Education and Innovation: the Long Shadow of the Cultural Revolution[*]

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Abstract

The Cultural Revolution deprived an entire generation of Chinese of their opportunities to receive higher education. We estimate the human capital cost of this tragedy and find that Chinese firms led by CEOs without college degrees spend less in R&D, generate fewer patents and receive fewer citations. The result is robust when we use an exogenous CEO turnover sample. Furthermore, we take the CEO's Cultural Revolution experience as an instrument for access to college education, and find that higher education indeed increases the CEO's human capital. This cannot be explained by changes in beliefs. Finally, by adopting a regression-discontinuity design, we estimate the causal effects of college education on human capital.

Keywords: China, the Cultural Revolution, Human Capital, Education, Innovation

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1. Introduction

A key insight in Romer (1990) is that the non-rival nature of ideas results in increasing returns to human capital in the production of ideas. Romer (1990) uses externalities to explain this: new ideas lead to positive knowledge spillovers that raise the productivity of other researchers. The process gives rise to endogenous economic growth, which can be sustained by accumulation of the inputs that generate the positive externalities.

The importance of the spillover effects has long been understood in the scientific community. Robert Oppenheimer's role in America's atomic program serves as a good example: Being hailed as "probably the best lab director", Oppenheimer's brilliance is displaced "from scientific invention to recruitment, synthesis and leadership". Oppenheimer is "empowered to function like a general in moving his scientific troops around", creating "the greatest school of theoretical physics the United States has ever known." (Biagioli and Galison, 2002, page 286).

Thus the spillover effects are not limited to imitation and spread of new ideas, one important aspect is the management of innovation. The leadership of an organization who understands the process of innovation and appreciates the subtlety of production of ideas is crucial for the ultimate success of innovators.

In this paper, we look into a particular historical episode of China-- the Cultural Revolution (1966-1976) ----one of the largest political events in the 20th century, to explore how human capital and education affects innovation. The Cultural Revolution not only persecuted millions of Chinese, political elites and ordinary people alike, but also denied an entire generation their access to proper education by shutting down all colleges and universities. College entrance was not possible until 1978, when Deng ended this episode and began the journey of China's reform and open-up. The interruption of college education lasted for ten years---- such a long time that a whole generation missed their right chance to enter any college. It also took quite a long time for China's higher education system to recover from this tragedy. The number of college students had been dragged for too long and only began to climb up slowly in the 1980s. In fact, when the Cultural Revolution was finally put to an abrupt end in 1978, those who had missed the chance of going to college would have to give up their working positions for the purpose of college study. To put it another way, the

Cultural Revolution brought an exogenous dash to citizens' education opportunity costs, for reasons largely out of their control, which in turn provides us with an exogenous natural experiment to take a glimpse into how higher education actually changes innovation.

We assess the long-run human capital cost of this special historical episode by examining the education background of CEOs of listed companies in China. As a result of the aforementioned political turmoil, 49.21% of CEOs in China now do not have a college degree, which is a large fraction indeed, in sharp contrast to their peers in the West, When using firm-year observations in our 2008-2016 sample, 45.7% of observations were performed by CEOs with no college degree, whereas in the U.S., when using Forbes 800 data ranging from 1987 to 1999, only 8.3% observations were performed by CEOs with no college degree (Jalbert, Rao and Jalbert, 2002; Jalbert, Jalbert and Perrina, 2004) . We focus on managerial education and corporate innovation.

Using data from China Stock Market & Accounting Research Database and Wind Economic Database ranging from the year of 2008 to 2016, we construct panel data for all listed companies in China. This year-firm panel consists of 21158 observations. Our empirical strategy takes two parts and the main findings are as below:

1. We look into three aspects--companies' innovation input, innovation output and innovation efficiency. First, we do a series of panel regressions with core explanatory variable as College Degree and dependent variables as measurements of firm's innovation. And we find that lacking college education significantly depresses corporate R&D expenditure, the number of patent applications, the number of granted patents up to 2016 and patent citations. The results hold when we control for year fixed effects, firm fixed effects. We also implement a diff-in-diff test around CEO turnovers. The results show that innovation differences between firms are indeed related to changes of CEOs' college degree.

2, To deal with endogenous problems, we first use an exogenous CEO turnover sample (Dittmar and Duchin, 2016). Turnovers at retirement age are less likely to be caused by changes in the firm's conditions. Thus we define exogenous turnovers by retirement age. We run panel regressions and the result shows that even in this retirement sample, lacking a college degree still matters significantly.

Further, we implement an instrument variable (IV) method. In this paper, we choose a special instrument variable----a binary variable, denoted as Unlucky. Unlucky equals 1 if the CEO was born during 1948-- 1958, which means he reached his 18 during the Cultural Revolution, so he may have very little chance to go to college. Unlucky equals 0 if otherwise. This instrument variable is highly correlated with our core explanatory variable, College Degree, and should have little impact on firm's innovation policies except through the channel of CEO education. We use Unlucky both in whole sample regression and in exogenous turnover sample regression. In this way, we remove the concerns of various types of endogeneity.

3. To establish a causal relationship between education and human capital stock, we apply a regression discontinuity design methodology using the 1978 policy shock. CEOs who reached the age of 18 before 1978 had less chances of going to college: they either had to prepare for the entrance exam while still working full time, or had to opt for part-time college studies. Thus if they do not have college degrees, it is less likely a result of their incapability. If we focus on CEOs who reached the age of 18 around 1978, differences in corporate innovation activities of firms led by college CEOs and those led by no college CEOs can be viewed as the effect of education on human capital stock. Results are positive for different measures of innovation, using both reduced form RDD and fuzzy RDD. Thus we reach to the conclusion that CEO's higher education really makes a significant difference on firm innovation.

Our paper contributes to three strands of literature. A first strand of the literature focuses on human capital and economic development. Mincer (1958) first discovers a positive correlation between education and labor market outcomes. Schultz (1961) introduces the concept of human capital into modern economic analysis. Then Mincer (1974) creates the Mincer earnings function, which has been tested empirically by lots of papers (Fleisher, Belton and Wang, 2004; Zhang, Zhao, Park, and Song, 2005; Cohen and Soto, 2007). Griliches and Zvi (1977) also prove accounting for the endogeneity of schooling and ability bias does not alter the estimates of this equation. Gradually the role of human capital in the promotion of economic growth is noticed. Lucas (1988) finds changes in human capital promote growth; then Romer (1990) includes human capital into production function and finds human capital stock determines the rate of growth. Mankiw, Romer and Weil (1992) show an augmented Solow model that includes the accumulation of human capital provides an excellent description of cross-country data. But has the role of human capital in economic growth been vastly overstated? Benhabib and Spiegel (1994)'s results indicate human capital enters insignificantly in explaining per capita growth rates. However, Barro (2001) emphasizes the role of education as a determinant for long term growth. Stroombergen et al. (2002) conclude human capital as an important source of innovation, an important factor for sustainable development, and for reducing poverty and inequality. Later Gennaioli, La Porta, Lopez-de-Silanes, and Shleifer (2012) point to the paramount importance of human capital in accounting for regional differences in development. Fleisher and Chen (1997) find human capital has played a significant role in the Chinese economic miracle. Fleisher, Li and Zhao (2009) find human capital also has an important effect on reducing regional inequality in China. Related to the above topic, our paper emphasizes how human capital influences corporate innovation activity in China, through the higher education received by CEOs.

Our study also contributes to a second strand of the literature which explores what would influence corporate innovation. Hirshleifer, Teoh and Low (2012) show overconfidence helps CEOs exploit innovative growth opportunities. Atanassov (2013) find that antitakeover laws are associated with a decrease in corporate innovation. He and Tian (2013) find firms covered by a larger number of analysts generate fewer patents. There is also evidence for a stable positive correlation of institutional ownership and patents (Aghion, Reenen and Zingales, 2013). Amore, Schneider and Žaldokas (2013) show that interstate banking deregulation promote innovation. Fang, Vivian, Tian, Tice (2014) find an increase in liquidity causes a reduction in innovation. Cornaggia, Mao, Tian and Wolfe (2014) show banking competition reduces state-level innovation. Bernstein (2015) finds going public changes firms' strategies in pursuing innovation. Bénabou, Ticchi and Vindigni (2015) notice greater religiosity is associated with less innovation. Blanco and Wehrheim (2017) find firms with more options trading activity innovate more. Mukherjee, Singh and Žaldokas (2017) show an increase in taxes reduces future innovation. Fang, Lerner and Wu (2017) find empirically that intellectual property rights (IPR) protection strengthens firms' incentives to innovate.

Lastly, our findings also complement the recent corporate finance literature on the impact of CEO personal traits. Daellenbach, McCarthy and Schoenecker (1999) first notice that CEOs' with technical work experience are associated with higher R&D spending. Then Bertrand and Schoar (2003) investigate whether and how individual managers affect corporate behavior and performance. Following their work, a lot of research has been carried on CEO traits. Malmendier and Tate (2009) show a negative impact of CEOs achieving superstar status on the performance of their firms. Malmendier, Tate and Yan (2011) find overconfident managers use less external finance and CEOs with Depression experience are averse to debt. Kaplan, Klebanov and Sorensen (2012) show subsequent performance is positively related to CEOs' general ability and execution skills. Davidson, Dey and Smith (2013) find CEOs with a legal record are more likely to perpetrate fraud. Fee, Hadlock and Pierce (2013) find that firm policy changes after exogenous CEO departures do not display abnormally high levels of variability, casting doubt on the presence of idiosyncratic-style effects in policy choices. Shortly after their discovery, Dittmar and Duchin (2014) show firms run by CEOs who experienced distress have less debt and invest less than other firms. Custodio and Metzger (2014) find financial expert CEOs are more financially sophisticated. Benmelech and Frydman (2015) show military service has a significant explanatory power for managerial decisions and firm outcomes. Sunder, Sunder and Zhang (2017) find evidence that pilot CEOs innovate better. Schoar and Zhou (2017) show that economic conditions at the beginning of a manager's career have lasting effects on the career path as a CEO. Islam and Zein (2018) find that firms led by "Inventor CEOs" are associated with higher quality innovation. And we contribute as we show how the human capital stock of managers influences corporate innovation.

The remainder of the paper is organized as follows. Section 2 describes the interruption of higher education during the Cultural Revolution. Section 3 presents the data and summary statistics. We present our empirical strategy, and discuss the empirical relation between CEO's college education and firm innovation in Section 4. We address endogeneity concerns in Section 5 and deal with causality issues in Section 6. We conclude in Section 7, and discuss what we have learned from the results.

2. The Cultural Revolution (1966-1976) and the interruption of higher education

2.1. Background

In 1966, Mao Zedong launched the Cultural Revolution shortly after the event of the Great Leap Forward, after which Mao was marginalized inside the party. The Cultural Revolution in China was a massive social political movement. Mao announced that inside the Chinese Communist Party (CCP) there were some members who became bourgeois and acted not on behalf of people, forgetting their original revolutionary ideology. Mao called on people to act against those bourgeois members.

Under such encouragement, millions of young people changed into “the Red Guards”. Despite of the original intention of this movement, due to the schemes of the Gang of four, the movement went out of control gradually. People took actions around the nation to strike and fully wipe out the bourgeois practices, in which process they went too crazy and ruined thousands of hundreds of Chinese traditional classic cultural heritages: historic sites, art craft, books, etc. Also, different gangs of the so-called Red Guards fought with each other neglecting the original intention of this movement. Countless individuals died during this movement as a result of violence. As people went into meaningless wild fights, the whole economic environment was hurt severely. As a matter of fact, the economy halted and it took a long time for it to recover.

2.2. Interruption of higher education

Blamed for foster to spread bourgeois values, higher education was suspended during the Cultural Revolution. Colleges and universities were shut down, and the core staff, the faculty members of different departments in universities were sent down to special “schools” to reform through labor. Also, professors, engineers, doctors and artists are persecuted by the Red Guard. They were humiliated and assaulted in front of crowds of people and their houses were searched and property was confiscated. Some of them were sent to May 7 cadre school (named after Mao Zedong's May 7 Directive of 1966). Their study contents were manual labor: farming, picking up manure, raising pigs, cooking, carrying water, drilling wells, building houses... Many people are overwhelmed by the disease caused by overworked torture. And some of them committed suicide to end their pain both mentally and physically. Mao also asked the school to shorten its educational system, to revolutionize education, and not to allow the bourgeoisie to rule schools.

Meanwhile, the college entrance examination was canceled in 1966, right at the beginning of the Cultural Revolution. As a consequence, the number of university students dropped significantly during the ten years of this massive movement. A whole generation was deprived of the right to receive higher education. Instead, they stopped learning after high school and went to factories as workers.

2.3. The restart of college entrance exam

At the death of Mao Zedong in October 1976, the Cultural Revolution ended immediately. The Gang of Four who had been in charge of the CCP, and mistakenly taken advantages from this movement was sent to jail shortly after Mao’s death.

In August of 1977, Deng Xiaoping hosted a meeting on science and education in Beijing. During this meeting, Deng Xiaoping decided to change the rules of college entrance to restart the college entrance exam. Right in the same year, China resumed the college entrance examination. This wonderful news has activated the hearts of millions of educated youths to take the exam and embrace a whole new bright future. In Dec., 1977, the first college entrance examination after the Cultural Revolution was held. 5.7 million candidates took the college entrance examination, which had been closed for a decade. In that year, 273,000 freshmen were admitted to colleges and universities nationwide. In the spring of 1978, Class 1977 entered the university. The college entrance examination was held again in the summer of 1978, with 6.1 million applicants and 420,000 enrolled. Class 1978 entered the university in the autumn of 1978, only half a year apart. On May 15th, 1978, China formally resumed the postgraduate entrance examination, and 10,000 students were accepted.

However, the resumption of college entrance exam didn’t give the higher education system a swift recovery. In 1976, the number of teachers engaged in scientific research in colleges is less than 10% of the total number of teachers in service, and laboratories and equipment were seriously damaged. Take Tsinghua University as an example, from June 1966 to April 1977, the loss of instruments and equipment in Tsinghua University was about 18 million RMB (nearly half of the total value of original instruments and equipment). More than 10,000 pieces of laboratory furniture were lost, and the number of laboratory staff was reduced from 1100 to 500, among which the number of laboratory technicians was reduced from 480 to 180. Though countless people desired to enter universities, universities themselves at that time lacked the faculty and equipment to take students. Consequently, in 1980s, there were few college graduates. The higher education system was deeply hurt in this ten year calamity, casting a long shadow on Chinese human capital storage and growth. It was only in 1990s that universities began to expand enrollment. But those 1990s college graduates are now in their forties, too young to be a senior manager of a listed company in many cases. This is why nearly half of China's CEOs of listed companies lack a college degree.

Those who would have regained the right to attend university, born between 1948 and 1959, suffered severely and negatively from the unexpected shock of the Cultural Revolution. Their opportunity cost to attend university or prepare for college became a lot higher as they grew older and went to work and host their own families. Consequently, although those older unlucky cohorts were declared to own the right to take the exam after the year of 1977, many of them simply chose not to take the reopened examination at all, for it had been too many years since they graduated from high school. Some of them may become frustrated in themselves and change their beliefs about the pros and cons of receiving higher education, while some of them may have forgotten what they had learned years ago in high school so they were afraid they might have lost competitiveness in the Gaokao and they were not that determined to put efforts into regaining knowledge and reviewing for the exam. Besides, many of them already had a job and had an entire family to raise, they were unable to afford the various costs and risk to quit job and take exam to enter college any longer. Generally speaking, though the college entrance exam never set limits on the age of exam takers, a whole unlucky generation missed the opportunity and time to receive higher education.

3. Data and summary statistics

This section provides descriptions of our sample, definitions of dependent variables, the core independent variable and our control variables, and presents the summary statistics. Details of all variables' definitions are presented in Appendix A.

3.1. Sample construction

Our sample is consisted of companies that are listed in China's two major exchanges, the Shanghai A-share stock market and the Shenzhen A-share stock market. We construct a year-firm panel data set to verify whether or not college education has any influence on CEO's performance on firm innovation. The CSRC released the Accounting Rules of China's Enterprises (2006 version) in 2006, requiring all listed firms to report their annual R&D expenditures. Companies began to disclose their R&D expenses in annual reports since 2007, so the R&D input before 2007 was mostly blank. In order to ensure the accuracy of the sample, the data we use are from the China Stock Market Trading Database and Wind Economic Database, from 2008 to 2016.

Following Jayanthi Sunder, Shyam V. Sunder and Jingjing Zhang (2017), our sample consists of firms operating in the 2-digit industrial classification of the China Securities Regulatory Commission (CSRC) industries where the average patent count per firm in the industry is at least one. In this way we are enabled to take firms with zero patents into account, while excluding firms in which innovation activity is not that crucial. And we exclude financial firms.

3.2. Variable measurement

3.2.1. Measuring education background

In our dataset, each CEO's degree is measured by a dummy variable, Degree. Degree takes 1 when CEO graduated from a secondary school. Degree takes 2 when CEO graduated from a junior college. Degree takes 3 when CEO graduated from an undergraduate school. Degree takes 4 when CEO is a master graduate student. Degree takes 5 when CEO is a doctoral graduate student. Degree is denoted as missing when CEO has no degree at all.

To study how undergraduate education affects company innovation, we generate a binary variable: College Degree. Variable College Degree takes 1 when Degree is at least 3, otherwise it equals 0. In section 4 we run first difference regressions using this binary variable as core independent variable and focus our attention on the coefficient of this binary variable.

3.2.2. Measuring corporate innovation

We construct our main innovation variables from China Stock Market & Accounting Research Database and Wind Economic Database and measure innovation from three aspects. Firstly, we use firms' R&D spending from Wind Economic Database as the measure of innovation input. In our empirical analysis, we take R&D expenditures scaled by total assets, and designate it as R&D/Assets. Secondly, we use patenting activity to measure firms' innovation output. Previous literatures have shown that patent application is closer to the actual timing of innovation (Griliches, Pakes, and Hall, 1987). So we use a patent's application year instead of its grant year. Another thing that is worth noting is that, in China many companies are not necessarily listed as a whole; in addition, many companies have also invested in some non-listed company. So some Chinese companies will make patent application via branches. All together, we use two metrics to proxy for the firm's innovation output. The first metric is the number of patent applications that are filed for each firm-year, by the listing firm and its branches. This proxy better describes the actual timing of innovation, yet every coin has two sides, it lacks the ability to capture variations in a patent's technological and economic importance. To make up for the first method, our second metric is the number of patent applications filed in a year by the listing firm and its branches that have been eventually granted up to 2016.

However, the ultimately granted patents count suffers from a truncation problem because there is, on average, a two-year lag between a patent's application date and grant date. Following prior work (Hall, Jaffe and Trajtenberg, 2005; Fang, Lerner and Wu, 2017), to reflect the long-term nature of patent assets, we construct the patent stock measure as follows:

$$K_{i,t} = (1-\theta)\, K_{i,t-1} + r_{i,t} \tag{1}$$

Where

• $K_{i,t}$ is the patent stock of firm i in year t

• θ is the rate of depreciation of the patent stock, which is set to 15% in accordance with prior work

• $r_{i,t}$ is the ultimately granted patents applied for by firm i in year t.

Thirdly, to further assess a patent's influence, we use patent citation. We hand-collect patent citation information for every listing firm from the Chinese State Intellectual Property Office (CSIPO). Unfortunately, we are not able to collect citations for patents applied by the listing firm's branches. So we use the number of citations a listing firm's patents received. Besides, we also use citations-per-patent to better capture the importance of innovation output. Yet citations suffer from two imperfections. First, citations also have the truncation problem, as they are received for many years after the patent is applied for and granted. Second, citation intensities vary across industries. To adjust for these problems, we follow Hall, Jaffe, and Trajtenberg (2001), and divide the number of citations-per-patent for each firm by the mean of the number of citations-per-patent received by all patents in that year in the same industry as the patent. The adjusted variable is constructed to capture relative citation strength. If it is higher than one, then it implies that a particular patent is cited more than the average patent successfully filed for in the same year in the same industry.

Due to the right-skewed distributions of patent counts and citations, we take natural logarithm for patent applications, granted patent applications, patent stock, citation counts, citations-per-patent and relative citation strength. To avoid losing firm-year observations with zero patents or citations, we add one to the actual values when calculating the natural logarithm. Thus besides R&D/Assets, we generate six variables to measure innovation respectively. Patent Application is the number of patents applied for during the year by the listing firm and its branches. Successful Patent Application is the number of patent applications filed in a year by the listing firm and its branches that have been eventually granted up to 2016. Patent Stock is the stock of granted patents, calculated as equation (1). Citation is the number of citation a listing firm's patents received, and Citation per Patent is citations-per-patent measurement. Relative Citation Strength is the number of citations-per-patent for each firm scaled by the mean of the number of citations-per-patent in the same year-industry cohort to which the patent belongs.

All in all, R&D expenses reveals the commitment of firm's resources to innovation, patent metrics show the innovation output in generating new knowledge that can in principle be appropriated by the firm, and citations indicate the extent to which those innovations turn out to be "important" and hence presumably more valuable to the firm.

3.2.3. Control variables

We control for a series of different variables which stand for multiple time-varying firm characteristics that are considered to be important for company innovation. Control variables includes LnPPE (the natural logarithm of the ratio of net property, plant and equipment to the number of employees), CEO's Age, Tobin's Q (the market value of assets divided by the book value of assets), ROA (return on assets), Firmsize (the natural logarithm of total assets) , Cash flow (cash flow from operation, scaled by lagged firm size), Chairman CEO (Chairman CEO equals 1 when CEO is also the chairman of the board, otherwise it equals 0), SOE (SOE takes the value of 1 if the company is a state owned enterprise and takes 0 otherwise).

3.3. Summary statistics

Table 1 presents the summary statistics for our main variables. The sample is divided into two groups, one with college degree, the other one without. In Table 1, we show the t-statistics of a t-test between these two groups. Comparing the sample means for firms run by CEOs with college degrees and firms run by CEOs without college degrees, we find important differences in the characteristics of firms. CEOs with college degrees are less likely to work in state-owned firms, invest more in R&D and generate more patent applications, get more patents successfully granted, hold more patent stock, receive more citations and possess higher relative citation strength.

We implement a Diff-in-Diff t-test to show that what happened for firms when College Degree changes from 0 to 1, what happened for firms when College Degree changes from 1 to 0 and what happened for firms when College Degree remains 0 are different. The result is shown in Table 2. We provide Diff-in-Diff t-test results of main dependent variables around CEO turnovers in a [-3, +3] window, where the turnover years are excluded. We first take the mean of each firm's innovation before and after turnover, and therefore calculate firm diffs. For each treatment firm (where turnover does happens), we generate firm diffs for all firms in the same industry around using the same turnover year, and take the median of these diffs as control industry diff. Panel A to Panel C each represents the results for different types of treatment firms' CEO turnovers, with each table reports the mean of firm diffs, the mean of industry diffs, and the t-statistics for diff-in-diff, and the last 2 columns of each table reports the results when treated firms' diffs are winsorized at 1% and 99% levels. The results imply that the innovation differences of firms are indeed related to changes of CEOs' college degree.

However, these differences we've observed from Table 1 and Table 2 still may be driven by firm characteristics and other unobserved factors. Therefore, we'll take a further look at the relationship between college education and corporate behavior in a multivariate regression setup in section 4. In addition, we would like to include year, industry and province fixed effects in the multivariate first-difference OLS regressions to address the concern that unobserved systematic variations cross year, industry and province may also tend to drive the results.

4. CEO college education and corporate innovation

In this section, we examine empirically whether firm innovation varies with different CEO's higher education background. The sample is based on all China's listed companies from 2008 to 2016 with non-missing values and consists of firms operating in the 2-digit industrial classification of the China Securities Regulatory Commission (CSRC) industries where the average patent count per firm in the industry is at least one. Financial firms are excluded. We set up multivariate regression models to investigate the relation between college education and corporate behavior. Also, we include year, industry and province fixed effects to rule out the possibility that unobserved characteristics of these aspects might drive the results.

Following literature on CEO styles, we begin our analysis by running panel OLS regressions that relate CEO's college experience to a variety of corporate innovation measures. We focus on three main types of innovation measures: R&D spending decisions, counts of patent number, and citations. Specifically, we estimate the following model as our baseline regression:

$$y_{it} = \beta * \text{College Degree}_{it} + \alpha * X_{it} + V_t + V_j + V_p + \varepsilon_{it} \quad (2)$$

y_{it} represents the dependent variables, which include R&D expenses, number of patent application, number of patent application that have got granted, patent stock, number of citations and citations-per-patent, respectively. The regression results of these dependent variables are shown in order.

Regressions for model (2) include year fixed effects V_t, Firm fixed effects or standard industrial classification (The SFC industry classification, 2016) industry fixed effects V_j. When V_j stands for firm fixed effects, we cluster standard errors at firm level. When V_j stands for industry fixed effects, we would also include province fixed effects and year*industry fixed effects to control for time trends and variations across industries and provinces, and cluster standard errors at province*year level. The coefficient of interest in our regressions is β, which relates college education to corporate innovation behaviors. In other words, the independent variable of interest is variable College Degree, which captures the different backgrounds of CEOs' college education. The baseline results of our paper are presented in Table 3, from Panel A to Panel B. For brevity, we don't report the coefficients of control variables in our tables.

We first present firm fixed effect regressions in Panel A. When firm fixed effect is included in regressions, the regressions will only take those observations into consideration---the 2 observations right before and right after the change of variable College Degree. However, we know patent and citation each has time lags, different from R&D/Assets. So the patent right before the change of X might not be effective to show the real patent condition of that year. The same logic applies for the observation right after the change of College Degree. So we take year mean of all dependent variables before turnover, and the year mean of them after turnover, and exclude CEO turnover year.

It can be seen from Panel A that R&D expenditures are significantly much higher when firms switch to college CEOs, which imply that when companies hire CEOs who have received higher education, they would perform significantly better in respective to innovation input. This may be due to the possible cause that CEOs will value research and innovation more after they themselves have received college education. When making firm budget constraint decisions, as these college CEOs themselves know more about the specific professional knowledge or know more about the importance of research and development, they may allocate more resources and money into innovation input. Also, when hiring employees, these CEOs may tend to hire those with a better education background, which in turn will lead to the whole company spend more on R&D. However, as the unlucky generation who got into their eighteens during the Cultural Revolution missing the right time and opportunity to get into college are now generally in their fifties and sixties, a majority age cohort for CEOs in China nowadays, nearly half of the CEOs of Chinese listed companies are in position, without college degree. This is, technically speaking, quite rare compared to the west. One can imagine because of the lack of managerial college education, nearly half of listed companies in China invest less in R&D, which is no doubt a crucial element in driving technology changes and economic development. Taking the market as a whole, so many companies should have invested much more in R&D.

Although companies may spend a lot on innovation input, there is no guarantee that more input will turn into more output. So next we take a look at the innovation outcomes, measured by a variety metrics of patenting activity and citations those patent received. We can see that college degree CEOs generate a significantly larger number of patent applications. As noted before in section 3, it have been studied and shown that application of patents occur more closely after the real innovation take place, compared to the occurrence of granting of patents, which generally lag two or more years after the application of patent. So we use the application number of patents to measure the output of innovation to ensure timelines. Also, when CEOs have college degrees, the number of patents applications that finally got granted is significantly higher. When the long term nature of patent assets are considered by the measurement of Patent Stock, companies with college CEOs still do significantly better.

Panel B show within industry differences. Our results still holds. Besides, it shows that when we use the number of citation as dependent variable to better illustrate the technological validity and economic contribution of corporate patent activities, the coefficient of independent variable, College Degree, is positive and significant. When we change the dependent variable to citations-per-patent, or when we use Relative Citation Strength to better capture the essence of citation, the coefficients of College Degree are still significant. In sum, all these empirical results indicate that companies with college CEOs not only invest more in R&D, but also perform better in patenting activities. Thus the innovation input and output of these companies are significantly better than their peers.

Taken together, the implication of our baseline result is that, companies with college graduated CEOs perform significantly better in innovation activity than those without. One thing we know for sure is that, these two types of companies differ in their policy and innovation efficiency. But there are still some concerns left to be discussed. What if the board deliberately replaces the CEO and meanwhile changes the company's policies? In section 5 we further examine these concerns by using a retirement sample and by using an instrument variable.

5. Dealing with endogeneity

In the previous section, we conclude that companies of which CEO has a college degree behave differently from those of which CEO has no college degree in terms of innovation. But there are still concerns about various conditions of endogeneity. For instance, the board may choose to switch into a new CEO and, in the meantime, decide to change the company's policies, including the policies about R&D. Or the economic environment where the company located in changes abruptly, leading to the turnover of CEO, thus leading to the change of the degree of CEO. Yet due to this economic shock any newly hired CEO would choose the same policy. Or some unobserved characteristics of the firm change, which could be related with the changing of CEO, yet related to firm's innovation and investment policies as well. Like, maybe the old CEO did a poor job on innovation and investment, so he was fired. Under such circumstances, his succession would implement new policies about innovation and investment. There are dozens of possible endogenous factors that may lead to the same empirical results.

In this section, we use an exogenous CEO turnover sample– the retirement sample to deal with these concerns, and implement an instrument variable approach by making use of the Cultural Revolution episode.

5.1 CEO turnover and natural retirement

To address endogeneity concern, we now take a close look at the college degree change of the CEO caused by exogenous turnovers.

When speaking of exogenous CEO turnovers, we basically refer to the replacement of CEO due to natural reasons such as death or sickness, natural retirements (not forced abruptly by the board, in contrast). To make our analysis accurate and solid, we thus choose to use the CEO turnovers as a result of natural retirement. For our sample, strict natural retirement is defined as this: male CEO who leaves his position after the age of 60 is considered to be naturally retired, while female CEO who departs from her position after the age of 55 is regarded as naturally retired. In this turnover sample of retirement, we include the firm-year observations of the naturally departing CEO and his or her succession. Then we can exploit the change of innovation activity caused by the natural turnover of CEO. These turnovers, as they are generally exogenous, have very little possibility to be related with any change of firm characteristics or the leaving CEO's historical performance in innovation.

Let's first take a look at this retirement sample. Panel A of Table 4 introduces the detailed conditions of this retirement sample. In this subsample, there are in total 231 times of CEO changes, among which 82 times cause the subsequent change of CEO's college degree. Among these 82 times of degree changes, there are 59 times in which the departing CEO has no college degree, while the successive CEO has one. We can conclude that due to natural retirement events, quite a few firms begin to have college degree CEOs.

To further investigate the degree to which college degree influence innovation when only considering exogenous turnover, we run OLS regressions. One concern is that, as the saying goes, a new broom sweeps clean. To avoid the abrupt change of firm policies due to the change of CEO, we exclude the observations that fall into the range of (-1 year, +1 year) of the turnover event. Then we run the regressions. Due to limited sample size when we use retirement as a criterion, the regressions containing firm fixed effect will not be significant. Thus Panel B of Table 4 doesn't contain firm fixed effect. Panel B of Table 4 provides regression results around natural CEO retirement events. The dependent variables are R&D/Assets, Patent Application, Successful Patent Application and Patent Stock. We could see that the coefficients of interest are positive. The effect of college degree on Patent Application is significantly positive at 10%. The effect of college degree on Successful Patent Application is significantly positive at 5%. R&D/Assets has too many missing values to show significance, we can tell this from the difference of observations of R&D/Assets and those of Patent Application and Successful Patent Application. Citation and Citation per Patent are not shown in Panel B. As we have noted in section 3, we can only collect citations for listing firms, not for branches. So citation numbers are much less for firms whose branches also apply for patents. Besides, on average, one patent only receive 0.07 citations, which means we have much less non-zero observations for citation than patent. So when it comes to the small retirement sample, citations won't work. Thus we didn't include citation metrics in Table 4, Panel B or Table 6.

5.2 Unlucky generation as IV

In this section, we use an IV approach to deal with endogeneity concerns. Our IV is a binary variable, denoted as Unlucky. Unlucky equals 1 if the CEO was born during the cohort of 1948-1958, which means he reached his 18 during the period of the Cultural Revolution (1966—1977). Unlucky equals 0 if otherwise. Next firstly we take a look at our IV regression results.

5.2.1 IV results

Our main strategy in this section is to implement an IV model. Table 5 provides us with the empirical results of IV regression. From Panel A of Table 5, we can observe that by using Unlucky as a valid instrument, we clarify the relationship between CEO's college education and firm innovation. Also, we show F-statistic, Kleibergen-Paap rk LM statistic, Kleibergen-Paap wald rk F statistic, Anderson-Rubin Wald statistic to ensure the validity of our IV. Shea's Partial R-Squared are included in the table as well. As shown in Panel A, Table 5, except Successful Patent Application, all measurements for innovation are significantly positive in IV regressions, which confirm the managerial college degree effect on innovation.[†] Table 5, Panel B is the regression of College degree against Unlucky. As the first stage IV result, not surprisingly, it shows consistency with our assumption that those unlucky ones are less likely to have a college degree. Panel B of Table 5 shows that the coefficient of Unlucky is negative, significant at 1%.

One may ask why our coefficients for IV regression are bigger than those in baseline regression. Here we provide two things as explanations. First, for Unlucky, compliers include those who wouldn't go to college if they were born during 1948-1958----they are supposed to have no ability to afford to prepare for the college entrance exam again in their middle age or attend school while raising a family. Compliers include those who would definitely go to college if they were born out of the range of 1948-1959----they have such a strong willingness to attend college. In other words, the subgroups whose decisions are affected by the "Unlucky" supply-side shock were constrained by the marginal cost of schooling, rather than by the lack of either desire or ability to benefit from college education. So the return to education for these compliers may be higher than other subgroups. Therefore the local treatment effect on the margin for the IV-compliers could exceed that of the population average treatment effect. That's why IV regressions produce larger coefficients. Second, looking back at section 5.1, we could see the regressions coefficients for the retirement sample are of the same magnitude as that of our whole sample IV regression, which further implies when endogeneous concerns

[†] Successful Patent Application has truncation problems. Many patent applications filed during the latter years in the sample were still under review and had not been granted. To address this problem, researchers follow Hall, Jaffe, and Trajtenberg (2001, 2005) to make adjustments to Successful Patent Application. This is a typical problem for patent data in the U.S., since patents appear in the NBER database only after they are granted. It's not a severe problem for Chinese patents, since we could obtain Patent Application.

are ruled out, the coefficients become larger, comparing to the baseline regression.

Moreover, in Table 6, we run the same set of regressions for exogenous turnover sample as in Table 4, Panel B, but this time using Unlucky as IV. Not surprisingly, the results improve relatively to the results in Table 4, Panel B, in terms of magnitude and significance. All dependent variables are significant at 1% level.

To conclude, after removing all possible endogeneity concerns by exploring retirement sample and creating IV, our baseline results still holds.

5.2.2 Validity of IV

As we have explained before, colleges and universities shut down during this movement and the college entrance exam was suspended for 10 years. The unlucky generation, as defined above, has little possibility to go for college, not to mention the chance to finish college and get a bachelor degree. This generation spent their entire youth not in college, but in factories and countryside as labors. When Gaokao was resumed, they might have considered it too costly to take the exam again, so most of them never got a college degree. Instead, they just bailed out of the competition of Gaokao. This logic confirms us that our IV, Unlucky, is highly correlated with our independent variable of interest, College Degree. Besides, intuitively, Unlucky appears to have little to do with firm characteristics or firm policies such as R&D or patent activity, thus assuring the validity of IV.

One may still argue that our IV, Unlucky, not only represents the rare possibility of this unlucky generation to attend college, but also contains these unlucky people's changes of beliefs. After all, they are unlucky, indeed. They not only lost the opportunity to head for colleges, but also are deprived the right to enjoy a free, peaceful decade. The mass political movement triggered fights among different groups of people, economic was dragged, and families of intellectuals were persecuted. How could we expect this unlucky generation to respect knowledge, research and innovation, when they didn't have the chance to experience a college life, and when some of them have witnessed the persecution of their parents or relatives? As a matter of fact, they may have suffered mentally and physically in the Cultural Revolution so that their attitude toward R&D investment is different from ordinary people. Then the exogenous nature of IV is in doubt. Unlucky could be in correlation with R&D

expenditures.

To deal with this concern, we use a set of regressions to check whether or not Unlucky does carry the elements of belief changing. In Table 7, Panel A, we reveal that for those firms led by CEOs without college degrees, whether CEOs have experienced the Cultural Revolution has little to do with firm innovation. This time we run regression where the dependent variable is innovation, independent variable of interest is Unlucky, in the sample where every CEO have no college degree. We can see that being lucky or unlucky does not have any impact on innovation. Also, we repeat the regressions at CEO-individual level, the result in Panel B of Table 7 is consistent with result in Panel A, Table 7. Till now, we empirically rule out the concerns for IV validity.

We have to admit that the Cultural Revolution might have a deep influence on this unlucky generation from a variety of aspects. It not only changed individuals' education experience, but also might have changed their attitudes towards a lot of things, which are far beyond concerns in this paper. However, we have verified that at least the Cultural Revolution doesn't change CEOs' attitude towards innovation. Thus our IV Unlucky isn't related with corporate innovation. Unlucky is an exclusive IV.

6. Causality

Finally, we take a look into causality concerns. What if the college degree itself is only a signal for higher personal capabilities? To establish a causal relationship between managerial education and human capital stock, we apply a regression discontinuity design (RDD), using the year of 1978 (A.K.A. birth year of 1960) as the cut-off point. As we have discussed earlier, CEOs who reached the age of 18 before 1978 faced more difficulties in entering college. Thus if they do not have a college degree, it is less likely a result of their incapability. In contrast, it may be largely due to reasons which are out of their control. We focus on CEOs who reached the age of 18 at years surrounding 1978. We assume that CEOs born in this cohort have no other observed or unobserved systematic differences, the result of owning or not owning a college degree is simply a random sampling outcome by "The hand of God". If firms led by those CEOs still show differences in innovation according to degree differences, then we can say that education does change CEOs' human capital stock, leading to different corportate innovation behaviors.

We adopt both reduced form RDD and fuzzy form RDD. The specific polynomial model is shown below:

$$y_i=\beta\ POST_i+\ \alpha\ POST_i*EventTime_i+\alpha*X_i+V_j+V_p+\varepsilon_i \quad (3)$$

Where y_i represents dependent variables. Treatment variable POST, is a dummy variable, equal to 1 if the year is larger than 1977, and zero otherwise. EventTime equals to year minus 1977. X_i contains control variables. Industry fixed effect and province fixed effect are added. All variables are averaged at CEO individual level, and regressions are run at CEO individual level as well. To reflect the long run nature of patent assets, we also include lagged patent application number and lagged successful patent application number as dependent variables to show robustness of the results.

We conduct standard check for RDD validity. Generally, people cannot choose their birth year. So the randomness of sample assignments around cut-off year is guaranteed. Next, we check whether control variables included in the RDD regressions are continuous around the cut-off-point. Appendix B presents regression for covariates. Panel I shows the results using a (-3 year, +3 year) window. Panel II shows the results using a (-4 year, +4 year) window. Panel III shows the results using a (-5 year, +5 year) window. The coefficients of POST are insignificant. In this way we assure there's no significant jump of covariates at the cut-off-point. Besides, we do a SUR test for these regressions to test the null hypothesis that there's no statistical difference among the coefficients for these regressions. For example, when using the (-3 year, +3 year) window, the p-value for SUR test is 0.1303, so we can't reject the null hypothesis.

After examining the validity of RDD design, we come to test the effect of the resumption of the Gaokao on education outcomes. As shown in Table 8, College Degree is regressed against POST in a probit model. The marginal effects are significantly positive, ensuring the treatment effect on college degree.

Finally we do analysis about degree effect on innovation. We run both reduced form RDD and fuzzy form RDD. In the reduced form RDD, we regress innovation against POST as what we have shown in model (3). Results are shown in Table 9. For fuzzy RDD model, we use treatment dummy POST directly as the actual IV for College Degree, and run the IV regressions, with results shown in Table 10. For each table, Panel A shows the results using a (-3 year, +3 year) window. Panel B shows the results using a (-4 year, +4 year) window. Panel C shows the results using a (-5 year, +5 year) window. Patenting activities show significant difference surrounding the cut-off-year, and R&D also show some, though not much, difference.

All put together, we use a regression discontinuity design to deal with causality concerns, and reach the conclusion that college education does change CEOs' human capital stock and therefore changes companies' innovation behavior. For those CEOs who have never got a chance to receive formal college education due to the Cultural Revolution, their firms perform worse in innovation activity.

7. Conclusions

This paper is the first to explore the relationship between managerial education and corporate innovation by looking into the special episode of the Cultural Revolution. We reveal that firms with and without college-degree CEOs behave differently in the field of innovation, such as R&D expenditure, patent application, patent authorization and citation. Some may argue there're endogeneity concerns. Getting inspirations from the generation born during 1948-1959 who suffer from the Cultural Revolution in their eighteens, we implement an instrument variable, Unlucky, to adopt procedures of IV method. Also, we use an exogenous retirement sample. We run both OLS and IV regressions within this subsample. In this way, we fully solved endogeneity, to reach to the conclusion that CEOs' college degree does matter for corporate innovation. Finally, to cope with causality issues, we apply a discontinuity regression design around the cut-off-year, 1978, when college entrance exam was resumed again. Results show that college education does increase CEOs' human capital stock, making firms to involve more in innovation. Since nearly half of China's CEOs of listed companies still have no college degree, their firms' innovation capacity and effectiveness suffer.

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Table 1

Summary statistics of main variables, by firm-year

This table provides summary statistics of main variables for both firms led by CEOs with no college degrees and firms led by CEOs with college degrees.

	With College Degree			Without College Degree			Difference
	Mean	Std. dev.	Observations	Mean	Std. dev.	Observations	t-Test
Dependent variables							
R&D/Assets	17.375	1.548	8472	17.096	1.750	5853	10.044
Patent Application	2.119	1.773	11133	1.713	1.715	9611	16.678
Successful Patent Application	1.870	1.687	11133	1.538	1.629	9611	14.343
Patent Stock	2.648	1.986	9174	2.241	1.967	7784	13.350
Citation	0.368	0.907	8753	0.326	0.831	7367	3.036
Citation per Patent	0.076	0.232	8753	0.073	0.232	7367	0.717
Relative Citation Strength	0.406	1.200	8403	0.343	1.077	7083	3.447
Independent variable							
College Degree	1.000	0.000	11133	0.000	0.000	9611	
Control variables							
ROA	0.043	0.060	11132	0.034	0.067	9610	9.393
Cash flow	0.086	5.596	10082	-0.019	8.740	9067	0.998
FirmSize	21.600	1.321	10092	21.599	1.265	9078	-0.078
CEO's Age	48.314	6.269	11123	49.067	6.600	9594	-8.415
Chairman CEO	0.291	0.454	11133	0.205	0.404	9611	14.268
Tobin's q	3.001	2.744	10871	2.608	2.689	9409	10.277
LnPPE	11.737	1.766	11037	11.731	2.025	9485	0.211
SOE	0.356	0.479	11133	0.500	0.500	9611	-21.123

Table 2
Diff-in-Diff t-test for innovation around CEO turnovers

This table provides Diff-in-Diff t-test results of main dependent variables around CEO turnovers in a [-3, +3] window, where the turnover years are excluded. We first take the mean of each firm's innovation before and after turnover, and therefore calculate firm diffs. For each treatment firm (where turnover does happens), we generate firm diffs for all firms in the same industry around using the same turnover year, and take the median of these diffs as control industry diff. Panel A to Panel C each represents the results for different types of treatment firms' CEO turnovers, with each table reports the mean of firm diffs, the mean of industry diffs, and the t-statistics for diff-in-diff, and the last 2 columns of each table reports the results when treated firms' diffs are winsorized at 1% and 99% levels. Panel A is based on the sample where treatment firms' CEO turnovers make CEOs' degrees change from 0 to 1(from no college degree to college degree). Panel B based on the sample where treatment firms' CEO turnovers make CEOs' degrees change from 0 to 0. Panel C is based on the sample where treatment firms' CEO turnovers make CEOs' degrees change from 1 to 0.

Panel A: Treatment firms: turnovers that make CEOs' degrees change from 0 to 1

	Treated Firms		Control Firms(Industry Median)	Diff-in-Diff	Winsorized Treated Firms	Diff-in-Diff
	Mean of firm diff	#Firms	Mean of industry diff	T-statistic	Mean of firm diff	T-statistic
R&D/Assets	1.052	55	0.81	1.411	1.047	1.402
Patent Application	0.812	55	0.43	3.105	0.812	3.105
Successful Patent Application	0.685	55	0.269	3.572	0.685	3.572

Table 2
Diff-in-Diff t-test for innovation around CEO turnovers

Panel B: Treatment firms: turnovers that make CEOs' degrees change from 0 to 0

	Treated Firms		Control Firms(Industry Median)	Diff-in-Diff	Winsorized Treated Firms	Diff-in-Diff
	Mean of firm diff	#Firms	Mean of industry diff	T-statistic	Mean of firm diff	T-statistic
R&D/Assets	0.993	127	0.758	1.384	1.027	1.715
Patent Application	0.374	127	0.382	-0.135	0.374	-0.139
Successful Patent Application	0.262	127	0.269	-0.137	0.264	-0.102

Panel C: Treatment firms: turnovers that make CEOs' degrees change from 1 to 0

	Treated Firms		Control Firms(Industry Median)	Diff-in-Diff	Winsorized Treated Firms	Diff-in-Diff
	Mean of firm diff	#Firms	Mean of industry diff	T-statistic	Mean of firm diff	T-statistic
R&D/Assets	0.55	22	0.638	-0.314	0.569	-0.257
Patent Application	-0.077	22	0.381	-2.034	-0.035	-2.026
Successful Patent Application	-0.067	22	0.26	-1.586	-0.029	-1.535

Table 3
Effect of CEO's college degree on firm innovation, OLS results

This table provides OLS regression results of the main dependent variables against our core independent variable, College Degree. This sample is based on China's listed companies from 2008 to 2016 with non-missing values, consisting of companies operating in the 2-digit industrial classification of the China Securities Regulatory Commission (CSRC) industries where the average patent number per company in the industry is at least one. Financial firms are excluded. Panel A reports the firm fixed effects regression results. Panel B represents the industry fixed effects regression results for seven different dependent variables, R&D/Assets, Patent Application, Successful Patent Application, Patent Stock, Citation, Citation per Patent and Relative Citation Strength. All variables are defined as in the Appendix A. Control variables are included in each regression. In Panel B, Year fixed effects, industry fixed effects, province fixed effects, year*industry fixed effects are added into each regression. The standard errors are clustered at province*year level. T-statistics are in parentheses.* Indicates significance at 10% level; ** significance at 5% level; *** significance at1% level.

Panel A: Within firm changes: Firm fixed effects

Dependent variable	R&D/Assets	Patent Application	Successful Patent Application	PatentStock	Citation	Citation per Patent	Relative Citation Strength
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
College Degree	0.341**	0.288**	0.312**	0.370***	0.0475	0.0398	0.046
	(2.05)	(2.25)	(2.48)	(2.96)	(0.36)	(0.97)	(0.78)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1884	1929	1929	2006	1732	1454	1848
R-squared	0.147	0.274	0.144	0.453	0.214	0.316	0.176

Table 3
Continued

Panel B: Within industry differences: Industry fixed effects

Dependent variable	R&D/Assets	Patent Application	Successful Patent Application	PatentStock	Citation	Citation per Patent	Relative Citation Strength
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
College Degree	0.236***	0.0905***	0.0698***	0.0392*	0.0315**	0.00682**	0.0158**
	(3.92)	(4.04)	(3.16)	(1.81)	(2.04)	(2.00)	(2.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at Province*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12392	18240	18240	16764	14109	14109	14336
R-squared	0.5154	0.4937	0.4796	0.4893	0.3879	0.2857	0.2398

Table 4
Retirement sample
This table shows what happens around natural CEO retirement events. Panel A introduces the detailed conditions of this retirement sample. Panel B provides regression results around natural CEO retirement events. All variables are defined as in the Appendix A. The same of control variables, as in Table 3, are included in every regression in Panel B. One concern is that, as the saying goes, a new broom sweeps clean. In Panel B, to avoid the abrupt change of firm policies due to the change of CEO, we exclude the observations that fall into the range of (-1 year, +1 year) of the turnover event before we run regressions. Year fixed effects, industry fixed effects, province fixed effects, year*industry fixed effects are added into each regression. The standard errors are clustered at province*year level.* Indicates significance at 10% level; **significance at 5% level; *** significance at1% level.

Panel A: Details of exogenous CEO changes

	Exogenous changes	College Degree Change	Begin to have college degree
♯number	231	82	59

Panel B: Effect of CEO’s college degree on innovation

Dependent variable	R&D/Assets	Patent Application	Successful Patent Application	Patent Stock
	(1)	(2)	(3)	(4)
College Degree	0.277	0.264*	0.298**	0.114
	(0.78)	(1.82)	(2.08)	(0.64)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Cluster at Province*Year	Yes	Yes	Yes	Yes
Observations	380	734	734	588
R-squared	0.703	0.666	0.658	0.6887

Table 5
IV

This table provides empirical regression results of whole-sample IV regression. Panel A shows the results of the second stage of IV. Year fixed effects, industry fixed effects, province fixed effects are added respectively into each regression. Panel B presents the first stage regression of IV. College degree is run against independent variable Unlucky. The standard errors are clustered at province*year levels. T-statistics are in parentheses.* Indicates significance at 10% level; **significance at 5% level; *** significance at1% level.

Panel A: IV second stage

Dependent variables	R&D/Assets	Patent Application	Successful Patent Application	Patent Stock	Citation	Citation per Patent	Relative Citation Strength
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
College Degree	1.607**	0.679*	0.389	0.647*	0.864**	0.170**	0.349**
	(2.21)	(1.94)	(1.19)	(1.81)	(2.52)	(1.99)	(2.4)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at Province*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	56.22	59.53	59.53	58.26	35.3	35.3	38.4
Kleibergen-Paap rk LM statistic	38.56	41.93	41.93	39.772	28.5	28.5	30.679
Kleibergen-Paap wald rk F statistic	56.22	59.53	59.53	58.257	35.3	35.3	38.404
Anderson-Rubin Wald statistic	5.58	5.43	2.18	3.74	8.76	4.71	6.62
Shea's Partial R2	0.004	0.003	0.003	0.004	0.003	0.003	0.003
Observations	12392	18242	18242	16764	14111	14111	14336
R-squared	0.2393	0.4758	0.4753	0.5335	0.091	0.074	0.059

Table 5
Continued

Panel B: IV first stage

Dependent variable	College Degree
Unlucky	-0.097***
	(-7.59)
Controls	Yes
Year fixed effects	Yes
Industry fixed effects	Yes
Province fixed effects	Yes
Cluster at Province*Year	Yes
Observations	12385

Table 6

CEO retirement sample with instrument variable

This table shows an IV regression result around natural CEO retirement events with College Degree instrumented by Unlucky. All variables are defined as in the Appendix A. The same control variables, as in Table 3, are included in every regression. Same as in Table 4, Panel C, we exclude the observations that fall into the range of (-1 year, +1 year) of the turnover event before we run regressions. Year fixed effects, industry fixed effects, province fixed effects, year*industry fixed effects are added into each regression. The standard errors are clustered at province*year level.* Indicates significance at 10% level; **significance at 5% level; *** significance at1% level.

Dependent variable	R&D/Assets	Patent Application	Successful Patent Application	Patent Stock
	(1)	(2)	(3)	(4)
College Degree	3.138***	1.761***	1.747***	2.521***
	(2.77)	(4.56)	(4.84)	(4.42)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Cluster at Province*Year	Yes	Yes	Yes	Yes
Observations	379	733	733	587
R-squared	0.387	0.628	0.614	0.631

Table 7
No college degree sample

This table provides empirical regression results to support the validity of IV. We run regression where the dependent variables stand for innovation, independent variable of interest is our IV, in the sample where every CEO has no college degree. All variables are defined as in the Appendix A. Control variable CEO's age is excluded from these regressions. Year fixed effects, industry fixed effects, province fixed effects, year*industry fixed effects are added into each regression. The standard errors are clustered at province*year level. T-statistics are in parentheses.* Indicates significance at 10% level; **significance at 5% level; *** significance at1% level.

Panel A: Effect of the Cultural Revolution on innovation, using the sample where CEOs have no college degree, firm-year level

Dependent variable	R&D/Assets	Patent Application	Successful Patent Application	Patent Stock	Citation	Citation per Patent	Relative Citation Strength
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unlucky	-0.114	0.043	0.039	0.039	0.029	0.008	0.0136
	(-1.49)	(1.18)	(1.10)	(1.09)	(1.05)	(1.00)	(1.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at Province*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5182	8631	8631	7692	6570	6570	6684
R-squared	0.5055	0.4903	0.472	0.4769	0.3756	0.3013	0.2765

Table 7
Continued

Panel B: CEO individual level: Effect of the Cultural Revolution on innovation, using the sample where CEOs have no college degree

Dependent variable	R&D/Assets	Patent Application	Successful Patent Application	Patent Stock	Citation	Citation per Patent	Relative Citation Strength
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unlucky	-0.0676	-0.0821	-0.0865	-0.111	0.0320	0.0162	0.0208
	(-0.61)	(-1.39)	(-1.53)	(-1.56)	(0.80)	(1.16)	(0.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year*Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at Province*Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1787	2623	2623	2470	2286	2286	2286
R-squared	0.4540	0.5828	0.5683	0.5672	0.4297	0.3773	0.3851

Table 8
RDD Treatment effect of College Degree

This table shows result of the RDD Treatment effect of College Degree. Variable College Degree is regressed against treatment dummy POST in a probit model to examine the RDD treatment effect of College Degree. K represents the polynomial order of RDD model. Window represents the bandwidth. Industry fixed effects, province fixed effects are added. The standard errors are clustered at province level. T-statistics are in parentheses.* Indicates significant at 10%; **significant at 5%; *** significant at1%.

Dependent variable	College Degree		
POST	0.067**	0.039***	0.038***
	(2.34)	(3.77)	(4.98)
Industry fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes
K	1	1	1
Window	(-3,+3)	(-4,+4)	(-5,+5)
Observations	1232	1883	2431
Pseudo R2	0.1016	0.0883	0.0804

Table 9
Degree effect on innovation, using reduced form RDD

This table shows results of the degree effect on innovation, using reduced form RDD. Innovation measures are regressed against treatment dummy POST. K represents the polynomial order of RDD model. Window represents the bandwidth. Panel A shows the results using a (-3 year, +3 year) window. Panel B shows the results using a (-4 year, +4 year) window. Panel C shows the results using a (-5 year, +5 year) window. All variables are defined as in the Appendix A. The same set of control variables, as in Table 3, is included in every regression. Industry fixed effects, province fixed effects are added into each regression. The standard errors are clustered at province level. T-statistics are in parentheses.* Indicates significant at 10%; **significant at 5%; *** significant at1%.

Panel A: (-3 year, +3 year) Window, using reduced form RDD

Dependent variable	R&D/Assets	Patent Application	Lagged Patent Application	Successful Patent Application	Lagged Successful Patent Application
	(1)	(2)	(3)	(4)	(5)
POST	0.317*	0.233***	0.307***	0.163**	0.3***
	(1.80)	(3.08)	(2.83)	(2.37)	(2.81)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1
Window	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)
Observations	837	1201	1095	1201	1095
Adjusted-R2	0.2963	0.5866	0.591	0.5653	0.573

Table 9
Continued

Panel B: (-4 year, +4 year) Window, using reduced form RDD

Dependent variable	R&D/Assets	Patent Application	Lagged Patent Application	Successful Patent Application	Lagged Successful Patent Application
	(1)	(2)	(3)	(4)	(5)
POST	0.095	0.257***	0.275***	0.189***	0.255***
	(0.39)	(3.74)	(2.56)	(2.79)	(3.20)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1
Window	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)
Observations	1320	1802	1644	1802	1644
Adjusted-R2	0.3064	0.5609	0.5602	0.5456	0.5494

Table 9
Continued

Panel C: (-5 year, +5 year) Window, using reduced form RDD

Dependent variable	R&D/Assets	Patent Application	Lagged Patent Application	Successful Patent Application	Lagged Successful Patent Application
	(1)	(2)	(3)	(4)	(5)
POST	0.258	0.302***	0.326***	0.221***	0.284***
	(1.21)	(5.80)	(5.39)	(4.24)	(4.39)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1
Window	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)
Observations	1701	2322	2131	2322	2131
Adjusted-R2	0.3048	0.5576	0.5609	0.5424	0.5494

Table 10
Degree effect on innovation, using fuzzy form RDD

This table shows results of the degree effect on innovation, using fuzzy form RDD. Innovation measures are regressed against treatment dummy POST. K represents the polynomial order of RDD model. Window represents the bandwidth. Panel A shows the results using a (-3 year, +3 year) window. Panel B shows the results using a (-4 year, +4 year) window. Panel C shows the results using a (-5 year, +5 year) window. All variables are defined as in the Appendix A. The same set of control variables, as in Table 3, is included in every regression. Industry fixed effects, province fixed effects are added into each regression. The standard errors are clustered at province level. T-statistics are in parentheses.* Indicates significant at 10%; **significant at 5%; *** significant at1%.

Panel A: (-3 year, +3 year) Window, using fuzzy form RDD

Dependent variable	R&D/Assets	Patent Application	Lagged Patent Application	Successful Patent Application	Lagged Successful Patent Application
	(1)	(2)	(3)	(4)	(5)
POST	2.749	3.811*	5.369	2.747*	5.250
	(0.56)	(1.78)	(1.28)	(1.68)	(1.31)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1
Window	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)
Observations	873	1201	1095	1201	1095
Adjusted-R2	0.476	0.3834	-0.1133	0.5226	-0.2478

Table 10
Continued

Panel B: (-4 year, +4 year) Window, using fuzzy form RDD

Dependent variable	R&D/Assets	Patent Application	Lagged Patent Application	Successful Patent Application	Lagged Successful Patent Application
	(1)	(2)	(3)	(4)	(5)
POST	0.271	1.946***	2.158***	1.407***	1.952***
	(0.13)	(3.26)	(2.38)	(2.86)	(2.22)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1
Window	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)
Observations	1320	1802	1644	1802	1644
Adjusted-R2	0.6015	0.7062	0.6697	0.7266	0.6571

Table 10
Continued

Panel C: (-5 year, +5 year) Window, using fuzzy form RDD

Dependent variable	R&D/Assets	Patent Application	Lagged Patent Application	Successful Patent Application	Lagged Successful Patent Application
	(1)	(2)	(3)	(4)	(5)
POST	1.256	2.326***	2.563***	1.66***	2.197***
	(0.56)	(4.22)	(3.45)	(3.77)	(3.02)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1
Window	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)
Observations	1701	2322	2322	2322	2131
Adjusted-R2	0.5743	0.6477	0.6004	0.6921	0.6118

Appendix A

Variables	Description
Dependent variables	
R&D/Assets	Research and development expenditures, scaled by total assets.
Patent Application	The natural logarithm of one plus the number of patents applied for during the year by the listed company itself, and its branches.
Successful Patent Application	The natural logarithm of one plus the number of patents granted during the year by the listed company itself, and its branches.
Patent Stock	The stock of granted patent computed according to equation (1), to reflect the long-term nature of patent assets.
Citation	The natural logarithm of one plus the number of citations by the patents of the listed company itself.
Citation per Patent	The natural logarithm of one plus citations-per-patent of the listed company itself.
Relative Citation Strength	The natural logarithm of one plus citations-per-patent corrected using HJT (2001)'s fixed effect method.
Independent variables	
College Degree	An indicator variable equal to 1 if the CEO at least owns a bachelor degree, and zero otherwise.
LnPPE	The natural logarithm of the ratio of net property, plant and equipment to the number of employees.
CEO's Age	CEO age in years.
Tobin's Q	The market value of assets divided by the book value of assets.
ROA	Return on assets.
Firmsize	The natural logarithm of total assets.
Cash flow	Cash flow from operation, scaled by lagged firm size.
Chairman CEO	An indicator variable equal to 1 when CEO is also the chairman of the board, and zero otherwise.
SOE	An indicator variable equal to 1 if the company is a state owned enterprise, and zero otherwise.
Unlucky	An indicator variable equal to 1 if the CEO was born during the cohort of 1948-1959, and zero otherwise.
POST	An indicator variable equal to 1 if the year exceeds 1977, and zero otherwise.
EventTime	A distance variable equal to year minus 1977.

Appendix B
Balanced covariates

This table shows the balanced check for covariates of RDD. Covariates are regressed against treatment variable, POST, to examine whether covariates are continuous around the cut-off-year. K represents the polynomial order of RDD model. Window represents the bandwidth. Panel I shows the results using a (-3 year, +3 year) window. Panel II shows the results using a (-4 year, +4 year) window. Panel III shows the results using a (-5 year, +5 year) window. Definitions of covariates are provided in Appendix A. Industry fixed effects, province fixed effects are added into each regression. We didn't test CEO's Age as it's for sure related with running variable. The standard errors are clustered at province level. T-statistics are in parentheses.* Indicates significant at 10%; **significant at 5%; *** significant at1%.

Panel I: (-3 year, +3 year) Window

Dependent variable	ROA	Cash Flow	Firmsize	Chairman CEO	Tobin's Q	LnPPE	SOE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
POST	0.001	-0.092	-0.161*	0.004	0.116	-0.036	-0.018
	(0.2)	(-1.19)	(-1.93)	(0.19)	(0.61)	(-0.30)	(-0.56)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1	1	1
Window	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)	(-3,+3)
Observations	1260	1260	1206	1260	1260	1254	1260
Adjusted-R2	0.1453	0.2269	0.3201	0.0982	0.2348	0.2526	0.2984

Appendix B
Continued

Panel II: (-4 year, +4 year) Window

Dependent variable	ROA	Cash Flow	Firmsize	Chairman CEO	Tobin's Q	LnPPE	SOE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
POST	-0.002	0.644	-0.095	0.006	0.128	-0.038	-0.013
	(-0.54)	(0.65)	(-1.53)	(0.28)	(0.88)	(-0.36)	(0.72)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1	1	1
Window	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)	(-4,+4)
Observations	1898	1811	1813	1898	1898	1888	1898
Adjusted-R2	0.1266	0.0345	0.2999	0.0999	0.2231	0.2503	0.2677

Appendix B
Continued

Panel III: (-5 year, +5 year) Window

Dependent variable	ROA	Cash Flow	Firmsize	Chairman CEO	Tobin's Q	LnPPE	SOE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
POST	-0.003	0.397	-0.085	-0.008	0.127	-0.064	-0.006
	(-0.82)	(0.54)	(-1.55)	(-0.45)	(0.97)	(-0.64)	(-0.47)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster at Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K	1	1	1	1	1	1	1
Window	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)	(-5,+5)
Observations	2445	2334	2336	2445	2445	2432	2445
Adjusted-R2	0.1321	0.0265	0.2731	0.0926	0.2217	0.2362	0.2449