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THREE ESSAYS IN DEVELOPMENT ECONOMICS

by

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A thesis submitted to the
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Abstract

Investing in human capital is one of the keys to sustainable and equitable development. The road to inclusive growth is paved with tackling inequalities in gender, geography and the rural-urban divide. Human capital investment, particularly through education, is critical to overcoming these challenges. This research highlights the transformative power of human capital investment across multiple realms. Using empirical models of causal analysis, it explores the relationship between education policies and socioeconomic outcomes, examining how education policies affect educational attainment, labor market dynamics, economic development, as well as marriage patterns. By dissecting these relationships, the study aims to show how human capital investment through education promotes sustainable development. Specific chapters examine the impact of educational interventions: Chapter 1 evaluates how increased access to college education influences women's outcomes in marriage, labor market participation, consumption patterns, and their pursuit of secondary education. Chapter 2 estimates the causal effect of a college-educated workforce on local GDP. This chapter analyzes annual GDP levels, sectoral contributions (primary, secondary, and tertiary), and employment within these sectors. Chapter 3 examines the impact on the effects of school mergers and closures on both student enrollment and local employment. In summary, this research aims to contribute to academic knowledge and provide actionable insights for policymakers navigating the complexities of human capital reform for equitable and sustainable development.

Résumé

L'investissement dans le capital humain est l'une des clés du développement durable et équitable. Pour parvenir à une croissance inclusive, il faut s'attaquer aux inégalités liées au sexe, à la géographie et au fossé entre les zones rurales et urbaines. L'investissement dans le capital humain, notamment par le biais de l'éducation, est essentiel pour relever ces défis. Cette recherche met en évidence le pouvoir de transformation de l'investissement dans le capital humain dans de multiples secteurs. En utilisant des modèles empiriques d'analyse causale, elle explore la relation complexe entre les politiques éducatives et les résultats socio-économiques, en examinant comment les politiques éducatives affectent le niveau d'éducation, la dynamique du marché du travail, le développement économique, ainsi que les modèles de mariage. En disséquant ces relations, l'étude vise à montrer comment l'éducation favorise le développement durable. Des chapitres spécifiques examinent l'impact des interventions éducatives telles que la discrimination positive régionale et les programmes d'expansion de l'enseignement supérieur, en soulignant leur rôle dans le progrès sociétal. L'étude souligne également l'importance fondamentale de l'éducation de base et de l'enseignement supérieur, qui jettent les bases du développement futur du capital humain en influençant le marché du travail. Cette analyse complète vise à contribuer à la connaissance académique et à fournir des informations exploitables aux décideurs politiques qui naviguent dans les complexités de la réforme du capital humain en vue d'un développement équitable et durable.

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To my grandma, 由昌香.

Introduction

The first chapter examines the impact of gaining access to college education on women's marriage outcomes, labour market participation, consumption, and higher education attainment. We leverage exogenous variation in college education access created by a regional affirmative action policy implemented in Hubei Province, China between 2009 and 2016. Using data from the 2015 China micro-census and a difference-in-differences approach across regions and cohorts, we find that the exceptionally implemented policy led to a 3.1 percentage point increase in the probability of rural women attending college. It also led to a 3.2 percentage point decrease in the probability of rural women marrying before the age of 26 and a 2.5 percentage point increase in their probability of being employed. Finally, we document increased high school registration among women eligible for the affirmative action policy, which indicates they may respond to improved access to higher education by increasing early investments in human capital.

The second chapter investigates the impact of having a larger skilled labour force on local economic development, including economic growth and structural transformation. I leverage variations in the college-educated population created by a college expansion policy implemented in China starting in 1999. Using prefecture-level data and a two-way fixed effects estimation, I find that the establishment of one university results in a 1.3% increase in the share of the local population with higher education. By using the college numbers as an instrument for the people with higher education, I estimate that a 1% increase in the number of skilled workers leads to a 0.3% increase in GDP. Furthermore, an increase in the population with higher education indicates a decrease in the share of primary and secondary sector GDP, and a rise in the share of tertiary sector, providing evidence that higher education can contribute to structural transformation.

Between 2001 and 2012, approximately 25 percent of secondary schools in China were closed or merged, marking one of the largest school merger programs ever recorded. In the third chapter, I examine the impact of this program on school enrollment by leveraging regional differences in changes in the number of schools that came from the varied responses of local governments to the policy. Through the application of two-way fixed effects and instrumental variable methods, I estimate the effects of school mergers and closures on enrollment and local employment. The estimations reveal a decrease of 5.8 percent in secondary school enrollment due to the school merger and closure program from 2001 to 2012. Additionally, by using the variations in schooling induced by this policy as instrumental variables, I find an estimated elasticity of 0.196 between school enrollment rate and local employment. These findings highlight the impact of school infrastructure on both educational and employment outcomes.

Chapter 1

A Causal Analysis of Human Capital and Gender Role Change

1.1 Introduction

Despite global changes in expectations associated with sex, traditional gender roles are still perpetuated, especially in underdeveloped economies. Deeply rooted patriarchal social norms restrict women's well-being and potential, with rural women experiencing a larger disparity compared to men and their urban counterparts. The transformation of these roles is vital for development, not only in terms of enhancing women's economic empowerment and well-being but also in advancing gender equality and fostering a more inclusive and diverse society. As highlighted by Duflo (2012), women's empowerment and economic development are intricately linked, emphasizing that empowering women directly impacts overall development. The pervasive gender inequality, ingrained in traditional agricultural culture, is illustrated by the high sex ratios prevalent in developing countries, especially rural areas. It can also be seen in the higher early marriage rates for women and the lower labour participation rates.

The age of first marriage for rural women in developing countries, including China, remains persistently low. According to Lu and Wang (2013), the national average age of first marriage in China stood at 24.85 in 2010. Specifically, the average age was 25.86 for males and 23.89 for females. In rural areas, these figures were 24.79 for males and 22.77 for females. The early age of first marriage can pose challenges because women's age at marriage can significantly impact human capital, both for themselves and their offspring. Jensen and Thornton (2003) assert that women who marry at a young age tend to have lower educational attainment and start childbearing earlier. Furthermore, they usually have less decision-making power in their household, and are at a greater risk of experiencing domestic violence. Field and Ambrus (2008) find that delaying marriage by one year correlates with 0.22 additional years of education and a 5.6 percent increase in literacy rates. Additionally, deferring marriage can be associated with higher use of preventive health services. For instance, Chari et al. (2017) establish that putting off marriage leads to notably enhanced health and educational outcomes for children.

There has been a reduction in the disparity between male and female participation rates in the labour force, as evidenced by numerous studies, including extensive research such as Goldin (2014). However, inequalities persist, especially in less developed economies. In 2010, the worldwide female labour force participation rate (percentage of the population aged 15 and above) was 62.1%, compared to males at 75.8% and females at 49%. In low- and middle-income countries, the labour force participation rate is 62.5%, 77.8% for men and 48% for women, respectively.¹ According to the 2010 Census data, the overall labour market participation rate for individuals aged 15 and above in China was 71%, with males having a participation rate of 78.2% and females 63.7%, resulting in a gender gap of 14.5%. Although the gender gap in labour participation in China is lower than the global average, it remains significant.

This paper addresses these challenges by exploiting a unique affirmative action program specific to education, targeting specifically rural singleton² women in Hubei Province, China. The study empirically addresses two interconnected questions: Can education and human capital induce shifts in gender roles? Is affirmative action transformative for women? From 2009 to 2016, more than 100,000 rural women

¹The data are sourced from the International Labour Organization's Labour Force Statistics (LFS) database in ILO-STAT.

²In the context of family structure, a singleton refers to an individual who is the only child in a family, with no siblings.

benefited from this policy, which awarded extra points to individuals applying to Hubei provincial colleges. Our findings indicate that the treated group witnessed a surge in college degree attainment, a postponement of the first marriage, an increase in labour market participation, and a rise in secondary education investment.

The impact of this affirmative action policy is identified in two steps by using 1% of the China National Population Sample Survey in 2015 (2015 Micro Census). First, we estimate the policy's effect on rural women's college education attainment. Second, we use the policy as an instrument for analysing the labour and marriage market outcomes. An individual's exposure to the program is determined by both residence in Hubei and whether she belongs to the eligible birth cohorts that applied for universities during the policy's implementation. This approach enables the causal identification of the impact through the interaction term between two dummy variables: one indicating residence in Hubei and the other signifying whether the person belongs to the cohorts that applied to colleges during the policy timeframe. After verifying the province of residence and birth cohort, the interaction term is considered exogenous, thereby serving as an instrument to analyse outcomes in the labour and marriage markets.

Our findings show that for the eligible cohorts, this affirmative action resulted in a 3.1 percentage point increase in the likelihood of rural women attending college in Hubei. This represents a 21.7% advantage compared to the sample mean. On the marriage market, the policy led to a 3.16 percentage point decrease in the probability of marriage before the age of 26, reflecting a 4.4% reduction compared to the sample mean. On the labour market, there was a 2.52 percentage point increase in the probability of being employed or pursuing further studies, marking a 3.6% rise compared to the sample mean. The policy also contributed to a 4.98 percentage point increase in the high school attainment rate, representing an 11.8% edge scaled by the sample mean.

1.2 Literature Review

College education can be transformative for women's gender roles through various mechanisms. Primarily, it increases human capital on the labour market. Goldin (2006) provides a comprehensive analysis for the transformations that happened in women's employment in the United States, where education is underpinned as a positive labour supply shifter. Goldin, Katz, and Kuziemko (2006) document the narrowing of the gender gap in college degree attainment and its reversal in the United States from the 1950s to the 1990s. They find that the changes in college investments appear to be driven by increases in girls' expected economic returns to college, which in turn arises from improvements in perceived labour market opportunities and an increase in the age of first marriage. Qian (2008) estimates the impact of sex-specific income on the sex-differential survival of children, which is used as a measurement for gender inequality. The study reveals that both sex imbalance and educational attainment respond quickly to changes in sex-specific incomes, indicating that a female wage disadvantage could contribute significantly to the growth of missing women in China. In tea-producing areas, where post-Mao reforms in rural China have influenced sex-specific incomes, the number of missing women is lower compared to other regions. Her finding underscores the importance of economic mechanisms in improving the condition of women and influencing changes in gender roles, even in the presence of strict family planning policies and strong son preferences, especially in rural areas. Field, Pande, et al. (2021) document the prevalence of conservative gender norms around work roles in India, and they find that increasing control over earnings can encourage a woman to work, and thereby influence norms around gender roles.

In addition to the labour market, receiving college education could also have a big impact also on the marriage market. In literature, it is generally stated that women's age of first marriage is positively correlated with education level in several countries such as Pakistan and Nepal. Singh and Samara (1996) state that education and age at first marriage are correlated both at the individual level and at the societal level: a woman with a secondary school degree is less likely to marry during adolescence. Maubrigades (2017) argues that if we see women's age at first marriage as a measure of women's bargaining power over the marrying decision, a college degree can give women an edge over this power as they have more alternatives in order to economically sustain; therefore women's age at first marriage might be significantly postponed. As stated, after receiving higher education, women are more likely to invest their time in their careers in which the expected return is higher. Therefore, the willingness to get married early decreases. Lindsey (2020) analyzes gender issues in education and argues that a girl's education is linked to decreased child death rates, dramatic drops in infant mortality, delayed marriage, and poverty reduction.

When estimating the impact of education on economic outcomes, identification challenges emerge. Many scholars have investigated the causal relationship between education and economic outcomes while addressing the potential ability bias. Card (1999) documents the causal relationship of education on earnings, and he claims that some evidence suggests that marginal returns to schooling for relatively disadvantaged groups with low education outcomes are higher than the average marginal returns to education in the population as a whole. Duflo (2001) uses an Indonesian school construction policy to estimate economic returns to education, with an increase in wages ranging from 6.8 to 10.6 percent. Also, many studies have been conducted to analyze women's growing access to education, especially college education, in the past decades globally. Evidence from the economic literature shows that college education has a definite impact on women's performance in the labour market. For example, Joy (2000) notes that women are shortchanged by the college education they receive; on the other hand, Dougherty (2005) states that investment in women's education is in general more profitable than that in men's.

Although the positive impact of education on human capital is widely acknowledged, individuals' decisions regarding educational investment and labour market participation depend on their expected returns. Jensen (2010) finds that students provided with information about the higher measured returns of education completed more years of secondary school. Jensen (2012) uses an initiative aimed at enhancing the visibility and accessibility of employment opportunities for women and finds that it has led to increased investments in human capital for girls, resulting in delayed marriage and childbirth for women. Furthermore, women express a desire to work more and tend to have fewer offspring during their lifetime by reflecting their growing career aspirations.

Affirmative actions are implemented and studied in response to multi-dimensional inequality in social realms, including the aforementioned gender-based inequality. While it is generally stated that education has a positive causal effect on human capital, educational affirmative actions can impact their beneficiaries in either a positive or negative way. Numerous scholars, including Rothstein and Yoon (2008), have raised the potential mismatch problem associated with affirmative actions. Arcidiacono and Lovenheim (2016)

review the literature on affirmative action, mostly targeting racial minorities in undergraduate education in the United States, addressing the trade-off between institutional quality and the fit between a school and a student. They find evidence suggesting that match effects can dominate quality effects, indicating that affirmative action might be harmful to educational outcomes. On the other hand, studies such as Bagde, Epple, and Taylor (2016) argue that affirmative actions in education based on gender increase the probability of beneficiaries having access to school and do no harm, using an Indian setup.

In addressing a common challenge in the literature of casual impact identification of education on economic outcomes, our paper tackles the potential bias in determining the impact magnitude of women's education due to endogeneity. Education and other outcomes are often influenced by factors such as family and community background variables, which are closely linked to perceptions about gender roles. Educational attainment can be endogenous for labour and marriage market outcomes, creating ability bias. One key contribution of our paper is using an exogenous policy for this identification. Hubei rural singleton women were selected based solely on having a sibling or not, and the policy was announced shortly before implementation, which eliminates reverse causality concerns as rural parents had insufficient time to respond through fertility decisions for having only one girl. The lottery-winning type of affirmative action policy was exclusive to Hubei for a limited period and originated in China's family planning policy, which is deemed exogenous to educational outcomes. This natural experiment can significantly reduce ability bias when estimating the causal effect.

Our paper contributes to the aforementioned bodies of literature on women's choices in the labour market, marriage market, and human capital investment, by providing causal identification through the examination of the exogenous policy shock. It also sheds light on the effectiveness of affirmative action policies addressing gender inequality. On the labour market, the policy shock leads to an increased participation rate, underscoring the transformative impact of education on gender role changes, particularly in work-related roles. Concerning the marriage market, we demonstrate that receiving a college education causally results in a postponed age of first marriage and a reduced fertility rate, with estimations of the magnitude of these impacts. Our paper also complements existing literature on the causal impact of expected returns on human capital investment. We find that with updated beliefs about the future returns of tertiary education and improved labour market outcomes, individuals have more incentives to invest in secondary education. Additionally, our paper extends the discussion on the impact evaluation of affirmative action policy, illustrating that gender-based affirmative action can have a substantial causal impact on educational outcomes, as well as on labour and marriage markets.

An notable ambiguity arises in our discussed mechanisms: the challenge of distinguishing between education and skill when estimating the magnitude of human capital increase, as noted by Hanushek, Schwerdt, et al. (2015). The question remains whether attending college significantly enhances skills or whether the primary advantage lies in credentialism — lying on formal education certifications for labour market acceptance, a common practice in Chinese society. While a substantial increase in human capital is anticipated post-college, the distinction between the transformative impact of the degree itself and enhanced skills remains unclear. In our context, the impact of the affirmative action encompasses both potential causal paths: the influence of formal credentials and skill development.

1.3 Methods

1.3.1 Empirical Background

The initiation of the policy

In March 2009, Hubei Province, China announced an affirmative action in education for rural singleton women, exclusively granting them extra points, in the National College Entrance Examination, i.e. Gaokao (which I will use in the remainder of the paper). The policy was implemented from 2009 to 2016, and aimed to achieve two objectives, as documented by Hubei’s government records: first, as a complementary measure to China’s family planning policy, and second, to promote social progress by addressing the high sex ratio and influencing societal perspectives on marriage and fertility. The initiation of the policy could be viewed as an exogenous decision by the Hubei government. In contrast to provinces with policies benefiting singleton children of both genders or non-educational policies, Hubei’s incentive to introduce this policy was a creative approach to encourage compliance with the one-child policy and push societal progress.

The first motivation behind this educational policy was to complement China’s broad birth quota program, commonly known as the one-child policy (1979-2015). Although named the “one-child policy”, exceptions were introduced in the early 1980s, allowing rural parents in most of China to have a second child if the first-born was a girl due to prevalent son preference in rural areas. Over two decades later, in 2009, the Hubei government reinforced the one-child policy, rewarding those who voluntarily chose to have only one child, despite being permitted to have two. Introducing this policy is expected to motivate people to comply with government policies by increasing their expected returns for compliance in the long term.

The second motivation stemmed from the high sex ratio. In 2015, for children under one year old, the national sex ratio in China was 119 boys for every 100 girls. Hubei’s sex ratio of 128 exceeded the national average of 119, however, it did not rank among the highest. The affirmative action aimed to induce a shift in societal perceptions of gender roles, aligning with the overall policy directive to reduce gender inequality and foster opportunity equity.

To contextualize the significance of the policy, we use the demographic data from the 2010 census to demonstrate the scale of the population in Hubei: the 2010 census for the age group 15-19 enumerated 2,246,474 women (therefore around 449,295 per cohort) and 2,560,263 men in Hubei. Hence, the approximate number of rural women in the 15-19 age group is 1,020,802 (204,160 per cohort). This number is large compared to the number of beneficiaries. The population of rural singleton girls who benefited from the rewarding measures fluctuated between 3,000 to 7,000. This rate reached its peak in 2013 and 2014. In 2009, a total of 233,580 women took the exam in Hubei. Rural women represented around 50% of that figure. The statistics of the 2010 census further indicate that among beneficiaries in 2010, the proportion of benefited singleton rural women compared to the total number of rural women (the smallest identifiable cell in our data) was $4,208 / 204,160 = 2.061\%$. This suggests a severe underestimation of the treatment effect of the measures undertaken, assuming that the spillover effect does not exist.

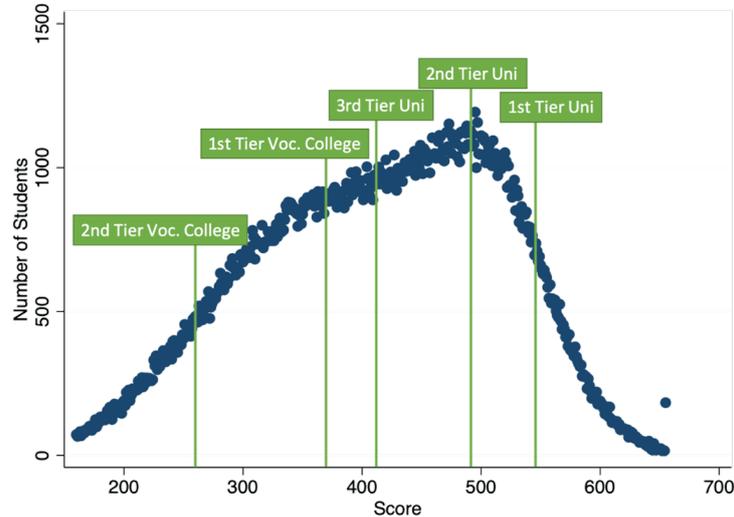
The implementations of the policy

The educational affirmative action was implemented for eight years from 2009 to 2016. From 2009 to 2014, ten extra points were granted to qualified beneficiaries who took Gaokao and applied to universities within Hubei province. From 2015 to 2016, only five extra points were granted. In 2017, the affirmative action was revoked, following China’s transition from the one-child policy to the two-child policy, effective from January 2016. See Table A5 for more details.

The policy had a substantial impact on its beneficiaries by giving additional points in the Gaokao, the nationally mandated college entrance exam in China. Given that this exam is a prerequisite for admission to all higher education institutions across the country, the given extra points significantly increased the likelihood of admission to a university. In China, the ranking based on the Gaokao grade serves as the only criterion for tertiary education admissions. Therefore, the policy played a crucial role in expanding opportunities for rural singleton women pursuing higher education. To contextualize the magnitude of ten extra points in university admission, Figure 1.1 depicts the score distribution of students (represented by dots) in the 2009 Hubei Gaokao. The vertical lines denote admission scores for different tiers of undergraduate institutions³. In the densest segment of the distribution, roughly

³University tiers are based on the admission scores of each institution. The higher the tier, the more prestigious the university is perceived to be.

from 420 to 520 points, there are 1,000 or more students per score point. Since admission depends on a student’s ranking rather than the absolute score, gaining 10 extra points in the 420 to 520 point interval would enable an individual to surpass approximately 10,000 others in the province. The significant upward shift in ranking is a game-changer in terms of the extensive margin, i.e. whether they secure admission to an undergraduate institution.



Notes: Data is from the public record of 2009 Gaokao scores in Hubei

Figure 1.1: Gaokao score distribution and admission thresholds, Hubei 2009, science

On the other hand, by having 10 extra points, the benefit can be in the form of an intensive margin, as the beneficiaries could end up going to a better institution. To illustrate the economic significance of this intensive margin, we conducted a mapping of the 2009 Hubei Gaokao admission scores for 113 high-ranked universities in China. Detailed regression results are available in the appendix, Table A6. Our estimations show that for individuals graduating in 2013, each additional Gaokao point correlated with a noteworthy increase of 41.5 Chinese Yuan in their monthly wage by 2018 (approximately 6.3 USD). Consequently, 10 extra points in the 2009 Hubei Gaokao would correspond to an estimated 63 USD monthly wage increase. These figures underscore the substantial impact that different university tiers, based on Gaokao scores, can have on future income.

In light of this, we argue that the benefits of the policy can be measured by analyzing two parameters: the extensive margin and the intensive margin, thanks to the extra points granted. The beneficiaries not only increased their quantity of college education but also enhanced its quality by allowing them to attend a more prestigious institution.

1.3.2 Data and Outcomes of Interest

The data used in this study is a 10% sample from the 2015 China Micro Census (1% of the entire population). And we keep the sample including cohorts 1984 to 1993 for our reduced form identification.

We identify two sets of outcomes. First, we identify the impact of the affirmative action, the outcome being whether we observe a higher college degree attainment rate in the eligible group in our data; second, we identify whether the eligible group has a significant difference in terms of employment and marriage.

For the first identification, the outcome is whether a person has a college degree. Both vocational and academic colleges are included in the sample, as the policy was eligible for both types. Summary statistics for the relevant variables are shown in Table A1 in the Appendix, including national data for both genders, covering birthing cohorts from 1984 to 1993. Then, we construct the outcomes of employment and marriage. Summary statistics for these outcomes are shown in Table A2 in the Appendix. The “Ever married” dummy highlights people who are ever married by the time they were surveyed, including being married, divorced, or widowed. The dummy of being currently married is also available, along with a fertility rate measurement by the dummy “Ever given birth”. The “being employed” dummy

sets apart the case where people have a job or are on temporary work leave with a job title. There are five other measurements for labour market participation, which are combinations of the employed case above, people who searched for jobs in the past three months, people who can start to work in the next two weeks, and people who are still in school. The last three dummies in the labour market outcome session measure details about the unemployment or employment: whether this person is unemployed due to housekeeping, whether this person is employed in the primary sector, and whether this person is employed in the position of manager or skilled worker.

There are some more consumption outcomes that have been included in our analysis. There are three housing characteristics indicators: house size per household member, car ownership in the household, and flushing toilet establishment in the household. In addition, there is a dummy indicating whether the person has social health insurance. The summary statistics are shown in Table A3 in the Appendix.

For secondary education outcomes, we use high school degree attainment as the main outcome. The summary statistics are in Table A4 in the Appendix. The cohorts that registered in high schools during the policy implementation are different from those in colleges, therefore, a new set of demographic data summary is also provided.

1.3.3 Identification Strategy

To exploit the variation in treatment across Hubei and non-Hubei regions and different cohorts, a regression framework can be used to identify the difference in differences by equation 1.1:

$$Y_{ijk} = \beta_0 + \beta_1 ELG_k + \beta_2 Hubei_j + \beta_3 ELG_k \times Hubei_j + \alpha_j + \gamma_k + \varepsilon_{ijk} \quad (1.1)$$

Y_{ijk} is an outcome of individual i residing in province j and born in year k . $Hubei$ is a dummy that takes value 1 if the person's place of residence is Hubei in 2010. ELG_k is a dummy that takes value 1 if the individual was born in eligible cohorts (1989-1998), meaning that when the policy was effective, their birthing cohorts were qualified for the policy. An alternative explanation to the regression is that a person's birth cohort and the region of birth jointly determine the individual's exposure to the affirmative action policy. This interaction term identifies the causal relationship between college education and socioeconomic status for rural women.

The standard errors are clustered by groups defined by ELG and different provinces. In Figure A9 and Figure A10 in the Appendix, we show that the residuals are heterogeneous across different provinces for the college degree attainment dummy. Figure A11 and Figure A12 in the Appendix show the residuals that are more homogeneous across different birth cohorts for college degree attainment, and we group the birth cohorts into two groups for precision, i.e. $ELG = 1$ and $ELG = 0$. In our sample, we have 31 provinces and 2 groups defined by birth cohorts, so we have 62 clusters for the standard errors in the estimations using Equation 1.1.

The following subsections discuss the construction of the dummy independent variables in detail, meanwhile, some challenges in the empirical study are addressed.

The dummy Hubei

One can ask, as people can move across different provinces, the domestic migration coming in and out of Hubei can lead to bias in our treatment effects. In our setting, it should not be a major concern due to the following reasons: first, the policy was implemented to benefit young women who applied for a university within Hubei province, i.e. they did not benefit from the policy if they wanted to apply for a university outside of Hubei. This already eliminates the case where many people move to the city where their universities are. Second, in the intercensus dataset, we can identify an individual's resident place in 2010. For people who benefited from the policy, their places of residence would not have been outside of Hubei. We, therefore, restrict the identified Hubei rural female group by excluding people who were not residing in Hubei in 2010. This can also eliminate people who came to Hubei for their university from another province. For people who might have moved out of Hubei after they attained a degree in Hubei, they must have been in Hubei in 2010, as they were either in a high school in Hubei, or they were in a Hubei college, as the policy started in 2009. Therefore, for people who were not in Hubei in 2015, if they were residing in Hubei in 2010, they are included in the treated sample.

One can also be concerned by parents' migration to rural Hubei so their daughters can benefit from the policy. This question is not concerning due to the system of household registration in China, i.e. Hukou. The policy rules specify that only those girls who were born in rural Hubei and whose parents are both residents of rural Hubei can benefit. Certificates of Hukou records from local governments had

to be provided for validation of their qualifications. Therefore, it is virtually infeasible to benefit from the policy of domestic migrations.

Another factor that can cause bias, and potential underestimation of the treatment effect is migration across provinces. The beneficiaries were studying in high school in Hubei during the implementation of the policy. As the policy only benefited rural women who applied to colleges within Hubei Province, there is a group of rural women that ended up going to colleges outside of Hubei, on whom the policy impact cannot be identified. From 2011, Hubei started to allow students to apply to multiple institutions, and some women who were qualified for the policy applied to institutions both in Hubei and outside of Hubei. These women might have ended up enrolling in a better institution outside Hubei. Furthermore, if the effect happened under a mechanism, that is when qualified rural women invested more effort in studying because of their granted advantage at the exam, then this hypothesis cannot be estimated by our identification and can therefore also cause an underestimation of the policy.

The dummy ELG

The birth cohorts influenced by the policy are mostly from 1990 to 1998. In China, people take the college entrance exam and go to undergraduate institutions at the age of 18 on average, in accordance with the compulsory education law that children are expected to register in primary school at the age of 6 (and it generally takes 12 years to finish primary school, junior high school, and senior high school). However, in rural areas, children typically start primary school at the age of 7 due to the relatively limited education resources, which results in the age of attending university being 19. On top of that, there is a significant number of people who retake the college entrance exam, therefore, the age of attending university could be postponed to the age of 20. Figure A13 in the Appendix shows that in our 2015 data, the birth cohort 1991 has the highest rate of earning a college degree. Due to the college degree attainment increase trend in China, we expect to observe an upward-sloping line, yet it starts to decline after cohort 1991. This means that most of the cohort 1991 finished university by the age of 24 in 2015, while a large part of cohort 1992 has not finished university by the age of 23. As university education in China typically takes four years, we can also infer that a lot of people start university at the age of 20 so they finish at the age of 24. The policy started to be implemented in the year 2009 in rural Hubei, therefore, the earliest treated cohort is individuals born in 1989 who were 20 years old when the policy was implemented in rural Hubei. And the youngest cohort that was influenced by the policy should be 1998, as they were 18 years old in 2016 which was the last year of the implementation of the policy.

We adjust the birthing cohort by academic years. According to the education rules, students' ages are taken on September 1st, when the school year typically starts in China. For example, if a student was born in September 1992, on 1st September 1998, their age will be 5 years and therefore they are not qualified to register in primary school. Therefore, this student would attend school in 1999 at the age of 6, or in 2000 at the age of 7. Therefore, when this person's month of birth is from September to December, their birthing cohort is defined to be the same as people who were born from January to August in the following year.

The 2015 intercensus data that we are using were collected in November 2015. This indicates that the cohorts impacted in our dataset are from 1990 to 1997. Therefore, when we do the first-stage policy impact analysis, i.e. whether we observe a significantly higher rate of attending college in our treated group, the dummy ELG_k should take the value 1 if the person's birthing cohort is from 1990 to 1997, and the comparison group includes the symmetrical cohorts before, i.e. from 1982 to 1989. However, as our main interest is to see the outcome on the marriage and labour markets, we cannot use the cohorts from 1990 to 1997. The reasoning is that by the time the data was collected in 2015, people born from 1994 to 1997 are still in university, as it typically takes 3 to 4 years to finish university studies. So we shall define the ELG_k dummy to take value 1 if a person's birthing cohort is from 1989 to 1993, in order to perform our second-stage outcome analysis. And the corresponding symmetrical comparison group includes the cohorts from 1984 to 1988. This ELG_k dummy is of our main interest.

Other identification issues

One problem for identification is that it is not yet possible to identify whether an individual is a singleton in our dataset. There is no direct measurement for the number of singleton people in the census data. Based on the observation that over 99% of women in China give birth before the age of 40, r. Huang (2009) uses the number of women from 40 to 50 years old in the 2000 China Census data and gives an estimation of 25.3% as the national mean for the percentage of singleton children of age 25 and below. For Hubei, 23.1% is the estimated rate of singleton children, which is close to the national average. For the rural

female population in China, the singleton rate is expected to be lower. This leads to an underestimation of the treatment effect as we take the Hubei rural women in the eligible cohorts (both singleton and non-singleton) as our treated group. As the policy takes effects on singleton girls only, the treatment effect is potentially diluted by women who are not singleton. On top of the effect diluted by non-treated samples, as the non-singleton rural women were also “competitors” while applying for universities and on the labour market, the reverse effect on the non-singleton girls can further cause the underestimation of the effect of the policy. As our difference in differences identification uses non-Hubei and symmetrical earlier cohorts as the control group, this does not create major concerns for our estimation of treatment effects. This is because in both Hubei and non-Hubei regions, during the late 80s and early 90s, we generally don’t observe a change in the family-planning policy in the majority part of China. For the very few regions that changed, controls are added.

In reality, a spillover effect could also exist for groups outside of the treated group. For example, as rural singleton women are given extra points in Gaokao, non-singleton rural women who were not benefited might either react to the policy by working harder to be more competitive or alternatively they might have lost motivation because of the lack of this advantage. Whichever the case, our treated group in the identification includes both singleton and non-singleton women and therefore incorporates the spillover effect. However, this effect cannot be identified due to missing singleton measurements.

One might also wonder whether there are similar policies that can potentially bias our estimation. The policy was uniquely implemented by Hubei Province for singleton women. Although there were some other provinces implementing policies targeting rural singleton individuals (both men and women), these policies started to be implemented before 2009 and ended in or after 2016. Therefore, these policies would not affect our analysis.

1.4 Results

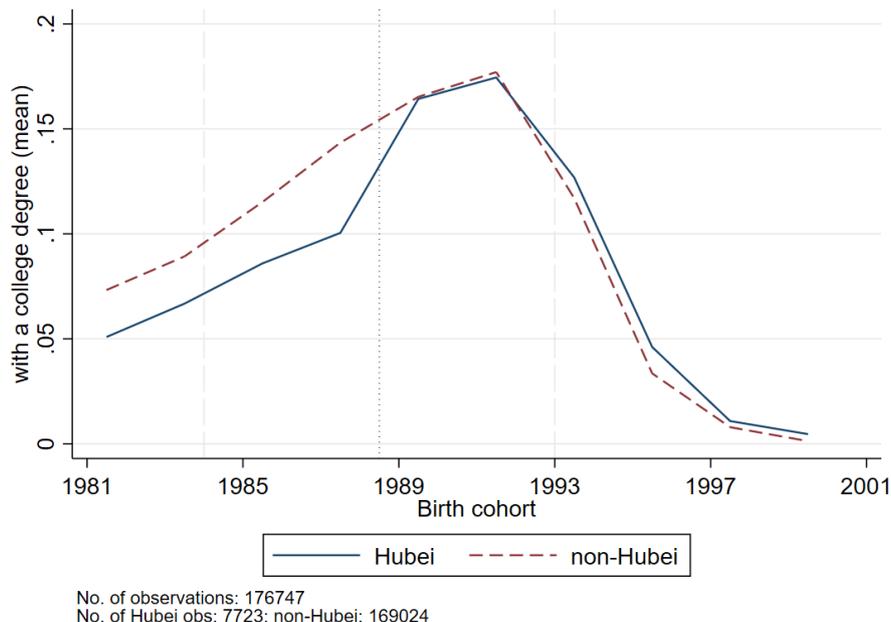
1.4.1 Policy Effect on College Education

We first identify the magnitude of the policy effect on college education in our data. Figure 1.2 shows the rate of college degree attainment by birth cohorts in 2015 for the rural female sample. The dashed line denotes means collapsed by cohorts in non-Hubei regions, while the other line shows means for Hubei. The first benefited birth cohorts are 1989-1990. It shows that the first treated cohort has a significant college degree attainment rate after common trends.

Figure 1.3 rechecks the parallel assumption by estimating the equation 1.2, under an event study framework:

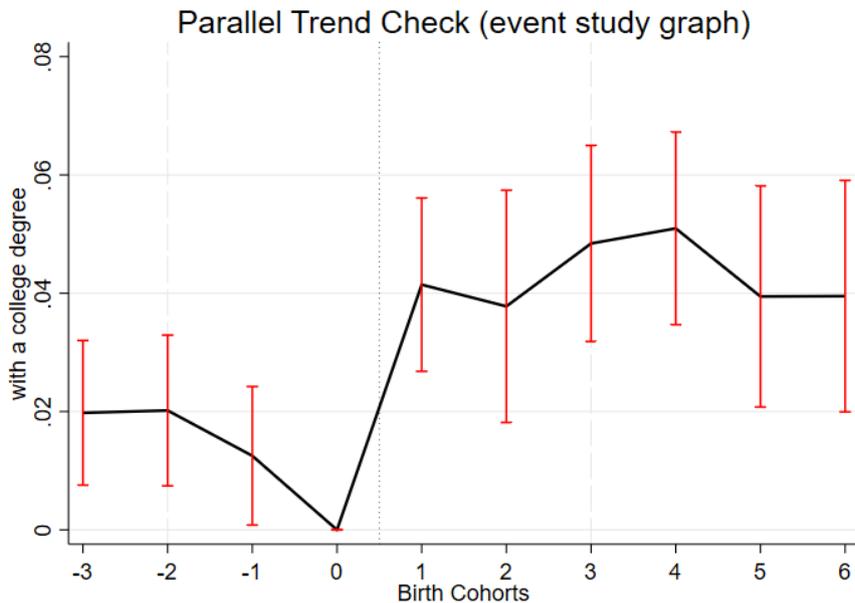
$$Y_{ijk} = \beta + \sum_{k \neq 0} \beta_k \times cohort_k \times Hubei_j + \alpha_j + \gamma_k + \varepsilon_{ijk} \quad (1.2)$$

The event study graph shows that there is an increase for the treated cohorts. Ideally, we would like to see the coefficients of cohorts -3, -2, and -1 to be zero. Estimated by our data, they are not. However, the impact of the policy is still significantly positive, and there was no upward-sloping trend before the treatment.



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. For example, cohort 1989.5 in the graph includes birth cohorts 1989 and 1990. First treated cohort: 1989-1990.

Figure 1.2: Parallel trend check of college degree attainment: means by birth cohorts



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on the 0.01 level.

Figure 1.3: Event study of college degree attainment: by birth cohorts

As stated in the previous section, we identify the difference in differences of education, i.e. the first stage policy impact, by the following reduced form equation 1.1.

For our first reduced form identification, Y_{ijk} is the education outcome of individual i residing in province j and born in year k . In this estimation, it is a dummy denoting whether this person has a college degree. Using the rural female sample in our data, the results are shown in Table 1.1. The coefficient of the interaction term shows that for the eligible cohorts, this affirmative action increased

the possibility of rural women going to college in Hubei by 3.14 percentage points, which is a 21.7% edge compared to the sample mean.

Table 1.1: Dependent variable: whether has college degree dummy

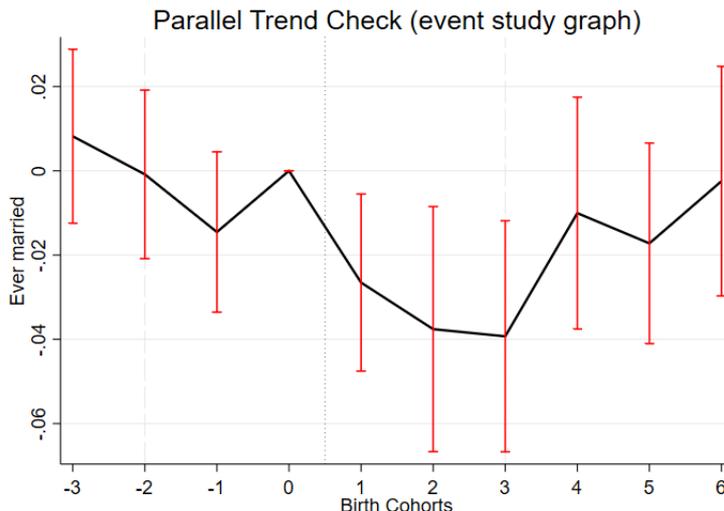
	with a college degree
Hubei=1	-0.307*** (0.00254)
Born in 1989-93=1	0.0561*** (0.00717)
Hubei=1 \times Born in 1989-93=1	0.0314*** (0.00327)
Constant	0.362*** (0.00471)
Observations	102803
Adjusted R squared	0.0305
Mean of Dep. Variable	0.145
Standard errors in parentheses	
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$	

In reality, the magnitude and statistical significance of the difference in differences coefficient is larger. This is because the policy not only gave the benefited rural singleton women extensive margin by increasing their possibility to register in a college in general, but also gave them intensive margin by allowing them to go to a better college. Because we can't observe what college an individual ends up going to in the dataset, there is an underestimation of the magnitude of the impact of the policy on the college education dummy, i.e. the magnitude can only capture the extensive margin of the policy, yet not the intensive margin. And the intensive margin is non-trivial as the affirmative action gives a large edge during the college admission. On the other hand, when we analyse the other outcomes including performances on marriage and labour markets, the total effect is attributable to both extensive and intensive margins of the policy.

1.4.2 Policy Effect on Marriage Market

On the marriage market, our main outcome is whether this rural woman is married. The parallel trend check is shown by Figure A3 in the Appendix. We observe that the two lines of marriage rates of Hubei and non-Hubei regions experienced a change in order to reverse after the first treated cohort 1989-1990.

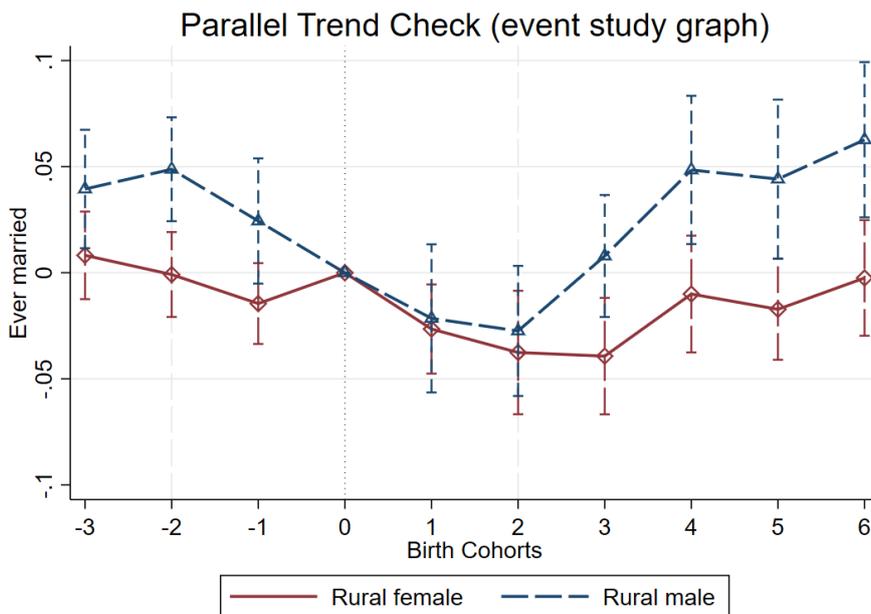
And event study by Equation 1.2 is also estimated and shown in Figure 1.4. we see that we cannot reject the assumption that the pre-trends are parallel between Hubei and non-Hubei for different cohorts. After the treatment, there was a significant decline in marriage rate. In the Appendix, we also provide the same figure for the fertility dummy in Figure A6.



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on 0.01 level.

Figure 1.4: Event study of being ever married: by birth cohorts

For the outcomes on the marriage market, it might be concerning that there is some underlying endogenous change in Hubei. To provide more evidence on causality, we use the rural male sample for the same estimation. These results are shown in Figure 1.5. We see that for the rural male sample, there is no statistically significant effect from cohorts 1 to 3, while the effects are significantly negative for the rural female sample. The estimation using a rural male sample can only be an inaccurate placebo test for reference: because of the structure of marriage, the rural marriage market in our sample cannot be divided by gender in reality. Therefore, we observe a similar trend in the two genders as a lot of rural men and women get married to each other, yet effects for the rural female sample are with larger magnitudes and significantly negative.



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on the 0.01 level.

Figure 1.5: Event study of being ever married: by birth cohorts

The same identification strategy can be used to estimate the Equation 1.1 on marriage market outcomes. Y_{ijk} is the outcome on marriage market in 2015 of individual i residing in province j and born in year k . Note that here, the dummy ELG takes the value 1 if the cohorts are 1989 to 1993, which had graduated in November 2015 when the micro census was conducted. This is also because in China it generally takes four years to graduate from an undergraduate institution. The vast majority of later cohorts should still be in the university if they attended one, and we do not focus on these cohorts.

Results for marriage outcomes are shown in Table 1.2. It shows that for the eligible rural women group, the difference of probability of getting married before the age of 26 declines by 3.16 percentage points, which is a 4.4% decrease compared to the sample mean. The second column shows consistent results by presenting the outcome “whether this person is married now”, and the magnitude of the increase is similar. The last column in the table gives results of fertility rate. The results show that the probability of having given birth is 1.55 percentage points lower before the age of 26, which is a 2.55% decrease in terms of the sample mean.

Table 1.2: Marriage outcomes as dependent variables

	Ever married	Married now	Ever given birth
Hubei=1	0.00333 (0.00272)	0.00385 (0.00298)	0.0752*** (0.0167)
Born in 1989-93=1	-0.584*** (0.0124)	-0.568*** (0.0130)	-0.616*** (0.0120)
Hubei=1 \times Born in 1989-93=1	-0.0316*** (0.00617)	-0.0325*** (0.00653)	-0.0155*** (0.00573)
Constant	0.938*** (0.00616)	0.921*** (0.00638)	0.794*** (0.0183)
Observations	100057	100057	100057
Adjusted R squared	0.182	0.168	0.168
Mean of Dep. Variable	0.722	0.710	0.607

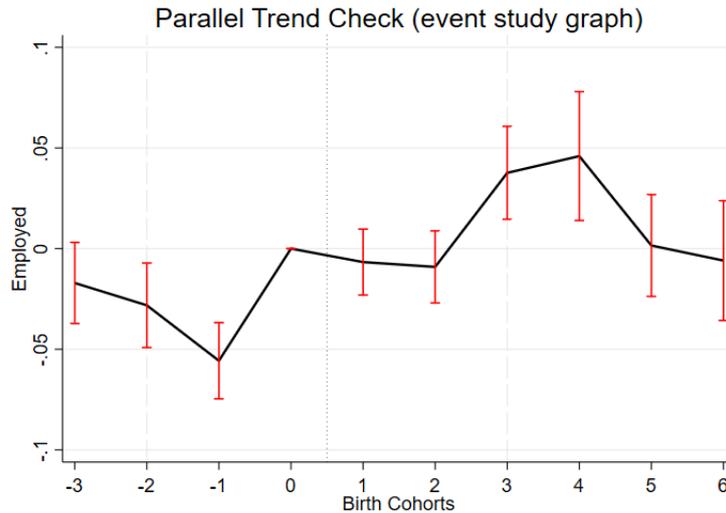
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.4.3 Policy Effect on Labour Market

On the labour market, our main outcome is whether this rural woman is currently employed. The parallel trend check is shown by Figure A4 in the Appendix. In the graph, the lines intersect after cohort 1991. Our first treated cohorts being 1989-1991, the graph shows positive effects, although not immediately following the policy.

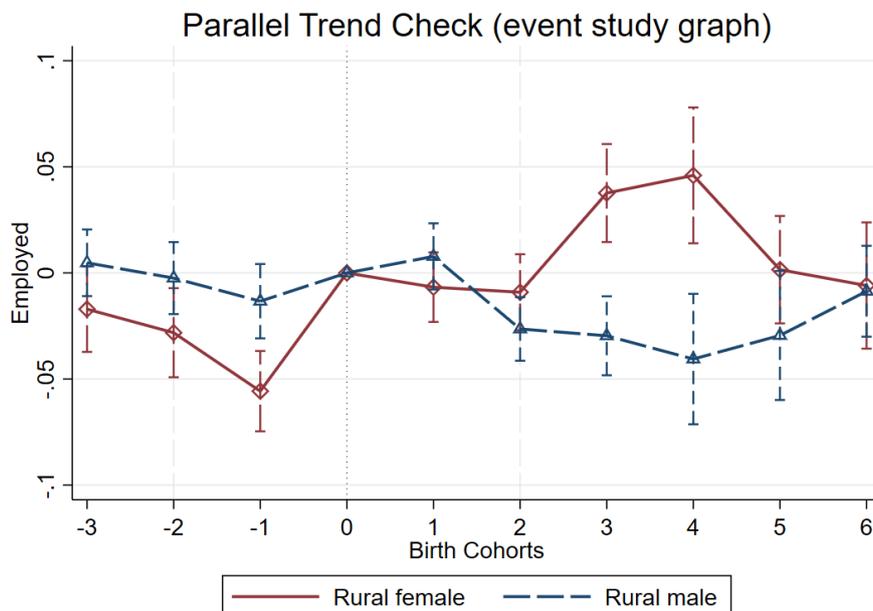
An event study by Equation 1.2 is shown in Figure 1.6 for the dummy of whether this person is currently employed. We see that the average means before and after the first treated cohort are significantly different. There was a surge from period -1 to period 0. This pre-trend change could come from various sources. In our data, one check we do is to use a different measurement for the employment outcome. If we not only include people who are currently employed, but also people who have been searching for a job in the past three months and people who are able to start to work within two weeks, the size of the surge in pre-trend has shrunk significantly, as shown in Figure A7 in the Appendix.



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on the 0.01 level.

Figure 1.6: Event study of being currently employed: by birth cohorts

As on the marriage market, we also provide more evidence on causality by using the rural male sample for the same estimation on the labour market. These results are shown in Figure 1.7. We see that for the rural male sample, there are either statistically insignificant effects or negative effects, while for the female sample the effects are mostly significantly positive. The estimation using rural male sample can be used as a placebo test if we assume no correlation between labour markets for two genders. The significantly negative effects for the rural male sample in some late cohorts can result from the local competition during recruitment for the same positions. The same estimations for the other employment measurement including others in the labour force are shown in Figure A8 in the Appendix.



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on the 0.01 level.

Figure 1.7: Event study of being currently employed: by birth cohorts

Using Equation 1.1, the labour market outcome estimations are shown in Table 1.3 and Table 1.4.

Table 1.3 shows results for the dummy measuring labour market participation. The first column shows the dummy indicating whether an individual has been employed in the past week. The second column shows the dummy that takes value 1 if the person is employed, or this person has been hunting for jobs (de facto, unemployed) in the past three months. The third column estimates the effect on the dummy that takes value 1 if the person is employed, hunting for jobs in the past three months, or able to start working in the next two weeks. And the outcome dummy in the fourth column specifies the case where the person is employed or currently in school.

We can read from the first column that the probability of being employed increased by 2.52 percentage points, which is a 3.63% edge regarding the sample mean. We see that the probability of being employed or continuing to do further studies increased by 2.18 percentage points, which is a 3% increase compared to the sample mean.

Table 1.4 shows results of more labour market outcomes as dependent variables. The first column shows that the probability of being out of labour force due to housekeeping reduces by 1.32 percentage points, a 7.1% edge compared to the sample mean. The probability of being employed in primary sectors decreases by 3.16 percentage points, also a 7.1% decrease compared to the sample mean. The last column shows that the probability of being employed in the position of manager or skilled worker increases by 0.6 percentage points, a 4.6% edge in terms of the sample mean.

Table 1.3: Labour market outcomes as dependent variables

	Employed	Employed or unemployed	Employed, unemployed, or able	Employed or studying	Employed, unemployed, or studying	Employed, unemployed, studying, or able
Hubei=1	-0.0451 (0.0292)	-0.0212 (0.0258)	0.0103 (0.0199)	-0.0331 (0.0199)	-0.0107 (0.0139)	0.0223** (0.0107)
Born in 1989-93=1	-0.122*** (0.0122)	-0.0902*** (0.00954)	-0.107*** (0.00923)	0.0332*** (0.0104)	0.0603*** (0.00789)	0.0479*** (0.00699)
Hubei=1 × Born in 1989-93=1	0.0252*** (0.00464)	0.0133*** (0.00434)	0.0153*** (0.00364)	0.0218*** (0.00378)	0.0126*** (0.00391)	0.0119*** (0.00289)
Constant	0.754*** (0.0300)	0.778*** (0.0264)	0.821*** (0.0206)	0.743*** (0.0209)	0.778*** (0.0148)	0.811*** (0.0117)
Observations	100057	100057	100057	100057	100057	100057
Adjusted R squared	0.0239	0.0225	0.0181	0.0188	0.0187	0.0136
Mean of Dep. Variable	0.694	0.757	0.839	0.725	0.802	0.870

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.4.4 Policy Effects on Consumption measurements

Table 1.5 shows outcomes of consumption measurements. According to our identification, the first column shows that rural women in the treated group have on average 0.649 square meters more in terms of house size per household member. Then, it is 5.7% more likely that the woman's household has a car. The probability of having a flushing toilet in household increases by 2.3%. And the probability of the woman having social health insurance increases marginally by 0.7%.

1.4.5 Policy Effects on Secondary Education Attainment

Figure A5 in the Appendix checks the collapsed means for high school degree attainment. As stated above, most Chinese rural children start primary school at the age of 6-7, which means that they need to decide whether to continue to study in high school at the age of 15-16. The affirmative action policy started in 2009, therefore, the first cohort that could have been potentially influenced for high school enrollment was the cohort 1993. In 2009, a lot of students from cohort 1993 were in their last year in junior high school, and they needed to decide whether to continue to study at a senior high school. We

Table 1.4: More labour market outcomes as dependent variables

	Housekeeping only	Employed in primary sector	Employed as manager or skilled
Hubei=1	0.0526*** (0.00467)	0.330*** (0.0167)	-0.246*** (0.00437)
Born in 1989-93=1	-0.0982*** (0.00839)	-0.0700*** (0.0109)	0.0304*** (0.00736)
Hubei=1 × Born in 1989-93=1	-0.0132*** (0.00403)	-0.0316*** (0.00314)	0.00661** (0.00317)
Constant	0.173*** (0.00659)	0.133*** (0.0181)	0.362*** (0.00653)
Observations	100057	69483	69302
Adjusted R squared	0.0228	0.0478	0.0209
Mean of Dep. Variable	0.187	0.442	0.145

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Consumption outcomes as dependent variables

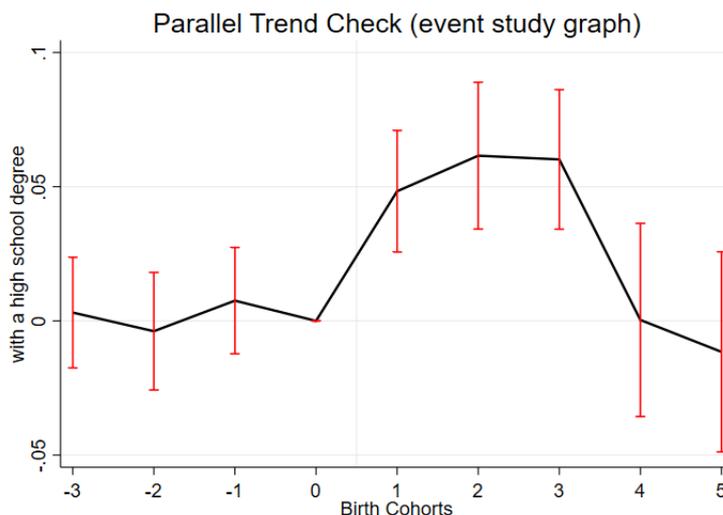
	House area by person	Car in household	Flushing toilet in household	social health insurance
Hubei=1	6.775*** (0.427)	-0.298*** (0.0429)	-0.0541*** (0.0125)	0.0846*** (0.00457)
Born in 1989-93=1	1.995*** (0.301)	-0.0587*** (0.00750)	-0.0174** (0.00743)	-0.0151*** (0.00391)
Hubei=1 × Born in 1989-93=1	0.649*** (0.108)	0.0121*** (0.00353)	0.0103*** (0.00281)	0.00644*** (0.00137)
Constant	25.47*** (0.484)	0.469*** (0.0429)	0.602*** (0.0138)	0.880*** (0.00499)
Observations	96966	96966	96966	100057
Adjusted R squared	0.0557	0.0411	0.214	0.0220
Mean of Dep. Variable	29.77	0.213	0.446	0.959

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

could observe that Hubei experienced a large surge in high school attainment rate from cohorts 1993-1994 onward.

Event study estimation using Equation 1.2 is shown in Figure 1.8. We could see that the parallel assumption is satisfied here, and we observe a large treatment effect. Cohort 4 onward corresponds to birth cohort 1999 onward, and these people were 16 years old or younger in 2015. People typically finish secondary education at the age of 18-19 years old, therefore, the effect returns to zero for these young cohorts.



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on the 0.01 level.

Figure 1.8: Event study of high school degree attainment: by birth cohorts

Again we use Equation 1.1 to identify the magnitude of the difference in differences in high school degree attainment rates. Table 1.6 shows that the high school attainment rate increases by 4.98 percentage points, which is an 11.8% edge scaled by the sample mean.

Table 1.6: Dependent variable: whether has high school degree dummy

	with a high school degree
Hubei=1	-0.321*** (0.0304)
Born in 1993-97=1	-0.0190 (0.0121)
Hubei=1 × Born in 1993-97=1	0.0498*** (0.00552)
Constant	0.678*** (0.0310)
Observations	93375
Adjusted R squared	0.0456
Mean of Dep. Variable	0.421

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5 Robustness Checks

1.5.1 First reduced form: including people who are currently in college

In the main results, we used college degree attainment as the first-stage outcome, because in our second-stage outcome analysis, it makes more sense to only focus on people who already got their degrees, instead of including people who are still in school. For the robustness check, we can redo the first stage including people who were in college in 2015 in order to identify the effect of the policy on college degree attainment. The dropout rate in Chinese colleges was reported to be below 1%, according to a report by the Ministry of Education in 2011, therefore we can assume that people who enter colleges can end up having a college degree, and therefore they are combined with people with a college degree. Our results are robust. Parallel trend check and event study graphs are Figure A1 and Figure A2 in the Appendix.

1.5.2 Effect of college education on Labour and Marriage Markets: 2-Stage Least Squares

When we estimate the policy impact above, we assume that without the policy, the evolution of outcomes and education attainment for individuals does not systematically vary across different regions. We now make another assumption that the policy did not affect outcomes conditional on the impact on education attainment. Given this assumption of exogeneity, we use this policy to construct instrumental variables to identify the impact of attaining a college degree on labour and marriage outcomes. This assumption is rather reasonable under our context here as the policy was on a relatively small scale, even within the rural female group in Hubei as singleton women are not the majority based on reports of family size from the National Bureau of Statistics of China, also the rural women who take college exam take up a low proportion (as shown in Table 1.1, the national average for rural women is around 14.5%).

$$Y_{ijk} = \delta_0 + \delta_1 S_{ijk} + \alpha_j + \gamma_k + \eta_{ijk} \quad (1.3)$$

Results are shown in Table A7 and Table A8 in the Appendix. The results imply that going to college decreases the probability of getting married at the age of 21 to 26 by 97.1 percentage points, and it increases the probability of being employed or continuing to study by 77.5 percentage points. The magnitudes of the coefficients are very large compared to sample means, both exceeding a change over 100%. This is because the coefficient in the first stage has a small magnitude, despite not being a weak instrument according to the F-statistics.

Under the local average treatment effect framework, The small magnitude of the first stage coefficient indicates that there is a small number of compliers in our identified treated group. There are two explanations for this study. First, it is consistent with our setup, because our smallest identifiable cell is a group of rural women born in certain cohorts residing in a certain province. Our treated group is identified as rural women born from 1989 to 1993 and residing in Hubei province. Not everybody benefited from the policy, as the majority of people did not go to high school to be qualified for the policy (as shown in Table 1.6, the sample mean of high school degree attainment is 42.1% in our used sample). Also, since only singleton women benefited, and yet we do not have an identifier indicating whether the person is singleton or not, the non-singleton women are included in our treated group, which will further dilute the actual treated group. Second, we can only identify the extensive margin in our first stage, i.e. whether these women ended up going to a university thanks to this affirmative action policy. That is to say, the intensive margin of the impact of the policy cannot be seen in our estimations. With the intensive margin that beneficiaries go to a better university, the effect will not show in the first stage. However, this intensive margin is not trivial and can probably show in the second-stage outcomes. As has been shown in Table A6, the expected wages on the labour market are dependent on the universities with different admission scores. In conclusion, it is difficult to have a precise estimation using two-stage least squares.

1.5.3 Two-way fixed effects and differences-in-differences with heterogeneous treatment effects

There is an increasing literature on caveats about using difference in differences in the presence of heterogeneous treatment effects, for example, works by de Chaisemartin and D'Haultfoeuille. The identification in this paper is not concerned. The difference in differences method is unbiased with a staggered treatment, when there is no treatment effect heterogeneity across units, nor dynamic treatment effects. We

use a cohort-based method, with one staggered treatment (i.e. cohorts from 1989 to 1993 in Hubei were all treated in our cross-sectional census data). And the treated group being eligible cohorts in Hubei province, the other provinces were not treated by this policy during this period and these provinces are grouped together. In our analysis we keep the rural female sample, further fortifying the assumption that there are no heterogeneous treatment effects across Hubei and non-Hubei units.

1.6 Conclusions

The findings in this paper suggest that the exceptionally implemented affirmative action in college admission in Hubei province increased women's chances of receiving a degree and simultaneously had a significant impact on the marriage outcome and the labour market. This effect took two forms: one was to increase the quantity of education by giving advantages to the treated group when being selected to enter college; the other was to improve the quality of education by granting them access to more prestigious colleges. The decrease in the marriage rate and fertility rate for women in the age range of 22-26 suggests that education has an impact on the outcome of rural women in the marriage market. What is more, the increase in the employment rate for the treated group indicates that college education has decisive implications for human capital in the labour market. In short, affirmative action in education is transformative for rural women under our setup. We also document an increase in high school registration among women eligible for the affirmative action policy, indicating they may respond to improved access to higher education by increasing early investments in human capital.

We interpret these results as evidence that promoting educational equality between genders can contribute to reducing gender inequality by providing women with more equal opportunities. Especially in rural areas of developing countries, women often face restrictions imposed by traditional gender roles rooted in patriarchal systems, which limit their access to higher education. This constraint impedes women's social and economic progress by harming their employment prospects. Our study demonstrates that these women positively respond to educational affirmative action when the expected returns of pursuing education increase, which later leads to changes in their gender roles from primarily being child-bearing housewives to active participants in the labor market.

Due to data accessibility, this study only evaluates the short-term impact of college education on rural singleton women in Hubei province. With an updated census dataset (for example, the 2020 China Census), it will be possible to assess the long-term effects of affirmative actions in education in China and to unveil further interesting results.

Chapter 2

Higher Education and Local Economic Development

2.1 Introduction

Globally, higher education has become mass education for most of the developed countries, as evident from literature including Marginson (2016). Meanwhile, developing countries have made progress in expanding access to higher education, but they still lag behind developed countries in terms of the ratio of the population with college education. The expansion of mass higher education is often seen as an important driver of economic development, as it can lead to the development of a more skilled and productive workforce. This paper quantitatively estimates the causal relationship between the college-educated labour force and economic development by using a Chinese college expansion policy. I find that a larger skilled workforce has a positive impact on GDP growth and a negative impact on the share of primary sector.

Why China? China has experienced very high economic growth in recent decades, one of the highest in the world. Meanwhile China experienced an unprecedentedly significant increase in college enrollment rates starting in the late 1990s and early 2000s, reaching the largest capacity of higher education in 2006 with over 25 million current university students. Figure 2.1 shows the drastic increase in the number of college institutions and number of university freshmen and graduates. In the early 2000s, the increase is exponential: for example, for yearly university graduates, the number has a ten-fold increase in less than ten years.

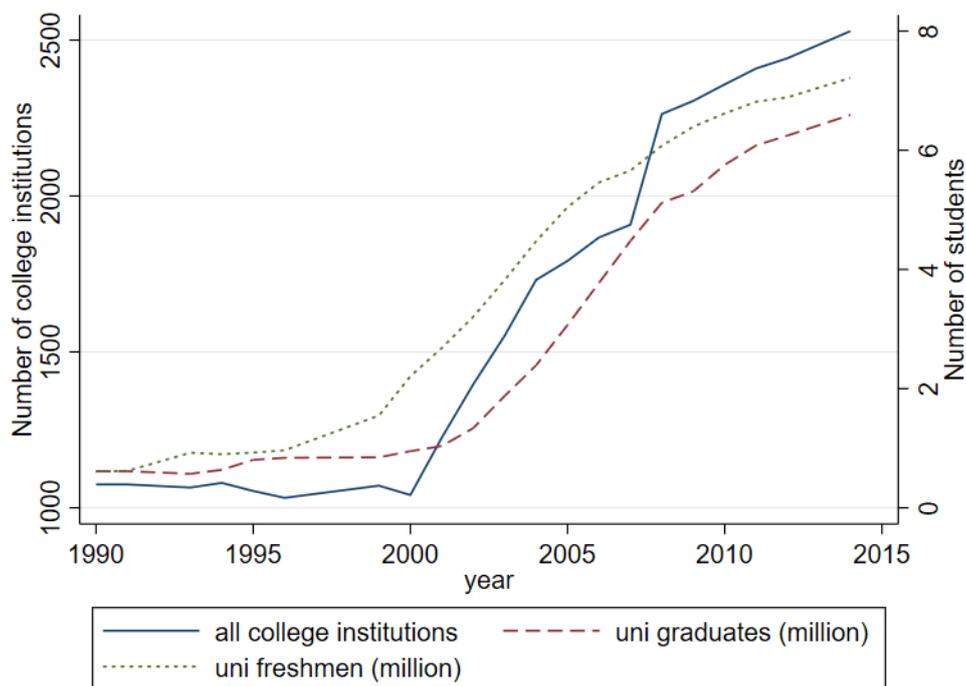


Figure 2.1: Timeline: national numbers of colleges and students

This paper exploits the large variations created by this Chinese college expansion policy by using this policy as a natural experiment. Using the China City Statistical Yearbook data from 1991 to 2017, I estimate the causal effect of the college-educated labour on local GDP, specifically focusing on annual GDP levels, sectoral contributions to GDP (primary, secondary, and tertiary sectors), and employment within these sectors. A Two-Stage Least-Squares (2SLS) estimation is implemented to identify the magnitude of the causal effect. As the college-educated labour could be endogenous to GDP, the labour force with higher education is instrumented by the time lag of the number of universities. The exclusion restriction requires that universities should not impact GDP except by producing more graduates. To address this, two measures are taken in the regression: accounting for construction costs through capital stock inclusion and mitigating the impact of additional college-hired immigrant workers by controlling for population.

Results show that the increase in the college-educated population has a positive impact on GDP growth, with an elasticity of around 0.3. The surge in population with higher education also has a significant impact on structural transformation. The increase significantly reduces the ratios of the primary sector in GDP and employment in the primary sector, while significantly increasing the ratio of GDP and employment in the tertiary sector. For the secondary sector, the share in GDP decreases as the population with high education increases, while the number of workers increases.

The causal relationship between skilled labour force and economic growth has often been addressed in the economic literature, due to its ability to explain the differences in productivity growth that lead to heterogeneity in development both theoretically and empirically. Since the early work including Becker (1962), the concept of “human capital” has been introduced, analogous to physical capital for generating returns for individuals when investing in education. Griliches (1970) is one of the earliest works that use education variables in aggregate production functions, where he constructs the quality of labour index by years of school completed. More recent classical studies employ the number of years of schooling to find a positive correlation between education and economic growth, including Barro (1991) and Mankiw, Romer, and Weil (1992). Despite the significant correlations found, Bils and Klenow (2000) raises the potential reverse causality problem and claims that the bulk of the empirical relationship documented by Barro and others should not be interpreted as reflecting the impact of schooling on growth. Krueger and Lindahl (2001) give a literature review, emphasizing the difficulty of separating the causal effect of education from the positive income demand for education in cross-country data over long time periods. They propose that researchers identify natural experiments in schooling attainment similar to those that have been exploited in the microeconomic literature. Works including Hanushek

and Woessmann (2008), Hanushek and Woessmann (2015) and Valero (2021) also provide comprehensive literature reviews including the mechanism of the impact of the number of years of schooling on economic growth. Unlike most of the previous studies using cross-country data, this paper uses a domestic natural experiment that creates a shock in the supply of college education, and continues to provide evidence that schooling attainment has a positive causal effect on economic growth.

My paper also contributes to the literature exploring the impact of human capital on structural transformation, which is another crucial aspect of economic development alongside growth. Porzio, Rossi, and Santangelo (2022) use cohort-specific educational attainment to show that the increase in schooling for more recent cohorts contributed to their lower agricultural employment by using the Integrated Public Use Microdata Series (IPUMS) data for 69 countries at different levels of development. Lee and Malin (2013) explore education's role in China's structural transformation. They claim that education facilitates labour reallocation from the agricultural sector to the non-agricultural sector. This study builds upon the ongoing discussion by leveraging regional-level data to show evidence of the significant impact of higher education on structural transformation.

There is also literature on the specific impact of higher education on economic development as many scholars argue that education is important both as an investment in human capital and in facilitating research and development and the diffusion of technologies. For example, Vandebussche, Aghion, and Meghir (2006) claim that initial phases of education are more important for imitation while higher education is essential for innovation by using panel data of OECD countries. Works including Katz and Murphy (1992) and Krusell et al. (2000) define "skilled workers" to be those with college completion. Acemoglu (1998) finds that an increase in the supply of college graduates induces a skill-biased technical change in the United States. Hanushek and Woessmann (2015) state that the U.S. higher education system has growth-enhancing effects but there is a lack of robustness outside of the United States. For China, Li, Loyalka, et al. (2017) argues that the increase in the college supply has a positive long-run effect on the economy. This paper contributes to this literature by a causal identification analysis to reinforce the argument that higher education has a positive impact on economic development. Throughout the paper, I use the term "skilled workers" to denote college-educated individuals, following the convention in Katz and Murphy (1992) and Krusell et al. (2000). Using this terminology does not resolve the challenge of distinguishing between education and skill when quantifying human capital increase, as highlighted by Hanushek, Schwerdt, et al. (2015). However, based on the aforementioned literature, I assume that education serves as a good proxy for skills.

This study leverages a college expansion policy in China as a natural experiment to estimate its returns and externalities, which taps into the literature about other college expansion programs implemented in several countries. The aforementioned Acemoglu (1998) analyzes the impact of the rapid increase of college graduates in the U.S. in the 1970s on technological change and skill premium. Katz and Murphy (1992) argue that the growth of the relative supply of college graduates explains the rising inequality and changes in the wage structure in the U.S. from the 1960s to the 1980s. More recently, to name a few, Belskaya, Sabirianova Peter, and Posso (2020) estimates the effects of a college expansion policy on wages in Russia using an individual dataset. Carneiro, K. Liu, and Salvanes (2023) uses the construction of new colleges in the 1970s in Norway to find that the increase in the higher education supply also increases skilled wages and the productivity of skilled labour and investments in R&D. There is also a growing literature exploiting variations created by China's college expansion policy. Li, Y. Ma, et al. (2017) and B. Huang et al. (2022) use the policy to exploit the skill premium and heterogeneity in wages among different groups. On the firm level, Che and L. Zhang (2018) find heterogeneity in gains in total factor productivity across industries and firms. S. Feng and Xia (2022) find that there are significant adjustments in capital and R&D within firms in response to an enlarged college-educated labour force. Consistent and additional to the aforementioned literature, this paper exploits the variation to identify the heterogeneity in development due to the supply shock of higher education.

Along with the GDP growth and surge in college education, countries worldwide, including China, have experienced a significant upswing in physical capital investment. This might shed light on the mechanism through which skilled labour stimulates growth, as physical capital and skill are often regarded complementary in economic literature. The capital-skill complementarity implies that growth in physical capital stock or skilled labour increases the marginal product of each other, while the growth in physical capital or unskilled labour does not reinforce each other's productivity. One of the pioneering research to explore the complementarity between capital and skills is Griliches (1969). He formulates the hypothesis of capital-skill complementarity which is tested by the U.S. manufacturing data. Some research follows this hypothesis, including Krusell et al. (2000) quantitatively evaluating how much capital-skill complementarity has affected the skill premium. Duffy, Papageorgiou, and Perez-Sebastian (2004) use two-level

CES (constant elasticity of substitution) production functions to examine the complementarity. They use the Penn World Table data of national accounts, while defining skilled labour force using different educational thresholds and find that there is a complementarity between college-educated labour and capital. In this study, with the skilled labour and capital stock data, I verify empirically that there is a co-movement of capital and skill.

The variation exploited in this paper is on the regional level. The impact evaluation of this kind of place-based policy has been extensively explored across a wide range of topics in the literature. Moretti (2004) finds that higher education increases wages for all groups with different education, accounting for unobservable city-specific demand shocks. Audretsch and Feldman (1996) is one of the early research addressing the geography of innovation knowledge and production, finding that universities and skilled labour generate knowledge externality that leads to clustering of innovative activities, ultimately growth. Kline and Moretti (2013) provide analysis on place-based hiring subsidies. They note that even when workers are mobile across places, local heterogeneity such as the job matching productivity makes place-based policies effective. The college expansion policy used in this research has been implemented differently across regions, which creates heterogeneous supply shocks to the college-educated labour. The results provide evidence that the place-based supply shocks have an impact on local economies.

2.2 Conceptual Framework

From early work such as Griliches (1970), to more recent work including Caselli and Ciccone (2019) and Jones (2019), human capital has been measured from a production point of view. A Cobb-Douglas production function is still often assumed for simplicity and its assumption of the constant elasticity of substitution (i.e. CES, thus the constant marginal rate of technical substitution between labour and capital). The basic form is given $Y = AH^\beta K^\alpha$, where Y is defined as GDP, K as a physical capital input, and H as a human capital input.

For the measurement of human capital, there are multiple ways to incorporate both the quality and quantity of labour. One way is to define human capital input as $H = EL$, where E denotes the quality of labour and L denotes the quantity of labour. Therefore, following Griliches (1970), the aggregate production function can be written as in equation 2.1.

$$Y = AE^{\psi_1} L^{\psi_2} K^{\psi_3} \quad (2.1)$$

Another general way to define human capital is to write H as a CES function $H = [(e_1 L_1)^{\frac{\varepsilon-1}{\varepsilon}} + (e_2 L_2)^{\frac{\varepsilon-1}{\varepsilon}}]^{\frac{\varepsilon}{\varepsilon-1}}$, where L_1 and L_2 are two types of labour forces that can be categorized by higher education attainment. This form is used by papers including Jones (2014). If we assume $\varepsilon \rightarrow 1$, then we can also assume H to take a Cobb-Douglas form. Then the aggregate production function is given as equation 2.2. The multiplicative equations could be linearized by logarithmic transformations, which can be used for the data analysis using Ordinary least squares (OLS) or Two-Stage Least Squares (2SLS) regressions.

$$Y = AL_1^{\beta_1} L_2^{\beta_2} K^{\beta_3} \quad (2.2)$$

In order to assess capital-skill complementarity, we require a versatile functional form capable of accommodating various elasticities of substitution. To illustrate this, as introduced in the works of Sato (1967) and Duffy, Papageorgiou, and Perez-Sebastian (2004), there is a specific form of the two-level CES production function. The production function is represented by equation 2.3, wherein the elasticities of substitution between capital (K) and low-type labour (L_2) and between low-type labour (L_2) and skilled labour (L_1) are assumed to be equal. When $\rho > \theta$, the condition of capital-skill complementarity is met, as shown in Duffy, Papageorgiou, and Perez-Sebastian (2004). In my empirical analysis, I verify the greater co-movement between capital and skilled labour compared to the co-movement between capital and unskilled labour.

$$Y = A\{a[bK^\theta + (1-b)L_1^\theta]^{\frac{\rho}{\theta}} + (1-a)L_2^\rho\}^{\frac{1}{\rho}} \quad (2.3)$$

2.3 Methods

2.3.1 Empirical background

The natural experiment this paper uses is a national-wide college expansion policy starting at the beginning of the century. The policy was officially announced in June 1999. On June 16, 1999, the General Office of the CPC Central Committee and the General Office of the State Council announced decisions on reforms of education, including the goal of increasing higher education enrollment rate from 9% to 15% before the year 2010. And then in 2001, the goal has been modified so that a 15% rate would be achieved before 2005. And this goal was achieved in 2002 already, and in 2006, the higher education enrollment rate reached 23%. The speed and scale of the policy are unprecedented and unique.

Why was such a policy initiated? The abrupt expansion policy originated in 1998 from a letter by Min Tang and Xiaolei Zuo, economists at that time working for the Asian Development Bank. The central government decided to take their suggestions the following year. Lanqing Li, the first-ranked Vice Premier of the People's Republic of China between 1998 and 2003, documents the reasons why they decided on the expansion. First, the college enrollment rate in China was lower than the minimum international Mass Higher Education rate of 15%, which did not correspond to the economic development in China. Second, the general public hopes to get more opportunities to enter colleges. Third, higher education can postpone participation in the labour markets to reduce competition with the laid-off workers in the 1990s reform, while it can stimulate people to spend more on education. Last, under the one-time College Entrance Exam (Gaokao) based selection system for higher education, the competition due to the shortage in the supply of colleges hindered the improvement of education quality by keeping the education exam-oriented. The policy was driven by both educational and economic development objectives.

The expansion happens in two ways: the expansion of the existing universities and the construction of new universities. During the implementations, a large regional heterogeneity can be observed, which is the main variation that I exploit in my data analysis. Figure 2.2 shows the long difference in the numbers of universities from 2000 to 2010. In the heat map, 76.7% prefectures with non-missing data experienced a positive change in the number of universities from 2000 to 2010.

One might be concerned that the increase in university number is mainly driven by GDP growth. The heat map in Figure 2.3 shows the GDP growth rates from 2000 to 2010, corresponding to Figure 2.2. There is seemingly no visible correlated pattern between the two heat maps. Another check I do is by plotting change in the number of colleges against GDP growth (i.e. the first difference of the GDP measurement) before the expansion policy started in Figure 2.4. It shows that before the expansion started, the change in number of colleges is not correlated with GDP growth, indicating that the pre-expansion data shows no evidence for the concern that the changes in university numbers are endogenous to GDP. Later in this paper, robustness checks are conducted using differences-in-differences with dynamic treatment effects. The event study graphs demonstrate flat pre-trends, which further diminishes this concern regarding endogeneity. I conduct the same verification for structural transformation, as illustrated in Figure 2.5. It demonstrates that before the expansion began, the change in the number of colleges is not correlated with the share of the tertiary sector in GDP. This suggests that the pre-expansion data provides no evidence supporting the concern that the changes in university numbers are endogenous to structural transformation.

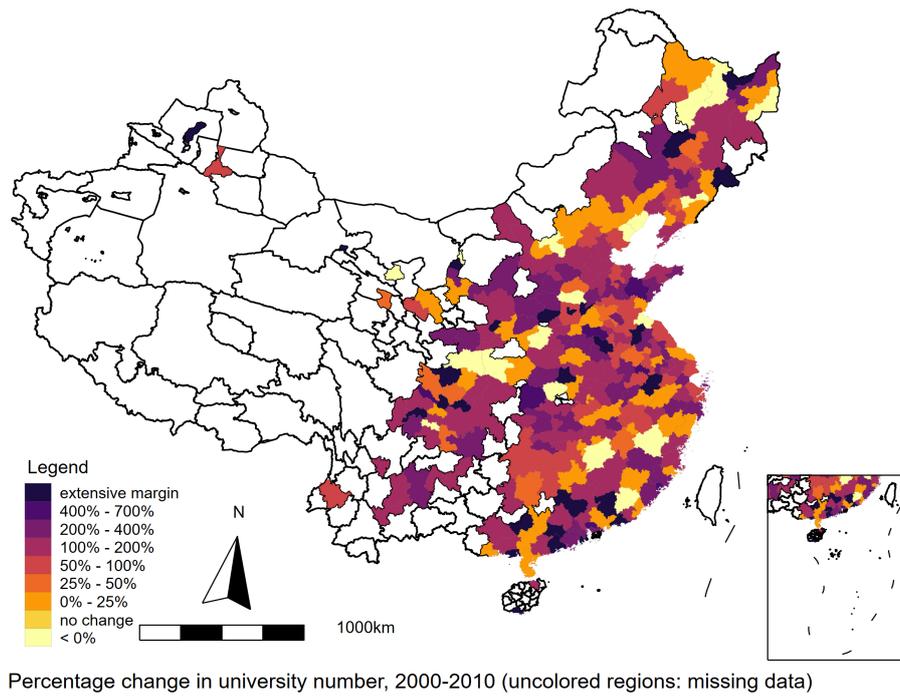


Figure 2.2: Percentage change in university numbers from 2000 to 2010, by prefecture

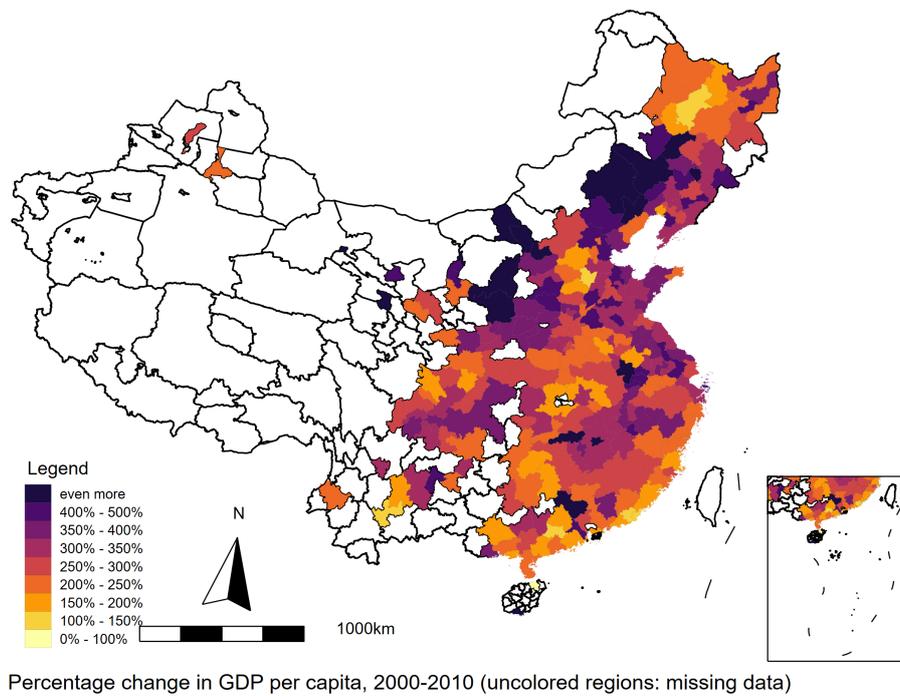


Figure 2.3: Percentage change in GDP per capita from 2000 to 2010, by prefecture

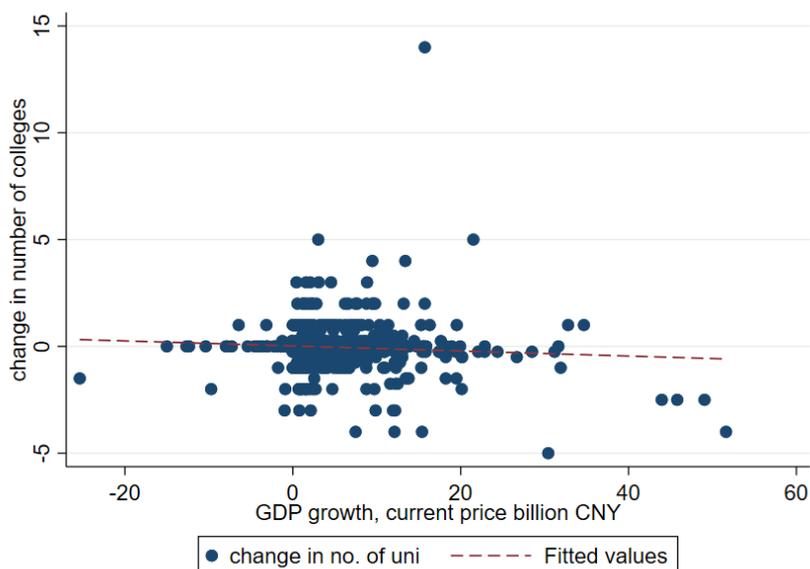


Figure 2.4: pre-expansion changes in numbers of colleges - GDP driven?

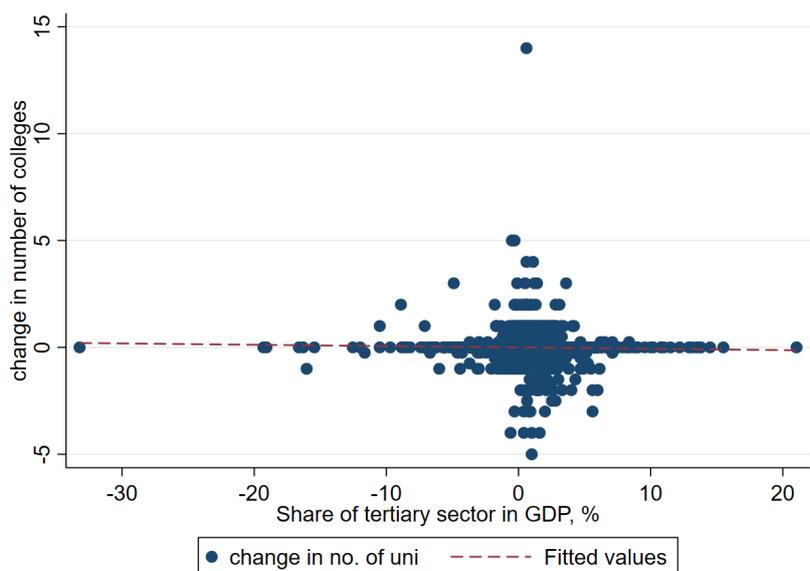


Figure 2.5: pre-expansion changes in numbers of colleges - structural transformation driven?

One can also posit that the changes in university numbers are demand-driven, which means local governments establish new universities based on their projections of incoming students. This can lead to an endogenous problem when we use the number of universities as an instrumental variable. To address this concern, I use the variable "current middle school students" including students in junior and senior middle school. It takes typically 3 years to finish junior/senior middle school respectively (6 years in total). Some people drop off during middle school, including a sizable group who do not continue to senior high school after finishing junior high. If I also assume the eligible cohort to enroll in universities enlarges by year in general, I can claim first-year junior high school students make up the largest share of the current middle school student measurement. To roughly estimate incoming demand based on cohort size, I can use the 6th lag of current middle school students because within 6 years, the 1st-year middle school students will enter a university. Figure 2.6 plots change in number of colleges against the 6th lag of change in middle school students (middle schools consist of junior and senior middle school,

which typically takes 6 years in total). The data shows no correlation between the change in university numbers and their new demands measured by the lagged number of changes in middle school students.

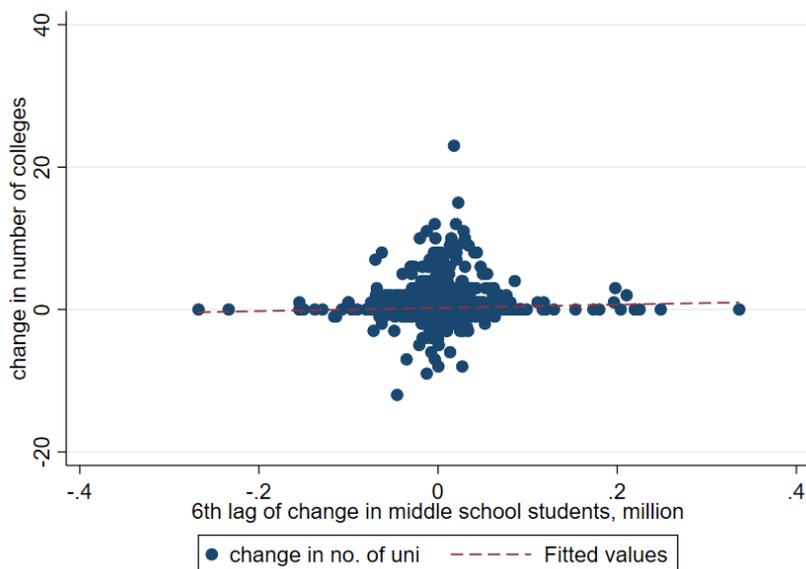


Figure 2.6: Changes in number of colleges: demand-driven?

2.3.2 Data and outcomes of interest

The data used in this paper is sourced and manually coded from the China City Statistical Yearbook spanning the years 1991 to 2017. Since the yearbooks correspond to the preceding year, the data encompasses the period from 1990 to 2016. The data pertains to the prefecture level. In 2000, China comprised 259 prefecture cities, while approximately 200 cities are typically included in the yearbooks. Notably, the missing prefectures primarily consist of autonomous administrative divisions associated with one or more ethnic minorities. These regions differ from the majority of China in terms of their geographical location, smaller populations, and lower population densities.

The original yearbook data presents several instances of missing variables across different years. To maintain consistency in the analysis, only samples containing complete data for all the main variables used are retained. With the inclusion of around 50% of the entire Chinese population, the data is deemed representative. In 2000, this percentage stands at 50.8%. For detailed summary statistics, refer to Table 2.1.

Table 2.1: Summary statistics

	Mean	SD	Min	Median	Max	N
number of colleges, 4th lag	7.70	12.31	0.00	3.00	91.00	3748
skilled population, million	0.18	0.34	0.00	0.07	3.25	3748
population, million	4.14	2.59	0.12	3.57	15.20	3748
GDP current price, billion CNY	133.96	231.63	0.30	57.88	2817.86	3748
share of primary sector in GDP	14.19	9.58	0.03	12.30	51.40	3748
share of secondary sector in GDP	48.62	10.64	16.60	48.95	89.70	3748
share of tertiary sector in GDP	37.19	9.10	8.44	36.08	80.23	3748
number of workers in primary sector, million	0.19	0.45	0.00	0.01	4.51	3748
number of workers in secondary sector, million	0.35	0.41	0.01	0.21	4.40	3748
number of workers in tertiary sector, million	0.34	0.48	0.01	0.21	6.41	3748
capital stock, billion CNY	300.35	548.83	0.40	80.17	6191.57	3748
fixed asset investment, billion CNY	73.83	123.02	0.07	21.24	1304.80	3748

Measurement of skilled labour: The stock of labour force with higher education

The measurement of skilled labour is the population with higher education, which includes both people in the labour force and not in the labour force. This variable that is used in the analysis is constructed using the stock and flow data for college students. In the city yearbook dataset, the variable “Current college student number” $F_{i,t}$ describes how many students are registered in a college at a place i in a given year t . To get a baseline stock of the population with higher education, I use the 1990 China Census to get the regional stock number of the population that completed a college education. I decided to use the 1990 census as it is the last census conducted before the expansion policy. To estimate the stock of skilled labour force $S_{i,t}$, I assume $S_{i,1989} = S_{i,1990} = S_{i,1991} = S_{i,1992}$. Since it typically takes around 4 years for people to graduate college, any $F_{i,t-4}$ will enter $S_{i,t}$ after 4 years. I can recover the stock of skilled labour force for any $t \geq 1993$ by recursively using:

$$S_{i,t} = S_{i,t-4} + F_{i,t-4}$$

For example, for the year 1993, $S_{i,1993} = S_{i,1989} + F_{i,1989}$. With my assumption, $S_{i,1993} = S_{i,1990} + F_{i,1989}$ where $S_{i,1990}$ is recovered from the 1990 China Census. And for the year 1997, $S_{i,1997} = S_{i,1993} + F_{i,1993}$, and etc. I also assume that the current student number can be used as a proxy for prospective students with a higher education because the dropout rate in Chinese colleges has consistently been reported to be below 1%, as indicated by reports from the Ministry of Education spanning the 2000s to the 2010s.

The stock of the population with higher education is estimated using the data from the 1990 China Census and the China City Statistical Yearbook. I also use the provincial level data from Educational Statistics Yearbook of China to check the accuracy of the estimation of the stocks of college educated population. The correlation between the two constructed variables is 0.999, and all results are robust. These results indicate that the estimation of the college educated population stock is rather accurate for the analysis.

The stock of capital K

As the number of population with a higher education, there is no direct measurement for capital stock in the dataset. A measurement of capital flow is “fixed asset investment”, which I use to recover the capital stock. The capital stock $K_{i,t}$ can be estimated by $K_{i,t} = (1 - \delta) * K_{i,t-1} + I_{i,t}$ where δ is the depreciation rate, and $I_{i,t}$ is the capital flow that can be measured by investment. For the depreciation rates, Jun Zhang, G. Wu, and Jipeng Zhang (2004) and Shan (2008) carefully review and compare the estimation for the depreciation rate for the Chinese economy and document a rate of 10% is a reasonable assumption for simplicity. To get the initial capital stock, I follow Young (2003) by using investment flow in 1984 (the earliest available yearbook data) divided by the depreciation rate, plus the average annual growth of investment flow between 1984 and 1990.

2.3.3 Identification Strategy

I use Two-Stage Least-Squares (2SLS) to estimate the causal impact of a college educated labour force on economic development. This is to account for the mutual causation between the college educated population and the economic development. A causal graph can be illustrated as in Figure 2.7:

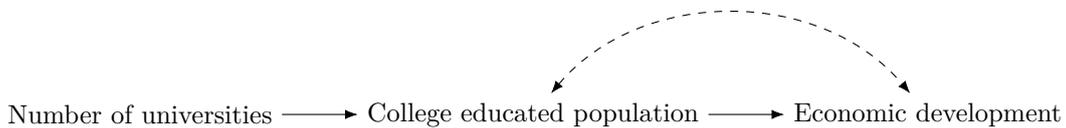


Figure 2.7: Causal graph: higher education and economic development

Under the 2SLS framework, a robust first stage and adherence to the exclusion restriction are essential. The college expansion policy results in a significant increase in both college construction and attendance, thereby verifying the relevance condition for the population with higher education. The exclusion restriction requires that the number of universities does not impact GDP, except for supplying more college graduates. The two measurements used in the regression can partially address potential violations of this assumption. First, by including the capital stock in the regression, I account for the increased construction expenditure resulting from college expansions as the costs are part of the fixed

asset investment measurement. Second, controlling for population helps mitigate the impact of the additional immigrant workforce hired by the colleges. Another concern is the potential impact of the increase in university staff. However, the data reveals that the increase in the number of university staff is significantly smaller compared to the increase in the number of students. This is seen by the substantial rise in teacher-student ratios in universities, which increased from 7 students per teacher to around 17 students within the time window of my data.

The first stage specification is given by equation 2.4. This first-stage regression estimates the effect of changes in the number of universities on the logarithmic college educated population. Both of the population measurements are logarithmically transformed.

$$\ln(\text{Skilled_population}_{it}) = \delta_0 + \delta_1 \text{no_university}_{i,t-4} + \delta_2 \ln(\text{population}_{it}) + \alpha_i + \gamma_t + v_{it} \quad (2.4)$$

The second stage is specified as equation 2.5. And when the outcome is logarithmic GDP, the second stage could be seen as the log linearization of equation 2.2.

$$Y_{it} = \beta_0 + \beta_1 \ln(\widehat{\text{Skilled_population}})_{it} + \beta_2 \ln(\text{population}_{it}) + \tilde{\alpha}_i + \tilde{\gamma}_t + e_{it} \quad (2.5)$$

A reduced-form analysis could also be performed by regressing the number of universities on (logarithmic) economic outcomes as in equation 2.6. When the outcome is (logarithmic) GDP, i.e. $Y_{it} = \ln(\text{GDP}_{it})$, this reduced form could be derived from taking the logarithm of equation 2.1, where E is defined as the quality of education that can be approximated by the number of universities at a place.

$$Y_{it} = \psi_0 + \psi_1 \text{no_university}_{i,t-4} + \psi_2 \ln(\text{population}_{it}) + \alpha'_i + \gamma'_t + \varepsilon_{it} \quad (2.6)$$

The underlying relevance between the instrument and the instrumented variable can be observed from the increase in college educated population as well as university numbers for almost all of the prefectures. Under the Local Average Treatment Effect (LATE) estimation framework when using instrumental variables, it is intuitive that the “compliers” on the regional level (i.e. the places with a larger college educated population due to the increase in the university number) are the majority. There might be some “always-taker” prefectures that would have a larger skilled labour force without having new universities but it will not violate the monotonicity assumption for the natural experiment.

On an individual basis, when new universities are built, the affected population is the group of students who could not have been admitted given the previous quota. One of the motivations of the policy was to meet the severe imbalance between demand and supply in college education. In 1998, 3.2 million attended the college entrance exam (Gaokao) and the acceptance rate in the college is 33.8%. Therefore, if we assume that academic performance indicates people’s ability, the individual compliers of the policy are people with lower ability levels than the pre-expansion college educated population. The magnitude of the empirical results is dependent on the population that was affected during the college expansion.

The analysis assumes that college graduates stay in the prefecture city where they finish university. The validity of the assumption is underpinned by the existence of the hukou system. As highlighted by Li, Loyalka, et al. (2017), the hukou system is a significant factor influencing the geographic residency of the population. This system imposes constraints on inter-prefecture migration by enforcing limitations on residency within the labour force. However, as some migration does occur, the estimates of the effects of college expansion might be conservative as outcomes could potentially increase in control areas.

2.4 Results

Prior to presenting the findings on economic growth and structural outcomes, I report the results of the first stage regressions for the 2SLS analysis by equation 2.4, as depicted in Table 2.2. The analysis indicates that the number of colleges is a non-weak instrument for the skilled population. Both of the columns show that upon not controlling or controlling for population and capital stock, the establishment of a single university leads to an increase of 1.3% in the skilled population stock after four years in the sample. These results remain consistent across all of the outcome variables.

Table 2.2: 2SLS - first stage regressions

	ln(skilled population)	ln(skilled population)
number of colleges, 4th lag	0.0129*** (0.00241)	0.0130*** (0.00220)
ln(population)	0.627*** (0.135)	0.617*** (0.139)
ln(K stock, billion CNY)		0.159*** (0.0585)
Observations	3748	3748
F-statistics	28.63	34.89

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.1 Outcome: GDP

First, I estimate how much the skilled labour force contributes to economic growth. The outcome variable is the logarithmic current price GDP in a year since using proportional changes in GDP can take into account the large heterogeneity in the absolute magnitudes of GDP. The population with higher education, population and capital stock are all logarithmically transformed for the same reason. This logarithmic transformation is also consistent with the Cobb–Douglas production function in which elements are multiplicative and taking logarithms is appropriate for the linear regressions. Results are reported in Table 2.3. The first two columns reports results from equation 2.6, and the second column adds capital stock as control. The third to fourth columns show results of OLS regressions to compare with results of 2SLS. The fifth to the sixth columns report the second-stage outcomes of 2SLS regressions and the last column includes capital stock as a control.

The reduced-form regressions in the first two columns show that a one-unit increase in the number of colleges will approximately produce an expected increase in GDP of 0.4% after four years. The inclusion of capital stock as a control variable results in a larger coefficient.

The OLS results in columns three and four show no significant correlation between the logarithmic population with higher education and logarithmic GDP, mirroring the pattern depicted in Figure 2.4. This can be attributed to the strong influence of the number of higher education institutions on the skilled population, which is not closely linked to higher GDP per capita due to policy-driven factors. According to Cui and Xu (2020), many inland universities were established or relocated for political and developmental balance in the 1950s to 1970s, and some universities were relocated to these inland areas for military considerations. These institutions continue to produce local college-educated labour.

And the second stage results reported in the fifth column show that a 1% increase in college educated population increases GDP by 0.3%. After including capital stock as a control in the last column, the elasticity between college educated population and GDP becomes larger and more statistically significant. This provides evidence that college expansions contribute to economic growth by expanding the local skilled workforce.

2.4.2 Outcome: structural transformation based on the three-sector model

Share of the three sectors in GDP

To see whether a larger college educated population is structurally transformative, the shares of three sectors in GDP are used as outcomes. The shares are also logarithmically transformed to get proportional changes in the shares. Results for the logged share of the primary sector are reported in Table 2.4. The first two column shows that building one college will produce an expected decrease in the ratio of the primary sector in GDP of 1.1% after four years. The fifth and sixth columns indicate that a 1% increase in college educated population reduces the share of the primary sector in GDP by 0.84%.

Results for the logged share of the secondary are reported in Table 2.5. For the secondary sector, the results show that building universities and a larger college educated population has a negative effect on the ratio of secondary sector in GDP as for the primary sector. However, the magnitudes are smaller for the secondary sector than the first. The magnitudes of the coefficients of our interests for the OLS and

Table 2.3: Outcome: $\ln(\text{GDP curr. p})$

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	0.00382** (0.00190)	0.00400** (0.00162)				
$\ln(\text{population})$	0.575*** (0.0751)	0.561*** (0.0588)	0.593*** (0.0758)	0.606*** (0.0587)	0.390*** (0.141)	0.371*** (0.131)
$\ln(\text{K stock, billion CNY})$		0.235*** (0.0311)		0.240*** (0.0316)		0.187*** (0.0449)
$\ln(\text{skilled population})$			0.00307 (0.0304)	-0.0358 (0.0235)	0.296* (0.158)	0.308** (0.148)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	24.72	24.72	24.72	24.72	24.72	24.72

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the IV regressions are all approximately half of those of the primary sector.

For the tertiary sector, the results are of the opposite sign compared to the other two sectors, as shown in Table 2.6. The first two columns show that building one college will produce an expected increase in the ratio of tertiary sector in GDP of 0.2% after four years. The fifth and sixth columns indicate that a 1% increase in college educated population increases the share of tertiary sector in GDP by 0.2% approximately.

These results show evidence that higher education has an impact on structural transformation. By enlarging the college educated population, an increase in higher education supply reduces the share of the primary and the second sectors in GDP, especially for the primary sector, while increasing the share of the tertiary sector.

Table 2.4: Outcome: $\ln(\text{share of primary sector in GDP})$

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.0109*** (0.00259)	-0.0110*** (0.00272)				
$\ln(\text{population})$	0.170 (0.305)	0.180 (0.312)	0.192 (0.310)	0.184 (0.311)	0.698* (0.421)	0.700* (0.424)
$\ln(\text{K stock, billion CNY})$		-0.151** (0.0661)		-0.135** (0.0680)		-0.0174 (0.0975)
$\ln(\text{skilled population})$			-0.112** (0.0500)	-0.0906** (0.0453)	-0.843*** (0.272)	-0.844*** (0.271)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	2.363	2.363	2.363	2.363	2.363	2.363

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Outcome: ln(share of secondary sector in GDP)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.00509*** (0.00123)	-0.00498*** (0.000945)				
ln(population)	-0.0672 (0.0414)	-0.0757** (0.0328)	-0.0999*** (0.0357)	-0.0921*** (0.0306)	0.180 (0.125)	0.160 (0.104)
ln(K stock, billion CNY)		0.138*** (0.0189)		0.141*** (0.0197)		0.199*** (0.0405)
ln(skilled population)			0.00899 (0.0261)	-0.0138 (0.0224)	-0.395*** (0.140)	-0.383*** (0.105)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	3.858	3.858	3.858	3.858	3.858	3.858

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Outcome: ln(share of tertiary sector in GDP)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	0.00230*** (0.000853)	0.00225*** (0.000787)				
ln(population)	-0.147*** (0.0438)	-0.143*** (0.0419)	-0.148*** (0.0402)	-0.152*** (0.0401)	-0.259*** (0.0888)	-0.250*** (0.0811)
ln(K stock, billion CNY)		-0.0617*** (0.0199)		-0.0667*** (0.0202)		-0.0892*** (0.0255)
ln(skilled population)			0.0183 (0.0181)	0.0291 (0.0182)	0.178** (0.0789)	0.173** (0.0675)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	3.585	3.585	3.585	3.585	3.585	3.585

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Using bounded outcome variables, like GDP ratios of the three sectors in percentages (ranging from 0 to 1, or from negative infinity to 1 after taking the logarithm), can introduce potential issues. Logarithms may not accurately represent the true error distribution, affecting the validity of statistical inferences. To address this, I use the logit function to transform percentages and mitigate potential problems: $\text{logit}(s) = \ln\left(\frac{s}{1-s}\right)$. Results are shown in Table 2.7, Table 2.8 and Table 2.9. All of the coefficients of interest remain the same sign and statistically significant. For the main outcome of interest, the last column in Table 2.7 shows that a 1% increase in college educated population reduces the odds ratio of share of the primary sector in GDP by 0.764%. The last column in Table 2.8 shows that a 1% increase in college educated population reduces the odds ratio of share of the primary sector in GDP by 0.698%. Likewise, Table 2.9 shows that a 1% increase in college educated population increases the odds ratio of share of the primary sector in GDP by 0.455%.

Table 2.7: Outcome: logit(share of primary sector in GDP)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.00979*** (0.00261)	-0.00994*** (0.00276)				
ln(population)	0.268 (0.311)	0.280 (0.319)	0.304 (0.315)	0.294 (0.317)	0.743* (0.416)	0.751* (0.422)
ln(K stock, billion CNY)		-0.200*** (0.0693)		-0.183** (0.0705)		-0.0785 (0.0945)
ln(skilled population)			-0.126** (0.0565)	-0.0963* (0.0499)	-0.759*** (0.259)	-0.764*** (0.264)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	-2.082	-2.082	-2.082	-2.082	-2.082	-2.082

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Outcome: logit(share of secondary sector in GDP)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.00900*** (0.00213)	-0.00880*** (0.00163)				
ln(population)	-0.107 (0.0766)	-0.123** (0.0619)	-0.162** (0.0669)	-0.147** (0.0589)	0.331 (0.223)	0.294 (0.186)
ln(K stock, billion CNY)		0.260*** (0.0366)		0.266*** (0.0379)		0.367*** (0.0711)
ln(skilled population)			0.0112 (0.0465)	-0.0318 (0.0399)	-0.698*** (0.243)	-0.676*** (0.179)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	-0.0570	-0.0570	-0.0570	-0.0570	-0.0570	-0.0570

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Outcome: logit(share of tertiary sector in GDP)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	0.00587*** (0.00173)	0.00579*** (0.00154)				
ln(population)	-0.227*** (0.0721)	-0.221*** (0.0687)	-0.220*** (0.0674)	-0.227*** (0.0671)	-0.512*** (0.181)	-0.495*** (0.163)
ln(K stock, billion CNY)		-0.105*** (0.0300)		-0.115*** (0.0311)		-0.176*** (0.0516)
ln(skilled population)			0.0345 (0.0296)	0.0531* (0.0294)	0.455** (0.176)	0.445*** (0.146)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	-0.543	-0.543	-0.543	-0.543	-0.543	-0.543

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Employment in three sectors

In order to cast light on the mechanism of higher education's effect on structural transformation, a measurement of workers in three sectors is also used as an outcome. The workers measured by this variable in the yearbooks do not comprise all workers. It only includes people who work and get salary in urban units, which account for around half of the total labour force in the economy (For example, for the year 2016, the number is 46.9%). We can expect that this measurement is not representative of the entire economy of the sample, as the agricultural workers are not included. However, this is the best available measurement in the data.

I use the logarithmic number of workers in three different sectors to check the effect of college educated population on structural transformation in employment. Table 2.10 shows that building universities has a negative impact on the number of workers working in the primary sector. The fifth and the sixth column shows that a 1% increase in college educated population decreases the number of workers in the primary sector by -1% approximately.

Table 2.11 and Table 2.12 show the results of employment outcomes for the secondary and tertiary sectors. For the secondary sector, a 1% increase in college educated population increases the number of workers by 0.727% while for the tertiary sector the number is 0.747%.

Results for the logarithmic share of workers in the first sector are reported in the Appendix Table A26. The first two columns indicate that one extra university corresponds to approximately an expected decrease in share of workers in primary sector of 2.5%. And the 2SLS results show that the elasticity between skilled population and share of workers in primary sector is -1.9, i.e. an expected 1.9% decrease in share of workers in primary sector when college educated population increases by 1%.

Results for the logged share of workers in the secondary and tertiary sector are reported in the Appendix in Table A27 and Table A28. The elasticities are both negative and statistically insignificant.

Table 2.10: Outcome: ln(no. of workers in sector 1)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.0132** (0.00566)	-0.0136** (0.00585)				
ln(population)	1.152*** (0.287)	1.184*** (0.263)	1.287*** (0.264)	1.260*** (0.248)	1.794*** (0.404)	1.830*** (0.403)
ln(K stock, billion CNY)		-0.530*** (0.166)		-0.494*** (0.167)		-0.364** (0.179)
ln(skilled population)			-0.294* (0.167)	-0.214 (0.147)	-1.025** (0.447)	-1.047** (0.467)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	9.410	9.410	9.410	9.410	9.410	9.410

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Outcome: ln(no. of workers in sector 2)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	0.00948*** (0.00283)	0.00947*** (0.00286)				
ln(population)	0.780*** (0.110)	0.781*** (0.109)	0.739*** (0.114)	0.737*** (0.114)	0.319 (0.232)	0.332 (0.229)
ln(K stock, billion CNY)		-0.0127 (0.0434)		-0.0359 (0.0436)		-0.128* (0.0652)
ln(skilled population)			0.130*** (0.0488)	0.136*** (0.0483)	0.736*** (0.228)	0.728*** (0.235)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	12.31	12.31	12.31	12.31	12.31	12.31

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: Outcome: ln(no. of workers in sector 3)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	0.00974*** (0.00161)	0.00969*** (0.00162)				
ln(population)	0.800*** (0.0907)	0.804*** (0.0913)	0.816*** (0.0960)	0.812*** (0.0972)	0.326 (0.229)	0.345 (0.221)
ln(K stock, billion CNY)		-0.0677** (0.0317)		-0.0794** (0.0342)		-0.186*** (0.0663)
ln(skilled population)			0.0496* (0.0288)	0.0624** (0.0266)	0.756*** (0.194)	0.745*** (0.178)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	12.31	12.31	12.31	12.31	12.31	12.31

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.3 Additional outcome: capital stock

The capital-skill complementarity hypothesis posits a stronger correlation between capital and skilled labour in the production process compared to the correlation between capital and unskilled labour. In other words, physical capital is more complementary to skilled labour than to unskilled labour. To verify the complementarity between capital and skilled labour using this paper's setup, I use the capital stocks as the outcome as in equation 2.7. The 2SLS specification is given by equation 2.8 and equation 2.9. Results are reported in Table 2.13. The first column reports that having one extra university is correlated with a 40.82 billion Chinese Yuan increase in capital stock after four years. And the third column shows that an increased skilled population leads to a larger increase in capital stock compared to the total population. In my sample, a one million increase in college educated population leads to a 1387 billion Chinese Yuan increase in capital stock.

This positive coefficient of college educated population indicates complementarity between skilled labour and capital. By construction, the entire population consists of the sum of the population with higher education and the one without. If the skilled population variables in the 2SLS regressions are replaced by the unskilled population, the coefficients of the skilled population variable are with the exact same magnitudes but with negative signs. Equivalently, a one million increase in population without higher education leads to a 1387 billion Chinese Yuan decrease in capital stock.

$$K_{it} = \xi_0 + \xi_1 no_university_{i,t-4} + \xi_2 population_{it} + \mu_i + \tau_t + u_{it} \quad (2.7)$$

$$Skilled_population_{it} = \delta'_0 + \delta'_1 no_university_{i,t-4} + \delta'_2 population_{it} + \alpha'_i + \gamma'_t + v'_{it} \quad (2.8)$$

$$K_{it} = \beta'_0 + \beta'_1 \widehat{Skilled_population}_{it} + \beta'_2 population_{it} + \tilde{\alpha}'_i + \tilde{\gamma}'_t + e'_{it} \quad (2.9)$$

Table 2.13: The impact of college expansion on capital stock

	capital stock, billion CNY	skilled population, million	capital stock, billion CNY
number of colleges, 4th lag	40.82*** (7.484)	0.0294*** (0.00288)	
population, million	80.96** (37.91)	0.0396** (0.0161)	26.06 (26.77)
skilled population, million			1387.4*** (198.1)
Observations	3748	3748	3748
F-statistics	25.43	104.5	46.04

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5 Robustness Checks

2.5.1 Two-way fixed effects and differences-in-differences with dynamic treatment effects

For the two-way fixed effects empirical estimations so far in the paper, I assume that there is no dynamic nor heterogeneous treatment effect for the number of universities. This is a strong assumption as we can expect that building universities will have dynamic effects as they start to provide a consistent flow of supply of college graduates after being built. There is a large emerging literature tackling this identification problem. Here I use two different methods to check the robustness of the results for the first stage in the 2SLS regressions.

First, I use Callaway and Sant'Anna (2021)'s Difference-in-Differences (DiD) estimation allowing multiple time periods, variation in treatment timing, and when the "parallel trends assumption" holds potentially only after conditioning on observed covariates. The graph is shown as Figure 2.8, with the outcome being the logarithmic number of population with higher education. The treatment is defined as

the first treatment year, and in my analysis, I highlight the first positive change in university numbers in or after the year 2001, when the large increase in the university number starts. The figure shows that building universities produces dynamic increase in college graduates. This method has its drawback: it eliminates a lot of information about the college expansion by only keeping the first year when there is a positive increase in university numbers, no matter how large the increase is. It is also common that some places experience constant changes over several years and this method fails to exploit this information. Yet the graph results show that the first-stage results are robust when dynamic and heterogeneous effects are allowed using Callaway and Sant'Anna (2021)'s method.

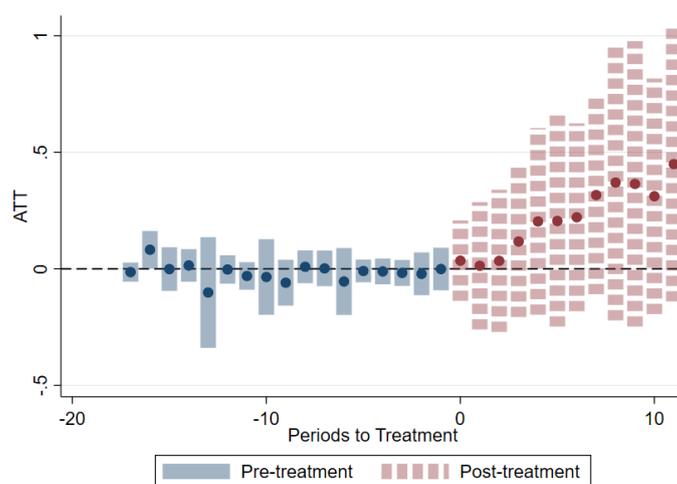


Figure 2.8: Dynamic treatment effects on $\ln(\text{skilled population})$, by Callaway and Sant'Anna (2021)

Second, I use the estimator suggested by De Chaisemartin and d'Haultfoeuille (2022). In this approach, the treatment can be non-binary, may not be absorbing, and its impact on the outcome might be influenced by its time lags. The method redefines the event as the first time a group's treatment changes (an increase in college number), which yields an event study graph in Figure 2.9 using my outcome (the logarithmic number of college educated population), with reduced-form estimates of the effect of having been exposed to a weakly higher amount of treatment for l periods, while controlling for population. The figure shows that college number has dynamic effects on the increase of university graduates, and the magnitude in general expands over the years. The magnitudes of the effects closely mirror the first stage results presented in Table 2.2 for the initial three years, and they progressively increase over time. The graph results show that the first-stage results are robust when dynamic and heterogeneous effects are allowed by using De Chaisemartin and d'Haultfoeuille (2022)'s method.

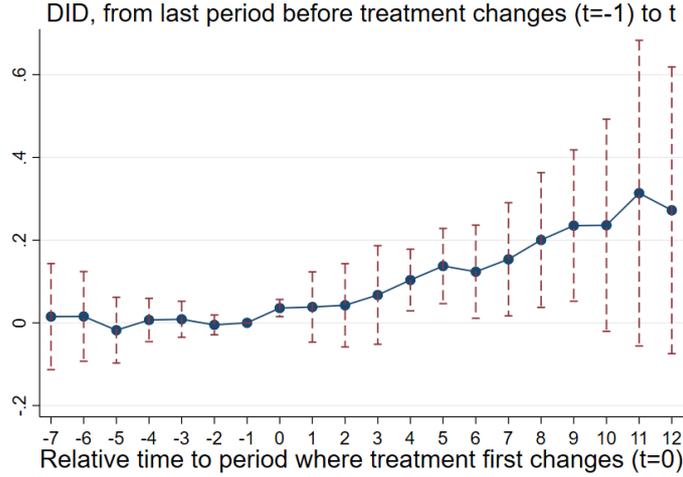


Figure 2.9: Dynamic treatment effects on $\ln(\text{skilled population})$, by De Chaisemartin and d’Haultfoeuille (2022)

2.5.2 Double/Debiased machine learning for estimating average treatment effects under unconfoundedness

Machine learning has emerged as a trending and powerful tool for making causal inferences, as highlighted by Athey and Imbens (2019). Using machine learning allows for more flexible identification of causal parameters by relaxing the assumption of a linear regression form in the data-generating process. For my study, I employ the double/debiased machine learning method proposed by Chernozhukov et al. (2018) as a robustness check for causal inferences. I choose the double/debiased machine learning method, because the method addresses potential issues with regularization bias in estimating causal parameters, a concern not adequately addressed by similar semi- or non-parametric estimations. To estimate the average treatment effects of the number of universities (ψ_1) in the reduced form equation 2.6, I include the logarithmic population and logarithmic capital stock as control variables, along with prefecture and year indicators. The double/debiased machine learning approach treats data analysis as an optimization problem, effectively balancing the covariates included in the regression specifications. The method also allows for a partially linear model in the reduced form equation 2.6, i.e. the specification becomes equation 2.10, wherein $prefecture_i$ and $year_t$ serve as dummy indicators for different prefectures and years. Furthermore, equation 2.11 addresses confounding, specifically the dependence of the treatment variable on controls. Although this equation is not the main focus, it plays a crucial role in characterizing and removing regularization bias.

$$Y_{it} = \psi_1' no_university_{i,t-4} + g(population_{it}, K_{it}, prefecture_i, year_t) + \epsilon'_{it} \quad (2.10)$$

$$no_university_{i,t-4} = m(population_{it}, K_{it}, prefecture_i, year_t) + \epsilon_{it} \quad (2.11)$$

Similarly, for the 2SLS regressions, equation 2.12 and 2.13 are specified.

$$Y_{it} = \beta_1' \widehat{Skilled_population}_{it} + j(population_{it}, K_{it}, prefecture_i, year_t) + e'_{it} \quad (2.12)$$

$$no_university_{i,t-4} = h(population_{it}, K_{it}, prefecture_i, year_t) + \epsilon'_{it} \quad (2.13)$$

While estimating the partially linear specifications, I use various machine learners, including OLS, LASSO, random forest, and gradient boosting. It is also possible to stack all these learners during estimation. The results for specification 2.10 and 2.11 are presented in the Appendix, from Table A9 to Table A15, and for specification 2.12 and 2.13 in Tables A16 to Table A22. Remarkably, the results persist robustly in terms of magnitudes and significance levels. However, it is relevant to note a caveat concerning the standard errors presented in the tables. The double/debiased machine learning method estimates the outcome, treatment, and instrument variables specifications using the specified learners mentioned at the top of the tables. Then, OLS or 2SLS regressions are performed using the fitted values

obtained from the predictions of the estimated models. Since the last step regression employs fitted values that have different measurement errors from the observed data, the standard errors in the tables might not be accurate and could be upward biased. Caution should be exercised when interpreting the inferences.

2.6 A Cost and Benefit Analysis

A cost and benefit analysis is conducted to evaluate the expenditure of building universities, and the results are presented in Table 2.14. The first column indicates that, on average, having one extra university increases education expenditure by 0.228 billion CNY. The second column uses the same specification as the second column in Table 2.3. I redo the regression here to maintain the same sample with information on education expenditure. With the GDP level around its mean, the analysis shows that constructing one university increases the local GDP by 0.258 billion CNY after four years, suggesting a return of 30 million CNY per college built after four years compared to the expenditure. This further highlights the positive economic impact of investing in higher education.

Table 2.14: Cost and benefit analysis of college expansion

	education expenditure, billion	ln(GDP curr. p)
number of colleges	0.228*** (0.0660)	
number of secondary schools	-0.00856 (0.0102)	
number of primary schools	0.00102 (0.000690)	
population, million	2.215** (1.106)	
number of colleges, 4th lag		0.00338** (0.00161)
ln(population)		0.551*** (0.0790)
ln(K stock, billion CNY)		0.262*** (0.0307)
Observations	3111	3111
F-statistics	4.554	38.03
Mean of Dep. Variable	1.871	25.06

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.7 Conclusions

Exploiting the substantial college expansion policy in China since 1999, this paper reveals that the increase in the college-educated population, resulting from the construction and expansion of universities, has a significantly positive impact on GDP growth and structural transformation. My estimation indicates an elasticity of 0.3 between the population with higher education and GDP, as well as an elasticity of 0.173 between the population with higher education and the share of the tertiary sector in the economy. The study also uncovers evidence of complementarity between capital and skills. These results highlight the role that higher education plays in economic development by increasing human capital. Overall, the study provides further evidence supporting education's significance as a driving force behind economic development.

These findings from China have policy implications that may affect developing countries with low rates of higher education. Though substantial increase in capital can boost an economy, a skilled workforce is equally vital to complement physical capital for promoting economic growth and structural transformation. It is not feasible to create a counterfactual development scenario for China without the college expansion policy. However, my analysis of data from almost 200 prefectures over a span of nearly 30 years provides compelling evidence that the expansion of higher education, and thereby the increase of human capital, played a pivotal role in the rapid growth of the Chinese economy.

Chapter 3

Educational Inequality, School Attendance, and Labour Market Participation

3.1 Introduction

In developing countries, the impact of school infrastructure on human capital development remains an important question. Unequal access to education can exacerbate disparities in school enrollment rates, perpetuating educational inequality and restricting individuals' social and economic progress by hindering their employment prospects. This paper uses a large-scale school merger policy in China as a natural experiment to assess the causal impact of school infrastructure on school enrollment and on the local labour market. I find that reductions in school infrastructure have a detrimental effect on school enrollment rates, simultaneously leading to a decrease in local employment rate.

To explore the causal relationship between school infrastructure and its impact on educational and economic outcomes, a significant methodological challenge arises due to the non-random allocation of schools across different regions. To address this challenge, this study exploits an unconventional large-scale negative shock that occurred on the supply side of primary and secondary education in China. The figure of number of secondary schools per million people in China is shown in Figure 3.1. Since the initiation of the policy in 2001, there has been a significant decrease in the number of secondary schools. Over the span of eleven years, there was an approximate 25% decline in the number of secondary schools per million people from 2001 to 2012 (approximately a decline of 15,000 in secondary school numbers). These efforts made by local governments, driven by different goals of reducing expenditure and achieving political milestones, have led to geographical variations as exogenous factors influencing educational and economic outcomes. This policy of school closures and mergers provides a unique context to examine the effects of this distinct negative shock on school supply, which resulted in a decline in school enrollments and subsequent economic consequences.

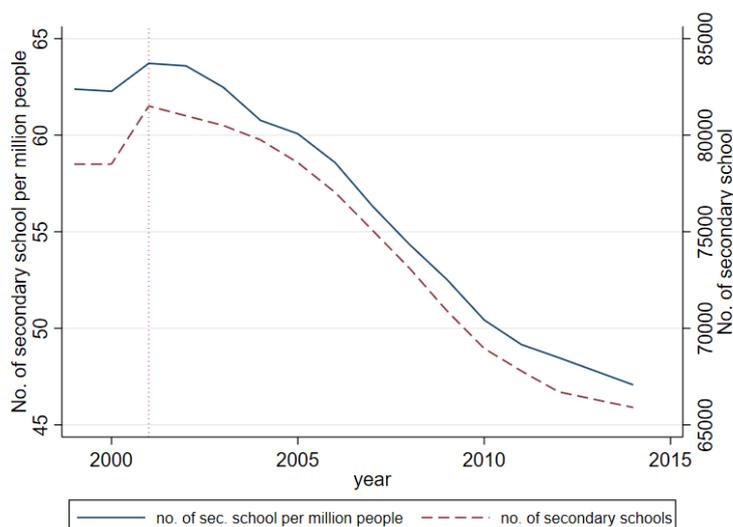


Figure 3.1: Number of secondary schools per million people in China, 1999-2014

Notes: Data is from Educational statistics yearbooks of China

Using data from the China City Statistical Yearbook spanning from 1999 to 2017, I estimate the causal effect of secondary school numbers on school enrollment rates and local employment rate at the prefecture level. The analysis leverages the variations in the reduction of school numbers, which are attributable to the heterogeneous responses of local governments to the policy directive issued by the central government. To address endogeneity concerns arising from the potential bidirectional relationship between school enrollment and employment in the labour market, a Two-Stage Least-Squares (2SLS) estimation technique is employed. Specifically, the number of enrolled students in secondary school is instrumented by the number of secondary schools. The underlying assumption is that the number of secondary schools can predict the number of students attending secondary school, while being uncorrelated with the error term after controlling eligible cohort size and population. I use this instrument in light of the shock induced by the school merger policy.

The findings show a significant relationship between changes in secondary school numbers and both secondary school enrollment rates and local employment. Specifically, the elasticity estimates suggest a 1% decrease in the number of secondary schools is associated with a 0.231% decrease in the secondary school enrollment rate; a 1% decrease in secondary school numbers corresponds to a 0.0383% decrease in the local employment. Moreover, using the 2SLS analysis, results show that a 1 percentage point decrease in enrollment in secondary schools leads to a 0.277 percentage point decrease in local employment.

In the literature, many papers have shown that increasing the availability of school infrastructure has a positive impact on school enrollment. Duflo (2001) examines the impact of school construction programs in Indonesia on educational outcomes and earnings. She finds positive effects of building schools. More specifically, each primary school constructed per 1,000 children led to an average increase of 0.12 to 0.19 years of education, as well as a 1.5 to 2.7 percent increase in wages. Similar positive effects of school supply have also been documented in other contexts. Birdsall (1985) combines household data with school availability measurements in Brazil and finds similar positive effects. Lillard and Willis (1994) leverages the rapid development of the school system in Malaysia to reach comparable conclusions. Lavy (1996) documents the positive impact of school supply on education attainment in Ghana. In general, studies investigating the impact of school supply on educational and economic outcomes rely on variations resulting from positive shocks associated with social and economic development.

The economic literature extensively examines the impact of education on economic outcomes. Woessmann (2016) provides a comprehensive overview of empirical studies that demonstrate the positive economic effects of education. Methodologically, establishing a causal relationship between education and economic outcomes poses challenges due to the potential endogeneity of educational attainment indicators, which are often influenced by unobserved abilities. An early contribution in addressing this endogeneity issue is the study by Angrist and Krueger (1991), which quantitatively investigates the impact of compulsory schooling on earnings using the quarter of birth as an instrumental variable for education. Subsequently, a growing body of literature has emerged, aiming to identify the causal effect of education on economic outcomes. In this context, the aforementioned study by Duflo (2001) makes

a significant contribution to the research literature by employing a two-way fixed effect approach and leveraging a natural experiment to identify the positive impact of educational attainment on labour market performance.

There is a body of literature examining the implications of school consolidation and school size. Noteworthy among these works is Berry (2006), which delves into the school consolidation policies implemented in the United States from 1930 to 1970. The study finds little evidence to suggest that the movement towards school consolidation influenced measures of inequality. Berry and West (2010) extends the investigation, employing reduced form estimations to corroborate that students from states with larger schools experienced diminished wages in their later lives. Moreover, their research underscores that any gains stemming from district consolidation were heavily outweighed by the detrimental consequences of larger schools. Across global contexts, Abalde (2014) offers a comprehensive literature review on similar policies in America, Asia, Europe, and Oceania. Generally, the exploration of school size's impact on effectiveness and efficiency, as well as the evaluation of consolidation outcomes, faces challenges due to the policy's limited scale, data constraints, and threats of endogeneity. In the specific case of China's school merger and closure policies, numerous Chinese studies document different aspects, however, little evidence of causal impact has been identified.

This paper contributes to the aforementioned three bodies of literature by providing more evidence on the causal impact of a school supply shock on educational outcomes. Leveraging a large-scale natural experiment in China that affected millions of children and adolescents, it stands out from existing research focused on positive school supply shocks. The findings reinforce the positive influence of school supply on both educational and economic outcomes by showing the consequences of a reverse case. This study also addresses a gap in the literature regarding causal identification for the effects of school consolidation on school enrollment and labour market outcomes.

3.2 Methods

3.2.1 Institutional setting

The natural experiment used in this study is a nationwide school merger and closure policy implemented at the beginning of the century in China. In May 2001, the State Council of the PRC announced the Decisions on Reform and Development of Basic Education, which introduced explicit instructions regarding school closures and mergers. These decisions aimed to improve the efficiency of educational resource distribution by adjusting the school layouts according to the local government's discretion. As a result, a significant number of school mergers and closures occurred across China. Both primary and secondary schools experienced considerable decreases, with large variations in terms of timing and locations. The geographical changes in school numbers at the prefecture level in China from 2001 to 2012 are depicted in Figure 3.2 and Figure 3.3. The figures illustrate that most regions witnessed a substantial decline in school numbers. Also, the changes in primary and secondary school numbers exhibited divergence, creating an additional source of variation.

This study exploits the geographical variation in school closures and mergers, which arises from the heterogeneous responses of local governments to the central government's announcement. A study by Lei and Jingmei Zhang (2010) examines 172 local policy texts and reveals that approximately half of them lacked specific instructions regarding the standards for adjustment. This indicates a decentralized policy implementation process, granting local authorities substantial discretion in determining the specific measures to be taken. Consequently, the lack of uniformity resulted in heterogeneity in the scale of school mergers and closures across different regions. Regarding the decision-making process of local governments, Pang and Han (2005) document that many regions formulated ambitious plans in response to the central government's policy initiation. Numerous local governments implemented clear policies aimed at rapidly reducing the number of schools. For instance, in 2001, Jiangsu Province announced a goal of reducing 10,000 primary and junior secondary schools before 2005. Similarly, Jiangxi Province declared in 2003 that the number of rural primary and secondary schools had been reduced by 5,000 in a single year, representing a 19% reduction rate, surpassing the target initially planned to be achieved in three years. Slogans such as "firmly close and merge the schools of small sizes" also emerged in various locations. These efforts by local governments motivated by political achievements have created geographical variations as exogenous factors influencing educational and economic outcomes.

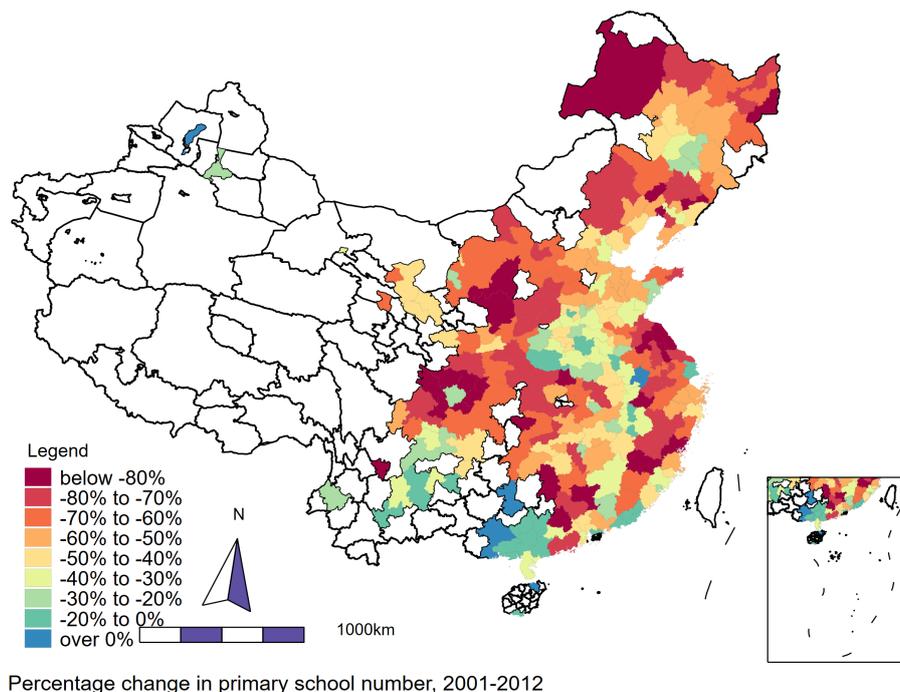


Figure 3.2: Percentage change in primary school number, 2001-2012

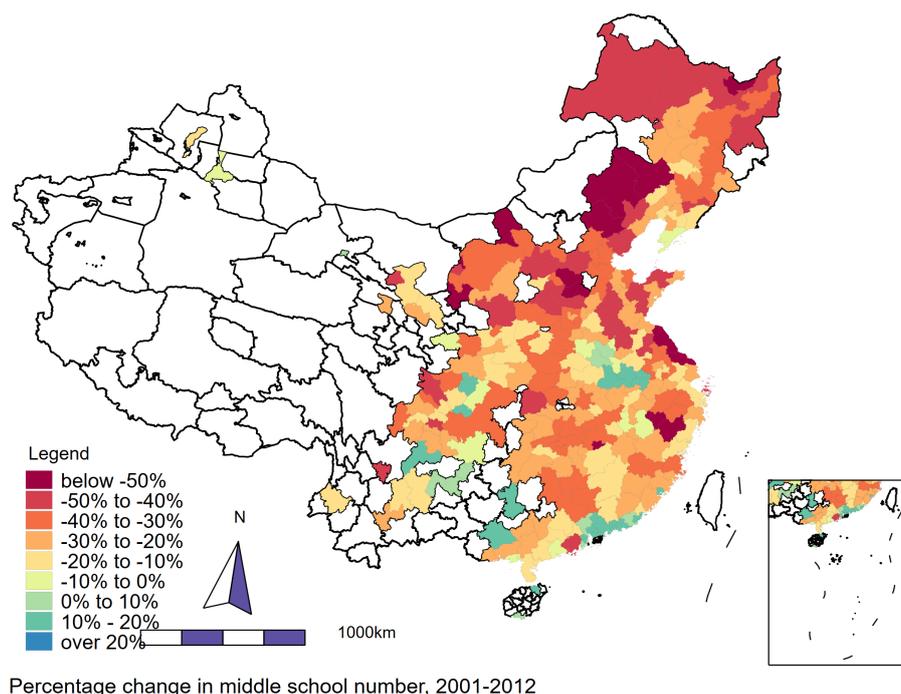


Figure 3.3: Percentage change in secondary school number, 2001-2012

The policy, which countered the global trend of education expansion, have three main motivations. First, it can be traced back to a rural tax reform initiated by the central government of China in 2000. This reform aimed to shift the financial responsibility from rural households to local governments, primarily at the county level. The objective was to alleviate the burden on rural households and place greater fiscal responsibility on local governments. To cope with the increased financial obligations, the policy suggested the closure or merger of rural schools to reduce the financial burdens faced by local governments. Driven by the goal of saving costs through more efficient management of smaller schools, local governments sought to reduce the number of schools. According to Z. Wu and Shi (2011), this shift in financial responsibility resulted in approximately 30% of the total rural expenditure in education being transferred from households to local governments. This substantial change in financial dynamics became the primary motivation for implementing school closures and mergers.

Another significant motivation was the decline in the number of new students within the eligible age group. In rural China between 2000 and 2010, the number of new primary school students decreased by 27%, from 12,537,476 to 9,151,503, despite a stable enrollment rate for primary schools. This decline can be primarily attributed to variations in the sizes of birthing cohorts, which resulted from the family planning policy implemented in China during the late 1970s and early 1980s. As the majority of children typically start attending school at the age of 6-7, the decrease in live births by 25% nationwide from 1993 to 2003 directly corresponds to the decline in new rural primary school students. Notably, the rate at which schools were decreasing exceeded the decline in student numbers, with the former being approximately twice as rapid. More specifically, the number of primary schools and teaching sites dropped from 597,803 to 267,341, a decrease of 55.3%.

The third motivation was to enhance education efficiency beyond achieving universal access to primary and secondary education. By 1999, primary and junior secondary school enrollment rates had reached approximately 90% and 85% of the national population in China, respectively, due to dedicated efforts to expand education access. In 2001, the State Council officially declared universal compulsory education in China. With universal access achieved, the focus shifted to enhancing overall education quality and efficiency. This shift enabled local governments to reorganize rural schools without excessive concern about enrollment rates. Nevertheless, ensuring universal access to education remained a vital national goal of the central government, with local governments bearing the responsibility of maintaining low dropout rates.

Why was there such a large number of schools to be merged? The substantial stock of primary and secondary schools available for merging can be attributed to the rapid development of the educational

system during the Cultural Revolution, particularly in rural areas. From 1962 to 1976, the enrollment rate for the eligible age group in primary schools increased significantly, rising from 56% to 97%. Moreover, among these primary school graduates, approximately 93% continued their education in secondary schools, which experienced a corresponding rise from 44%. Therefore, the accumulation of a large number of schools available for merging can be mainly attributed to the development of the educational system during the Cultural Revolution.

One might also wonder how the policy has been received by the public considering how substantial it is for millions of households. The rapid closures and mergers of schools faced substantial criticism from local residents and the media. This criticism stemmed from several factors, including the significantly larger scale of closures and mergers in relation to the reduction in student numbers and the lack of consideration given to the resulting increase in costs associated with accessing schools. These criticisms align with observed surges in school dropout rates, impacting many cohorts of students, as evidenced by multiple sources. According to statistics from the Education Ministry, the primary school dropout rate decreased from 24.77‰ in 1991 to 4.58‰ in 2000. However, from 2008 to 2011, the dropout rates increased to 5.99‰, 8.97‰, 8.22‰, and 8.89‰, by year respectively. Dropout rates in junior secondary schools are much higher, especially in rural areas. A survey conducted by Yuan et al. (2004) revealed that in the sporadic surveyed counties, dropout rates ranged from 3.66% to 54.05%. The No.2 Report published by the National Audit Office of the PRC in 2013 found a 112.8% increase in dropout cases from 2006 to 2011 in intensively surveyed counties due to school closures and mergers.¹ The speed and the magnitude of these changes, along with the adverse effects on students and communities, contributed to the discontent and concerns raised by the stakeholders.

3.2.2 Data and outcomes of interest

The data utilized in this study is sourced from the China City Statistical Yearbook, covering the years 2000 to 2017. As the yearbooks represent data from the preceding year, the analysis encompasses the period from 1999 to 2016. The manually coded data focuses on the prefecture level, including information from approximately 200 cities out of the 259 prefecture cities that existed in China in 2000. It should be noted that the missing prefectures primarily consist of autonomous administrative divisions associated with ethnic minorities. These regions differ from the majority of China in terms of their geographical location, smaller populations, and lower population densities.

To ensure consistency in the analysis, only samples with complete data for all the main variables used are retained (sample size is 4262), given that the original yearbook data may have instances of missing variables across different years. The data is considered representative as it includes approximately 50% of the entire Chinese population, with this percentage reaching 50.8% in 2000. For detailed summary statistics, please refer to Table 3.1.

Table 3.1: Summary statistics

	Mean	SD	Min	Median	Max	N
population, million	4.33	3.01	0.15	3.70	33.75	4262
no. of secondary school students, million	0.25	0.18	0.01	0.21	1.92	4262
no. of primary school students, million	0.34	0.25	0.01	0.28	2.78	4262
no. of secondary schools	234.24	150.60	9.00	204.00	1564.00	4262
no. of primary schools	951.92	843.88	18.00	738.00	10966.00	4262
average secondary school size, students	1068.25	284.50	342.13	1033.58	2438.16	4262
average primary school size, students	474.04	326.53	57.87	374.48	3305.08	4262
no. of secondary school per million people	56.94	15.01	22.24	54.71	140.75	4262
no. of registered unemployed population	25330.30	29395.22	918.00	18570.50	316138.00	4262
number of registered employed workers, million	0.51	0.75	0.04	0.32	9.87	4262
secondary school enrollment rate, %	67.68	13.13	25.71	66.82	169.90	4262
employment rate, %	94.25	3.25	61.83	94.74	99.71	4262

¹It is worth mentioning that although the Compulsory Education Law of the PRC holds guardians responsible for children who drop out of primary or junior secondary school, specific punishments for failure to fulfill this obligation are not specified. This lack of enforcement contributes to the presence of dropout rates in both junior secondary and primary schools, preventing them from reaching zero.

School enrollment rates

There is no direct measurement of the secondary school enrollment rates in the data. I employ the variables “current students in secondary school” and “current students in primary school” to construct an estimate of the enrollment rates for secondary school. In China, primary school typically lasts for six years, and secondary school (comprising both junior and senior secondary schools, three years each) also spans six years. To approximate the secondary school enrollment rate for prefecture i in year t , I calculate it as follows:

$$\text{enrollment rate}_{i,t} = \frac{\text{secondary school students}_{i,t}}{\text{primary school students}_{i,t-6}}$$

To illustrate this, consider the case where $t = 1999$. The variable “lag six of primary school students” corresponds to the number of primary school students in the year $t - 6 = 1993$. Assuming a 100% rate of continuous enrollment and no migrations, we would expect all these students to have progressed to secondary school by 1999. Nevertheless, the actual number is measured in the data by the variable “current students in secondary school”. Additionally, given the close-to-100% enrollment rate for primary school, the ratio between the two variables provides an approximation of the enrollment rate in secondary schools.

Based on the logic above, I include the sixth lag of the variable “current primary school students” as a control variable in my regressions when using the absolute number of middle students as an outcome. This control variable is essential for accounting for “demand-driven” changes, which refer to fluctuations in secondary school students resulting from variations in cohort sizes. By incorporating this control variable, I aim to mitigate the potential influence of cohort size changes on the observed outcomes in my regression analyses.

Local employment rates measurement

Similar to enrollment rates for secondary school, there is no direct measurement of employment rates. The universally accepted definition of the employment rate is the employment-to-population ratio, a statistical measure that gauges the proportion of a region’s working-age population (typically aged 15 to 64) that is gainfully employed. As there is no measurement available for the total employment and working age population in my dataset, I rely on two relevant variables present in the data, namely the “number of registered employed workers” and the “number of registered unemployed workers”. The sum of the two variables are therefore registered labour force. To approximate employment rates, I divide the first variable by the sum of the two.

My approach to measuring employment rates deviates from the standard employment-to-population ratio in two aspects. First, by using the sum of the unemployed and employed population as the denominator, my method exclusively includes individuals actively engaged in or seeking employment, namely, those within the labour force. Therefore, my employment rate measurement expresses the proportion of the labour force that is currently employed. Second, the inclusion of employed and unemployed workers in the variables presented in the yearbooks represents only a subset of the overall workforce, as indicated by the term “registered” in the variable names. This designation implies that these figures pertain specifically to individuals formally recognized or documented within the system, offering a more restricted perspective on workforce dynamics. Specifically, the number of employed workers encompasses individuals employed in urban or township units who receive a salary, constituting approximately half of the total labour force in the economy (e.g., 46.9% in 2016). Therefore, this measurement may not provide a comprehensive representation of the entire economy within the sample, as it excludes agricultural workers. In terms of the count of registered unemployed workers, it includes individuals above the age of 16 who are registered as unemployed at local offices and belong to the non-agricultural category. Similar to the measurement for employed workers, this figure does not encompass the entirety of the unemployed labour force.

Despite deviating from the standard definition of employment rates, this measurement can serve as an approximate indicator in the labour markets of urban and town areas for two reasons. First, while using the labour force as the rate denominator, I include regional fixed effects in my regression analysis to control for regional time-invariant population structures. Although, adherence to the standard definition still requires assuming homogeneity in working age population dynamics across prefectures. Second, the registered labour force remains a consistent measurement in my dataset, which can be a uniform assessment of employment across urban and town areas. As a lot of the school mergers happen in

more rural areas, using this measurement can underestimate the impact of school consolidations on employment.

3.2.3 Identification Strategy

To quantify the causal effect of the (logarithmic) number of secondary schools on the rates (or logarithmic numbers) of secondary school students enrollment, I use the equation 3.1, for prefecture i in year t . Throughout the subsequent specifications, I use the abbreviations “SS” to represent the secondary school number and “PS” to represent primary school.

$$enrollment_{i,t} = \delta_0 + \delta_1 \ln(SS_{i,t}) + \delta_2 \ln(PS_students_{i,t-6}) + \delta_3 \ln(population_{i,t}) + \alpha_i + \gamma_t + v_{i,t} \quad (3.1)$$

Two control variables are included in the specifications. First, as previously mentioned, I incorporate the logarithmic sixth lag of the variable “current primary school students” $PS_students_{i,t-6}$ as a control variable in my regressions to address demand-driven changes resulting from fluctuations in cohort sizes. Under the assumption that there is no migration of students across different prefectures before they complete secondary school, this control variable provides an accurate measurement of the expected cohort size for secondary school enrollment, assuming a 100% enrollment rate in primary school. Second, to account for potential migration effects, I relax the assumption of no migration by including the logarithm of the population, $\ln(population_{i,t})$, as an additional control variable. The population variable is expected to be positively correlated with both the number of secondary schools and the number of students in secondary school. By controlling population, I address the migration-induced co-movement between the number of schools and the number of students. This control allows for a more accurate estimation of the relationship between school numbers and student counts by accounting for the potential influence of population dynamics.

After verifying the relevance between the number of schools and students, the previous estimations can serve as the first stage regression within a Two-Stage Least Squares (2SLS) framework when analyzing employment (or unemployment) outcomes in the labour market. And the second stage is specified as equation 3.2, in which the variable $employment_{i,t}$ can represent the employment rate measurement, or logarithmic number of employed workers: $\ln(\text{no. of registered employed population})$.

$$employment_{i,t} = \beta_0 + \beta_1 \ln(\widehat{SS_students}_{i,t}) + \beta_2 \ln(PS_students_{i,t-6}) + \beta_3 \ln(population_{i,t}) + \tilde{\alpha}_i + \tilde{\gamma}_t + e_{i,t} \quad (3.2)$$

The exclusion restriction condition requires the instruments affect employment rates only through the number of students in secondary schools. Namely, the number of schools affect local employment only through the number of enrolled students. One potential violation is the number of school staffs that were laid off. The National Audit Office of the PRC documents that the majority of teachers were rehired in the merged schools, where more students and subjects were added. Therefore, this potential violation may not be a cause for concern.

One caveat to consider is the control variable “population”, as there is a potential impact of employment rates on population through migration. Including population as a control variable in the estimations may introduce bias due to this endogeneity. However, migration patterns influenced by employment rates can lead to changes in population size, which in turn could affect the number of secondary schools and students. In my 2SLS analysis, both specifications with population and without population are estimated. By comparing the results from both specifications, I can examine the potential impact of population on the estimated relationships and assess the robustness of the findings.

A reduced-form analysis could also be performed by regressing the number of secondary schools on employment outcomes as in equation 3.3.

$$employment_{it} = \psi_0 + \psi_1 \ln(SS_{i,t}) + \psi_2 \ln(PS_students_{i,t-6}) + \psi_3 \ln(population_{it}) + \tilde{\alpha}'_i + \tilde{\gamma}'_t + \varepsilon_{it} \quad (3.3)$$

In summary, the estimations can be illustrated by a causal graph as in Figure 3.4. The causal graph demonstrates how supply shocks of number of secondary schools can have an impact on employment rates, by affecting number of students in secondary schools.

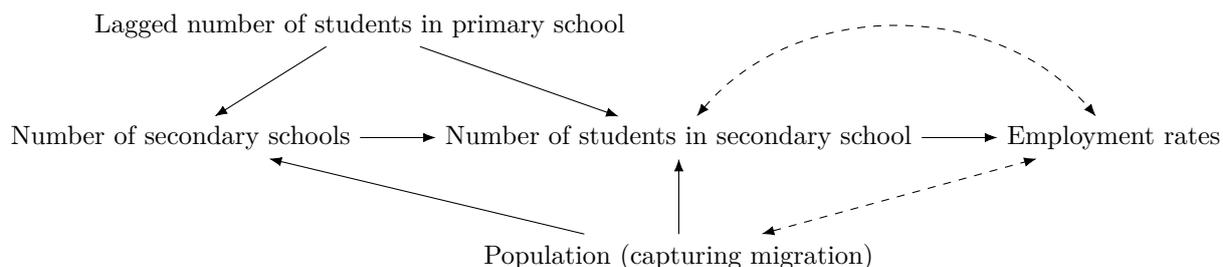


Figure 3.4: Causal graph of main education and employment outcomes

3.3 Results

3.3.1 Impact of secondary school numbers on school enrollment

First, I estimate how much the number of secondary schools affects students' enrollment of secondary school. The outcome is measured by the variable "number of current students in secondary school", and I report both of the original and logarithmic results in Table 3.2, using equation 3.1. I note that in the first two columns, I employ enrollment rates, and in the last two columns, I use logarithms of student numbers. Despite this difference, comparability is maintained. If I use logarithmic enrollment rates in the last two columns, it would still give identical coefficients for the number of secondary schools, because of the inclusion of lagged logarithmic primary students as a control variable. I avoid logarithmizing enrollment rates due to their bounded nature, which can cause bias in inference. Aligned with the outlined conceptual framework, the coefficients of our variables of interest have a positive sign, indicating a concurrent movement between the number of schools and the number of students. This result supports that increases or decreases in the number of schools directly relate to corresponding shifts in student enrollment. The findings in the second column indicate that a decrease of one percent of secondary school is associated with an expected reduction of $14.9/100 = 0.149$ percentage points in enrollment rate of secondary school, according to the interpretation of the coefficient of a semi-logarithmic (linear-log) model. The results in the last column present elasticity estimates, indicating that a 1% decrease in the number of secondary schools corresponds to a 0.231% decline in the number of secondary school students. I highlight that a significant majority of the samples in this estimation, specifically 3,161 out of 4,262 samples (74.2%), experienced a non-positive change in the number of secondary schools.

In order to contextualize my findings, I conduct a comparative analysis with existing literature through surveys in sporadic areas. From 2001 to 2012, the total number of secondary schools in China witnessed a decrease of around 25%. Based on the results of my study, this change corresponds to a reduction of $14.9 \times \ln((100 + 25)/100) = 3.32$ percentage point, which corresponds to an overall reduction of $25 \times 0.231 = 5.8$ percent in secondary school enrollment rates. Notably, Yuan et al. (2004)'s survey conducted in 2003 examined dropout rates in rural secondary schools within their surveyed counties, reporting a range of 3.66% to 54.05%. Drawing a parallel, I use my data to assess the changes in secondary school numbers during the same period. Among the surveyed locations, it was observed that 57.1% experienced a decline, 8.6% witnessed no change, and 38.6% observed an increase in secondary school numbers. Notably, the most substantial decline amounted to 100 to 140 schools. Using the coefficient from Table 3.2 in the second column, this decline corresponds to a percentage point decrease of 8.2% to 11.5% for school enrollment. Although these upper-bound numbers are much smaller than the documented dropout rates, it is consistent with the records from Yuan et al. (2004) for two reasons. First, I only identify the effect of changes in dropout rates due to changes in school numbers, which does not reflect the dropouts due to other reasons. Second, my analysis includes both rural and urban secondary schools, with rural areas having larger declines compared to urban areas, therefore, taking the average of the two will reduce the magnitude.

3.3.2 Impact of secondary school students on local labour market

Table 3.3 presents the reduced-form results examining the impact of the number of secondary schools on employment rates. The second column indicates that a reduction of one percent in secondary school is associated with a decrease of 0.04 percentage points in the local employment rate. The last column

Table 3.2: First stage, impact of secondary school numbers on school enrollment

	secondary school enrollment rate	secondary school enrollment rate	ln(secondary school students)	ln(secondary school students)
ln(no. of secondary school)	24.31*** (4.542)	14.90*** (2.862)	0.331*** (0.0524)	0.231*** (0.0469)
ln(primary school students, lag 6)	-27.11*** (2.421)	-30.23*** (2.317)	0.608*** (0.0349)	0.575*** (0.0333)
ln(population)		45.10*** (9.629)		0.481*** (0.0910)
Observations	4262	4262	4262	4262
Adjusted R-squared	0.702	0.725	0.978	0.979
Mean of Dep. Variable	67.68	67.68	12.19	12.19

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

shows an elasticity estimation, indicating that a 1% decrease in secondary school numbers corresponds to a 0.0383% decrease in the local employment rate.

Table 3.3: Reduced form, impact of school numbers on employment

	employment rate	employment rate	ln(no. of registered employed population)	ln(no. of registered employed population)
ln(no. of secondary school)	3.130*** (0.757)	4.125*** (0.833)	0.0263*** (0.00803)	0.0383*** (0.00894)
ln(primary school students, lag 6)	-1.577*** (0.460)	-1.248*** (0.450)	-0.0200*** (0.00496)	-0.0161*** (0.00485)
ln(population)		-4.767*** (1.291)		-0.0585*** (0.0140)
ln(no. of registered labour force)			1.020*** (0.00329)	1.020*** (0.00312)
Observations	4262	4262	4262	4262
Adjusted R-squared	0.543	0.548	0.999	0.999
Mean of Dep. Variable	94.25	94.25	12.74	12.74

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4 presents the results of the 2SLS regressions, controlling for population. The last column indicates that a 1 percentage point decrease in secondary school enrollment rates is associated with a 0.277 percentage point decrease in local employment rates.

These findings highlight the significant influence of secondary school enrollment changes on local labour market dynamics, emphasizing the crucial role of education in shaping employment outcomes.

3.3.3 Impact of primary school closures on primary school dropouts

I also examine the influence of primary school numbers on enrolled primary school students, as presented in Table 3.5. Notably, a vast majority of the samples, specifically 3,910 out of 4,262 samples (91.7%), observe a decrease in the number of primary schools compared to the previous year. Due to the absence of a measurement to control for the changes in cohort sizes, the magnitudes of the results may be upward biased. The findings show significant positive correlations, albeit with lower magnitudes, indicating a

Table 3.4: 2SLS, impact of enrollment on employment rates, %

	First stage	Second stage	First stage, w/control	Second stage, w/control
ln(no. of secondary school)	24.31*** (4.542)		14.90*** (2.862)	
ln(primary school students, lag 6)	-27.11*** (2.421)	1.913** (0.855)	-30.23*** (2.317)	7.123*** (2.145)
secondary school enrollment rate		0.129*** (0.0433)		0.277*** (0.0782)
ln(population)			45.10*** (9.629)	-17.26*** (5.165)
Observations	4262	4262	4262	4262
F-statistics	28.66	4.782	27.08	4.375

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

decrease in primary enrollment rates that is not as substantial as in secondary schools. These results align with the documented patterns of dropout rates in both primary and secondary schools.

Table 3.5: Impact of primary school numbers on student numbers

	primary school students	primary school students	ln(primary school students)	ln(primary school students)
no. of primary school	91.75*** (10.71)	95.20*** (11.80)		
population		0.0461*** (0.0159)		
ln(no. of primary school)			0.222*** (0.0239)	0.124*** (0.0186)
ln(population)				1.254*** (0.130)
Observations	4262	4262	4262	4262
Adjusted R-squared	0.949	0.951	0.968	0.974
Mean of Dep. Variable	337617.0	337617.0	12.47	12.47

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4 Mechanisms

The decrease in school density and the increase in school district size have been extensively documented as one of the main reasons for school discontinuation. The National Audit Office of the PRC conducted a large-scale survey in 2012, and their No.2 report in 2013 revealed that from 2006 to 2011, approximately 70% of the surveyed counties experienced a significant increase in the size of school districts as a result of school closures and mergers. The radii of junior secondary school districts increased by 26% to 8.34 km, while the radii of primary school districts increased by 43% to 4.23 km. These larger school districts imposed additional costs on many students in terms of travel distance and commuting expenses, especially in some remote rural areas where schools are less available. In addition to the rise in transportation costs, dropout rates may increase due to safety concerns during the commute, particularly among girls. For example, a study by Yang (2009) conducted in rural Guizhou Province, China, found that parents

expressed concerns regarding the safety of their children, especially girls, which led to high dropout rates in primary and junior secondary school. Furthermore, a larger number of students discontinue their education after finishing junior secondary school. This may also be attributed to the elevated distances, resulting in higher time and monetary expenses when commuting to senior secondary schools as evidenced by Zhao and Fan (2011).

In addition to dropouts resulting from longer commuting distances, school mergers can also contribute to increased dropout rates due to the disruption of students' learning environment. Chinese citations such as L. Ma and W. Feng (2014) and W. Liu (2015) have documented a pattern of augmentation in class sizes subsequent to the augmentation in school sizes after the school mergers and closures. In the economic literature, the impact of class sizes on varied outcomes is extensively explored. Early studies, exemplified by Angrist and Lavy (1999) and Krueger (1999), highlight a substantive and favorable effect resulting from class size reduction. Conversely, papers by Hanushek (2006) and Duflo, Dupas, and Kremer (2011) report negligible influence. More recently, studies including De Giorgi, Pellizzari, and Woolston (2012) and Fredriksson, Öckert, and Oosterbeek (2013) demonstrate a notable and positive effect of reduced class size on both educational and economic outcomes. In addition, new classmates, and teachers can make it challenging for students to readjust, which can lead to an increased likelihood of students discontinuing their studies.

The decrease in school enrollment can affect employment rates through two channels. First, individuals who discontinue their education and enter the labour market create a positive shock to the labour supply, leading to a decline in employment rates under the assumption that new vacancies don't adjust fully. Second, consistent with findings by Riddell and Song (2011), individuals who prematurely leave school have lower human capital, making it more challenging for them to be employed. In my research, using prefecture-level data, it is not possible to identify specific individuals who become unemployed after the policy implementation. Therefore, the change in employment rates reflects the combined effect of both these mechanisms.

3.5 Robustness Checks

3.5.1 Two-way fixed effects and differences-in-differences with dynamic treatment effects

In this paper's two-way fixed effects empirical estimations, I've assumed the absence of both dynamic and heterogeneous treatment effects related to the number of secondary schools, when there are different treatments across regions and over time. However, this assumption is strong, considering that reductions in secondary school numbers can likely have dynamic effects across multiple cohorts. To address this, I employ two methods to assess the first-stage results' robustness in the 2SLS regressions.

I first use Callaway and Sant'Anna (2021)'s Difference-in-Differences estimation, which accommodates multiple time periods, varying treatment timings, and assumes the parallel trends potentially after conditioning on observed covariates. Figure 3.5 illustrates the outcome, which is the logarithmic count of current secondary school students, after controlling for the sixth lag of primary school students. The treatment is defined as the initial treatment year, which is when a place encounters a reduction in secondary school numbers exceeding 4 (within my dataset, approximately 32% of the samples depict a reduction in school numbers larger than 4), either in or after the year 2001 (the year when policy was initiated). The graph demonstrates that such reductions lead to a dynamic and significant decline in student numbers. However, this approach has a drawback: there is information loss regarding ongoing changes over multiple years in some areas, as it retains only the first significant decline in school numbers. This could result in an overestimation of the effects' magnitudes, given the consistent decrease in school numbers following the initial defined treated year. Despite this limitation, the graph's outcomes show the first-stage results' robustness even in the presence of dynamic and heterogeneous effects.

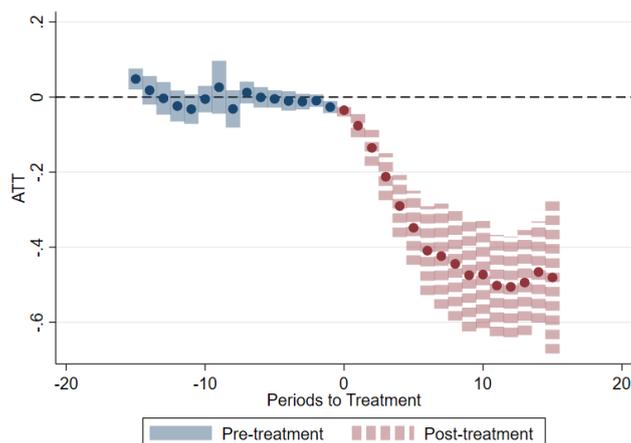


Figure 3.5: Dynamic treatment effects on $\ln(\text{student number})$, by Callaway and Sant'Anna (2021)

I also use the method by De Chaisemartin and d'Haultfoeuille (2022), suitable for panel datasets wherein groups may undergo multiple variations in their treatment exposure. I present an event study graph in Figure 3.6, using the logarithmic number of current secondary school students as the outcome variable. This graph displays reduced-form estimates of the effect resulting from an enlarged treatment intensity over l periods. The continuous treatment variable is defined as the negative of the secondary school number, ensuring that an increase in this variable corresponds to a reduction in the number of secondary schools. Due to limited control group samples where school numbers did not decrease, I redefine the event as the first instance of a group's treatment changing by more than 4 schools, aligning with the approach in Figure 2.8 for comparison. The graph illustrates that decreasing secondary school numbers leads to dynamic effects on the decline in secondary school student enrollment, with the magnitude increasing over time.

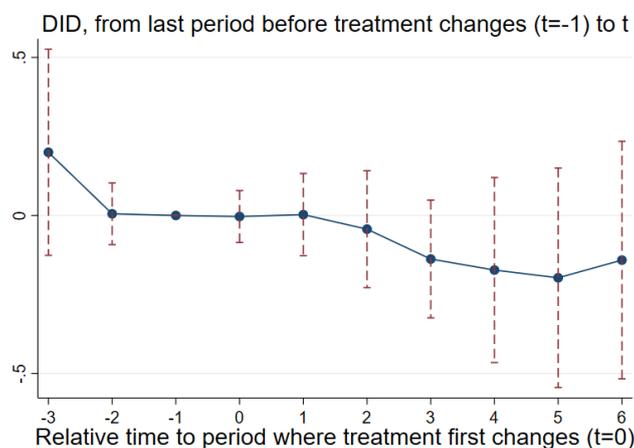


Figure 3.6: Dynamic treatment effects, $\ln(\text{student number})$, De Chaisemartin and d'Haultfoeuille (2022)

3.5.2 Heterogeneous effects for regions with non-positive changes in school numbers

To address the concern that the observed changes may be primarily driven by a few places experiencing an increase in school supplies, I conduct a regression analysis focusing only on samples that do not experience a positive change in school numbers compared to the previous year. The results, shown in Table 3.6, demonstrate the robustness of the findings. Out of 4,262 samples, 3,161 (74.2%) experienced a non-positive change in secondary school numbers. The effects remain statistically significant, and the magnitudes are slightly larger, providing further support to the conclusions.

Table 3.6: First stage, impact of secondary school numbers on enrollment rates (only samples with decreased/unchanged no. of secondary schools per million people)

	secondary school enrollment rate	secondary school enrollment rate	ln(secondary school students)	ln(secondary school students)
ln(no. of secondary school)	26.83*** (4.675)	17.57*** (3.302)	0.371*** (0.0572)	0.273*** (0.0545)
ln(primary school students, lag 6)	-25.94*** (2.312)	-28.41*** (2.163)	0.621*** (0.0364)	0.594*** (0.0349)
ln(population)		46.00*** (8.453)		0.485*** (0.0759)
Observations	3161	3161	3161	3161
Adjusted R-squared	0.718	0.739	0.978	0.979
Mean of Dep. Variable	67.69	67.69	12.22	12.22

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Conclusions and Policy Implications

In this paper, I have examined the impact of school mergers and closures on school enrollment rates and local employment in China. I have provided empirical evidence on the consequences of this large-scale school merger program. The findings indicate that the reduction in secondary schools resulted in a significant decrease in school enrollment rates, with a corresponding decline in local employment rates. For example, from 2001 to 2012, my estimations suggest a decrease of 5.8 percent in secondary school enrollment due to the program, which corresponds to a 1.6 percent decrease in local employment rates. The results of this study highlight the importance of education infrastructure in shaping educational and employment outcomes. These findings contribute to the understanding of the linkages between education and labour market outcomes in the context of educational reforms.

The paper has significant implications for the exacerbation of inequality in China. Given that education is often recognized as a key driver of social mobility, the decline in school numbers increases heterogeneity in access to education. This increased disparity poses barriers to upward mobility in socioeconomic positions for many individuals. As shown from the data and the discussion on mechanisms, the negative shock to access to secondary education disproportionately impacts children with lower family endowments. Their lower ability to cover the increased costs of attending school increases the challenges they face. Marginalized and disadvantaged groups, including those from low-income backgrounds, rural areas, or minority communities, may encounter barriers hindering their regular attendance at school. Also, the safety concerns of parents in remote areas regarding increased commuting times to school disproportionately impact girls more than boys. These factors collectively contribute to the exacerbation of inequalities along geographical, urban/rural, economic endowment, and gender dimensions in terms of educational and economic outcomes. Educational inequality, rooted in economic inequality, can reversely lead to and perpetuate economic inequality.

Conclusion

This dissertation underscores the profound impact of human capital investment on China's socio-economic landscape. Chapter 1's affirmative action analysis reveals its transformative impact on women's education, marriage choices, and labor market participation, highlighting its potential to promote gender equality and empower individuals. Chapter 2's examination of college expansion demonstrates a positive link between higher education and economic growth, emphasizing human capital's role in driving economic transformation. Finally, Chapter 3's investigation of school mergers sheds light on the complex interplay between education infrastructure, enrollment, and local employment, revealing ramifications associated with such reforms.

Collectively, these findings illuminate the critical role of human capital investment in shaping individual opportunities, economic prosperity, and societal progress. By promoting educational equity and expanding access to basic and higher education, policymakers can foster inclusive growth, enhance social mobility, and mitigate disparities.

Appendix

Table A1: Summary statistics: basic info and college degree attainment outcome

	Mean	SD	Min	Max	N
<i>Demographic</i>					
Hubei	0.051	0.219	0	1	273424
Female	0.495	0.500	0	1	273424
Rural	0.773	0.419	0	1	273424
Born in 1989-93	0.501	0.500	0	1	273424
<i>Education outcome</i>					
with a college degree	0.222	0.416	0	1	273424

Table A2: Summary statistics: main outcomes

	Mean	SD	Min	Max	N
<i>Marriage market outcome</i>					
Ever married	0.619	0.486	0	1	265125
Married now	0.605	0.489	0	1	265125
Ever given birth	0.389	0.488	0	1	192280
<i>Labor market outcome</i>					
Employed	0.773	0.419	0	1	265125
Employed or unemployed	0.834	0.372	0	1	265125
Employed, unemployed, or able	0.889	0.314	0	1	265125
Employed or studying	0.810	0.392	0	1	265125
Employed, unemployed, or studying	0.884	0.320	0	1	265125
Employed, unemployed, studying, or able	0.926	0.262	0	1	265125
Housekeeping only	0.090	0.286	0	1	265125
Employed in primary sector	0.324	0.468	0	1	205058
Employed as manager or skilled	0.172	0.377	0	1	204405

Table A3: Summary statistics: consumption outcomes

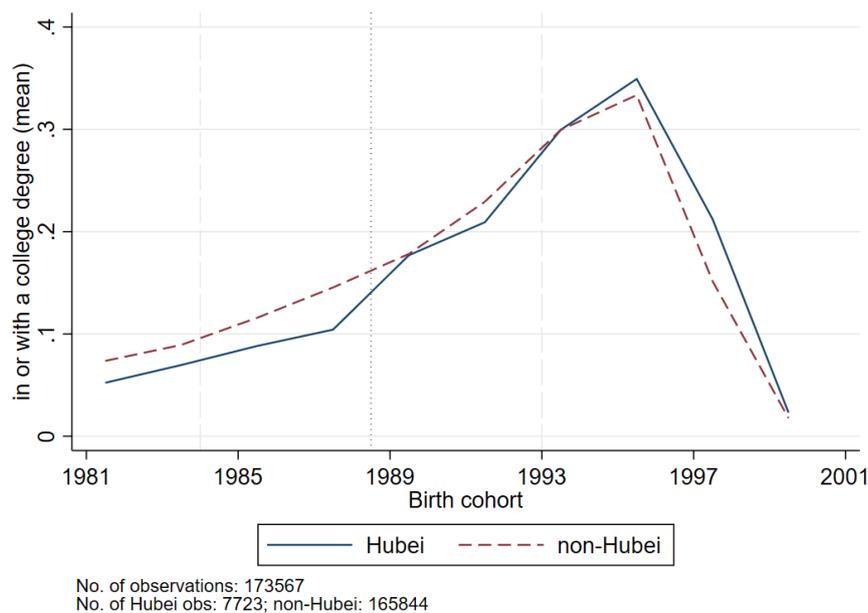
	Mean	SD	Min	Max	N
<i>Consumption outcome</i>					
House area by person	30.997	20.960	0.250	800.000	252328
Car in household	0.232	0.422	0	1	252328
Flushing toilet in household	0.539	0.498	0	1	252328
social health insurance	0.937	0.243	0	1	265125

Table A4: Summary statistics: impact on high school degree attainment

	Mean	SD	Min	Max	N
<i>Education outcome</i>					
with a high school degree	0.501	0.500	0	1	247839
<i>Demographic</i>					
Hubei	0.050	0.217	0	1	247839
Female	0.488	0.500	0	1	247839
Rural	0.780	0.414	0	1	247839
Born in 1993-97	0.419	0.493	0	1	247839

Table A5: Number of points for the policy and population of beneficiary

year	Points	Application number	Benefited number
2009	10	11566	3632
2010	10	13871	4208
2011	10	15406	3255
2012	10	15764	5729
2013	10	16347	6799
2014	10	15862	6509
2015	5	14517	3660
Sum	-	103333	33792

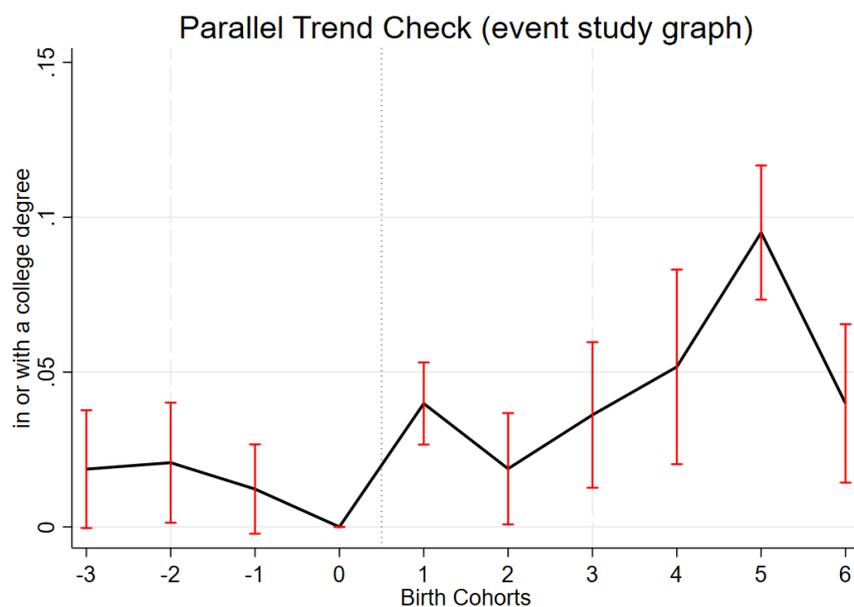


Notes: Cohorts are regrouped into every two years in order to reduce standard errors. For example, cohort 1989.5 in the graph includes birth cohorts 1989 and 1990. First treated cohort: 1989-1990.

Figure A1: In college or with a college degree: means collapsed by birth cohorts

Table A6: Regression of income on Gaokao admission score by university, monthly wage in Chinese Yuan

	2018 wage of graduates in 2013	2018 wage of graduates in 2015	2018 wage of graduates in 2017
Admission score	41.51***	35.02***	29.02***
2009 Hubei Gaokao	(10.23)	(10.28)	(10.13)
Observations	113	113	113



Notes: Cohorts are regrouped into every two years in order to reduce standard errors. First treated cohort: 1989-1990.

Figure A2: In college or with a college degree: event study

Table A7: 2SLS regression: marriage as 2nd stage

	with a college degree	Ever married
interact	0.0326*** (0.00347)	
with a college degree		-0.971*** (0.207)
Observations	100057	100057
F-statistics	88.18	21.93
Mean of Dep. Variable		0.722

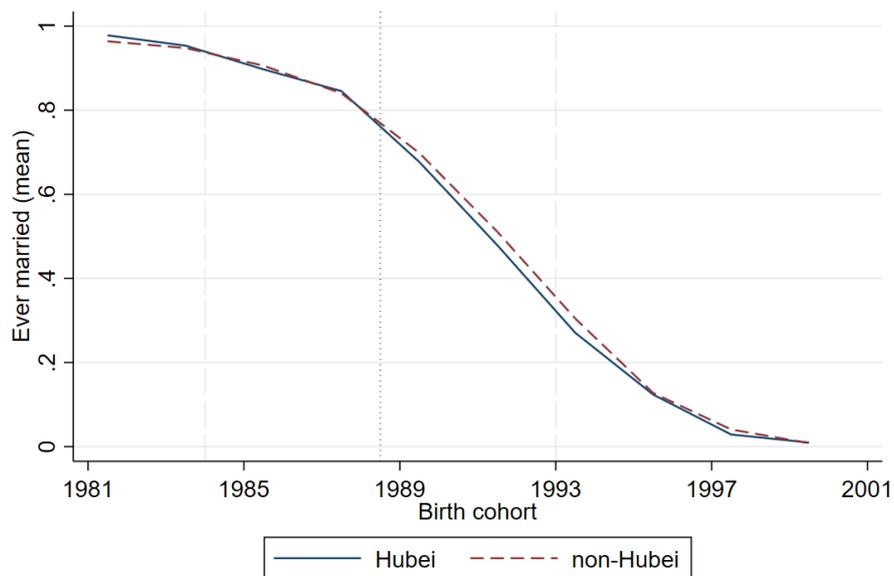
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: 2SLS regression: whether employed as 2nd stage

	with a college degree	Employed
interact	0.0326*** (0.00347)	
with a college degree		0.775*** (0.188)
Observations	100057	100057
F-statistics	88.18	16.98
Mean of Dep. Variable		0.694

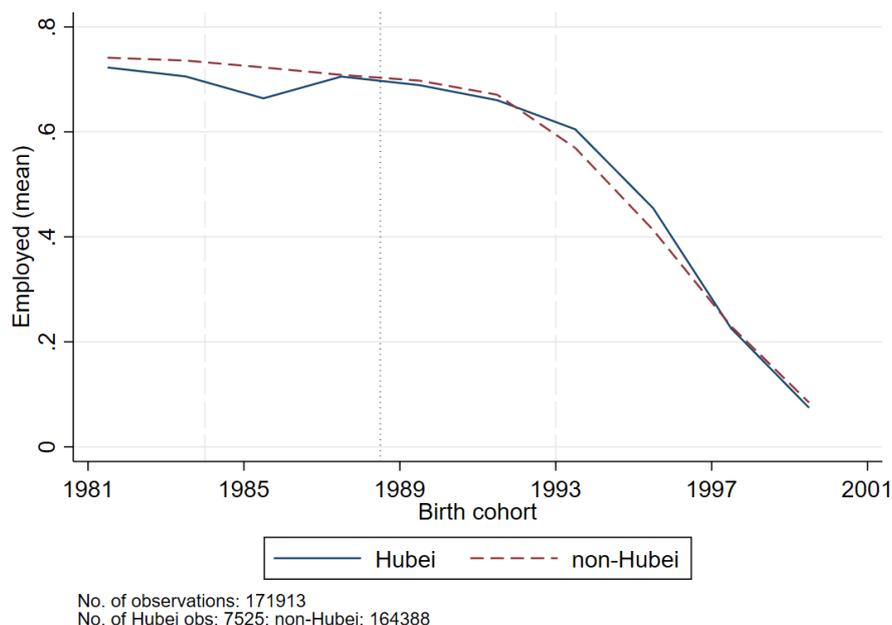
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ 

No. of observations: 171913
 No. of Hubei obs: 7525; non-Hubei: 164388

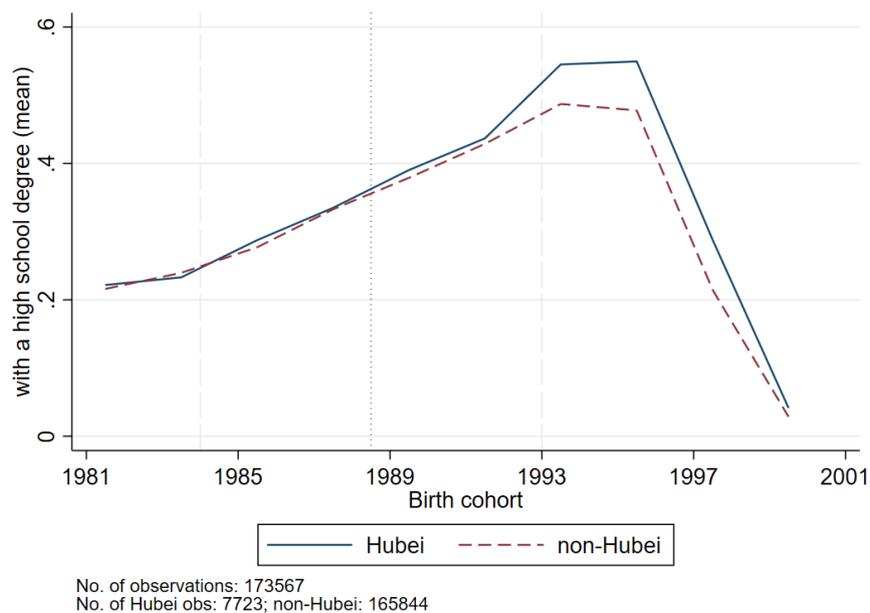
Notes: Cohorts are regrouped into every two years in order to reduce standard errors. For example, cohort 1989.5 in the graph includes birth cohorts 1989 and 1990. First treated cohort: 1989-1990.

Figure A3: Parallel trend check of being ever married: means by birth cohorts



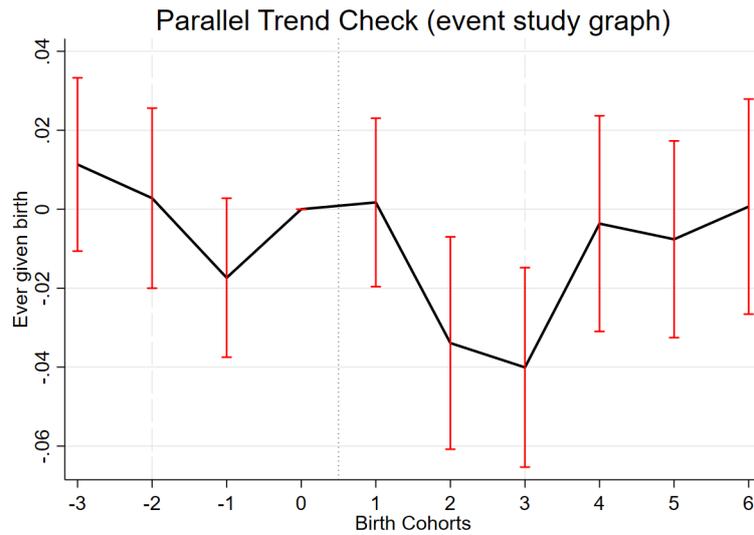
Notes: Cohorts are regrouped into every two years in order to reduce standard errors. For example, cohort 1989.5 in the graph includes birth cohorts 1989 and 1990. First treated cohort: 1989-1990.

Figure A4: Parallel trend check of being currently employed: means by birth cohorts



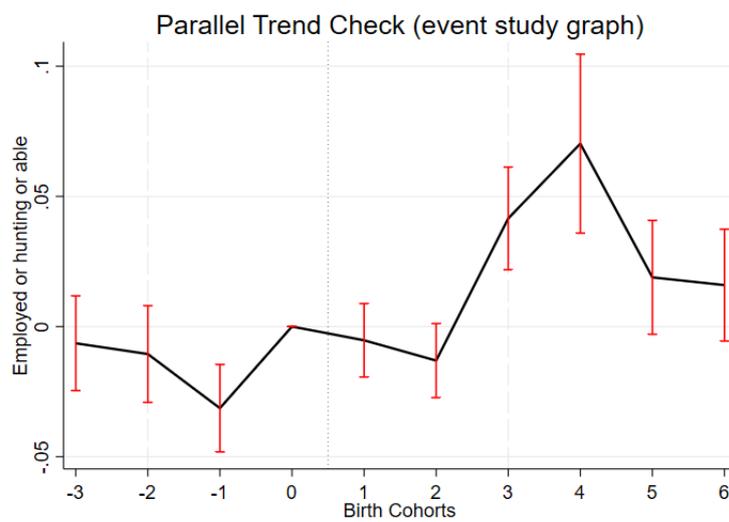
Notes: Cohorts are regrouped into every two years in order to reduce standard errors. For example, cohort 1989.5 in the graph includes birth cohorts 1989 and 1990. First treated cohort: 1993-1994

Figure A5: Parallel trend check of high school degree attainment: means by birth cohorts



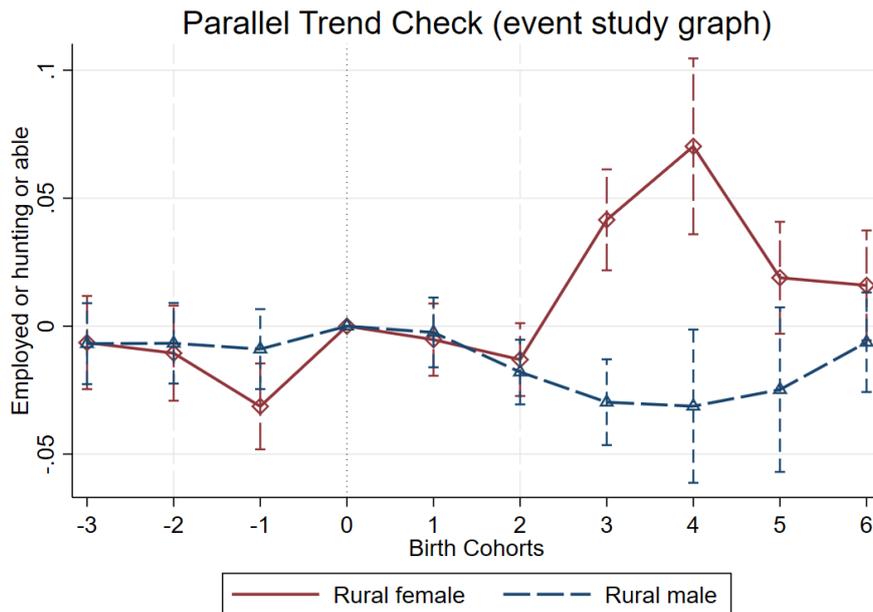
Notes: Cohorts are regrouped into every two years in order to reduce standard errors. First treated cohort: 1989-1990.

Figure A6: Event study of having ever given birth: by birth cohorts



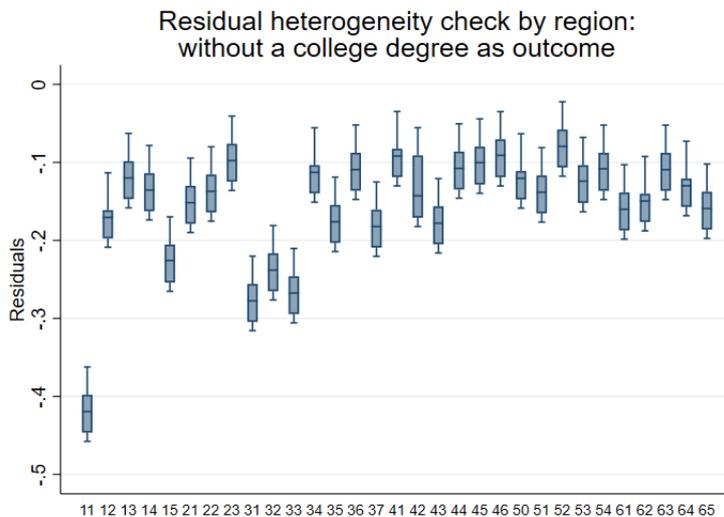
Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on 0.01 level.

Figure A7: Event study of being currently employed, hunting for jobs or able to work: by birth cohorts



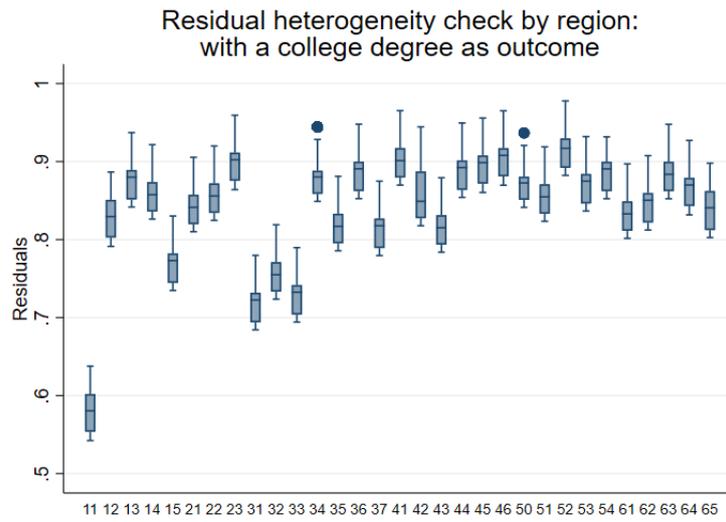
Notes: Cohorts are regrouped into every two years in order to reduce standard errors. Clustered standard errors are on 0.01 level.

Figure A8: Event study of being currently employed, hunting for jobs or able to work: by birth cohorts



Notes: The two digit codes are official Chinese provincial codes

Figure A9: Residual plot by province: dummy of college degree attainment = 0



Notes: The two digit codes are official Chinese provincial codes

Figure A10: Residual plot by province: dummy of college degree attainment = 1

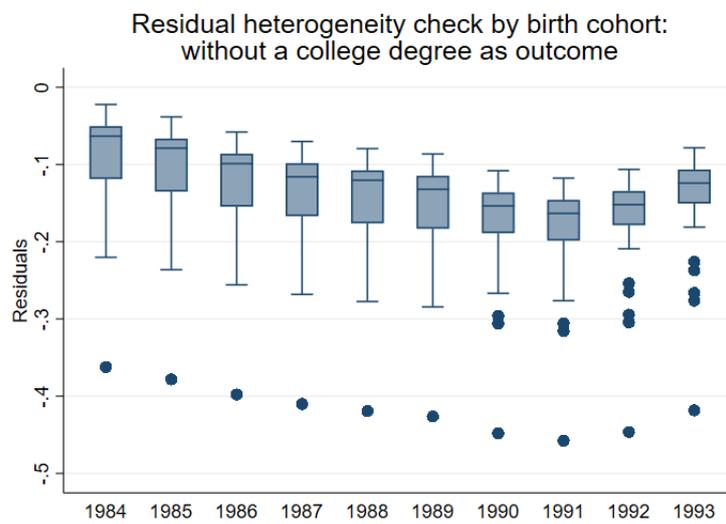


Figure A11: Residual plot by year of birth: dummy of college degree attainment = 0

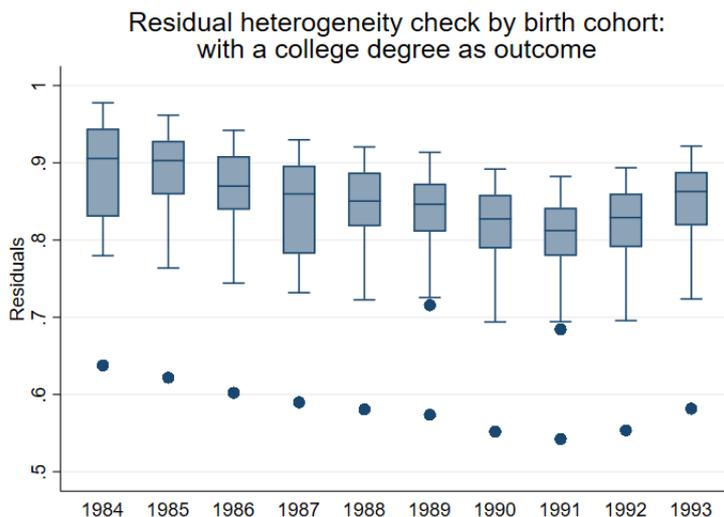
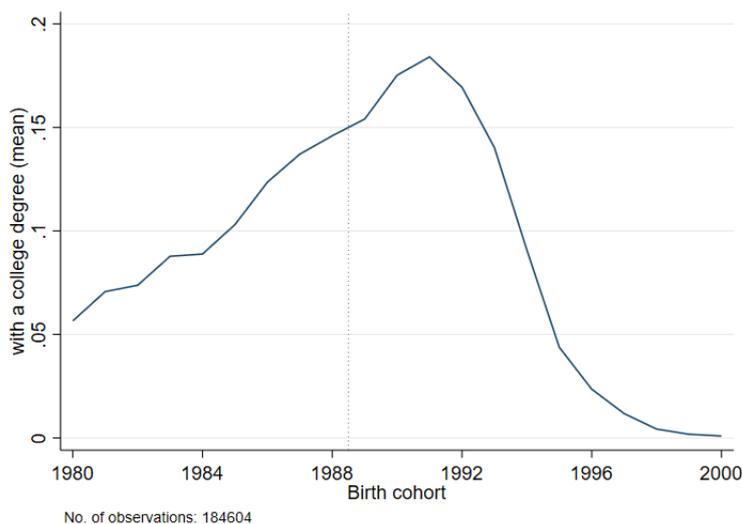


Figure A12: Residual plot by year of birth: dummy of college degree attainment = 1



Notes: The peak point of the graph is birth cohort 1991.

Figure A13: College degree attainment: means collapsed by birth cohorts

Table A9: Outcome: $\ln(\text{GDP curr. p})$, DDML

	OLS	LASSO	Random forest	Gradient boosting	stacked
number of colleges, 4th lag	0.00409*** (0.00157)	0.00365** (0.00159)	0.00290** (0.00142)	0.00140** (0.000707)	0.00282* (0.00152)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Outcome: logit(share of primary sector in GDP), DDML

	OLS	LASSO	Random forest	Gradient boosting	stacked
number of colleges, 4th lag	-0.00993*** (0.00275)	-0.00972*** (0.00282)	-0.00148 (0.00173)	-0.00129 (0.00127)	-0.00856*** (0.00231)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Outcome: logit(share of secondary sector in GDP), DDML

	OLS	LASSO	Random forest	Gradient boosting	stacked
number of colleges, 4th lag	-0.00904*** (0.00167)	-0.00888*** (0.00163)	-0.000904 (0.00126)	-0.000646 (0.000988)	-0.00198 (0.00185)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Outcome: logit(share of tertiary sector in GDP), DDML

	OLS	LASSO	Random forest	Gradient boosting	stacked
number of colleges, 4th lag	0.00545*** (0.00158)	0.00559*** (0.00153)	0.00795*** (0.00171)	0.000193 (0.000756)	0.00335** (0.00155)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Outcome: ln(no. of workers in sector 1), DDML

	OLS	LASSO	Random forest	Gradient boosting	stacked
number of colleges, 4th lag	-0.0133** (0.00590)	-0.0158*** (0.00598)	0.00463 (0.00670)	-0.00349 (0.00394)	-0.00354 (0.00617)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Outcome: ln(no. of workers in sector 2), DDML

	OLS	LASSO	Random forest	Gradient boosting	stacked
number of colleges, 4th lag	0.00937*** (0.00283)	0.00962*** (0.00279)	0.00800*** (0.00272)	0.00960*** (0.00287)	0.00459* (0.00260)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Outcome: $\ln(\text{no. of workers in sector 3})$, DDML

	OLS	LASSO	Random forest	Gradient boosting	stacked
number of colleges, 4th lag	0.00989*** (0.00162)	0.00993*** (0.00171)	0.000185 (0.00229)	0.00989*** (0.00166)	0.00973*** (0.00133)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Table A16: Outcome: $\ln(\text{GDP curr. p})$, DDML IV

	OLS	LASSO	Random forest	Gradient boosting	stacked
$\ln(\text{skilled population})$	0.317** (0.148)	0.278* (0.145)	0.298 (0.211)	0.202 (0.149)	0.222** (0.0954)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Table A17: Outcome: $\text{logit}(\text{share of primary sector in GDP})$, DDML IV

	OLS	LASSO	Random forest	Gradient boosting	stacked
$\ln(\text{skilled population})$	-0.740*** (0.260)	-0.794*** (0.260)	-0.0359 (0.188)	-0.255 (0.257)	-0.343*** (0.118)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Table A18: Outcome: $\text{logit}(\text{share of secondary sector in GDP})$, DDML IV

	OLS	LASSO	Random forest	Gradient boosting	stacked
$\ln(\text{skilled population})$	-0.714*** (0.193)	-0.669*** (0.177)	-0.123 (0.144)	-0.702*** (0.190)	-0.138* (0.0748)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Table A19: Outcome: $\text{logit}(\text{share of tertiary sector in GDP})$, DDML IV

	OLS	LASSO	Random forest	Gradient boosting	stacked
$\ln(\text{skilled population})$	0.452*** (0.147)	0.417*** (0.143)	0.889** (0.353)	0.426*** (0.136)	0.259** (0.102)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A20: Outcome: $\ln(\text{no. of workers in sector 1})$, DDML IV

	OLS	LASSO	Random forest	Gradient boosting	stacked
$\ln(\text{skilled population})$	-1.029** (0.470)	-1.298*** (0.490)	0.590 (0.690)	-1.132** (0.464)	-0.336 (0.353)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A21: Outcome: $\ln(\text{no. of workers in sector 2})$, DDML IV

	OLS	LASSO	Random forest	Gradient boosting	stacked
$\ln(\text{skilled population})$	0.716*** (0.242)	0.710*** (0.235)	0.902** (0.444)	0.741*** (0.221)	0.232* (0.124)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A22: Outcome: $\ln(\text{no. of workers in sector 3})$, DDML IV

	OLS	LASSO	Random forest	Gradient boosting	stacked
$\ln(\text{skilled population})$	0.686*** (0.178)	0.755*** (0.183)	0.339 (0.232)	0.686*** (0.160)	0.356*** (0.103)
Observations	3748	3748	3748	3748	3748

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A23: Outcome: $\ln(\text{GDP current price})$, primary sector

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.00704*** (0.00231)	-0.00698*** (0.00216)				
$\ln(\text{population})$	0.746*** (0.281)	0.741*** (0.279)	0.785*** (0.286)	0.791*** (0.279)	1.088*** (0.361)	1.071*** (0.348)
$\ln(\text{K stock, billion CNY})$		0.0840 (0.0597)		0.105* (0.0601)		0.169** (0.0707)
$\ln(\text{skilled population})$			-0.109*** (0.0369)	-0.126*** (0.0365)	-0.546** (0.219)	-0.536*** (0.188)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	22.48	22.48	22.48	22.48	22.48	22.48

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A24: Outcome: ln(GDP current price), secondary sector

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.00127 (0.00257)	-0.000978 (0.00184)				
ln(population)	0.508*** (0.0963)	0.485*** (0.0641)	0.493*** (0.0924)	0.514*** (0.0630)	0.570*** (0.159)	0.532*** (0.108)
ln(K stock, billion CNY)		0.373*** (0.0399)		0.381*** (0.0395)		0.385*** (0.0426)
ln(skilled population)			0.0121 (0.0472)	-0.0496 (0.0352)	-0.0983 (0.204)	-0.0751 (0.140)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	23.98	23.98	23.98	23.98	23.98	23.98

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A25: Outcome: ln(GDP current price), tertiary sector

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	0.00612*** (0.00183)	0.00625*** (0.00171)				
ln(population)	0.428*** (0.0853)	0.418*** (0.0780)	0.446*** (0.0849)	0.455*** (0.0748)	0.131 (0.183)	0.121 (0.181)
ln(K stock, billion CNY)		0.174*** (0.0331)		0.173*** (0.0342)		0.0973* (0.0565)
ln(skilled population)			0.0212 (0.0347)	-0.00678 (0.0300)	0.475*** (0.174)	0.481*** (0.173)
Observations	3747	3747	3747	3747	3747	3747
Mean of outcome	23.70	23.70	23.70	23.70	23.70	23.70

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A26: Outcome: ln(% of workers in sector 1)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.0249*** (0.00589)	-0.0252*** (0.00588)				
ln(population)	0.245 (0.300)	0.269 (0.291)	0.363 (0.287)	0.344 (0.280)	1.456*** (0.520)	1.465*** (0.520)
ln(K stock, billion CNY)		-0.390** (0.152)		-0.338** (0.156)		-0.0825 (0.202)
ln(skilled population)			-0.357** (0.162)	-0.302** (0.150)	-1.933*** (0.527)	-1.938*** (0.527)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	0.824	0.824	0.824	0.824	0.824	0.824

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A27: Outcome: $\ln(\%$ of workers in sector 2)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.00222 (0.00154)	-0.00213 (0.00129)				
$\ln(\text{population})$	-0.126* (0.0684)	-0.134** (0.0631)	-0.185*** (0.0611)	-0.178*** (0.0578)	-0.0184 (0.109)	-0.0335 (0.0930)
$\ln(\text{K stock, billion CNY})$		0.127*** (0.0307)		0.120*** (0.0290)		0.153*** (0.0360)
$\ln(\text{skilled population})$			0.0678* (0.0369)	0.0483 (0.0325)	-0.173 (0.135)	-0.163 (0.109)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	3.726	3.726	3.726	3.726	3.726	3.726

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Table A28: Outcome: $\ln(\%$ of workers in sector 3)

	Reduced form	Reduced form, w/K	OLS	OLS, w/K	2SLS, 2nd stage	2SLS, 2nd stage, w/K
number of colleges, 4th lag	-0.00196* (0.00111)	-0.00191 (0.00125)				
$\ln(\text{population})$	-0.106 (0.0649)	-0.111* (0.0588)	-0.108 (0.0665)	-0.104* (0.0605)	-0.0110 (0.0905)	-0.0205 (0.0864)
$\ln(\text{K stock, billion CNY})$		0.0723*** (0.0262)		0.0766*** (0.0264)		0.0956*** (0.0293)
$\ln(\text{skilled population})$			-0.0128 (0.0260)	-0.0252 (0.0247)	-0.152* (0.0859)	-0.147 (0.0962)
Observations	3748	3748	3748	3748	3748	3748
Mean of outcome	3.723	3.723	3.723	3.723	3.723	3.723

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A29: 2SLS, impact of student numbers on employment rates, %

	First stage	Second stage	First stage, w/control	Second stage, w/control
$\ln(\text{no. of secondary school})$	0.331*** (0.0524)		0.231*** (0.0469)	
$\ln(\text{primary school students, lag 6})$	0.608*** (0.0349)	-7.329*** (2.245)	0.575*** (0.0333)	-11.53*** (3.418)
$\ln(\text{secondary school students})$		9.457*** (2.951)		17.89*** (5.205)
$\ln(\text{population})$			0.481*** (0.0910)	-13.36*** (3.952)
Observations	4262	4262	4262	4262
F-statistics	39.94	5.327	24.17	4.159

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A30: 2SLS, impact of student numbers on ln(employed workers)

	First stage	Second stage	First stage, w/control	Second stage, w/control
ln(no. of secondary school)	0.344*** (0.0512)		0.244*** (0.0457)	
ln(primary school students, lag 6)	0.612*** (0.0350)	-0.0669*** (0.0213)	0.579*** (0.0333)	-0.107*** (0.0312)
ln(no. of registered labour force)	-0.0325** (0.0144)	1.022*** (0.00356)	-0.0377*** (0.0137)	1.026*** (0.00405)
ln(secondary school students)		0.0766*** (0.0276)		0.157*** (0.0469)
ln(population)			0.491*** (0.0887)	-0.136*** (0.0369)
Observations	4262	4262	4262	4262
F-statistics	45.04	28362.0	28.37	19045.1

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A31: Consequent impact of school numbers on ln(unemployed workers) after one year

	OLS	OLS, w/control	IV 1st	IV 2nd	IV 1st, w/control	IV 2nd, w/control
lag 1, ln(M-schools)	-0.186 (0.113)	-0.347*** (0.114)	0.232*** (0.0465)		0.130*** (0.0397)	
ln(primary school students, lag 6)	0.284*** (0.0772)	0.211*** (0.0780)	0.639*** (0.0338)	0.797** (0.403)	0.592*** (0.0329)	1.788** (0.798)
ln(population)		0.927*** (0.208)			0.587*** (0.0925)	2.491*** (0.870)
ln(secondary school students)				-0.802 (0.555)		-2.664** (1.264)
Observations	4262	4262	4262	4262	4262	4262
F-statistics	6.795	11.20	24.84	5.653	10.75	4.250

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A32: Contemporaneous impact of school numbers on unemployment rates, %

	Unemployment rate	Unemployment rate	logit(unemployment rate)	logit(unemployment rate)
no. of secondary school	-0.0107*** (0.00287)	-0.0111*** (0.00291)		
primary school students, million, lag 6	2.338** (0.959)	2.623*** (0.956)		
population, million		0.589* (0.326)		
ln(no. of secondary school)			-0.617*** (0.140)	-0.784*** (0.152)
ln(primary school students, lag 6)			0.178** (0.0885)	0.123 (0.0875)
ln(population)				0.800*** (0.249)
Observations	4262	4262	4262	4262
Adjusted R-squared	0.539	0.541	0.628	0.631
Mean of Dep. Variable	5.752	5.752	-2.945	-2.945

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A33: Contemporaneous impact of student numbers on logit(unemployment rates)

	First stage	Second stage	First stage, w/control	Second stage, w/control
ln(no. of secondary school)	0.331*** (0.0524)		0.231*** (0.0469)	
ln(primary school students, lag 6)	0.608*** (0.0349)	1.311*** (0.434)	0.575*** (0.0333)	2.077*** (0.674)
ln(secondary school students)		-1.864*** (0.586)		-3.399*** (1.044)
ln(population)			0.481*** (0.0910)	2.433*** (0.806)
Observations	4262	4262	4262	4262
F-statistics	39.94	5.114	24.17	3.682

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Bibliography

- Abalde, Macarena Ares (Nov. 2014). *School Size Policies: A Literature Review*. OECD Education Working Papers 106. OECD Publishing. DOI: [10.1787/5jxt472ddkjl-en](https://doi.org/10.1787/5jxt472ddkjl-en). URL: <https://ideas.repec.org/p/oec/eduaab/106-en.html>.
- Acemoglu, Daron (1998). “Why do new technologies complement skills? Directed technical change and wage inequality”. In: *The quarterly journal of economics* 113(4), pp. 1055–1089.
- Angrist, Joshua D and Alan B Krueger (1991). “Does compulsory school attendance affect schooling and earnings?” In: *The Quarterly Journal of Economics* 106(4), pp. 979–1014.
- Angrist, Joshua D and Victor Lavy (1999). “Using Maimonides’ rule to estimate the effect of class size on scholastic achievement”. In: *The Quarterly journal of economics* 114(2), pp. 533–575.
- Arcidiacono, Peter and Michael Lovenheim (2016). “Affirmative action and the quality-fit trade-off”. In: *Journal of Economic Literature* 54(1), pp. 3–51.
- Athey, Susan and Guido W Imbens (2019). “Machine learning methods that economists should know about”. In: *Annual Review of Economics* 11, pp. 685–725.
- Audretsch, David B and Maryann P Feldman (1996). “R&D spillovers and the geography of innovation and production”. In: *The American economic review* 86(3), pp. 630–640.
- Bagde, Surendrakumar, Dennis Epple, and Lowell Taylor (2016). “Does affirmative action work? Caste, gender, college quality, and academic success in India”. In: *American Economic Review* 106(6), pp. 1495–1521.
- Barro, Robert J (1991). “Economic growth in a cross section of countries”. In: *The quarterly journal of economics* 106(2), pp. 407–443.
- Becker, Gary S (1962). “Investment in human capital: A theoretical analysis”. In: *Journal of political economy* 70(5, Part 2), pp. 9–49.
- Belskaya, Volha, Klara Sabirianova Peter, and Christian M Posso (2020). “Heterogeneity in the effect of college expansion policy on wages: Evidence from the russian labor market”. In: *Journal of Human Capital* 14(1), pp. 84–121.
- Berry, Christopher (2006). “School consolidation and inequality”. In: *Brookings Papers on Education Policy*(9), pp. 49–75.
- Berry, Christopher and Martin R West (2010). “Growing pains: The school consolidation movement and student outcomes”. In: *The Journal of Law, Economics, & Organization* 26(1), pp. 1–29.
- Bils, Mark and Peter J Klenow (2000). “Does schooling cause growth?” In: *American economic review* 90(5), pp. 1160–1183.
- Birdsall, Nancy (1985). “Public inputs and child schooling in Brazil”. In: *Journal of development Economics* 18(1), pp. 67–86.
- Callaway, Brantly and Pedro HC Sant’Anna (2021). “Difference-in-differences with multiple time periods”. In: *Journal of Econometrics* 225(2), pp. 200–230.
- Card, David (1999). “The causal effect of education on earnings”. In: *Handbook of labor economics* 3, pp. 1801–1863.
- Carneiro, Pedro, Kai Liu, and Kjell G Salvanes (2023). “The supply of skill and endogenous technical change: evidence from a college expansion reform”. In: *Journal of the European Economic Association* 21(1), pp. 48–92.
- Caselli, Francesco and Antonio Ciccone (2019). “The human capital stock: A generalized approach: Comment”. In: *American Economic Review* 109(3), pp. 1155–74.
- Chari, AV et al. (2017). “The causal effect of maternal age at marriage on child wellbeing: Evidence from India”. In: *Journal of Development Economics* 127, pp. 42–55.
- Che, Yi and Lei Zhang (2018). “Human capital, technology adoption and firm performance: Impacts of China’s higher education expansion in the late 1990s”. In: *The Economic Journal* 128(614), pp. 2282–2320.

- Chernozhukov, Victor et al. (2018). *Double/debiased machine learning for treatment and structural parameters*.
- Cui, Yanan and Li Xu (2020). “On the Relocation of Colleges and Universities in the Period of the Third Front Construction”. In: *Social Sciences in Ningxia (Chinese)*(04), pp. 147–157.
- De Chaisemartin, Clément and Xavier d’Haultfoeuille (2022). *Difference-in-differences estimators of intertemporal treatment effects*. Tech. rep. National Bureau of Economic Research.
- De Giorgi, Giacomo, Michele Pellizzari, and William Gui Woolston (2012). “Class size and class heterogeneity”. In: *Journal of the European Economic Association* 10(4), pp. 795–830.
- Dougherty, Christopher (2005). “Why are the returns to schooling higher for women than for men?” In: *Journal of Human Resources* 40(4), pp. 969–988.
- Duffy, John, Chris Papageorgiou, and Fidel Perez-Sebastian (2004). “Capital-skill complementarity? Evidence from a panel of countries”. In: *Review of Economics and Statistics* 86(1), pp. 327–344.
- Duflo, Esther (2001). “Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment”. In: *American economic review* 91(4), pp. 795–813.
- Duflo, Esther (2012). “Women empowerment and economic development”. In: *Journal of Economic literature* 50(4), pp. 1051–79.
- Duflo, Esther, Pascaline Dupas, and Michael Kremer (2011). “Peer effects, teacher incentives, and the impact of tracking: Evidence from a randomized evaluation in Kenya”. In: *American economic review* 101(5), pp. 1739–1774.
- Feng, Shuaizhang and Xiaoyu Xia (2022). “Heterogeneous firm responses to increases in high-skilled workers: Evidence from China’s college enrollment expansion”. In: *China Economic Review* 73, p. 101791.
- Field, Erica and Attila Ambrus (2008). “Early marriage, age of menarche, and female schooling attainment in Bangladesh”. In: *Journal of political Economy* 116(5), pp. 881–930.
- Field, Erica, Rohini Pande, et al. (2021). “On her own account: How strengthening women’s financial control impacts labor supply and gender norms”. In: *American Economic Review* 111(7), pp. 2342–75.
- Fredriksson, Peter, Björn Öckert, and Hessel Oosterbeek (2013). “Long-term effects of class size”. In: *The Quarterly journal of economics* 128(1), pp. 249–285.
- Goldin, Claudia (2006). “The quiet revolution that transformed women’s employment, education, and family”. In: *American economic review* 96(2), pp. 1–21.
- Goldin, Claudia (2014). “A grand gender convergence: Its last chapter”. In: *American economic review* 104(4), pp. 1091–1119.
- Goldin, Claudia, Lawrence F Katz, and Ilyana Kuziemko (2006). “The homecoming of American college women: The reversal of the college gender gap”. In: *Journal of Economic perspectives* 20(4), pp. 133–156.
- Griliches, Zvi (1969). “Capital-skill complementarity”. In: *The review of Economics and Statistics*, pp. 465–468.
- Griliches, Zvi (1970). “Notes on the role of education in production functions and growth accounting”. In: *Education, income, and human capital*. NBER, pp. 71–127.
- Hanushek, Eric A (2006). “School resources”. In: *Handbook of the Economics of Education* 2, pp. 865–908.
- Hanushek, Eric A, Guido Schwerdt, et al. (2015). “Returns to skills around the world: Evidence from PIAAC”. In: *European Economic Review* 73, pp. 103–130.
- Hanushek, Eric A and Ludger Woessmann (2008). “The role of cognitive skills in economic development”. In: *Journal of economic literature* 46(3), pp. 607–668.
- Hanushek, Eric A and Ludger Woessmann (2015). *The knowledge capital of nations: Education and the economics of growth*. MIT press.
- Huang, Bin et al. (2022). “Returns to education in China: Evidence from the great higher education expansion”. In: *China Economic Review* 74, p. 101804.
- Huang, runlong (2009). “The amount of China’s only children: number, structure and risks”. In: *Journal of Nanjing College for Population Programme Management*(1), pp. 5–10.
- Jensen, Robert (2010). “The (perceived) returns to education and the demand for schooling”. In: *The Quarterly Journal of Economics* 125(2), pp. 515–548.
- Jensen, Robert (2012). “Do labor market opportunities affect young women’s work and family decisions? Experimental evidence from India”. In: *The Quarterly Journal of Economics* 127(2), pp. 753–792.
- Jensen, Robert and Rebecca Thornton (2003). “Early female marriage in the developing world”. In: *Gender & Development* 11(2), pp. 9–19.
- Jones, Benjamin F (2014). “The human capital stock: a generalized approach”. In: *American Economic Review* 104(11), pp. 3752–3777.

- Jones, Benjamin F (2019). "The human capital stock: a generalized approach: reply". In: *American Economic Review* 109(3), pp. 1175–1195.
- Joy, Lois (2000). "Do colleges shortchange women? Gender differences in the transition from college to work". In: *American Economic Review* 90(2), pp. 471–475.
- Katz, Lawrence F and Kevin M Murphy (1992). "Changes in relative wages, 1963–1987: supply and demand factors". In: *The quarterly journal of economics* 107(1), pp. 35–78.
- Kline, Patrick and Enrico Moretti (2013). "Place based policies with unemployment". In: *American Economic Review* 103(3), pp. 238–243.
- Krueger, Alan B (1999). "Experimental estimates of education production functions". In: *The quarterly journal of economics* 114(2), pp. 497–532.
- Krueger, Alan B and Mikael Lindahl (2001). "Education for growth: Why and for whom?" In: *Journal of economic literature* 39(4), pp. 1101–1136.
- Krusell, Per et al. (2000). "Capital-skill complementarity and inequality: A macroeconomic analysis". In: *Econometrica* 68(5), pp. 1029–1053.
- Lavy, Victor (1996). "School supply constraints and children's educational outcomes in rural Ghana". In: *Journal of Development Economics* 51(2), pp. 291–314.
- Lee, Soohyung and Benjamin A Malin (2013). "Education's role in China's structural transformation". In: *Journal of Development Economics* 101, pp. 148–166.
- Lei, Wanpeng and Jingmei Zhang (2010). "School layout adjustment should return to the essence of education: An empirical analysis of school merger criteria". In: *Educational Research and Experiment*(3), pp. 6–10.
- Li, Hongbin, Prashant Loyalka, et al. (2017). "Human capital and China's future growth". In: *Journal of Economic Perspectives* 31(1), pp. 25–48.
- Li, Hongbin, Yueyuan Ma, et al. (2017). "Skill complementarities and returns to higher education: Evidence from college enrollment expansion in China". In: *China Economic Review* 46, pp. 10–26.
- Lillard, Lee A and Robert J Willis (1994). "Intergenerational educational mobility: Effects of family and state in Malaysia". In: *Journal of Human Resources*, pp. 1126–1166.
- Lindsey, Linda L (2020). *Gender: Sociological Perspectives*. Routledge.
- Liu, Wenli (2015). "The effect of the school merger policy in rural areas of China and the countermeasures to improve it". In: *Legal System and Society (in Chinese)*(021), pp. 205–208.
- Lu, Jiehua and Xiaofei Wang (2013). "Change of the Marital Status in Mainland China since 1990s". In: *Social Sciences of Beijing* 3.
- Ma, Li and Wenquan Feng (2014). "Research on the Policy Changes and Countermeasures of the Primary and Secondary School Distribution in China". In: *Journal of Leshan Normal University (in Chinese)* 29(1), pp. 122–126.
- Mankiw, N Gregory, David Romer, and David N Weil (1992). "A contribution to the empirics of economic growth". In: *The quarterly journal of economics* 107(2), pp. 407–437.
- Marginson, Simon (2016). "The worldwide trend to high participation higher education: Dynamics of social stratification in inclusive systems". In: *Higher education* 72, pp. 413–434.
- Maubrigades, Silvana (2017). "Connections between women's age at marriage and social and economic development". In: *Gender Inequalities and Development in Latin America during the Twentieth Century*. Routledge, pp. 45–67.
- Moretti, Enrico (2004). "Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data". In: *Journal of econometrics* 121(1-2), pp. 175–212.
- Pang, Lijuan and Xiaoyu Han (Jan. 2005). "The adjustment of the distribution of elementary and secondary schools in rural areas: problems, reasons and the strategies". In: *Journal of Educational Studies* 1(4), pp. 90–96.
- Porzio, Tommaso, Federico Rossi, and Gabriella Santangelo (2022). "The human side of structural transformation". In: *American Economic Review* 112(8), pp. 2774–2814.
- Qian, Nancy (2008). "Missing women and the price of tea in China: The effect of sex-specific earnings on sex imbalance". In: *The Quarterly Journal of Economics* 123(3), pp. 1251–1285.
- Riddell, W Craig and Xueda Song (2011). "The impact of education on unemployment incidence and re-employment success: Evidence from the US labour market". In: *Labour Economics* 18(4), pp. 453–463.
- Rothstein, Jesse and Albert H Yoon (2008). *Affirmative action in law school admissions: What do racial preferences do?* Tech. rep. National Bureau of Economic Research.
- Sato, Kazuo (1967). "A two-level constant-elasticity-of-substitution production function". In: *The Review of Economic Studies* 34(2), pp. 201–218.

- Shan, Haojie (2008). “Reestimating the Capital Stock of China: 1952-2006”. In: *The Journal of Quantitative & Technical Economics (Chinese)* 25(10), pp. 17–31.
- Singh, Susheela and Renee Samara (1996). “Early marriage among women in developing countries”. In: *International family planning perspectives*, pp. 148–175.
- Valero, Anna (2021). “Education and economic growth”. In.
- Vandenbussche, Jérôme, Philippe Aghion, and Costas Meghir (2006). “Growth, distance to frontier and composition of human capital”. In: *Journal of economic growth* 11, pp. 97–127.
- Woessmann, Ludger (2016). “The economic case for education”. In: *Education Economics* 24(1), pp. 3–32.
- Wu, Zhihui and Ningzhong Shi (2011). “The Trends and Policy Issues for Rural School Layout and Adjustment in the Last Decade in China”. In: *EDUCATIONAL RESEARCH*(7), pp. 22–30.
- Yang, Lan (2009). “Call back teaching sites, suppress rebounding dropout rate”. In: *Zhongxiaoxue Guanli*(10).
- Young, Alwyn (2003). “Gold into base metals: Productivity growth in the People’s Republic of China during the reform period”. In: *Journal of political economy* 111(6), pp. 1220–1261.
- Yuan, Guilin et al. (2004). In: *Journal of Chinese Society of Education*(2), pp. 1–5.
- Zhang, Jun, Guiying Wu, and Jipeng Zhang (2004). “The Estimation of China’s provincial capital stock: 1952—2000”. In: *Economic Research Journal (Chinese)*(10), pp. 35–44.
- Zhao, Dan and Xianzuo Fan (2011). “The Problem of Difficulties in School Attendance for Students in Remote Rural Areas and Consideration of Countermeasures - With School Layout Adjustment as the Background.” In: *Journal of Hebei Normal University (Educational Science Edition) (in Chinese)* 13(12), pp. 37–41.