Gender Difference in Intergenerational Effects of Laid-off Parents*

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Abstract

This paper evaluates the gender difference in intergenerational effects of laid-off parents on children's adult outcomes. By exploiting China Health and Nutrition Survey (CHNS) over 1991–2015, we construct the children's durations of exposure to fathers'/mothers' layoffs from state-owned enterprises (SOEs) retrenchment starting in 1990s before turning to 18-year-old. We find that, when experiencing fathers' layoffs for a longer period, only girls suffer significant reduction in education outcomes and hence are more likely to have manual occupations; when suffering mothers' layoffs for a longer period, boys' education levels increase but this advantage does not reduce their probabilities of having manual occupations. Although the gender difference in children's education persists in their occupations, girls do not underperform boys with similar family background in adult earnings. Instead, for girls with manual occupations, fathers' layoffs increase their gardening income.

Keywords: intergenerational effect, parents' layoffs, gender difference.
JEL classification: J13, J16, J24, J31, J63

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1 Introduction

It is well documented that significant gender differences exist in adult outcomes, which could be explained by the different responses to family background and/or childhood environment across gender (Chetty et al., 2016; Brenøe and Lundberg, 2018; Figlio et al., 2019). When families' economic status change, not only girls often response differently from boys in education attainment (Johnston et al., 2014; Liu and Hannum, 2017), but also parents invest differently in children's human capital based on gender (Brown and Park, 2002; Bhalotra and Rawlings, 2011; Duflo, 2012; Roy, 2015). However, it is still not well discussed whether or not such different responses could persistently affect children's labor market performances when they grow up.[1]

A typical example is China's SOE retrenchment starting in 1990s, during which period many urban workers suffered involuntary layoffs (Giles et al., 2006; Naughton, 2006). Losing "iron bowl" jobs lead to substantively negative impacts on these workers' family income, social ties, and health conditions (Dong and Xu, 2008; Tian et al., 2022). Also, their children, who have grown up and entered labor market in nowadays, received less investment from parents during that period of time (Liu and Zhao, 2014). Would such a shortage of investment suffered in their childhood lead to further disadvantages in their labor market performance? Such an investigation still remains unanswered.

To this end, this paper examines gender difference in the effects of laid-off parent(s) on children's adult outcomes in China by exploiting nine waves of longitude data from CHNS over 1991–2015. These waves cover both the entire period of SOE retrenchment starting from 1990s and its post era. Our sample restricts attention on individuals who were below 18-year-old over the period 1991–2004 and whose parent(s) had working history in public institutions, SOEs, or collective enterprises in this period. Individuals' adult outcomes are collected from wave 2006 to 2015 in CHNS.

To identify the intergenerational effects, we construct the duration of exposure, which is equal to eighteen minus one's age when an individual's parent(s) suffered layoff from SOEs plus one. The coefficient of the duration of exposure measures the treatment effect. This is because a dummy variable of layoff itself could not capture the multi-valued treatment when a child experienced the layoff for a longer period During the SOE retrenchment period, a child's characteristics barely affect his/her father's and/or mother's decision of quitting from an "iron bowl" job. Being laid-off from such a job would lead to significant negative shock on family income and economic status. We consider three scenarios of layoffs separately: 1) an individual only has a laid-offer father; 2) he/she only has a laid-off mother; 3) he/she has a laid-off father and/or mother. To alleviate potential bias, we control individuals' characteristics at individual, family, community, and provincial level, along with individuals' birth year fixed effect and wave fixed effect. Moreover, to emphasize the potential gender difference in individuals' adult outcomes, we construct the interaction term between an

[1] Both Liu and Zhao (2014) and Pieters and Rawlings (2020) find heterogeneous effects on children's health across gender in the short run. Oreopoulos et al. (2008) show that the negative effect for boys on earnings is similar to that for girls in Canada. Huttunen and Riukula (2019) suggest that the effects on careers decisions do not show gender difference in Finland.

individual's gender and his/her duration of exposure to the father's/mother's layoff, which measures the increment of the effects for being a girl compared to being a boy.

We investigate the intergenerational effects by analyzing children's long term outcomes, including education and labor market outcomes. We find significant gender differences in children's education and occupational outcomes: when being exposed to fathers' layoffs for a longer period, only girls suffer significant reduction in education outcomes and hence are more likely to have manual occupations. Instead, when being exposed to mothers' layoffs for a longer period, only boys' education levels increase. However, these differences do not lead to disadvantages for girls in adult earnings. Our results also suggest that investing in children's education based on gender is not efficient for Chinese families.

Specifically, when suffering fathers' layoffs for a longer period, only girls have lower education levels while boys' are not affected. When suffering mothers' layoffs for a longer period, boys have higher education years and a higher probability of having a college degree; by contrast, relative to boys, girls experience lower education years and lower probabilities of having a college degree. The existence of gender difference in education outcomes from fathers'/mothers' layoffs implicitly shows unequal family investment in children's education across children' gender. When a family suffered a negative economic/income shock, relative to a boy, a girl suffers more from the re-balance between family expenditures and investment in children's education. Thus, together with the perception of gender role (Johnston et al., 2014), she is more likely to drop out from the school and work to subside the loss of family income. Instead, a boy is less likely to be asked to do so. Though a laid-off mother, whose salary is not the main source of the family income, could spend more time on taking care of children (Liu and Zhao, 2014), we only observe a significant positive effect on education for boys.

Following Acemoglu and Autor (2011) and Cortes et al. (2017), we consider the cognitive dimension of occupations according to task content and categorize occupations in two groups: cognitive ones and manual ones. When suffering fathers' layoffs for a longer period, girls are more likely to work in manual occupations relative to cognitive ones that require a certain level of education. Instead, boys with similar family background are not affected. Such a gender difference is the persistent result of the gender difference in education from fathers' layoffs. When suffering mothers' layoffs for a longer period, a similar result is also obtained.[2] This is also caused by the gender difference in education from mothers' layoffs . The significant increase in boys' education from mothers' layoffs does not reduce the probabilities of having manual occupations. This is due to the less important role of mothers in children's career choices (Huttunen and Riukula, 2019).

We demonstrate that boys do not outperform girls in adult earnings even though they receive more family support. For boys, neither education nor occupations are affected by fathers' layoffs, so their adult earnings are also not affected. However, girls' adult earnings are also not affected given the significant negative impacts on their education and occupations. For girls with manual

[2]Notice that the corresponding estimate for girls is significant under Logistics specification while it is not under OLS specification. Thus, we should be cautious when interpreting the significant effect of mothers' layoffs on girls' occupational outcome. Details are shown in Table 2.

occupations, even though they suffer losses in education, they earn more in gardening income relative to boys with similar family background.

We apply both a placebo test and instrumental variable (IV) approach to guarantee our results' robustness. In the placebo test, we randomly assign the treatment group and construct placebo treatment status for the same sample of individuals as that in our main analysis. Following Xiao et al. (2017), after 500 times bootstraps, we show that our baseline regression results lie outside the range of those in our placebo tests and the corresponding p-values are all zero. In the IV approach, we exploit the percentage reduction in numbers of workers in SOE and collective enterprises at the individual's corresponding province when he/she suffered the father's/mother's layoff occurred. Based upon this proxy, we calculate the quasi-exposure and interact it with the gender dummy. The results from 2SLS estimations show the robustness of our conclusions.

This paper contributes to the studies on the long-term impact of laid-off parents in the following two folds. In the first place, we emphasize the existence of gender difference in the intergenerational effects. Oreopoulos et al. (2008) and Hilger (2016) show a significant negative effect of laid-off fathers on children's adult earnings in Canada and the US, while Bratberg et al. (2008), Hilger (2016) and Fradkin et al. (2019) document that such effect does not exist in Norway or Belgium. None of them suggest heterogeneous intergenerational effects across gender. In terms of effects on school performance (Rege et al., 2011), education investment (Pan and Ost, 2014) , and career choices (Huttunen and Riukula, 2019), the current literature also does not suggest a significant difference between boys and girls. In the contrary, we find that only girls suffer lower education levels from laid-off fathers and hence higher probabilities of having manual occupations. Moreover, the significant gender difference in negative effects of mothers' layoffs on children's education is persistent in their occupations, which is also absent in the previous studies.

In the second place, this paper complements the evidence of the intergenerational effects of laid-off parents on children in developing countries. The existing conclusions are based on studies in western developed countries, such as Canada (Oreopoulos et al., 2008), Finland (Huttunen and Riukula, 2019), Norway (Bratberg et al., 2008), the US (Hilger, 2016), and Belgium (Fradkin et al., 2019), while the evidence in developing countries is still limited. China, the largest developing country, has been experiencing urban labor market reform since the middle of 1980s, and massive workers suffered involuntary job loss from SOEs since 1990s. Scholars have discussed how such a reform affects workers of that generation or the second generation's short run outcomes (Liu and Zhao, 2014; Liu and Hannum, 2017; Kong et al., 2019). However, it is still unknown how this reform affects the successive generation in the long run.[3] In nowadays, most of children who experienced the father's and/or mother's layoff from SOEs had been over 18-year-old, providing an opportunity for us to investigate their performances. To our best knowledge, this is the first paper examining the intergenerational effects of laid-off parents on children in developing countries.

This paper also relates to studies that discuss the gender difference in effects of family back-

[3] Although Liu and Zhao (2014) show the short-term effect on children's health, the discussions on the long-term outcomes of these children are missing. Tian et al. (2022) show the long term effect on laid-off workers, but the intergenerational effects are not discussed.

ground and/or childhood environment on child development and hence adult outcomes (Chetty et al., 2016; Brenøe and Lundberg, 2018; Figlio et al., 2019). These papers conclude that boys benefit (suffer) more from an advantageous (disadvantageous) family than do girls in terms of cognitive and behavioral outcomes. In contrast, we investigate whether gender gaps also exist in intergenerational effects when a family's socio-economic background suffers a negative shock, i.e., layoff. We show that, boys do not outperform girls in terms of adult earnings, though they received more family support than girls. Thus, the education investment on children based on gender is inefficient.

The rest of the paper is organized as follows. Section 2 summarizes the background of SOE retrenchment in China. Section 3 describes the dataset, measures of key variables, and empirical strategy that we apply. Section 4 demonstrates the main results of our analysis as well as tests for robustness. Section 6 finally concludes. Detailed variable definitions are shown in Appendix A.

2 Background of SOE retrenchment in China

Before the end of 1992, China's reform was labeled as "reform without losers", during which the position of workers in SOEs and collectively owned firms was protected (Lau et al., 2000; Naughton, 2006, p.90). The severe labor redundancy problem made SOEs unprofitable and were draining local government budget (Dong and Putterman, 2003; Liu and Zhao, 2014). In 1992, the "iron bowl", providing lifetime job security and generous non-wage welfare benefits, was criticized in the official press (Berkowitz et al., 2017).

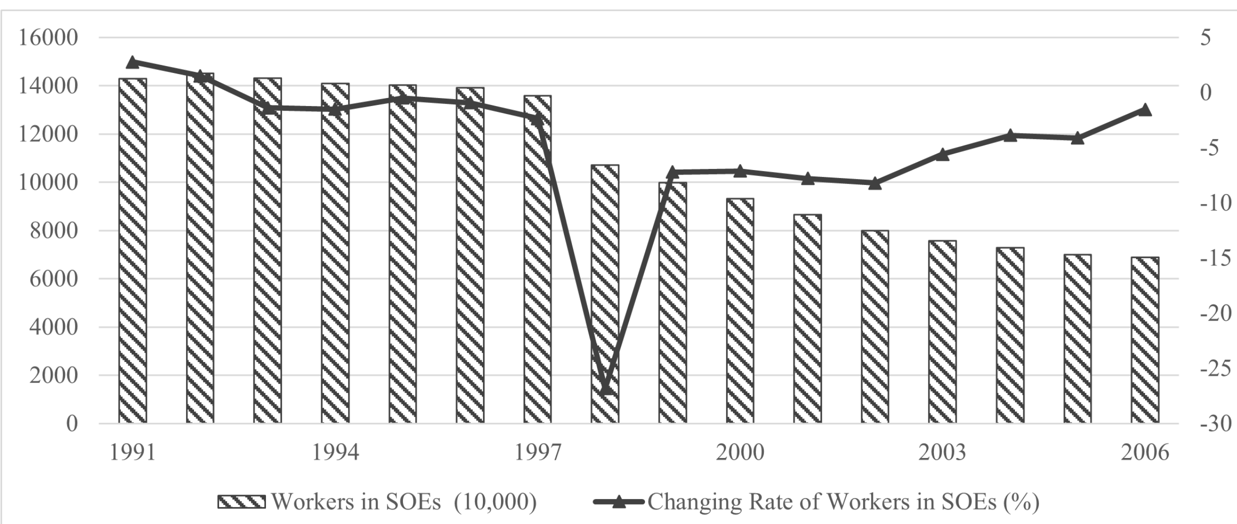

Figure 1: Workers in SOEs from CSMAR.

To reverse the loss, SOE retrenchment gradually began, following Deng Xiaoping's "south tour" and the 14th National Congress of the Communist Party in 1992.[4] This retrenchment was labeled

[4]This congress convened and endorsed a "socialist market economy", making clear that markets must

as "reform with losers" (Naughton, 2006, p.91). In this phase, millions of employees involuntarily lost their jobs from SOEs, collective enterprises, and public service units. Layoffs exceeded 50 million employees between 1993 and 2004 (Dong and Xu, 2008). We show a similar trend in Figure 1 by using the data from the China Stock Market & Accounting Research (CSMAR). In Figure 1, the number of SOEs workers began to shrink since 1993, and the most massive layoffs occurred in 1998. The growth rate of SOE's workers remains negative between 1999 and 2006.

Being laid-off from such an "iron bowl" job would lead to significant negative shock on family income and economic status. Giles et al. (2006) demonstrates that "nearly two-thirds of job separation was involuntary during the retrenchment period, and of those who left jobs voluntarily, 62.3% found new jobs within a year, while the re-employment rate was only about 30% for those losing their jobs because of restructuring or other involuntary reasons. Tian et al. (2022) find that workers displaced during the SOE reform suffered substantial and long-lasting earnings losses, because they were more likely to work in low-skilled occupations, in the private sector, less likely to receive bonuses, tended to receive smaller bonuses, and were more likely to have temporary jobs.

3 Data and empirical strategy

3.1 Regression sample

We exploit nine waves of data from CHNS in 1991–2015. This longitudinal survey is an international collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health (former National Institute of Nutrition and Food Safety) at the Chinese Center for Disease Control and Prevention.

CHNS covers 15 out of 31 provinces in China, which includes coastal, middle, northeastern, and western provinces.[5] It took place over a 7-day period using a multistage, random cluster process to draw a sample in municipal cities. Currently, there are about 7,200 households with over 30,000 individuals in multiple urban and rural areas, which vary widely across geography, economic development, public resources, and health indicators. It has collected ten waves data in 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, 2015. This is the only available longitudinal survey that covers both the entire period of SOE retrenchment starting from 1990s and its post era. Also, it covered those provinces that were affected hugely during the SOE retrenchment period.

Our sample consists of individuals in CHNS in 2006–2015 who satisfy the following characteristics: the individual lived in urban area, was born after 1973, below 18-year-old over the period 1991–2004, and above 16-year-old, which is the lowest legal working age in China, over the period

extend to all main sectors of the economy. Detailed information could be found in the following link: http://www.chinatoday.com/org/cpc/cpc_14th_congress_standing_polibureau.htm.

[5] CHNS was designed to examine the effects of the health, nutrition, and family planning policies and programs implemented by national and local governments and to see how the social and economic transformation of Chinese society is affecting the health and nutritional status of its population. The impact on nutrition and health behaviors and outcomes is gauged by changes in community organizations and programs as well as by changes in sets of household and individual economic, demographic, and social factors. Detailed community data were collected in surveys of food markets, health facilities, family planning officials, and other social services and community leaders.

2006–2015.

3.2 Measures of adult outcomes

In the main analysis, we investigate children's education and labor market outcomes.

Education outcomes could be treated as the measure of human capital accumulation. Higher education level is positively associated with higher cognitive skill (Cunha et al., 2006, chapter 12; Cunha and Heckman, 2007). On the one hand, a child with a higher cognitive skill is more likely to achieve a higher education level (Cunha and Heckman, 2008). On the other hand, education in the school could also improve a child's cognitive skill (Todd and Wolpin, 2003; Carlsson et al., 2015). The following three variables are considered separately: *education years*, *high school diploma*, and *college degree*. *Education years* are calculated as the logarithm of an individual's education years. *High school diploma* is a dummy variable. It is equal to 1 if an individual has a high school, technical, or vocational degree, and it is 0 otherwise. *College degree* is also a dummy variable, which is 1 if an individual holds a college or university degree or above and is 0 otherwise.

As labor market outcomes, we include occupational outcomes and adult earnings. As occupational outcomes, following Acemoglu and Autor (2011) and Cortes et al. (2017), we consider the "cognitive" versus "manual", in which the distinction is based on the extent of mental versus physical activity. Thus, we construct a dummy variable *Manual*, which indicates whether an individual's occupation belongs to manual ones. The default type of occupations is then cognitive ones, in which a certain level of education, such as college degree, is necessary.

As adult earnings, we consider both the individual's *wage* and *annual income*. *Wage* is individual's salary from his/her job while *annual income* is an individual's total yearly net income. Both of them are inflated to year 2015 and the logarithms are taken.

3.3 Control variables

To control potential omitted variable bias, we consider several levels of control variables over the period 2006–2015. All detailed variable definitions are shown in Table A1 in Appendix.

Individual level. To exclude the effect of individual characteristics on the labor market performances, following Carneiro et al. (2021), we control an individual's birth year fixed effect, *age*, *marital status*. In addition, we also control individual's urban household registration, *urban*.[6]

Family level. Since family characteristics are correlated to intergenerational human capital transmission, we control a set of variables measured at the family level. To control the characteristics of parents, following Coelli (2011), we control father's/mother's average income during the layoff period 1991–2004, whether the father/mother has a highschool diploma when during the layoff period, and *high school rate*, measuring the proportion of family members with at least a

[6] *Urban* indicates whether an individual has an urban household registration, which is considered as an important determinant of labor market outcomes in China. See Wang and Zuo (1999), Liu (2005), and Pi and Zhang (2016).

high school diploma.[7] Also, we control other family characteristics, which include: whether the father or mother was the household head; *home scale*, measuring the number of family members; *flat*, indicating whether the family owns flats/houses or not; *vehicle*, indicating whether the family owns a vehicle; and *transfers*, measuring the amount of money received from parents in a year.[8]

Community level. We include the *urbanicity scale*, which is constructed by using CHNS and is a multicomponent scale measuring urban features at the community level (Jones-Smith and Popkin, 2010).

Provincial level. We include *provincial dummies* to control the province-fixed effect. Other characteristics at regional level also play a role in the analysis (Oreopoulos et al., 2008; Coelli, 2011; Huttunen and Riukula, 2019). To exclude the effect of economic growth and labor market tightness, we control the *number of enterprises above designated size*, *number of private firms*, *number of self-employed business*, *unemployment rates*, and *GDPs*. To control the impact of University Enrollment Expansion starting from the late 1990s, both the *number of college students* and the *number of high school students* at the provincial level are included. At last, since China's accession to the World Trade Organization (WTO) has a positive effect on China's economy, we control the *provincial level of foreign direct investment (FDI)*, and *provincial consumption level.* All of these variables are all measured at the provincial level over waves from 2006 to 2015, and are collected from the National Bureau of Statistics of China.

Moreover, we also control the wave-fixed effect by including the wave dummies to exclude the impact of policies and macroeconomic environment at the national level.

3.4 Empirical Strategy

In our sample, we identify a laid-off parent(s) over the period 1991–2004 by the following criteria: the parent(s), who worked in public institutions, SOEs, or collective enterprises in the previous wave, reported job transitions from full to part-time or from working to unemployed in the current wave.[9] An individual is not included in our treatment group if his/her parents did not work in public institutions, SOEs, or collective enterprises but still experienced changes of employment status between two consecutive waves. The change of employment status due to retirement is also excluded. As Giles et al. (2006) and Tian et al. (2022) mentioned before, being laid-off from an job in SOEs or collective enterprises would lead to significant negative shock on family income and economic status, the laid-off worker cannot found a job which is stable and has good welfare as before. Such a definition is also applied in Liu and Zhao (2014) and Tian et al. (2022). Also, notice that the survey took place in every 3 or 4 years, it is very unlikely for a working-age adult with working experience to be still unemployed after suffering lay-off several years ago.

Thus, we say an individual suffered the father's(mother's) layoff in wave k if a laid-off father

[7] Coelli (2011) show that both education and income levels of parents could children's long-term performance through the accumulation of human capital.

[8] Mörk et al. (2020) shows the importance of household economic status and they control household disposable income. According to the availability of CHNS, we control the important properties in a family: vehicles and flats.

[9] CHNS did not distinguish workers in SOEs from those in public institutions in its questionnaires before 2000.

(mother) is identified in wave k, where $k \in \{1993, 1997, 2000, 2004\}$. Accordingly, we introduce a set of dummy variables: $Layoff\_k_i$ equals 1 if the individual i suffered the father's/mother's layoff in wave k, and is 0 otherwise. An individual is in the reference group if his/her parents did not experience such a layoff. We also introduce the duration of exposure to the father's/mother's layoff. It is defined as follows:

$$Exposure_i = \begin{cases} 18 - (k - Birth\_Year_i) + 1 & \text{if } Layoff\_k_i = 1 \text{ and } k - birth\_year_i \leq 18 \\ 0 & \text{if } Layoff\_k_i = 0 \end{cases}. \tag{1}$$

If an individual suffered the father's/mother's layoff, their duration of exposure is equal to 18 minus their age in wave k plus 1; if they did not suffer the father's/mother's layoff in wave k, the duration equals 0. In our sample, individuals who suffered the father's/ mother's layoff are all below 18 years old. Thus, the values of the duration variable are always non-negative. Since some individuals suffered the father's/mother's layoff when they were just 18 years old, the difference between 18 and their age in wave k is 0 for them. To distinguish these observations from those in the reference group, we shift up the values of the duration by 1. The duration of exposure is always zero for those in the reference group.

Noticing the different roles of fathers and mothers in families, we consider the following three scenarios of being exposed to the father's/mother's layoff separately: 1) an individual only has a laid-off father; 2) he/she only has a laid-off mother; 3) he/she has a laid-off father and/or mother. Thus, the aforementioned variables, $Exposure_i$ and $Layoff\_k_i$, would also be calculated according to these three scenarios, respectively. In particular, when considering a laid-off parent(s), if both the individual's father and mother were laid-off, we choose the longer duration of exposure between the one calculated from the laid-off father and that from the laid-off mother.

Since $Exposure_i$ and $Layoff\_k_i$ do not vary across survey waves, a fixed-effected model could not applied. Otherwise, these indicators would be eliminated by the within-group difference. Instead, following Xiao et al. (2017), we construct a quasi-experiment as difference-in-differences (DID) in Pooled OLS estimation.

Equation (2) and (3) show two most comprehensive models of different estimated specifications that we apply in this paper:

$$Y_{i,t} = \tilde{\beta}_0 + \tilde{\beta}_1 Exposure_i + \sum_{k=1993}^{2004} \tilde{\gamma}_k Layoff\_k_i + \tilde{\beta}_3 Female_i + \mathbf{X}_{i,t}\tilde{\boldsymbol{\phi}} + \sum_l \alpha_l Birth\_Year\_l_i + \tilde{\epsilon}_{i,t}, \tag{2}$$

$$\begin{aligned} Y_{i,t} =& \beta_0 + \beta_1 Exposure_i + \beta_2 Exposure_i \times Female_i + \sum_{k=1993}^{2004} \beta_k Layoff\_k_i \times Female_i + \beta_3 Female_i \\ &+ \sum_l \alpha_l Birth\_Year\_l_i \times Female_i + \sum_{k=1993}^{2004} \gamma_k Layoff\_k_i + \mathbf{X}_{i,t}\boldsymbol{\phi} + \sum_l \alpha_l Birth\_Year\_l_i + \epsilon_{i,t}. \end{aligned} \tag{3}$$

$Y_{i,t}$ is individual i's adult outcome in wave $t \in \{2006, 2009, 2011, 2015\}$, including *education years*, *high school diploma*, *college degree*, *manual*, *wage*, and *annual income*, which are defined in Section 3.2. $Exposure_{i,t}$ and $Layoff\_k_i$ are defined as before, which are calculated and discussed accordingly in three different scenarios: laid-off father only, laid-off mother only, and laid-off parent(s). $Female_i$ is the gender dummy indicating whether an individual is female. $Birth\_Year\_l_i$ is individual i's birth-year dummy variable, indicating whether he/she was born in year l. $\mathbf{X}_{i,t}$ is a collection of control variables at individual, family, community, and provincial level. Details of the outcome $Y_{i,t}$ and control variables are discussed in Section 3.2 and 3.3, respectively.

We mainly focus on the coefficient of $Exposure_i$ in Equation (2) and coefficients of $Exposure_i$ and $Exposure_i \times Female_i$ in Equation (3). Since fathers'/mothers' layoffs from SOEs, where jobs were considered as "iron bowl", happened before individuals turned to 18-year-old, observations in our sample are randomly assigned to the treatment or control group. Also, a child's characteristics barely affect a father's decision of quitting from an "iron bowl" job, whose income is the main source of family income. Though $Layoff\_k_i$ helps compare individuals suffering fathers'/mothers' layoffs with those not suffering such layoffs, it could not capture the multi-valued treatment of fathers'/mothers' layoffs across time. Thus, by introducing $Exposure_i$ in Equation (2), $\tilde{\beta}_1$ could evaluate the increment of the intergenerational effect when an individual was exposed to fathers'/mothers' layoffs for a longer period.[10]

Moreover, to capture the gender difference in these intergenerational effects, we interact *Female_i* in Equation (3) with $Exposure_i$, $Layoff\_k_i$, and *Birth_Year_i*. In this model specification, given others constant, β_1 is interpreted as the increment of the effect of fathers'/mothers' layoffs for male children, and $\beta_1 + \beta_2$ is the increment of the effect for female children. Therefore, β_2 measures the gender difference in the increment of the intergenerational effect of fathers'/mothers' layoffs.

In addition, for those individuals who are surveyed in multiple waves of CHNS, standard errors in our empirical results might be under-estimated due to serial correlation. To overcome this concern, we have clustered robust standard errors at the individual level.

3.5 Descriptive statistics

Table A2 displays the summary statistics of individual's adult outcomes in the full sample, boys-only sample, and girls-only sample. It shows the number of observations, sample means, and standard deviations of variables that measure children's adult outcomes over years 2006–2015. A2 also presents the summary statistics of control variables at individual, family, and community and provincial level, respectively.

Table A3 illustrates the average durations of exposure in boys-only, girls-only, and full sample, separately. The durations of exposure with laid-off parent(s), father and mother are also displayed separately.

[10]Specifically, consider two individuals: both of them suffer fathers' layoffs in wave k, and the first individual's age is 12 and the second one is 13-year-old. Thus, given others constant, the effect for the first individual is $\tilde{\beta}_1 \times (18 - 12 + 1) + \tilde{\gamma}_k$ and the effect for the second one is $\tilde{\beta}_1 \times (18 - 13 + 1) + \tilde{\gamma}_k$. By taking the difference of these two levels, $\tilde{\beta}_1$ then measures the increment of the effect.

4 Results

We first examine the effect(s) of the father's and/or mother's layoff on children's education outcomes, and then investigate children's labor market performance, including occupational choices and adult earnings. Tables 1–2 report the main results of our empirical strategy. Each table discusses the impacts of laid-off parent(s), father, and mother, separately. The detailed discussions are presented in the following subsections.

4.1 Children's education outcomes

From Table 1, it is evident that girls suffer significantly more in human capital accumulation compared to boys when being exposed to fathers' layoffs for a longer period. Our suggest that boys' education years are not affected, as well as the probabilities of having a high school diploma and college degree. However, relative to boys, girls' education years are lowered by 3.3%, are 6.6% less likely to have a high school diploma, and are 6.7% less likely to have a college degree.

When being exposed to mothers' layoffs for a longer period, Table 1 also suggests a significant gender difference in children's education outcomes. Our results show that boys have higher education years and a higher probability of having a college degree, while their probabilities of having a high school diploma are not affected. In the contrast, relative to boys, girls suffer lower education years and lower probabilities of having a college degree when suffering mothers' layoffs for a longer period. Moreover, the magnitude of coefficients on the interaction term are larger than those on Exposure_i.

These gender differences could be explained as follows. A girl normally receives less family support than does a boy (García et al., 2018; Kim et al., 2018), such a patriarchy thinking also dominated in the 1990s and 2000s of China. When parent(s) suffered from losing an "iron bowl" job, there is a reduction in economic status and a tightened household budget constraint. Thus, when a family suffered a negative economic/income shock, a girl is more likely to drop out from the school and work to subside the loss of family income. Instead, a boy is less likely to be asked to do so relative to a girl. Therefore, when a family experiences negative shock on economic status, the investment on girls' human capital drops sharply.

The negative effect for girls could also be treated as gender role attitudes. As is argued in Johnston et al. (2014), girls are expected to take less education, especially when mothers are laid-off. Our results show that mothers' layoffs have positive effects on boys' education outcomes. This is because a mother, whose salary is normally not the main source of family income, could spend more time on catering children, such as providing teaching and homework assistance (Rege et al., 2011). However, such a positive effect does not exist for girls. This could still be treated as the consequences of gender-role. This result implies the existence of gender-role attitudes.

Table 1: Education outcomes

	Laid-off parent(s)		Laid-off father		Laid-off mother	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: education years (Ln)						
Exposure	-0.001	0.012*	-0.003	0.009	0.001	0.037**
	(0.005)	(0.007)	(0.006)	(0.006)	(0.008)	(0.018)
Exposure × Female		-0.029***		-0.033***		-0.050**
		(0.010)		(0.013)		(0.020)
Controls	YES	YES	YES	YES	YES	YES
N	1,255	1,255	1,145	1,145	1,088	1,088
Adjusted R-sq	0.516	0.517	0.512	0.510	0.494	0.496
Panel B: high school diploma						
Exposure	-0.010	-0.002	-0.026**	-0.018	0.004	0.026
	(0.009)	(0.012)	(0.013)	(0.016)	(0.013)	(0.037)
Exposure × Female		-0.026		-0.066**		-0.031
		(0.020)		(0.026)		(0.041)
Controls	YES	YES	YES	YES	YES	YES
N	1,259	1,259	1,149	1,149	1,092	1,092
Pseudo R-sq	0.485	0.505	0.499	0.524	0.476	0.502
Panel C: college degree						
Exposure	0.017	0.045**	0.007	0.029	0.026	0.080**
	(0.012)	(0.018)	(0.017)	(0.022)	(0.016)	(0.040)
Exposure × Female		-0.054**		-0.068*		-0.092**
		(0.024)		(0.038)		(0.043)
Controls	YES	YES	YES	YES	YES	YES
N	1,244	1,244	1,134	1,134	1,080	1,080
Pseudo R-sq	0.357	0.389	0.367	0.400	0.357	0.397

Notes: This table reports the intergenerational effect of father's and/or mother's layoff on children's education outcomes, which include logarithm of education years, high school diploma dummy, and college degree dummy. Panel A reports results from OLS regressions. Panel B and C report marginal effects of exposure from Logistics regressions. All regressions include control variables at individual, family, community, and provincial level as well as birth-year fixed effect. Standard errors are clustered at the individual level and shown in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

4.2 Children's occupational outcomes

As a direct outcome of education, we now investigate how the father's and/or mother's layoff affect children's occupational outcomes. In the corresponding regressions, the sample is restricted to those having jobs. We include the results from both Logistics and OLS regressions in Table 2.

Panel A of Table 2 suggests that, when suffering fathers' layoffs for a longer period, girls are 10.2% more likely to have manual occupations relative to cognitive ones, while such a negative effect

Table 2: Children's occupational outcomes

	Laid-off parent(s)		Laid-off father		Laid-off mother	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Manual occupations (Logistics)						
Exposure	0.017	-0.017	0.019	-0.041	0.017	-0.117*
	(0.017)	(0.025)	(0.024)	(0.034)	(0.020)	(0.060)
Exposure × Female		0.048		0.102*		0.136**
		(0.035)		(0.057)		(0.066)
Controls	YES	YES	YES	YES	YES	YES
N	1,020	1,020	931	931	877	877
Adjusted R-sq	0.205	0.236	0.208	0.245	0.199	0.242
Panel B: Manual occupations (OLS)						
Exposure	0.016	-0.020	0.015	-0.048	0.021	-0.060
	(0.018)	(0.031)	(0.024)	(0.036)	(0.023)	(0.040)
Exposure × Female		0.050		0.096**		0.082
		(0.039)		(0.045)		(0.051)
Controls	YES	YES	YES	YES	YES	YES
N	1,020	1,020	931	931	877	877
Adjusted R-sq	0.195	0.204	0.194	0.207	0.180	0.197

Notes: This table reports the intergenerational effects of fathers'/mothers' layoffs on children's occupational outcomes, in which the dependent variable indicates whether an individual has a manual occupation or not. Samples are restricted to those who have jobs. Panel A reports the marginal effects from the Logistics regressions. Panel B reports the results from OLS regressions. All regressions include control variables at individual, family, community, and provincial level as well as birth-year fixed effect. Education variables are not included due to the concern of bad controls. Standard errors are clustered at the individual level and shown in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

is not significant for boys. Such a gender difference in occupation could be explained as follows. Notice that cognitive occupations require high levels of formal education, a college degree may be necessary when applying such occupations. Since girls are less likely to have a college degree relative to boys under mothers' layoffs (Column (6) in Panel C of Table 1), it is very difficulty for girls to find a job requiring high human capital. Thus, they have to comprise to jobs with low barriers to entry, i.e., manual ones. Instead, boys with similar family background do not suffer losses in education investment when they are young (in Table 1). Thus, this gender difference in occupation is a persistent result from the gender difference in education due to fathers' layoffs. Similar results are also obtained in the OLS specification in Panel B of Table Table 2.

When suffering mothers' layoffs for a longer period, Panel A of Table 2 suggests that only girls suffer a higher probability of having manual occupations. But, under OLS specification, Panel B of Table 2 does not suggest significant effects of mothers' layoffs or gender difference. Thus, we need to be cautious when interpreting the significant gender difference due to mothers' layoffs in Panel

A. Though boys education levels increase (Column (6) of Table 1), this advantage does not reduce their probabilities of having manual occupations. This is because, relative to fathers, mothers play a less important role in children's occupations (Huttunen and Riukula, 2019).

4.3 Children's adult earnings

Table 3 demonstrates the impacts of fathers'/mothers' layoffs on children's wages and annual income, which are all measured with the price in 2015. These results suggest neither significant intergenerational effects on children's adult earnings nor the significance gender differences in these effects.

Table 3: Children's adult earnings

	Laid-off parent(s)		Laid-off father		Laid-off mother	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: wages (Ln)						
Exposure	-0.025	-0.013	-0.035	-0.032	-0.024	-0.020
	(0.027)	(0.042)	(0.040)	(0.043)	(0.041)	(0.070)
Exposure × Female		-0.030		-0.011		-0.028
		(0.059)		(0.057)		(0.103)
Controls	YES	YES	YES	YES	YES	YES
N	963	963	884	884	827	827
Adjusted R-sq	0.303	0.313	0.308	0.318	0.282	0.286
Panel B: annual income (Ln)						
Exposure	0.048	0.015	0.037	-0.003	0.072	0.124
	(0.037)	(0.041)	(0.053)	(0.048)	(0.051)	(0.129)
Exposure × Female		0.028		0.080		-0.104
		(0.063)		(0.082)		(0.144)
Controls	YES	YES	YES	YES	YES	YES
N	1,259	1,259	1,149	1,149	1,092	1,092
Adjusted R-sq	0.193	0.199	0.197	0.205	0.169	0.168

Notes: This table reports the intergenerational effects of fathers'/mothers' layoffs on children's adult earnings, including the logarithms of wages and annual income, which are are measured with the price in 2015. Samples are restricted to those who have jobs and who report annual income in Panel A and B, respectively. All regressions include control variables at individual, family, community, and provincial level as well as birth-year fixed effect. Education and occupation variables are not included due to the concern of bad controls. Standard errors are clustered at the individual level and shown in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Consider boys first. The aforementioned insignificant effects from fathers' layoffs for boys could be explained by the insignificant intergenerational effects in boys' education. Also, since the positive effect in boys' education from mothers' layoffs does not reduce their probabilities of having manual occupations, their wages and annual income are also not affected.

It worth noticing that, given the significant negative impacts on girls' education and occupations when being exposed to fathers' layoffs for a longer period, our results in Table 3 do not show a significant drop in girls' wages and income. This result means that, although girls receive less family support in education and hence have higher probabilities of having disadvantage occupations, they do not underperform in adult wages or annual income compared to boys.

In addition, when fathers are laid off, mothers increase their labor supply to compensate for the loss of household income (Blundell et al., 2016; Halla et al., 2020). As a role model, mothers labor market participation would increase daughters' intention to work (Morrill and Morrill, 2013; Bredtmann et al., 2020). Such a link then increases girls' adult earnings for those who experiencing fathers' layoffs.

We then further investigate children's adult earnings for those with manual occupations. Table 4 suggest that, when being exposed to fathers' layoffs for a longer period, girls with manual occupations earns more in non-wage income, which is defined as the difference between the annual income and wages in CHNS. However, boys' adult earnings in such occupations are not affected. Thus, though these girls have disadvantages in education and occupations, they must experience positive effects in work-related traits and hence have higher earnings. In the other words, girls seem to outperform boys in adult earnings given the education outcomes. This observation implicitly suggest an inefficiency in Chinese family investment in children's education based on gender.

The insignificant results from fathers' layoffs in Table 3 are similar with Bratberg et al. (2008), but differ from the significant negative effects in Oreopoulos et al. (2008) and Hilger (2016). In the contrast, these works do not suggest a significant gender differences in children's education outcomes, leading to different interpretations on these insignificant results.

We further categorize the difference between the individual's annual income and wage income. In Panel C of Table 4, we show that the gardening income, including orchard and vegetable gardens, is higher for those women who suffered fathers'/mothers' layoffs and then worked in manual occupations. This result implies that, besides their main jobs, these women are more willing to seek various ways of increasing income by taking extra work, such as gardening. Such a willingness is correlated with their childhood experience in fathers'/mothers' layoffs. Notice that operating orchards and vegetable gardens is one of the ways for laid-off workers to earn an income in China. On the one hand, laid-off workers themselves operate orchards and vegetable gardens by contracting for land and using land in the suburbs and factories. On the other hand, when local governments organize re-employment training for laid-off workers, they also include orchard and vegetable garden management skills as part of the training. Thus, in the presence of the role-model effect, girls are more likely to participate in operating orchards and vegetable gardens. In addition, farmland circulation is allowed since 2008, leaving possibilities for them to operate vegetable and orchard gardens by contracting for suburban land.

Table 4: Children's adult earnings in manual occupations

	Laid-off parent(s)		Laid-off father		Laid-off mother	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: wages in manual occupations (Ln)						
Exposure	-0.009	-0.024	0.010	-0.031	-0.049	-0.089
	(0.032)	(0.050)	(0.056)	(0.048)	(0.045)	(0.096)
Exposure × Female		0.031		-0.036		0.090
		(0.075)		(0.131)		(0.114)
Controls	YES	YES	YES	YES	YES	YES
N	542	542	503	503	470	470
Adjusted R-sq	0.370	0.380	0.363	0.377	0.365	0.375
Panel B: annual income in manual occupations (Ln)						
Exposure	0.061	-0.031	0.151	-0.044	-0.032	-0.109
	(0.057)	(0.054)	(0.116)	(0.052)	(0.054)	(0.103)
Exposure × Female		0.212		0.919***		0.108
		(0.134)		(0.327)		(0.112)
Controls	YES	YES	YES	YES	YES	YES
N	597	597	547	547	518	518
Adjusted R-sq	0.265	0.277	0.281	0.322	0.242	0.243
Panel C: gardening income in manual occupations (Ln)						
Exposure	-0.005*	-0.005	-0.006	-0.010	-0.001	-0.005
	(0.003)	(0.004)	(0.004)	(0.007)	(0.001)	(0.006)
Exposure×Female		-0.000		0.016*		0.004
		(0.007)		(0.008)		(0.007)
Controls	YES	YES	YES	YES	YES	YES
N	597	597	547	547	518	518
Adjusted R-sq	0.040	0.021	0.039	0.074	0.027	-0.006

Notes: This table reports the intergenerational effects of fathers'/mothers' layoffs on children's adult earnings for those with manual occupations, including the logarithms of wages, annual income, and non-wage income, which are are measured with the price in 2015. Samples are restricted to those who have manual occupations and who report annual income in Panel A, B, and C, respectively. Non-wage income is calculated by the difference between annual income and wages. All regressions include control variables at individual, family, community, and provincial level as well as birth-year fixed effect. Education and occupation variables are not included due to the concern of bad controls. Standard errors are clustered at the individual level and shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Notice that there are too few female who suffered mothers' layoffs, have manual occupations and have gardening income in the sample. Thus, the linear regression model could not accurately fit their gardening income, leading to a negative adjusted R-squared value.

5 Robustness

5.1 Placebo test

We conduct a permutation placebo test to guarantee the validity of our empirical strategy. The key identification assumption is the observed decreases in education attainment or occupation choices are much more likely to occur for the children who suffered fathers'/mothers' layoffs, but not for other reasons. The permutation test allows us to test whether our results are statistically significant or just due to random chance.

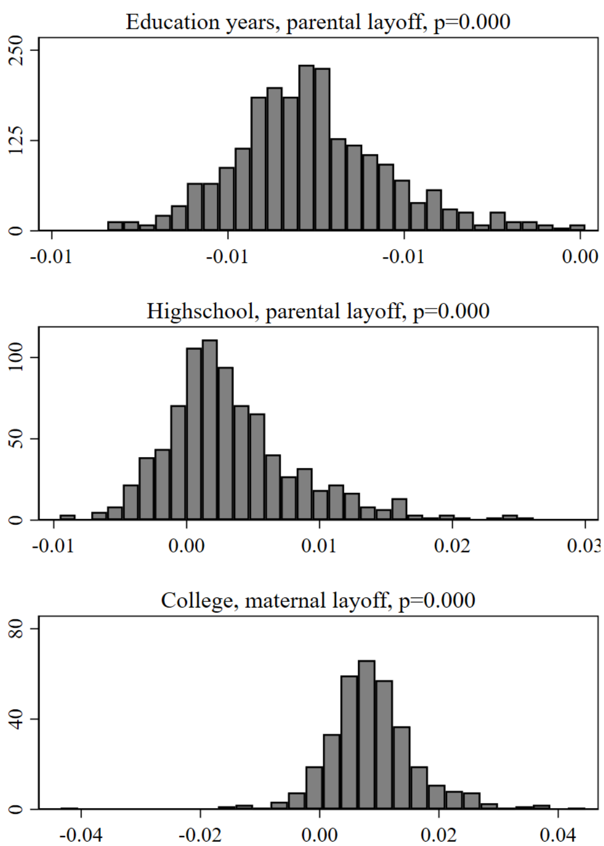

Figure 2: Results of placebo tests for interaction terms in education outcomes

Note: These five figures display the distributions of placebo estimates of $Exposure \times Female$ in education outcomes from 500 bootstraps random assignments, in which results from fathers' and mothers' layoffs are shown separately. The distributions of these estimates are all around zero. The corresponding p-values are also displayed. All y-axises are frequencies and x-axises are coefficient of placebo treatment effects.

We randomly assign the treatment group and construct placebo treatment status for the same sample of individuals as that in our main analysis. Following Xiao et al. (2017), the placebo test is then completed in the following steps: first, we take the absolute value of the coefficients that are derived from the 500 times bootstraps; second, we calculate the frequency that a bootstrap coefficient is greater than or equal to the corresponding coefficient from our main analysis in absolute value; third, the proportion of bootstrap coefficients that are greater than or equal to the corresponding coefficient from our main analysis in absolute value is the p-value of each permutation placebo test. Similar to Xiao et al. (2017), we only conduct placebo tests for those significant results in the main regression.

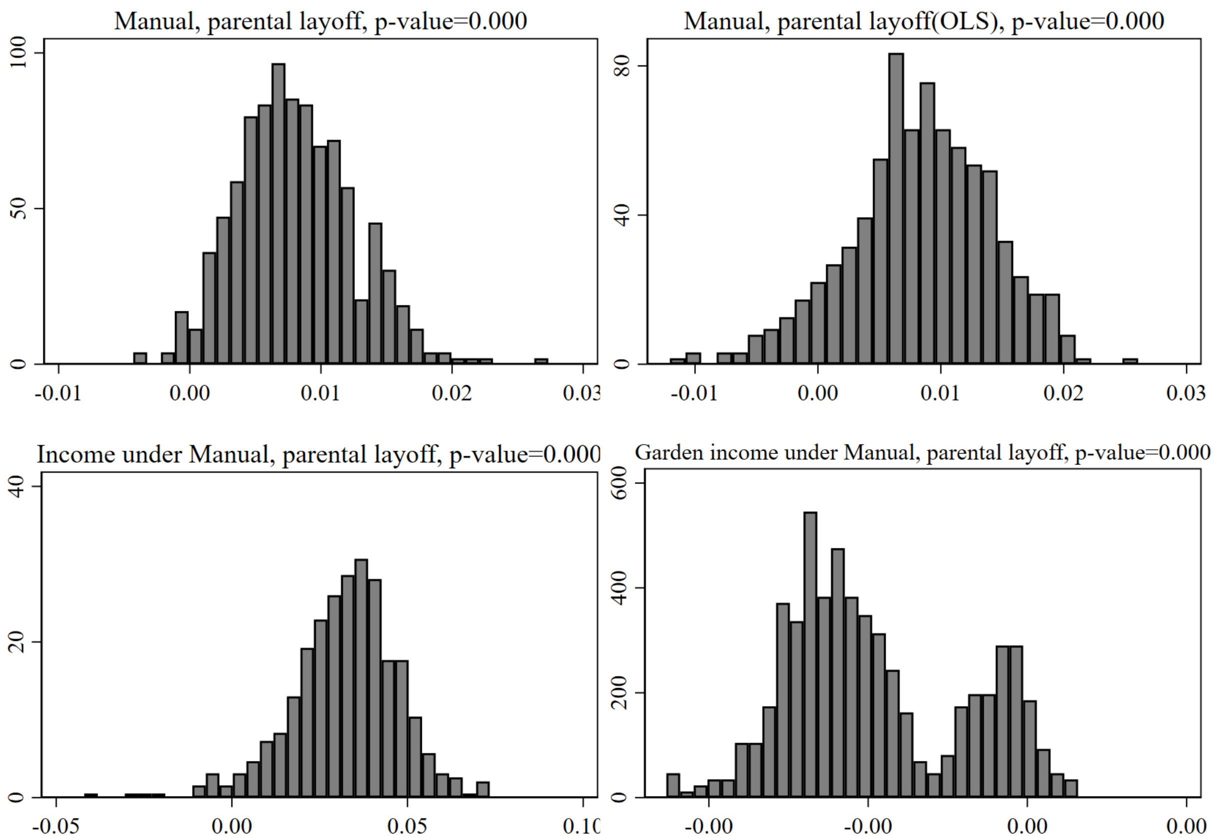

Figure 3: Results of placebo tests for interaction terms in labor market outcomes

Note: These four figures display the distributions of placebo estimates of $Exposure \times Female$ in labor market outcomes from 500 bootstraps random assignments, in which results from fathers' and mothers' layoffs are shown separately. The distributions of these estimates are all centered around zero. The corresponding p-values are also displayed. All y-axises are frequencies and x-axises are coefficient of placebo treatment effects.

5.2 Instrumental variable approach

One potential concern is that the measure applied in the main analysis might suffer random measure errors relative to the true duration of layoff exposure. This is because an individual's actual age of suffering the father's/mother's layoffs could be between two waves. Thus, the actual duration

Table 5: Education outcomes: second stage of 2SLS estimations

	Laid-off parent(s)		Laid-off father		Laid-off mother	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: education years						
Exposure	0.000	0.014**	-0.003	0.010	0.003	0.037**
	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.017)
Exposure×Female		-0.028***		-0.032**		-0.050***
		(0.010)		(0.013)		(0.019)
Controls	YES	YES	YES	YES	YES	YES
N	1,255	1,255	1,145	1,145	1,088	1,088
Adjusted R-sq	0.516	0.517	0.512	0.510	0.493	0.496
K-P stat	759.686	176.258	964.417	245.055	472.765	112.034
Panel B: high school diploma						
Exposure	-0.015	0.002	-0.031**	-0.013	-0.005	0.042
	(0.011)	(0.019)	(0.014)	(0.023)	(0.015)	(0.031)
Exposure×Female		-0.044*		-0.061**		-0.071*
		(0.025)		(0.029)		(0.038)
Controls	YES	YES	YES	YES	YES	YES
N	1,259	1,259	1,149	1,149	1,092	1,092
Adjusted R-sq	0.488	0.490	0.498	0.500	0.479	0.479
K-P stat	758.222	176.066	963.706	245.093	472.595	111.994
Panel C: college degree						
Exposure	0.018	0.049**	0.003	0.029	0.034	0.108**
	(0.016)	(0.019)	(0.018)	(0.021)	(0.024)	(0.054)
Exposure×Female		-0.060*		-0.050		-0.129**
		(0.032)		(0.042)		(0.060)
Controls	YES	YES	YES	YES	YES	YES
N	1,259	1,259	1,149	1,149	1,092	1,092
Adjusted R-sq	0.312	0.318	0.319	0.323	0.308	0.321
K-P stat	758.222	176.066	963.706	245.093	472.595	111.994

Notes: This table reports the second stage results in 2SLS estimations under the IV approach. Dependent variables in Panel A, B, and C are logarithm of education years, high school diploma dummy, and college degree dummy, respectively. All regressions include control variables at individual, family, community, and provincial level as well as birth-year fixed effect. Kleibegen-Paap Wald rk F statistics are also reported for the tests of weak instruments. Standard errors are clustered at the individual level and shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

of experiencing fathers'/mothers' layoffs might be larger than the measure in our main analysis. Such an error is randomly assigned to individuals. Thus, our results might be under-estimated. However, suppose the true estimates are indeed under-estimated, the significant gender differences that we have highlighted in the main analysis would still preserve.

Table 6: Children's occupations and adult earnings: second stage of 2SLS estimations

	Laid-off parent(s)		Laid-off father		Laid-off mother	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: manual occupation						
Exposure	0.017	-0.017	0.020	-0.047	0.015	-0.060
	(0.018)	(0.029)	(0.023)	(0.033)	(0.025)	(0.038)
Exposure×Female		0.048		0.096**		0.082*
		(0.039)		(0.044)		(0.048)
Controls	YES	YES	YES	YES	YES	YES
N	1,020	1,020	931	931	877	877
Adjusted R-sq	0.195	0.204	0.194	0.207	0.180	0.197
K-P stat	523.451	203.513	623.451	96.760	442.400	104.838
Panel B: wages						
Exposure	-0.025	-0.017	-0.034	-0.035	-0.021	-0.020
	(0.027)	(0.047)	(0.041)	(0.048)	(0.039)	(0.066)
Exposure×Female		-0.022		-0.007		-0.028
		(0.060)		(0.057)		(0.095)
Controls	YES	YES	YES	YES	YES	YES
N	963	963	884	884	827	827
Adjusted R-sq	0.303	0.313	0.308	0.318	0.282	0.286
K-P stat	503.131	180.336	758.167	96.617	400.894	95.003
Panel C: annual income						
Exposure	0.059	-0.001	0.052	-0.017	0.077	0.124
	(0.041)	(0.043)	(0.062)	(0.049)	(0.051)	(0.123)
Exposure×Female		0.078		0.140		-0.104
		(0.071)		(0.096)		(0.138)
Controls	YES	YES	YES	YES	YES	YES
N	1,259	1,259	1,149	1,149	1,092	1,092
Adjusted R-sq	0.193	0.199	0.197	0.205	0.169	0.168
K-P stat	758.222	176.066	963.706	245.093	472.595	111.994

Notes: This table reports the second stage results in 2SLS estimations under the IV approach. Dependent variables in Panel A, B, and C are manual occupation dummy, the logarithm of wages and the logarithm of annual income, respectively. All regressions include control variables at individual, family, community, and provincial level as well as birth-year fixed effect. Education and occupation variables are not included due to the concern of bad controls. Kleibegen-Paap Wald rk F statistics are also reported for the tests of weak instruments. Standard errors are clustered at the individual level and shown in parentheses. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

The distributions of placebo estimates of *Exposure×Female* from 500 bootstraps random assignments are displayed in Figures 2 and 3, in which results from fathers' and mothers' layoffs are shown separately. The distributions of these estimates are all around zero. Our baseline regression results clearly lie outside the range of those in our placebo tests and the corresponding p-values are

Table 7: Adult earnings in manual occupations: second stage of 2SLS estimations

	Laid-off parent(s)		Laid-off father		Laid-off mother	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: wages in manual occupations						
Exposure	-0.003	-0.037	0.023	-0.036	-0.046	-0.089
	(0.031)	(0.053)	(0.055)	(0.049)	(0.046)	(0.087)
Exposure×Female		0.071		-0.015		0.090
		(0.077)		(0.127)		(0.102)
Controls	YES	YES	YES	YES	YES	YES
N	543	543	503	503	470	470
Adjusted R-sq	0.370	0.380	0.363	0.377	0.365	0.375
K-P stat	334.879	119.778	263.847	119.976	265.160	62.837
Panel B: annual income in manual occupations						
Exposure	0.098	-0.050	0.220	-0.054	-0.031	-0.109
	(0.067)	(0.058)	(0.134)	(0.054)	(0.056)	(0.094)
Exposure×Female		0.346**		1.246***		0.108
		(0.153)		(0.390)		(0.102)
Controls	YES	YES	YES	YES	YES	YES
N	597	597	547	547	518	518
Adjusted R-sq	0.264	0.276	0.280	0.318	0.242	0.243
K-P stat	316.174	73.919	222.217	76.638	242.906	57.563
Panel C: gardening income in manual occupations						
Exposure	-0.005*	-0.005	-0.006	-0.007	-0.001	-0.005
	(0.003)	(0.003)	(0.004)	(0.005)	(0.001)	(0.006)
Exposure×Female		-0.001		0.012**		0.004
		(0.006)		(0.006)		(0.007)
Controls	YES	YES	YES	YES	YES	YES
N	597	597	547	547	518	518
Adjusted R-sq	0.040	0.021	0.039	0.073	0.027	-0.006
K-P stat	316.174	73.919	222.217	76.638	242.906	57.563

Notes: This table reports the second stage results in 2SLS estimations under the IV approach for those with manual occupations, where dependent variables in Panel A, B, and C are the logarithm of wages, the logarithm of annual income, and gardening income, respectively. All regressions include control variables at individual, family, community, and provincial level as well as birth-year fixed effect. Education and occupation variables are not included due to the concern of bad controls. Kleibegen-Paap Wald rk F statistics are also reported for the tests of weak instruments. Standard errors are clustered at the individual level and shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Notice that there are too few female who suffered mothers' layoffs, have manual occupations and have gardening income in the sample. Thus, the linear regression model could not accurately fit their gardening income, leading to a negative adjusted R-squared value.

all zero. Thus, our empirical strategy is valid.

To further examine this concern, we apply IV approach by exploiting the percentage reduction in numbers of workers in SOE and collective enterprises at the individual's corresponding province when he/she suffered the father's/mother's layoffs occurred, i.e.,$Layoff\_k_i = 1$. Between two consecutive waves in CHNS, we treat the year that has the largest percentage reduction in numbers of workers in SOE and collective enterprises as the proxy of the real year when an individual suffered the father's/mother's layoff. Based upon this proxy, we calculate the other measure of exposure, i.e., *quasi-exposure*, by using function (1). This quasi-exposure is close to the actual duration of experiencing fathers'/mothers' layoffs, which is the IV for *Exposure* in regression (2) and (3). Notice that both "layoff" and Exposure are affected. That is, in regression (3), the interaction of an individual's gender and his/her exposure is also an endogenous variable in our concern. Thus, we also construct the second instrumental variable by interacting an individual's gender and the aforementioned quasi-exposure. We then apply 2SLS estimations to examine all of our baseline regressions.

We reported the corresponding second stage results of 2SLS estimations in Table 5–7. These results confirm that those significance of those coefficients in our baseline regressions still hold. In addition, we report the corresponding Kleibergen-Paap rk Wald F (K-P) statistics to detect potential weak instrument problem. All K-P statistics are way above 16.38, indicating our regressions do not suffer from s weak instrument problem. As a result, our baseline results are robust.

6 Conclusion

This paper provides evidence on the gender difference in intergenerational effects of laid-off parents on children's adult outcomes. We demonstrate that, when experiencing fathers'/mothers' layoffs for a longer period before 18-year-old, girls experience worse education outcomes while such negative effects are not significant for boys with similar family background. This could be interpreted as girls receive less family support in education when families suffer a negative resource shock.

When investigating children's occupational outcomes, our results suggest that girls have a significant higher probability of having manual occupations relative to boys when experiencing fathers'/mothers' layoffs for a longer period. Such a gender difference in occupation from is the persistent result of the gender difference in education from fathers'/mothers' layoffs. We further show that the above mentioned gender differences are not persistent in children's adult earnings. Instead, for girls with manual occupations, fathers' layoffs increases their gardening income. Our results are still robust after applying placebo tests.

This paper could help to better understand the long-term impact of SOE retrenchment starting from 1990s in China. The rises of private enterprises and market economy improve people's average economic status. However, we show that the gender difference in the negative impacts still persist among the second generation of those whose parent(s) suffered involuntary layoffs in the retrenchment. Our results implicitly suggest an inefficiency in Chinese family investment, which was based on gender, in children's education.

Our results provide useful insights into polices for children in disadvantaged families. For instance, the persistent impacts of children's education and occupations from laid-off parents highlight the potential value of compensatory programs targeting basic education. For the disadvantaged youths who have already left the formal schooling system, training programs are a potential solution to the problem of lack of skill.[11]

In addition, the existence of gender difference in the long term effect of laid-off parents provides necessity of implementations of programs that aim to improve women's education and labor market outcomes, such as gender empowerment programs, subsidies aiming at increasing women's school enrolment or completion, and woman-specific vocational training intervention. Moreover, future polices should keep eliminating gender-based employment barriers in the labor market, especially for those that are caused by restricted mobility, culture, and social norms.

References

Acemoglu, D. and D. Autor (2011). "Skills, tasks and technologies: Implications for employment and earnings". *Handbook of Labor Economics 4*, 1043–1171.

Attanasio, O., A. Kugler, and C. Meghir (2011). Subsidizing vocational training for disadvantaged youth in colombia: Evidence from a randomized trial. *American Economic Journal: Applied Economics 3*(3), 188–220.

Berkowitz, D., H. Ma, and S. Nishioka (2017). "Recasting the iron rice bowl: The reform of China's state-owned enterprises". *Review of Economics and Statistics 99*(4), 735–747.

Bhalotra, S. and S. B. Rawlings (2011). Intergenerational persistence in health in developing countries: The penalty of gender inequality? *Journal of Public Economics 95*(3-4), 286–299.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). "Consumption inequality and family labor supply". *American Economic Review 106*(2), 387–435.

Bratberg, E., Ø. A. Nilsen, and K. Vaage (2008). "Job losses and child outcomes". *Labour Economics 15*(4), 591–603.

Bredtmann, J., L. S. Höckel, and S. Otten (2020). "The intergenerational transmission of gender role attitudes: Evidence from immigrant mothers-in-law". *Journal of Economic Behavior & Organization 179*, 101–115.

Brenøe, A. A. and S. Lundberg (2018). "Gender gaps in the effects of childhood family environment: Do they persist into adulthood?". *European Economic Review 109*, 42–62.

[11] Attanasio et al. (2011) and Chakravarty et al. (2019) find these programs improve poverty youths' hard and soft skills, increasing their employment and wages in the long term.

Brown, P. H. and A. Park (2002). Education and poverty in rural china. *Economics of Education Review 21*(6), 523–541.

Carlsson, M., G. B. Dahl, B. Öckert, and D.-O. Rooth (2015). “The effect of schooling on cognitive skills”. *Review of Economics and Statistics 97*(3), 533–547.

Carneiro, P., I. L. García, K. G. Salvanes, and E. Tominey (2021). Intergenerational mobility and the timing of parental income. *Journal of Political Economy 129*(3), 757–788.

Chakravarty, S., M. Lundberg, P. Nikolov, and J. Zenker (2019). Vocational training programs and youth labor market outcomes: Evidence from nepal. *Journal of Development Economics 136*, 71–110.

Chetty, R., N. Hendren, F. Lin, J. Majerovitz, and B. Scuderi (2016). “Childhood environment and gender gaps in adulthood”. *American Economic Review 106*(5), 282–88.

Coelli, M. B. (2011). Parental job loss and the education enrollment of youth. *Labour Economics 18*(1), 25–35.

Cortes, G. M., N. Jaimovich, and H. E. Siu (2017). “Disappearing routine jobs: Who, how, and why?”. *Journal of Monetary Economics 91*, 69–87.

Cunha, F. and J. J. Heckman (2007). “The technology of skill formation”. *American Economic Review 97*(2), 31–47.

Cunha, F. and J. J. Heckman (2008). “Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation”. *Journal of Human Resources 43*(4), 738–782.

Cunha, F., J. J. Heckman, L. Lochner, and D. V. Masterov (2006). “Interpreting the evidence on life cycle skill formation”. *Handbook of the Economics of Education 1*, 697–812.

Dong, X.-Y. and L. Putterman (2003). “Soft budget constraints, social burdens, and labor redundancy in China’s state industry”. *Journal of Comparative Economics 31*(1), 110–133.

Dong, X.-Y. and L. C. Xu (2008). “The impact of China’s millennium labour restructuring program on firm performance and employee earnings”. *Economics of Transition 16*(2), 223–245.

Duflo, E. (2012). Women empowerment and economic development. *Journal of Economic literature 50*(4), 1051–79.

Figlio, D., K. Karbownik, J. Roth, M. Wasserman, et al. (2019). “Family disadvantage and the gender gap in behavioral and educational outcomes”. *American Economic Journal: Applied Economics 11*(3), 338–81.

Fradkin, A., F. Panier, and I. Tojerow (2019). “Blame the parents? how parental unemployment affects labor supply and job quality for young adults”. *Journal of Labor Economics 37*(1), 35–100.

García, J. L., J. J. Heckman, and A. L. Ziff (2018). "Gender differences in the benefits of an influential early childhood program". *European Economic Review 109*, 9–22.

Giles, J., A. Park, and F. Cai (2006). "How has economic restructuring affected china's urban workers?". *The China Quarterly 185*, 61–95.

Halla, M., J. Schmieder, and A. Weber (2020). "Job displacement, family dynamics, and spousal labor supply". *American Economic Journal: Applied Economics 12*(4), 253–87.

Hilger, N. G. (2016). "Parental job loss and children's long-term outcomes: Evidence from 7 million fathers' layoffs". *American Economic Journal: Applied Economics 8*(3), 247–83.

Huttunen, K. and K. Riukula (2019). "Parental job loss and children's careers". No. 12788. *IZA Discussion Papers*.

Johnston, D. W., S. Schurer, and M. A. Shields (2014). "Maternal gender role attitudes, human capital investment, and labour supply of sons and daughters". *Oxford Economic Papers 66*(3), 631–659.

Jones-Smith, J. C. and B. M. Popkin (2010). "Understanding community context and adult health changes in China: Development of an urbanicity scale". *Social Science & Medicine 71*(8), 1436–1446.

Kim, J. H., W. Schulz, T. Zimmermann, and K. Hahlweg (2018). "Parent–child interactions and child outcomes: Evidence from randomized intervention". *Labour Economics 54*, 152–171.

Kong, N., L. Osberg, and W. Zhou (2019). "The shattered "iron rice bowl": Intergenerational effects of chinese state-owned enterprise reform". *Journal of Health Economics 67*, 102220.

Lau, L. J., Y. Qian, and G. Roland (2000). "Reform without losers: An interpretation of China's dual-track approach to transition". *Journal of Political Economy 108*(1), 120–143.

Liu, H. and Z. Zhao (2014). "Parental job loss and children's health: Ten years after the massive layoff of the soes' workers in China". *China Economic Review 31*, 303–319.

Liu, X. and E. Hannum (2017). "Early poverty exposure predicts young adult educational outcomes in China". *China Economic Review 44*, 79–97.

Liu, Z. (2005). "Institution and inequality: the hukou system in China". *Journal of Comparative Economics 33*(1), 133–157.

Mörk, E., A. Sjögren, and H. Svaleryd (2020). "Consequences of parental job loss on the family environment and on human capital formation-evidence from workplace closures". *Labour Economics 67*, 101911.

Morrill, M. S. and T. Morrill (2013). "Intergenerational links in female labor force participation". *Labour Economics 20*, 38–47.

Naughton, B. J. (2006). *"The Chinese Economy: Transitions and Growth"*. MIT press.

Oreopoulos, P., M. Page, and A. H. Stevens (2008). "The intergenerational effects of worker displacement". *Journal of Labor Economics 26*(3), 455–483.

Pan, W. and B. Ost (2014). "The impact of parental layoff on higher education investment". *Economics of Education Review 42*, 53–63.

Pi, J. and P. Zhang (2016). "Hukou system reforms and skilled-unskilled wage inequality in China". *China Economic Review 41*, 90–103.

Pieters, J. and S. Rawlings (2020). "Parental unemployment and child health in china". *Review of Economics of the Household 18*(1), 207–237.

Rege, M., K. Telle, and M. Votruba (2011). "Parental job loss and children's school performance". *The Review of Economic Studies 78*(4), 1462–1489.

Roy, S. (2015). Empowering women? inheritance rights, female education and dowry payments in india. *Journal of Development Economics 114*, 233–251.

Tian, X., J. Gong, and Z. Zhai (2022). "The effect of job displacement on labor market outcomes: Evidence from the chinese state-owned enterprise reform". *China Economic Review*, 101743.

Todd, P. E. and K. I. Wolpin (2003). "On the specification and estimation of the production function for cognitive achievement". *The Economic Journal 113*(485), F3–F33.

Wang, F. and X. Zuo (1999). "Inside China's cities: Institutional barriers and opportunities for urban migrants". *American Economic Review 89*(2), 276–280.

Xiao, Y., L. Li, and L. Zhao (2017). "Education on the cheap: The long-run effects of a free compulsory education reform in rural china". *Journal of Comparative Economics 45*(3), 544–562.

Appendix A

Table A1: Variable definitions

Layoff_k	A dummy variable where $k \in \{1993, 1997, 2000, 2004\}$. It is equals 1 if the individual i suffered the father's/mother's layoff in wave k, and is 0 otherwise. It is calculated in the three scenarios separately: (1) he/she suffers the father's or mother's layoff; (2) he/she suffers the father's layoff; and (3) he/she suffers the mother's layoff.
Exposure	It equals to $1 + k - Birth\_Year_i$ if $Layoff\_k_i = 1$ for individual i, and it is 0 if $layoff\_k_i = 0$. It is calculated in the three scenarios separately: (1) he/she suffers the father's or mother's layoff; (2) he/she suffers the father's layoff; and (3) he/she suffers the mother's layoff.
Female	A dummy variable. It is 1 if an individual is female and is 0 otherwise.
Children's adult outcomes	
Education years (Ln)	Natural logarithm of education years. Pre-primary education years are not counted. We scale up the education years by 1 before the logarithm is taken.
Highschool doploma	A dummy variable. It is equal to 1 if an individual has a high school, technical, or vocational degree, and it is 0 otherwise.
College degree	A dummy variable. It is equal to 1 if an individual has a college or university degree or above, and it is 0 otherwise.
Wages (Ln)	Natural logarithm of an individual's salary (1,000 CNY) from his/her job. It is inflated to year 2015 and is scaled up by 1 before the logarithm is taken.
Income (Ln)	Natural logarithm of an individual's total yearly net income (1,000 CNY). It is inflated to year 2015 and is scaled up by 1 before the logarithm is taken.
Cognitive	A dummy variable. It equals 1 if an individual's primary occupation is senior professional/technical worker, junior professional/technical worker, administrator/executive/manager, athlete, actor, musician, or office staff and it is 0 otherwise.
Manual	A dummy variable. It equals 1 if an individual's primary occupation is service worker, skilled worker, non-skilled worker, or driver, and it is 0 otherwise. Particularly, Cognitive+Manual= 1. In the corresponding regressions, we focus on those who have jobs, and exclude individuals whose occupations are ordinary soldier, army officer, policeman, police officer, farmer, fisherman, and hunter in our sample.
Control variables	
Birth_year_l	A dummy variable. It is i if an individual was born in year l and is 0 otherwise.
Age	An individual's age.
Marital status	A dummy variable. It is 1 if an individual is married or remarried and is 0 otherwise.
Urban	A dummy variable. It is 1 if an individual holds an urban hukou and is 0 otherwise.
Income_father	Natural logarithm of father's average income during the layoff period, which is inflated to year 2015.
Income_mother	Natural logarithm of mother's average income during the layoff period, which is inflated to year 2015.
Education_father	A dummy variable. It is 1 if the father has a highschool diploma and is 0 otherwise.
Education_mother	A dummy variable. It is 1 if the mother has a highschool diploma and is 0 otherwise.

House_head_p	A dummy variable. It is 1 if the father was the household head during the layoff period and is 0 otherwise.
Home scale	Number of family members.
Flat	A dummy variable. It is 1 if the family owns a flat or house and is 0 otherwise.
Vehicle	A dummy variable. It is 1 if the family owns a car and is 0 otherwise.
Highschool_rate	Proportion of family members with at least a high school diploma.
Transfers	Natural logarithm of money received from parents in a surveyed wave over the period 2006–2015, which is inflated to year 2015.
Urbanicity scale	It is constructed by using CHNS and is a multicomponent scale measuring urban features at the community level (Jones-Smith and Popkin, 2010), and is counted in each surveyed wave over the period 2006–2015.
Enterprises	Number of enterprises above designated size in the province where an individual lives, which is counted in each surveyed wave over the period 2006–2015.
Private firms	Number of private firms in the province where an individual lives, which is counted in each surveyed wave over the period 2006–2015.
Self-employment	Number of self-employed business in the province where an individual lives, which is counted in each surveyed wave over the period 2006–2015
Unemployment	unemployment rates in the province where an individual lives, which is counted in each surveyed wave over the period 2006–2015.
GDPs	Real GDPs in the province where an individual lives, which is inflated to year 2015 and is counted in each surveyed wave over the period 2006–2015. The unit is 100,000,000 CNY.
College students	Number of college students in the province where an individual lives, which is counted in each surveyed wave over the period 2006–2015.
Highschool students	Number of high school students in the province where an individual lives, which is counted in each surveyed wave over the period 2006–2015.
FDI	Provincial level of foreign direct investment in a surveyed year, which is inflated to year 2015. The unit is 1,000,000 USD.
Consumption	Provincial consumption level per capita in each surveyed wave over the period 2006–2015,which is inflated to year 2015. The unit is 1 CNY per capita.
Provincial dummies	A set of dummy variables that control the province-fixed effect.

Table A2: Summary statistics

	Full sample			Boys-subsample			Girls-subsample		
Variable	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.
Education years(Ln)	1,346	2.521	0.256	904	2.495	0.268	442	2.575	0.221
Highschool diploma	1,350	0.490	0.500	908	0.439	0.497	442	0.595	0.491
College degree	1,350	0.293	0.455	908	0.250	0.433	442	0.382	0.487
Income (Ln)	1,350	9.512	1.845	908	9.518	2.012	442	9.499	1.443
Wages (Ln)	1,021	7.560	0.879	660	7.637	0.848	361	7.420	0.918
Manual	1,021	0.574	0.495	660	0.633	0.482	361	0.465	0.499
Female	1,350	0.327	0.469	908	0	0	442	1	0
Control variables									
Age	1,350	27.80	5.426	908	28.49	5.382	442	26.39	5.247
Urban	1,350	0.627	0.484	908	0.623	0.485	442	0.633	0.482
Marital status	1,350	0.451	0.498	908	0.541	0.499	442	0.267	0.443
Flat	1,350	0.406	0.491	908	0.416	0.493	442	0.385	0.487
Vehicle	1,350	0.158	0.365	908	0.157	0.364	442	0.158	0.366
Home scale	1,350	4.706	1.607	908	4.753	1.606	442	4.609	1.606
Highschool_rate	1,350	0.458	0.373	908	0.429	0.375	442	0.517	0.362
Transfers (Ln)	1,350	0.112	0.866	908	0.124	0.910	442	0.0871	0.770
Education_father	1,350	0.197	0.398	908	0.204	0.403	442	0.183	0.387
Education_mother	1,350	0.143	0.350	908	0.141	0.348	442	0.147	0.355
Income_father	1,350	7.482	3.394	908	7.500	3.364	442	7.445	3.459
Income_mother	1,350	7.039	3.356	908	6.969	3.376	442	7.184	3.312
House_head_p	1,350	0.926	0.262	908	0.915	0.279	442	0.948	0.222
Urbanicity scale	1,350	77.74	16.68						
Private firms	1,350	35.06	33.90						
Enterprises	1,350	16397	14994						
Unemployment	1,350	3.760	0.623						
Self-employment	1,350	161.4	83.19						
College students	1,350	96.80	45.85						
Highschool students	1,350	112.4	45.37						
FDI	1,350	823,532	882,330						
Consumption	1,350	11,005	4,871						
GDPs	1,350	20,615	14,418						

Notes: This table show the summary statistics of our sample. Summary statistics of control variables at the community and provincial level are reported only in the full sample, which are the same in the boys-only and girls-only subsamples. The consumption level, FDI and GDP are all calculated according to the price of 2015.

Table A3: The average duration of exposure

	Laid-off parent(s)	Laid-off father	Laid-off mother
Boys	5.905	4.286	2.667
	(3.875)	(4.008)	(3.830)
Girls	4.438	2.917	2.083
	(3.476)	(3.494)	(3.524)
Total	5.122	3.556	2.356
	(3.720)	(3.784)	(3.661)

Notes: Standard errors are shown in parentheses.