Economic Restructuring and Children’s Educational Attainment: Lessons from China’s State-owned Enterprises Reform in the Mid-1990s

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Abstract: China’s state-owned enterprises (SOEs) reform in the mid-1990s changed the distribution of the labor earnings and family income vastly in the urban area. This paper studies the medium-term impact of the family income change induced by the economic restructuring on children’s educational attainment. I address the question by exploiting variations in childhood exposure to the policy change and shock intensity across sectors where fathers initially worked. The empirical results show that the earning gap between SOEs and other sectors was enlarged, and that children with fathers initially employed in SOEs were less likely to go to high school and college after the shock. Using additional geographical variation, I find evidence of a negative spillover effect, i.e., the impact of the shock is magnified in cities with higher percentage of laid-off workers or SOE workers. Families with fewer siblings were also more adversely affected, suggesting the possible existence of informal insurance among the extended family members. As further evidence, I show that credit-constrained SOE families receive more gift money from siblings than non-SOE families.

Keywords: economic restructuring, children’s education, mass layoffs, informal insurance, family structure, difference-in-difference

JEL classification: I25, O15, J62, J63, P31

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1. Introduction

Economic restructuring may occur during economic crisis, economic transitions and industry churning caused by globalization, technological change, or specific industrial policy. A rapid economic restructuring can result in large family income redistribution through changes of employment or labor earnings in a short period of time, especially in places lack of well-functioning social transfer programs. Previous studies have shed light on the relocative costs of job separations and income inequality associated with the economic restructuring\(^1\). A likewise policy-relevant but understudied question is whether such impact has been transmitted to the next generation.

The impact of the economic restructuring on children’s education is a priori ambiguous. On the one hand, families that experienced economic restructuring might be subected to permanent negative income shock, and their children would be forced out of school to supplement family income if these families are poor and live on subsistence consumption (Jalan and Ravallion, 2001). On the other hand, the shock may also boost educational expenditure, as parents that suffer job loss might learn a lesson from it and realize the value of education afterwards. Alternatively, children could also postpone entering the labor market and stay in school longer when the economy is sluggish.

The SOE reform in China provides a rare opportunity to investigate this issue. The progressive economic restructuring unprecedentedly led to mass layoffs of around 43 million workers in the urban area between 1995 and 2001. Workers employed in wholly state-owned, majority state-owned, and collective enterprises are those most likely to experience layoffs and reduced earnings during this process. Most laid-off workers failed to find a new job quickly and stayers were also subjected to reduced cumulative earnings and welfares thereafter. The shock enlarged the income gap between SOE workers and those working other sectors, such as government agencies (GOV) or public institutions (PUB) in urban China\(^2\).

Using data from China Urban Labor Survey 2001 (CULS2001), I compare children’s education with fathers in SOEs and those in other sectors before and after the shock, and estimate the impact of economic restructuring on children’s educational attainment with a Difference-in-Difference (DID) strategy. My empirical analysis provides rigorous evidence that children with fathers working in economic-restructured sector were significantly less likely to enter high school or college.

Unlike the idiosyncratic layoff, mass layoffs stemming from the economic restructuring can have large general equilibrium effects on children’s educational attainment through labor market interactions and competitions over the limited educational resources\(^3\). On the one hand, unemployed workers can be even worse off in cities with widespread layoffs than otherwise, as the job finding rate and the equilibrium wage tend to be lower. On the other hand, the enrollment into high school and college is competitive. More students suffering father’s job loss may benefit anyone else in the same city

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\(^1\)See, for example, Keane and Prasad (2002)’s discussion on the rising inequality in transition economies, and Autor, Katz and Krueger (1998) and Acemoglu (2002) on how the skill-biased technical change may increase the wage inequality. Autor et al. (2014) and Walker (2013) show the structural relocation of labor induced by the trade competition and environmental regulations can reduce lifetime earnings for workers initially employed in the restructured industries.

\(^2\)With some abuse of terminology, government and public institution are thereafter referred as GOV and PUB, and state-owned enterprises and urban collective enterprises are referred as SOEs, unless otherwise noted.

\(^3\)Ananat et al. (2011), for example, discusses how the widespread changes in the income distribution could generate intergenerational spillovers due to general equilibrium considerations.
in terms of academic ranking and the possibility of enrolling in better schools. To understand these mechanisms, I develop a simple model that incorporates such labor market interaction and educational enrollment procedure to illustrate the two opposing spillover effects.

To test the spillover effect empirically, I use a Difference-in-Difference-in-Difference (DDD) strategy across districts, children’s cohort, and the sectors where fathers were employed. The estimated results are consistent with a negative spillover effect, i.e., the adverse impact of economic restructuring is amplified in places with higher percentage of layoff or higher share of SOE workers. More importantly, the DDD result rules out other time-varying confounders such as the divergence of return to education or ability, which could also affect individual income differentially across sectors.

As a second objective, I investigate how families cope with the substantial and persistent income loss in an environment lack of formal financial instruments. Prior studies find evidence of risk-sharing and informal insurance in places where financial markets are underdeveloped. For example, in Indonesia, households can receive more gifts or informal loans from friends and extended family members when experiencing negative income shock (Fafchamps and Lund, 2003, Fafchamps, 2011). In China, there is also evidence on the risk sharing in rural area (Jalan and Ravallion, 1999). To explore whether this channel holds in urban China, I first examine whether the impact of economic restructuring varies across families with different number of siblings. In addition, taking advantage of the fact that tertiary education is more costly than other educational stages in China, I study whether the gift money acquired increases for families with higher financial needs, particularly for those with children in college. These findings are in line with the informal insurance hypothesis.

This paper builds on a recent growing literature on the impact of family’s income and working status on children’s welfare. For example, Dahl and Lochner (2012) finds that cash transfers through the tax credit in US can improve children’s test score. Aizer et al. (2014) find long-term impacts of social welfare program on children’s educational attainment. Using Canadian data, Oreopoulos, Page and Stevens (2008) finds that children who experienced father’s job loss when young would have lower earnings compared to those who didn’t. Rege, Telle and Votrubac (2011) and Bratberg, Nilsen and Vaage (2008) using Norwegian data find negative effects of parental job loss on children’s school performance but fail to find any significant impacts on children’s future earnings. Hilger (2013) discusses these conflicting findings and points out that these studies using firm closure as exogenous variation for parental layoff are subject to the sorting of the firms problem. Using variation from the timing of father’s job loss, he finds that the impacts on children’s college attainment and future earning are either small or insignificant. Ananat et al. (2011), on the other hand, finds a short-term negative impact of state-wide job loss on children’s eighth-grade math scores.

Children in poor countries are more susceptible to economic downturns. This paper is also linked to several studies examining the long-term impact of economic crisis on children’s welfare in developing countries. For example, a series of paper studying 1997 Indonesian Financial Crisis find reduced education investment and increased dropout rates following the crisis(Frankenberg et al., 1999, Thomas et al., 2004). Paxson and Schady (2005) find that the infant mortality rate increases for those born during Peru’s economic crisis in the 1980s. Cameron (2009), on the other hand, finds that a scholarship program can effectively reduce the dropout rate in the lower secondary school during the Indonesian Financial Crisis.
In comparison with these studies, this paper is different from them in several ways. Firstly, to my knowledge, this is the first paper looking at the intergenerational consequences of a nation-wide economic restructuring. Since economic restructuring can cause massive structural unemployment, the induced income shock at the household level is usually much larger in scale and more permanent than that caused by cash transfer or idiosyncratic job displacement. In addition, this paper addresses the negative spillover effects of economic restructuring, which may even widen the gap between the economic winners and losers. Thirdly, this paper looks at children’s medium-term outcome, which is more policy-relevant than outcomes frequently used in the literature, such as children’s test scores or other schooling performance measure.

Interpreting these findings requires careful considerations of the research design. Firstly, this paper only identifies the relative effects of economic restructuring, as the control group is possibly affected by the shock as well. Secondly, since workers could possibly sort into safer sectors after the policy shock, what this paper presents is an intent-to-treat analysis and the estimate may understate the true effect of economic restructuring. Lastly, parental job displacement and family income change induced by the economic restructuring are probably the two main factors influencing children’s educational attainment, but they are not the only channels. Economic restructuring can affect parental networking, family’s attitude towards education, and parents’ and children’s physical and mental health due to the increased stress, etc. This paper does not disentangle all these mechanisms through which the economic restructuring took effect due to the paucity of data.

The paper proceeds as follows. Section 2 introduces the background of the SOE reform and education policies in China. Section 3 describes the data and provide descriptive statistics for the sample used in the analysis. Section 4 introduces the identification strategies and presents a simple model illustrating the mechanisms how the spillover effects work. Section 5 presents the estimation results and provides some robustness checks for the identification strategy. Section 6 explores the channels through which the household deals with the economic restructuring shock. Section 7 concludes the paper. The Appendix provides the proof of the propositions derived from the model in Section 4.

2. Historical Overview

2.1 Allocation of Urban Jobs

Before 1980s, three types of jobs were dominant in the urban area: government agencies, public institutions, and SOEs. All jobs were distributed through government plans, which assign job quotas to designated schools or residential districts and specify the number of new workers needed. Given these quotas, school or residential authorities decide how these quotas are allocated (Bian, 1994b). While there is limited information on how jobs are assigned at this level, anecdotes suggest that authorities

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4The control group could be affected directly by the economic restructuring shock through involuntary job loss or reduction of earnings, or indirectly through the spillover effect from the treatment group. For example, children with fathers working in SOE might become less advantageous in coursework after the shock, which in turn benefits children with fathers in GOV or PUB, given that the enrollment into high school and college is competitive.

5For example, Liu and Zhao (2014) finds that children’s health was adversely affected after the SOE reform. He et al. (2014) compares SOE and GOV workers, and finds that the former increase their precautionary saving when facing greater uncertainty of being laid off.
allocate jobs based on their knowledge and assessment about the job candidates, including age, gender, education, political background, family background, academic performance, and candidate’s personal interest.

Other less common forms of employment are either through replacement, namely that children take over their parents’ job after they retire, or through informal connections and recommendations. For vast majority of workers, once jobs assigned, they can enjoy lifetime employment without worrying about being dismissed. The flip side, however, is that workers are bound to their employees and working units. The labor mobility was almost zero during the planned economy era. Switching jobs from one sector to another could take tremendous effort and incur considerable administrative costs, possibly involving using connections or bribing (Bian, 1994a).

In 1986, the government introduced the contract labor system, requiring that all newly hired workers must be assigned with a five-year labor contract (Naughton, 1996). Since then, the proportion of contract workers in the labor force started increasing from about 4% of total employment in 1985 to 13% in 1990 and further to 39% in 1995 (Meng, 2000). Meanwhile, the government also gradually reduced state allocation and encouraged self-employment or open recruitment by enterprises. State-assigned jobs gradually phased out of the economy after 1996.

2.2 Competitive Pressure on SOEs

Before the opening up policy in 1978, SOEs can generate before-tax cash flows around 14 percent of GNP. This number had been decreasing since then. By 1993, SOEs conversely received support from the government more than 4 percent of GNP to maintain its expenditure on workers’ wage and other expenditures (Brandt and Zhu, 2000).

The declining profit in SOEs roots fundamentally in its role in the planned economy era. SOEs guarantee the full employment of the economy. The permanent employment system that prohibits SOEs from freely dismissing workers leads to overstaffing and lowers workers’ incentives. Also, unlike normal firms, SOEs are multifunctional social units that are not only engaged in production but also dedicated for a variety of social goals. They provided workers from cradle to grave with the necessities of life, such as schools, housing, health care, child care etc (Lee, 2000).

These social responsibilities burdened SOEs when the market became increasingly competitive. One of the challenge comes from the rise of TVEs in the 1980s. With less support from the government, TVEs had a period of high-speed growth after 1985, benefiting from the policy of freeing up the price and the lower labor cost in the rural area. The rise of TVEs and other private sectors exposes the inefficiency of SOEs and drives down the profitability significantly (Yusuf, Nabeshima and Perkins, 2006, Naughton, 2007). On the other hand, government agencies and public institutions such as hospitals, schools, or other non-profit organizations, were spared from such competitive pressure.

The reforms on SOEs started as early as after 1979, when the government introduced profit-retention system, in order to provide SOEs with stronger profit-oriented incentives. In the mid-1980s, the government also adjusted the wage system linking workers’ wage to the economic performance of SOEs. Yet the reform of SOEs was stagnated after the Tiananmen Square protests in 1989. Possibly

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6TVEs were historically considered as collective enterprises in villages and towns, but actually most of them are private enterprises. See Huang (2008)
out of the concern of stability, the political power at the top was fragmented and there was lack of consen-
sus on whether to continue reforming SOEs after the incident (Naughton, 2008). It was not until Deng’s fam-
ous tour in southern provinces in 1992 that essentially reduced the ideological stigma associated with the private sectors. Since then, China stepped into a period of fast marketization and the government made up mind for a radical SOE restructuring after 1995 in order to maximize economic efficiency.

### 2.3 Economic Restructuring after 1995

Despite the rapid growth of private sectors after 1992, the data shows that state sector was still dom-
inant by 1995. State-sector employees accounted for around 94.1% of total labor force in the five cities surveyed, and only about 5.2% were working in private enterprises (PE), foreign invested enterprises (FIE), or self-employed.

SOEs were well protected by the government until after the *zhua da fang xiao* (Grasping the large, letting go of the small) policy was implemented in 1994, which literately means allowing small loss-making SOEs either shut down or privatized while keeping reforming and maintaining the large SOEs. The Labor Law passed in 1994 also laid the legal foundations for SOEs to dismiss no-fault workers to reduce surplus labors (Cai, Park and Zhao, 2008).

For a long period of time, SOEs were supported by the funding from the government bank. The Asian Financial Crises in 1997, however, reminded the government of the risk of the national banking system, which had accumulated large amount of nonperforming loans due to the low profitability of SOEs. Since then, a stricter investment approval process was implemented, which even worsen off SOEs. Altogether, these polices led to mass layoffs around 43 million workers from 1995 to 2001 including 34 million from the state sector (Giles, Park and Cai, 2006).

The registered unemployment rate reported by the official labor statistics is misleading, as it only counts the unemployed as those who registered for unemployment benefit and thereby significantly understates the true unemployment rate (Giles, Park and Zhang, 2005, Feng, Hu and Moffitt, 2015). To get a picture of what was really happening, I plot the distribution of the reported year of unemployment from 1985 to 2001 using data from CULS2001. Figure 1(b) shows that the density of unemployment rises gradually after 1990, then jumps to a new level after 1995, and peaks after the Asian financial crisis in 1997. The fact that most unemployment is highly concentrated from 1995 to 2000 highlights the tremendous impact of the policy change.

The shock was mainly targeted on SOEs, whereas GOV and PUB were only mildly affected. Figure 2 displays how the unemployment risk differs across two sectors. Those who were born before 1940 mostly had been retired by 1995 when the economic restructuring took place. So there is no significant difference between SOE and GOV in the fraction of laid-off workers. But for younger cohorts, the bifurcation of the two groups after 1940 suggests that SOE workers were much more likely subjected to layoff than GOV workers after the shock.

The economic restructuring has heterogeneous impacts on workers with different characteristics.

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7 Shanghai, Qinghai, and Heilongjiang launched the policy slightly earlier than others. In the robustness check, I drop Shanghai to double check the main results are not driven by the inconsistency of timing.

8 China’s retirement age for men and women is 60 and 50 respectively. The average retirement age is 55.
For example, the female, less educated, and middle-aged are more likely to lose jobs during the mass layoff period (Appleton et al., 2002). In areas where the state sector historically dominates - e.g., especially in the old industrial area in the northeast - the impact of the shock was more prevalent.

Many laid-off workers failed to find a new job quickly. The data shows that among those who experienced unemployment between 1995 and 2001, only 34.8% were able to get re-employed within 12 months, and 44.7% were re-employed by 2002 (Giles, Park and Cai, 2006). There are three main unemployment compensations, i.e., the public subsidies (including xiagang subsidies, unemployment subsidies, and Minimum Living Standard Programme (MLSP, also known as Dibao) payments), the pension for the early forced retiree, and the lump-sum severance payments. These compensations actually played a limited role in mitigating the shock. Using CULS2001, Giles, Park and Cai (2006) find that men aged 40-55 and women aged 40-50 were covered by subsidies with more than half, whereas for other age groups, only less than half were covered. In addition, the annualized unemployment subsidy and the pension income are 607 RMB per capita and 2172 RMB per capita respectively for families with one unemployed man. As comparison, the national average disposable income for urban residents in 2001 is 6860 RMB and the income per capita for household without any laid-off member in the data is 9840 RMB, which suggests that a large proportion of income loss was not insured. In fact, families with laid-off member mostly relied on their own savings or other family member’s income to survive the period of hardship.

Even if workers were not unemployed, the economic status of SOE workers deteriorated in comparison with the GOV workers. Figure 3 plots the evolution of the average wage by sector throughout the 1990s. The average earning gap between SOE workers and GOV workers emerged after 1993, and was enlarged as early as after 1998. Shocks to SOE workers were also reflected from the wage arrears, reduced benefit including lost health insurance and health expenditure reimbursement, reduced pension benefits, and changes in housing benefits.

2.4 Development of Senior Secondary Education and Higher Education

Previous studies on secondary education in China mainly focus on rural area. The detailed cost of high school in urban area is not well documented. Liu et al. (2009) estimated the tuition fee for high school in rural China to be around $160 in 2006. The real cost could be even larger if other related fees accounted. In CULS2001, the average school expenditure for high school in the five cities surveyed is over 2,200 RMB (see Figure 5).

High school enrollment rate in urban area is much higher than that in rural area. Table 2 shows that the average high school attainment in five cities is around 68% \(^9\). In contrast, this number is close to 12% in rural area based on the rural survey of Chinese Household Income Project 2002(CHIP2002). During the Cultural Revolution, college enrollment was almost zero for ten years, whereas the high school enrollment was only mildly affected. The impact on high school is mainly embodied in education quality, such as shortened length of schooling, and increased farm work, physical exercises, etc. College reopened after 1977 and the enrollment had gradually increased since then. The college tuition was waived for all students before 1992, as China’s higher education had been fully funded by

\(^9\) Liu et al. (2009) estimates that the enrollment rate for high school for urban students might be lower, as there might be promotion from middle school in rural area.
the government. The tuition cost gradually increased reaching around 2,769 RMB in 1999 (Shen and Li, 2003).

In 1999, a policy to expand the college enrollment was initiated. Statistics from the World Bank shows that the Gross Enrollment Ratio (GER) has a dramatic increase after 2001. Shen and Li (2003) documents that there was also a sharp increase in tuition fee accompanying with this policy. The expansion of enrollment and sudden increase in college tuition may affect SOE and GOV family at different margin. If so, the effect of economic restructuring on children’s college attainment may be confounded by the college expansion policy. I address this concern in section 6.4.

The education expenses for college is a big burden for family in urban area as compared to expenses on other schooling stages. The estimated college expenditure as a percentage of average disposable income per urban resident is roughly 50% by 2001, whereas it only accounts around 38% for private schools in US as a comparison. Moreover, children from poor families in US heavily rely on financial aid, own work, than their parental income (Hilger, 2013). By contrast, nationwide student loan starts from 2000, and other financial instruments are extremely underdeveloped in China. It’s common that children rely on their parents to finance their tuition expenses.

3. Data and Descriptive Statistics

The data used in this paper come from China Urban Labor Survey 2001 (CULS2001), which is administered by the Institute of Population Studies at the Chinese Academy of Social Sciences. The sample frame for the survey is constructed based on the 2000 census. It surveys 3500 urban permanent resident households and around 8100 individuals aged above 16. The survey is designed primarily to study the impacts of the SOE reform on the labor market, covering cities of Fuzhou, Shanghai, Shenyang, Wuhan, and Xi’an, with remarkable regional diversity and variation in the size of the state versus the private sectors and the shock intensity10.

The survey consists of an individual and a household questionnaire. One unique feature of the individual survey is that it traces out the detailed employment history for those still working in 1996, from which I can observe the sectors where they were employed before the shock, which is crucial for this study. In addition, the survey contains rich information on the family tree so that each child can be uniquely identified via the connection to their parents from the adult survey, even if the children don’t currently live with their parents. Other relevant information include respondent’s education, marriage, occupation, early life experiences, family structure, etc. Details on the sample and the construction of key variables are described below.

3.1 Data and Definition of variables

A standard measure for the educational attainment in the literature is the years of schooling. However, I focus instead on children’s high school attainment and college attainment in this paper for two

10The size of the five cities are relatively bigger than average cities in China. The share of state sectors in these cities may be accordingly bigger as well. The focus on large cities of the survey thus may overstate the overall impact of economic restructuring in urban China (Giles, Park and Cai, 2006).
reasons. First, the survey was conducted in 2001, close to the end of the SOE reform. Some children, although affected by the shock, were not old enough to observe their ultimate educational attainment, but enough to see whether or not they were attending high school or college. To fully utilize the information, I include those children in my analysis as well. Second, there is lack of variation for children with attainment on middle school or below, because the compulsory schooling law promulgated in 1986 requires that all the students at least be enrolled in middle school.

In this context, the measures for the educational attainment are dummies taking values of one if students ever attained high school or college by their schooling age. High schools are only referred to the academic high schools and do not include vocational schools or other post-junior educational institutions. I define children’s exposure to the policy change as the sectors where fathers worked prior to children’s schooling age and before the shock occurred 11. Children in the treatment group encompass those with fathers working in state-owned enterprises or urban collective enterprises before 1992, and the control group includes fathers working in either government or public institutions 12.

In the triple-difference analysis, shock intensity at the city level is defined in three ways. First, I extract information from the 2001 survey measuring intensity as the share of total workers who report “ever was laid off last six years”. Second, for robustness, I also create a binary variable indicating whether the city is more severely affected by the policy shock. Lastly, I use the city-wide employment share of SOE workers before the shock to capture the idea that cities concentrated with more SOE sectors might have been more greatly affected by the shock. These information are collected from different city-level statistical yearbooks 13.

There are two reasons why I do not use the unemployment rate as the measure of the shock intensity. First, the official labor statistics in China are not informative about the true unemployment rate as aforementioned, for the registered urban unemployment rate is not calculated based on a representative sample survey 14. Moreover, the de facto unemployment rate may fail to capture the true layoff intensity, as the unemployed, mostly poor, may take whatever jobs coming up to sustain their life during the crisis (Jayachandran, 2006). As an example, Fallon and Lucas (2002) documents that during the 1997 Asian Financial Crisis, the unemployment rate was not soaring and the labor force participation rate could even expand, because the informal sector was able to absorb considerable amount of layoffs.

In analyzing how family cope with the negative income shock, I turn to the household survey from CULS2001, which contains detailed information on family members’ demographics, family expenditure, housing condition, durable good consumption, etc. There are 3489 households in the survey. I merge household sample with individual sample to identify the family member who experienced the layoff shock. The independent variable “layoff” is a dummy taking value of one if the household has

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11 This definition may not be entirely accurate. Fathers might have changed jobs before the shock and the job they held by then was not necessarily the one when children was adolescent and ready for school. However, using this approximate definition is less a concern in the context of China. As documented in section 2.2, the labor market in urban area was rigid before 1992. Most jobs were lifetime jobs, and it’s hard, if possible, for workers to switch from one sector to another.

12 The definition of the control group is robust to including all the other non-state sectors. See Section 5.3 for more details.

13 This information is subject to availability. All the cities in the sample report these statistics except Shanghai.

14 In an attempt to uncover China’s true unemployment rate, Giles, Park and Zhang (2005) re-estimated the unemployment rate using CULS2001, a follow-up survey in 2002, and CULS2005. Figure 1(a) plots their results as compared with the registered unemployment rate reported by the government. The unemployment rate reported by Giles, Park and Zhang (2005) is far above the registered urban unemployment rate, and has increased from 6% in 1995 to above 11% in 2002.
at least one family member that has ever been laid off\textsuperscript{15}. The main outcome variable of interest is the gift money received by the household from friends and relatives. This information is available in the household survey and measured in three ways, the absolute value, the log value, and a dummy taking value of one if the gift money is greater than 1000 RMB.

3.2 Sample and Summary Statistics

The adult survey in 2001 asks each individual’s number of children and their gender, birth year, education, etc. Based on these information, I construct two children samples, the college sample and the high school sample, which differ in children’s cohorts included\textsuperscript{16}. As aforementioned, to fully exploit the information from the survey, I include all the children as long as I can observe whether they have attended or are attending high school/college by 2001. Therefore, the youngest cohort in the high school sample are born in 1985, and that in the college sample are born in 1983. The oldest cohort for high school sample are born in 1954, while that for college sample are slightly younger and born in 1964. The reason for the difference is that people born before 1964 might have experienced the closure of college during Cultural Revolution.

Table 1 reports the summary statistics for the workers in the individual survey. As expected, workers employed in SOE before 1992 are significantly different from those with those employed in GOV or PUB along a number of characteristics. SOE workers are younger, less educated, and more likely to be party members before work. Table 2 describes the high school sample and college sample for the children respectively. Children with fathers initially employed in SOEs are also younger and less educated. These observations suggest that the distribution of labor across sectors is not random and simple comparison between these two groups may lead to biased results.

Table 3 presents the summary statistics of the data for the analysis of informal insurance. The average amount of gift received by each family is 769 RMB. There are around 12% households with children in college and around 56% with children in school.

4. Empirical Strategy

4.1 The Impacts of Economic Restructuring on Children’s Education

My identification strategy exploits the variation in childhood exposure to the economic restructuring shock. The pre-shock group constitutes those who have already attained high school or college by 1995 and are too old to experience the economic restructuring. The post-shock group refers to those younger cohorts not eligible for college or high school by 1995. There is no sharp temporal cutoff distinguishing the pre-shock from the post-shock group, as the likelihood of being affected by the economic restructuring depends on how much children’s adolescent period overlaps the window of the restructuring period, and gradually decreases in children’s age.

The second dimension of variation I explore is the intensity of the shock across sectors. As demon-

\textsuperscript{15}This definition also includes laid-off workers who were later able to get re-employed.

\textsuperscript{16}For details on how I construct the children sample, see Appendix C
strated in Figure 2 and Figure 3, the economic restructuring was mainly targeted on SOE sectors, where workers experienced slower wage growth and higher risks of being laid off than those employed in government or public institutions. Children with fathers initially working in SOE are therefore more likely to be affected by the economic restructuring.

The specification of the empirical model is the following:

$$E_{ias} = \alpha_0 + \alpha_1 SOE_s \times Post\,shock_a + \rho_a + \eta_s + \theta^tX_i + \epsilon_{ias}$$ (1)

where $E_{ias}$ is the educational attainment of children $i$, in age group $a$, with father or mother employed in sector $s$. $SOE_s$ is a dummy taking value of one if children $i$’s father or mother was employed in SOE before 1992. The post-shock group ages from 12 to 15 in 1995 for the college sample and from 10 to 14 for the high school sample. $\rho_a$ is children’s cohort fixed effect and $\eta_s$ is parental sector fixed effect. $X_i$ is a rich set of children and father controls, which includes father’s education, party membership, height, occupation dummies, industry dummies, early life experiences, school ranking, school quality, etc, and the number of children’s siblings, sisters, and brothers.

The validity of the DID strategy hinges on that workers do not anticipate the shock and self-select into sectors beforehand. There are two reasons why this assumption appears to hold in the context of China. First, the economic restructuring in urban area is unexpected before 1992. As discussed in section 2.2, there was lack of consensus among the top whether to deepen the reform and there was no sign of radical reform in urban China before Deng’s famous southern tour. It is thus unlikely for people to anticipate and make the corresponding adjustment ahead of time. Second, the labor market mobility was almost zero before 1992. Labor assignment was controlled by the personnel department and most positions are permanent once jobs are assigned. It’s thus difficult and costly for workers to switch jobs from SOE to GOV or the other way around, if possible. Overall, the job mobility is very limited across sectors before 1992.

Nevertheless, by the definition of $SOE_s$, I acknowledge that there might exist post-shock sorting for workers in the SOE group - fathers could find new jobs in safer sectors after 1992 when the labor market started to become less rigid. In that sense, my identification strategy only permits me to identify an ITT (Intent-to-Treat) effect. The identified average treatment effect of the economic restructuring on children’s educational attainment is just a lower bound of the worst-case scenario.

Another concern is related to the allocation of jobs. As shown in Table 1 and Table 2, SOE and GOV workers are different in many aspects. The former, for example, are younger, less educated, and less likely to be party members before working. It is important to emphasize that although my identification strategy doesn’t rely on the assumption of random job assignment, it does require no omitted cohort-varying and sector-specific effect correlated with the allocation of jobs. This assumption could potentially be violated if there is a mean divergence in return to education or ability. Since fathers working in SOE are on average less educated, if children from less educated families had increasingly got less chance of education, we could possibly observe a negative estimate of $\alpha_1$ even in the absence of the policy shock. To deal with the concern, I propose three different strategies. First, I relax the parallel-trend assumption and allow a linear sector-specific trend by adding trend terms into equation

\footnote{This definition is similar to Autor et al. (2014), which defines the exposure to the trade shock as the sectors where workers were initially employed prior to the shock.}
Second, I add a variety of father demographic control variables, which might predict the allocation of father’s jobs, and interact them with the post-shock cohort dummy. Third, a triple difference strategy is adopted, as described in the next subsection, to difference out any other cohort-varying and sector-specific changes.

The exclusive focus on father’s job change misses an important fact that China’s female labor force participation rate is particularly high compared to other countries. Although father is typically considered the main family supporter, mother’s wage is also an important part of family income in urban China. For this reason, I also report the estimated impact of economic restructuring from mother’s side on children’s education in section 5.1.

4.2 The Spillover Effect

In this section, I investigate whether the impacts of economic restructuring on children vary across regions with different economic structure.

4.2.1 Theoretical Considerations

The geographical concentration of a particular industry can benefit surrounding firms from within-industry externalities, but meanwhile, the aggregate economic risk induced by the structural change can also rise in regions with a highly specialized economy. GM layoffs in Metro Detroit and mine closure in resource-exhausted cities are examples of such situations, where workers often find it difficult to get re-employed once laid off, with the local economy damaged across the board and the local labor market becoming increasingly saturated to absorb newly unemployed workers with similar skills. These workers can be even worse off if their labor supply is inelastic due to poverty, high cost of migration, or underdeveloped financial market. In these situations, poor workers have no choice but to sell their labor even when the wage is low, and this could further drive down the equilibrium wage or prolongs the unemployment spell.  

The SOEs reform starting from 1995 has such features as well. The old industrial areas with historically high percentage of SOEs employment, such as Shenyang, Wuhan, and Shanghai, are among those that suffered the most. Children with fathers living in those cities are thus likely more adversely affected by the shock. By comparison, children living in Fuzhou and Xi’an, where there was less proportion of workers employed in the public firms, were less affected.

On the other hand, economic restructuring may also have positive spillover effect. The enrollment into high school and college in China is competitive. Students must pass a city-wide and a nationwide exam, i.e., the so-called High School Entrance Exam (Zhongkao) and College Entrance Exam (Gaokao). Only those who score above a certain threshold may enter the high school or the college, and the threshold is an increasing function of the number of the exam takers and their competitiveness. In a city with widespread layoffs, it would thus be relatively easier for any children, even including those with fathers laid off, to compete against others, if we generally assume that the test score is an

---

18 Jayachandran (2006), for instance, illustrates how those factors could exacerbate the productivity shock for the poor in rural India as a result of their inelasticity of labor supply.

19 For more detailed description on the High School Entrance Exam, see Dee and Lan (2015)
increasing function of family income. In that sense, more layoffs in a particular city could potentially benefit children for better chance of accessing to higher level of education.

4.2.2 The model

In the following paragraph, I construct a simple model formalizing the above idea. The model has $N$ cities. Each city has a mass with population 1, and each individual has one child. All the jobs offer the same wage $w$ and everyone is fully employed prior to the economic restructuring. After the shock, there is a proportion of $\tau_n$ ($0 < \tau_n < 1$) displaced workers competing for $\alpha_n$ vacancies of new jobs in city $n$. The expected wage for laid-off workers after the shock is $\frac{\alpha_n}{\tau_n}w$, where $\tau_n > \alpha_n$ and $\alpha_n/\tau_n$ is the probability of acquiring a new job and captures the general equilibrium effect that the more displaced workers in the city, the harder for anyone to find jobs, or simply the lower the equilibrium wage. Meanwhile, I assume that the wage of survivor workers is not affected by the shock to keep the model simple.

High school enrollment

Each child is required to take the high school entrance exam, and only those who score above the city mean are able to enter high school. Children’s score of the high school entrance exam is a linear function of the parents’ private investment and city $n$’s public investment in education plus a disturbance term

\[
\begin{align*}
G_s &= f(w) + g(\tau_n) + \varepsilon & \text{Survivor worker} \\
G_l &= f\left(\frac{\alpha_n}{\tau_n}w\right) + g(\tau_n) + \varepsilon & \text{Displaced worker}
\end{align*}
\]

where $\varepsilon \sim N(0, 1)$ and $f'(\cdot) > 0$. $g(\cdot)$ denotes the public education investment in city $n$ and $g'(\cdot) < 0$. Both $g(\cdot)$ and $f(\cdot)$ are bounded between 0 and 1. The mean of the scores for the high school entrance exam in city $n$ is

\[
M^H = (1 - \tau_n)G_s + \tau_n G_l
\]

the probability of going to high school or college for children with displaced fathers is

\[
\pi^H = \text{Prob}(G_l > M^H)
\]

College enrollment

One difference between the probability of enrolling college and enrolling high school is the threshold. Note that the college exam is nation-wide. The threshold of college entrance is the national mean of the test scores rather than the city mean. And the former is exogenously given from the perspective of the exam-takers in a particular city.

The probability of going to college for children with displaced fathers thus is

\[
\pi^C = \text{Prob}(G_l > \bar{M})
\]

where $\bar{M}$ is the nation-wide average scores for the college entrance exam.

\[20\]Here I simply assume that all the children prefer to have higher education
**Proposition 1.** If \( f(w) - f\left( \frac{aw}{w} \right) < \frac{(1-\tau_n)f'aw}{C_2} \), father’s job displacement induced by the economic restructuring has a negative spillover effect on children’s high school enrollment, i.e., \( \partial \pi^H / \partial \tau_n < 0 \).

If \( f(w) - f\left( \frac{aw}{w} \right) > \frac{(1-\tau_n)f'aw}{C_2} \), father’s job displacement has a positive spillover effect, i.e., \( \partial \pi^H / \partial \tau_n > 0 \).

*proof.* see Appendix B1.

**Proposition 2.** Father’s job displacement induced by the economic restructuring has a negative spillover effect on children’s college enrollment, \( \partial \pi^C / \partial \tau_n < 0 \), and \( \partial \pi^C / \partial \tau < \partial \pi^H / \partial \tau_n \).

*proof.* see Appendix B2.

Proposition 1 shows two opposing spillover effects of economic restructuring at work simultaneously on children’s high school enrollment. On the one hand, the increase of city-wide displaced workers intensifies the labor market competitiveness over the limited vacancies and accordingly lower the expected re-employment wage. As a consequence, families with laid off workers decrease their investment in education, which lowers children’s test score, and is reflected by the decrease of \( f\left( \frac{aw}{w} \right) \). The negative spillover effect is scaled by \( (1-\tau_n) \), because the marginal negative spillover effect on each individual is smaller when there are already lots of workers unemployed\(^{21} \). The overall negative spillover effect is thus captured by the marginal decrease of \( f\left( \frac{aw}{w} \right) \) multiplied by \( (1-\tau_n) \), which is equal to \( \frac{(1-\tau_n)f'aw}{C_2} \).

On the other hand, more workers being laid off implies more children suffer from the family income loss. On the whole, the city-wide average score would fall, making the threshold lower and entering high school easier for everyone, even including those children with father laid off. Since the threshold is an increasing function of \( \tau_n f\left( \frac{aw}{w} \right) \) and a decreasing function of \( \tau_n f(w) \), the lower \( f\left( \frac{aw}{w} \right) \) is and the higher \( f(w) \) is, the more the threshold would decrease caused by the increase of \( \tau_n \). The marginal decrease of the threshold is thus captured by the term \( f(w) - f\left( \frac{aw}{w} \right) \), which represents the positive spillover effect. Theoretically, if the gap between \( f(w) \) and \( f\left( \frac{aw}{w} \right) \) is large enough, the positive spillover effect can dominate the negative spillover effect. However, it turns out that the opposite is more likely to be true, as the \( f(w) - f\left( \frac{aw}{w} \right) < 1 \) by definition and is thus generally less than \( \frac{(1-\tau_n)f'aw}{C_2} \) when \( \tau_n \) is small.

Proposition 2, however, depicts a slightly different pattern. It states that the spillover effect on college enrollment is always negative regardless the scale of the layoff, and the negative spillover effect on college enrollment is much stronger than that on high school enrollment. There are two reasons that drive the results.

Firstly, the supply side of education, such as school construction, could possibly increase children’s educational attainment (Duflo, 2001). Yet the mass layoff induced by the economic restructuring damaged the local economy and incentivized the government to reduce the public investment on education. Children living in the city that is the most affected therefore suffer the most from the reduced supply of education. Nonetheless, this is not the case for high school enrollment. Such effect is mostly canceled out, because the competitors for high school are from the same city.

\(^{21}\)To understand why, consider the extreme case where everyone is laid off. The family’s private investment in education would not make any difference in children’s school performance. In that case, children’s scores are normally distributed, and the negative spillover effect is almost zero.
Secondly, the college enrollment is nation-wide rather than city-wide. The probability of enrolling college does not depend on the city-wide average score but the national average score, which is exogenously given. Accordingly, the threshold is no longer a function of the scale of the layoff as in the case of high school enrollment analysis. Its overall negative spillover effect is therefore smaller than that on college enrollment, as the former also has the positive spillover effect, which could partly offset its negative spillover effect.

4.2.3 The Empirical Setup

Proposition 1 and 2 provide testable hypotheses for the spillover effect of economic restructuring on high school enrollment and college enrollment respectively. The idea is captured by the following regression

\[ E_{iasc} = \alpha_0 + \alpha_1 SOE_s \times Postshock_a \times Intensity_c + \tau_{cs} + \lambda_{as} + \mu_{ac} + \theta^J X_i + \epsilon_{iasc} \]  

where \( c \) denotes city, \( s \) sector, and \( a \) age group. \( E_{iasc} \) is children \( i \)'s education outcome. \( Intensity_c \) is the layoff intensity in city \( c \). \( SOE_s \) is equal to 1 if children \( i \)'s father works in state-owned enterprises before 1992. \( Postshock_a \) represents the post-shock age group, i.e., children aged from 12 to 16 in 1995. The specification includes a full set of double interactions, namely city-sector(\( \tau_{cs} \)), age-sector(\( \lambda_{as} \)), age-city(\( \mu_{ac} \)), and \( \epsilon_{iasc} \) is a random disturbance term.

In this setting, migration could be a concern if people can freely migrate to cities less affected by the SOEs reform. However, this seems unlikely in this context. First, the scale of migration across cities in China is limited by 2000, despite the prevalence of the rural-to-urban migration. According to the census in 2000, the percentage of cross-city migrants over the last five years takes up less than 4\%\textsuperscript{22}. In addition, one advantage of the 2001 survey is that it was completed right after the end of the reform. For workers that intend to migrate out after the shock, they might not be able to adjust that quickly by 2001.

5. Results

5.1 Impacts of Economic Restructuring on Children’s Education

Table 4 presents the results estimated with difference-in-difference strategy. According to columns 1 and 3, the economic restructuring significantly reduces children’s opportunity of enrolling in high school and college. I allow for sector-specific trends in columns 2 and 4 by adding interactions of children’s cohort and the sectors where father were employed. In the robustness check, I further control cohort-varying variables that may be correlated with father’s initial job assignment, i.e., father’s educational attainment, height, party membership before work, and early life experience dummies. Including these additional controls does not change the results significantly.

\textsuperscript{22}The cross-city migrants are defined as those whose origins is the city and the out-migrating destination is another city. The percentage of cross-city migrants is the number of cross-city migrants divided last five years by the total amount of urban residents from the original city in the census.
Controlling these interactions can alleviate the concern of mean divergence stemming from the systematic differences in father’s observables, but does not rule out that resulted from father’s unobservables. For example, GOV workers may be more political connected and the return to political connection could have increased during the SOE reform. Children with father employed in GOV therefore could benefit more from fathers’ political resources and get better education opportunities. In the triple-difference regression, however, I show that this hypothesis is not supported by the evidence. As displayed in Table 6, the impact of economic restructuring on children is significantly larger in cities with higher percentage of laid-off workers or SOE workers, which is very much in line with an negative spillover effect. On the other hand, if the result is driven by the increase of return to political connection or other cohort-varying unobservables, it is hard to explain such regional variation.

Throughout this paper, I follow the literature focusing on the impact of fathers’ employment status on children’s educational attainment, as fathers are typically considered the main supporter of the family. However, China’s female labor participation rate was particularly high as documented by Maurer-Fazio et al. (2011) and Meng (2012). Mother’s income may also play an important role influencing children’s education. To exclude mother’s effect and estimate the impact of economic restructuring purely from the father’s side, mothers’ working status must be controlled, as father’s earnings may well predict mother’s earnings given the assortative matching of marriage. I thus add into equation (1) dummies of the sectors where mother worked and its interactions with children’s post-shock cohorts. The results presented in columns 4 and 8 show that the impacts of economic restructuring from fathers side alone can significantly reduce children’s educational attainment.

The impact of economic restructuring from the mother side is explored in the same manner. Results are presented in Table 4 panel B. Interestingly, mother’s working status appears to have significant impacts on children’s college enrollment, but not on high school enrollment. One explanation is that the college expenditure costs so much for the family in the urban area that mother’s income is as relevant as father’s income in the decision of sending children to the college. Since the nationwide student loan for college just started in 2000, children from the credit-constrained families might forgo their opportunity of receiving further education and start entering the job market earlier. By contrast, the decision of entering high school is less likely to be a concern of credit-constraint, as the cost of enrolling in high school is significantly lower than college and more affordable for most urban families. Father’s working status affecting children’s high school enrollment thus may work not through channels of credit-constraint but others that could worsen children’s school performance or competitiveness.

5.2 Discussion on the Mechanisms

Economic restructuring led to larger magnitude of layoffs and lower cumulative earning in the SOE sector. In this subsection, I discuss these two factors that may contribute to the rising educational gap for children between SOE and GOV/PUB groups.

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23Women’s labor participation rate is historically high in China - around 70% as compared to 59% in US in 2001 (Data from world bank). In the urban area, Meng (2012) estimates that in 1988, the employment rate for women was 75%, while in OECD countries the level is 52.4%.

24Since the labor force participation rate for mother is lower, the sample size is reduced from 1858 and 2824 to 1624 and 2423 for high school sample and college sample respectively.
The impact of parental layoff on children’s education can be ambiguous ex ante. On the one hand, family income loss induced by job separation may discourage education investment and worsen children’s school performance. On the other hand, the layoff shock could be partially offset by unemployment insurance or student loans, if available, and laid-off workers may find better job with higher salary after job loss. Moreover, displaced workers might be able to devote more time taking care of children and monitoring their school attendance. Figure 4 (c) and (d) plot the fraction of children experiencing father’s layoff prior to their schooling entry age. The likelihood of experiencing father’s layoff dramatically increases from almost zero to around 10% and 15% for the youngest cohort, highlighting the impact of mass layoffs induced by the economic restructuring. Children with fathers employed in SOE are more likely to experience father’s layoff after the shock, and this fact coincides with the divergence of educational attainment illustrated in Figure 4 (a) and (b).

To more accurately capture the impacts of economic restructuring on the possibility that children experience father’s layoff, I estimate a reduced-form model with the following specification,

\[
Layoff_{ias} = a_0 + a_1 \text{SOE}_{s} \times \text{Postshock}_{a} + \rho_a + \eta_s + \theta'X_i + \epsilon_{ias}
\]

where \(Layoff_{ias}\) is defined as a dummy taking value of one if the child experienced father’s job loss before entering college or high school and older than than 6. \(\text{SOE}_{s} \times \text{Treated}_{a}\) serves as an instrument variable for \(Layoff_{ias}\). The results presented in Table 5 confirm with the visual evidence that the economic restructuring shock significantly increases the likelihood for the children to experience father’s layoff. Overall, these results, though not conclusive, suggest that father’s layoff might have contributed to children’s reduced educational attainment.

Since the family income throughout a child’s adolescent period cannot be observed from CULS2001 data, there is no easy way to isolate the income effect from the layoff effect. Nevertheless, based on the fact that the estimated impacts on experiencing father’s layoff are relatively small, it appears that the impact of reduced earning plays a bigger role. This is consistent with the finding from Fallon and Lucas (2002) and McKenzie (2004), in which they show that the real wage decrease are the main contributor to the fall of average income during the financial crisis in Argentina in 2002 and in Southeast Asia in 1997.

5.3 Other reforms in the 1990s

The Chinese government introduced numerous policies to reform the socialist system during the mid-1990s. In this subsection, I conduct a survey on some of these reforms that might affect SOE and GOV workers differently.

Wage Reform Since 1956, urban wages were centrally regulated and scaled based on a series of indicators, such as regions, occupations, industries, sectors, level of management of enterprises (central or local), characteristics of the workplace, etc (Yueh, 2004). This wage system was maintained for almost 30 years and had become increasingly rigid after China’s economic reform in 1978. In 1985,
the MOL (Ministry of Labor) started overhauling the old system by linking wage budgets to public enterprises’ profitability, in an effort to provide workers with better incentives. The wage system for GOV and PUB on the other hand were mostly intact except for several mild adjustments.

Starting from 1993, the MOL issued new rules, allowing SOEs to set their own internal wage structure within the budget established by the government. GOV wages were still following a nation-wide standard system, whereas wages in PUB were encouraged to be more flexible and market-oriented, with some institutions permitted to follow firms setting their own wages.

The concern is that the wage reform in 1993 might have led to an abnormal earning change for GOV and PUB workers that was not internalized by the market. For example, if earnings in GOV and PUB grow much faster than SOEs in cities like Shenyang or Wuhan, where the shock intensity was among the largest, then the resulting variation of children’s educational gap between the two sectors might also increase in shock intensity, and therefore the DDD result is confounded.

Using data from China Household Income Project 2002 (CHIP2002), I plot the average personal income for GOV and PUB workers over years between 1998 and 2002 in selected cities. If the above hypothesis holds, wages in GOV and PUB should have grown faster in Wuhan or Shenyang than in other cities during this period. Figure 8 shows that, to the contrary, the income growth in GOV or PUB is mostly parallel among all the selected cities, and that Wuhan even experienced a particularly lower wage growth in GOV and PUB. This result is not surprising, given that Wuhan is one of the cities that were most affected by the reform. The lower wage growth rate in its public service sectors probably reflects the reduced fundings from the government during this period.

**Housing Reform**  New housing stock was historically allocated to urban residents through state work units since 1949. Starting from 1994, individuals in state-owned housing were allowed to buy full or partial property rights to their current homes. The price was highly subsidized and most buyers paid less than 15% of the market value for their own homes (Wang, 2010, Gao, 2010). If the householder employed in GOV was more likely to reside in public housing than those employed in SOE prior to the reform, the former would have benefited more from the housing subsidy and could potentially confound the impacts of economic restructuring.

I use data from the urban survey of Chinese Household Income Project 1988 (CHIP1988) and 1995 (CHIP1995) to check whether the residence of housing differs between SOE and GOV/PUB. As shown in Table 10, the percentage of households residing in public housing is 0.845 and 0.88 for the householder employed in SOE and GOV/PUB respectively in 1988, and the two figures are 0.452 and 0.465 respectively in 1995. While this figure is close to each other for SOE and GOV/PUB, for households working private sectors, the number is lower to 0.564 and 0.315 in 1988 and 1995 respectively. These figures demonstrate that the proportion of the public housing allocated to the SOE and GOV/PUB group are more or less balanced.

**Increase of enrollment and tuition for tertiary education**  The government expanded the tertiary education enrollment and increased the college tuition fee after 1999. Both of these changes may have different implications for children with fathers employed in SOE and GOV. If the policy disproportionately favors the rich family, children with fathers in GOV would have benefited more from the policy. In that case, the education policy could be a confounder to the shock of economic

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27The selection is subject to availability and based on the principle for ease of comparison. See Figure 8 for more details.
restructuring. To rule out this possibility, I provide following two robustness checks. First, not all the children from the post-shock group are exposed to the college expansion policy except for those born after 1981. I therefore drop these children from the sample and re-estimate the impacts of economic restructuring at the cost of losing part of statistical power. In Table 11 columns 3 and 4, the results show that the estimates seems robust to these changes and remains negative.

Moreover, if the education policy does affect families at different margin, one implication of the “favoring-the-rich” hypothesis is that children living in urban area would benefit more from the policy than those in rural area, given the large rural-urban income gap in China. I check this hypothesis using data from China Family Panel Survey 2010 (CFPS2010), which provides information on respondents’ educational attainment and residential area when 12. Based on these information, I plot the fraction of people who attained college over age and by their residential area when young. As displayed in Figure 7, the fraction of people attending college increased over time for both groups of children. The gap of college attainment between the two group also increased. However, the new policy on tertiary education in 1999 appears not to especially benefit those living in urban area, as otherwise there would be a jump of the gap of college attainment after 1982.

5.4 Additional Robustness Checks

This section provides several additional robustness checks for the main results obtained in section 5.1.

Drop Shanghai  As a direct-controlled municipality by the central government, Shanghai is different from other cities in many aspects. The special economic zone set up in 1990 is also a sign that Shanghai may have implemented different economic policies in the 1990s. In addition, as pointed out by Huang (2008), Shanghai, together with Heilongjiang and Qinghai, implemented the SOE reform slightly earlier than other provinces. Given the unique political and economic position of Shanghai, I drop it from the sample to make sure that my results are not driven by Shanghai’s special policy. As seen in Table 11 columns 1 and 2, dropping Shanghai doesn’t greatly affect the results.

Use all non-state sectors as the control group  Since Chinese reforms follow a gradual trajectory in the 1980s, the growing private sectors might have attracted considerable amount of labors that would otherwise work in SOEs or GOV. In that case, the treatment group and comparison group in the 1980s would have drawn from a different population than that before 1980, and the composition of the two group might have changed over time.

Nevertheless, it’s worth emphasizing that the job mobility in the 1980s is still low especially for SOE workers that already had a job, and the private sectors in urban area were almost negligible before 199228. As an additional robustness check, I use all non-state sector as the control group instead of only the government and public institutions. In this exercise, I rely on a weaker assumption by allowing GOV/PUB workers to freely move to private sectors. The results presented in Table 12 column 3 indicates that the results are not driven by the inappropriate definition of the control group.

Add father’s demographic interactions  As shown in Table 1, father’s pre-treatment characteristics are unbalanced between the treated and the control group. These systematic differences may be associated with the dynamics of the outcome variables. To control for the these potential cohort-varying observables, I add children’s cohort dummy interacted with a rich set of father’s demographic

28See the discussion in 2.1 and 4.1
variables including education, height, party membership, and personal early life experience, such as being sent down to rural area after 16 and living in urban area before 16, etc. The results presented in column 4 of Table 11 indicates that adding these demographic interactions do not make a big difference.

The divergence of the return to education and other observables Using Urban Household Survey, Meng (2012) and Ge and Yang (2014) documented the divergence of return to education in urban China. Returns to college-and-above education have risen from around 16% in 1988 to over 50% by 2003, while the returns to junior high school remain below 20%. Since SOE workers are generally less educated than GOV workers, their income might have changed not because of the economic restructuring but the divergence of returns to education. To rule out this possibility, I add interactions of children’s post-shock cohorts with father’s educational attainment, school ranking, and school performance into the DID regression, to control for the cohort-varying variables related to father’s educational attainment and cognitive skills. As shown in Table 12, most coefficients of these interactions are not significant, suggesting that adding these controls do not greatly change the main results.

Falsification exercises using placebo post-shock cohort I perform a falsification test to check if there are time-varying unobservables driving the results. In the main analysis, the treated cohort is defined as the youngest cohort of children not eligible for college or high school by 1995. In the falsification test, I use an earlier cohort - those not eligible for college or high school by 1990 - as the placebo post-shock group. If the results are driven by time-varying unobservables, we would see a negative effect even in absence of the economic restructuring. The results presented in Table 14, however, do not support this hypothesis. Most of the estimates are either insignificant or wrong-signed.

Mortality attrition Including more cohorts lends more statistical power to the study, but also raises the concern of mortality attrition, because older cohorts are more likely subjected to fathers’ death and disappear from the sample. If the attrition is systematically different by education level and socioeconomic status, it would bias the DID estimates. Assuming that younger cohorts are less likely subjected to the mortality attrition, I estimate equation (1) using younger cohorts to make sure that the results are not driven by the the mortality attrition. The results presented in Table 13 suggests that the mortality attrition is not a threat to the identification strategy.

6. Sibling Effect

6.1 Sibling Effect

In China, there are anecdotal evidence that informal social network, usually formed by extended family members or friends, plays an important role in household’s risk smoothing. For example, siblings could provide informal insurance such as gift money, informal loans, or other non-monetary support for families that suffer income shock directly. Also, they could use their social connections and help the laid-off families indirectly by facilitating them to get re-employed. In this section, I investigate
whether having more parental siblings could alleviate the adverse impacts of economic restructuring on children’s education.

The number of parental siblings is possibly correlated with the unobserved family characteristics, which could potentially shift along the same dimension as the former does and consequently confound the sibling effect. For example, richer families might have more siblings and they are less vulnerable to the shock. Zhou (2014) proposes a strategy dealing with this issue. In her paper, she argues that the sex of a child is determined by the nature, given the fact that the ultrasound technology adopted in detecting children’s gender was introduced in China after the 1980s. Since the parents studied in this research are mostly born before 1970s, having one more brother or sister is plausibly random. The total number of brothers or sisters are thus arguably exogenous conditional on the total number of siblings. Also, having more parental brothers could be more beneficial to the family, as male siblings are generally considered more financially capable and helpful than female siblings. For these reasons as well as a robustness check, I also investigate how having one more parental brother relative to sister could possibly alleviate the shock for children. To do so, I replace the number of parental sibling with the number of brothers and control for the total number of parental siblings.

The empirical specification is the following

\[ E_{iash} = \alpha_0 + \alpha_1 \text{SOE}_s \times \text{Postshock}_s \times \text{Sib}_h + \alpha_3 \text{SOE}_s \times \text{Postshock}_s + \beta' \bar{X}_i + \varepsilon_{iash} \]  

(7)

where \( \text{Sib}_h \) is a count variable of the total number of siblings or brothers that the children’s parents have. I control for \( S^f \) and \( S^m \), the number of paternal siblings and maternal siblings respectively. In the specification for the brother effect, I also control for the total number of brothers in addition to the total number of siblings. If having more siblings or brothers relative to sisters does mitigate the shock of the economic restructuring, we are expected to observe a positive \( \alpha_1 \) and a larger negative \( \alpha_3 \) as compared to that in equation (1).

Table 7 report the results in equation (7). As shown in columns 1 and 3, having one more parental sibling significantly reduces the impact of the economic restructuring on children’s educational attainment. In addition, children in families without any parental siblings suffered even more from the shock. Column 2 and 4 show that the results remain robust and significant even after I replace the regressor with the number of parental brothers. Taken together, these evidence suggest that parental siblings can provide certain form of informal insurance to buffer against the impact of economic restructuring shock on children’s education.

6.2 Sibling Effect: mechanisms

There are multiple ways through which parental siblings could alleviate the economic restructuring shock. While it’s hard to distinguish them all empirically, I present evidence on the existence for

\[ (29) \text{One caveat of this strategy is that the household might take the stopping rule because of the son preference, which is a common practice in some Asian countries including China. If the household’s fertility decision is biased towards the son, the number of male siblings could still be endogenous. However, when studying the brother effect on the household saving in China, Zhou (2014) shows that her result is robust to controlling the son preference for urban China, which suggests that the gender preference appear not be a major problem in urban area.} \]
one of them - i.e., the monetary gift sending among extended family members. Using data from
the household survey of CULS2001, I first conduct a cross-section data analysis to examine whether
families with workers initially employed in SOEs before the economic restructuring received more
gift money than other families. Then I provide evidence that the siblings, especially the male ones, do
send more gift money for families with more financial pressure.

6.2.1 Informal insurance for families in need

Fafchamps and Lund (2003) shows that risk sharing through gift money exchanging among extended
family members in rural Philippines. The anecdote suggests that this practice is also prevalent in
urban China. Yet there has been lack of rigorous evidence on that regard. In this section, I investigate
whether household with family members employed in SOEs sector before 1992 relies on gift money
to cope with the economic restructuring shock. Nevertheless, a naive OLS regression is likely subject
to the omitted variable bias, as the unobservable characteristics at the family level may determine the
allocation of jobs before 1992 as well as the amount of gift money received simultaneously.

Instead, I focus on whether the gift money acquired by SOE families varies by their financial need.
In particular, tertiary education is costly and can impose a big burden for families in China. Families
with children in college could be more vulnerable and financially sensitive to economic restructuring
shocks. SOE families with children in college thus are more likely to seek for financial support, and
the gift money acquired by them is therefore expected to be larger.

The CULS2001 provides rich information on gift money received at the household level. Using
data from the household survey, I estimate the following equation with a Difference-in-Difference
setup

\[
Gift_h = \lambda_0 + \lambda_1 SOE_h \times \text{College}_h + \lambda_2 SOE_h \times \text{School}_h + \lambda_3 SOE_h
+ \lambda_4 \text{College}_h + \lambda_5 \text{School}_h + \theta X_h + \epsilon_h
\] (8)

where \(Gift_h\) is the amount of gift money received from relatives and friends of household \(h\) in
2000. \(SOE_h\) represents the SOE family and is taking value of one if the household head and his/her
spouse were both employed in SOEs before 1992. \(\text{College}_h\) is a dummy equal to 1 if household \(h\)
has a child in college, and 0 otherwise. A vector of controls include city fixed effect, household
head birth year fixed effect, gender and education level of the household head, and the size of the
family. In order to narrow the comparison between families with children in college and families with
children in school but not in college, I also add dummy \(\text{School}_h\), which indicates whether the family
has children in school, and its interaction with \(SOE_h\). The coefficient of interest, \(\lambda_1\), is expected to
be positive and interpreted as the insurance effect in response to economic restructuring shock. The
difference-in-difference specification allows for unobservables to be correlated with the employment
status or the likelihood of having children in college, as they are absorbed by the main effects of \(SOE_h\)
and \(\text{College}_h\).

\(^{30}\)Figure 5 shows how the educational expenses including tuition and miscellaneous fees vary across schooling stages.
On average, college tuition costs around 4000 RMB per year - roughly 2000 RMB higher than that on all other schooling
stages.

---

\(^{30}\) Figure 5 shows how the educational expenses including tuition and miscellaneous fees vary across schooling stages.
On average, college tuition costs around 4000 RMB per year - roughly 2000 RMB higher than that on all other schooling
stages.
Table 8 presents the estimated results based on equation (4). Column 1 shows that for families with children in college, the gift money received from relatives and friends is 687 RMB larger on average for SOE families than non-SOE families. After adding controls of School$_h$ and its interaction with SOE$_h$, I find the estimates are still large and significant at 1% level. Columns 3-6 show that the result is robust to different measures. On average, being employed in SOE in 1992 increases the inflow of gift money by around 80% for household with children in college, as depicted in column 3. Columns 5 and 6 show that the likelihood of receiving gift money greater than 1000 is significantly larger as well. The impact of being working in SOEs before 1992 on gift money is mostly negative - though not significant except that in column 1, which highlights the potential endogeneity between the job allocation and the amount of gift money acquired. This might be caused by the fact that less capable workers were more concentrated in SOEs, and their friends and relatives are poorer, so their ability to borrow is also confined. Therefore, if simply running the regression of the amount of gift money on the layoff, we probably end up underestimating the true effect.

An alternative interpretation for the positive $\lambda_1$ is that SOE families without children in college might acquire less money than non-SOE families. This is plausible, for instance, if SOE workers are more isolated and less willing to interact with others, and accordingly having weaker social ties would discourage their gift money received. To get a sense whether the effect is driven by such channel, I plot the marginal effect of being a SOE worker before 1992 on the gift money acquired for two groups of families: those with children in college and those without. The results presented in Figure 6 show that the change appears mainly driven by the increase of gift money received by the family with children in college rather than the decrease of that received by the family without children in college. This result is thus inconsistent with the alternative hypothesis mentioned above.

### 6.2.2 Informal insurance and the brother effect

In this section, I provide evidence that brother could help families in need through sending gift money. If the change of gift money reflects informal insurance among extended family members, the received gift is expected to vary across the number of siblings, as more siblings means a larger capacity that one can borrow. On the other hand, if the change of gift money is driven by the varying unobserved family characteristics, the impact of layoff on gift money is not expected to change across the number of siblings.

To implement this idea, I estimate a saturated DDD model with the following specification

$$
Gift_h = \lambda_0 + \lambda_1 SOE_h \times College_h \times Brothers + \lambda_2 SOE_h \times Brothers + \lambda_3 SOE_h \times College_h + \lambda_4 College_h \times Brothers + College_h + Brothers_h + SOE_h + Siblings + \theta X_h + \epsilon_h
$$

where the variable of interest is Layoff$_h \times College_h$ interacted with the total number of brothers the household head and her spouse have. If the hypothesis of informal insurance on educational expenses holds, $\lambda_1$ is expected to be positive. Since the number of siblings might be correlated with certain family characteristics, I use brothers as a proxy for siblings while controlling for the total
number of siblings in the same way as in equation (8). The results presented in Table 9 are essentially in line with the hypothesis.

7. Conclusion

China’s SOE reform in the mid-1990s provides a good opportunity to examine the intergenerational consequences of economic restructuring. Compared to workers employed in GOV and PUB, SOE workers experienced lower cumulative earnings and were more likely to lose jobs over the 1995-2001 period. This short-term impact also has striking long-run implications. Children with fathers initially employed in SOEs were less likely to enter college or high school afterwards. Moreover, I present the evidence that children in families where parents have less financially-capable siblings were more adversely affected, and that siblings can provide families in need with informal insurance by sending them gift money.

Furthermore, this paper develops a conceptual framework to understand the mechanisms of two opposing spillover effects of economic restructuring. Based on the model predictions, I examine heterogeneity across cities with different level of SOE workers. The empirical results support the evidence of a negative spillover effect. The shock of economic restructuring was amplified in cities where there is a higher percentage of unemployed workers or SOE workers.

These evidence establish the adverse impact of economic restructuring on children’s educational attainment in a society lack of well-designed social transfer programs and underdeveloped credit market. Although shocks can be partially alleviated through informal social networks, the overall impact is still large, persistent, and transmitted to the next generation. The magnitude of these effects suggest that intergenerational costs of economic restructuring to affected families with children before schooling age are a relevant cosideration for policy makers.

The relocation of resources by SOE reform increased the economic efficiency and possibly spurred the economic growth (Song, Storesletten and Zilibotti, 2011). Yet the large distributional consequences of the policy hasn’t be fully explored. Existing empirical evidence suggests that the economic efficiency is achieved to a large extent at the cost of SOE workers, which may have contributed to an enlarged income gap in the urban area. Taking a further step, an implication of the paper is that the increased income inequality may have led to inequality in educational attainment for the next generation. Given higher return to more years of schooling, exploring to what extent the income distribution of the next generation in the urban area is altered by the economic restructuring could be an important topic for future research.

---

31 There are some successful experiences in targeting laid-off families with children in school in developing countries during economic crisis. See, for example, Cameron (2009), Galasso and Ravallion (2004).

32 Based on the calculation from Ravallion and Chen (2007), both the relative and absolute Gini index in the urban area increased dramatically after 1990 as compared to rural area. Also see Xia et al. (2014), Benjamin et al. (2008), Knight and Song (2003) for more discussion on China’s rising inequality associated with the SOEs reform in the 1990s.
References


Figures and Tables

Figure 1: The unemployment shock

(a) Unemployment Rate

(b) The distribution of the reported year of unemployment, 1985-2001

All the data sources come from CULS2001 unless otherwise noted.
Source: CULS2001. The unemployment is defined as people who are laid off, involuntary retirees, registered as unemployment, or without work and actively searching for work.

Sources: China Statistical Yearbook 1991-2003. All wages are deflated using the price indices in the urban area. The calculation of the average wage for GOV and PUB is weighted by the number of workers employed in the two sectors.
Figure 4: Children's educational attainment and adolescent experience of father's layoff

Sources: CULS2001. Y axis represents the unweighted average of educational attainment and the likelihood of experiencing father’s layoff when young for a given cohort.
Figure 5: Average schooling expenditure per person for various educational stages

Data source: CULS2001
Source: CULS2001. The gift money is measured at three different ways: the absolute value, the log value, and a dummy taking value of one if gift money received is greater than 1000 RMB. Each figure plots the predicted value of the gift money and 95% confidence interval from Equation 8. These figures show that SOE families with children in college have higher gift money received than other three types of family, and the results are robust to different measures of gift.
Table 1: Unweighted summary statistics: SOE vs GOV/PUB workers

<table>
<thead>
<tr>
<th></th>
<th>SOE</th>
<th>GOV/PUB</th>
<th>Diff</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Layoff</td>
<td>0.193</td>
<td>0.091</td>
<td>0.102***</td>
</tr>
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<td>Age</td>
<td>47.87</td>
<td>50.02</td>
<td>-2.15***</td>
</tr>
<tr>
<td>Male</td>
<td>0.488</td>
<td>0.519</td>
<td>-0.032**</td>
</tr>
<tr>
<td>Years of Education</td>
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<td>11.66</td>
<td>-1.654***</td>
</tr>
<tr>
<td>Marriage</td>
<td>0.855</td>
<td>0.870</td>
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<tr>
<td>Height</td>
<td>165.3</td>
<td>165.6</td>
<td>-0.289</td>
</tr>
<tr>
<td>Lives in city before 16</td>
<td>0.860</td>
<td>0.805</td>
<td>0.054***</td>
</tr>
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<td>Party Member (before work)</td>
<td>0.138</td>
<td>0.234</td>
<td>-0.096***</td>
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<tr>
<td>Children</td>
<td>1.432</td>
<td>1.568</td>
<td>-0.136***</td>
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<tr>
<td>Siblings</td>
<td>2.038</td>
<td>1.787</td>
<td>0.251***</td>
</tr>
<tr>
<td>Brother</td>
<td>1.030</td>
<td>0.934</td>
<td>0.097***</td>
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<tr>
<td>Sister</td>
<td>1.007</td>
<td>0.852</td>
<td>0.155***</td>
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<td>0.00400</td>
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<td>0.0630</td>
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<tr>
<td>Run a business</td>
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<td>0.0770</td>
<td>-0.166***</td>
</tr>
<tr>
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<td>0.0470</td>
<td>-0.043***</td>
</tr>
<tr>
<td>Technician</td>
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<td>0.0300</td>
<td>-0.067***</td>
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Table 2: Summary statistics of main analysis samples

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<th>GOV/PUB</th>
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<td><strong>College Sample</strong></td>
<td></td>
<td></td>
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<tr>
<td>College Attainment</td>
<td>0.435</td>
<td>0.381</td>
<td>0.539</td>
</tr>
<tr>
<td>Age</td>
<td>27.15</td>
<td>26.68</td>
<td>28.07</td>
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<tr>
<td>Gender</td>
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<td>1.483</td>
<td>1.472</td>
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<tr>
<td>Siblings</td>
<td>1.032</td>
<td>0.949</td>
<td>1.196</td>
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<tr>
<td>Sisters</td>
<td>0.369</td>
<td>0.347</td>
<td>0.414</td>
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<tr>
<td>Brothers</td>
<td>0.361</td>
<td>0.330</td>
<td>0.422</td>
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<td>Observations</td>
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<td>1232</td>
<td>623</td>
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<table>
<thead>
<tr>
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<th>GOV/PUB</th>
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</thead>
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<td><strong>High School Sample</strong></td>
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<td></td>
<td></td>
</tr>
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<td>High School Attainment</td>
<td>0.679</td>
<td>0.651</td>
<td>0.728</td>
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<tr>
<td>Age</td>
<td>30.30</td>
<td>29.41</td>
<td>31.91</td>
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<tr>
<td>Gender</td>
<td>1.481</td>
<td>1.484</td>
<td>1.475</td>
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<tr>
<td>Siblings</td>
<td>1.374</td>
<td>1.299</td>
<td>1.511</td>
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<tr>
<td>Sisters</td>
<td>0.574</td>
<td>0.543</td>
<td>0.629</td>
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<tr>
<td>Brothers</td>
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<td>0.652</td>
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<td>1832</td>
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Table 3: Summary statistics (household sample)

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<td><strong>Household’s Characteristics</strong></td>
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<td></td>
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<tr>
<td>Gift received</td>
<td>769.0</td>
<td>3273</td>
</tr>
<tr>
<td>Dummy: gift received</td>
<td>0.119</td>
<td>0.323</td>
</tr>
<tr>
<td>Gift sent out</td>
<td>712.3</td>
<td>1795</td>
</tr>
<tr>
<td>Dummy: gift sent out</td>
<td>0.385</td>
<td>0.487</td>
</tr>
<tr>
<td>Children in college</td>
<td>0.119</td>
<td>0.323</td>
</tr>
<tr>
<td>Children in high school</td>
<td>0.0906</td>
<td>0.287</td>
</tr>
<tr>
<td>Children in school</td>
<td>0.561</td>
<td>0.496</td>
</tr>
<tr>
<td>Family size</td>
<td>3.119</td>
<td>1.030</td>
</tr>
<tr>
<td><strong>Household Head’s Characteristics</strong></td>
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<td></td>
</tr>
<tr>
<td>Age</td>
<td>48</td>
<td>13.73</td>
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<tr>
<td>Gender</td>
<td>1.283</td>
<td>0.450</td>
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<tr>
<td>Education</td>
<td>10.91</td>
<td>5.169</td>
</tr>
<tr>
<td>Laid-off</td>
<td>0.278</td>
<td>0.448</td>
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<tr>
<td>Siblings</td>
<td>1.889</td>
<td>1.810</td>
</tr>
<tr>
<td>Brothers</td>
<td>0.962</td>
<td>1.152</td>
</tr>
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<td>Sisters</td>
<td>0.926</td>
<td>1.131</td>
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<td><strong>Observations</strong></td>
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### Table 4: Difference-in-Difference

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<th>DEP VARIABLES</th>
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<tbody>
<tr>
<td>College</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>-0.0564*</td>
<td>-0.111***</td>
<td>-0.0863*</td>
<td>-0.0803***</td>
<td>-0.0784**</td>
<td>-0.132***</td>
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<tr>
<td></td>
<td>(0.0318)</td>
<td>(0.0391)</td>
<td>(0.0444)</td>
<td>(0.0180)</td>
<td>(0.0378)</td>
<td>(0.0423)</td>
</tr>
<tr>
<td>Mean of Outcome Variable</td>
<td>0.4345</td>
<td>0.4345</td>
<td>0.4494</td>
<td>0.6871</td>
<td>0.6871</td>
<td>0.6936</td>
</tr>
<tr>
<td>Observations</td>
<td>1,855</td>
<td>1,855</td>
<td>1,620</td>
<td>2,822</td>
<td>2,822</td>
<td>2,412</td>
</tr>
<tr>
<td>Children and Parental Controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Children’s Cohort × Parental Job FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Spouse Controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

| High School                            |      |      |      |      |      |      |
| Post-shock Cohort × Mother in SOE      | -0.0514* | -0.111** | -0.191** | 0.0109 | 0.00788 | -0.0445 |
|                                         | (0.0294) | (0.0487) | (0.0781) | (0.0538) | (0.0522) | (0.0447) |
| Mean of Outcome Variable               | 0.4119 | 0.4119 | 0.4419 | 0.6622 | 0.6622 | 0.6810 |
| Observations                           | 1,964 | 1,964 | 1,609 | 3,200 | 3,200 | 2,517 |

Note: *** p<0.01, ** p<0.05, * p<0.1. (C: College sample includes children whose birth year ranges from 1964 to 1983, and high school sample ranges from 1956 to 1985. The post-shock cohort for college sample are born from 1980 to 1983, and for high school sample born from 1981 to 1985. Cohort fixed effect and job sector fixed effect are included in all specifications. Parental controls include the parent’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls include the number of children’s siblings, sisters, and brothers. Spouse controls include dummies of sectors where mother worked and its interactions with children’s post-shock cohorts.)
Table 5: Likelihood of experiencing father’s job loss when young

<table>
<thead>
<tr>
<th>SPECIFICATIONS</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>College Sample</td>
<td>High School Sample</td>
</tr>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>0.0526*</td>
<td>0.0539**</td>
</tr>
<tr>
<td></td>
<td>(0.0286)</td>
<td>(0.0267)</td>
</tr>
<tr>
<td>Mean of Outcome Variable</td>
<td>0.0410</td>
<td>0.0269</td>
</tr>
<tr>
<td>Observations</td>
<td>1,855</td>
<td>2,822</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at community level (70 clusters). The dependent variable is a dummy taking value of one if the child experienced father’s job loss when her age was between 6 and 18 for college sample, and between 6 and 15 for high school sample, respectively. The post-shock group for college sample are born from 1980 to 1983, and for high school sample born from 1981 to 1985. Father controls include father’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls include the number of children’s siblings, sisters, and brothers. Cohort fixed effect, job sector fixed effect, father controls, and children controls are included in all specifications.
Table 6: Triple difference (DDD)

<table>
<thead>
<tr>
<th>INTENSITY MEASURE</th>
<th>College</th>
<th>High School</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Layoff Share</td>
<td>(2) SWS</td>
</tr>
<tr>
<td>Post-shock Cohort × Father in SOE × Intensity</td>
<td>-0.409*  (0.228)</td>
<td>-0.208** (0.103)</td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Job FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>City Dummy × Father’s Job FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>City Dummy × Post-shock Cohort</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean Outcome of Variable</td>
<td>0.4345  1,855</td>
<td>0.4345  1,855</td>
</tr>
<tr>
<td>Observations</td>
<td>1,855</td>
<td>1,855</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at community level (70 clusters). Dependent variables are college enrollment and high school enrollment. The post-shock group for college sample are born from 1980 to 1983, and for high school sample born from 1981 to 1985. College sample includes children whose birth year ranges from 1964 to 1983. High school sample ranges from 1956 to 1985. Layoff Share is defined as the share of workers who report ever being laid off during the mass layoff period from the sample. SWS is a dummy taking value of one if the city is Shenyang, Wuhan, or Shanghai, where the shock intensity is significantly larger. SOE Share is the city-wide employment share of SOE workers before the shock. This information is available for all cities except Shanghai. Father controls include father’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls include the number of children’s siblings, sisters, and brothers. Father and children controls are included in all specifications.
Table 7: Sibling effect

<table>
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<th>SIBLING MEASURE</th>
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<th></th>
<th>High School</th>
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<td>Sibling FE</td>
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<td></td>
<td>Yes</td>
<td>Yes</td>
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</tr>
<tr>
<td>Brother FE</td>
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<td>Yes</td>
<td></td>
<td>No</td>
<td>Yes</td>
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</tr>
<tr>
<td>Mean Outcome of Variable</td>
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<td>0.4345</td>
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<td>0.6871</td>
<td>0.6871</td>
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</tr>
<tr>
<td>Observations</td>
<td>1,855</td>
<td>1,855</td>
<td></td>
<td>2,822</td>
<td>2,822</td>
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</tbody>
</table>

Post-shock Cohort $\times$ Father in SOE $\times$ Parental Siblings

<table>
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<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Sibling</td>
<td>0.0165**</td>
<td>0.0394***</td>
<td></td>
<td>0.0189**</td>
<td>0.0207***</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>(0.00721)</td>
<td>(0.0100)</td>
<td></td>
<td>(0.00734)</td>
<td>(0.00661)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th></th>
<th>(3)</th>
<th>(4)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Sibling</td>
<td>-0.142***</td>
<td>-0.164***</td>
<td></td>
<td>-0.179***</td>
<td>-0.137***</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>(0.0504)</td>
<td>(0.0297)</td>
<td></td>
<td>(0.0365)</td>
<td>(0.0257)</td>
<td></td>
</tr>
</tbody>
</table>

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors are clustered at community level (70 clusters). Dependent variables are college enrollment and high school enrollment respectively. The post-shock cohort for college sample are born from 1980 to 1983, and for high school sample born from 1981 to 1985. Sibling and Brother are the total amount of siblings and brothers from both mother and father sides. Father controls include father’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls include the number of children’s siblings, sisters, and brothers. Cohort fixed effect, job sector fixed effect, father controls, and children controls are included in all specifications.
<table>
<thead>
<tr>
<th>DEP VARIABLES</th>
<th>(1) Gift</th>
<th>(2) Gift</th>
<th>(3) Log(Gift)</th>
<th>(4) Log(Gift)</th>
<th>(5) I(Gift&gt;1000)</th>
<th>(6) I(Gift&gt;1000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>College x SOE</td>
<td>687.1**</td>
<td>916.8***</td>
<td>0.833**</td>
<td>0.989**</td>
<td>0.0637</td>
<td>0.0907**</td>
</tr>
<tr>
<td></td>
<td>(328.8)</td>
<td>(345.3)</td>
<td>(0.376)</td>
<td>(0.395)</td>
<td>(0.0391)</td>
<td>(0.0408)</td>
</tr>
<tr>
<td>College</td>
<td>155.8</td>
<td>-14.54</td>
<td>-0.0433</td>
<td>-0.0922</td>
<td>0.0229</td>
<td>-0.00486</td>
</tr>
<tr>
<td></td>
<td>(179.9)</td>
<td>(218.1)</td>
<td>(0.230)</td>
<td>(0.266)</td>
<td>(0.0235)</td>
<td>(0.0271)</td>
</tr>
<tr>
<td>School x SOE</td>
<td>-404.3**</td>
<td>-0.498*</td>
<td>-0.0560**</td>
<td>-0.498*</td>
<td>-0.0560**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(159.2)</td>
<td>(0.257)</td>
<td>(0.0246)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>School</td>
<td>262.3**</td>
<td>0.245</td>
<td>0.0352*</td>
<td></td>
<td>0.0352*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(126.2)</td>
<td>(0.187)</td>
<td>(0.0183)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOE</td>
<td>-190.0**</td>
<td>-13.54</td>
<td>-0.0603</td>
<td>0.0744</td>
<td>-0.0171</td>
<td>0.00766</td>
</tr>
<tr>
<td></td>
<td>(74.98)</td>
<td>(100.5)</td>
<td>(0.124)</td>
<td>(0.192)</td>
<td>(0.0117)</td>
<td>(0.0183)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean of Outcome Variable</td>
<td>769.0</td>
<td>774.1</td>
<td>2.506</td>
<td>2.506</td>
<td>0.119</td>
<td>0.119</td>
</tr>
<tr>
<td>Observations</td>
<td>3,484</td>
<td>3,433</td>
<td>3,484</td>
<td>3,433</td>
<td>3,433</td>
<td>3,433</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Gift is the total gift money received last year from relatives and friends by the household head and her spouse. I(Gift>1000) is an indicator representing the gift money received over 1000 RMB. College is a dummy equal to 1 if the household has at least one child in college or above, and 0 otherwise. SOE is a dummy taking value of one if both household head and spouse were employed in SOEs before 1992. Controls include household head’s gender, education, and birth year, as well as the size of the family and the city fixed effect.
Table 9: Informal insurance from siblings (triple difference)

<table>
<thead>
<tr>
<th>DEP VARIABLES</th>
<th>(1) Gift</th>
<th>(2) Log(Gift)</th>
<th>(3) I(Gift&gt;1000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>College × SOE × Brothers</td>
<td>55.66</td>
<td>0.430*</td>
<td>0.0412*</td>
</tr>
<tr>
<td></td>
<td>(214.9)</td>
<td>(0.233)</td>
<td>(0.0240)</td>
</tr>
<tr>
<td>College × Brothers FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SOE × Brothers FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SOE × College</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean of Outcome Variable</td>
<td>769.0</td>
<td>2.506</td>
<td>0.119</td>
</tr>
<tr>
<td>Observations</td>
<td>3,433</td>
<td>3,433</td>
<td>3,433</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. College is a dummy equal to 1 if the household has at least one child in college or above, and 0 otherwise. SOE is a dummy taking value of one if both household head and spouse were employed in SOEs before 1992. Total number of brothers and total number of siblings household head and her spouse have are controlled in all specifications. Controls include household head’s gender, education, and birth year, as well as the size of the family and the city fixed effect.
Appendix A: Figures and Tables

Figure 7: College attainment, rural versus urban

Source: CFPS2010. Rural and urban area refers to the place where the individuals lived at 12 years old. College attainment is the fraction of people who

Figure 8: Income growth in GOV/PUB across selected cities

Source: CHIP2002. Personal income is defined as income earned from all enumerated sources throughout the year. The data covers two out of five cities studied in this paper, Wuhan and Shenyang. The comparison cities are chosen to be as similar as possible to Wuhan and Shenyang in terms of average personal income, and are subject to availability in the data. Personal income are retrospective data except for that in 2002.
Figure 9: Difference coefficients for high school and college enrollment

Source: CULS2001. Each panel plots regression coefficients and 95% confidence interval from estimating equation (16).
Table 10: Percentage of households residing in public housing

<table>
<thead>
<tr>
<th>Year</th>
<th>SOE</th>
<th>GOV/PUB</th>
<th>Private Sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1988</td>
<td>0.845</td>
<td>0.880</td>
<td>0.564</td>
</tr>
<tr>
<td>Observations</td>
<td>5908</td>
<td>2086</td>
<td>188</td>
</tr>
<tr>
<td>1995</td>
<td>0.452</td>
<td>0.465</td>
<td>0.315</td>
</tr>
<tr>
<td>Observations</td>
<td>4169</td>
<td>2082</td>
<td>124</td>
</tr>
</tbody>
</table>

*Note:* Households are divided into three categories, SOE, GOV/PUB, and Private sectors, based on the economic sector that the household head is employed. Data come from CHIP1988 and CHIP1995 for year 1988 and 1995 respectively.
Table 11: Robustness checks for DID

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Dep Var = College Attainment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>-0.121**</td>
<td>-0.112*</td>
<td>-0.120***</td>
<td>-0.100**</td>
</tr>
<tr>
<td></td>
<td>(0.0469)</td>
<td>(0.0591)</td>
<td>(0.0423)</td>
<td>(0.0405)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,498</td>
<td>1,646</td>
<td>1,962</td>
<td>1,855</td>
</tr>
</tbody>
</table>

|                |           |           |           |           |
| **Panel B: Dep Var = High school Attainment** |           |           |           |           |
| Post-shock Cohort × Father in SOE | -0.0790*  | -0.0807*  | -0.0743** |
|                     | (0.0457)  | (0.0431)  | (0.0348)  |
| Observations        | 2,271     | 3,003     | 2,821     |

**Note:** Dependent variables are college enrollment in Panel A, and high school enrollment in Panel B. Except in columns 1, college sample includes children born from 1964 to 1983, and high school sample from 1956 to 1985. The post-shock cohort for college sample are born from 1980 to 1983, and for high school sample born from 1981 to 1985. Father controls include father’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls include the number of children’s siblings, sisters, and brothers. Cohort fixed effect, job sector specific trend, father controls, and children controls are included in all specifications. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at community level (70 clusters).

**Specifications:**
2. Drop Shanghai from the sample.
3. Use children with fathers in all non-SOEs as the control group.
4. Include father’s demographic interactions, which are children’s cohort dummy interacted with father’s education, height, party membership, and personal early life experience including whether was sent down to rural area after 16 and whether lived in urban area before 16.
Table 12: Divergence of return to education and ability

<table>
<thead>
<tr>
<th>DEP VARIABLES</th>
<th>(1) College</th>
<th>(2) College</th>
<th>(3) College</th>
<th>(4) High School</th>
<th>(5) High School</th>
<th>(6) High School</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>-0.100** (0.0405)</td>
<td>-0.0886** (0.0387)</td>
<td>-0.0879** (0.0387)</td>
<td>-0.0743** (0.0348)</td>
<td>-0.0649* (0.0352)</td>
<td>-0.0729** (0.0353)</td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Education</td>
<td>0.0109 (0.00749)</td>
<td>0.00599 (0.00729)</td>
<td>0.00419 (0.00741)</td>
<td>0.000996 (0.00645)</td>
<td>0.00194 (0.00804)</td>
<td>0.00137 (0.00582)</td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Pschool Quality</td>
<td>0.160*** (0.0593)</td>
<td>0.150** (0.0735)</td>
<td>0.158* (0.0623)</td>
<td>0.0941 (0.0681)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Mschool Quality</td>
<td>0.226* (0.127)</td>
<td>0.209* (0.125)</td>
<td>0.0977 (0.0720)</td>
<td>0.124** (0.0593)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Hschool Quality</td>
<td>-0.0211 (0.0739)</td>
<td>-0.0376 (0.0722)</td>
<td>0.0325 (0.0922)</td>
<td>0.0312 (0.0951)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Pschool Ranking</td>
<td>-0.147** (0.0627)</td>
<td>0.0176 (0.122)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Mschool Ranking</td>
<td>0.0817 (0.186)</td>
<td>0.0704 (0.177)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-shock Cohort × Father’s Hschool Ranking</td>
<td>0.0899 (0.0857)</td>
<td>-0.192 (0.132)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean of Outcome Variable</td>
<td>0.4345</td>
<td>0.4345</td>
<td>0.4345</td>
<td>0.6871</td>
<td>0.6871</td>
<td>0.6871</td>
</tr>
<tr>
<td>Observations</td>
<td>1,855</td>
<td>1,855</td>
<td>1,855</td>
<td>2,821</td>
<td>2,822</td>
<td>2,821</td>
</tr>
</tbody>
</table>

Note: College sample includes children whose birth year ranges from 1964 to 1983, and high school sample ranges from 1956 to 1985. The post-shock cohort for college sample are born from 1980 to 1983, and for high school sample born from 1981 to 1985. Father controls include father’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls include the number of children’s siblings, sisters, and brothers. Demographic interactions are children’s cohort dummy interacted with father’s education, height, party membership, and personal early life experience including whether was sent down to rural area after 16 and whether lived in urban area before 16. Cohort fixed effect, job sector specific trend, father controls, children controls, demographic interactions are included in all specifications.

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at community level (70 clusters).
### Table 13: Mortality attrition

#### Panel A: College

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>-0.0670** (0.0327)</td>
<td>-0.113*** (0.0377)</td>
<td>-0.0973** (0.0384)</td>
<td>-0.0576 (0.0387)</td>
<td>-0.101** (0.0425)</td>
<td>-0.0839* (0.0440)</td>
<td>-0.108** (0.0407)</td>
<td>-0.108** (0.0407)</td>
<td>-0.0859** (0.0405)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,549</td>
<td>1,549</td>
<td>1,549</td>
<td>1,130</td>
<td>1,130</td>
<td>1,130</td>
<td>803</td>
<td>803</td>
<td>803</td>
</tr>
<tr>
<td>Father and Children Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Children’s Cohort × Father’s Job FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Father’s Demographic Interactions</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

#### Panel B: High School

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>-0.0637*** (0.0227)</td>
<td>-0.0710* (0.0362)</td>
<td>-0.0689* (0.0358)</td>
<td>-0.0724*** (0.0224)</td>
<td>-0.0845* (0.0400)</td>
<td>-0.0823** (0.0398)</td>
<td>-0.0832** (0.0347)</td>
<td>-0.0832** (0.0347)</td>
<td>-0.0806** (0.0338)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,951</td>
<td>1,951</td>
<td>1,950</td>
<td>1,504</td>
<td>1,504</td>
<td>1,503</td>
<td>1,071</td>
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<td>1,070</td>
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<td>Father and Children Controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Children’s Cohort × Father’s Job FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Father’s Demographic Interactions</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Note:** Dependent variables are college enrolment in Panel A, and high school enrolment in Panel B. The post-shock cohort for college sample are born from 1980 to 1983, and for high school sample born from 1981 to 1985. Father controls include father’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls are the number of children’s siblings, sisters, and brothers. Father’s demographic interactions are children’s cohort dummies interacted with father’s education, height, party membership, and personal early life experience including whether was sent down to rural area after 16 and whether lived in urban area before 16. Father and children controls are included in all specifications. ** *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at community level (70 clusters).
Table 14: Falsification exercises using placebo treatments

**Panel A: College**

<table>
<thead>
<tr>
<th>Cohorts Sample</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>0.0796 (0.0507)</td>
<td>0.0854 (0.0631)</td>
<td>0.0934 (0.0658)</td>
<td>0.101* (0.0568)</td>
<td>0.101* (0.0568)</td>
<td>0.121* (0.0628)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,131</td>
<td>1,131</td>
<td>1,131</td>
<td>712</td>
<td>712</td>
<td>712</td>
</tr>
<tr>
<td>Father and Children Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Children’s Cohort × Father’s Job FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Father’s Demographic Interactions</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Panel B: High School**

<table>
<thead>
<tr>
<th>Cohorts Sample</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
<th>(12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-shock Cohort × Father in SOE</td>
<td>0.0144 (0.0391)</td>
<td>0.0148 (0.0569)</td>
<td>0.0258 (0.0581)</td>
<td>0.0368 (0.0537)</td>
<td>0.0368 (0.0537)</td>
<td>0.0512 (0.0528)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,369</td>
<td>1,369</td>
<td>1,369</td>
<td>922</td>
<td>922</td>
<td>922</td>
</tr>
<tr>
<td>Father and Children Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Children’s Cohort × Father’s Job FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Father’s Demographic Interactions</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Note:** Dependent variables are college enrollment in Panel A, and high school enrollment in Panel B. The placebo post-shock cohort for college sample are born from 1976 to 1979, and for high school sample born from 1976 to 1980. Father controls include father’s education, party membership, height, occupation dummies, industry dummies, early life experience, school ranking, school quality, etc. Children controls are the number of children’s siblings, sisters, and brothers. Father’s demographic interactions are children’s cohort dummies interacted with father’s education, height, party membership, and personal early life experience including whether was sent down to rural area after 16 and whether lived in urban area before 16. Cohort fixed effect, job sector specific trend, father controls, children controls, demographic interactions are included in all specifications.

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are clustered at community level (70 clusters).
Appendix B: Proof

Proof of proposition 1:

Proof. Combing equation 2 and 3 and plugging 3 into 4, we have

\[
\pi^H = \text{Prob}[f(\frac{\alpha_n}{\tau_n}) + g(\tau_n) + \varepsilon > (1 - \tau_n)f(w) + \tau_n \cdot f(\frac{\alpha_n}{\tau_n}w) + g(\tau_n)]
\]

(10)

\[
= \text{Prob}[\varepsilon > (1 - \tau_n) \cdot (f(w) - f(\frac{\alpha_n}{\tau_n}w))]
\]

\[
= \Phi[(1 - \tau_n) \cdot (f(\frac{\alpha_n}{\tau_n}w) - f(w))]
\]

This gives

\[
\frac{\partial \pi^H}{\partial \tau_n} = \Phi' \cdot [f(w) - f(\frac{\alpha_n}{\tau_n}w) - \frac{(1 - \tau_n) \cdot f'(\alpha_n w)}{\tau_n^2}]
\]

(11)

Since \(\Phi' > 0\), we have \(\frac{\partial \pi^H}{\partial \tau_n} > 0\) if \(f(w) - f(\frac{\alpha_n}{\tau_n}w) < \frac{(1 - \tau_n) \cdot f'(\alpha_n w)}{\tau_n^2}\) and \(\frac{\partial \pi^H}{\partial \tau_n} < 0\) if \(f(w) - f(\frac{\alpha_n}{\tau_n}w) > \frac{(1 - \tau_n) \cdot f'(\alpha_n w)}{\tau_n^2}\).

Proof of proposition 2:

Proof. Consider the probability of going to college for children whose father lost jobs

\[
\pi^C = \text{Prob}[f(\frac{\alpha_n}{\tau_n}) + g(\tau_n) + \varepsilon > \bar{M}]
\]

(12)

\[
= \Phi[f(\frac{\alpha_n}{\tau_n}) + g(\tau_n) - \bar{M}]
\]

This gives

\[
\frac{\partial \pi^C}{\partial \tau_n} = \Phi' \cdot [-\frac{f'(\alpha_n w)}{\tau_n^2} + g'(\tau_n)]
\]

(13)

Since \(f' > 0\) and \(g' < 0\), we have \(\frac{\partial \pi^C}{\partial \tau_n} < 0\).

Rearranging equation 10 yields

\[
\frac{\partial \pi^H}{\partial \tau_n} = \Phi' \cdot [f(w) - f(\frac{\alpha_n}{\tau_n}w) + \frac{f'(\alpha_n w)}{\tau_n} - \frac{f'(\alpha_n w)}{\tau_n^2}]
\]

(14)

Since \(f(w) - f(\frac{\alpha_n}{\tau_n}w) > 0, \frac{f'(\alpha_n w)}{\tau_n} > 0, \) and \(g' < 0\), comparing (13) with (12), we have

\[
\frac{\partial \pi^H}{\partial \tau_n} > \frac{\partial \pi^C}{\partial \tau_n}
\]

(15)

\[\square\]
Appendix C: Sample and Variable Definition

C.1 The Children Sample

In this appendix, I describe the procedure of how I obtain the children’s sample from the adult’s survey. Specifically, it involves the following four steps:

1. Keep only males in the adult survey.

2. Expand the data based on the number of children each male adult has and generate children’s demographic variables including the gender, birth year, and educational attainment based on the information from the adult survey.

3. Keep only those children whose fathers work in state sectors.

4. Drop those whose fathers’ initial job started before 1949.

After imposing these restrictions, I obtain the final college sample with 1855 observations, and the high school sample with 2822 observations. The sample for the analysis includes all the children identified from the adult survey except those whose mothers are either widow or divorced. In that case, I cannot directly observe these children’s father’s information. The sample for the analysis of mother’s job status is constructed in the same way. And similarly, for those male widow and divorced, their children are out of the sample for mother’s job analysis.

C.2 Definition of Father’s Job

Now I discuss the definition of father’s job in more details. Ideally, I would like to have the control and the treatment group as two parallel tracks that people cannot freely cross. But in fact people do change jobs, which makes it hard to accurately capture and define father’s jobs. The labor market barrier in China, however, provides an opportunity to deal with this issue. In China, most of jobs before 1990s are assigned to be life-time jobs, the so-called “Iron Rice Bowl”. It is difficult for people to switch jobs across firms, if possible. The job mobility was almost before 1990s and the composition of control and treatment group was thus relatively stable over time. Therefore, even though I cannot directly observe father’s job when children is younger than their schooling age, I can use father’s initial jobs or jobs right before the shock to approximate.

For those not working in 1996, the survey asks detailed information about their their initial jobs including job types, sectors, industries, how to get the jobs, etc. For the people, I simply define father’s jobs as their initial jobs, while for those still working in 1996, the survey does not only ask their initial jobs, but also records their detailed employment history. To fully utilize this information, I define father’s jobs for this group of people as the one held in 1992, right before the labor market reform.

34 For males born before 1965, there are less than 4% that don’t have any children.
35 To check the robustness, I also use children with fathers employed in all non-state enterprises as the control group. The results are robust to these changes. See Table 11.
36 For example, the CULS2001 data shows that for people whose work started in 1970s, only 0.5% had ever changed their jobs by 1996.
Appendix D: Dynamic effects

The results presented in panel (a) and (b) of Figure 4 only serve for illustrative purpose. In this appendix, I estimate a restricted model with discrete interaction terms and show analytically how the economic restructuring shock evolves,

\[ E_{ias} = \alpha_0 + \sum_{a=1}^{A} \beta_a (SOE_i \times Cohort_{ia}) + \rho_a + \eta_a + \theta' X_i + \varepsilon_{ias} \]  

(16)

where \( Cohort_{ia} \) is a dummy that indicates whether children \( i \) is in age group \( a \). Each coefficient can be interpreted as an estimate of the impact of the shock on the educational attainment for a given cohort. Figure 9 plots these coefficients and their 90% confidence intervals for high school sample and college sample respectively. Similar to the unrestricted comparison shown in Figure 4, the gap between the SOE and GOV/PUB group is relatively constant until age group 76-80, and then increases considerably for the post-shock group for the high school sample. In terms of the college attainment, the difference between the two groups has been shrinking until after 76-79, and then grows for the post-shock group 80-83.