms' human capital and performance.

To gauge corporate human capital, we consider both firm managers and employees, who may enter the production function and influence firm performance distinctly (Gennaioli *et al.*, 2013). Specifically, we check whether a firm's top executives (i.e., CEO and board chairman) were born or obtained college degrees outside the region where the firm is domiciled, or whether they studied or worked abroad. Managers with diverse backgrounds and foreign experience are found to lead to better firm performance (Giannetti, Liao and Yu, 2015; Chemmanur *et al.*, 2019). We also calculate the proportion of highly educated employees and the proportion of skilled employees. Highly educated and skilled workers are important corporate human capital and significantly contribute to the improvement of firm productivity (Haltiwanger, Lane and Spletzer, 1999; Ashraf and Ray, 2017). Our diagnostic tests show that these measures are effective in capturing the quality of firm management and employees.

Based on the sample of firms publicly listed on the Shanghai and Shenzhen stock exchanges from 2000 to 2016, the estimates of the three empirical settings lend support to *the brain drain hypothesis*. First, the DID estimates show that, after the inception of the monitoring program, the probability of having a non-locally born or educated top executive significantly decline by 5.9% or 5.6%, respectively, for firms located in more polluted areas. Moreover, the possibility of employing highly educated or skilled employees decreases by 4.2% or 6.8%, respectively, in the post-event period. Interestingly, there is no significant reduction in the proportion of employees with low levels of education and that of non-technical employees, suggesting air pollution mainly affects skilled individuals. Using executive turnover data, we further find that firms are less likely to poach executive talents from areas with clean air, but are more likely to lose talents who move to work in clean areas, after the inception of the monitoring program.

Second, the RDD shows that, relative to firms located on the non-heating side of the QH boundary, those located on the heating side suffer a significantly lower probability of having an executive who was non-locally born, non-locally educated, or has overseas experience. Firms located on the heating side also have a significantly lower proportion of employees with high education and technical skills. The results still hold when we focus on areas within a narrow margin along the QH boundary. Third, our 2SLS regression shows that the average level of air pollution is higher in areas where thermal inversions are more frequent, and the instrumented air quality is positively related to the level of high-quality firm executives and employees. To explore regional heterogeneity in individuals' concern for their health, we show that the negative effect of air pollution on corporate human capital is stronger in regions where air pollution is more likely to trigger people's attention to health. This finding further suggests that air pollution affects corporate human capital through the channel of environmental health risk.

Next, we examine whether the brain drain effect of air pollution manifests itself in firm performance. Previous studies suggest that top management quality and employee skills are important determinants of firm productivity and firm value (Haltiwanger, Lane and Spletzer, 1999; Ashraf and Ray, 2017; Chemmanur *et al.*, 2019). Following this notion, we investigate how air pollution affects firms' total factor productivity and Tobin's Q. We first show that firms in polluted areas experience a significant decline in productivity and firm value in the post period of the monitoring program. We then find that firms located on the heating side of the QH boundary have a significantly lower level of productivity and firm value than those on the non-heating side. We also document similar results for air pollution instrumented by thermal inversions. These results all suggest that air pollution impedes corporate productivity and impair shareholder value.

To tighten the link between the brain-drain effect and firm performance, we examine whether the effect of air pollution on firm performance is more pronounced in firms that rely more on human capital. We estimate the dependence of firm performance on human capital by regressing firms' total factor productivity and Tobin's Q on either the measure of executive talent or the proportion of high-quality employees in each industry over the past five years, respectively. We find that the effect of air pollution on firm performance is more pronounced in industries with a higher estimated dependence on human capital. Moreover, the effect of air pollution on firm performance is stronger in firms with higher average employee compensation and in those in innovative industries. These results are consistent with the human capital channel through which air pollution affects firm performance.

This paper contributes to two strands of the literature: that on corporate human capital and that on the economic consequences of environmental pollution. To the literature on corporate human capital, we document an important non-economic factor that affects the accumulation of corporate human capital, while previous studies, mainly relying on regional analysis, focus on economic factors such as local wages and land rents (Rauch, 1993), organizational change (Bresnahan, Brynjolfsson and Hitt, 2002), financial deregulation (Philippon and Reshef, 2012), and local productivity change (Diamond, 2016). Moreover, we provide micro evidence that the stock of talent with respect to both management and employees is essential for the improvement of corporate productivity and shareholder value, while prior studies primarily focus on the role of human capital in regional growth and development.

This paper also adds to the literature on the economic consequences of environmental pollution. Millions of households in developing countries are facing extremely high levels of air pollution. However, the extant studies show that people's willingness to pay for air quality improvement is low (Smith and Huang, 1995; Greenstone and Gallagher, 2008; Sullivan, 2016), which puzzles economists and sociologists. We shed light on this puzzle by proposing that migration sorting is an alternative defensive behavior to prevent exposure to air pollution, especially for skilled labor. Furthermore, recent finance studies have explored the *short-term* impact of air pollution on capital market participants, such as its effect on investor trading behavior (Heyes, Neidell and Saberian, 2016; Meyer and Pagel, 2017; Huang, Xu and Yu, 2019; Li *et al.*, 2019) and analyst forecasts (Dong *et al.*, 2019). However, the *long-term* impact of air pollution on corporate decision-makers and key employees remains unknown. Understanding this effect is important, given the significance of the economic outputs of publicly listed firms.

Finally, our study provides a timely policy implication. At the 2009 United Nations Climate Conference, many countries refused to commit to mandatory emissions reduction targets.[13] A key source of contention is to what extent air pollution affects their economic growth. Regulators raise the concern that environmental regulations may hurt firms' competitiveness. This study documents that the accumulation of corporate human capital is an important channel through which environmental regulation can actually benefit an economy.

2.2 Hypothesis development and background

2.2.1 Human capital and its role in firm performance

The role of human capital in economic growth has been of constant interest to economists and social scientists. The concentration of talent and skilled workers in a particular place reduces the costs of transmitting knowledge and sharing information, which leads to the "diffusion and growth of knowledge" (Jovanovic and Rob, 1989). The accumulation of human capital generates positive externalities that enhance productivity and economic growth (Lucas, 1988). As a result, the economic growth in a region crucially depends on its ability to attract and retain "brains."

A large body of literature has documented that a high level of human capital (e.g., labor with higher education and richer work experience) is associated with high regional income and productivity (Rauch, 1993; Black and Lynch, 1996). In particular, using a large dataset of 110 countries, Gennaioli *et al.* (2013) study the determinants of regional development such as geography, natural resources, institutions, human capital, and culture. They find that the level of education of workers and entrepreneurs emerges as the most consistently important determinant of regional income and productivity.

[13] "The UN Climate Change Conference, 2009 (COP 15)", ACCA, August 2009. Available at: https://research-repository.st-andrews.ac.uk/bitstream/handle/10023/3767/ACCA-2009-UN-Climate-Change.pdf?sequence=1&isAllowed=y

While human capital plays a vital role in regional development, the study of its corporate impact is still in its infancy, probably due to the difficulty of measuring corporate human capital. Corporate human capital refers to both firm employees and managers. Among early studies of firm employees, Haltiwanger, Lane and Spletzer (1999) use demographic and firm information from the U.S. Census Bureau and show that firm productivity is significantly higher when there is a higher fraction of highly educated workers, consistent with the human capital model that holds that skilled workers make firms more productive.

Ashraf and Ray (2017) examine the reduction in the quota of H-1B visas in 2004 as a shock to skilled immigrant workers and find that firm-level innovation outcomes decline for immigrant-dependent firms in the post-period of the policy. Consistent with this study, Kerr and Lincoln (2010) find that H-1B admissions increase the employment of science and engineering workers and patenting by Chinese and Indian inventors in cities and firms dependent on the H-1B visa program. The critical role of employee human capital in corporate performance has also been highlighted across various aspects including employee incentives (Chang *et al.*, 2015), employee age (Ouimet and Zarutskie, 2014), tolerance for failure (Tian and Wang, 2014), and labor law and unionization (Acharya, Baghai and Subramanian, 2013; Bradley, Kim and Tian, 2017).

Recent studies have started to look at the impact of managerial human capital on corporate performance using managers' characteristics extracted from their resumes. For example, Chemmanur *et al.* (2018) construct an index based on the top management's education and past experience. They find that higher quality managers are able to select better projects and thus have superior operating performance and, consequently, higher firm value and stock returns. Using the same managerial quality index, Chemmanur *et al.* (2019) find that higher quality managers have better foresight into the potential value of innovation opportunities and create a failure-tolerant environment that attracts skilled workers. In line with this view, Custódio, Ferreira and Matos (2017) find that CEOs with general skills have better external job opportunities and thus have a greater tolerance for failure. Moreover, CEOs with skills transferable across firms and industries help to create a firm without boundaries that is beneficial for knowledge transfer.

Notwithstanding, firm workers and managers may influence firm production functions; it has been suggested that both, in different ways, are key factors that drive the economic performance of a firm (Gennaioli *et al.*, 2013). Given its substantial influence, it is important to understand the factors that affect the accumulation of corporate human capital. Previous studies suggest that the accumulation of human capital is shaped by a number of economic and financial factors such as local wages and land rents (Rauch, 1993); firms' technical changes, such as the adoption of information technology; complementary workplace reorganization; the introduction of new products and services (Bresnahan, Brynjolfsson and Hitt, 2002); financial deregulation (Philippon and Reshef, 2012); the introduction of policies to attract talented immigrants (Giannetti, Liao and Yu, 2015), and local productivity change (Diamond, 2016). However, the impact of non-economic factors is under-investigated

2.2.2 The impact of air pollution on human capital

Air pollution imposes high health risks on humans. Medical studies have shown that air pollution can cause numerous health problems such as respiratory and cardiovascular illnesses (Seaton *et al.*, 1995), heart disease (Dominici *et al.*, 2006), stroke (Hong *et al.*, 2002), and lung cancer (Kabir, Bennett and Clancy, 2007). Recent studies find that air pollution may increase infant mortality (Tanaka, 2015) and reduce life expectancy (Chen *et al.*, 2013). Moreover, air pollutants such as particulate matter can be absorbed into the bloodstream and travel into the central nervous system, eventually causing cerebrovascular damage (Genc *et al.*, 2012). Exposure to air pollution can damage brain function and reduce individuals' cognitive skills (Lavy, Ebenstein and Roth, 2014).

Given the high environmental risks of air pollution for human health, people facing high exposure to air pollution may adopt defensive behaviors, such as purchasing air purifiers (Ito and Zhang, 2019). However, householders' willingness to invest in these defensive behaviors is estimated to be low in developing countries (Smith and Huang, 1995; Greenstone and Gallagher, 2008; Sullivan, 2016). An alternative defensive behavior is re-location and migration. This intuition is built on the most popular and influential model of individual location sorting, developed by Tiebout (1956). His model suggests that people "vote with their feet" to find the community that provides them with the optimal bundle of public goods. Banzhaf and Walsh (2008) provide empirical evidence to support this model. Given that not everyone has the flexibility to move around, we expect air pollution to have a more relevant impact on skilled labor.

Skilled and highly educated people are more likely to be a high-income group. They tend to have a higher quality of life requirements and are more sensitive to air pollution. They also have a greater economic ability to move to cities where better air quality is capitalized into housing prices (Chay and Greenstone, 2005). Moreover, they have better knowledge on the harmful effects of air pollution and thus lower tolerance for poor air quality. They could also have more information on job opportunities and face lowers costs in searching for new jobs (Arntz, 2010). In line with this view, Levine, Lin and Wang (2018) find that firms exposed to toxic plant openings are more likely to experience CEO turnover.

Combining the discussion of the two strands of literature above, we hypothesize that, firms located in more polluted areas are less likely to recruit and retain high-quality individuals, leading to the loss of human capital and poor firm performance. This prediction is named *the brain drain hypothesis*:

H1. Air pollution is negatively associated with a firm's human capital and performance.

2.2.3 Air pollution in China

The rapid economic growth of China in the past three decades has lifted more than 600 million people out of poverty. However, great economic achievement comes at the expense of environmental pollution. The particulate matter concentration in China is seven times the level in the U.S. and is also higher than that in India (Greenstone and Hanna, 2014). A recent green paper published by the Chinese Academy of Social Sciences indicates that the problem of haze and fog in China has hit a record level and that China is currently facing its worst air pollution problems since 1961.

The problem of haze in China has risen rapidly since the beginning of this century (Gao, 2008). In 2000, the Ministry of Environmental Protection (MEP) began publishing the daily Air Pollution Index (API) for major cities in China.[14] A study of 1,701 monitoring stations in China shows that the annual average number of haze days increased from 6 in 2000 to 18 in 2012 (Han *et al.*, 2016). More than 92% of residents in China have been exposed to particulates concentration exceeding 10 μg/m3 since 2000. This exposure rate increased to 98% in 2012. During the same time, Western countries such as the U.K. and the U.S. have experienced a significant decline to levels below 20% (Hsu *et al.*, 2014).

In 2012, China launched a program to intensify the real-time monitoring of primary pollutants and published an updated real-time Air Quality Index (AQI). AQI updates API by further

[14] API synchronizes air pollutants, including SO_2, NO_2, CO, and O_3, and PM_{10} (suspended particulates with a diameter of 10 μm or less). Only 42 cities had API in 2000. This number increases to 86. However, during this period, the visibility data are incomplete for some cities. In particular, the API data for all cities are missing on June 4, 2008 for an unknow reason (Chen *et al.*, 2012).

incorporating PM2.5 (suspended particulates with a diameter of 2.5 μm or less), which has been the major air pollutant in Chinese cities since the 2000s. Since the introduction of the monitoring program, the regularly occurring haze began to draw extensive public attention. Many cities, especially those in the north, have experienced very serious haze. For example, in December 2013, China suffered a severe bout of air pollution with thick haze stretching from Beijing to Shanghai, a distance of 750 miles. The levels of PM2.5 in Beijing peaked at 35 times the World Health Organization's (WHO) recommended limit and were stuck at tremendous levels for weeks (Zhang, Liu and Li, 2014). Direct consequences were observed: residents were seen wearing face masks; schools and airports were closed; children were kept indoors; hospital admissions for respiratory problems increased, and social networks exploded with complaints about the heavy blanket of smog.

The terrible air pollution is also leading to an exodus of expatriates fleeing China.[15] Many companies complain that it is harder to recruit talent from outside to work in northern China.[16] Executive recruitment firms also state that it is getting harder to attract top talent to China, including both expatriates and Chinese nationals educated abroad.[17] The monitoring program starting in 2012 allows private parties to access and stream data directly from the website of MEP, which has spurred a surge in private websites and mobile phone applications that report real-time air quality information. The availability of computers or smartphones allows anyone to match their

[15] See "Why leave job in Beijing? To breathe", *The Wall Street Journal*, April 14, 2013. Available at: https://www.wsj.com/articles/SB10001424127887324010704578418343148947824

[16] "Airpocalypse' drives expats out of Beijing", *Financial Times*, April 1, 2013. Available at: https://www.ft.com/content/46d11e30-99e9-11e2-83ca-00144feabdc0

[17] See, "Execs fleeing China because of bad air", CBS News, January 29, 2013. Available at: https://www.cbsnews.com/news/execs-fleeing-china-because-of-bad-air/ .

data with the choking clouds in front of them. It is reported that strategies for leaving Beijing have become a hot topic on Weibo (China's Twitter).[18]

2.3 Air pollution and intended places of work

2.3.1 Search volume index

We start with our analysis by testing the individual sorting argument. To this end, we examine whether air pollution influences individuals' intended places of work. Specifically, we examine how people's intentions with respect to the site of work change when air pollution occurs in their location.

To conduct the test, we first identify the emergence of air pollution in each region (a municipal city). We measure air pollution using AQI, which is published by China's MEP. AQI synchronizes various types of air pollution, including SO_2, NO_2, PM_{10} (suspended particulates with a diameter of 10 μm or less), $PM_{2.5}$ (suspended particulates with a diameter of 2.5 μm or less), CO, and O_3. A higher AQI level means a higher level of air pollution. Air quality is considered to be good when the AQI is below 100. An AQI above 100 indicates pollution.

Some studies suggest that AQI data are subject to manipulation by city governments at the margin of 100 because they are motivated by the blue-sky award (a blue-sky day is defined as a day with AQI below 100) (Ghanem and Zhang, 2014). To mitigate this concern, we conduct a McCrary density test (McCrary, 2008) based on daily AQI from 2000 to 2016.[19] The results are shown in Figure IA.1. We find that the distribution of AQI is smooth, and the manipulation at the margin of 100 is negligible.[20] To identify the emergence of air pollution in a region, we examine whether there is a large increase in AQI. Specifically, a region is identified as experiencing an air

[18] "Smog dents Beijing's expat appeal", *Financial Times*, April 5, 2013. Available at: https://www.ft.com/content/b29afeae-9dc9-11e2-bea1-00144feabdc0
[19] Published by the Chinese Ministry of Environmental Protection (MEP) since 2000.
[20] The results are similar for the sample period from 2011 to 2016.

pollution day if the increase in daily AQI exceeds a one standard deviation change in daily AQI in the past year in the region.

We measure people's intended places of work using Baidu's Search Volume Index (SVI, similar to Google SVI). As the largest search engine in China, Baidu started to reveal the SVI of words for which people commonly search online in 2011. It provides daily SVI for a specific word at both country and city levels. We use the city-level SVI to measure the intention of people from one city to work in another city. Specifically, we use the word of "$城市找工作" (to work in $city), where $city is one of the top cities where people intend to work in China based on a study conducted by the ChinaHR Research Institute in 2018.[21] In such, $SVI_{r,d}$, indicates the daily SVI of people in city *r* who are hoping to work in city *d*. *r* refers to the Chinese city in which people reside, and *d* denotes one of the top work-destination cities. We collect the daily SVI and AQI data and conduct the analysis for the period from 2011 to 2016.

In Panel A of Figure 3, we plot the average searches for information about finding work in Beijing and Shenzhen around air pollution days (Day 0) across all cities. Beijing and Shenzhen are selected for comparison for two reasons: 1) the two cities are the dream work destinations for many young people in China; 2) the two cities have a substantial difference in air quality (the average AQI of Beijing and Shenzhen from 2011 to 2016 is 106 and 54, respectively). Interestingly, we find that, when air pollution occurs at their location, people increase their search for job opportunities in Shenzhen while decreasing such searches with respect to Beijing. Specifically, the level of searches for job opportunities in Shenzhen (Beijing) increases (decreases) by around 12% (6%) from day 0 to day 3 as compared to the average level from day -16 to day -6.

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[21] ChinaHR Research Institute, 2019. "The 16th China college student best employers survey." The top cities where people intend to work in China include Beijing, Shanghai, Guangzhou, Hangzhou, Shenzhen, Chengdu, Wuhan, Tianjin, Nanjing, Xian, Chongqing, Jinan, Zhengzhou, Changsha, and Shenyang.

To show a more general pattern, we plot the search volume for more workplaces with various levels of air pollution. Specifically, we divide the top work-destination cities into more and less polluted city groups based on their average AQI during our sample period. The more polluted city group includes the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian), and the less polluted city group consists of the five least polluted cities (Shenzhen, Shanghai, Guangzhou, Hangzhou, and Chengdu). The average search for job opportunities in the two city groups is presented in Panel B. The pattern is similar. The figure shows that, when air pollution occurs in a city, people search more often for work in places that have less pollution while searching less often for work in places that have more pollution.

2.3.2 Regression analysis

We then conduct a more formal analysis by running regressions with city characteristics controlled. The model is specified as follows:

$$SVI_{r,t} = \alpha_1 + \alpha_2 Pollution\ days_{r,t} + City_r + Date_t + Control_{r,t} + \epsilon_{r,t}, \quad (1)$$

where the dependent variable ($SVI_{r,t}$) denotes the intention of people in city *r* on day *t* to work in another city, including Beijing ($To\ work\ in\ Beijing_{r,t}$), Shenzhen ($To\ work\ in\ Shenzhen_{r,t}$), the more polluted city group ($To\ work\ in\ more\ polluted\ cities_{r,t}$), and the less polluted city group ($To\ work\ in\ less\ polluted\ cities_{r,t}$).

$Pollution\ days_{r,t}$ indicates a five-day window following an air pollution day in city *r*. Specifically, it takes a value of one for days *t*, *t+1*, *t+2*, *t+3*, and *t+4* if city *r* experiences air pollution on day *t* and zero otherwise. We include city fixed effects ($City_r$) and date fixed effects ($Date_t$) in the model. As a result, the coefficient on $Pollution\ days_{r,t}$ (α_2) is a difference-in-difference (DID) estimate. The first difference is the difference in SVI in a city between pollution and non-pollution days, and the second difference is the difference in SVI between cities experiencing air pollution and those not experiencing air pollution.

We control for city-level economic and demographic characteristics that may relate to people's searches for places of work. These variables include a city's *GDP growth*, *GDP per capita*, *Education expenditure* (government expenditure on education/GDP), and *Population* (log of population size). We also control for climate characteristics in a city, including *Temperature*, *Relative humidity*, *Precipitation*, and *Sunshine hours*. Table IA.2 provides detailed definitions and sources for these variables. We estimate Equation (1) based on the sample period from 2011 to 2016. The summary statistics for variables used in this analysis are reported in Panel A of Table 2.1.

The estimates of Equation (1) are presented in Table 2.2. We find that the coefficient on $Pollution\ days_{r,t}$ in Column (1) (Column 2) is significantly negative (positive), suggesting that people reduce (increase) their search for job opportunities in Beijing (Shenzhen) during air pollution days. The results in Columns (3) and (4) suggest that people's intention to work in more (less) polluted cities declines (increases) when air pollution occurs in their location. The DID estimates thus confirm the pattern, as shown in Figure 3.

To ensure that the pattern we identify is falsifiable, we conduct a placebo test by making random assignments of air pollution days to each city. The assignments are made such that the frequency of randomly assigned air pollution days is the same as the frequency of true air pollution days. We create a variable $Pollution\ days\ (random)_{r,t}$, referring to a five-day window following the randomly assigned air pollution day in a city. We re-estimate Equation (1) using $Pollution\ days\ (random)_{r,t}$. The results are presented in Table IA.3. We find that the coefficients on $Pollution\ days\ (random)_{r,t}$ are not significantly different from zero. The results suggest that our findings, as shown in Table 2.2, are genuine and falsifiable.

2.3.3 Heterogeneity in individuals' concern for health

We conduct additional tests to understand the mechanism behind the pattern we identify. As air pollution may have a large negative impact on human health, we examine whether people change their intended places of work due to concern for their health. With this conjecture, we expect to see a stronger effect of air pollution on intended workplaces in cities where air pollution is more likely to trigger people's concern about their health.

To test the conjecture, we estimate the sensitivity of SVI of health to air quality in a city. Specifically, we regress the percentage change in the daily SVI of the word, "健康" (health), on the percentage change in daily AQI in each city in each year. The estimated beta on the change in AQI is our measure of people's intensity of pollution-induced concern for their health, notated by $Health\ Beta_{r,t}$. A more positive beta means that people's attention to health increases when air pollution emerges, thus indicating a greater concern with health. We add the interaction term between $Health\ Beta_{r,t}$ and $Pollution\ days_{r,t}$ in Equation (1) and re-estimate the model. The results are presented in Table 2.3.

We find that the coefficients on the interaction term are significant and have the same sign as the standalone $Pollution\ days_{r,t}$. The results thus suggest that people reduce (increase) their intentions of working in a more (less) polluted place when their concerns for health are more sensitive to air pollution. The results thus support our argument that air pollution influences individuals' workplace decisions by way of environmental health risks.

2.4 Air pollution and corporate human capital

Given the evidence above that air pollution has an influence on individuals' workplace decisions, in this section we examine whether the effects are compounded into companies' human capital formation.

2.4.1 Corporate human capital measures

To measure corporate human capital, we consider both top management and firm employees. We gauge the quality of top management by assessing whether the CEO or chairman in a firm was born or obtained a college degree outside the location where the firm is domiciled, or whether they had work or study experience abroad.

Specifically, we define *Non-locally born executives* as a dummy that equals one if the CEO or chairman was born in a region outside the province where the firm is domiciled and zero otherwise; *Non-locally educated executives* as a dummy that equals one if the CEO or chairman obtained a degree from a university or college in a region outside the province where the firm is domiciled and zero otherwise, and *Executives with overseas experience* as a dummy that equals one if the CEO or chairman has experience studying or working overseas and zero otherwise.

To examine the effectiveness of these three variables in capturing management quality, we relate them to the announcement returns of executive resignations or appointments, controlling for firm and regional attributes.[22] The results are reported in Table IA.4. We find that, as shown in columns (1)-(3), the departure of executives who are non-locally born or educated, or have foreign experience is associated with lower abnormal returns than the departure of executives without external experiences. In addition, we find that, as shown in columns (4)-(5), the appointment of executives with external experience is associated with higher returns than that without such

[22] The same set of firm and regional attributes as used in Equations (2)-(4).

experiences. The results suggest that our three measures can effectively capture management quality.

We measure the strength of a firm's employees based on the composition of employees by their education levels and job functions. Specifically, we define *% of highly educated employees* as the number of employees with a bachelor's degree or above scaled by the total number of employees; *% of employees with a low level of education* as the fraction of employees whose highest education level is either high school or below; *% of skilled employees* as the fraction of technical employees; *% of production and sales employees* as the number of production and sales employees, and *% of financial and administrative employees* as the fraction of financial, HR, and administrative employees.[23]

To test the effectiveness of these variables in capturing the quality of firm employees, we relate the variables to firms' operating performance as measured by net profit margin (net income/total revenues). We are not able to conduct a similar analysis using the announcement returns, because the dates of employee resignations and appointments are not publicly available. The results are reported in Table IA.5. We find that *% of highly educated employees* and *% of skilled employees* are significantly and positively related to net profit margin. Interestingly, we find no significant relationship between net profit margin and other employee variables. The results are consistent with prior studies that emphasize the importance of highly educated and skilled workers on firm performance improvement.

We collect the background information of CEOs and board chairman from the China Corporate Figure Characteristics Series database (GTA_TMT) in China Stock Market and

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[23] Please note, the sum of *% of highly educated employees* and *% of employees with low levels of education* is not 100% since employees in the middle level of education, such as those having associate degrees, are also included. The sum of the employee percentage by job function is also not 100% since some employees are not classified by the job function.

Accounting Research (CSMAR) for the period from 2000 to 2016. For those with missing information, we manually search firms' annual reports, company websites, and other online sources (e.g., Google.com and Baidu.com). We collect the information on employee composition from the Wind Financial Database (WIND). Chinese listed firms started to disclose their employee structure information since 2011. For this reason, we reduce our sample for the analysis of employee human capital to the period from 2011 to 2016. The human capital variables are filled with a missing value if there is no information.

2.4.2 The air pollution monitoring program and corporate human capital

To examine the effect of air pollution on corporate human capital, we use a DID approach that exploits the staggered introduction of the air quality monitoring and disclosure program across cities in China.

2.4.2.1 The air pollution monitoring program and the DID Model

In 2012, to promote the market-based abatement of air pollution, China launched a nationwide, real-time air quality monitoring and disclosure program. The objective is to establish an efficient system to monitor air quality and to disclose air quality information to the public in real time. The program was for the first time to monitor $PM_{2.5}$, which has become the primary air pollutant in recent years. The program was slated to implement in some cities earlier and take effect nationwide in 2016.

In specific, a comprehensive monitor network was installed in three waves. In the first wave, 74 major cities that represented the nation's key population and economic centers were included in the program. Real-time data on all major air pollutants were posted online since December 31, 2012. In the second wave, 116 cities of the list of the Environmental Improvement Priority Cities and the National Environmental Protection Exemplary Cities were added to the program and completed by October 31, 2013. The final wave included the remaining 177 cities and was completed by November 20, 2014. Figure 4 shows the roll-out of the program. An important feature of the program is that the roll-out dates are a top-down decision determined by the physical constraints of installing monitoring stations and thus independent from the daily variation in local pollution (Barwick *et al.*, 2019).

Meanwhile, the program established a dissemination system to display the monitoring results in real time on the MEP's website. AQI and the concentrations of $PM_{2.5}$, PM_{10} , SO_2, NO_2, CO, and O_3, both at individual station and city levels, are published hourly and daily. Importantly, private parties can access and stream data directly from the website and incorporate the data into their private websites and mobile applications, which largely enhances the dissemination of air quality information to the public. Barwick *et al.* (2019) show that, shortly after the program, mobile applications streaming air pollution data quintupled, and the purchases of air purifiers doubled. Barwick *et al.* (2019) conclude that the information program significantly increases public access to pollution information and householders' awareness about air pollution. The program thus provides us an ideal setting to examine the effect of pollution awareness on residential sorting and therefore corporate human capital.

We expect that increased access to pollution information to cause significant sorting in more polluted areas. This is exactly what we find in Figure 5. We define high pollution cities as those whose average AQI before the program (years 2011 and 2012) are above the median of all cities in China. In the post years of the monitoring program, the percentage of executives non-locally born and educated and with overseas experience decline from 34% to 30% for firms operating in high pollution cities, while the percentage increases from 40% to more than 50% for firms in low pollution cities. The patterns of the two groups before the program inception are parallel.

To formally test our hypothesis, we specify the DID model as follows.

$$y_{i,t} = \beta_1 + \beta_2 High\,pollution_c + \beta_3 High\,pollution_c \times Monitor_{i,c,t} + \beta_4 Monitor_{i,c,t} + X_{i,t} + T + C + I + u_{i,t}, \quad (2)$$

where *c* indexes city, *i* indexes firm, and *t* indexes year. $y_{i,t}$ is one of our corporate human capital measures. $High\,pollution_c$ is the ex-ante air pollution measure, and takes the value of one for cities where the average AQI before the program (years 2011 and 2012) is above the median of all cities. $Monitor_{i,c,t}$ is the monitoring treatment dummy, and takes the value of one for firm *i* in the period after city *c* the firm locates implements the monitoring program based on the staggered roll-out schedule. We include year fixed effects (vector *T*), city fixed effect (vector *C*), and industry fixed effects (vector *I*) to control for time-invariant regional and industry attributes.

We further include a variety of firm and city characteristics ($X_{i,t}$) to control for time-variant factors. Specifically, we control for firm characteristics that may affect firms' demand for human capital (Hirshleifer, Low and Teoh, 2012; Bradley, Kim and Tian, 2017). These include *Firm size* (log(total assets)), *Leverage* (total liability/total assets), *Cash flow* (operating income before depreciation and amortization/total assets), *Capital expenditure* (Capex/total assets), *Firm age*, *Executive age* (the average age of CEO and board chairman), and *SOEs* (the state-owned enterprises indicator).

We use the same set of city controls as used in Section 3. In specific, we control for economic and demographic characteristics (*GDP growth*, *GDP per capita*, *Education expenditure*, and *Population*), because they may relate to employment opportunities and human capital supply in firms' location. We also control for city climate characteristics (*Temperature*, *Relative humidity*, *Precipitation*, and *Sunshine hours*) in firms' location, because prior studies suggest that weather and climate conditions may affect people's sorting decisions (Jessoe, Manning and Taylor, 2017).

β_3 is the DID estimate. A negative estimated β_3 would imply that firms experience a decline in human capital when free access to pollution information becomes available in the cities they locate. We estimate Equation (2) for the period from 2011 to 2016, such that there are balanced observations before and after the program inception. The summary statistics of variables used in this analysis are presented in Panel B of Table 2.1.

2.4.2.2 Results of the DID model

The estimates of the effect of the monitoring program on firm management using probit regression are reported in Table 2.4. Standard errors are estimated by clustering at the firm level. The standalone *High pollution* is absorbed by the city fixed effect. We find that the coefficients on *High pollution* × *Monitor* in the models of *Non-locally born executives* and *Non-locally educated executives* are significantly negative. It suggests that firms located in polluted areas become less attractive to non-locally born or educated executives in the post-program period.

The findings have economic significance. The marginal effect of the estimates (reported at the bottom of the columns) suggests that, in high pollution areas, the implementation of the monitoring program reduces the probability of having a non-locally born executive by 5.9%, and the probability of having a non-locally educated executive by 5.6%. We also find that, as shown in the last column, high pollution areas become less attractive to executives with overseas experience, but the finding is lack of statistical power.

Turning to control variables, we find that executives from outside and those who have foreign experience tend to be young. They are more likely to choose to work in large firms and non-SOEs, implying that talented executives are tempted by firms with better resources and greater dynamism.

The estimates of the effect on firm employees are reported in Table 2.5, namely, OLS estimates of Equation (2). Panel A reports the estimates for employee human capital by education.

In Column (1), the dependent variable is *% of highly educated employees*. We find that the coefficient on *High pollution* × *Monitor* is –0.011, significant at the 5% level. It implies that, in high pollution areas, the monitoring program reduces the proportion of firm employees holding a bachelor's degree or above for an average firm by 4.2% (i.e., 0.011/.26). However, in the model of *% of employees with a low level of education* (Column 2), the coefficient on the interaction term is insignificant. The results suggest that access to air pollution information only causes a decline in the composition of highly educated employees.

Panel B of Table 2.5 reports the estimates for employee human capital by job function. We find that the coefficient on *High pollution* × *Monitor* for the fraction of technical employees is significantly negative. In contrast, the coefficients for the fractions of the other two types of employees are insignificant. The estimate for the model of technical employees has economic significance. Specifically, it implies that, in high pollution areas, the monitoring program reduces the proportion of technical or skilled employees by 6.8% (i.e., 0.013/0.19). Taken together, the results of Table 2.5 indicate that public access to air pollution information reduces the accumulation of highly educated and skilled employees for firms located in polluted areas.

Next, we ask whether the reduction in human capital is indeed driven by human capital movement and, in more specific, whether the reduction is driven by the less incoming of talents (a pull effect) or the more departure of talents (a push effect). To answer these questions, we track the movement of senior managers and directors across firms and identify the appointment of new executives from and the resignation of executives to areas with relatively clean air.

Specifically, we calculate the percentage of new executives moving from areas with relatively clean air using the number of new executives that come from firms located in an area with AQI lower than the AQI in the location of the current firm over the total number of new executives in a year. Similarly, we calculate the percentage of resigned executives going to areas with relatively clean air using the number of resigned executives that move to firms located in an area with AQI lower than the AQI in the location of the previous firm over the total number of resigned executives in a year. We use these two measures as the dependent variables and re-estimate Equation (2).

The results are reported in Table 2.6. We find, as shown in column (1), the implementation of the monitoring program inhibits the incoming of executives from areas with relatively clean air to join firms located in high pollution areas. In line with this finding, the estimate in column (2) shows that the implementation of the program will speed up the departure of executives to areas with relatively clean air. Put together, the results suggest that the introduction of the monitoring program has both pull and push effects, consistent with the prior that the access to air pollution reduces the accumulation of corporate human capital.

2.4.3 The QH heating policy and corporate human capital

One feature of the monitoring program setting is that it places an exogenous shock to people's access to air pollution information and also their awareness of air pollution but not to the level of air pollution *per se*. In this section, we further examine whether the change in air pollution does matter for corporate human capital. To answer this question, we use a regression discontinuity design (RDD) that exploits the discontinuous variation in air pollution created by China's central heating policy.

2.4.3.1 The QH heating policy and the RDD model

During the central planning period from the 1950s to the 1980s, China established a central heating policy (or the Huai River policy) to provide winter heating in northern China. When initiating the policy, the Chinese government arbitrarily divided the territory into northern and southern China by the line formed by the Qinling Mountains and the Huai River (QH), which follows the January

0 ℃ average temperature line (see Figure 6). Free heating was provided to cities north of the line. The reason for choosing this dividing line was that the Chinese government faced a budgetary constraint and was not able to supply free heating to all areas of China. This heating system has worked for more than 50 years and is still in operation today.

The centralized heating system rests on the use of coal-based hot water boilers, which is inflexible and energy inefficient. Hot water needs to travel a certain distance from the heating provider to each household in a city, causing substantial energy loss. As documented by Almond *et al.* (2009), the incomplete combustion of coal in boilers releases a significant amount of air pollutants, especially particulate matter. As a result, the heating policy generates a discontinuous change in air quality across the QH boundary, which provides us a regression discontinuity design (RDD) to test the effect of air pollution on corporate human capital.

A valid RDD requires that 1) the heating policy causes the change in the assignment of pollution, and 2) the assignment *per se* be independent of firm outcomes. To assess the first condition, we first plot out the average *AQI* from 2000 to 2016 in each Chinese city.[24] As shown in Figure 6, we find the areas with *AQI* above 100 (shaded in red) and the areas with *AQI* below 100 (shared in green) are well partitioned by the QH boundary. We further make the regression discontinuity plots of *AQI* in Panel A of Figure 7. We find that the level of *AQI* on the heating side of the boundary (1 degree above the boundary) is about 16 points (or 21%) higher than that on the non-heating side (1 degree below the boundary). The difference is significant at the 1% level. The results suggest that the arbitrary heating policy indeed causes a discontinuous change in air pollution.

[24] As the central heating policy is activated in the winter, in the analysis of the RDD of QH, we follow Ito and Zhang (2019) and define *AQI* as the average of daily AQI in the winter months (Oct, Nov, Dec, Jan, Feb, and Mar).

To verify the second condition, we examine whether there is a discontinuity in other covariates that are correlated with corporate human capital and firm performance at the boundary. In Panel A of Table IA.6, we present the differences in the firm and regional characteristics between the two sides of the heating boundary by a small margin (two degrees around the QH boundary). We find that there are no significant differences in firm characteristics (except *SOEs*) and GDP growth. The heating side has higher expenditure on education but lower GDP per capita than the non-heating side, with the net effects on human capital unclear.

Moreover, we test the differences in expected corporate human capital between the two sides. Specifically, we regress human capital variables on the firm and regional covariates. The fitted values obtained from the regressions are our measures of expected human capital. We find that, as shown in Panel B, the expected human capital measures are not significantly different for firms on the two sides. Overall, the diagnostic tests suggest that the determinants of corporate human capital are independent of the treatment assignment.

The results provide us with the confidence to carry out the RDD analysis. With a view to precision, we strictly follow Almond *et al.* (2009), Chen *et al.* (2013), and Ito and Zhang (2019) and estimate the following reduced-form regression:

$$y_{i,t} = \gamma_1 + \gamma_2 QH_{i,t} + f\left(Lat_{i,t}\right) + X_{i,t} + T + I + L + u_{i,t}, \quad (3)$$

where $QH_{i,t}$ equals one if firm *i* is located in the heating area formed by the QH boundary in year *t* and zero otherwise. $f\left(Lat_{i,t}\right)$ denotes a smooth control function for the latitude of firm location, allowing for different polynomials of the distance between firm location and the QH boundary.[25] We control for the same set of firm and city characteristics ($X_{i,t}$) as used in the previous section.

[25] We use the cubic polynomial of distance between firm location and the QH boundary. We also alternatively use the quadratic polynomial and find consistent results.

We also control for year fixed effects (vector *T*) and industry fixed effects (vector *I*). To reduce the scope of unobserved factors on either side of the heating border spanning from the west to the east, we include the fixed effects of longitude decile (vector *L*).

A negative estimated γ_2 would indicate that firms located in more polluted regions have a lower level of human capital accumulation. To identify a long-term impact, we estimate Equation (3) by relating executive talent measures to *QH* over the period from 2000 to 2016. We estimate the effect on employee human capital for the period from 2011 to 2016 since the data on employee starts in 2011. The summary statistics for variables used in this RDD analysis are provided in Panel C of Table 2.1.

2.4.3.2 The results of the RDD model

The RDD estimates of the impact of air pollution on firm management are reported in Table 2.7. We find that the coefficients on *QH* are negative and statistically significant, suggesting that air pollution hurts the accumulation of executive talent. The impact is also economically significant. From the marginal effects as reported on the bottom of the columns, we find that being located on the heating side of the QH boundary leads to a 23% decline in the probability of having a non-locally born executive, a 19% decline in the probability of having a non-locally educated executive, and a 7% decline in the probability of having an executive with overseas experience.

To visualize our results, we plot the average of high-quality executives (i.e., the average of *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*) across the central heating boundary in Panel B of Figure 7. We find that there is a discontinuous drop in high-quality executives at the boundary when moving from the non-heating side to the heating side.

The RDD estimates of the effect of air pollution on employee quality are reported in Table 2.8. We find a similar pattern as in our previous DID analysis. The coefficients on *QH* in the models of *% of high education employees* and *% of skilled employees* are significantly negative. The results are also economically significant: the proportion of firm employees holding a bachelor's degree or above for firms on the heating side is 20% lower (i.e., 0.051/.26) than that for firms on the non-heating side. Likewise, the proportion of technical or skilled employees for firms on the heating side is 15% lower (i.e., 0.028/0.19) than that for firms on the non-heating side. However, the coefficients on *QH* in other models are insignificant, confirming that air pollution only causes a decline in the composition of skilled employees.

We also repeat the analysis using artificially assumed alternative latitude lines other than the QH boundary. We find *QH* coded based on the artificial latitude lines has no significant relationship with both management and employee human capital, suggesting our setting of QH is falsifiable.[26]

Although the RDD setting allows us to control for regional factors, we might still miss certain unobservable regional factors that may bias our estimates. We further address this concern by running local RDD by focusing on firms located within a small margin around the QH boundary. The basic idea is that unobservable factors such as economic conditions and social capital effects are likely to be similar in neighboring regions, whereas air pollution has a sharp difference across the border. For the test, we conduct local RDD by focusing on firms located in places with a distance smaller than two degrees in latitude from the QH boundary. The estimated results are reported in Table IA.7.

[26] The results will be provided upon request.

Panel A presents the results for executive talent measures. We find that the coefficients on *QH* are negative and highly significant, indicating that firms located on the heating side of the QH boundary by a small margin are less likely to have CEOs or chairmen who were born or educated outside or had foreign experience than firms located on the non-heating side. Panels B and C present the estimates for the human capital measures of employees. We again find that the composition of better educated and skilled employees is significantly lower on the heating side than on the non-heating side.

We also estimate local RDD using alternative bandwidths (i.e., different latitudes of distance from the QH boundary). The coefficients on *QH* with different bandwidths are presented in Figure IA.2. We find that the coefficients are largely negative for a small bandwidth. The coefficients continue to be negative for a larger bandwidth, although the magnitude gets smaller. The figure suggests that our findings are robust for the use of different distances from the QH boundary.

Overall, the results indicate that our findings of the RDD are unlikely to be driven by unobservable regional factors.

2.4.4 Thermal inversion and corporate human capital

While the RDD has strong local validity, its external validity is weak. To deal with this problem, we adopt a two-stage least square (2SLS) approach where an instrument variable is used to capture the extensive variation in air pollution. Specifically, we use the thermal inversion strength as an IV for air pollution (Chen, Oliva and Zhang, 2017) and relate the instrumented air pollution to corporate human capital.

2.4.4.1 Thermal inversions and the 2SLS model

Thermal inversions occur when the above-ground temperature is higher than the ground temperature in a region. Given that air moves from hot to cool regions, when thermal inversions occur, air pollutants are trapped near the ground, leading to higher air pollution concentrations. This process is pictured in Figure 8. Thermal inversions are a common meteorological phenomenon that is independent of human activity. As a result, the occurrence of thermal inversions can be used as an IV to capture the variation in air pollution.

The strength of thermal inversion has been widely used as an IV for the variation in air pollution (Arceo, Hanna and Oliva, 2016; Chen, Oliva and Zhang, 2017). We follow the extant studies and run the following 2SLS model.

$$AQI_{i,t} = \gamma_0 + \gamma_1 TI_{i,t} + X_{i,t} + T + I + L + u_{i,t}, \tag{4.1}$$

$$y_{i,t} = \theta_0 + \theta_1 \widehat{AQ}I_{i,t} + X_{i,t} + T + I + L + u_{i,t}, \tag{4.2}$$

where $AQI_{i,t}$ is the average of daily AQI in the city where firm i locates in year t. $TI_{i,t}$ is the average thermal inversion strength in the city where firm *i* locates in year *t*. Following Chen, Oliva and Zhang (2017), we measure the strength of thermal inversions using the above-ground temperature minus ground temperature. The data is obtained from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by the U.S. National Aeronautics and Space Administration (NASA).[27] The data are recorded every six hours for each 0.5 degree × 0.625 degree latitude by longitude grid. We aggregate the data from grid to city and then average to the annual level across winter months.[28]

We include the same set of controls and run the equations over the same sample period as in the RDD analysis. The summary statistics of variables used in this analysis are presented Panel C of Table 2.1.

[27] The data is collected at: https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_V5.12.4/summary?keywords=Aerosols# .

[28] We alternatively average to annual level across all months and find similar results.

2.4.4.2 The result of the 2SLS model

The results of the 2SLS model are reported in Table 2.9. Columns (1) and (2) present the 1st and the 2nd stage estimated results for the model of *Non-locally born executives*, respectively. Indeed we find that *TI* is positively related to *AQI*. The *t*-value of the *TI* coefficient is 5.19, suggesting that the relationship between *TI* and *AQI* is statistically strong. The *F*-statistic of testing the strength of the IV, as reported on the bottom of the column, is 26.9, confirming the validity of the IV. The coefficient on the *fitted AQI*, as shown in column (2), is significantly negative. It suggests that firms are less likely to have a CEO or chairman that is non-locally born when the level of air pollution in their locations is high.

Columns (3) and (4) report the 2nd stage estimates for the models of *Non-locally educated executives* and *Executives with overseas experience*. The coefficient on the *fitted AQI* is also significantly negative, suggesting that air pollution is likely to reduce the accumulation of *Non-locally educated executives* and *Executives with overseas experience*.

The 2SLS estimates for the models of employee quality are reported in Table 2.10. Columns (1) and (2) present the 1st and the 2nd stage results for the model of *% of high education employees*, respectively. The *fitted AQI* is significantly related to *% of high education employees*, suggesting that the fraction of highly educated employees of firms in polluted areas is lower than in less polluted areas.

Columns (4) and (5) present the 1st and the 2nd stage results for the model of *% of skilled employees*, respectively. We find the coefficient on *fitted AQI* is negative but is not statistically significant. Similar to the pattern that we find before, there is no significant relationship between the air pollution level and the proportion of employees with low levels of education and production and sales employees, confirming the significant impact of air pollution on skilled employees only.

2.4.5 Heterogeneity in individuals' concern for health

So far, our findings show that corporate human capital is lost in polluted areas, which is consistent with our *brain drain hypothesis*. In this section, we substantiate this view by examining how the brain drain effect of air pollution varies with regional heterogeneity in individuals' concern for their health. If executive talent and skilled employees leave firms in polluted areas and head to less polluted areas because of concerns over health risks, the brain drain effect will be more pronounced when such concern is more salient.

To conduct the test, we use *Health Beta*, as discussed in section 3.3, to measure the intensity of people's concern for health due to air pollution in a region. A higher *Health Beta* means more attention to health (more searches for health online) when air pollution emerges. To conduct the test, we partition our sample into regions with high and low *Health Beta*. We re-estimate Equations (2)-(4) by augmenting the interaction term between the indicator of regions with high health beta (*High beta*) and variables of interest in the equations. The results are reported in Table 2.11.

Panel A reports the DID estimates. We find that the coefficients on *High pollution* × *Monitor* in most models of interest are significantly negative. Our key results are the coefficients on *High pollution* × *Monitor* × *High beta*, which are significantly negative in the models of *Non-locally born executive*, *Non-locally educated executives*, and *% of skilled employees*. The results suggest that the implementation of the air pollution monitoring program reduces the human capital of firms in polluted areas more intensively when people living in those areas are more sensitive to the influence of air pollution.

Panel B reports the RDD estimates. The standalone *HQ* is absorbed by city fixed effects. We find that the coefficients on *QH* × *High beta* are significantly negative in our models of interest (except the model of *Executives with overseas experience*), suggesting that the impact of the heating policy is more pronounced in regions with the higher sensitivity of health concern to air pollution. Panel C reports the 2SLS estimates. We find that the coefficients on *Fitted AQI* × *High beta* in all models of interest are negative and significant.

Overall, the results suggest that the brain drain effect of air pollution is stronger in cities that have a greater elasticity of attention to health, which confirms our view that that air pollution induces concern over health risks and eventually affects firms' human capital accumulation.

2.5 Air pollution and firm performance

Thus far, we have obtained robust evidence that air pollution has a negative effect on corporate human capital. Given the importance of human capital for corporate long-term growth and success, in this section we examine whether air pollution has an impact on firms' performance and whether such effect acts through the channel of human capital.

2.5.1 Corporate productivity and shareholder value

Previous studies suggest that top management quality (as indicated by, e.g., education and past experience) and employee skills are important determinants of corporate productivity (Haltiwanger, Lane and Spletzer, 1999) and firm valuation (Chemmanur *et al.*, 2018). To the extent that air pollution hurts corporate human capital, we expect that air pollution would impede corporate productivity and reduce firm value. We test this prediction in this section.

We estimate a firm's productivity using total factor productivity (*TFP*) as in Levinsohn and Petrin (2003). We use Tobin's Q, defined as the market value of total equity over book value of total equity (*Q*), to measure firm value. We re-estimate Equations (2)-(4) by replacing the dependent variables with *TFP* and *Q*. The estimated results are presented in Table 2.12.

Columns (1) and (2) present the DID estimates. The coefficients on *High pollution* × *Monitor* are negative and highly significant in both models of *TFP* and *Q*. The results suggest that the introduction of the monitoring program reduces firms' productivity and value in polluted areas, consistent with the conjecture that the access to air pollution intensifies brain drain. The results also have economic significance. Specifically, after the inception of the monitoring program, an average firm in polluted areas would experience a 19% (i.e., 0.023/0.12) decline in *TFP* and a 7.8% (i.e., 0.211/2.71) decline in *Q*.

Columns (3) and (4) report the RDD estimates. The coefficients on *QH* are negative and significant, suggesting that firms have lower *TFP* and *Q* when locating in heating areas. Specifically, Column (3) suggests that the *TFP* of firms in heating areas is likely to be lower by around 58% (i.e., 0.069/0.12), relative to the average firm in non-heating areas. Column (4) suggests that being located on the heating side of the QH boundary leads to a 13.7% (i.e., 0.370/2.71) decline in *Q*. Columns (5) and (6) report the 2SLS estimates. We find similar results. The instrumented *AQI* is negatively related to *TFP* and *Q*. Both are significant at the 1% level.

Overall, the results suggest that air pollution has a negative impact on corporate productivity and shareholder value.

2.5.2 Human capital dependence

The previous section shows that air pollution is detrimental to firm performance. Next, we examine whether this effect indeed acts through the channel of corporate human capital.

First, if air pollution harms firm performance through hurting the accumulation of corporate human capital, the effects of air pollution on firm performance should be more pronounced when firms' performance depends more on human capital. To conduct the test, we estimate the sensitivity of firm performance to human capital to measure firms' human capital dependence.

Specifically, we regress *TFP* and *Q* on management human capital (the average of *Non-locally born executives, Non-locally educated executives,* and *Executives with overseas experience*) and employee human capital (the average of *% of highly educated employees* and *% of skilled employees*), respectively. We run the regressions within each industry in each year using data over the past five years, with firm characteristics (i.e., *Firm size*, *Leverage*, *Cash flow*, *Capital expenditure*, *Firm age*, *Executive age,* and *SOEs*) included as control variables.

The coefficients on the human capital variables proxy for human capital dependence for each industry. They gauge the degree to which firm performance in an industry relies on skilled executives and employees, with a higher value indicating higher dependence. We then partition firms into those with high and low human capital dependence. *EXED* and *EMPD* denote those with high dependence on executive talents and skilled employees, respectively. We re-estimate the models of firm performance by adding *EXED* and *EMPD* and their interaction with our variables of interest in Equations (2)-(4). The estimated results are reported in Table 2.13.

Panels A and B present the estimates for the dependence on executive talents and skilled employees, respectively. We find that, as shown in columns (1) and (2), the effect of the monitoring program on *TFP* and *Q* is more pronounced when firms' human capital dependence in an industry is higher. We also find that the heating policy (columns 3 and 4) and the instrumented *AQI* (columns 5 and 6) have a greater impact on *TFP* and *Q* in industries with high human capital dependence.[29] These results suggest that the effect of air pollution on firm performance is most potent when skilled executives and employees are important to firm performance.

Furthermore, we employ several alternative measures to proxy for firms' human capital dependence. Specifically, we examine whether the effect of air pollution on firm performance is more pronounced for firms with higher average pay or for those in innovative industries. Because high-quality individuals are paid higher salaries, higher average employee compensation is a signal

[29] We include city fixed to absorb *QH*.

of greater dependence on human capital (Ouimet and Zarutskie, 2014). Moreover, innovative industries need the input of talented people to generate creative ideas and thus have a greater reliance on human capital.

To conduct the test, we create *High pay*, which is equal to one if a firm has an average employee compensation above the sample median in a year, and *Innovative industries*, which is equal to one if a firm operates in several industries including information technology, scientific research, and technical service, or health and social work (Ouimet and Zarutskie, 2014). We repeat our analysis by adding the interaction of the two variables in our models. The estimated results are reported in Panels C and D, respectively. As expected, we find that the negative effect of air pollution on firm performance is stronger in firms with higher average compensation and in innovative industries.

Overall, the results in this section suggest that air pollution influences firm performance via the channel of human capital.

2.6 Conclusion

This paper examines whether air pollution is detrimental to the accumulation of corporate human capital and impairs firm performance. We develop *the brain drain hypothesis*. The hypothesis is built on Tiebout's location sorting model, which proposes that people have heterogeneous preferences for public goods and seek to settle in locations that match their preferences. To substantiate this argument, we first examine how individuals determine or change their intended places of work in response to air pollution. Consistent with the location sorting model, we find that people increase (decrease) searches for work in less (more) polluted areas when air pollution emerges in their location.

Next, we examine whether the sorting effect of air pollution is compounded into firms' human capital formation. We use three empirical settings to explore this question, including the exogenous change in public access to air pollution information and awareness of air pollution as a result of the implementation of the air pollution monitoring program in China, the discontinuous difference in air pollution as a result of China's central heating policy, and the variations in air pollution as a result of thermal inversions. In all settings, we find consistent evidence that air pollution has a negative impact on the accumulation of both management and employee human capital. Moreover, this brain drain effect is more pronounced in regions where air pollution is more likely to trigger people's concern about their health.

We finally show that the brain drain effect of air pollution manifests itself in corporate performance. Specifically, firms located in more polluted areas have a lower level of total factor productivity and firm value than those located in less polluted areas. Furthermore, this negative relationship between air pollution and corporate performance is more salient in firms that have a greater dependence on human capital, in firms where employees are paid higher, and in industries that are more innovative. The results suggest that human capital is the channel through which air pollution affects firm performance.

Overall, we show that air pollution is a crucial non-economic factor that has a significant impact on corporate performance by influencing the accumulation of corporate human capital.

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Appendices

Appendix A: Figures

Figure 1: Number of dual-class firms

Figure 1 shows the timeline of the number of dual-class firms existing in the market from 1994 to 2014.

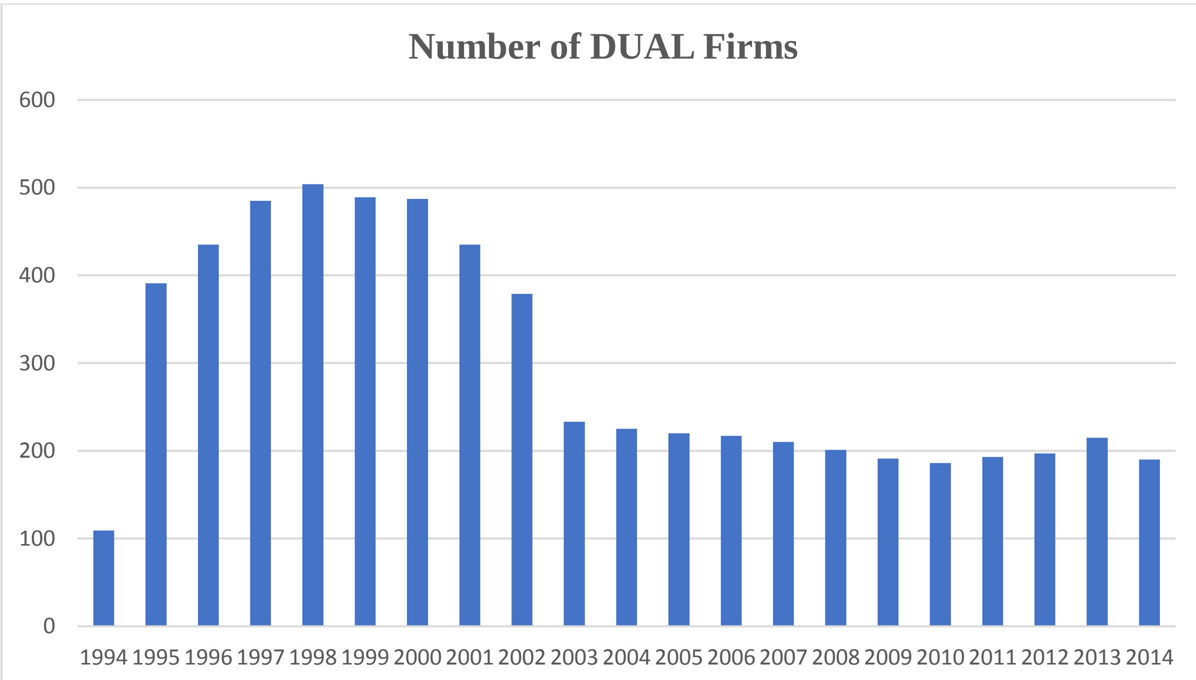
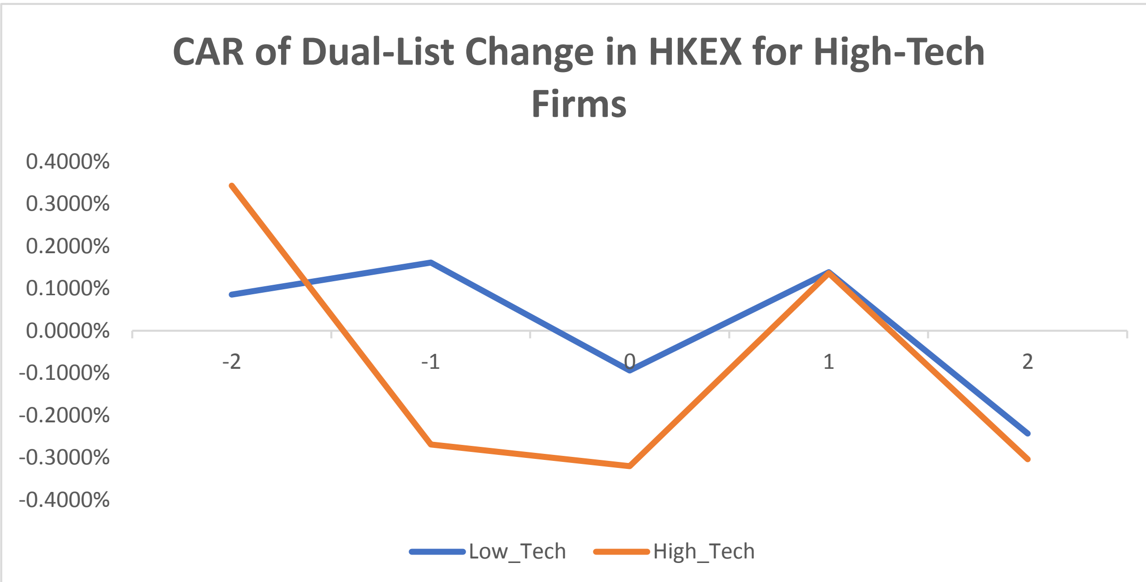


Figure 2: CAR of Dual-class List Change in HKEX

By using the data from DataStream, the cumulative abnormal returns (CARs) are calculated. Day 0 means April 24, 2018. The HKEX suddenly allows the dual-class IPO. Panel A shows the CARs for high-tech and low-tech firms. Panel B shows the CARs for high R&D and low R&D firms.

Panel A



Panel B

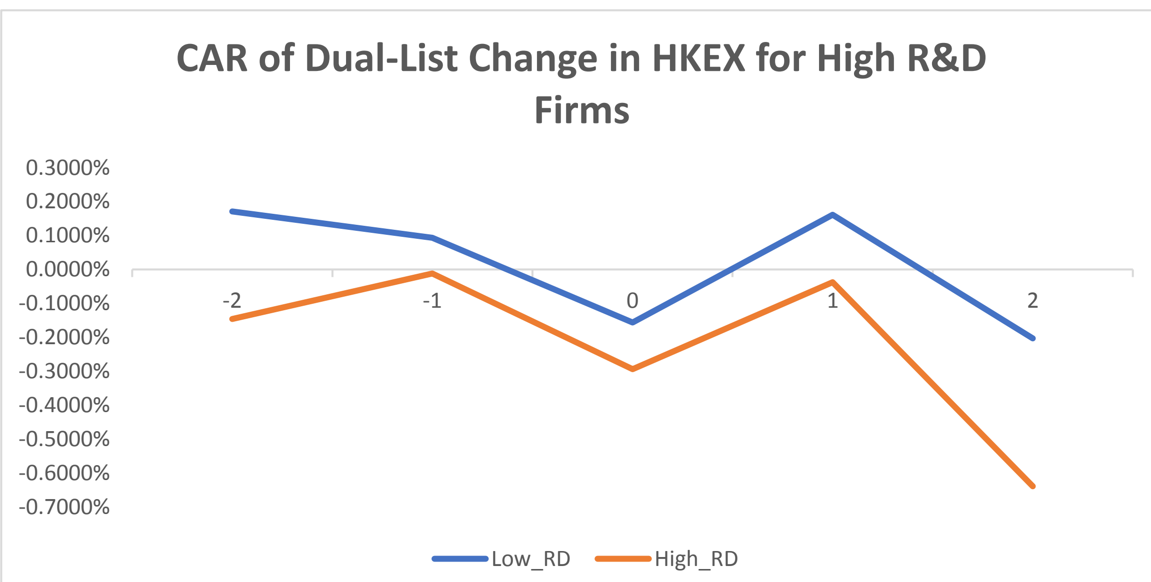
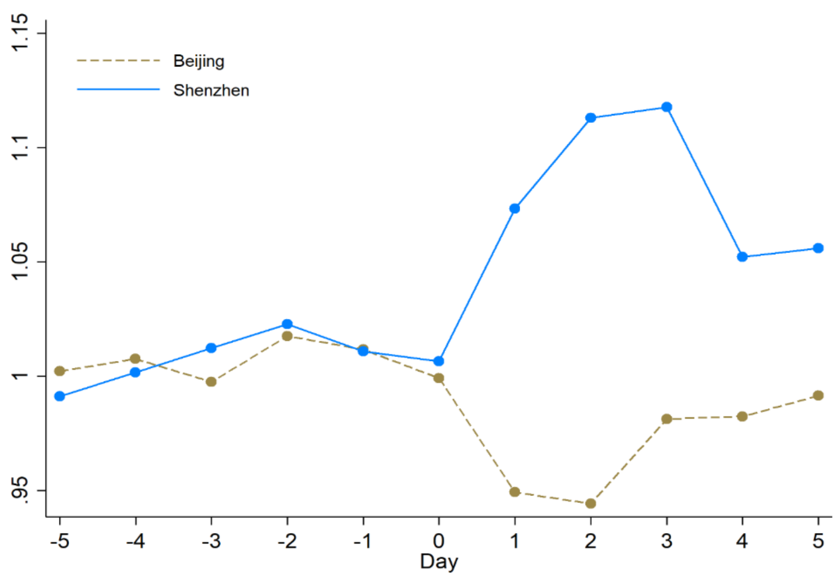


Figure 3: Workplace Searching Activities around Air Pollution Days

A region is defined as experiencing a pollution day (day 0) if the increase in daily AQI exceeds one standard deviation of the daily AQI change in the past year in the region. The y-axis represents the average Baidu Search Volume Index (SVI) across all regions that experience a pollution day. The daily SVI from day -5 to day 5 in a region is scaled by the average daily SVI from day -16 to day -6 in the region. Panel A shows the average SVI of "北京找工作" (to work in Beijing) and the SVI of "深圳找工作" (to work in Shenzhen). Panel B shows the average SVI for work in five least polluted cities (Shenzhen, Shanghai, Guangzhou, Chengdu, and Hangzhou) and the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian) of the top work-intended cities.

Panel A: SVI for workplaces of Beijing and Shenzhen



Panel B: SVI for work in more and less polluted cities

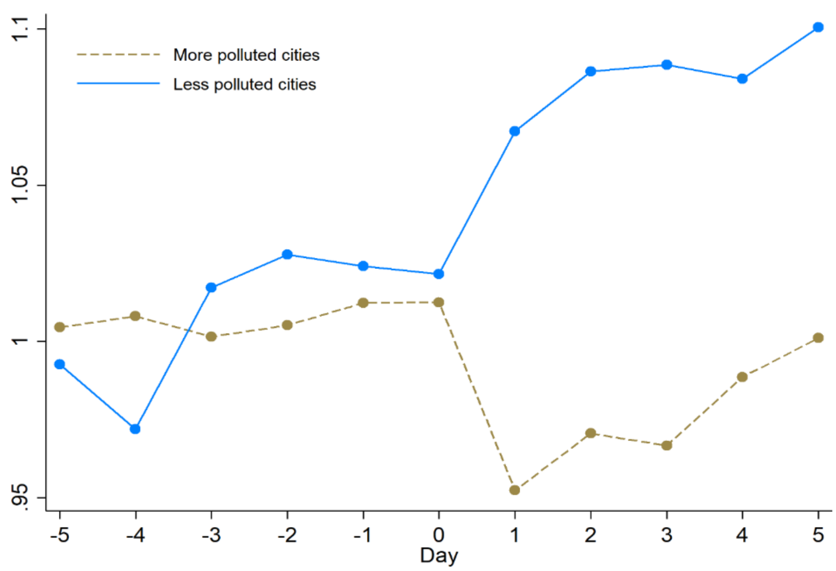


Figure 4: The Three Waves of the Air Pollution Monitoring and Disclosure Program

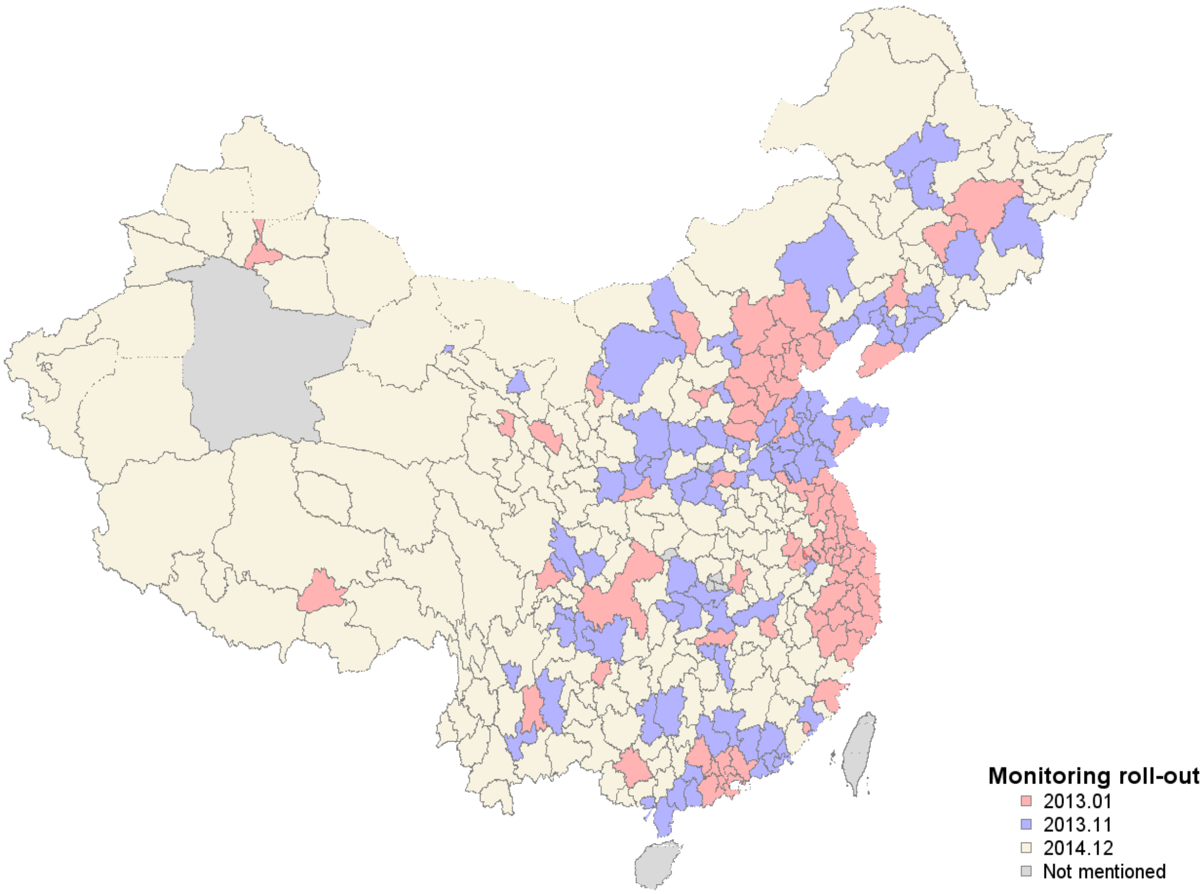


Figure 5: Corporate Executive Talents around the Announcement of the Air Pollution Monitoring Program

This figure presents corporate executive talent around the announcement of the air pollution monitoring program (year 0 is the announcement year). Executive talent is measured by the average of *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*. The solid line represents the average executive talent of firms located in polluted cities (AQI above the sample median). The dashed line represents the average executive talent of firms located in less polluted cities (AQI below the sample median).

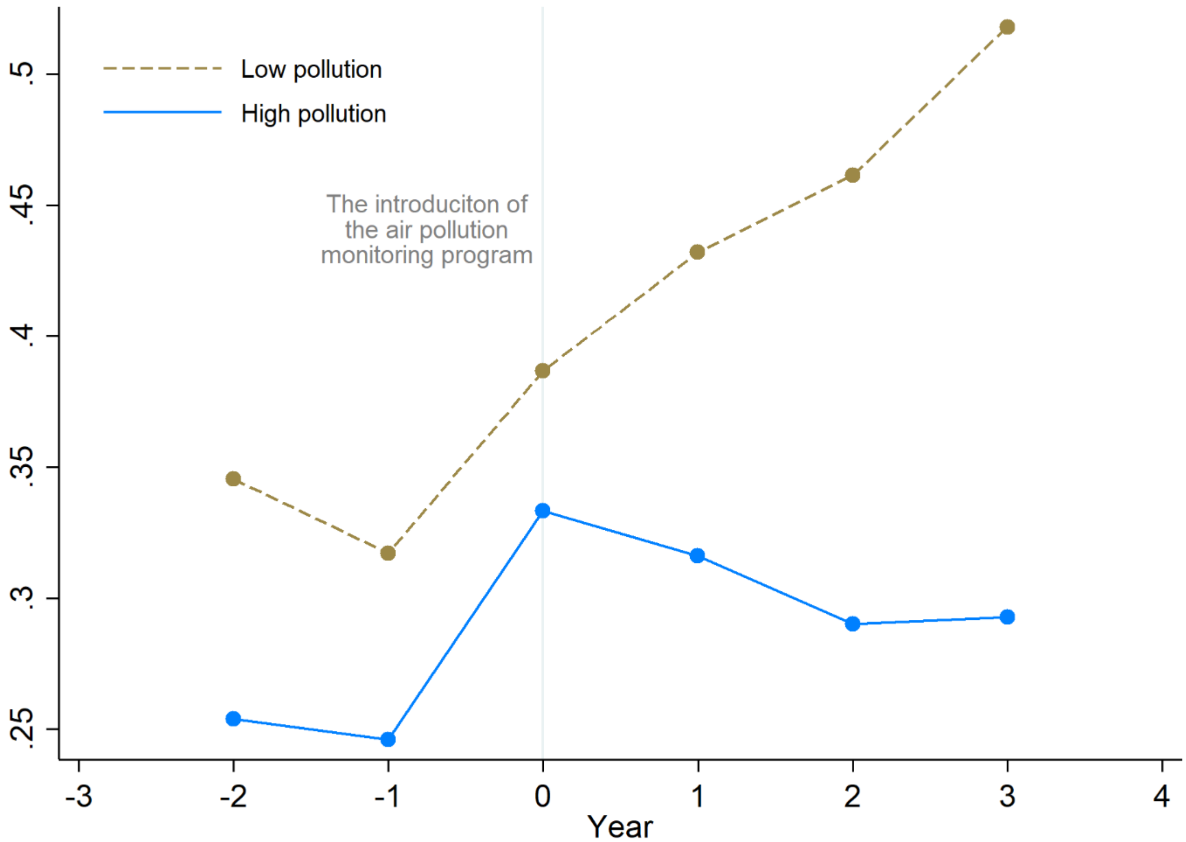


Figure 6: Qinling-Huai River and Air Pollution by Regions in China

The blue line represents the boundary of the Qinling-Huai River. The areas with average Air Quality Index (*AQI*) from 2000 to 2016 above (below) 100 are marked in red (green). The red dots represent cities where listed firms are domiciled. The regions on the north side of the Qinling-Huai River boundary are the heating area, and the regions on the south side of the boundary are the non-heating area.

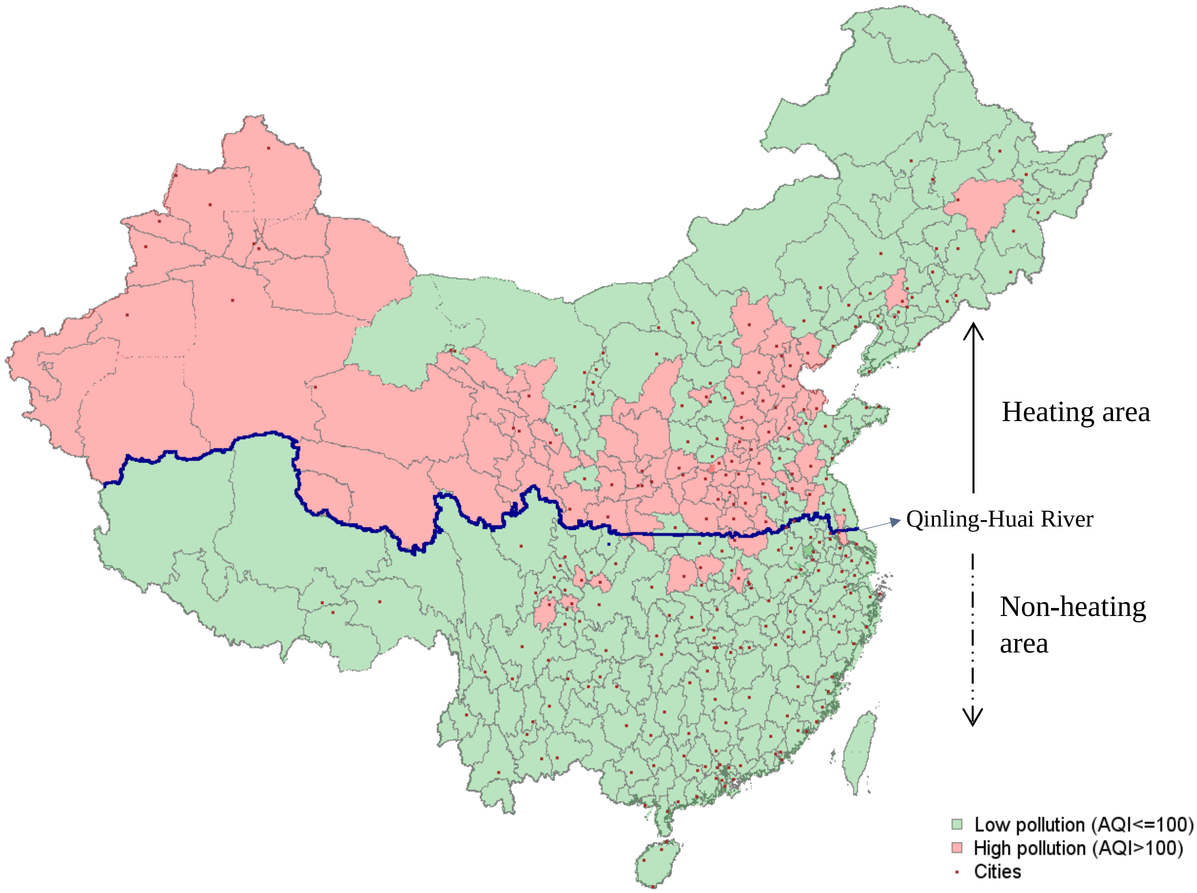
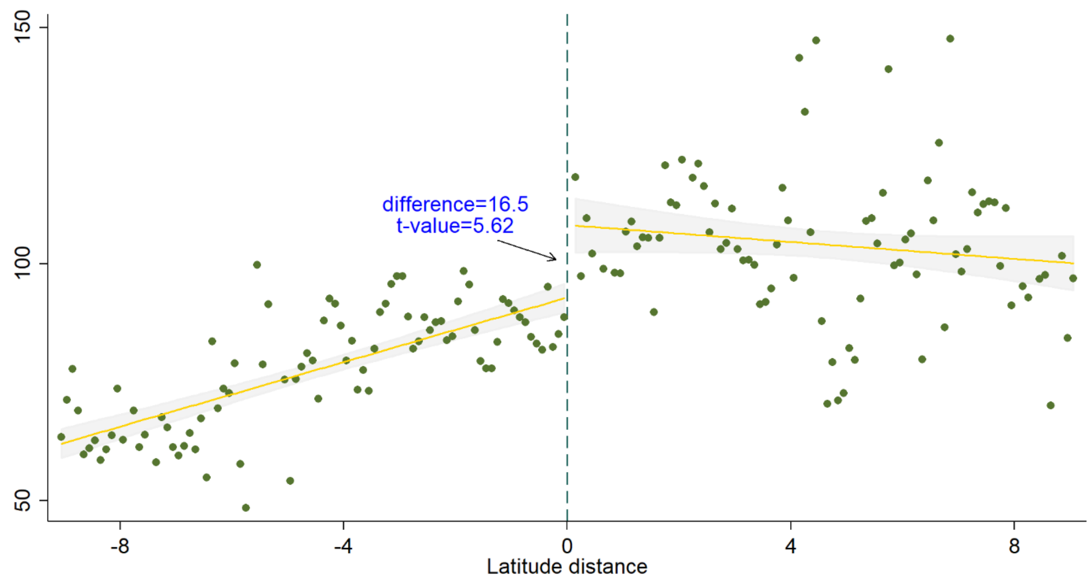


Figure 7: Regression Discontinuity Plots of AQI and Talent

Panel A plots the Air Quality Index (*AQI*) across the Qinling-Huai River heading boundary. Panel B plots the average executive talent, the average of *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*, across the boundary. Each dot is generated by averaging *AQI* and executive talent across locations within 0.1° of latitude. The x-axis is latitude degree distance from the heating boundary, with positive (negative) degrees indicating areas on the heating (non-heating) side of the boundary. The line represents the fitted values of *AQI* and executive talent from a linear regression. The shaded area represents a 90% confidence interval around the fitted value. The difference in *AQI* and executive talent between 1 degree above and below the heating boundary is calculated and tested.

Panel A: *AQI*



Panel B: Executive talent

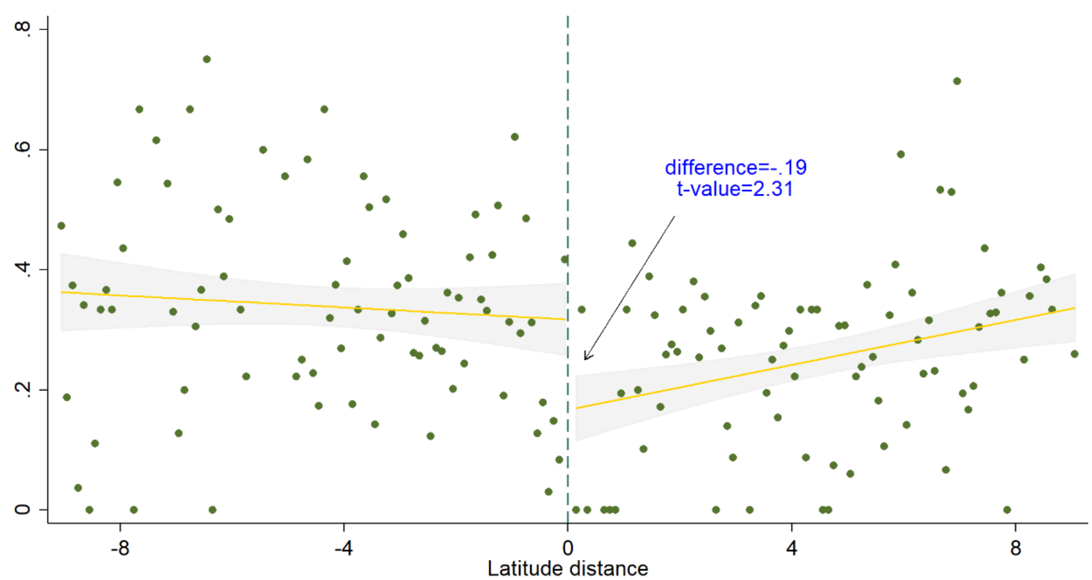
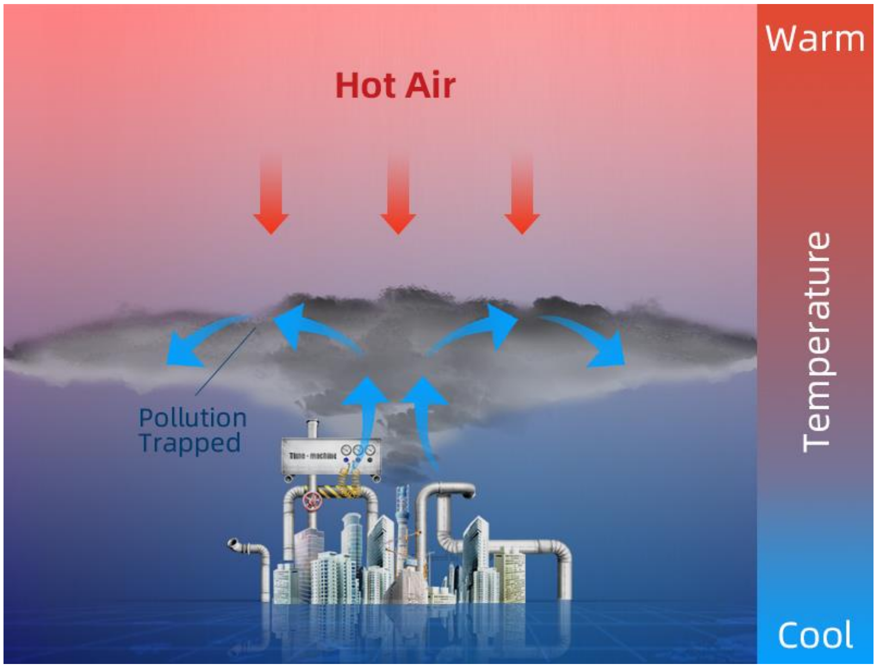
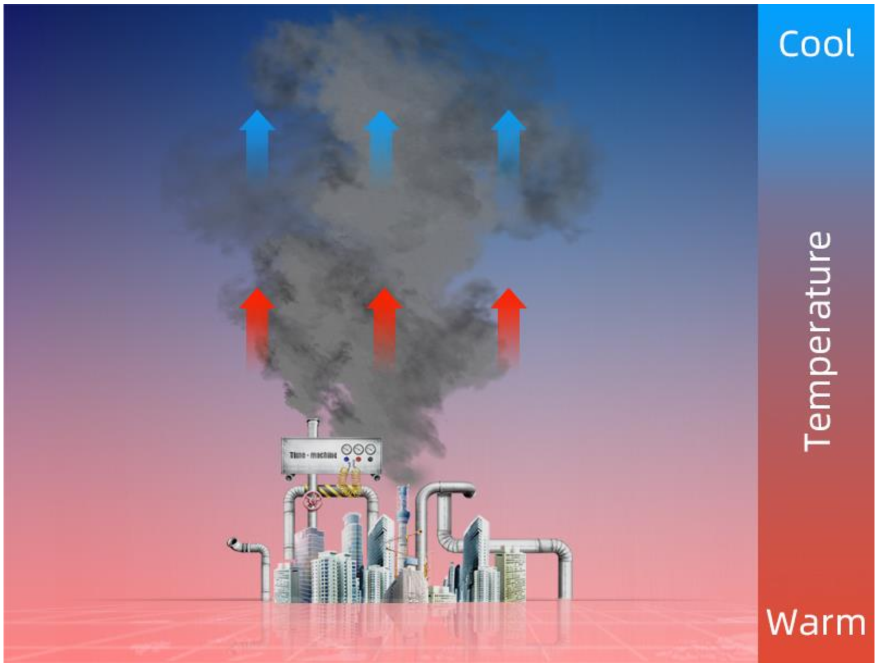


Figure 8: Thermal Inversion

The figure shows the mechanics of thermal inversion. Air moves from hot to cool regions. When the above-ground temperature is higher than the ground temperature in a region, as shown in Panel A, a thermal inversion occurs and air pollutants are trapped near the ground, leading to high air pollution concentrations. When the above-ground temperature is lower than the ground temperature, as shown in Panel B, thermal inversion does not occur and air pollutants spread away with the flowing air.



Panel A: Thermal inversion



Panel B: No thermal inversion

Appendix B: Tables for Chapter 1

Table 1.1: Descriptive Statistics

This table presents the summary statistics for the sample. The sample consists of 26,867 single-class firms and 939 dual-class firms from 1994-2014. Variable definitions are given in Table IA.1.

	Single		Dual		Dual-Single
	Mean	S.D.	Mean	S.D.	Difference
Number of Firms	26,867		939		
Log (1+Total Asset)	5.3766	2.4523	6.4567	2.0211	1.0801***
Sales Growth	0.0552	0.3189	0.0347	0.1930	-0.0205***
ROA	-0.0176	0.3514	0.0839	0.1988	0.1015***
Tobin's Q	2.3663	5.5824	1.8691	2.2146	-0.4971***
Mkt Leverage	0.1672	0.1869	0.2106	0.2035	0.0434***
Tangibility	0.2654	0.2733	0.2683	0.2331	0.0028
CAPEX	0.5668	38.9586	0.2815	1.5723	-0.2853
R&D	1.5237	76.5805	0.4915	31.4053	-1.0321*
Dividend	0.1057	8.9939	0.0334	1.3461	-0.0723
Firm Age	13.7698	14.4598	15.5760	14.6589	1.8061***
Net Financing	2.0844	2.2109	2.8927	2.3667	0.8083***

YEAR	No. of Firms	Total No. of Firms	Dual %	Market Value of Dual	Total Assets of Dual
1994	109	8859	1.23%	1083.69	1434.44
1995	391	9250	4.23%	885.76	1609.84
1996	435	9838	4.42%	960.88	1625.35
1997	485	10078	4.81%	1287.28	2107.78
1998	504	9927	5.08%	1437.56	2823.05
1999	489	9619	5.08%	2339.18	3141.50
2000	487	9325	5.22%	2146.79	3897.66
2001	435	8634	5.04%	1819.54	3338.06
2002	379	7954	4.76%	1974.01	3958.81
2003	233	7514	3.10%	3844.50	4115.81
2004	225	7383	3.05%	4866.40	4712.51
2005	220	7403	2.97%	5895.98	5781.16
2006	217	7496	2.89%	7364.42	7016.85
2007	210	7734	2.72%	8577.74	8193.01

2008	201	7436	2.70%	4780.65	7317.95
2009	191	7208	2.65%	6265.08	7516.24
2010	186	7177	2.59%	6462.04	8471.91
2011	193	7190	2.68%	6797.63	8926.05
2012	197	7203	2.73%	7586.21	9430.81
2013	215	7264	2.96%	10086.72	9829.04
2014	190	7501	2.53%	13266.83	11357.06

SIC 2-Digits	Industry Description	Number of Firms
48	Communications	130
73	Business Services	100
36	Electronic & Other Electrical Equipment & Components	47
28	Chemicals and Allied Products	38
20	Food and Kindred Products	36
67	Holding and Other Investment Offices	31
27	Printing, Publishing and Allied Industries	28
35	Industrial and Commercial Machinery and Computer Equipment	28
63	Insurance Carriers	27
59	Miscellaneous Retail	22
37	Transportation Equipment	21
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	21
51	Wholesale Trade - Nondurable Goods	18
50	Wholesale Trade - Durable Goods	17
60	Depository Institutions	17
79	Amusement and Recreation Services	17
54	Food Stores	15
62	Security & Commodity Brokers, Dealers, Exchanges & Services	15
78	Motion Pictures	15

Table 1.2: Characteristic of Dual Class Listing

This table presents results from probit regression using the IPO data from 1980-2015. The dependent variable is the indicator of dual listed and measures the probability that an IPO firm is a dual-class firm.

	(1)	(2)
	Prob (Dual=1)	
Post Hightech	0.049	0.193**
	(0.067)	(0.080)
Post High R&D	-0.148**	-0.111
	(0.070)	(0.084)
Post Highivol	0.268***	0.315***
	(0.083)	(0.104)
Post High Analyst Dispersion	0.533***	0.387***
	(0.065)	(0.079)
Post LowIO	-0.240***	-0.166**
	(0.059)	(0.075)
Post No Analyst Cover	0.905***	0.773***
	(0.096)	(0.122)
Post Low Investor Turnover	-0.195***	-0.173**
	(0.062)	(0.079)
Log Offer Value		0.111***
		(0.040)
Lagged Market Return		0.742
		(0.784)
NASDAQ-listed		-0.024
		(0.072)
Underwriting Fee%		0.043***
		(0.006)
Privated Equity Backed		-0.266***
		(0.089)
Venture Backed		-0.518***
		(0.090)
Institutional Investors		-0.001
		(0.089)
Equity-Spinoff		0.022
		(0.075)
Log_Proceeds		0.110**
		(0.045)
Constant	-2.692***	-5.706***
	(0.058)	(0.775)
Observation	12362	7207

Table 1.3: Operating Performance

This table presents results from OLS regressions using the entire sample from 1994 to 2014. The dependent variable is ROA in Panel A, Gross Margin in Panel B, and Assets Turnover in Panel C. The primary explanatory variables are interactions between Dual and Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover, Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA (t+1)							
Dual	0.007	-0.003	-0.021	-0.003	-0.001	-0.006	-0.004	0.002
	(0.006)	(0.006)	(0.014)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Hightech*Dual		0.029**						
		(0.013)						
Hightech		-0.084***						
		(0.009)						
High R&D*Dual			0.049***					
			(0.017)					
High R&D			-0.083***					
			(0.007)					
Highivol*Dual				0.019**				
				(0.009)				
Highivol				-0.033***				
				(0.003)				
High Analyst Dispersion*Dual					0.025***			
					(0.008)			
High Analyst Dispersion					-0.075***			
					(0.003)			
LowIO*Dual						0.029**		
						(0.013)		
LowIO						-0.037***		
						(0.004)		
No Analyst Cover*Dual							0.017*	
							(0.009)	
No Analyst Cover							-0.037***	
							(0.004)	
Low Investor Turnover*Dual								0.016*
								(0.009)
Low Investor Turnover								-0.022***
								(0.003)
Log Assets	0.081***	0.080***	0.117***	0.072***	0.046***	0.074***	0.077***	0.057***

	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Sales Growth	-0.028***	-0.027***	-0.036***	-0.042***	-0.073***	-0.043***	-0.024***	-0.048***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.015)	(0.008)	(0.007)	(0.011)
Leverage	0.029***	0.013	0.023	0.014	-0.011	0.048***	0.014	-0.036***
	(0.011)	(0.011)	(0.018)	(0.010)	(0.012)	(0.011)	(0.011)	(0.012)
Tangibility	0.109***	0.097***	0.093***	0.112***	0.132***	0.116***	0.085***	0.133***
	(0.011)	(0.011)	(0.021)	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)
R&D	-0.000**	-0.000**	-0.000**	-0.000**	-0.000***	-0.000**	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout Ratio	0.388***	0.355***	0.310***	0.319***	0.330***	0.382***	0.320***	0.428***
	(0.044)	(0.044)	(0.074)	(0.042)	(0.037)	(0.052)	(0.038)	(0.045)
Interest	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NetFinancing	-0.036***	-0.035***	-0.049***	-0.030***	-0.016***	-0.035***	-0.034***	-0.024***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Age	0.000***	0.000**	0.001***	0.000**	-0.000	0.000**	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.449***	-0.403***	-0.561***	-0.382***	-0.212***	-0.394***	-0.401***	-0.294***
	(0.014)	(0.014)	(0.018)	(0.016)	(0.017)	(0.017)	(0.014)	(0.015)
Obs	56855	56855	31107	49381	24252	40776	56855	36180
adj. R-sq	0.242	0.248	0.303	0.248	0.258	0.251	0.274	0.212
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Gross Margin (t+1)							
Dual	0.136*	-0.018	-0.223	-0.080	0.094	-0.025	-0.107	0.173**
	(0.075)	(0.066)	(0.194)	(0.073)	(0.073)	(0.084)	(0.077)	(0.079)
Hightech*Dual		0.402**						
		(0.193)						
Hightech		-1.261***						
		(0.142)						
High R&D*Dual			0.844***					
			(0.275)					
High R&D			-0.984***					
			(0.161)					
Highivol*Dual				0.446***				
				(0.129)				
Highivol				-0.205***				
				(0.061)				

High Analyst Dispersion*Dual					0.168*			
					(0.099)			
High Analyst Dispersion					-0.331***			
					(0.076)			
LowIO*Dual						0.406**		
						(0.201)		
LowIO						-0.254***		
						(0.092)		
No Analyst Cover*Dual							0.270**	
							(0.128)	
No Analyst Cover							-0.410***	
							(0.089)	
Low Investor Turnover*Dual								0.026
								(0.120)
Low Investor Turnover								0.055
								(0.087)
Log Assets	0.706***	0.689***	1.030***	0.684***	0.407***	0.711***	0.624***	0.479***
	(0.043)	(0.042)	(0.066)	(0.051)	(0.055)	(0.056)	(0.040)	(0.046)
Sales Growth	0.371	0.380	0.384	0.262	-1.043	0.419	0.486**	-0.521
	(0.232)	(0.232)	(0.332)	(0.279)	(0.724)	(0.286)	(0.228)	(0.379)
Leverage	1.017***	0.785***	0.758**	0.908***	0.369	1.069***	0.716***	0.263
	(0.186)	(0.183)	(0.329)	(0.181)	(0.249)	(0.217)	(0.194)	(0.205)
Tangibility	0.978***	0.797***	0.784*	1.080***	1.134***	1.036***	0.545**	1.142***
	(0.235)	(0.235)	(0.455)	(0.238)	(0.257)	(0.299)	(0.272)	(0.256)
R&D	-0.006**	-0.006**	-0.005**	-0.006**	-0.026*	-0.005**	-0.005**	-0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.015)	(0.002)	(0.003)	(0.008)
Payout Ratio	3.665***	3.180***	3.165***	3.246***	2.243***	4.633***	2.682***	2.426***
	(0.646)	(0.639)	(0.905)	(0.734)	(0.521)	(0.723)	(0.628)	(0.717)
Interest	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NetFinancing	-0.409***	-0.396***	-0.600***	-0.385***	-0.202***	-0.475***	-0.364***	-0.263***
	(0.029)	(0.029)	(0.046)	(0.031)	(0.033)	(0.038)	(0.027)	(0.030)
Firm Age	0.007***	0.005*	0.010**	0.006**	0.005**	0.007**	0.003	0.008***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Constant	-6.185***	-5.514***	-7.871***	-5.948***	-3.666***	-6.430***	-5.237***	-4.447***
	(0.465)	(0.448)	(0.725)	(0.526)	(0.525)	(0.614)	(0.421)	(0.513)
Obs	56744	56744	31054	49445	24405	40664	56744	36347
adj. R-sq	0.090	0.093	0.119	0.096	0.096	0.100	0.125	0.086
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel C

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales/Asset (t+1)							
Dual	-0.036	-0.041	-0.094*	-0.010	0.022	-0.015	-0.020	-0.026
	(0.024)	(0.029)	(0.050)	(0.033)	(0.040)	(0.031)	(0.022)	(0.032)
Hightech*Dual		0.004						
		(0.049)						
Hightech		-0.208***						
		(0.031)						
High R&D*Dual			0.131**					
			(0.054)					
High R&D			-0.100***					
			(0.019)					
Highivol*Dual				-0.032				
				(0.037)				
Highivol				0.001				
				(0.014)				
High Analyst Dispersion*Dual					-0.060			
					(0.038)			
High Analyst Dispersion					0.032***			
					(0.011)			
LowIO*Dual						-0.094**		
						(0.047)		
LowIO						0.037**		
						(0.015)		
No Analyst Cover*Dual							-0.031	
							(0.032)	
No Analyst Cover							-0.024**	
							(0.010)	
Low Investor Turnover*Dual								-0.009
								(0.043)
Low Investor Turnover								0.006
								(0.014)
Log Assets	-0.038***	-0.041***	-0.024***	-0.031***	-0.033***	-0.014**	-0.044***	-0.060***
	(0.005)	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)	(0.005)	(0.007)
Sales Growth	-0.054***	-0.052***	-0.046***	-0.089***	-0.182***	-0.097***	-0.037***	-0.109***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.017)	(0.011)	(0.010)	(0.015)
Leverage	0.231***	0.193***	0.307***	0.161***	-0.005	0.238***	0.207***	0.174***
	(0.034)	(0.035)	(0.046)	(0.036)	(0.048)	(0.042)	(0.031)	(0.045)
Tangibility	-0.254***	-0.286***	-0.056	-0.251***	-0.264***	-0.300***	-0.216***	-0.301***
	(0.036)	(0.036)	(0.052)	(0.037)	(0.049)	(0.044)	(0.038)	(0.046)
R&D	-0.000	-0.000	-0.000	-0.000	-0.001**	-0.000	-0.000	-0.001***

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout Ratio	0.107	0.024	0.047	0.243*	0.314**	0.454***	0.157	0.248
	(0.138)	(0.137)	(0.175)	(0.144)	(0.160)	(0.163)	(0.115)	(0.168)
Interest	-0.000**	-0.000*	-0.000**	-0.000***	-0.000***	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NetFinancing	-0.044***	-0.042***	-0.050***	-0.044***	-0.032***	-0.058***	-0.038***	-0.034***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Firm Age	0.004***	0.004***	0.005***	0.004***	0.003***	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	1.167***	1.278***	1.114***	1.136***	1.178***	1.119***	1.216***	1.333***
	(0.030)	(0.034)	(0.031)	(0.042)	(0.041)	(0.041)	(0.028)	(0.044)
Obs	57321	57321	31392	49804	24453	40940	57321	36510
adj. R-sq	0.334	0.339	0.396	0.351	0.418	0.345	0.445	0.380
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.4: Valuation Regressions

This table presents results from valuation regressions using the entire sample from 1994 to 2014. In Panel A, the dependent variable is Tobin's Q, which is the ratio of the market value of assets to the book value of assets. In Panel B, the dependent variable is industry adjusted Tobin's Q, followed by Gompers, Ishii, and Metrick (2009). The primary explanatory variables are interactions between Dual and Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover, Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tobin's Q (t+1)							
Dual	-0.031	-0.171***	-0.098	-0.173***	-0.103	-0.069	-0.032	-0.028
	(0.052)	(0.043)	(0.085)	(0.054)	(0.081)	(0.049)	(0.046)	(0.067)
Hightech* Dual		0.320***						
		(0.122)						
Hightech		0.359***						
		(0.062)						
High R&D*Dual			0.347**					
			(0.142)					
High R&D			0.154***					
			(0.050)					
Highivol* Dual				0.261***				
				(0.079)				
Highivol				-0.059				
				(0.043)				
High Analyst Dispersion*Dual					0.153**			
					(0.077)			
High Analyst Dispersion					-0.514***			
					(0.025)			
LowIO*Dual						0.046		
						(0.081)		
LowIO						-0.131***		
						(0.026)		
No Analyst Cover*Dual							0.006	
							(0.064)	
No Analyst Cover							-0.149***	
							(0.023)	
Low Investor Turnover*Dual								-0.048
								(0.083)

Low Investor Turnover								-0.212***
								(0.028)
Log Assets	-0.211***	-0.217***	-0.246***	-0.215***	-0.067***	-0.047***	-0.037***	-0.065***
	(0.026)	(0.028)	(0.019)	(0.027)	(0.012)	(0.010)	(0.007)	(0.015)
R&D	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-2.057***	-1.935***	-2.355***	-2.053***	-2.155***	-1.835***	-2.316***	-2.265***
	(0.092)	(0.085)	(0.126)	(0.090)	(0.086)	(0.065)	(0.063)	(0.087)
Firm Risk	-0.618***	-0.667***	-0.800***	-0.600***	-0.124*	-0.486***	-0.156***	-0.423***
	(0.056)	(0.061)	(0.072)	(0.054)	(0.070)	(0.045)	(0.038)	(0.055)
Cash Flow	-1.047***	-1.081***	-0.909***	-1.045***	-1.644***	-1.092***	-1.671***	-1.498***
	(0.117)	(0.117)	(0.135)	(0.117)	(0.197)	(0.100)	(0.090)	(0.146)
Firm Age	-0.047**	-0.038*	-0.087***	-0.049**	-0.063***	-0.098***	-0.052***	-0.089***
	(0.021)	(0.022)	(0.022)	(0.020)	(0.016)	(0.013)	(0.011)	(0.019)
Constant	3.437***	3.320***	3.658***	3.494***	3.354***	3.117***	2.709***	3.320***
	(0.133)	(0.145)	(0.124)	(0.157)	(0.105)	(0.088)	(0.070)	(0.110)
Obs	52491	50633	30245	52491	45286	73046	63500	61767
adj. R-sq	0.229	0.237	0.248	0.230	0.243	0.244	0.217	0.215
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Industry Median Adjusted Tobin's Q (t+1)							
Dual	-0.032	-0.172***	-0.079	-0.188***	-0.095	-0.068	-0.037	-0.036
	(0.052)	(0.043)	(0.080)	(0.055)	(0.082)	(0.049)	(0.045)	(0.067)
Hightech* Dual		0.323***						
		(0.123)						
Hightech		0.386***						
		(0.063)						
High R&D*Dual			0.330**					
			(0.140)					
High R&D			0.131***					
			(0.049)					
Highivol* Dual				0.284***				
				(0.078)				
Highivol				-0.114***				
				(0.043)				
High Analyst Dispersion*Dual					0.134*			
					(0.077)			

High Analyst Dispersion					-0.467***			
					(0.025)			
LowIO*Dual						0.043		
						(0.082)		
LowIO						-0.126***		
						(0.026)		
No Analyst Cover*Dual							0.000	
							(0.063)	
No Analyst Cover							-0.148***	
							(0.022)	
Low Investor Turnover*Dual							0.002***	
							(0.000)	
Low Investor Turnover								-0.030
								(0.082)
Log Assets								-0.191***
								(0.027)
R&D	-0.201***	-0.212***	-0.233***	-0.208***	-0.062***	-0.047***	-0.031***	-0.060***
	(0.026)	(0.028)	(0.019)	(0.027)	(0.012)	(0.010)	(0.007)	(0.015)
Leverage	-1.884***	-1.875***	-2.119***	-1.874***	-1.937***	-1.781***	-2.083***	-2.059***
	(0.091)	(0.085)	(0.126)	(0.090)	(0.085)	(0.065)	(0.062)	(0.086)
Firm Risk	-0.601***	-0.650***	-0.788***	-0.558***	-0.231***	-0.495***	-0.172***	-0.444***
	(0.055)	(0.060)	(0.072)	(0.054)	(0.069)	(0.045)	(0.038)	(0.055)
Cash Flow	-1.080***	-1.083***	-0.935***	-1.075***	-1.664***	-1.083***	-1.610***	-1.523***
	(0.117)	(0.117)	(0.135)	(0.117)	(0.198)	(0.100)	(0.090)	(0.146)
Firm Age	-0.035*	-0.036	-0.071***	-0.039*	-0.053***	-0.098***	-0.037***	-0.070***
	(0.021)	(0.022)	(0.022)	(0.020)	(0.016)	(0.013)	(0.011)	(0.018)
Constant	1.785***	1.718***	1.817***	1.899***	1.690***	1.548***	1.083***	1.655***
	(0.132)	(0.145)	(0.123)	(0.156)	(0.103)	(0.088)	(0.069)	(0.108)
Obs	52491	50633	30245	52491	45286	73046	63500	61767
adj. R-sq	0.157	0.159	0.182	0.157	0.148	0.157	0.135	0.138
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.5: Sales Growth

This table presents results from OLS regressions using the entire sample from 1994 to 2014. The dependent variable is Sales Growth, measured by the annual growth rate from year t to year t+1 The primary explanatory variables are interactions between Dual and Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover, Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales Growth (t+1)							
Dual	0.011	0.001	0.033*	-0.001	-0.023**	-0.013	-0.008	-0.008
	(0.007)	(0.008)	(0.018)	(0.008)	(0.010)	(0.009)	(0.008)	(0.009)
Hightech*Dual		0.033*						
		(0.018)						
Hightech		-0.013*						
		(0.008)						
High R&D*Dual			0.030					
			(0.023)					
High R&D			-0.009					
			(0.008)					
Highivol*Dual				0.030**				
				(0.015)				
Highivol				-0.006				
				(0.005)				
High Analyst Dispersion*Dual					0.039***			
					(0.013)			
High Analyst Dispersion					-0.100***			
					(0.005)			
LowIO*Dual						0.040**		
						(0.018)		
LowIO						-0.030***		
						(0.007)		
No Analyst Cover*Dual							0.040***	
							(0.014)	
No Analyst Cover							-0.013***	
							(0.005)	
Low Investor Turnover*Dual								0.012
								(0.014)
Low Investor Turnover								-0.045***
								(0.005)
Log Assets	0.004***	0.004***	0.011***	0.006***	-0.002	0.006***	0.003**	0.002*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)

Leverage	-0.271***	-0.274***	-0.301***	-0.285***	-0.164***	-0.311***	-0.268***	-0.224***
	(0.014)	(0.014)	(0.020)	(0.016)	(0.021)	(0.018)	(0.014)	(0.015)
Capex	-0.000	-0.000	-0.000	0.000	-0.000***	0.002***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D	0.000**	0.000**	0.000**	0.000**	0.002**	0.001**	0.000**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Interest	-0.120**	-0.121**	-0.118*	-0.254***	-0.240	-0.069	-0.120**	-0.268***
	(0.057)	(0.057)	(0.066)	(0.096)	(0.187)	(0.107)	(0.057)	(0.100)
ROA	-0.472***	-0.474***	-0.453***	-0.504***	-0.692***	-0.575***	-0.474***	-0.554***
	(0.029)	(0.029)	(0.035)	(0.032)	(0.049)	(0.035)	(0.029)	(0.037)
Cost of Debt	0.000***	0.000***	0.000***	0.000***	0.000***	0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Payout	-0.011***	-0.011***	-0.017***	-0.011***	-0.009***	-0.014***	-0.011***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cash Flow	0.167***	0.168***	0.147***	0.192***	0.193***	0.218***	0.167***	0.208***
	(0.021)	(0.021)	(0.026)	(0.024)	(0.037)	(0.025)	(0.021)	(0.029)
Firm Age	-0.075***	-0.075***	-0.077***	-0.076***	-0.063***	-0.083***	-0.075***	-0.070***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Constant	0.290***	0.296***	0.259***	0.280***	0.359***	0.335***	0.301***	0.316***
	(0.013)	(0.013)	(0.018)	(0.016)	(0.016)	(0.018)	(0.013)	(0.014)
Obs	73352	73352	40296	64356	34612	53611	73352	48301
adj. R-sq	0.087	0.087	0.091	0.092	0.145	0.103	0.087	0.107
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.6: Baseline Results in Propensity Score Matched Sample

This table presents results from OLS regressions using the propensity matched sample from 1994 to 2014. Panel A shows the summary statics between unmatched and matched samples. Panel B to Panel D have the dependent variable as ROA, Tobin's Q, and sales growth. The primary explanatory variables are interactions between Dual and Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover, Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. All the regressions have included industry fixed effect (SIC2 digit) and year fixed effect. *, **, and *** represent significance at the 10%, 5% and 1% levels respectively.

Panel A

Dual- and propensity-matched single-class firms						
		Dual-class firms	Single-class firms	Difference	t-statistics	P-value
Log (Assets)	Unmatched	6.175	5.071	1.104	28.73	0.000
	Matched	6.175	6.229	-0.055	-1.14	0.253
Sales Growth	Unmatched	0.049	0.065	-0.017	-3.1	0.002
	Matched	0.049	0.046	0.002	0.39	0.698
Leverage	Unmatched	0.227	0.174	0.053	16.87	0.000
	Matched	0.227	0.228	-0.001	-0.12	0.906
Tangibility	Unmatched	0.282	0.267	0.015	3.53	0.000
	Matched	0.282	0.296	-0.015	-2.54	0.011
Payout Ratio	Unmatched	0.018	0.014	0.004	6.07	0.000
	Matched	0.018	0.018	0.000	-0.33	0.745
Interest Expense	Unmatched	59.803	41.190	18.613	7.72	0.000
	Matched	59.803	64.674	-4.871	-1.33	0.184
Net Financing	Unmatched	2.985	2.233	0.752	19.92	0.000
	Matched	2.985	3.048	-0.063	-1.18	0.238
Firm Age	Unmatched	14.442	13.542	0.900	3.81	0.000
	Matched	14.442	14.799	-0.357	-1.06	0.289

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ROA (t+1)				
Dual	0.016**	0.011*	-0.000	0.016***	0.008	0.011*	0.005	0.011
	(0.007)	(0.006)	(0.018)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Hightech*Dual		0.010**						
		(0.003)						
Hightech		-0.079***						
		(0.013)						
High R&D*Dual			0.029**					
			(0.011)					
High R&D			-0.045***					
			(0.016)					
Highivol*Dual				0.000*				
				(0.000)				
Highivol				-0.039***				
				(0.007)				
High Analyst Dispersion*Dual					0.014***			
					(0.004)			
High Analyst Dispersion					-0.065***			
					(0.006)			
LowIO*Dual						0.015*		
						(0.008)		
LowIO						-0.040***		
						(0.011)		
No Analyst Cover*Dual							0.005	
							(0.011)	
No Analyst Cover							-0.033***	
							(0.008)	
Low Investor Turnover*Dual								0.010
								(0.010)
Low Investor Turnover								-0.022***
								(0.006)
Log Assets	0.056***	0.055***	0.090***	0.047***	0.025***	0.048***	0.053***	0.039***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Sales Growth	-0.048**	-0.046**	-0.051*	-0.052**	-0.100***	-0.060***	-0.042**	-0.080***
	(0.020)	(0.020)	(0.027)	(0.020)	(0.032)	(0.021)	(0.020)	(0.030)
Leverage	-0.020	-0.034**	-0.008	-0.019	-0.020	-0.008	-0.045***	-0.062***
	(0.014)	(0.014)	(0.025)	(0.014)	(0.017)	(0.017)	(0.015)	(0.015)
Tangibility	0.086***	0.073***	0.049	0.088***	0.097***	0.089***	0.072***	0.109***
	(0.018)	(0.017)	(0.034)	(0.018)	(0.018)	(0.023)	(0.018)	(0.020)

	-0.004**	-0.004**	-0.004*	-0.004**	-0.013***	-0.005	-0.004*	-0.003**
R&D	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.001)
	0.258***	0.235***	0.407***	0.221***	0.253***	0.324***	0.223***	0.281***
Payout Ratio	(0.050)	(0.049)	(0.101)	(0.052)	(0.064)	(0.074)	(0.048)	(0.058)
	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
Interest	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	-0.017***	-0.017***	-0.030***	-0.015***	-0.008***	-0.017***	-0.016***	-0.012***
NetFinancing	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000	0.000
Firm Age	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	-0.291***	-0.254***	-0.443***	-0.211***	-0.062**	-0.219***	-0.252***	-0.168***
Constant	(0.025)	(0.024)	(0.040)	(0.027)	(0.028)	(0.030)	(0.026)	(0.025)
	7906	7906	3731	7121	3958	5896	7906	5317
Obs	0.225	0.234	0.309	0.224	0.220	0.218	0.267	0.189
adj. R-sq	0.242	0.248	0.303	0.248	0.258	0.251	0.274	0.212
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel C

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tobin's Q (t+1)							
Dual	-0.038	-0.190***	-0.105	-0.133**	0.042	-0.008	0.040	0.071
	(0.061)	(0.048)	(0.127)	(0.055)	(0.134)	(0.078)	(0.080)	(0.105)
Hightech* Dual		0.472***						
		(0.154)						
Hightech		0.602***						
		(0.111)						
High R&D*Dual			0.331*					
			(0.183)					
High R&D			0.009					
			(0.139)					
Highivol* Dual				0.220**				
				(0.096)				
Highivol				-0.111*				
				(0.064)				
High Analyst Dispersion*Dual					0.019*			
					(0.011)			
High Analyst Dispersion					-0.329***			
					(0.077)			
LowIO*Dual						0.158*		
						(0.079)		
LowIO						-0.138*		

						(0.072)		
No Analyst Cover*Dual							0.143	
							(0.102)	
No Analyst Cover							-0.173***	
							(0.063)	
Low Investor Turnover*Dual								0.169
								(0.122)
Low Investor Turnover								-0.164**
								(0.069)
Log Assets	-0.211***	-0.212***	-0.170***	-0.169***	-0.137***	-0.203***	-0.236***	-0.179***
	(0.032)	(0.031)	(0.051)	(0.032)	(0.033)	(0.035)	(0.032)	(0.039)
Sales Growth	0.322*	0.305*	0.003	0.299*	0.500	0.318*	0.323*	0.554**
	(0.177)	(0.176)	(0.226)	(0.163)	(0.374)	(0.164)	(0.177)	(0.258)
Leverage	-1.651***	-1.442***	-2.252***	-1.951***	-2.067***	-1.793***	-1.607***	-1.859***
	(0.161)	(0.154)	(0.283)	(0.158)	(0.179)	(0.182)	(0.158)	(0.180)
Capex	0.260	0.254	0.263	0.255	0.521*	0.279	0.257	0.216
	(0.223)	(0.219)	(0.272)	(0.230)	(0.293)	(0.254)	(0.222)	(0.188)
R&D	0.019	0.019	0.010	0.019	0.026	0.002	0.020	0.041***
	(0.014)	(0.014)	(0.013)	(0.014)	(0.034)	(0.005)	(0.014)	(0.005)
Payout	-0.917**	-1.562***	(1.328)	-0.909**	-1.064**	(0.638)	-0.962**	-1.339***
	(0.380)	(0.326)	(0.810)	(0.401)	(0.506)	(0.527)	(0.378)	(0.500)
Interest Expense	0.001***	0.001***	0.000	0.001***	0.001***	0.001***	0.001***	0.001***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NetFinancing	0.123***	0.113***	0.140***	0.113***	0.065***	0.101***	0.122***	0.106***
	(0.016)	(0.015)	(0.025)	(0.016)	(0.017)	(0.018)	(0.016)	(0.018)
Firm Age	-0.003*	(0.002)	(0.004)	-0.004**	(0.003)	(0.002)	(0.002)	-0.004**
	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Constant	2.893***	2.624***	2.844***	2.796***	2.764***	2.990***	3.075***	2.841***
	(0.205)	(0.198)	(0.294)	(0.221)	(0.275)	(0.236)	(0.216)	(0.256)
Obs	7067.000	7065.000	3413.000	6356.000	3407.000	5284.000	7067.000	4752.000
adj. R-sq	0.159	0.180	0.179	0.170	0.196	0.157	0.163	0.170
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel D

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sales Growth (t+1)							
Dual	0.031**	0.008	0.046	0.025	0.025	0.029	0.021	0.019
	(0.014)	(0.015)	(0.032)	(0.015)	(0.022)	(0.018)	(0.016)	(0.017)
Hightech*Dual		0.062*						
		(0.031)						
Hightech		0.018						
		(0.036)						

High R&D*Dual			0.017					
			(0.040)					
High R&D			(0.020)					
			(0.031)					
Highivol*Dual				0.027*				
				(0.015)				
Highivol				0.022				
				(0.019)				
High Analyst Dispersion*Dual					0.027***			
					(0.006)			
High Analyst Dispersion					-0.087***			
					(0.019)			
LowIO*Dual						0.033***		
						(0.006)		
LowIO						-0.050*		
						(0.026)		
No Analyst Cover*Dual							0.019**	
							(0.007)	
No Analyst Cover							0.014	
							(0.017)	
Low Investor Turnover*Dual								0.010
								(0.026)
Low Investor Turnover								-0.060***
								(0.017)
Log Assets	-0.002	-0.003	0.008	0.002	-0.007	-0.012*	0.000	-0.007
	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)
Leverage	-0.227***	-0.225***	-0.221***	-0.245***	-0.084	-0.249***	-0.232***	-0.174***
	(0.034)	(0.034)	(0.058)	(0.040)	(0.051)	(0.045)	(0.035)	(0.042)
Capex	0.003	0.003	0.001	0.000	0.115**	-0.006	0.004	0.047
	(0.019)	(0.019)	(0.021)	(0.019)	(0.047)	(0.017)	(0.020)	(0.041)
R&D	0.007*	0.007*	0.007*	0.007	0.031**	0.006	0.007*	0.011***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.016)	(0.005)	(0.004)	(0.004)
Payout	-0.264***	-0.260***	-0.171**	-0.261***	-0.248***	-0.226***	-0.262***	-0.203***
	(0.056)	(0.056)	(0.078)	(0.059)	(0.071)	(0.071)	(0.056)	(0.064)
Firm Age	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.183***	0.180***	0.154**	0.129***	0.213***	0.269***	0.170***	0.218***
	(0.039)	(0.039)	(0.062)	(0.047)	(0.053)	(0.055)	(0.039)	(0.049)
Obs	7726	7726	3654	6961	3899	5805	7726	5208
adj. R-sq	0.077	0.077	0.064	0.082	0.098	0.087	0.077	0.075
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.7: Intangible Investment

This table presents results from OLS regressions using the entire sample from 1994 to 2014. The dependent variable is the ratio of intangible investment, measured by R&D /(R&D+CAPEX). The primary explanatory variables are interactions between Dual and Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover, Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. All the regressions have included industry fixed effect (SIC2 digit) and year fixed effect. *, **, and *** represent significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	R&D /(R&D+CAPEX) (t+1)						
Dual	-0.020**	0.003	-0.011	-0.033***	-0.037***	-0.015	-0.036***
	(0.008)	(0.008)	(0.008)	(0.012)	(0.011)	(0.010)	(0.013)
Hightech*Dual		0.027*					
		(0.016)					
Hightech		-0.123***					
		(0.006)					
Highivol*Dual			0.002				
			(0.012)				
Highivol			0.023***				
			(0.004)				
High Analyst Dispersion*Dual				0.021*			
				(0.011)			
High Analyst Dispersion				0.004			
				(0.004)			
LowIO*Dual					0.038**		
					(0.017)		
LowIO					-0.027***		
					(0.006)		
No Analyst Cover*Dual						0.029**	
						(0.013)	
No Analyst Cover						-0.029***	
						(0.004)	
Low Investor Turnover*Dual							0.051***
							(0.017)
Low Investor Turnover							-0.038***
							(0.005)
Log Assets	0.000	-0.004***	0.004**	-0.005**	-0.000	-0.001	-0.005**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Labor	-0.000***	-0.000	-0.000***	-0.000*	-0.000**	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Leverage	-0.176***	0.000	-0.154***	-0.207***	-0.187***	-0.116***	-0.190***
	(0.011)	(0.001)	(0.010)	(0.015)	(0.014)	(0.012)	(0.015)
Tangibility	-0.257***	-0.075***	-0.236***	-0.318***	-0.260***	-0.224***	-0.260***
	(0.012)	(0.009)	(0.013)	(0.017)	(0.016)	(0.013)	(0.016)
ROA	-0.228***	-0.110***	-0.208***	-0.295***	-0.249***	-0.197***	-0.261***
	(0.008)	(0.007)	(0.008)	(0.016)	(0.011)	(0.009)	(0.012)
Cash	0.243***	-0.094***	0.161***	0.293***	0.216***	0.148***	0.247***
	(0.013)	(0.007)	(0.013)	(0.019)	(0.015)	(0.013)	(0.018)
Payout Ratio	-0.192***	0.146*	-0.049	-0.124***	-0.275***	-0.097**	-0.162***
	(0.032)	(0.083)	(0.030)	(0.044)	(0.056)	(0.039)	(0.056)
Interest	0.000	0.112***	-0.000	0.000*	0.000	0.000*	0.000***
	(0.000)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	-0.000***	0.001	0.000	-0.000	-0.001***	-0.000	-0.000**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.388***	0.112***	0.336***	0.424***	0.429***	0.408***	0.444***
	(0.011)	(0.010)	(0.012)	(0.016)	(0.017)	(0.012)	(0.016)
Obs	93192	93192	82899	45780	40020	53217	33847
adj. R-sq	0.590	0.079	0.672	0.649	0.607	0.647	0.619
Industry FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y

Table 1.8: Innovation

This table presents results from OLS regressions using the entire sample from 1994 to 2014. The dependent variable is the number of patents in Panel A and the citation divided by patents in Panel B The primary explanatory variables are interactions between Dual and Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover, Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (1+ Citation/Patents) (t+1)							
Dual	-0.007	0.006	0.046*	-0.004	-0.042**	-0.031**	-0.033**	-0.040**
	(0.011)	(0.012)	(0.025)	(0.014)	(0.019)	(0.016)	(0.014)	(0.016)
Hightech*Dual		-0.038						
		(0.025)						
Hightech		0.005						
		(0.042)						
High R&D*Dual			-0.073**					
			(0.036)					
High R&D			0.116***					
			(0.012)					
Highivol*Dual				-0.004				
				(0.019)				
Highivol				0.030***				
				(0.007)				
High Analyst Dispersion*Dual					0.044**			
					(0.022)			
High Analyst Dispersion					0.002			
					(0.008)			
LowIO*Dual						0.050**		
						(0.024)		
LowIO						-0.072***		
						(0.009)		
No Analyst Cover*Dual							0.057***	
							(0.017)	
No Analyst Cover							-0.088***	
							(0.007)	
Low Investor Turnover*Dual								0.050**
								(0.021)
Low Investor Turnover								-0.057***
								(0.009)
Log Assets	0.024***	0.024***	0.000	0.023***	0.001	0.016***	0.016***	0.013***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)

Sales Growth	0.041***	0.041***	0.050***	0.044***	0.084***	0.043***	0.042***	0.057***
	(0.008)	(0.008)	(0.010)	(0.009)	(0.023)	(0.010)	(0.008)	(0.013)
ROA	0.017**	0.017**	0.059***	0.013	-0.047*	-0.014	0.008	-0.000
	(0.008)	(0.008)	(0.011)	(0.010)	(0.027)	(0.012)	(0.008)	(0.015)
Tobin's Q	0.013***	0.013***	0.012***	0.017***	0.017***	0.015***	0.012***	0.014***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Leverage	-0.209***	-0.209***	-0.276***	-0.210***	-0.174***	-0.188***	-0.181***	-0.189***
	(0.015)	(0.015)	(0.025)	(0.017)	(0.028)	(0.020)	(0.014)	(0.019)
Tangibility	-0.020	-0.021	0.024	-0.013	-0.079**	-0.009	-0.027*	-0.021
	(0.017)	(0.017)	(0.031)	(0.019)	(0.035)	(0.023)	(0.017)	(0.024)
Capex	0.000**	0.000**	0.000*	0.000	0.000	0.000	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D	-0.000	-0.000	0.000	-0.000	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	-0.005*	-0.005*	-0.021***	0.002	0.005	-0.007*	-0.003	-0.004
	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)
Constant	-0.104***	-0.106***	0.597***	-0.146***	0.229***	-0.047**	-0.027*	-0.021
	(0.014)	(0.021)	(0.023)	(0.018)	(0.026)	(0.021)	(0.015)	(0.020)
Obs	83964	83964	45699	75366	37407	64590	83964	54486
adj. R-sq	0.146	0.146	0.166	0.152	0.193	0.159	0.150	0.172
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (1+Patents) (t+1)							
Dual	-0.111***	-0.113***	-0.069	-0.144***	-0.191***	-0.163***	-0.130***	-0.137**
	(0.031)	(0.032)	(0.042)	(0.042)	(0.062)	(0.043)	(0.044)	(0.055)
Hightech*Dual		0.004						
		(0.075)						
Hightech		0.195**						
		(0.099)						
High R&D*Dual			0.128					
			(0.102)					
High R&D			0.413***					
			(0.024)					
Highivol*Dual				0.083*				
				(0.047)				
Highivol				0.115***				
				(0.015)				

High Analyst Dispersion*Dual					0.169***			
					(0.058)			
High Analyst Dispersion					0.006			
					(0.015)			
LowIO*Dual						0.052		
						(0.054)		
LowIO						0.052***		
						(0.017)		
No Analyst Cover*Dual							0.039	
							(0.048)	
No Analyst Cover							-0.061***	
							(0.016)	
Low Investor Turnover*Dual								0.040
								(0.057)
Low Investor Turnover								-0.027
								(0.023)
Log Assets	0.210***	0.210***	0.267***	0.239***	0.290***	0.244***	0.204***	0.235***
	(0.006)	(0.006)	(0.009)	(0.007)	(0.011)	(0.009)	(0.007)	(0.009)
Sales Growth	0.034***	0.034***	0.039***	0.028***	0.013	0.019*	0.035***	0.031**
	(0.008)	(0.008)	(0.011)	(0.010)	(0.025)	(0.010)	(0.008)	(0.015)
ROA	-0.077***	-0.077***	-0.137***	-0.105***	-0.195***	-0.114***	-0.083***	-0.099***
	(0.015)	(0.015)	(0.019)	(0.018)	(0.047)	(0.020)	(0.015)	(0.026)
Tobin's Q	0.027***	0.027***	0.026***	0.035***	0.049***	0.034***	0.026***	0.039***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)
Leverage	-0.556***	-0.554***	-0.615***	-0.665***	-0.680***	-0.652***	-0.537***	-0.564***
	(0.034)	(0.034)	(0.058)	(0.039)	(0.067)	(0.042)	(0.034)	(0.045)
Tangibility	-0.102**	-0.101**	0.004	-0.062	-0.052	-0.063	-0.107**	-0.069
	(0.043)	(0.043)	(0.072)	(0.048)	(0.093)	(0.052)	(0.043)	(0.062)
Capex	0.000	0.000	-0.000	0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
R&D	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age	0.073***	0.073***	0.110***	0.077***	0.071***	0.051***	0.074***	0.074***
	(0.008)	(0.008)	(0.012)	(0.009)	(0.013)	(0.009)	(0.008)	(0.010)
Constant	-1.282***	-1.355***	-0.736***	-1.563***	-1.169***	-1.343***	-1.229***	-1.476***
	(0.049)	(0.061)	(0.046)	(0.059)	(0.073)	(0.066)	(0.053)	(0.071)
Obs	83964	83964	45699	75366	37407	64590	83964	54486
adj. R-sq	0.379	0.379	0.467	0.394	0.459	0.397	0.380	0.412
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.9: CEO Compensation

This table presents results from OLS regressions using the entire sample from 1994 to 2014. The dependent variable is total compensation in Panel A, equity pay ratio in Panel B. The primary explanatory variables are indicators including Dual, Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover and Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(3)	(7)	(8)
	CEO Total Compensation							
Dual	-0.503**	0.090	-0.112	-0.050	-0.303	-0.354	-0.173	-0.163
	(0.234)	(0.287)	(0.507)	(0.054)	(0.291)	(0.244)	(0.233)	(0.238)
Hightech*Dual		-1.429***						
		(0.521)						
Hightech		1.329***						
		(0.163)						
High R&D*Dual			-0.031					
			(0.576)					
High R&D			-0.136					
			(0.170)					
Highivol*Dual				-0.133*				
				(0.078)				
Highivol				-0.007				
				(0.022)				
High Analyst Dispersion*Dual					-0.277			
					(0.275)			
High Analyst Dispersion					-0.124			
					(0.091)			
LowIO*Dual						-1.445*		
						(0.851)		
LowIO						0.121		
						(0.138)		
No Analyst Cover*Dual							-1.233**	
							(0.510)	
No Analyst Cover							0.282**	
							(0.143)	
Low Investor Turnover*Dual								-0.567
								(0.446)
Low Investor Turnover								-0.201
								(0.144)
Log Assets	2.249***	1.679***	2.127***	0.456***	2.060***	2.191***	1.998***	2.009***
	(0.068)	(0.066)	(0.090)	(0.011)	(0.076)	(0.069)	(0.066)	(0.076)

Leverage	-4.040***	-2.998***	-5.840***	-0.473***	-3.333***	-4.006***	-4.149***	-3.367***
	(0.470)	(0.432)	(0.595)	(0.080)	(0.589)	(0.489)	(0.507)	(0.565)
Tobin's Q	0.357***	0.326***	0.315***	0.049***	0.391***	0.328***	0.328***	0.391***
	(0.056)	(0.053)	(0.072)	(0.010)	(0.075)	(0.055)	(0.066)	(0.070)
R&D	0.024***	0.014***	0.032***	0.006***	0.198***	0.013**	0.022***	0.176***
	(0.008)	(0.005)	(0.011)	(0.001)	(0.065)	(0.005)	(0.005)	(0.057)
Interest Exp	0.000*	0.000	0.005***	-0.000	0.004***	0.001***	0.004***	0.004***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Capex	-0.019	-0.029	-0.594	-0.000	-0.973**	-0.014	-0.020	-0.815*
	(0.024)	(0.028)	(0.401)	(0.002)	(0.437)	(0.019)	(0.021)	(0.421)
Advertising Exp	2.195	2.666	0.606	0.156	0.934	1.179	1.837	1.157
	(1.781)	(1.819)	(1.500)	(0.285)	(1.789)	(1.636)	(1.624)	(1.679)
Ind.Adj. ROA	0.650*	1.295***	1.312**	0.273***	2.011***	0.485	1.664***	1.901***
	(0.380)	(0.444)	(0.521)	(0.088)	(0.556)	(0.342)	(0.478)	(0.498)
Abnormal Ret	0.059	-0.081	0.610***	0.095***	0.816***	0.043	0.849***	0.781***
	(0.100)	(0.096)	(0.139)	(0.015)	(0.108)	(0.106)	(0.105)	(0.102)
Stock Return Volatility	2.070***	1.852***	2.240***	0.092*	1.840***	2.004***	1.423***	1.665***
	(0.251)	(0.254)	(0.291)	(0.052)	(0.348)	(0.271)	(0.275)	(0.313)
Firm Age	-0.006	-0.003	-0.003	-0.000	-0.003	-0.002	-0.005	-0.003
	(0.004)	(0.004)	(0.004)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
CEO Tenure	-0.005	-0.003	0.010	-0.005**	0.022**	-0.002	0.016	0.020**
	(0.010)	(0.009)	(0.009)	(0.002)	(0.010)	(0.010)	(0.010)	(0.010)
CEO Ownership	0.095**	0.107***	0.000	-0.007	-0.000	0.079*	0.000	0.000
	(0.039)	(0.037)	(0.000)	(0.008)	(0.000)	(0.040)	(0.000)	(0.000)
Constant	-12.500***	-12.586***	-9.717***	4.785***	-10.989***	-12.061***	-10.066***	-10.611***
	(0.594)	(0.562)	(0.747)	(0.096)	(0.775)	(0.609)	(0.733)	(0.760)
Obs	28072	28072	14001	28072	19231	25435	28072	19699
Adj R-sq	0.395	0.253	0.440	0.515	0.436	0.429	0.411	0.438
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equity Pay/ Total Compensation							
Dual	-0.510***	-0.130	-0.012	-0.556***	-0.051***	-0.043***	-0.035***	-0.040***
	(0.129)	(0.132)	(0.021)	(0.150)	(0.013)	(0.011)	(0.012)	(0.012)
Hightech*Dual		-0.683***						
		(0.255)						
Hightech		0.599***						
		(0.098)						
High R&D*Dual			-0.048*					
			(0.026)					

High R&D			0.042***					
			(0.011)					
Highivol*Dual				0.197				
				(0.207)				
Highivol				0.198**				
				(0.082)				
High Analyst Dispersion*Dual					0.039***			
					(0.015)			
High Analyst Dispersion					-0.022***			
					(0.005)			
LowIO*Dual						0.027		
						(0.027)		
LowIO						-0.041***		
						(0.008)		
No Analyst Cover*Dual							-0.024	
							(0.022)	
No Analyst Cover							-0.018***	
							(0.007)	
Low Investor Turnover*Dual								0.024
								(0.024)
Low Investor Turnover								-0.073***
								(0.007)
Log Assets	0.956***	0.698***	0.034***	0.964***	0.037***	0.039***	0.039***	0.036***
	(0.045)	(0.039)	(0.004)	(0.045)	(0.003)	(0.003)	(0.003)	(0.003)
Leverage	-2.302***	-1.437***	-0.192***	-2.319***	-0.117***	-0.148***	-0.148***	-0.142***
	(0.333)	(0.281)	(0.030)	(0.333)	(0.026)	(0.023)	(0.022)	(0.026)
Tobin's Q	0.286***	0.226***	0.008***	0.287***	0.013***	0.010***	0.010***	0.015***
	(0.058)	(0.045)	(0.003)	(0.058)	(0.003)	(0.003)	(0.003)	(0.003)
R&D	0.011***	0.005**	0.001**	0.012***	0.011**	0.002***	0.002***	0.009**
	(0.003)	(0.003)	(0.001)	(0.003)	(0.005)	(0.001)	(0.001)	(0.004)
Interest Exp	0.000	0.000	-0.000	0.000	-0.000**	-0.000**	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capex	-0.000	0.004	0.026	-0.001	-0.012	0.001	0.001	-0.004
	(0.010)	(0.008)	(0.022)	(0.011)	(0.022)	(0.001)	(0.001)	(0.021)
Advertising Exp	0.264	0.701	0.009	0.286	-0.008	0.026	0.021	-0.005
	(1.099)	(0.920)	(0.089)	(1.101)	(0.090)	(0.076)	(0.079)	(0.092)
Ind.Adj. ROA	1.185***	1.100***	0.099***	1.174***	0.082***	0.092***	0.093***	0.078***
	(0.345)	(0.312)	(0.029)	(0.343)	(0.031)	(0.027)	(0.025)	(0.028)
Abnormal Ret	0.403***	0.280***	0.005	0.404***	0.002	0.005	0.006	0.002
	(0.086)	(0.081)	(0.006)	(0.086)	(0.005)	(0.005)	(0.004)	(0.005)
Stock Return Volatility	1.488***	1.217***	0.083***	1.163***	0.129***	0.105***	0.083***	0.102***
	(0.198)	(0.178)	(0.019)	(0.209)	(0.019)	(0.015)	(0.014)	(0.017)

Firm Age	-0.004	-0.002	-0.000	-0.004	-0.000	-0.000*	-0.000**	-0.000
	(0.002)	(0.002)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
CEO Tenure	0.006	0.005	-0.001*	0.006	-0.001**	-0.001**	-0.001***	-0.001**
	(0.005)	(0.005)	(0.001)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
CEO Ownership	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CEO Age	-0.013**	-0.008	-0.003***	-0.013**	-0.002***	-0.002***	-0.002***	-0.002***
	(0.006)	(0.005)	(0.001)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-6.611***	-4.748***	0.008	-6.678***	-0.056	-0.041	-0.044	-0.036
	(0.462)	(0.401)	(0.041)	(0.468)	(0.036)	(0.033)	(0.031)	(0.035)
Obs	25153	25153	14001	25153	19231	23430	25153	19699
Adj R-sq	0.234	0.128	0.267	0.234	0.293	0.284	0.283	0.298
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.10: Payout

This table presents results from OLS regressions using the entire sample from 1994 to 2014. The dependent variable is the total payout in Panel A, payout ratio in Panel B, and cash dividend payout ratio in Panel C. The primary explanatory variables are interactions between Dual and Hightech, High R&D, Highivol, High Analyst Dispersion, Low IO, No Analyst Cover, Low Investor Turnover. Definitions of all variables are in Table IA.1. All standard errors are adjusted for sample clustering at the firm level and are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (1+Dividend+Repurchase)							
Dual	-0.125**	-0.061	-0.007	-0.197***	0.002	0.076	0.029	0.105
	(0.050)	(0.060)	(0.073)	(0.071)	(0.080)	(0.060)	(0.064)	(0.077)
Hightech*Dual		-0.219**						
		(0.107)						
Hightech		-0.418***						
		(0.037)						
High R&D*Dual			0.060					
			(0.132)					
High R&D			-0.230***					
			(0.029)					
Highivol*Dual				0.091				
				(0.073)				
Highivol				-0.808***				
				(0.022)				
High Analyst Dispersion*Dual					-0.074			
					(0.079)			
High Analyst Dispersion					-0.245***			
					(0.023)			
LowIO*Dual						-0.311***		
						(0.092)		
LowIO						0.044**		
						(0.022)		
No Analyst Cover*Dual							-0.343***	
							(0.082)	
No Analyst Cover							-0.013	
							(0.021)	
Low Investor Turnover*Dual								-0.336***
								(0.087)
Low Investor Turnover								0.232***
								(0.028)

Log Assets	0.500***	0.498***	0.487***	0.439***	0.649***	0.499***	0.497***	0.589***
	(0.007)	(0.007)	(0.011)	(0.008)	(0.013)	(0.010)	(0.008)	(0.010)
Sales Growth	-0.052***	-0.050***	-0.045***	-0.037***	-0.090***	-0.050***	-0.052***	-0.076***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.006)
Leverage	-1.303***	-1.355***	-1.211***	-1.117***	-1.705***	-1.414***	-1.291***	-1.576***
	(0.053)	(0.053)	(0.077)	(0.055)	(0.097)	(0.061)	(0.053)	(0.069)
Tobin's Q	0.010***	0.011***	-0.003	0.004	-0.008	0.006**	0.010***	0.015***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.007)	(0.003)	(0.003)	(0.004)
R&D	-0.333***	-0.060	-0.106	-0.193***	0.154	-0.340***	-0.339***	-0.262**
	(0.062)	(0.062)	(0.069)	(0.066)	(0.160)	(0.071)	(0.062)	(0.108)
ROA	-0.026	-0.016	-0.076***	-0.042	0.738***	0.037	-0.031	0.189***
	(0.023)	(0.022)	(0.023)	(0.028)	(0.102)	(0.032)	(0.022)	(0.049)
Firm Age	0.016***	0.016***	0.020***	0.014***	0.016***	0.023***	0.016***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capex	-1.533***	-1.538***	-1.376***	-1.347***	-2.325***	-1.217***	-1.550***	-1.844***
	(0.131)	(0.131)	(0.175)	(0.135)	(0.254)	(0.139)	(0.131)	(0.180)
Advertising Exp	0.650***	0.569***	0.597***	0.825***	1.289***	0.858***	0.634***	0.805***
	(0.156)	(0.150)	(0.209)	(0.160)	(0.298)	(0.178)	(0.154)	(0.218)
Cash	4.621***	4.524***	4.463***	6.258***	21.236***	6.999***	4.624***	5.868***
	(0.283)	(0.282)	(0.272)	(0.654)	(3.387)	(0.473)	(0.284)	(0.806)
Tangibility	0.613***	0.544***	0.605***	0.504***	0.957***	0.496***	0.617***	0.684***
	(0.066)	(0.066)	(0.104)	(0.069)	(0.117)	(0.072)	(0.066)	(0.085)
Market Value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.718***	-1.542***	-1.660***	-0.803***	-2.479***	-1.930***	-1.705***	-2.331***
	(0.047)	(0.050)	(0.063)	(0.060)	(0.092)	(0.069)	(0.053)	(0.073)
Obs	116253	116253	59835	103988	56298	87605	116253	78764
adj. R-sq	0.614	0.617	0.619	0.639	0.617	0.610	0.614	0.627
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(Dividend+Repurchase)/Market Value							
Dual	-0.002*	-0.001	0.002	-0.005***	-0.001	0.000	-0.000	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hightech*Dual		-0.002						
		(0.002)						
Hightech		-0.006***						
		(0.001)						
High R&D*Dual			-0.002					
			(0.002)					
High R&D			-0.006***					

			(0.001)					
Highivol*Dual				0.004***				
				(0.001)				
Highivol				-0.013***				
				(0.000)				
High Analyst Dispersion*Dual					-0.000			
					(0.001)			
High Analyst Dispersion					-0.000			
					(0.000)			
LowIO*Dual						-0.004***		
						(0.002)		
LowIO						-0.001		
						(0.001)		
No Analyst Cover*Dual							-0.003*	
							(0.002)	
No Analyst Cover							0.001	
							(0.000)	
Low Investor Turnover*Dual								-0.005***
								(0.002)
Low Investor Turnover								0.003***
								(0.001)
Log Assets	0.003***	0.003***	0.004***	0.002***	0.004***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***	-0.002***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Leverage	-0.007***	-0.008***	-0.008***	-0.000	-0.004*	-0.009***	-0.007***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Tobin's Q	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D	-0.011***	-0.007***	-0.005***	-0.009***	-0.007**	-0.011***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
ROA	0.004***	0.004***	0.001	0.005***	0.016***	0.003***	0.004***	0.009***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Firm Age	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capex	-0.026***	-0.026***	-0.016***	-0.022***	-0.038***	-0.018***	-0.025***	-0.038***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.003)	(0.003)	(0.005)
Advertising Exp	0.007**	0.006*	0.008**	0.012***	0.016**	0.013***	0.007**	0.008
	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)
Cash	0.045***	0.044***	0.035***	0.071***	0.249***	0.052***	0.045***	0.062***
	(0.009)	(0.009)	(0.005)	(0.009)	(0.033)	(0.006)	(0.009)	(0.014)
Tangibility	0.002	0.001	-0.006**	-0.002	0.007***	-0.001	0.002	0.007***

	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Constant	0.005***	0.007***	-0.004**	0.023***	0.002	0.000	0.004***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Obs	115874	115874	59647	103695	56262	87395	115874	78686
adj. R-sq	0.133	0.135	0.151	0.153	0.154	0.133	0.133	0.146
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel C

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dividend/Market Value							
Dual	-0.002***	-0.001	0.001	-0.004***	-0.002**	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hightech*Dual		-0.003**						
		(0.001)						
Hightech		-0.005***						
		(0.000)						
High R&D*Dual			-0.001					
			(0.002)					
High R&D			-0.005***					
			(0.000)					
Highivol*Dual				0.003***				
				(0.001)				
Highivol				-0.008***				
				(0.000)				
High Analyst Dispersion*Dual					0.001			
					(0.001)			
High Analyst Dispersion					0.001			
					(0.000)			
LowIO*Dual						-0.002**		
						(0.001)		
LowIO						-0.000		
						(0.000)		
No Analyst Cover*Dual							-0.002*	
							(0.001)	
No Analyst Cover							0.001***	
							(0.000)	
Low Investor Turnover*Dual								-0.002**
								(0.001)
Low Investor Turnover								0.003***
								(0.000)
Log Assets	0.002***	0.002***	0.003***	0.001***	0.003***	0.002***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Sales Growth	-0.001***	-0.001***	-0.001***	-0.000*	-0.001	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Leverage	-0.003**	-0.003***	0.000	0.002	-0.000	-0.005***	-0.003***	-0.007***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Tobin's Q	-0.000	-0.000	-0.000***	-0.000	-0.000***	-0.000***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D	-0.005***	-0.002**	-0.001	-0.004***	-0.005***	-0.003***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
ROA	0.003***	0.003***	0.000	0.003***	0.008***	0.002***	0.003***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Firm Age	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capex	-0.020***	-0.020***	-0.007**	-0.018***	-0.024***	-0.012***	-0.020***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)	(0.004)
Advertising Exp	-0.003	-0.004*	-0.003	-0.001	-0.004	0.002	-0.003	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)
Cash	0.042***	0.041***	0.026***	0.063***	0.185***	0.030***	0.041***	0.057***
	(0.008)	(0.008)	(0.004)	(0.009)	(0.025)	(0.004)	(0.008)	(0.013)
Tangibility	0.007***	0.006***	-0.004**	0.005***	0.011***	0.004***	0.007***	0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Constant	0.001	0.003***	-0.005***	0.013***	-0.002	-0.004***	0.000	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs	115874	115874	59647	103695	56262	87395	115874	78686
adj. R-sq	0.190	0.192	0.208	0.215	0.228	0.213	0.190	0.224
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Appendix C: Tables for Chapter 2

Table 1
Variables Summary Statistics

Pa presents the statistics of variables used in the analysis of intended places of work. Panel B presents the statistics of variables used in the analysis of air pollution monitoring program. Panel C presents the statistics of variables used in the analysis of the QH heating policy and the thermal inversion strength. All variables are defined in Table IA2.

Panel A: the analysis of intended places of work

Variables	(1) N	(2) Mean	(3) S.D.	(4) P25	(5) P50	(6) P75
To work in Beijing	282,630	1.01	1.81	0.00	0.00	0.00
To work in Shenzhen	282,630	0.84	1.69	0.00	0.00	0.00
To work in more polluted cities	282,630	1.07	1.47	0.00	0.00	2.52
To work in less polluted cities	282,630	1.42	1.60	0.00	0.00	2.58
Pollution days	282,630	0.39	0.49	0.00	0.00	1.00
Education expenditure	282,630	0.03	0.05	0.02	0.03	0.04
GDP growth	282,630	0.16	2.33	0.06	0.08	0.11
GDP per capita	282,630	6.10	5.33	2.91	4.54	7.15
Population	282,630	15.21	0.66	14.81	15.23	15.67
Temperature	282,630	15.15	4.56	13.96	16.00	17.42
Relative humidity	282,630	67.93	10.65	58.08	69.17	77.08
Precipitation	282,630	91.66	52.44	47.42	80.67	128.19
Sunshine hours	282,630	157.39	42.79	126.87	155.32	188.35
Health beta	282,630	0.01	0.13	-0.05	0.01	0.07

Panel B: the analysis of air pollution monitoring program

Variables	(1) N	(2) Mean	(3) S.D.	(4) P25	(5) P50	(6) P75
Non-locally born executives	9,243	0.37	0.48	0.00	0.00	1.00
Non-locally educated executives	9,990	0.47	0.50	0.00	0.00	1.00
Executives with overseas experience	12,593	0.10	0.30	0.00	0.00	0.00
% of highly educated employees	14,968	0.26	0.21	0.10	0.19	0.36
% of employees with a low level of education	15,641	0.70	0.42	0.41	0.66	0.92
% of skilled employees	15,109	0.19	0.15	0.09	0.14	0.24
% of production and sales employees	14,542	0.14	0.17	0.03	0.07	0.17
% of financial and administrative employees	14,095	0.14	0.11	0.07	0.12	0.18
TFP	15,817	0.14	0.31	0.01	0.04	0.12
Q	16,008	2.84	2.31	1.45	2.09	3.31
High pollution	14,765	0.51	0.50	0.00	1.00	1.00
Monitor	16,008	0.65	0.48	0.00	1.00	1.00
Firm size	16,008	22.02	1.39	21.04	21.82	22.75
Leverage	16,008	0.44	0.23	0.25	0.43	0.61
Cash flow	16,008	0.06	0.06	0.03	0.06	0.09
Capital expenditure	16,008	0.04	0.06	0.00	0.02	0.06
Firm age	16,008	2.00	0.95	1.39	2.20	2.83
Executive age	16,008	3.92	0.10	3.87	3.92	3.99
SOEs	16,008	0.37	0.48	0.00	0.00	1.00
Education expenditure	16,008	0.03	0.01	0.02	0.02	0.03
GDP growth	16,008	0.11	0.05	0.08	0.10	0.12
GDP per capita	16,008	13.41	11.07	5.95	11.01	16.38
Population	16,008	15.63	0.67	15.16	15.70	16.13
Temperature	16,008	16.43	3.92	14.57	16.79	18.16
Relative humidity	16,008	68.54	10.21	58.33	71.17	75.83

Precipitation	16,008	105.49	53.16	64.78	92.38	144.17
Sunshine hours	16,008	154.56	38.17	126.87	149.66	184.48

Panel C: the analysis of QH heating policy and thermal inversion strength

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	N	Mean	S.D.	P25	P50	P75
Non-locally born executives	17,952	0.36	0.48	0.00	0.00	1.00
Non-locally educated executives	15,998	0.49	0.50	0.00	0.00	1.00
Executives with overseas experience	19,114	0.09	0.29	0.00	0.00	0.00
% of highly educated employees	14,968	0.26	0.21	0.10	0.19	0.36
% of employees with a low level of education	15,641	0.70	0.42	0.41	0.66	0.92
% of skilled employees	15,109	0.19	0.15	0.09	0.14	0.24
% of production and sales employees	14,542	0.14	0.17	0.03	0.07	0.17
% of financial and administrative employees	14,095	0.14	0.11	0.07	0.12	0.18
TFP	31,393	0.12	0.29	0.01	0.03	0.09
Q	31,776	2.71	2.13	1.42	2.05	3.17
QH	31,776	0.36	0.48	0.00	0.00	1.00
AQI	26,366	87.91	26.85	70.27	82.64	98.87
TI	31,776	0.34	0.31	0.11	0.24	0.45
Firm size	31,776	21.68	1.35	20.77	21.50	22.36
Leverage	31,776	0.47	0.25	0.30	0.46	0.62
Cash flow	31,776	0.05	0.07	0.03	0.06	0.09
Capital expenditure	31,776	0.05	0.07	0.00	0.02	0.06
Firm age	31,776	1.91	0.90	1.39	2.08	2.64
Executive age	31,776	3.89	0.11	3.83	3.89	3.96
SOEs	31,776	0.40	0.49	0.00	0.00	1.00
Education expenditure	31,776	0.02	0.01	0.01	0.02	0.03
GDP growth	31,776	0.13	0.07	0.09	0.12	0.17
GDP per capita	31,776	9.59	9.99	2.97	6.51	13.15
Population	31,776	15.57	0.72	15.12	15.67	16.11
Temperature	31,776	16.31	4.17	14.08	16.79	18.22
Relative humidity	31,776	67.80	9.50	59.08	70.25	74.58
Precipitation	31,776	97.44	49.46	58.21	89.75	128.19
Sunshine hours	31,776	155.08	37.91	131.91	150.10	184.26

Table 2

The Impact of Air Pollution on Intended Workplaces

DID models estimate the effect of air pollution on people's intended workplaces. A day in a municipal region is defined to experience a pollution day (day 0) if the increase in daily AQI exceeds one standard of the daily AQI change in the past one year in the region. *Pollution days* refers to a five-day window from pollution day 0 to day 4 in a region. The intention of people in a region to work in a specific city is measured by the Baidu Search Volume Index (SVI). Columns (1) and (2) show the estimates for people's intention to work in Beijing and Shenzhen. Columns (3) and (4) show the estimates for people's intention to work in the top work-intended cities in China, which are grouped into more and less polluted cities. In all regressions, regional characteristics, city and date fixed effects are included. Variables are defined in Table IA.2. The sample period is from 2011 to 2016, with daily observations. t-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	*To work in Beijing*	*To work in Shenzhen*	*To work in more polluted cities*	*To work in less polluted cities*
Pollution days	**-0.075*****	**0.045*****	**-0.074*****	**0.015*****
	(-11.86)	**(7.15)**	**(-15.79)**	**(2.86)**
Education expenditures	1.048***	0.705***	0.679***	0.214***
	(13.75)	(10.26)	(12.18)	(3.44)
GDP growth	-0.002	0.002	0.002	-0.006***
	(-1.33)	(1.10)	(1.58)	(-5.91)
GDP per capita	0.168***	0.133***	0.130***	0.049***
	(31.11)	(27.41)	(35.11)	(12.15)
Population	1.515***	0.978***	1.459***	0.920***
	(18.45)	(14.90)	(24.26)	(14.33)
Temperature	0.048***	0.036***	0.053***	-0.028***
	(3.93)	(3.28)	(6.03)	(-3.07)
Relative humidity	-0.001	-0.004***	0.000	-0.005***
	(-0.39)	(-2.87)	(0.36)	(-3.89)
Precipitation	0.000	0.000**	0.001***	0.001***
	(0.92)	(2.41)	(4.25)	(4.80)
Sunshine hours	0.000	0.000	-0.001***	0.001***
	(0.55)	(1.23)	(-4.44)	(4.04)
City and date fixed effects	Yes	Yes	Yes	Yes
Observations	282,630	282,630	282,630	282,630
R-squared	0.409	0.380	0.521	0.524

Table 3
The Pollution-induced Health Concerns

DID models estimate how the effect of air pollution on people's intended places of work varies with health concern induced by air pollution. The intensity of people's concern for health is measured by *Health beta*, which is the sensitivity of the change in daily Baidu Search Volume Index of "health (健康)" to the change in AQI in a region in a year. A day in a municipal region is defined to experience a pollution day (day 0) if the increase in daily AQI exceeds one standard of the daily AQI change in the past one year in the region. *Pollution days* refers to a five-day window from pollution day 0 to day 4 in a region. The intention of people in a region to work in a specific city is measured by the Baidu Search Volume Index (SVI). Columns (1) and (2) show the estimates for people's intention to work in Beijing and Shenzhen. Columns (3) and (4) show the estimates for people's intention to work in the top work-intended cities in China, which are grouped into more and less polluted cities. In all regressions, regional characteristics, city and date fixed effects are included. Variables are defined in Table IA.2. The sample period is from 2011 to 2016, with daily observations. t-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	*To work in Beijing*	*To work in Shenzhen*	*To work in more polluted cities*	*To work in less polluted cities*
Pollution days × Health beta	**-0.082****	**0.106*****	**-0.052****	**0.082****
	(-2.48)	**(2.87)**	**(-1.98)**	**(2.41)**
Pollution days	-0.075***	0.043***	-0.074***	0.014***
	(-11.77)	(6.86)	(-15.74)	(2.61)
Health beta	-0.011	-0.303***	-0.005	-0.229***
	(-0.39)	(-10.00)	(-0.25)	(-8.65)
Education expenditures	1.050***	0.721***	0.680***	0.226***
	(13.78)	(10.49)	(12.20)	(3.64)
GDP growth	-0.002	0.001	0.002	-0.006***
	(-1.37)	(0.91)	(1.55)	(-6.13)
GDP per capita	0.168***	0.135***	0.130***	0.051***
	(31.12)	(27.82)	(35.05)	(12.64)
Population	1.502***	0.926***	1.451***	0.881***
	(18.31)	(14.17)	(24.24)	(13.74)
Temperature	0.048***	0.037***	0.053***	-0.026***
	(3.92)	(3.43)	(6.03)	(-2.94)
Relative humidity	-0.000	-0.003**	0.001	-0.004***
	(-0.25)	(-2.03)	(0.48)	(-3.19)
Precipitation	0.000	0.000**	0.001***	0.001***
	(0.90)	(2.27)	(4.24)	(4.68)
Sunshine hours	0.000	0.000	-0.001***	0.001***
	(0.59)	(1.25)	(-4.41)	(4.06)
City and date fixed effects	Yes	Yes	Yes	Yes
Observations	282,630	282,630	282,630	282,630
R-squared	0.409	0.381	0.521	0.525

Table 4
The Air Pollution Monitoring Program and Executive Talent

DID models estimate the impact of air pollution monitoring program on executive talent. The dependent variables are executive human capital measures, including *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*. The key independent variables are *High pollution* and *Monitor*. *High pollution* equals 1 if the average AQI of a city is above the median of all cities in 2011 and 2012. *Monitor* equals 1 if the city a firm located has been included in the air pollution monitoring and disclosure program, and 0 otherwise. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. The sample period is from 2011 to 2016. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
Dependent variables	*Non-locally born executives*	*Non-locally educated executives*	*Executives with overseas experience*
High pollution × Monitor	**-0.185*** **	**-0.158*** **	**-0.043**
	(-3.34)	**(-2.91)**	**(-0.60)**
Monitor	0.220***	0.266***	0.032
	(3.59)	(4.58)	(0.36)
Firm size	0.071**	0.037	0.113***
	(2.53)	(1.45)	(3.93)
Leverage	0.349**	0.231	-0.471***
	(1.98)	(1.59)	(-2.65)
Cash flow	-0.367	0.290	-0.460
	(-0.84)	(0.73)	(-0.91)
Capital expenditure	-0.119	-0.130	0.194
	(-0.37)	(-0.47)	(0.58)
Firm age	0.096*	0.143***	-0.107**
	(1.91)	(3.09)	(-1.99)
Executive age	-0.276	-0.532*	-0.681**
	(-0.88)	(-1.92)	(-2.05)
SOEs	0.027	-0.233***	-0.372***
	(0.35)	(-3.19)	(-4.45)
Education expenditure	-9.761***	-3.688	0.572
	(-3.12)	(-1.37)	(0.14)
GDP growth	-0.234	-0.015	-0.107
	(-0.59)	(-0.05)	(-0.21)
GDP per capita	-0.083***	-0.024	0.003
	(-4.91)	(-1.54)	(0.17)
Population	-0.552*	-0.777**	-0.268
	(-1.83)	(-2.38)	(-0.57)
Temperature	0.084***	0.081***	-0.017
	(2.97)	(2.68)	(-0.42)
Relative humidity	0.005	0.006	-0.003
	(0.72)	(0.99)	(-0.30)
Precipitation	0.003***	0.001	0.001
	(3.80)	(1.41)	(0.63)
Sunshine hours	-0.004***	-0.003***	0.000
	(-3.10)	(-2.81)	(0.20)
Year, industry, and city FEs	Yes	Yes	Yes
Observations	8,142	9,007	10,052
R-squared	0.153	0.104	0.116
Marginal effects	-0.059	-0.056	-0.007

Table 5
The Air Pollution Monitoring Program and Employee Human Capital

DID models estimate the impact of air pollution monitoring program on employee human capital. The dependent variables are employee human capital by education and job functions. Variables by education are *% of high education employees* and *% of low education employees*. Variables by job functions are *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. The key independent variables are *High pollution* and *Monitor*. *High pollution* equals 1 if the average AQI of a city is above the median of all cities in 2011 and 2012. *Monitor* equals 1 if the city a firm located is or has been included in the air pollution monitoring and disclosure program, and 0 otherwise. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. The sample period is from 2011 to 2016. t-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: by education		**Panel B: by job functions**		
	(1)	(2)	(3)	(4)	(5)
Dependent variables	*% of high education employees*	*% of low education employees*	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
High pollution × Monitor	**-0.011****	-0.002	**-0.013*****	-0.002	0.005
	(-2.06)	(-0.15)	**(-3.16)**	(-0.53)	(1.44)
Monitor	0.007*	-0.054***	0.006*	0.002	-0.002
	(1.84)	(-3.69)	(1.78)	(0.47)	(-0.79)
Firm size	0.010***	-0.029***	-0.002	0.005**	-0.016***
	(3.27)	(-5.04)	(-0.94)	(2.23)	(-8.65)
Leverage	-0.076***	0.094***	-0.066***	-0.017	0.019*
	(-4.56)	(2.98)	(-5.39)	(-1.23)	(1.91)
Cash flow	-0.014	-0.221**	-0.010	0.134***	-0.055**
	(-0.32)	(-2.49)	(-0.29)	(3.90)	(-2.18)
Capital expenditure	-0.260***	0.158***	-0.110***	-0.142***	-0.075***
	(-9.16)	(2.78)	(-5.47)	(-5.84)	(-4.62)
Firm age	-0.016***	0.034***	-0.015***	-0.013***	0.024***
	(-3.31)	(3.65)	(-3.91)	(-3.10)	(8.49)
Executive age	-0.070**	0.104*	0.031	0.035	-0.038**
	(-2.49)	(1.89)	(1.52)	(1.41)	(-2.49)
SOEs	0.010	0.002	0.007	-0.020***	-0.012***
	(1.23)	(0.13)	(1.18)	(-2.82)	(-2.68)
Education expenditure	-0.374	-0.632	-0.117	0.310	-0.039
	(-1.53)	(-0.94)	(-0.62)	(1.42)	(-0.25)
GDP growth	0.048	-0.184**	-0.004	0.000	0.003
	(1.44)	(-2.08)	(-0.15)	(0.00)	(0.14)
GDP per capita	-0.002*	0.001	-0.000	0.001	-0.000
	(-1.78)	(0.24)	(-0.45)	(0.65)	(-0.01)
Population	-0.041	-0.056	-0.005	-0.000	-0.016
	(-1.42)	(-0.75)	(-0.21)	(-0.02)	(-0.71)
Temperature	-0.000	0.002	0.002	0.002	0.001
	(-0.19)	(0.26)	(0.96)	(0.90)	(0.57)
Relative humidity	-0.000	-0.001	0.000	0.000	-0.000
	(-0.70)	(-0.44)	(0.52)	(0.23)	(-0.86)
Precipitation	-0.000	0.000	0.000	-0.000	0.000**
	(-0.48)	(0.06)	(0.31)	(-0.76)	(2.09)
Sunshine hours	-0.000	0.000	-0.000	-0.000	-0.000
	(-0.63)	(0.23)	(-0.29)	(-1.37)	(-1.59)
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes
Observations	13,763	14,416	13,897	13,341	12,949
R-squared	0.434	0.301	0.358	0.334	0.271

Table 6
The Air Pollution Monitoring Program and the Movement of Executives

DID models estimate the impact of air pollution monitoring program on executive movement. The dependent variables are the percentage of new executives (general managers and board of directors) that move from firms located in an area with AQI lower than the AQI in the area of the current firms (column 1), and the percentage of resigned executives that move to firms located in an area with AQI lower than the AQI in the area of the previous firms (column 2). The key independent variables are *High pollution* and *Monitor*. *High pollution* equals 1 if the average AQI of a city is above the median of all cities in 2011 and 2012. *Monitor* equals 1 if the city a firm located is or has been included in the air pollution monitoring and disclosure program, and 0 otherwise. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. The sample period is from 2011 to 2016. t-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)
Dependent variables	*New executives moving from clean areas/total new executives*	*Resigned executives going to clean areas/total resigned executives*
High pollution × Monitor	**-0.019***	**0.017****
	(-1.88)	**(2.19)**
Monitor	0.038***	0.008
	(2.81)	(0.69)
Firm size	0.005**	0.004*
	(2.28)	(1.82)
Leverage	0.012	0.008
	(0.88)	(0.75)
Cash flow	-0.025	-0.064
	(-0.49)	(-1.61)
Capital expenditure	-0.008	0.043
	(-0.19)	(1.35)
Firm age	-0.001	0.010***
	(-0.13)	(3.24)
Executive age	-0.011	-0.069***
	(-0.48)	(-3.57)
SOEs	-0.018***	-0.008*
	(-2.80)	(-1.65)
Education expenditure	-0.724	0.262
	(-1.02)	(0.37)
GDP growth	-0.159**	0.042
	(-2.03)	(0.72)
GDP per capita	0.009***	-0.000
	(2.78)	(-0.02)
Population	-0.128**	-0.074*
	(-2.31)	(-1.89)
Temperature	-0.009	0.010
	(-1.06)	(1.38)
Relative humidity	-0.002*	0.002
	(-1.77)	(1.62)
Precipitation	-0.000*	-0.000
	(-1.94)	(-0.70)
Sunshine hours	-0.001***	-0.000*
	(-2.71)	(-1.94)
Year, industry, and city FEs	Yes	Yes
Observations	14,765	14,765
R-squared	0.085	0.083

Table 7
The QH Heating Policy and Executive Talent

RDD models estimating the impact of Qinling Huai-River (QH) heating policy on executive talent. The dependent variables are executive human capital measures, including *Non-locally born executives, Non-locally educated executives*, and *Executives with overseas experience*. The key independent variable is *QH*, which equals 1 if a firm is located in a region where the central heating policy applies, and 0 otherwise. Variables are defined in Table IA.2. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. The sample period is from 2000 to 2016. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Dependent variables	(1) *Non-locally born executives*	(2) *Non-locally educated executives*	(3) *Executives with overseas experience*
QH	**-0.682*** **	**-0.529*** **	**-0.373** **
	(-3.60)	**(-3.06)**	**(-2.09)**
Firm size	0.085***	0.063***	0.088***
	(3.58)	(2.90)	(3.62)
Leverage	0.280**	0.045	-0.368***
	(2.13)	(0.41)	(-2.61)
Cash flow	-0.442	0.216	-0.350
	(-1.51)	(0.77)	(-0.88)
Capital expenditure	-0.108	-0.314	0.410*
	(-0.50)	(-1.47)	(1.65)
Firm age	0.092***	0.113***	-0.037
	(2.83)	(3.76)	(-1.17)
Executive age	-0.364*	-0.776***	-0.758***
	(-1.65)	(-3.58)	(-2.78)
SOEs	0.036	-0.200***	-0.324***
	(0.58)	(-3.31)	(-4.86)
Education expenditure	14.924***	4.908	3.301
	(4.24)	(1.48)	(0.80)
GDP growth	0.065	0.021	-0.096
	(0.24)	(0.07)	(-0.27)
GDP per capita	0.020***	0.015***	0.013***
	(5.41)	(4.47)	(3.84)
Population	0.103*	-0.156***	-0.001
	(1.80)	(-3.00)	(-0.01)
Temperature	0.031	-0.038	0.034
	(1.24)	(-1.62)	(1.20)
Relative humidity	-0.006	-0.011*	0.008
	(-1.04)	(-1.90)	(1.23)
Precipitation	-0.000	-0.001	0.000
	(-0.34)	(-1.35)	(0.35)
Sunshine hours	-0.001	-0.004***	-0.000
	(-0.61)	(-3.22)	(-0.15)
Polynomial	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	17,952	15,998	19,114
R-squared	0.087	0.081	0.065
Marginal effects	-0.231	-0.193	-0.068

Table 8
The QH Heating Policy and Employee Human Capital

RDD models estimating the impact of Qinling Huai-River (QH) heating policy on corporate employee human capital. The dependent variables are employee human capital by education and job functions. Variables by education are *% of high education employees* and *% of low education employees*. Variables by job functions are *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. The key independent variable is *QH*, which equals 1 if a firm is located in a region where the central heating policy applies, and 0 otherwise. Variables are defined in Table IA.2. In all regressions, cubic polynomials are included; firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. The sample period is from 2011 to 2016. t-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: by education		**Panel B: by job functions**		
	(1)	(2)	(3)	(4)	(5)
Dependent variables	*% of high education employees*	*% of low education employees*	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
QH	**-0.051*****	0.034	**-0.028****	-0.003	-0.005
	(-2.75)	(0.93)	**(-2.13)**	(-0.19)	(-0.50)
Firm size	0.011***	-0.027***	-0.001	0.006***	-0.017***
	(3.86)	(-4.98)	(-0.37)	(2.66)	(-9.68)
Leverage	-0.087***	0.075**	-0.074***	-0.033***	0.018*
	(-5.64)	(2.51)	(-6.78)	(-2.70)	(1.94)
Cash flow	-0.022	-0.321***	-0.017	0.123***	-0.032
	(-0.50)	(-3.67)	(-0.52)	(3.50)	(-1.31)
Capital expenditure	-0.280***	0.240***	-0.113***	-0.153***	-0.099***
	(-9.96)	(4.32)	(-5.59)	(-6.48)	(-6.26)
Firm age	-0.008**	0.048***	-0.008***	-0.007**	0.020***
	(-2.44)	(7.85)	(-3.30)	(-2.39)	(10.40)
Executive age	-0.061**	0.089*	0.029	0.034	-0.037**
	(-2.34)	(1.71)	(1.49)	(1.48)	(-2.56)
SOEs	0.017**	-0.023*	0.006	-0.023***	-0.009**
	(2.30)	(-1.66)	(1.22)	(-3.65)	(-2.26)
Education expenditure	-0.692**	0.998	-0.489**	0.444	0.083
	(-2.22)	(1.54)	(-2.15)	(1.49)	(0.44)
GDP growth	0.207***	-0.415***	0.047	0.150***	0.007
	(4.91)	(-4.60)	(1.51)	(4.04)	(0.27)
GDP per capita	0.001***	-0.001**	0.001**	0.000	-0.000
	(3.41)	(-2.08)	(2.32)	(1.35)	(-0.79)
Population	0.053***	-0.084***	0.026***	0.019***	0.013***
	(10.24)	(-7.90)	(6.92)	(4.37)	(4.84)
Temperature	0.002	-0.007	0.002	0.002	-0.001
	(0.98)	(-1.41)	(1.05)	(1.11)	(-0.95)
Relative humidity	-0.001	0.000	-0.001**	-0.000	-0.000
	(-1.12)	(0.15)	(-1.97)	(-0.53)	(-0.79)
Precipitation	-0.000**	0.000	0.000	-0.000	0.000
	(-2.56)	(1.26)	(1.22)	(-0.07)	(0.11)
Sunshine hours	0.000	-0.001*	-0.000	0.000	-0.000
	(1.10)	(-1.68)	(-0.60)	(1.47)	(-0.17)
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes	Yes
Observations	13,763	14,416	13,897	13,341	12,949
R-squared	0.434	0.301	0.358	0.334	0.271

Table 9
The Thermal Inversion Strength and Executive Talent

2SLS models estimating the impact of air pollution on executive talent. Executive human capital measures are *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience.* Air pollution is measured by *AQI.* The instrumental variable (IV) for *AQI* is the thermal inversion strength (*TI*), which is the daily average of above-ground temperature minus ground temperature in a region. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. The sample period is from 2000 to 2016. Columns 1 and 2 present the 1st and the 2nd stage estimated results for the model of *Non-locally born executives*, respectively. In other models, only the 2nd stage results are reported. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. The F-statistic of the IV strength test is reported on the bottom of the column. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	*AQI*	*Non-locally born executives*	*Non-locally educated executives*	*Executives with overseas experience*
TI	**0.031***** **(5.19)**			
Fitted AQI		**-1.513**** **(-2.24)**	**-4.215***** **(-2.95)**	**-3.004***** **(-3.55)**
Firm size	-0.000 (-0.02)	0.032*** (8.65)	0.028*** (4.38)	0.017*** (4.48)
Leverage	0.008 (1.25)	0.115*** (4.82)	0.089** (2.25)	-0.029 (-1.18)
Cash flow	0.015 (0.70)	-0.183** (-2.37)	0.192 (1.62)	0.038 (0.47)
Capital expenditure	-0.019 (-0.98)	-0.044 (-0.65)	-0.109 (-1.02)	0.042 (0.62)
Firm age	-0.003* (-1.89)	0.023*** (3.77)	0.023** (2.08)	-0.012** (-2.13)
Executive age	-0.034*** (-2.81)	-0.176*** (-3.68)	-0.234*** (-3.49)	-0.161*** (-3.62)
SOEs	-0.002 (-0.69)	0.013 (1.31)	-0.078*** (-4.74)	-0.045*** (-4.53)
Education expenditure	-3.329*** (-17.65)	2.337 (0.96)	-13.124** (-2.35)	-10.898*** (-3.20)
GDP growth	0.252*** (9.61)	0.364* (1.83)	1.380*** (2.91)	0.782*** (3.23)
GDP per capita	-0.000 (-0.19)	0.007*** (12.75)	0.003*** (3.43)	0.000 (0.67)
Population	0.019*** (7.31)	0.049*** (3.02)	0.031 (1.03)	0.051*** (3.14)
Temperature	0.026*** (21.23)	0.054*** (3.06)	0.085** (2.42)	0.081*** (3.60)
Relative humidity	0.001 (1.63)	0.002* (1.77)	-0.005** (-2.39)	0.005*** (3.58)
Precipitation	-0.001*** (-19.31)	-0.002** (-2.28)	-0.005*** (-2.99)	-0.004*** (-3.48)
Sunshine hours	-0.001*** (-15.67)	-0.002** (-1.99)	-0.006*** (-3.60)	-0.004*** (-3.44)
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes
Observations	14,980	14,980	13,907	16,751
F-statistic for weak identification		26.91	13.99	18.26

Table 10
The Thermal Inversion Strength and Employee Human Capital

2SLS models estimating the impact of air pollution on corporate employee human capital. Employee human capital is measured by education and job functions. Variables by education are *% of high education employees* and *% of low education employees*. Variables by job functions are *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. Air pollution is measured by *AQI*. The instrumental variable (IV) for *AQI* is the thermal inversion strength (*TI*), which is the daily average of above-ground temperature minus ground temperature in a region. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. The sample period is from 2011 to 2016. Columns 1 and 2 presents the 1st and the 2nd stage estimated results for the model of *% of high education employees*, respectively. Columns 4 and 5 presents the 1st and the 2nd stage estimated results for the model of *% of skilled employees*, respectively. In other models, only the 2nd stage results are reported. t-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. The F-statistic of the IV strength test is reported on the bottom of the column. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	Panel A: by education			**Panel B: by job functions**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variables	*AQI*	*% of high education employees*	*% of low education employees*	*AQI*	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
TI	**0.023***** **(4.27)**			**0.034***** **(5.41)**			
Fitted AQI		**-0.714**** **(-2.55)**	-0.162 (-0.36)		**-0.108** **(-0.58)**	-0.169 (-0.91)	-0.017 (-0.13)
Firm size	0.001 (1.26)	0.011*** (6.91)	-0.028*** (-9.71)	0.000 (0.24)	-0.000 (-0.12)	0.007*** (5.37)	-0.018*** (-22.06)
Leverage	0.013** (2.15)	-0.080*** (-7.61)	0.074*** (4.09)	0.007 (0.89)	-0.078*** (-11.65)	-0.032*** (-4.21)	0.020*** (4.01)
Cash flow	0.038* (1.89)	-0.023 (-0.68)	-0.332*** (-5.55)	-0.004 (-0.17)	-0.022 (-0.99)	0.116*** (4.69)	-0.037** (-2.30)
Capital expenditure	-0.013 (-0.70)	-0.303*** (-10.12)	0.268*** (5.03)	-0.010 (-0.47)	-0.132*** (-6.84)	-0.156*** (-7.00)	-0.097*** (-6.62)
Firm age	-0.002 (-1.60)	-0.009*** (-4.10)	0.048*** (11.97)	-0.002 (-1.52)	-0.008*** (-5.18)	-0.008*** (-4.36)	0.020*** (18.11)
Executive age	-0.019 (-1.63)	-0.076*** (-3.97)	0.070** (2.07)	-0.022* (-1.69)	0.035*** (2.81)	0.034** (2.41)	-0.032*** (-3.58)
SOEs	-0.000 (-0.07)	0.014*** (3.34)	-0.018** (-2.34)	-0.000 (-0.05)	0.006** (1.99)	-0.022*** (-7.07)	-0.010*** (-4.64)
Education expenditure	-3.845*** (-22.56)	-2.826*** (-2.79)	-0.158 (-0.10)	-3.433*** (-19.10)	-0.808 (-1.20)	-0.026 (-0.04)	0.140 (0.30)
GDP growth	0.258*** (10.05)	0.580*** (4.04)	-0.343 (-1.51)	0.463*** (13.58)	0.107 (1.20)	0.236*** (2.62)	0.024 (0.40)

GDP per capita	-0.000***	0.000	-0.001**	-0.001***	0.000	-0.000	-0.000
	(-3.24)	(0.36)	(-2.03)	(-7.26)	(1.46)	(-0.06)	(-0.84)
Population	0.016***	0.073***	-0.078***	0.027***	0.030***	0.024***	0.015***
	(6.60)	(8.85)	(-5.65)	(10.00)	(5.27)	(3.81)	(3.47)
Temperature	0.026***	0.016***	-0.004	0.021***	0.005	0.006	-0.002
	(22.83)	(2.76)	(-0.43)	(15.44)	(1.16)	(1.56)	(-0.76)
Relative humidity	0.001***	0.002**	-0.000	0.003***	-0.000	0.000	-0.000
	(4.21)	(2.46)	(-0.06)	(8.88)	(-0.37)	(0.62)	(-0.41)
Precipitation	-0.001***	-0.001***	0.000	-0.001***	-0.000	-0.000	-0.000
	(-22.35)	(-3.12)	(0.14)	(-20.84)	(-0.20)	(-0.89)	(-0.24)
Sunshine hours	-0.001***	-0.001*	-0.001	-0.002***	-0.000	-0.000	-0.000
	(-15.68)	(-1.85)	(-1.03)	(-17.84)	(-0.62)	(-0.19)	(-0.37)
Year, industry, and longitude FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,935	13,935	14,481	13,999	13,999	13,468	13,079
F-statistic for weak identification		22.91	29.27		21.03	26.54	23.62

Table 11

The Effect of Air Pollution and Heterogeneity on Concern for Health

The impact of heterogeneity in concern for health on the effect of air pollution. Panel A presents the DID estimates based on the setting of the air pollution monitoring program. *High pollution* equals 1 if the average AQI of a city is above the median of all cities in 2011 and 2012. *Monitor* equals 1 if the city a firm located is or has been included in the air pollution monitoring and disclosure program, and 0 otherwise. Panel B presents the RDD estimates based on the setting of the QH heating policy. *QH* equals 1 if a firm is located in a region where the central heating policy applies, and 0 otherwise. Panel C presents the 2SLS estimates. The instrumental variable (IV) for *AQ*I is the thermal inversion strength, which is the daily average of above-ground temperature minus ground temperature in a region. The dependent variables are executive human capital measures, *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience* (columns 1-3), employee measures by education, *% of high education employees* and *% of low education employees* (columns 4-5), and employee measures by job functions, *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees* (columns 6-7). The key independent variable is *High beta*, which equals 1 if the sensitivity of the change in daily Baidu Search Volume Index for the keyword "health (健康)" to the change in AQI (*Health beta*) in a region in a year is above the median, and 0 otherwise. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. The sample period is from 2011 to 2016. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: DID and the air pollution monitoring program

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables	*Non-locally born executives*	*Non-locally educated executives*	*Executives with overseas experience*	*% of highly educated employees*	*% of employees with a low level of education*	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
High pollution × Monitor × High beta	**-0.160*****	**-0.124****	**0.101**	**-0.007**	0.021	**-0.006***	0.000	-0.003
	(-2.94)	**(-2.45)**	**(1.43)**	**(-1.60)**	(1.23)	**(-1.87)**	(0.01)	(-0.66)
High pollution × Monitor	-0.117*	-0.122*	-0.118	-0.008	-0.008	-0.011***	-0.002	0.006
	(-1.82)	(-1.93)	(-1.38)	(-1.26)	(-0.52)	(-2.76)	(-0.40)	(1.41)
High pollution × High beta	0.042	-0.336	-0.822***	-0.007	-0.055	-0.006	0.003	-0.008
	(0.24)	(-1.48)	(-2.80)	(-0.56)	(-0.85)	(-0.59)	(0.12)	(-0.44)
Monitor × High beta	-0.012	-0.051	-0.075	0.001	0.012	0.004	-0.003	-0.000
	(-0.21)	(-0.94)	(-0.95)	(0.26)	(0.69)	(1.24)	(-0.40)	(-0.09)
Monitor	0.208***	0.285***	0.069	0.005	-0.061***	0.003*	0.003	-0.002
	(2.93)	(3.90)	(0.64)	(1.10)	(-2.92)	(1.70)	(0.35)	(-0.41)
High beta	0.024	0.074*	0.100	-0.002	-0.017	-0.002	0.001	0.002
	(0.52)	(1.67)	(1.52)	(-0.62)	(-1.40)	(-0.95)	(0.12)	(0.47)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,142	9,007	10,052	13,763	14,416	13,897	13,341	12,949
R-squared	0.154	0.104	0.117	0.434	0.301	0.358	0.334	0.271

Panel B: RDD and the QH heating policy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables	*Non-locally born executives*	*Non-locally educated executives*	*Executives with overseas experience*	*% of highly educated employees*	*% of employees with a low level of education*	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
QH × High beta	**-0.315*****	**-0.232*****	**-0.095**	**-0.009****	0.010	**-0.012*****	-0.007	-0.005
	(-6.54)	**(-5.30)**	**(-1.51)**	**(-2.27)**	(0.96)	**(-3.68)**	(-1.24)	(-1.20)
High beta	0.043*	0.038	0.072**	-0.002	-0.005	0.002	0.001	0.002
	(1.69)	(1.44)	(2.05)	(-0.82)	(-0.89)	(1.22)	(0.33)	(1.10)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,443	9,539	10,887	14,968	15,641	15,109	14,542	14,095
R-squared	0.154	0.109	0.104	0.442	0.304	0.367	0.331	0.260

Panel C: 2SLS and the thermal inversion strength

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables	*Non-locally born executives*	*Non-locally educated executives*	*Executives with overseas experience*	*% of highly educated employees*	*% of employees with a low level of education*	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
Fitted AQI × High beta	**-0.486*****	**-0.418*****	**-0.241****	**-0.023****	0.027	**-0.016*****	-0.009	-0.006
	(-5.77)	**(-5.27)**	**(-2.25)**	**(-2.47)**	(1.24)	**(-4.18)**	(-1.22)	(-0.87)
Fitted AQI	-1.872**	0.900	0.587	0.059	-0.095	-0.027	0.010	0.027
	(-2.04)	(0.99)	(0.57)	(0.93)	(-0.50)	(-1.00)	(0.21)	(0.70)
High beta	2.089***	1.817***	1.128**	0.095**	-0.124	0.071***	0.038	0.027
	(5.52)	(5.05)	(2.33)	(2.32)	(-1.26)	(4.06)	(1.18)	(0.90)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,965	9,047	10,477	13,935	14,481	13,999	13,468	13,079
R-squared	0.157	0.106	0.099	0.434	0.304	0.368	0.326	0.245

Table 12
The Impact of Air Pollution on Firm Performance

Firm performance is measured total factor productivity (*TFP*) and firm value (*Q*). Columns 1 and 2 report the DID estimates based on the setting of the air pollution monitoring program. *High pollution* equals 1 if the average AQI of a city is above the median of all cities in 2011 and 2012. *Monitor* equals 1 if the city a firm located is or has been included in the air pollution monitoring and disclosure program, and 0 otherwise. Columns 3 and 4 report the RDD estimates based on the setting of the QH heating policy. *QH* equals 1 if a firm is located in a region where the central heating policy applies, and 0 otherwise. Columns 5 and 6 report the 2SLS estimates. The instrumental variable (IV) for *AQI* is the thermal inversion strength, which is the daily average of above-ground temperature minus ground temperature in a region. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and longitude/city fixed effects are also included. The sample period is from 2011 to 2016 for the DID models, and from 2000 to 2016 for the RDD and the 2SLS models. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Settings	DID and the air pollution monitor program		RDD and the QH heating policy		2SLS and the thermal inversion strength	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*TFP*	*Q*	*TFP*	*Q*	*TFP*	*Q*
High pollution × Monitor	**-0.023****	**-0.211*****				
	(-2.48)	**(-3.19)**				
Monitor	0.004	0.171**				
	(0.49)	(2.52)				
QH			**-0.069*****	**-0.370*****		
			(-4.28)	**(-2.59)**		
Fitted AQI					**-0.877*****	**-5.752*****
					(-2.99)	**(-3.10)**
Firm size	-0.026***	-0.828***	-0.021***	-0.787***	-0.020***	-0.790***
	(-5.50)	(-21.89)	(-4.34)	(-25.47)	(-10.81)	(-69.99)
Leverage	0.029	0.513**	0.064***	0.561***	0.071***	0.728***
	(1.10)	(2.43)	(2.96)	(3.12)	(7.34)	(11.91)
Cash flow	1.322***	3.810***	1.054***	3.037***	1.155***	3.284***
	(16.63)	(6.16)	(19.59)	(7.70)	(35.74)	(16.19)
Capital expenditure	-0.673***	-0.706***	-0.584***	-0.766***	-0.683***	-0.975***
	(-18.85)	(-2.86)	(-21.70)	(-5.00)	(-22.18)	(-4.97)
Firm age	-0.028***	0.218***	-0.025***	0.002	-0.031***	-0.039**
	(-3.77)	(6.08)	(-5.84)	(0.08)	(-11.51)	(-2.31)
Executive age	-0.137***	-0.030	-0.071***	0.094	-0.087***	0.023
	(-3.64)	(-0.12)	(-2.91)	(0.61)	(-4.70)	(0.20)
SOEs	-0.025**	-0.273***	-0.025***	-0.148***	-0.031***	-0.178***
	(-2.22)	(-4.55)	(-3.20)	(-3.49)	(-6.73)	(-6.06)
Education expenditure	0.161	0.335	1.464***	12.689***	-1.353	-4.828
	(0.33)	(0.09)	(3.87)	(4.72)	(-1.27)	(-0.72)
GDP growth	0.025	0.904**	-0.038	0.877***	0.193**	2.509***
	(0.40)	(2.05)	(-1.09)	(4.04)	(2.31)	(4.72)
GDP per capita	-0.002	0.004	0.002***	0.011***	0.001***	0.009***
	(-0.95)	(0.19)	(4.56)	(3.41)	(4.94)	(4.62)
Population	-0.077	0.454	0.020***	0.111***	0.041***	0.220***
	(-1.39)	(1.01)	(3.98)	(3.09)	(5.19)	(4.44)
Temperature	0.004	-0.050	-0.001	0.009	0.019***	0.146***
	(0.75)	(-1.34)	(-0.33)	(0.51)	(2.87)	(3.48)
Relative humidity	0.001	-0.001	-0.001**	-0.006	-0.001**	-0.006*
	(1.27)	(-0.12)	(-2.11)	(-1.29)	(-2.09)	(-1.75)

Precipitation	0.000	0.001*	-0.000	0.001	-0.001***	-0.003**
	(0.17)	(1.79)	(-0.29)	(1.63)	(-2.80)	(-2.11)
Sunshine hours	-0.000	-0.000	-0.000	-0.003***	-0.001**	-0.009***
	(-0.07)	(-0.21)	(-0.59)	(-3.30)	(-2.26)	(-4.15)
Year, industry, and city FEs	Yes	Yes	-	-	-	-
Year, industry, and longitude FEs	-	-	Yes	Yes	Yes	Yes
Observations	14,588	14,765	31,393	31,776	25,997	26,366
R-squared	0.327	0.427	0.255	0.393	0.100	0.267

Table 13
Firm Performance and Human Capital Dependence

The impact of corporate human capital dependence on the effect of air pollution on firm performance. Firm performance is measured by total factor productivity (*TFP*) and firm value (*Q*). Measures of corporate human capital dependence include performance dependence on executive talent (*EXED*) (Panel A), performance dependence on high quality employees (*EMPD*) (Panel B), average compensation (*High pa*y) (Panel C), and industry innovation (*innovative industries*) (Panel D). Columns 1 and 2 reports the DID estimates based on the setting of the air pollution monitoring program. *High pollution* equals 1 if the average AQI of a city is above the median of all cities in 2011 and 2012. *Monitor* equals 1 if the city a firm located is or has been included in the air pollution monitoring and disclosure program, and 0 otherwise. Columns 3 and 4 report the RDD estimates based on the setting of the QH heating policy. *QH* equals 1 if a firm is located in a region where the central heating policy applies, and 0 otherwise. Columns 5 and 6 report the 2SLS estimates. The instrumental variable (IV) for *AQ*I is the thermal inversion strength, which is the daily average of above-ground temperature minus ground temperature in a region. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and city fixed effects are also included. The sample period is from 2011 to 2016 for the DID models, and from 2000 to 2016 for the RDD and the 2SLS models. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive human capital dependence

Settings	DID and the air pollution monitor program		RDD and the QH heating policy		2SLS and the thermal inversion strength	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*TFP*	*Q*	*TFP*	*Q*	*TFP*	*Q*
EXED	-0.004	-0.205**	-0.005	0.030	0.095*	0.504
	(-0.33)	(-2.40)	(-1.06)	(1.12)	(1.65)	(1.35)
High pollution × Monitor × EXED	**-0.041****	**-0.083**				
	(-2.37)	**(-0.57)**				
High pollution × Monitor	-0.001	-0.186*				
	(-0.04)	(-1.85)				
High pollution × EXED	0.028	-0.181***				
	(1.60)	(-3.23)				
Monitor × EXED	0.018	0.154				
	(1.29)	(1.48)				
Monitor	-0.006	0.101				
	(-0.38)	(0.95)				
QH × EXED			**-0.009**	**-0.120*****		
			(-1.41)	**(-3.06)**		
Fitted AQI × EXED					**-0.023***	**-0.117**
					(-1.79)	**(-1.39)**
Fitted AQI					0.022	0.091
					(0.38)	(0.25)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,588	14,765	31,393	31,776	31,393	31,776
R-squared	0.328	0.429	0.275	0.414	0.275	0.414

Panel B: High-quality employee human capital dependence

Settings	DID and the air pollution monitor program		RDD and the QH heating policy		2SLS and the thermal inversion strength	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*TFP*	*Q*	*TFP*	*Q*	*TFP*	*Q*

	(1)	(2)	(3)	(4)	(5)	(6)
EMPD	-0.003	0.201*	-0.007	0.299***	0.083	1.887***
	(-0.16)	(1.82)	(-0.78)	(4.91)	(1.09)	(3.58)
High pollution × Monitor × EMPD	-0.019**	-0.120**				
	(-1.96)	(-2.50)				
High pollution × Monitor	-0.017*	-0.129**				
	(-1.75)	(-2.28)				
High pollution × EMPD	-0.028***	-0.025				
	(-3.63)	(-0.42)				
Monitor × EMPD	0.004	0.065				
	(0.27)	(0.80)				
Monitor	0.006	0.135**				
	(0.44)	(2.26)				
QH × EMPD			-0.026**	-0.220***		
			(-2.03)	(-2.79)		
Fitted AQI × EMPD					-0.022	-0.371***
					(-1.31)	(-3.17)
Fitted AQI					0.032	0.377
					(0.40)	(0.71)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,588	14,765	31,393	31,776	15,817	16,008
R-squared	0.329	0.428	0.275	0.414	0.335	0.446

Panel C: High-pay firms

Settings	DID and the air pollution monitor program		RDD and the QH heating policy		2SLS and the thermal inversion strength	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*TFP*	*Q*	*TFP*	*Q*	*TFP*	*Q*
High pay	0.064***	0.233***	0.066***	0.251***	0.271***	0.964**
	(6.82)	(5.80)	(9.80)	(5.48)	(4.66)	(2.53)
High pollution × Monitor × High pay	-0.017**	-0.119*				
	(-2.39)	(-1.85)				
High pollution × Monitor	-0.007**	-0.087**				
	(-2.00)	(-2.14)				
High pollution × High pay	0.000	0.120				
	(0.03)	(1.28)				
Monitor × High pay	0.010*	0.057				
	(1.82)	(1.04)				
Monitor	-0.004	0.116				
	(-0.51)	(1.45)				
QH × High pay			-0.042***	-0.118*		
			(-4.12)	(-1.71)		
Fitted AQI × High pay					-0.050***	-0.170**
					(-3.78)	(-1.98)

Fitted AQI					0.020	0.054
					(0.35)	(0.15)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,588	14,765	31,393	31,776	31,393	31,776
R-squared	0.336	0.431	0.282	0.416	0.281	0.416

Panel D: Innovative industries

Settings	DID and the air pollution monitor program		RDD and the Qinglin Huai-River heating boundary		2SLS and the thermal inversion strength	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*TFP*	*Q*	*TFP*	*Q*	*TFP*	*Q*
High pollution* × *Monitor* × *Innovative industries	**-0.031****	**-0.281***				
	(-2.55)	**(-1.74)**				
High pollution × *Monitor*	-0.013***	-0.131***				
	(-2.85)	(-2.69)				
High pollution × *Innovative industries*	0.017**	0.026				
	(1.97)	(0.19)				
Monitor × *Innovative industries*	0.013	1.093***				
	(0.94)	(2.97)				
Monitor	-0.001	0.012				
	(-0.15)	(0.13)				
QH* × *Innovative industries			**-0.035***	**-0.257****		
			(-1.71)	**(-2.12)**		
Fitted AQI* × *Innovative industries					**-0.006****	**-0.033***
					(-2.27)	**(-1.77)**
Fitted AQI					0.012	0.045
					(0.22)	(0.12)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,588	14,765	31,393	31,776	31,393	31,776
R-squared	0.329	0.428	0.276	0.414	0.275	0.414

Appendix D: Internet Appendix

Figure IA.1: AQI Distribution

This figure represents the AQI distribution using McCrary density tests on daily AQI for each city during 2000–2016. The y-axis represents the density. The x-axis represents the AQI.

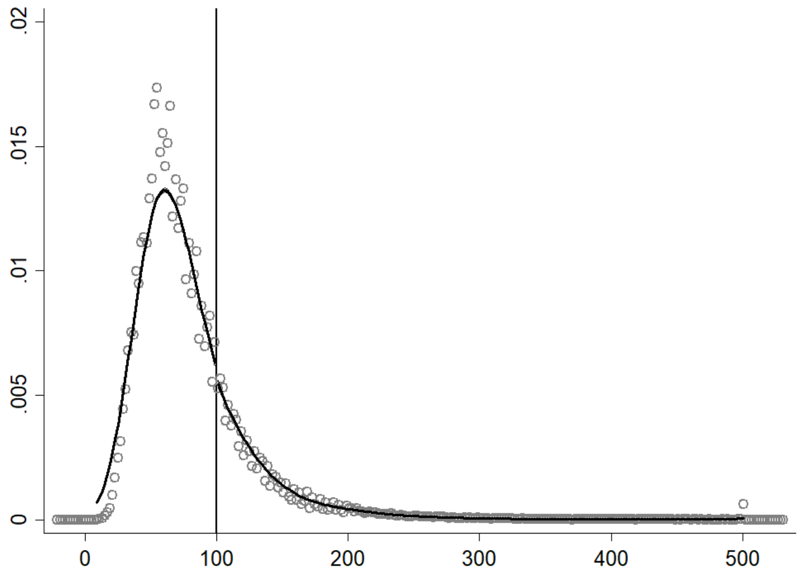


Figure IA.2: RDD Bandwidths and the Human Capital Effects

This figure plots the local RDD estimates with alternative bandwidths of the distance between firm location and the QH boundary. The x-axis represents the latitude distance from the QH boundary. The y-axis represents the estimated coefficients on QH in Equation (3), focusing a small margin around the QH boundary.

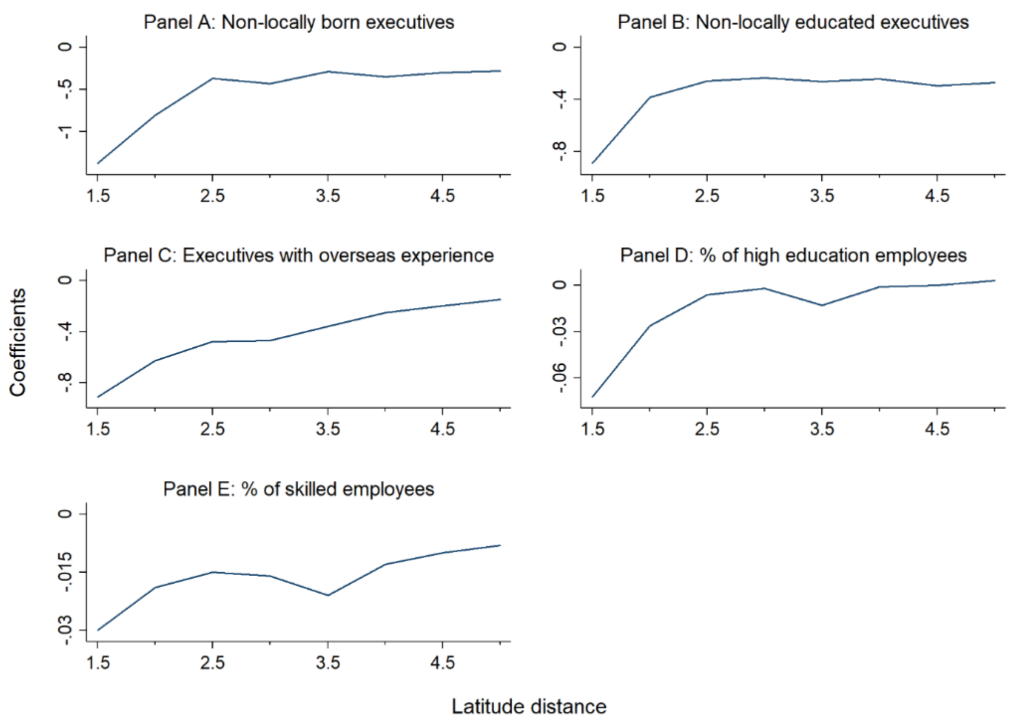


Table IA.1

Variable	Definition
Dual	Indicator equals to 1 if firm has multiple class of stock.
Log Assets	The log of assets (item 6) measured in millions of dollars during fiscal year t. Source: Compustat
Sales Growth	The first difference of the natural log of sales (item 12) in fiscal year t-1. Source: Compustat
Leverage	All debt (item 9 + item 34)/Market value of total assets (item 6 −item 60 + item 25 × item 199). Source: Compustat
Tangibility	Net PP&E (item 8) divided by total assets (item 6). Source: Compustat
Labor	Labor productivity; sales (item 46) divided by lagged number of employees (item 29). Source: Compustat
CAPEX	Capex/PPE: The ratio of capital expenditures (item 128) (set to 0 if missing) to gross property, plant, and equipment (item 7) in fiscal year t-1. Source: Compustat
R&D	R&D/Sales (item 46) (set to 0 if missing)/item 12. Source: Compustat
Dividend	Dividends/Book Equity: The ratio of dividends (item 21) to book equity (item 60) in fiscal year t-1. Source: Compustat
Interest	Interest (item 15). Source: Compustat
NetFinancing	New equity issues (item 108 − item 115) + Net new debt issues (item 111 − item 114). Source: Compustat
Firm Age	The natural log of firm age. Firm age is the number of years since a firm's first appearance in CRSP. Source: CRSP
ROA	EBITDA over book value of total assets (item 6). Source: Compustat
Hightech	Indicator equals to 1 if the firm is in high-tech industries. "High-tech" industries include Computers, Electronics, Biotech, and Telecom. A firm is in the "Biotech" industry if its primary SIC code is 2830 2839, 3826, 3841 3851, 5047, 5048, 5122, 6324, 7352, 8000 8099, or 8730 8739 excluding 8732. A firm is in the "Telecom" industry if its primary SIC code is 3660 3669 or 4810 4899. A firm is in the "Computers" industry if its primary SIC code is 3570 5379, 5044, 5045, 5734, or 7370 7379. A firm is in the "Electronics" industry if its primary SIC code is 3600 3629, 3643, 3644, 3670 3699, 3825, 5065, or 5063. Source: Compustat
High R&D	Indicator equals to 1 if the firm's R&D expense is above the median of its industry (SIC code).
Highivol	Indicator equals to 1 if the firm's idiosyncratic volatility is above the median in year t. The idiosyncratic volatility is the standard deviation of yearly excess stock returns. Excess return is defined using a CAPM market model estimated over the prior year. Source: CRSP
High Analyst Dispersion	Indicator equals to 1 if the firm's analyst forecast dispersion is above the median of its industry (SIC code). Dispersion is the standard deviation of analysts' forecasts deflated by the stock price five days before the earnings announcement date. Source: IBES
Low IO	Indicator equals to 1 if the firm's institutional ownership is above the median in year t (SIC code). Institutional ownership is measured by the percentage of shares holding by mutual fund investors. Source: Thomson Reuters Institutional (13f) Holdings
No Analyst Cover	Indicator equals to 1 if the firm is not covered by any analyst in year t. Source: IBES

Low Investor Turnover	Indicator equals to 1 if the firm's investor turnover is lower than the top third of the distribution of the entire universe in year t, which means lower investor turnover. The calculation of investor turnover is following Gaspara, Massab, and Matos (2005). Source: Thomson Reuters Institutional (13f)
Tobin's Q	Market value of assets over book value of assets: (item 6 − item 60 + item 25 × item 199)/item 6. Source: Compustat
Patents	Total number of patents filed (and eventually granted) by a firm in year t. Source: NBER Patent Citation Database
Citations/Patents	Total number of citations divided by the number of patents. Source: NBER Patent Citation Database
Repurchase	Based on the definition in Fama and French (2001), who define repurchases as net repurchases; i.e., after removing from share purchases the effect of shares issued to fund acquisitions and shares issued for employee stock option programs and other corporate purposes. Following their approach of using the increase in common treasury stock if the firm uses the treasury stock method for repurchases. If the firm uses the “retirement” method instead (which is inferred from the fact that treasury stock is zero in the current and prior year), repurchases are calculated as the difference between stock purchases and stock issuances from the statement of cash flows. If either of these amounts (the change in treasury stock or the difference between item 115 and item 108) is negative, repurchases are set to zero. Source: Compustat

Table IA.2

Variables	Definitions	Sources	Period
Firm-level variables:			
Non-locally born executives	1 if CEO or chairman was born in a region that is outside the province in which the firm is domiciled and 0 otherwise. It is filled with a missing value if the CEO and chairman’s birthplace information cannot be identified.	GTA_TMT/CSMAR, CCXE, and manually collected	2000–2016
Non-locally educated executives	1 if CEO or chairman received a degree from a university or college in a region that is outside the province in which the firm is domiciled and 0 otherwise. It is filled with a missing value if the CEO and chairman’s education information cannot be identified.	GTA_TMT/CSMAR, CCXE, and manually collected	2000–2016
Executives with overseas experience	1 if the CEO or chairman has study or work experience abroad and 0 otherwise. It is filled with a missing value if the CEO and chairman’s education and work information cannot be identified.	GTA_TMT/CSMAR, CCXE, and manually collected	2000–2016
% of highly educated employees	The number of employees with a bachelor’s degree or above, scaled by the total number of employees.	Employee structure/Wind	2011–2016
% of employees with a low level of education	The number of employees whose highest education level is high school or below, scaled by the total number of employees.	Employee structure/Wind	2011–2016
% of skilled employees	The number of technical employees, scaled by the total number of employees.	Employee structure/Wind	2011–2016
% of production and sales employees	The number of production and sales employees, scaled by the total number of employees.	Employee structure/Wind	2011–2016

% of financial and administrative employees	The number of financial, HR, administrative employees, scaled by the total number of employees.	Employee structure/Wind	2011–2016
TFP	Total factor productivity, estimated for each firm using the methodology developed by Levinsohn-Petrin (2003) where the output (y) is the firm's net profits (net value added) and firm labor (L) is the number of employees, and firm capital is property, plant, and equipment (PPE).	GTA_FS/CSMAR	2000–2016
Q	The market value of total equity over book value of total equity.	GTA_FS/CSMAR; GTA_TRD/CSMAR	2000–2016
QH	1 if a firm is located in a place where the region's latitude distance from the line of Qinling-Huai River (the former - the latter) is positive and 0 otherwise.	SAS Maps, and Manually collected	2000–2016
Firm size	Log(total assets).	GTA_FS/CSMAR	2000–2016
Leverage	Total liability/total assets.	GTA_FS/CSMAR	2000–2016
Cash flow	Operating income before depreciation and amortization/total assets.	GTA_FS/CSMAR	2000–2016
Capital expenditure	Capital expenditure over total assets.	GTA_FS/CSMAR	2000–2016
Firm age	Log of the number of years since the establishment of the firm.	GTA_TRD/CSMAR	2000–2016
Executive age	Log of the average age of firm CEO and chairman of the board of directors.	GTA_TMT/CSMAR	2000–2016
SOEs	1 if the firm is ultimately controlled by the state and 0 otherwise.	GTA_HLD/CSMAR	2000–2016
EXED	1 if the sensitivity of *TFP* or *Q* to executive talent is above the median and 0 otherwise. The sensitivity is estimated by regressing *TFP* or *Q* on the executive talent index (i.e., the average of *Non-locally born executives, Non-locally educated executives, and Executives with overseas experience*) within an industry over the past five years, with firm characteristics (i.e. *Firm size, Leverage, Cash flow, Capital expenditure, Firm age, Executive age, and SOEs*) included as controls. The estimated coefficient on the telnet index is the measure of performance dependence on executive talents.	GTA_FS/CSMAR, GTA_TMT/CSMAR, CCXE, and manually collected	2000–2016
EMPD	1 if the sensitivity of *TFP* or *Q* to employee capital human is above the median and 0 otherwise. The sensitivity is estimated by regressing *TFP* or *Q* on the high-quality employee index (i.e., the average of *% of highly educated employees and % of skilled employees*) within an industry over the past five years, with firm characteristics (i.e. *Firm size, Leverage, Cash flow, Capital expenditure, Firm age, Executive age, and SOEs*) included as controls. The estimated coefficient on the employee index is the measure of performance dependence on employees.	GTA_FS/CSMAR and the employee structure/Wind	2011–2016
High pay	1 if it has an average employee compensation (total employee compensation/total number of employees) is above the sample median in a year, and 0 otherwise.	GTA_FS/CSMAR	2000–2016
Innovative industries	1 if a firm operates in the industries of information technology, scientific research and technical service, or health and social work, and 0 otherwise.	GTA_TRD/CSMAR	2000–2016

Regional variables:			
To work in Beijing	Log of the daily Baidu SVI of "北京找工作" (to work in Beijing) in a municipal region.	Index.Baidu.com	2011–2016
To work in Shenzhen	Log of the daily Baidu SVI of "深圳找工作" (to work in Shenzhen) in a municipal region.	Index.Baidu.com	2011–2016
To work in more polluted cities	Log of the average daily Baidu SVI for workplaces of the five most polluted cities (Beijing, Tianjin, Zhengzhou, Jinan, and Xian) in a region.	Index.Baidu.com	2011–2016
To work in less polluted cities	Log of the average of the daily Baidu SVI for workplaces of the five least polluted cities (Shenzhen, Shanghai, Guangzhou, Chengdu, and Hangzhou) in a municipal region.	Index.Baidu.com	2011–2016
Pollution days	1 if the increase in daily AQI exceeds one standard of the daily AQI change in the past one year in a region.	GTA_CRE/CSMAR	2011–2016
Education expenditure	Government expenditure on education scaled by GDP for a region in a year.	GTA_CRE/CSMAR	2000–2016
GDP growth	GDP growth rate for a region in a year.	GTA_CRE/CSMAR	2000–2016
GDP per capita	Log(GDP per capita) for a region in a year.	GTA_CRE/CSMAR	2000–2016
Population	Log(number of population) for a region in a year.	GTA_CRE/CSMAR	2000–2016
Temperature	The monthly average temperature (℃) in a region in a year.	GTA_RES/CSMAR	2000–2016
Relative humidity	The monthly average relative humidity (%) in a region in a year.	GTA_RES/CSMAR	2000–2016
Precipitation	The monthly average precipitation (mm) in a region in a year.	GTA_RES/CSMAR	2000–2016
Sunshine hours	The monthly average sunshine hours (hrs) in a region in a year.	GTA_RES/CSMAR	2000–2016
Health beta	The estimated beta of the following time-series model: *%Change of Search_Health t*=beta**%Change of AQI t* + FEs + e t where *%Change of Search_Health t* is the percentage change of daily Baidu Search Volume Index by the word of "health (健康)" in a region on day t; *%Change of AQI t* is the percentage change of AQI in a region on day t. FEs are the month, weekday, and Chinese New Year fixed effects. The model is estimated for each municipal region in each year.	Index.Baidu.com, GTA_CRE/CSMAR	2011–2016
Monitor	1 if a prefecture-city is included in the air pollution monitoring and disclosure program in a year, and 0 otherwise.	the Ministry of Environmental Protection (MEP)	2011–2016
High Pollution	1 if the average AQI of a city is above the median of all cities in 2011 and 2012, and 0 otherwise.	GTA_CRE/CSMAR	2011–2016
AQI	The average daily Air Quality Index for a region in a year.	GTA_CRE/CSMAR	2000–2016
TI	The daily average of max(above-ground temperature minus ground temperature, 0) in a region in a year.	NASA	2000–2016

Table IA.3
Falsification Tests on the Impact of Air Pollution on Intended Workplaces

Falsification tests estimate the effect of air pollution on people's intended places of work. We make random assignments of air pollution days to each regional city. The assignments are made such that the frequency of randomly assigned air pollution days is the same as the frequency of true air pollution days. We create a variable *Pollution days (random)*, referring to a five-day window following the randomly assigned air pollution day in a region. Columns (1) and (2) show the estimates for people's intention to work in Beijing and Shenzhen. Columns (3) and (4) show the estimates for people's intention to work in the top work-intended cities in China, which are grouped into more and less polluted cities. In all regressions, regional characteristics, city and date fixed effects are included. Variables are defined in Table IA.2. The sample period is from 2011 to 2016, with daily observations. t-statistics are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	*To work in Beijing*	*To work in Shenzhen*	*To work in more polluted cities*	*To work in less polluted cities*
Pollution days (random)	0.005	0.006	-0.002	0.000
	(0.97)	(1.03)	(-0.52)	(0.10)
City and date fixed effects	Yes	Yes	Yes	Yes
Observations	282,630	282,630	282,630	282,630
R-squared	0.409	0.38	0.52	0.524

Table IA.4
Market Reaction to Executive Leave and Appointment

The dependent variable is a 11-day abnormal return around the announcement of executive leave or appointment. The key independent variables are executive human capital measures, including *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience*. In all regressions, firm and regional characteristics (as used in Equations 2-4) are controlled; year, industry, and city fixed effects are also included. t-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*CAR(-5, 5) of executive leave*			*CAR(-5, 5) of executive appointment*		
Non-locally born executives	-0.240***			0.072**		
	(-3.37)			(2.41)		
Non-locally educated executives		-0.270***			0.056*	
		(-2.98)			(1.69)	
Executives with overseas experience			-0.145*			0.064*
			(-1.74)			(1.80)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,054	1,606	2,794	3,104	2,820	4,607
R-squared	0.512	0.530	0.443	0.223	0.078	0.062

Table IA.5
Employee Measures and Firm Operating Performance

The dependent variable is net operating margin (net income/total revenues). The key independent variables are employee human capital by education, *% of high education employees* and *% of low education employees*, and employee human capital by job functions *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees*. In all regressions, firm and regional characteristics (as used in Equations 2-4) are controlled; year, industry, and city fixed effects are also included. t-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable			*Net operating margin*		
% of highly educated employees	0.063***				
	(3.48)				
% of employees with a low level of education		-0.012			
		(-1.42)			
% of skilled employees			0.048**		
			(2.21)		
% of production and sales employees				-0.012	
				(-0.59)	
% of financial and administrative employees					0.044
					(0.95)
Firm and regional controls	Yes	Yes	Yes	Yes	Yes
Year, industry, and city FEs	Yes	Yes	Yes	Yes	Yes
Observations	14,968	15,641	15,109	14,542	14,095
R-squared	0.419	0.396	0.398	0.399	0.399

Table IA.6

Differences of Characteristics on the Two Sides of the Heating Boundary

This table reports the differences in the characteristics of firms on the two sides of the heating boundary (2 degrees around the line of Qinling-Huai River). Panel A reports the mean and difference of firm and regional characteristics on the heating and non-heating sides of the boundary. Panel B reports the mean and difference of firm expected human capital and performance on the two sides of the boundary. The expected firm outcomes are the fitted values by regressing the outcome variables on firm characteristics (i.e., *Firm size*, *Leverage*, *Cash flow*, *Capital expenditure*, *Firm age*, *Executive age*, and *SOEs*). All variables are defined in Table IA.2. The p-value of testing the difference is reported in Column 4.

	Non-heating side	Heating side	Difference (heating – non-heating)	
	Mean	Mean	Estimate	p-value
	(1)	(2)	(3)	(4)
Panel A: Firm and regional characteristics				
AQI	88.532	100.248	11.715	0.000
Firm size	21.61	21.733	0.123	0.110
Leverage	0.451	0.445	-0.006	0.737
Cash flow	0.056	0.059	0.003	0.569
Capital expenditure	0.048	0.048	-0.001	0.894
Firm age	1.736	1.661	-0.076	0.283
Executive age	3.904	3.910	0.006	0.439
SOEs	0.339	0.492	0.153	0.000
Education expenditure	0.016	0.029	0.014	0.000
GDP growth	0.137	0.130	-0.007	0.102
GDP per capita	8.705	2.509	-6.197	0.000
Population	15.483	15.82	0.337	0.000
Temperature	16.530	16.237	-0.292	0.000
Relative humidity	71.469	68.366	-3.103	0.000
Precipitation	99.966	87.418	-12.548	0.000
Sunshine hours	155.847	154.872	-0.975	0.319
Panel B: Expected firm human capital and performance				
Non-locally born executives	0.191	0.191	0.000	0.947
Non-locally educated executives	0.289	0.283	-0.006	0.276
Executives with overseas experience	0.064	0.060	-0.004	0.203
% of highly educated employees	0.233	0.240	0.008	0.041
% of employees with a low level of education	0.667	0.657	-0.010	0.241
% of skilled employees	0.187	0.189	0.001	0.577
% of production and sales employees	0.127	0.126	-0.001	0.642
% of financial and administrative employees	0.113	0.110	-0.003	0.236
TFP	0.131	0.128	-0.002	0.744
Q	2.804	2.764	-0.040	0.620

Table IA.7
Local RDD and the Effect of Air Pollution on Corporate Human Capital

Local RDD models estimating the impact of Qinling Huai-River (QH) heating policy on corporate human capital. Only firms located in regions with a distance smaller than two degrees in latitude from the QH boundary are included. The dependent variables are executive human capital measures, *Non-locally born executives*, *Non-locally educated executives*, and *Executives with overseas experience* (Panel A), employee measures by education, *% of high education employees* and *% of low education employees* (Panel B), and employee measures by job functions, *% of skilled employees*, *% of production and sales employees*, and *% of financial and administrative employees* (Panel C). The key independent variable is *QH*, which equals 1 if a firm is located in a region where the central heating policy applies, and 0 otherwise. Variables are defined in Table IA.2. In all regressions, firm and regional characteristics are controlled; year, industry, and longitude fixed effects are also included. The sample period is from 2000 to 2016 for the analysis of executive talents, and from 2011 to 2016 for the analysis of employee human capital. *t*-statistics based on a robust standard error estimate clustering at firm levels are reported in parentheses. Significance at the 10%, 5% and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Executive talent

	(1)	(2)	(3)
Dependent variables	*Non-locally born executives*	*Non-locally educated executives*	*Executives with overseas experience*
QH	**-0.806*** **	**-0.384*** **	**-0.627*** **
	(-9.16)	**(-5.03)**	**(-5.09)**
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	4,332	3,799	4,644
R-squared	0.095	0.076	0.102

Panel B: Employee structure by education

	(1)	(2)
Dependent variables	*% of highly educated employees*	*% of employees with a low level of education*
QH	**-0.026** **	0.039*
	(-2.33)	(1.72)
Firm and regional controls	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes
Observations	4,057	4,212
R-squared	0.344	0.189

Panel C: Employee structure by job function

	(1)	(2)	(3)
Dependent variables	*% of skilled employees*	*% of production and sales employees*	*% of financial and administrative employees*
QH	**-0.019** **	0.010	0.003
	(-2.35)	(1.21)	(0.45)
Firm and regional controls	Yes	Yes	Yes
Year, industry, and longitude FEs	Yes	Yes	Yes
Observations	4,078	3,984	3,824
R-squared	0.278	0.318	0.267