THREE ESSAYS ON PUBLIC POLICIES AND INEQUALITY IN CHINA

by

Zhuo Zhang

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

at

Dalhousie University
Halifax, Nova Scotia
March 2021

To my son, Luke, in the hope that he grows up to a more just and inclusive world.

Table of Contents

List of Tables

List of Figures

Abstract

This dissertation contains three essays examining three influential public policies in China and their various outcomes over the last half-century. Some of the outcomes were intended and some were unintended. The first essay examines the quantity-quality trade-off induced by China's family control policy during the 1970s. Using two waves of Chinese census data, I find China's "Later, Longer, Fewer" policy from the 1970s significantly reduced fertility in the country. For families with limited resources, a smaller family size allows for the allocation of more resources to each child, thereby increasing the average child quality. The second essay measures and examines the earning gaps among local urban workers and migrant workers using the 2002 China Household Income Project (CHIP2002) survey data. Relative to the urban workers, this study finds negative earning differentials and lower education returns among migrant workers. Using the newly developed unconditional quantile method, I do not find a "glass ceiling" or "sticky floor" effect for migrant workers. Instead, there is an inverse U-shaped Hukou premium, which indicates that urban Hukou holders enjoy greater returns to urban Hukou in the middle part of the wage distribution. Oaxaca-Blinder decomposition shows that differences in the observable characteristics between locals and migrants explain more than half of the wage difference. The third essay investigates the impacts of railway expansion in China on the urban-rural income gap over the last three decades. Using provincial panel data through a difference in differences (DID) framework shows a positive relationship between railway expansion and improved urban-rural income inequality. Specifically, the results indicate that up to 20% of the total income gap decrease can be explained by the railway growth over the last 10 years.

List of Abbreviations and Symbols Used

AFR Age specific fertility

CDF Cumulative distribution function

CHIP China Household Income Project

CQR Conditional quantile regression

DID Difference in differences

FPP Family planing policy

HSR High-speed rail

LLF Later Longer Fewer

NBS National Bureau of Statistics

OCP One Child Policy

OB Oaxaca-Blinder

OLS Ordinary Least Squares

Q-Q Quantity-Quality tradeoff

RIF Recentered influence function

SAC Spatial Auto Correlation

SDY Sent Down Youth

Acknowledgements

Thanks to the many people who have helped me along the way. I am grateful for my supervisor and mentor, Mutlu Yuksel, whose wisdom and encouragement inspire me as an economist. I would also like to thank my thesis committee member, Mevlude Akbulut-Yuksel. She is so intelligent, yet modest and so knowledgeable and respectful of others. Her kindness and gentle nature have helped me become a better person. Additionally, I thank my committee member, Dozie Okoye, for his generous kindness and support. It has been a valuable experience working and learning from great professors and mentors. I am indebted to your guidance and it will continue to positively impact my future career and life.

My thanks also go to Professor Talan Iscan, Yulia Kotlyarova, Barry Lesser, and all the professors in the Department of Economics who have helped and inspired me. I am thankful to Weiyi, Zongming, Min, and all my friends who participated in my Ph.D. study.

On a personal note, I would like to thank my parents for their continued support. Finally, I give a special thanks to my husband, Chenghao, for his encouragement and company along the way.

Chapter 1

Introduction

The world economy has undergone tremendous change over the last half-century, leading to dramatic changes in economic inequalities. Across countries, global earnings inequality has fallen, driven primarily by high earning growth in China and other emerging economies. Conversely, within countries, income inequality has risen in most major economies (Hammar and Waldenström, 2020; Derviş and Qureshi, 2016). As the world's largest emerging economy, China is playing a growing role in shaping the world economy and the global income distribution pattern, and its impressive growth has attracted worldwide attention. Along with rapid economic development, China has also experienced other major transitions such as human capital development, infrastructure expansion, Hukou reforms, and urbanization. All of these transitions have had great impacts on China's economic inequality. This dissertation focuses on three major transitions resulting from public policies in China over the past half-century and studies how they affect China's income inequality pattern.

The first essay (Chapter 2) focuses on children's education investment in Chinese families. Specifically, I studied the quantity-quality trade-off using China's 1970s family control policy. Education is one of the main factors that affect one's future income, thus inequality in education may translate into income inequality. Furthermore, education is one of the most important pathways to upward income mobility. The "Later, Longer, Fewer" policy from the 1970s is a milestone in China's family planning history. Fertility in China experienced a larger decline during this policy period than it did during the One Child Policy period. This essay examines the impacts of the "Later, Longer, Fewer" policy on family size and children's educational investment. Large family size is detrimental to economic development because it significantly limits the resources available to children in large families. Given the exogenous decrease brought on by this policy, this essay finds that the family planning policy of the 1970s was effective in reducing family size by 0.4 children on average and had a positive impact on the first child's education. These findings provide supporting evidence for the quantity-quality trade-off in developing economies.

The second essay (Chapter 3) focuses on China's inequality in the early 2000s. It provides a snapshot of China's one unique income inequality feature: the urban-migrant wage gap. Specifically, this chapter examines the urban-migrant wage differentials at different quantiles using an unconditional quantile analysis. It then decomposes the differential into the contribution of each covariate using an extended Oaxaca-Blinder decomposition. Using nationally representative survey data, I find there are no glass ceiling or sticky floor effects. The Hukou premium widens in the middle part of the wage distribution.

The third essay (Chapter 4) focuses on urban-rural income inequality in China during the last three decades. Despite the urban-rural gap being one of the most significant economic problems facing China today, over the last decade, urban-rural income inequality has decreased. Using provincial panel data from the last three decades, I study this problem by analyzing the impacts of railway expansion in China on the urban-rural income gap. I utilize a difference-in-difference design to estimate the effects of railway expansion. Furthermore, I use the spatial econometric model in this study to deal with the transportation spillover effects. Results show increasing railway expansion negatively contributes to the urban-rural income gap.

Chapter 2

China's Family Planning Policy and Its Effects on Children's Education

2.1 Introduction

Over the last half-century, most countries in the world have witnessed a sustained decline in their population growth level. According to the World Bank, the global total fertility rate, which represents the average number of children that would be born to a woman over her lifetime, decreased from 5.03 in 1965 to 2.43 in 2017, though the specific determinants of such a phenomenon varied across regions over time. The long-term reduction in fertility rates has resulted in some unintended negative effects such as a rapidly ageing population and a gradually slackening economy in the global context. It has also had some unintended positive effects on children's educational investment because parents invest more in their children's education when the total number of children per family decreases. In the 1970s, China experienced a dramatic decline in the total fertility rate while simultaneously experiencing an improvement in children's education. The purpose of this study is to examine the relationship between a decrease in family size and children's educational investment in China.

Family size and children's educational choices are two major decisions for families and they are interrelated in many ways. Children's quantity and quality (Q-Q) trade off is a crucial question and identifying any causal relationship between children's quantity and quality relies on some exogenous variations in family size. The Chinese context provides a unique opportunity to study Q-Q trade off because of its distinct family planning policy. China has a long history of family control policies that have been successful in reducing its fertility rate. The most well known of these is the One Child policy (OCP), which has been studied extensively by researchers. China introduced its OCP in 1979. However, fertility rates had already dropped sharply before the implementation of the OCP (see Figure 2.1). Total fertility rate declined from 5.7 to 2.7 from 1969 to 1978. After the OCP came into place in 1979, the rate only dropped slightly to 2.5 in the succeding decade. It is important to note that the magnitude of the fertility decline during the 1970s was significantly larger than that of the post-1979 era. This largest decline in fertility rate corresponds with the 1970s family control policy period, which is summarized by its slogan "Later (marriage), Longer (birth interval), Fewer (children)" (LLF).[1] Four studies find that due to the policies in place in the period from 1971-1979, the additional effects contributed by the One Child Policy is fairly limited (Babiarz et al., 2018; Chen and Huang, 2018; Wang, 2014; Whyte et al., 2015). Unlike the effects of the OCP, the effects of the LLF policy during the 1970s remain unexplored. Therefore, it opens an opportunity for this paper to revisit the Q-Q trade off question incorporating the LLF policy period.

In this study, I exploit three main sources of variation to measure individuals' exposure to the family control policies. The first source of variation is different starting years of the LLF policy in different provinces. Figure 2.2 shows the establishment year of the Family Planning Leading Group in each province which varies from 1970 to 1975. Some may argue the timing of the LLF in each province is endogenously determined by local social/economic conditions. To address such concern, I compute several pairwise correlations between LLF establishment year, urbanization rate, and female's labor force participation rate. Furthermore, Chen and Fang (2018) conducted a regression of the LLF establishment years on a set of initial provincial conditions in 1969, including the total fertility rate, sex ratio, GDP per capita, share of the non-agricultural population, share of primary industry in GDP, and share of the secondary industry in GDP. All analyses regarding this concern find no evidence that the LLF establishment years are endogenously determined by any of those factors. My second source of variation is the mother's cohort. This is motivated by the fact that women encounter the LLF policy at different ages in their fertile stage. For example, if a woman encountered this policy when she was 60 years old, then any family control

[1]Though some other factors, such as changes in the status and role of women, may have contributed to the decline of the total fertility rate, Banister (1987) argues the decline was mostly attributed to China's pervasive family planning program of the 1970s.

policy should not affect her decision of having an additional child because she already past her fertile stage. The third variation is the different initial fertility rates in different provinces. Women in provinces with higher initial fertility rates were more exposed to the policy since otherwise, they would have more children without the policy.

My analysis consists of two set of outcomes. First, I check whether family planning polices were effective in reducing family size. Specifically, I examine a set of outcomes, including number of live births by women and birth spacing. Next, I analyse how these policies reshaped families' decisions about investing in their childrens educations by using the first-born childs total years of schooling as a measurement of school investment. Black et al. (2005) find that after controlling birth order, the Q-Q trade-off completely vanished, which suggests birth order could be another channel through which family size can affect children's education. Since multi-child families were very common in China during the study period, this paper focuses on the first-born child in order to avoid birth order complication. Further, to test the robustness of my results, I use the illiteracy level of the first-born children as an alternative measure of education investment.

I use Census 1982 and Census 1990 for my empirical analysis. Using Chinese census data provides some benefits because China is a developing country. For example, there is evidence that the Q-Q trade-off is fairly limited in developed countries (Black et al., 2005), perhaps because developed countries tend to have better public education or because higher-income families are not constrained from investing in their children's education. Conversely, the results from developing countries tend to support the Q-Q trade-off theory. Since China is a developing country, people had very limited resources during the study period and most families had limited resources available to allocate to their children's education; therefore, the trade-off may have been more pronounced.

This paper makes several contributions. First, it contributes to the understanding of the subsequent effects of China's 1970s' "Later, Longer, Fewer" policy. A large body of literature explores the effects of China's family planning policy on a number of outcomes including children's education (Rosenzweig and Zhang, 2009; Li and Zhang, 2017; Liu, 2014), labour supply (Wang et al., 2017) and marriage (Huang and Zhou, 2015); however, in these studies, the family planning policy solely refers to the One Child Policy. Almost all studies about the OCP take the pre-existing fertility conditions for the One Child Policy as exogenous, even though these conditions were outcomes of the 1970s LLF policy. Until recently, only a limited number of studies examined the impacts of the 1970s policy on fertility rate, parental health and gender selection (Chen and Huang, 2018; Chen and Fang, 2018; Babiarz et al., 2018), and no study examined the effects of the 1970s' family planning policy on children. To the best of my knowledge, my study is the first to investigate the impacts of the "Later, Longer, Fewer" policy on investment in children's education.

Second, this study also contributes to the growing body of literature examining the quantityquality trade-off. The main challenge in QQ studies is that family size and children's education investment are endogenous, that is, parents usually make simultaneous decisions, so the two variables are jointly influenced by parents preferences and other family characteristics. Some of the literature uses twins as an exogenous variation to overcome such endogeneity issues (Li et al., 2008; Rosenzweig and Zhang, 2009). Rosenzweig and Zhang (2009) explore twins as an exogenous shock to family size and find moderately positive impact on children's human capital. Similar findings also exist in Li et al. (2008). Additionally, Li et al. (2008) find the trade-off is more pronounced in rural China and that the effects diminish in urban areas.

There are several limitations for studies using twin families as the experiment group. First, twins usually have lower birth weights compared to singletons and birth weight can influence one's future social status such as human capital (Behrman and Rosenzweig, 2004). Second, tight birth spacing between twins and non-twin children can affect family resource allocation (Rosenzweig and Zhang, 2009). Close birth intervals constrain the allocation of family resources, which affects children's educational attainment. Third, Bhalotra and Clarke (2019) show that a mother's health is systematically and positively associated with twin birth, which indicates twin families are not a good representative sample of the general population. Consequently, I revisit the Q-Q trade-off topic without using twin data to tackle the endogeneity issue, and instead, I use the exogenous shock to the family size generated by the family control policies in China. While twins generally introduce a shock of only one additional child, the LLF policy period saw a decrease in family size of 3-4 children over 10 years, which enables a more comprehensive analysis in terms of shock size and time frame.

In sum, the LLF policy is effective in reducing family size by an average of 0.3 children. Furthermore, birth spacing is another crucial part of family structure. Longer time periods between births would provide a more balanced wealth accumulation path, ease the burden of child-rearing over time, benefit mothers' health and decrease infant mortality rates during pregnancy (Gates, 2109). Results show the LLF policy is more effective in increasing birth spacing compared to the OCP, and both the LLF and the OCP are effective in increasing first-born children's education investment. Lastly, I separately analyse the impacts on girls' and boys' educational investment. Results show the LLF policy has a more significant influence if the first-born child is a girl, which is consistent with past research. In the past, girls were usually at a disadvantage in accessing education. Thus, reducing family size could increase the number of resources available per child, which could help bridge the gender gap in education.

The paper is structured as follows. Section 2.2 describes background information on fertility and the "Later Longer Fewer" policy in China. Section 2.3 is my estimation specification. Section 2.4 describes the data I use. Section 2.5 discusses the results and section 2.6 reviews other contemporary events. Section 2.7 Concludes.

2.2 Background: History of China's Later Longer Fewer policy

The "Later, Longer, Fewer" policy spans from 1971-1979 and is the second of three major periods in China's family planning policy (FPP) history. It is preceded by a mild and narrowly implemented FPP (1963-1971) and followed by the one child policy period (1980-2015)(Wang, 2014). Of all three periods, the LLF policy period is especially significant because China's fertility rate experienced its largest decline during this time. Additionally, the LLF policy served as a stepping stone for the OCP policy. This section reviews the LLF policy implementation and its outcomes and identifies the importance of the starting time of the LLF policy in each province.

China resumed the second stage of its family planning program in the early 1970s. Unlike the first stage FPP in the 1960s, which was only implemented in urban areas, the LLF policy was much more widely implemented throughout the country and it carried coercive elements. From 1970 to 1975, China gradually created a large, reliable organization to carry out the policy. This network reached from the central government down to most villages. The country invested heavily into setting up family planning institutions and promoting research on birth control techniques (see Figure 2.3), many of which have been widely available ever since. Figure 2.4 from Chen and Huang (2018) presents different operations from 1971 to 1982. IUD insertion, which was the most popular birth control method, increased rapidly and almost tripled from 1971 to 1974. To investigate whether the increasing use of fertility control is voluntary or coercive, Chen and Huang (2018) use China Health and Retirement Longitudinal Study (CHARLS) survey data. Figure 2.5 and 2.6 show there is an increase in abortions due to the family planning policy of the 1970s. Apart from abortion enforcement, other coercive implementation methods existed. For example, birth planning workers periodically filled out forms to keep detailed records of each woman's fertility history, contraceptive use and menstrual cycles in order to detect out-of-quota pregnancies at an early stage. In some factories, women who became pregnant without permission were subjected to regular harassment to get an abortion and additional pressure was put on their husbands and other family members. In some villages, various distributions, such as the regular grain ratio, sugar, oil or fish, were eliminated for the fourth child (Whyte and Parish, 1985; Parish and Whyte, 1980). Overall, to promote the LLF policy, China invested heavily into constructing an efficient family planning network, and the implementation of the policy did not simply rely on persuasion or voluntary compliance as the policy makers claimed.

After the extensive implementation of the LLF, the total fertility rate dropped significantly, decreasing from 5.7 in 1970 to 2.7 in 1979.[2] The key to the success of the family planning policy of the 1970s and other ongoing family planning policies is the giant family planning network built in the 1970s. This network was not built all at once in China. The establishment year of the Family Planning Leading Group in each province represents the starting point of the LLF policy in that province. These provincial institutions were established between 1970 and 1975 in different provinces (See Figure 2.2). To investigate whether the LLF establishment year was affected by the pre-policy fertility conditions, Table 2.1 calculates the average provincial total fertility rate by the LLF establishment year. I do not find the systematic differentials in total fertility rates by the LLF implementation year. After carefully analysing the relationship between the LLF starting point and several predetermined macroeconomic conditions in each province, I realized those starting times were plausibly exogenous; however, this correlation is not sufficient to show that the decline was brought on by the LLF policy. To show that the downward trend of the total fertility rate was caused by the LLF policy, Figure 2.7 explores the fertility rate at the provincial level. Since the policy was not implemented in all provinces all at once, we should expect to see some variation in the timing of the fertility decline in different provinces. Figure 2.7 compares different trends in fertility rates between the early leading provinces and the provinces that implemented the policy later on. The leading provinces experienced faster fertility declines at an early stage and the provinces that followed saw a gradual and then solid decline after they started the LLF policy. This provides evidence that the fertility decline during the 1970s was a result of the LLF policy.

There were other events that happened during the study period that could have also impacted the fertility rate and children's education. One of these events is the Sent-Down Youth Program that occurred from 1966 to 1976. During the program, China relocated millions of young people from urban to rural areas. The targeted population was mostly junior and senior high-school students. This program could potentially confound the LLF results if the marriages of sent-down youths were affected by the

[2] Migration is very rare during the study period because China implemented the restricted Household Registration (Hukou) system, which made migration very hard to achieve.

program. Section 2.6 describes this program in great detail and also how it handles these confounding events.

In sum, as a result of the implementation of the LLF policy, China experienced a major decline in the total fertility rate during the 1970s. The starting point of the decline depends on when the LLF policy was established in each province. The establishment year of the LLF in a given province was plausibly exogenous. Therefore, in my analysis, I will explore the cross-provincial variation in the establishment year of the LLF to estimate the direct policy effects on total fertility rate and its indirect effects on the investment in children's education.

2.3 Empirical Framework

This section describes the estimation strategy used to exploit the effects of the Later, Longer, Fewer" policy on the investment in children's education. The hypothesis is that when families are exposed to the LLF policy, it affects their fertility choices and the resulting reduction in family size allows parents to allocate more resources to their first child (or existing children). There will be two sets of outcomes in my analysis. I will start by examining the effectiveness of the LLF policy in reducing family size using OLS estimation. The number of live births and birth spacing are potential outcomes of interests. Next, I will look at whether the LLF increases the investment in children's education.

The following regression examines the effects of the "Later, Longer, Fewer policy on family size.

$$Birth_{ipc} = \beta_0 + \beta_1 LLF_{pc} + \beta_2 \mathbf{X}_i + Prov_p + \epsilon_{ipc} \tag{2.1}$$

Where $Birth_{ipc}$ is the number of live births or birth spacing for a woman i living in province p whose cohort was c. LLF_{cp} is women's cohort-specific women's exposure to the LLF policy in province p. β_1 is the primary parameter of interest, and it captures the effect of the policy on families' fertility choices. When the dependent variable is the number of live births, a negative β_1 means the LLF will reduce women's birth rates. When the dependent variable is birth spacing, a positive β_1 means women will increase their birth intervals and potentially reduce their family size. $\mathbf{X}_i$ is the set of individual control variables including age, Hukou status, education, and employment status. I select the control variables that were predetermined before women made their fertility decisions. $Prov_p$ is the set of 27 provincial dummies. Standard errors in all my analyses are clustered at province by cohort level.

Next, I explore the relationship between family policy exposure and the educational outcome of the first child. Below is my estimation regression:

$$Education_i = \beta_0 + \beta_1 LLF_{pc}^{mother} + \beta_2 LLF_{pc}^{father} + \beta_3 \mathbf{X}_i + Prov_p + \epsilon_{ipc} \tag{2.2}$$

To measure the investment in children's education, the indicator for $Education_i$ is years of schooling for the first child. I focus on the first child's education since my hypothesis is that with a smaller family size, parents would be able to allocate more resources to the existing children. Birth order could also influence children's educational outcome, so by focusing on the first child, I ensure that birth order would not complicate the channels. The way I define first child is the oldest child who is still registered as a child in the same household as their parents.[3] I use both the mother's and father's exposure to the policy as my variable of interest. The family planning policy can be separated into the Later, Longer, Fewer" policy and the One Child Policy based on different starting times, coverage periods and initial fertility rates. Control variables include the parents' demographics, education and employment background. Provincial dummies enter the regression to capture variation in educational development across provinces.

The independent variable of interest in both estimations is family planning policy exposure. I modified Chen and Huang (2018)[4] to create my own measurement for the exposure to the LLF policy for cohorts born in year c in province p as

$$LLF_{p,c} = \sum_{a=15}^{49} AFR_p(a) I[T_p \leq c + a \leq 1979] \tag{2.3}$$

[3]It is not possible to identify children who left home and becomes household head

[4]Chen and Huang define policy exposure as $LLF_{p,c} = \sum_{a=15}^{49} AFR_p(a) I[c+a \geq T_p]$. Two reasons why their model does not work in my case: First, the LLF policy only lasted one decade before being replaced by the One Child Policy. Second, even if this policy has an impact on women's fertility, since I use the 1982 and 1990 censuses, the total impact was not fully realized until then.

The left-hand variable LLF_{cp} is the individual's exposure to the LLF policy. The variation comes from two sources denoted by the two subscripts p and c. The provincial variation within each cohort comes from (1) different years of establishment of the Family Planning Leading Group and (2) different initial fertility profiles. In terms of the right-hand variables, I is an indicator function and a is age. $AFR_p(a)$ is the age-specific fertility rate of province p in 1969, prior to the enforcement of any effective family planning policy. T_p is the establishment year of the Family Planning Leading Group in province p. The duration of the policy is between T_p and 1979 before it was replaced by the universal One Child Policy in 1980.By adding up age-specific fertility rates during this period, Equation (2.3) calculates the potential number of children that could have been born during the LLF policy period for a woman in province p; therefore, it captures the exposure to the policy. The One Child Policy is constructed in the same fashion (the starting year, T_p, is 1980 for all provinces and the upper boundary uses 1982 for Census 1982 and 1990 for Census 1990 [5]).

The construction of exposure to the policy is subject to one potential threat: Variations in the LLF establishment year may not be fully exogenous. In other words, those provinces that established the LLF policy earlier might carry some common features other than the policy that led to a greater decline in the fertility rate. To examine whether this is true, I compute the correlation between the LLF establishment year and a female's labour force participation rate. Additionally, I compute the correlation between the LLF establishment year and the urbanization rate. Both correlations are close to zero with no statistical significance. Additionally, Table 2.1 shows no systematic differentials in total fertility rates by the LLF implementation year. All of these tests show there is no systematic factors that made certain provinces adopt LLF at an early stage. It provides evidence that the construction of $LLF_{p,c}$ is free from endogeneity threat.

There are some potential threats in the second step analysis. First, the Sent-Down Youth event happened during the 1970s, which made it a confounding factor. The detailed description of this contemporary event can be found in Section 2.6. To tackle this problem, I constructed a measurement for the density of the Sent-Down Youth

[5] $OCP_{p,c} = \sum_{a=15}^{49} AFR_p(a) I[1980 \leq c + a \leq 1990]$

Program at the provincial level and added it as my control variable. Furthermore, I checked that there is no correlation between the intensity of sent-downs and the LLF at the provincial level. Second, during the same period, secondary education in rural China improved greatly. This results in years of schooling being subject to potential omitted variable bias without controlling for rural education progression during this period. My solution is to use an alternative dependent variable–illiteracy of the first child–as a robustness check since the illiteracy rate would hardly be affected by an improvement in secondary education.

2.4 Data and Descriptive Statistics

Data used in this study comes from three sources: (1) population chronicles from 27 Chinese provinces for calculating my main independent variable $LLF_{p,c}$; (2) Microdata from the 1982 and 1990 Chinese population censuses for my main analysis; (3) Local gazetteers gathered by Chen et al. (2018) to compute the confounding factor–the Sent-Down Youth Movement. Detailed descriptions of each dataset are provided below.

To construct my main independent variable, $LLF_{p,c}$, I obtained information on the establishment year of the Family Planning Leading Group for each province (T_p) from Chen and Huang (2018). They reviewed provincial chronicles documenting most of the establishment years of the Family Planning Leading Groups and each year can be treated as the start of the LLF in that province. They exclude Inner Mongolia, Chongqing, and Hainan for various reasons. The original sample consists of 27 provinces. Figure 2.2 plots the establishment year for provinces included in my sample, ranging from 1970 to 1975. Age-specific fertility rates ($AFR_p(a)$) prior to the implementation of the LLF policy are taken from Coale and Chen (1987). Combining both datasets using Equation 2.3 enables me to construct the policy exposure measurement.

In the main empirical analysis, I use Census 1982 and Census 1990 microdata collected by the National Bureau of Statistics (NBS) of China. Using census data has several advantages. First, census data provides rich information about each individual's demographic status including their age, gender, education, employment status, and Hukou status. It also contains family characteristics such as family size and relationship to the family head. Second, it is a random sample that covers the entire country. Lastly, the sample size is large. Each census wave contains over 10 million respondents and my restricted samples in the two-step analysis still contain 2.68 million and 0.67 million observations, respectively. A large dataset is ideal since it increases statistical accuracy and even moderate effects can be captured with a large dataset.

First, I examine the impacts of the family planning policy on women's fertility choices. To do this, I use Census 1990. I restrict my sample to women aged 15 to 64 because the census only recorded the number of births and number of surviving children for that age range. The advantage of using Census 1990 rather than Census 1982 is that women who were mostly affected by the 1970s' family planning policy were still quite young in 1982 and the effect of the policy on their fertility choice was probably not fully realized. Figure 2.8 illustrates this point using the Beijing sample. The upper panel shows different measurements of exposure to family planning polices and number of live births by a mother's cohort in Census 1982. The lower panel calculates similar information using Census 1990. As can be seen from the graph, the LLF policy strongly affected the 1950 to 1955 cohort (the demand trend). To be specific, the number of live births for cohort 1955 is only 0.5 children in Census 1982 and the number reaches over 1 in Census 1990. This is because in 1982, women in cohort 1955 were still very young and far from reaching the end of their fertile life. Using Census 1990 to study the 1970s' policy enables this study to investigate a longer time span.

Table 2.2 provides the summary statistics for women aged 15 to 64. As shown, the average exposure to the policy is 4.19 if computed using Chen and Huang (2018)'s method. After revising this method to Equation 2.3,the policy exposure for the 1970s Later, Longer, Fewer policy is 1.06 and it is 0.91 for the One Child Policy. We should note that the gap between my LLF and the LLF in Chen and Huang (2018)'s results because their method calculates the counterfactual number of children a woman would have for her whole fertile life, whereas I only calculate this number for the 1970s. Although the numbers for LLF and OCP exposure are close in my sample, the exposure to the 1970s' policy only lasted five years for women in some provinces, whereas women in all provinces experienced 10 years of exposure to the One Child Policy (up to 1990). In terms of employment status, 80% of women aged 15-64 were employed and around 16% stayed at home. The unemployment proportion is really small because most people living in rural area (79%). Additionally, unemployment in agriculture is fairly small (0.01%).

The second outcome of interest is the investment in children's education. I use Census 1980 at this stage.[6] I apply several restrictions to facilitate my analyses. First, I restrict my sample to only include children. Since I need to include their parents' demographic characteristics, I must identify their parents in my sample; however, there is no direct link between parents and children–I identify children as "child" and weakly identify their parents (female head or male head) as "head" or "spouse" if they are living in the same household. Second, to ensure the accurate order of children, I further restrict my sample to households in which all children are still living with their parents (i.e., number of children in the household equals the number of surviving children reported by the female head).

Table 2.3 shows the summary statistics for the first-born children in Census 1982 and Census 1990. Although I only use Census 1982 in the second stage, I still provide 1990 data summary statistics for comparison. There is no significant difference between the two censuses in terms of age and gender of the first-born children. I calculate years of schooling to measure each individual's education level. I use maximum years to complete the degree as years of schooling (I assign 0 if the person is illiterate or semi-literate; 6 if primary; 9 if junior middle school; 12 if senior middle school; 16 if college and above). In my sample, the average years of schooling is 6.2, which indicates the average education level for first-born children is primary school. The average number of siblings is 2.3 in Census 1982 and this number decreases to 1.4 in Census 1990. The reduction in family size is due to various family planning policies.

[6] The reason for not using the 1990 census is that China established 9-year Compulsory Education Law in 1986. This will lift children's education level in some cohorts but not others. By using the 1982 census, I circumvent this potential concern.

A mother's exposure to the LLF policy is 1.86 compared to her exposure to the One Child Policy which is 0.24 in Census 1982. Almost all fathers were employed in my sample and 85% of mothers were employed.

The last data used in this paper are from local gazetteers gathered by Chen et al. (2018).). I use this data to compute my confounding factor, the Sent-Down Youth (SDY) Movement. This movement overlapped with the LLF policy and influenced the education level of some cohorts. The detailed description of this contemporary event is in Section 2.6.2. To construct a variable that measures the Sent-Down Youth Program, I first identify the cohorts that would be influenced by the program. Chen and Huang (2018) use the 2010 wave of the China Family Panel Study, which provides information about whether individuals experienced the Sent-Down Youth Movement, along with the start and the end year. They find that cohorts born between 1945 and 1960 were the most severely impacted. I then use the number sent by each province divided by the number of people born between 1945 and 1960 to get the probability of being sent down. I assign this probability to the affected cohorts based on their province and assign 0 to people whose cohort did not fall between 1945 and 1960. The average risk of being sent down in my sample is 0.93%, which is quite small.

2.5 Empirical Results

The main results are presented in two parts. First, I provide evidence that the "Later, Longer, Fewer" policy had powerful effects in reducing family size. Second, I investigate the policy effects on the investment in children's education.

2.5.1 Effects of family planning policy on the number of live births and birth spacing

Table 2.4reports the effectiveness of the family planning policy in reducing family size using Equation 2.1. The outcome variables are total number of live births (columns (1) to (4)) and birth spacing (columns (5) and (6)) for women. In the first column, the main independent variableexposure to family control policyis constructed using Chen and Huang (2018)'s method. It shows that with an additional unit of exposure, the number of live births per woman decreased by 0.27. To separate the family planning policy into the LLF policy and the One Child Policy, I divide the family planning policy into LLF and OCP using Equation 2.3. Column (2) shows that both policies were effective in reducing family size and their coefficients' magnitudes are close to each other. More specifically, the estimates are -0.26 and -0.27 for LLF and OCP, respectively. This suggests that women who were more likely to have one additional child without the policies were less likely to have more children due to the policies. Given the average exposure to the LLF policy, it means that women reduced their number of births by an average of 0.4 during the LLF policy period. The reason the two policies yield similar coefficients might be due to the fact that the techniques they use are in fact, very similar. Columns (3) and (4) add additional controls including women's years of schooling and employment statuses. Again, all policy estimates are negative and they are all significant at the 1% level with the additional controls, suggesting that women who have greater exposure to the family planning policy further reduced their number of births. All the additional controls carry expected signs. Estimates on education and urban Hukou are negative. Women who are unemployed and who are doing housework have a greater number of children on average. Some may argue that the additional controls may suffer from reverse causality. For instance, women with more children may end school life early or quit their jobs and become full-time mothers, whereas women with fewer children may acquire further education; however, such cases seem to be very rare during the period of study. Moreover, the estimates for policies with additional controls did not differ much from the first two columns, which suggests the results are robust to the additional controls.

One other goal in the LLF policy is to promote longer birth intervals. In columns (5) and (6) of Table 2.4, , I assess whether the family planning policy is effective in increasing birth spacing. The dependent variable, birth spacing, is not readily available from the census since the census did not interview women about which year they gave birth. I define birth spacing as the number of gap years between the youngest child and the second-youngest child. I further restrict my data to include those who were born after 1970. Column (5) shows that with an additional unit exposure to the family control policy, women increase their birth spacing by 0.345

years. Column (6) separates the family control policy effect into the LLF and the OCP. Although the coefficient magnitude for the LLF (0.28) is smaller than it is for the OCP(0.38), given their average policy exposure, their overall effects on the promotion of longer birth spacing are almost identical. Overall, results from Table 2.4 provide evidence that China's family planning policies indeed reduced family size and increased women's birth spaces.

2.5.2 Effects of family planning policy on children's education

The results from the previous section provide evidence that the family planning policy of the 1970s was effective in reducing family size. This section explores the effects of family planning policy on children's educational investment. My hypothesis is that by reducing family size, families could have more resources for their existing children; therefore, the years of schooling for children may increase. To avoid complications caused by birth orders,[7] I focus on the first-born children. Table 2.5 displays the results for first-born children's years of schooling. Each column comes from a separate regression that controls for individual characteristics (age, age square, gender, parents age, years of schooling for each parent, each parent's employment dummy, dummies for each parent's status as a minority, whether or not parents work in the agricultural sector) and provincial dummies. In the first column, I use Chen and Huang (2018)'s measurement of mothers' and fathers' exposure to the family planning policy. A mother's exposure to the policy has a positive effect on the child's years of schooling even when controlled for number of siblings in the household. More specifically, with a mother's additional exposure to policy, the first child spends 0.38 more years in school. Considering the mean years of schooling is 6 years and the average age in my sample is 14, the policy improves the number of years a child attends school by more than 6%. In the second column, I exclude the number of siblings and the policy estimates become even larger, suggesting reduced family size resulting from the family planning policy increases children's years in school. Column (3) and (4) separate parents' policy exposure into the LLF and the OCP using Equation 2.2. All coefficients for the family control policies are significantly positive. The results indicate family

[7]Detailed study is from Black et al. (2005)

control policies effectively increased first-born children's years of schooling. Note that although the coefficient for the LLF policy is smaller than that for the OCP, the overall effect of the LLF policy is larger given its mean ($0.38 \times 1.86 = 0.7$ years for LLF; $1.19 \times 0.24 = 0.29$ years for OCP). The negative sign of number of siblings in column (3) further confirms the idea that with more children in the household, the resources that could be allocated to the first child decrease, resulting in less investment in the first child's education. Columns (5) and (6) further separate the policy exposure to that of mothers and fathers. I argue that using the mother's exposure is more accurate due to the fact that construction of exposure uses women's age-specific fertility rate. Table 2.5 provides supporting evidence for a quantityquality trade-off using the LLF policy, which effectively reduced the number of children.

Next, I use an alternative measure of children's education - a dummy variable of illiteracy. Table 2.6 displays the results. As shown, exposure to the policy is negative in all columns, indicating that with more exposure to family planning policies, the probability of the first child being illiterate drops. Again, the overall effect of the LLF is more pronounced ($-0.156 \times 1.86 = -0.29$) than the effect of the OCP ($-0.231 \times 0.24 = -0.06$).

In Table 2.7 and Table 2.8, I further explore the heterogeneous effects of the LLF policy on boys and girls. Girls are usually more vulnerable in families in China. Li et al. (2008) find that larger family size leads to more negative impacts on girls' education compared to boys' education. As family control policies can reduce potential male siblings, girls could benefit from the reduced family size. The first three columns of Table 2.7 are results for boys and the last three columns are for girls. The policy estimates are larger for girls than for boys. The LLF estimate for the girls' sample is 0.496, whereas the estimate for the boys' sample is 0.485. Although the difference does not seem significant at first glance, considering that the mean years of schooling is 5.86 and 6.7 for girls and boys, respectively, the LLF improves the number of years children spend in school by more than 15.7% for girls versus 13.5% for boys. Similar findings for LLF are shown in Table 2.8. Overall, Table 2.7 and Table 2.8 show that both the LLF and the OCP generate greater positive effects for girls than boys in increasing the number of years they spend in school and reducing their illiteracy.

2.6 Other contemporary events during this period

Other contemporary events that happened during the study period pose a potential threat to the validity of this study. This section carefully reviews these events. The aim of addressing contemporary events is to isolate the effects of the LLF policy from the effects of other events and provide more robust results.

2.6.1 China's education development

China's educational development during the 1970s is a contemporary event that overlapped with the LLF policy. Hannum (1999) reviewed and summarized China's educational development history from 1949 to 1990 (see Figure 2.9).China's education system alternates its goals between economic development and social equity. The Cultural Revolution (1966 to 1976) was a radical egalitarian movement during which the educational goal was to undercut the differences between rural and urban areas. Consequently, during this time, students were selected based on political and family backgrounds rather than academic achievements. Even though the quality of education suffered greatly during the Cultural Revolution, the policy implemented during this period appears to have been effective in promoting mass education of the rural population and decreasing the difference between urban and rural enrolment (see Figure 2.10). The mass improvement in education during the 1970s was mostly driven by the development of secondary education in rural areas (see Figure 2.9 and Figure 2.10).

Although secondary education improved in rural areas during the Chinese Cultural Revolution, the total number of primary schools and the rate of rural enrolment in primary schools remained constant during the period of study. In this study, the alternative measure of education illiteracy remains robust to this event and should not suffer from bias caused by the educational development in the 1970s. Results remain significant when using an alternative measure of educational investment, which confirms that the family control policy is effective in improving investment in children's education.

2.6.2 The Sent Down Youths program

Another confounding event that occurred around this same time period is the Sent-Down Youth Movement. The Sent-Down Youth Program started in 1968two years after the Cultural Revolution. From 1966 to 1976, 17 million young people were moved to rural areas. The official reason for moving young people from urban areas was to transform them into new people because the government believed they were contaminated by bourgeois values; however, the implicit practical reason for the program was the lack of employment opportunities in urban China. The increasing pressure on employment came from two sources: (1) the baby boomer's generation had reached working age (Banerjee et al., 2010)) and (2) fundamental damage to all aspects of the educational system had occurred during the Cultural Revolution (Bernstein, 1977). The target population in the Sent-Down Youth Program was mostly junior and senior high school students in their graduation year. The three major resettlement locations were rural villages, collective farms and state farms (see Figure 2.11). This movement came to be regarded as a political command and was more forced than voluntary. The number of sent-down youths varied from place to place and from year to year. The determinants of whether or not someone was sent-down were not related to their familys economic/social statu (Bonnin, 2009; Zhou and Hou, 1999). The main factors that influenced the probability of being selected as a sent-down youth were year and place of high school completion (Bonnin, 2009). Chen et al. (2018) complied a county-level dataset after reviewing over 3,000 book-length local gazetteers and micro-level population censuses (see Figure 2.12 and Appendix A). I will use the provincial variations in the sent-downs to address this confounding event.

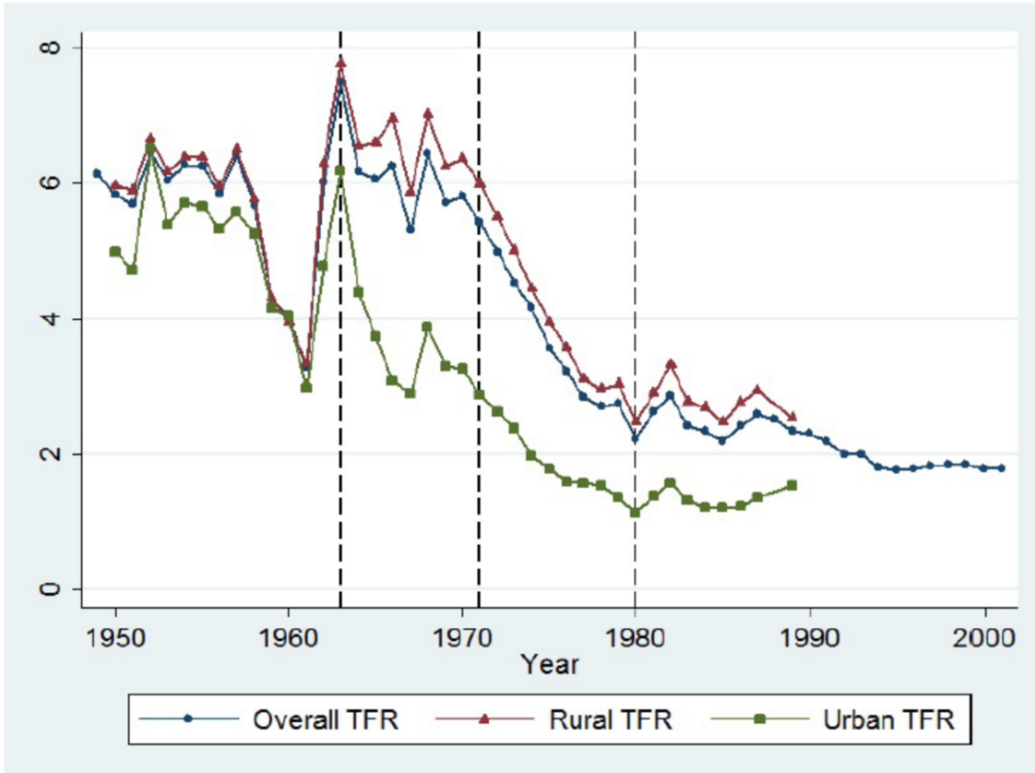
The Sent-Down Youth Program could possibly affect people's age of marriage, which could confound my results. To deal with the Sent-Down Youth Movement in the 1970s, I create a variable to measure the intensity of the movement, and I include it as a control variable. The average sent-down risk is 0.93%, which is negligible and should yield minor, if any, consequences for the analysis. Table 2.9 assesses the effects on years of school and illiteracy, controlling for the risk of being sent down. It shows that the coefficients for the SDY are not statistically significant in column (2) and only slightly decrease the years of schooling in column (1). Moreover, the SDY increases illiteracy in column (3) and is insignificant in column (4). All the estimates for LLF and OCP are similar to those in Tables 2.5 and 2.6 in terms of coefficients' magnitudes and significance levels. This might be due to the fact that the Sent-Down Youth Movement mainly affected large cities with low initial fertility rates, leaving no room to further decrease the fertility rate. Overall, after carefully addressing the Sent-Down Youth Movement, I continue to find that the LLF has positive impacts on children's educational investment.

2.7 Conclusion

Since 1970, China has experienced a significant fertility decline. China's family planning policy has a long history and is one of the tightest population control policies in the world. This paper examines the quantityquality trade-off by using several stages of China's family control policies, with a focus on the 1970s period. I quantify the exposure to policies by using the counterfactual number of children each woman could have. By regressing the number of live births on the policy exposure, the study finds the policy is effective in reducing family size and increasing birth spacing. I further explore the effects of family planning policies on the education of first children and find positive impacts. Based on my calculation, the LLF policy increased the number of years first children are in school by 0.7 until 1982. Comparisons between the "Later, Longer, Fewer" policy and the One Child Policy are made throughout this paper. Both the LLF and the OCP are effective in reducing the number of live births. Both policies increased first-born children's number of years in school and the effects for girls were more significant than those for boys. After carefully addressing other contemporary events, including the Sent-Down Youth Movement and the Cultural Revolution in China, the main results remain mostly unchanged.

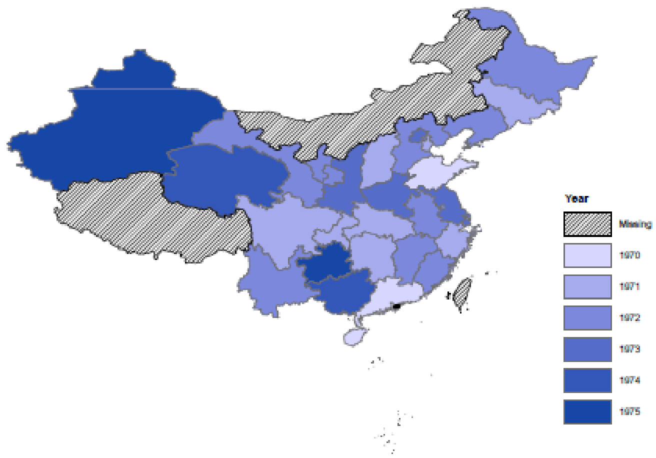
My findings provide evidence for a quantityquality trade-off using the Chinese case. The most important difference between this study and other Chinese family control studies is that this paper utilizes the LLF policy. It is the first of its kind that looks at the impact of the 1970s' policy on children's educational outcomes. Moreover, the LLF policy is less restrictive and controversial than the OCP, yet it is still effective in achieving its goals. This shows that extremely strict policies like the OCP are not the only way to ensure an expected outcome. Furthermore, this study may shed light on future research by highlighting the LLF policy period and providing a novel measurement to this policy.

Figure 2.1: Urban and rural total fertility rates over time



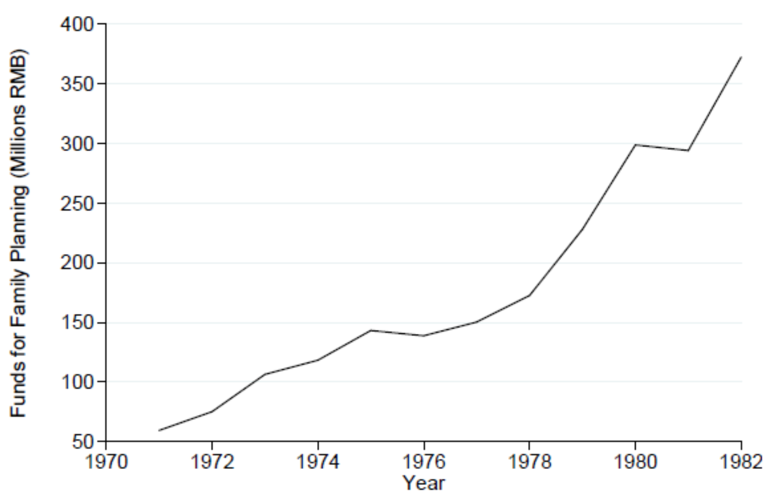
Source: Wang (2014)
This figure displays total fertility rates for overall population, rural areas, and urban areas. The dash lines represent different stages of China's family control policies. As shown in the figure, fertility rate saw most decline during 1970s which corresponds to the second stage of China's family control policies.

Figure 2.2: The Establishment Year of Family Planning Leading Group in Each Province



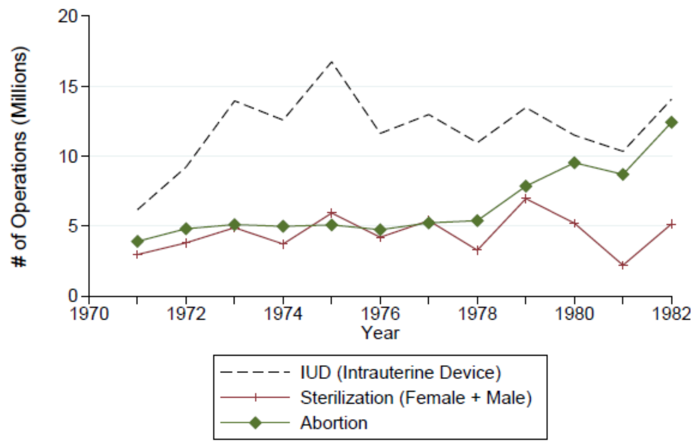
Chen and Huang, 2018
This figure shows variations of LLF starting times in different provinces. The starting times varies from 1970 to 1975.

Figure 2.3: Trends in funds in family planning



Note: Data from National Population and Family Planning Commission of P.R. China (2007).
Source: Chen and Huang, 2018

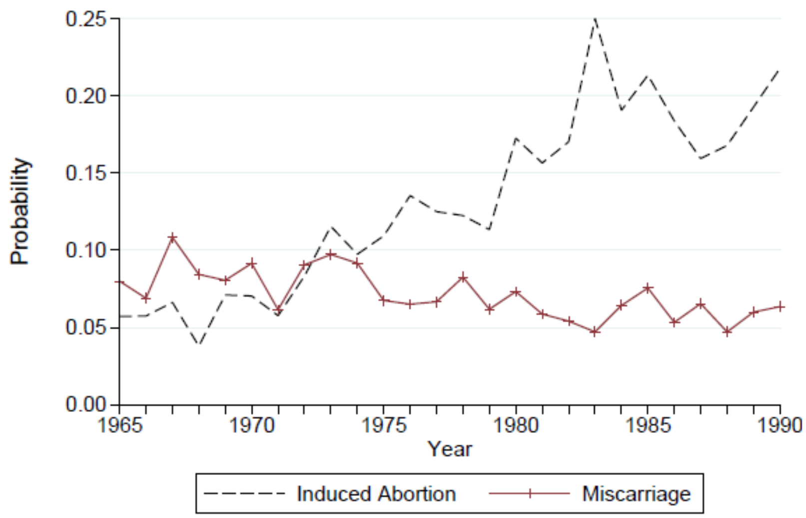
Figure 2.4: Different methods of birth control



Note: Data from National Family Planning Commission of P.R. China, Comprehensive Planning Department (1983)

Source: Chen and Huang, 2018

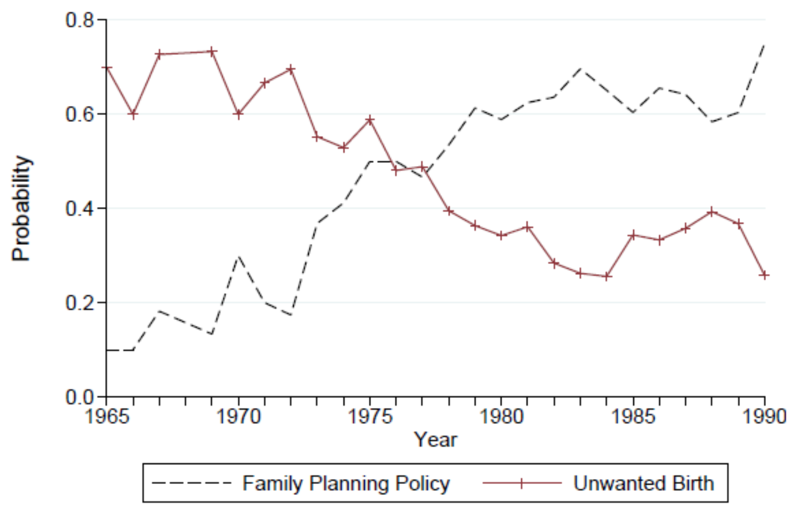
Figure 2.5: How a pregnancy Has ended



Note: Authors' calculation based on China Health and Retirement Longitudinal Study 2014.

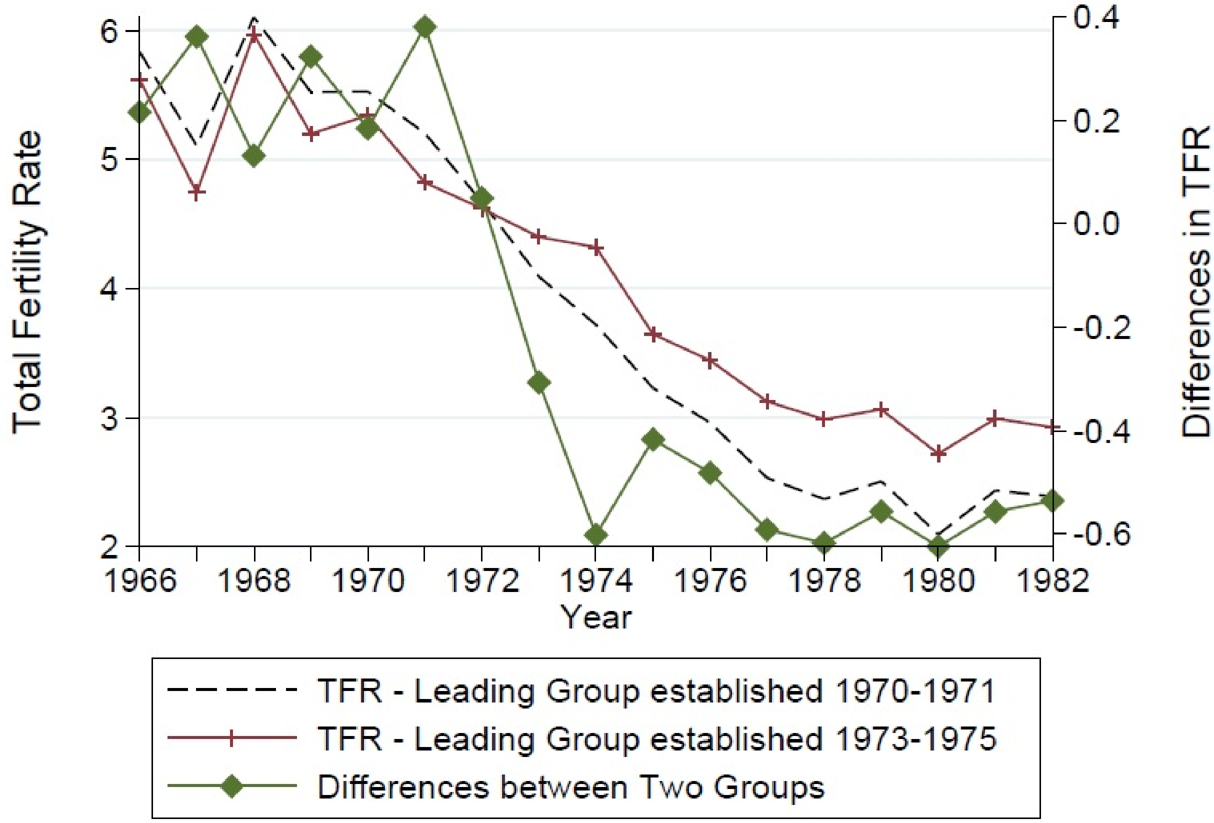
Source: Chen and Huang, 2018

Figure 2.6: Reasons for induced abortion



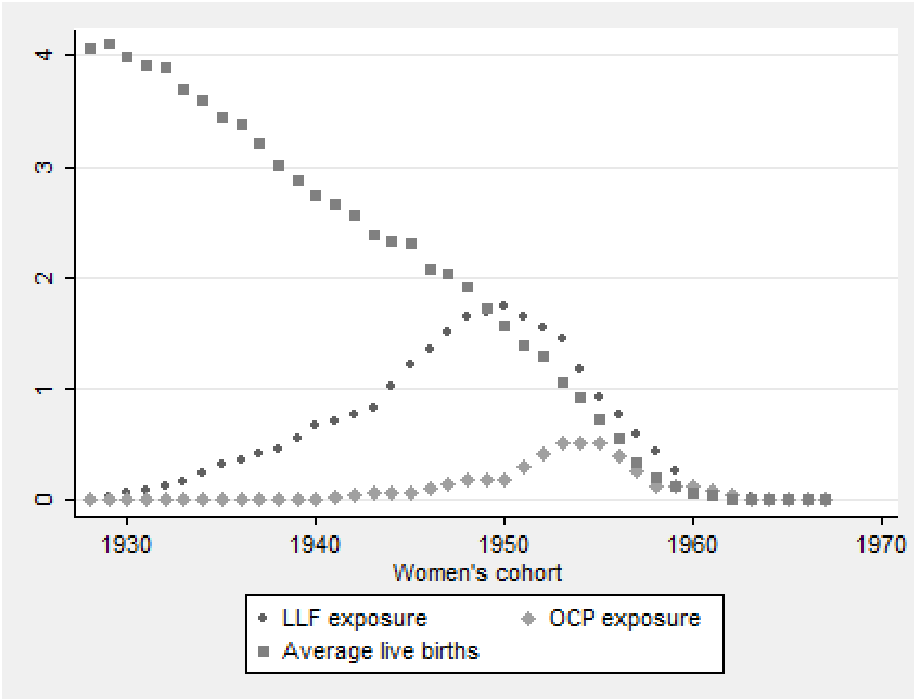
Note: Authors' calculation based on China Health and Retirement Longitudinal Study 2014.
Source: Chen and Huang, 2018

Figure 2.7: Trends of Total Fertility Rate, Early vs Late Establishment Provinces

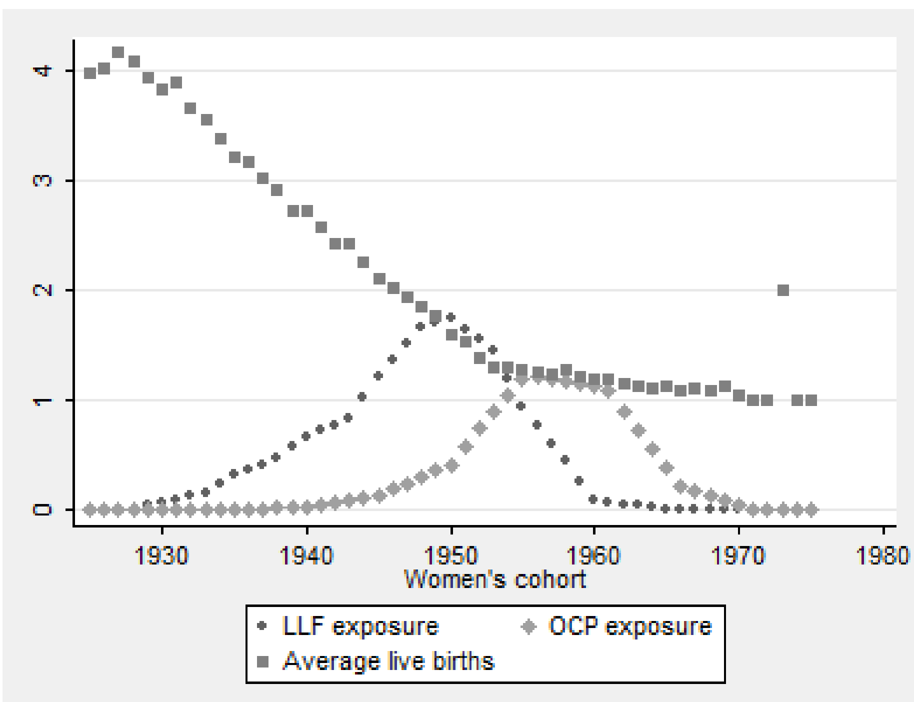


Source: Chen and Huang, 2018

Figure 2.8: Different measure of family planning policies, 1982 1990 Beijing



(a) 82



(b) 90

Source: Self calculation

These figures display exposure to different policies and average live births by cohorts in Beijing. The upper panel shows the above mentioned information in 1982 census. The lower panel calculates similar information using the 1990 census.

Figure 2.9: Total number of schools

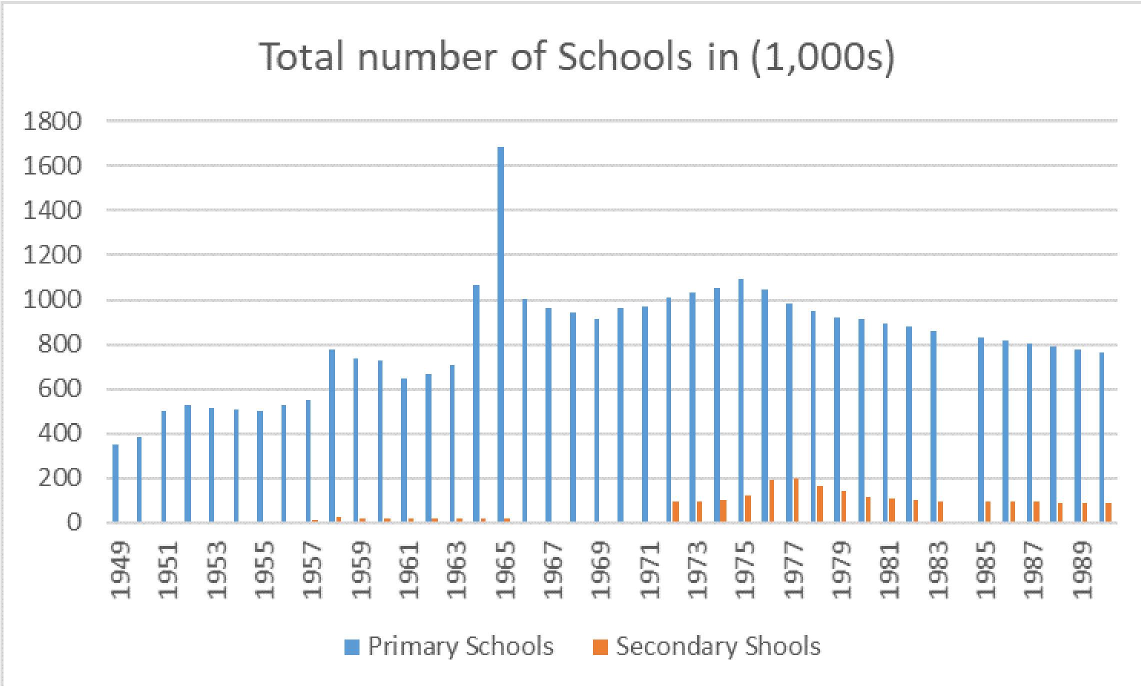


Figure 2.10: Percentage of Rural Enrollment

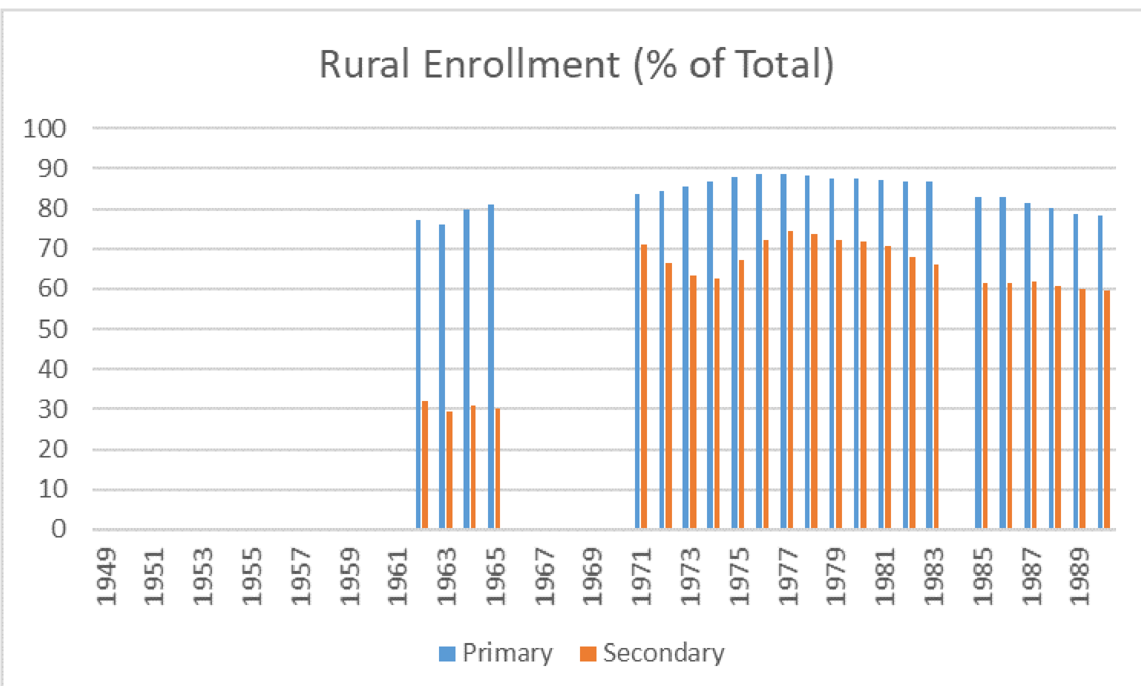
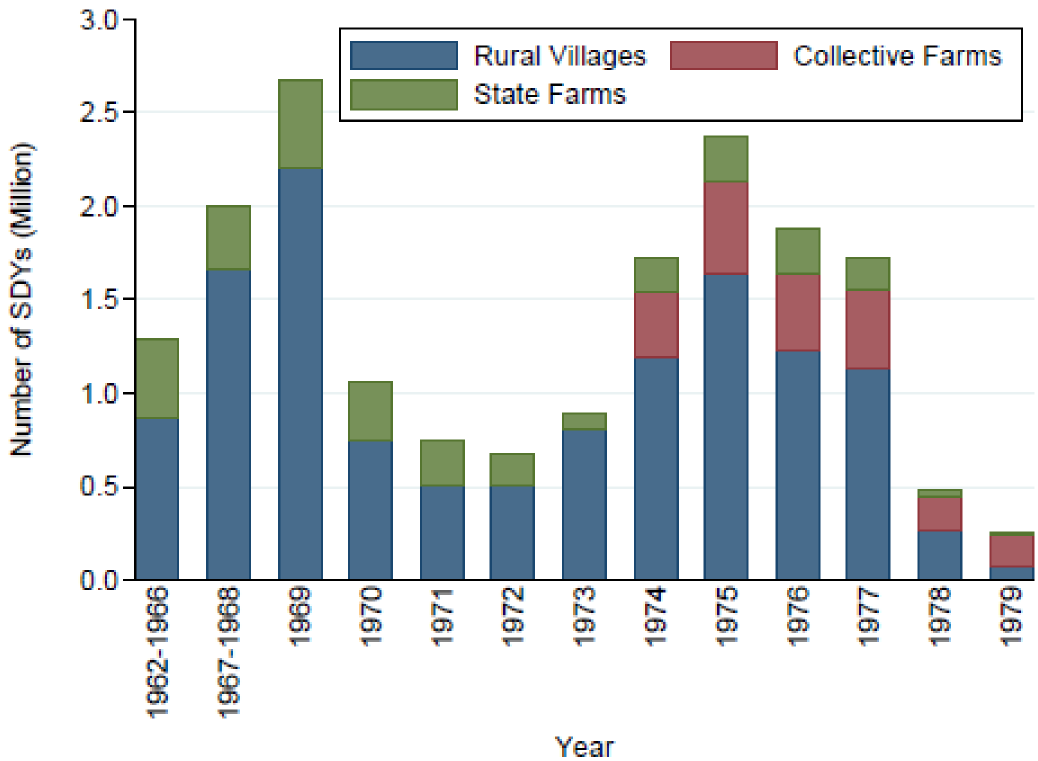
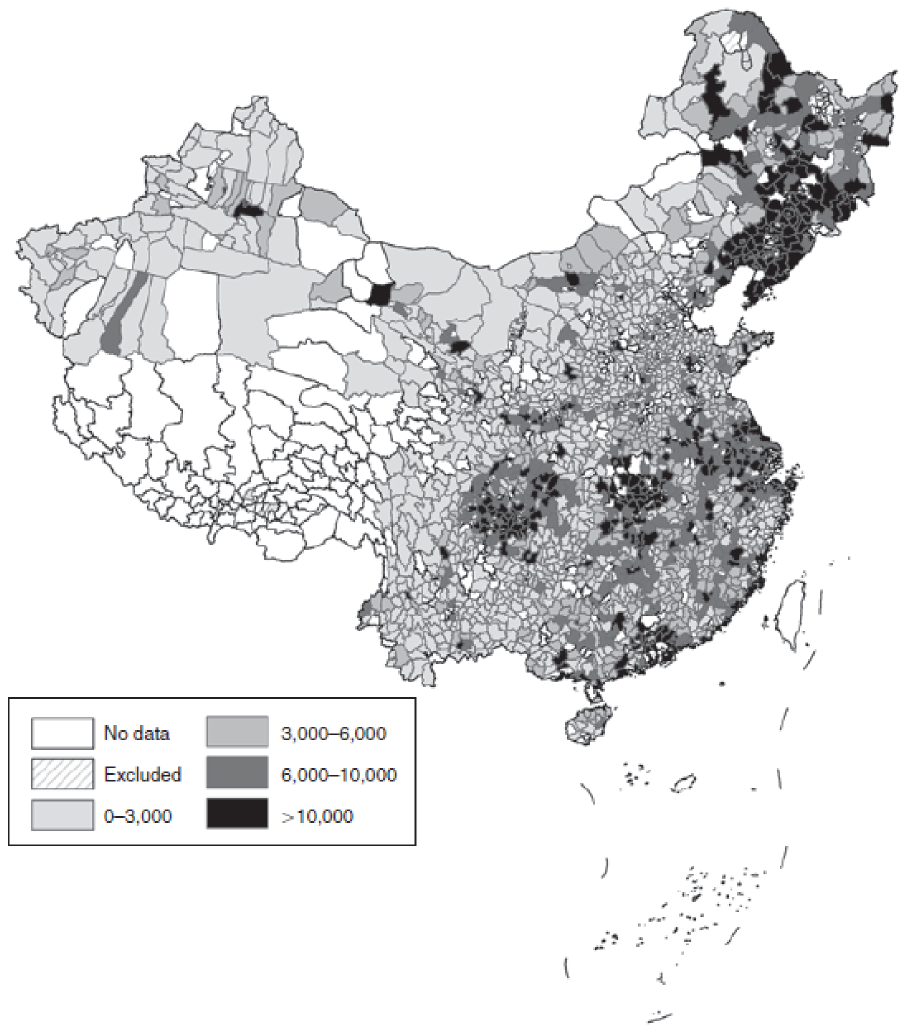


Figure 2.11: Number of sent-down youths by resettlement



Note: Data source is Gu (2009) "Chinese Educated City Youth: The Whole Story."

Figure 2.12: Number of Received Sent-Down-Youth in Each County



Source: Chen et al., 2020

Table 2.1: Province Total Feritility Rate by the LLF establishment year

LLF Establishment year		Average Provincial TFR			
	Obs	Mean	SD	Min	Max
1970	2	5.34	0.31	5.12	5.56
1971	7	5.57	1.07	3.39	6.49
1972	9	5.92	.80	4.57	6.71
1973	5	4.40	1.47	2.37	6.04
1974	2	5.88	0.10	5.82	5.95
1975	2	6.52	0.30	6.31	6.74
Total	27	5.55	1.09	2.37	6.74

Notes: Table shows average provincial total fertility rate in 1969 for provinces grouped by their LLF establishment years. It shows there is no systematic differences in the average of total fertility rate since there is great overlap considering the min and max for different groups.

Table 2.2: Summary sample statistics for women aged 15-64

Variables	1990			
	Mean	SD	Min	Max
Age	38.64	11.79	15	64
Years of schooling	5.25	4.16	0	16
# of surviving children	2.71	1.63	0	9
Exposure to policy	4.19	2.09	0	6.74
Exposure to LLF Policy	1.06	0.93	0	2.87
Exposure to One child Policy	0.91	0.76	0	2.96
Urban hukou	0.21	0.40	0	1
Employment status				
% Employed	79.94	40.04		
% Unemployed	0.22	4.7		
% Housework	16.21	36.85		
% In school	0.02	1.38		
% Retired	2.61	15.69		
% Disabled	0.87	9.27		
% Inactive	0.13	3.59		
Observations	2683401			

Notes: Table shows the means, standard deviations , minimum and maximum of variables used in the analyses. The sample are women aged 15-64 in 1990 Chinese Census. Exposure to policy is constructed using Equation 2.1. It is a proxy measure of counterfactual number of live births during the policy period if no policy implemented. Thus, a greater number of counterfactual number of births represents greater exposure to the family control policy.

Table 2.3: Summary sample statistics for first born children

Variables	1982		1990	
	Mean	SD	Mean	SD
%Male	52.6	49.9	52.52	49.94
Age	14.46	5.98 1	13.15	5.75
Years of schooling	6.20	3.47	6.50	2.81
Education level				
% Illiterate or semi-illiterate	18.13	38.52	9.69	29.58
% Primary School	48.27	49.97	61.11	48.75
% Junior middle schools	24.41	42.95	22.97	42.06
% Senior middle school	9.07	28.72	5.72	23.22
% College+	0.13	3.53	0.52	7.17
# siblings	2.33	1.31	1.42	1.08
Sent down risk (%)	0.93	3.36		
Mother's age	37.14	7.21	36.74	6.28
Mother's FPP	3.62	1.80	5.00	1.37
Mother's LLF	1.86	0.72	1.52	0.81
Mother's OCP	0.24	0.23	1.23	0.71
Mother's years of schooling	3.16	3.74	5.54	3.94
Mother's employment status				
% Employed	86.63	37.60	88.71	31.64
% Unemployed	0.05	2.15	0.11	3.35
% Housework	15.24	35.94	10.04	30.06
% In school	0.00	0.66	0.00	0.79
% Retired	0.71	8.42	0.82	8.99
% Other	0.37	6.07	0.31	5.55
Mother in agriculture sector	69.64	45.98	66.77	47.10
% Minority mother	6.38	24.44	6.79	25.16
Father's age	40.14	7.88	39.13	6.94
Father's FPP	2.95	1.81	4.61	1.57
Father's LLF	1.68	0.81	1.69	0.76
Father's OCP	0.17	0.19	1.02	0.72
Father's years of schooling	5.84	3.64	7.57	3.37
Father's employment status				
% Employed	97.99	14.04	98.43	12.42
% Unemployed	0.01	1.04	0.07	2.68
% Housework	0.68	8.22	0.17	4.15
% In school	0.01	0.89	0.01	1.13
% Retired	0.79	8.83	0.89	9.38
% Other	0.53	7.24	0.42	6.48
Father in agriculture sector	75.21	43.18	66.33	47.25
% Minority father	6.42	24.51	6.84	25.25
Observations	675936		950023	

Table 2.4: Effect of policy on family size

Dependent Var	Number of Surviving Children				Birth Spacing	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to Policy	-0.272***		-0.281***		0.345***	
	(0.0150)		(0.0150)		(0.0207)	
Exposure to the 1970s Policy		-0.261***		-0.281***		0.279***
		(0.0190)		(0.0189)		(0.0328)
Exposure to the One-Child Policy		-0.279***		-0.279***		0.382***
		(0.0165)		(0.0162)		(0.023)
N	2683401	2683401	2683401	2683401	1335755	1335755
adj. R^2	0.567	0.565	0.574	0.572	0.074	0.073
Controls	X	X	X	X	X	X
Additional Controls			X	X		

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Control variables include: age, age squared, dummies, urban Hukou dummy, and provincial dummies; Additional Controls include: years of schooling, unemployed dummy and housework dummy. Error term is clustered by women's birth year and province.

Table 2.5: Effect of policy on first child's education

Dependent Var	Years of schooling					
	(1)	(2)	(3)	(4)	(5)	(6)
Mother's exposure to policy	0.388***	0.445***				
	(0.0318)	(0.0321)				
Father's exposure to policy	0.0133	0.0356**				
	(0.0198)	(0.020)				
Mother's exposure to LLF			0.393***	0.376***	0.469***	
			(0.0431)	(0.0431)	(0.0407)	
Father's exposure to LLF			0.179***	0.219***		0.414***
			(0.0297)	(0.0299)		(0.0328)
Mother's exposure to OCP			1.055***	1.189***	1.338***	
			(0.168)	(0.168)	(0.164)	
Father's exposure to OCP			0.119	0.216**		0.649***
			(0.0915)	(0.0927)		(0.114)
Number of siblings	-0.209***		-0.226***			
	(0.00629)		(0.00636)			
N	675936	675936	675936	675936	635936	635936
adj. R^2	0.433	0.430	0.443	0.429	0.429	0.428
Individual Controls	X	X	X	X	X	X

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Control variables include: age, age squared, gender, each parent's age, each parent's years of schooling, each parent's agricultural dummies, each parent's employment status dummy, dummies for each parent's belong to minority groups and province dummies. Error term is clustered by mother's birth year and province.

Table 2.6: Effect of Policy on First Child's illiteracy

Dependent Var	Illiterate			
	(1)	(2)	(3)	(4)
Mother's exposure to policy	-0.134***			
	(0.0069)			
Father's exposure to policy	0.00995			
	(0.006)			
Mother's exposure to LLF		-0.124***	-0.156***	
		(0.00767)	(0.00693)	
Father's exposure to LLF		-0.0687***		-0.130***
		(0.00558)		(0.00588)
Mother's exposure to OCP		-0.227***	-0.231***	
		(0.0290)	(0.0292)	
Father's exposure to OCP		0.0344		-0.0247
		(0.02)		(0.0236)
N	675936	675936	675936	675936
adj. R^2	0.250	0.253	0.250	0.246
Individual Controls	X	X	X	X

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Control variables include: age, age squared, gender, each parent's age, each parent's years of schooling, each parent's agricultural dummies, each parent's employment status dummy, dummies for each parent's belong to minority groups and province dummies. Error term is clustered by mother's birth year and province.

Table 2.7: Effect of policy on first child education by gender

Dependent Var	Years of schooling					
	Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)
Mother's exposure to policy	0.457***			0.466***		
	(0.0327)			(0.0443)		
Father's exposure to policy	-0.045*			0.156***		
	(0.0203)			(0.0263)		
Mother's LLF		0.381***	0.485***		0.395***	0.496***
		(0.0426)	(0.0410)		(0.0524)	(0.0503)
Father's LLF		0.215***			0.292***	
		(0.0316)			(0.0390)	
Mother's OCP		1.019***	1.011***		1.406***	1.819***
		(0.154)	(0.152)		(0.211)	(0.204)
Father's OCP		-0.164			0.853***	
		(0.0968)			(0.123)	
N	355828	355828	355828	320108	320108	320108
adj. R^2	0.473	0.473	0.473	0.398	0.397	0.397

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Control variables include: age, age squared, gender, each parent's age, each parent's years of schooling, each parent's agricultural dummies, each parent's employment status dummy, dummies for each parent's belong to minority groups and province dummies. Error term is clustered by mother's birth year and province.

Table 2.8: Effect of Policy on First Child's illiteracy by gender

Dependent Var	Illiterate					
	Boys			Girls		
	(1)	(2)	(3)	(4)	(5)	(6)
Mother's exposure to policy	-0.130***			-0.144***		
	(0.00668)			(0.00763)		
Father's exposure to policy	0.0145***			0.00248		
	(0.00393)			(0.00456)		
Mother's exposure to LLF		-0.125***	-0.156***		-0.125***	-0.158***
		(0.00793)	(0.00708)		(0.00803)	(0.00743)
Father's exposure to LLF		-0.0649***			-0.0787***	
		(0.00571)			(0.00627)	
Mother's exposure to OCP		-0.231***	-0.218***		-0.231***	-0.261***
		(0.0296)	(0.0297)		(0.0306)	(0.0305)
Father's exposure to OCP		0.0747***			-0.0327	
		(0.0175)			(0.020)	
N	355828	355828	355828	320108	320108	320108
adj. R^2	0.262	0.268	0.264	0.251	0.251	0.249

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Control variables include: age, age squared, gender, each parent's age, each parent's years of schooling, each parent's agricultural dummies, each parent's employment status dummy, dummies for each parent's belong to minority groups and province dummies. Error term is clustered by mother's birth year and province.

Table 2.9: The Robustness of policy effects from the "Sent-Down-Youth" Movement

Dependent Var	Years of schooling		Illiterate	
	(1)	(2)	(3)	(4)
Sent down risk	-0.0116***	-0.00365	0.00363***	0.00056
	(0.00377)	(0.00369)	(0.00054)	(0.00046)
Mother's exposure to policy	0.45***		-0.136***	
	(0.0333)		(0.00687)	
Father's exposure to policy	0.0452*		0.00693	
	(0.0192)		(0.00391)	
Mother's exposure to LLF		0.375***		-0.124***
		(0.0431)		(0.0076)
Father's exposure to LLF		0.222***		-0.069***
		(0.0299)		(0.0056)
Mother's exposure to OCP		1.197***		-0.229***
		(0.017)		(0.0294)
Father's exposure to OCP		0.227*		0.0327
		(0.0909)		(0.171)
N	675936	675936	675936	675936
adj. R^2	0.430	0.0.429	0.251	0.253
Individual Controls	X	X	X	X

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Control variables include: age, age squared, gender, each parent's age, each parent's years of schooling, each parent's agricultural dummies, each parent's employment status dummy, dummies for each parent's belong to minority groups and province dummies. Error term is clustered by mother's birth year and province.

Chapter 3

Glass ceiling or sticky floor: China's Hukou premium using unconditional quantile analysis

3.1 Introduction

Since it opened its economy in 1978, China has experienced unprecedented growth; however, it has also experienced increasing inequality. As the urban-rural income gap widens and household registration (Hukou) relaxes, many rural residents are migrating to cities in search of the relatively higher-paying jobs found in urban areas. The number of rural–urban migrants has increased from 6.57 million in 1982 to 288 million (37% of the total workforce of 806 million) in 2018 (National Bureau of Statistics). This scale of rural-urban migration in such a short period is likely the largest in human history, and consequently, the welfare of the migrant population has attracted much attention from the public. Although migrant workers live and work in urban areas, they usually do not possess urban household registration status, also known as urban Hukou. The creation of Hukou in the late 1950s was a product of the central planning economy, which aimed to control the influx of the rural population into urban areas. Such institutional barriers to mobility excluded rural residents from the urban welfare system. When the Chinese economy shifted towards a market-oriented economy in 1978, the Chinese government finally relaxed restrictions on migration; however, it did not abolish the Hukou system. The Hukou system still differentiates urban and rural migrants in terms of job opportunities, social welfare insurance, and job mobility (Démurger et al., 2009). The growing participation of rural migrants in the Chinese urban labour market raises the issue of potentially discriminatory behaviours against migrants. This study tries to explore the extent of Hukou discrimination against rural migrant workers.

The Hukou discrimination against rural migrants can be viewed as opposite to the Hukou premium enjoyed by urban workers. In this study, I define the Hukou premium as the net wage gap between urban workers and migrant workers after adjusting/controlling their labour market endowment differences. Since wage heterogeneity exists in both groups, the Hukou premium is likely to vary across the pay distribution. The term "glass ceiling effect" describes situations where the Hukou premium widens at the top of the pay distribution, suggesting that migrant workers in upper income brackets have lower pay than their urban counterparts. In contrast, the term "sticky floor effect" refers to the fact that migrant workers at the bottom of the distribution are at a greater disadvantage and the gap is wider at the bottom. In other words, "sticky floor" effects are the Hukou premiums enjoyed by urban workers from the bottom wage distribution compared to their rural counterparts. To assess whether there is a glass ceiling or a sticky floor, I will use a quantile regression developed by Firpo et al. (2009) to assess the Hukou premium at different wage quantiles.

Upon finding the wage gap at different quantiles across the earning distributions, I further decompose the earning differentials into the part that can be explained by differences in labour market endowment (the so-called "composition effect") and the part resulting from different returns to their labour market characteristics (the "structure effect"). The latter part reflects the wage discrimination against migrant workers. Traditional Oaxaca-Blinder (OB) decomposition focuses only on the mean, which can veil important differences across the entire wage distribution. To perform the decomposition at different quantiles, I extended the OB decomposition to incorporate the quantile regression analysis.

The extended OB decomposition consists of two steps. In the first step, a counterfactual earning distribution is constructed using a reweighting approach. This counterfactual distribution tries to mimic the earnings that migrants would have earned had they received the same returns to their labour market characteristics as urban workers. Any gap between the actual urban wage distribution and the counterfactual reflects the "composition effect", and any wage gap between the counterfactual and migrant wage distribution reflects the "structure effect". Thus, the first step is very similar to a study conducted by DiNardo et al. (1996) in that both studies construct a counterfactual wage distribution using the reweighting approach. In the second step, I further divide the wage structure and composition effects into the contribution of each covariate using OB in conjunction with the RIF unconditional quantile method. This allows me to identify the specific characteristics that lead to the urbanmigrant earning gaps at different quantiles and how this occurred.

This study contributes to the existing literature on urban-migrant wage gaps in two ways. First, it is the first of its kind to construct a migrant counterfactual wage distribution using a reweighting approach. By plotting the wage distribution for the three groups (as shown in Figure 3.7), it is easy to see the full picture created by the earning gaps and the Hukou premiums across the entire distribution. Second, in this paper I conduct various decomposition methods and provide a more comprehensive analysis on the Hukou premium.

In my results, I do not find a "glass ceiling" or "sticky floor" effect for migrant workers. Instead, there is an inverse U-shaped Hukou premium, which indicates that urban Hukou holders enjoy greater returns to urban Hukou in the middle part of the wage distribution. The composition effect plays a major role in both the top and the bottom quantiles. The results indicate that although there is no single factor that appears to be able to fully explain the earning gap, education does seem to account for a significant part of wage inequality.

The remainder of the paper is organized as follows. Section 3.2 provides a brief history of China's Hukou system. Section 3.3 describes the data used in this study. Section 3.4 discusses the estimation methods. Section 3.5 discusses the results and Section 3.6 concludes.

3.2 Background: A brief overview of the Hukou system

For a number of decades, China has been run using a dual economic structure. Segregation between urban and rural areas is huge. The original segmentation process began when China introduced its household registration system, also known as the Hukou system, in the 1950s. The original purpose of the Hukou system was to prevent unplanned migration and to control the influx of rural residents to cities. Because China's economy uses a central planning system, the Hukou system, together with the ration system, played an important role in implementing central plans.

Under the Hukou system, everyone is registered either as urban or rural. An individual's Hukou status is inherited from their parents, and before the 1980s, internal movement was very rare. Thus, an individual's status is usually consistent with their place of birth. Most policies under the Hukou system were set in favour of urban residents. For a long time, urban Hukou holders were entitled to government-assigned jobs and the benefits that came along with these jobs, including pensions and health care. Children with urban Hukou could go to public schools without paying a high entry fee in cities. For rural Hukou holders to get an urban Hukou, it usually requires conversion, and there are only a few channels for conversion. Such channels include recruitment by state-owned enterprises (SOEs), obtaining a college degree, demobilization from military service, achieving an outstanding outcome in athletics or other discipline, and marriage. Because these channels were highly restricted and hard to achieve, before 1980, the actual annual conversion rate was 1.5% - 2% before 1980 (Chen and Fan, 2016).

One important factor that makes the Hukou policy effective in controlling population movement is the food ration system. Under the ration system, to buy necessities such as food and clothes in cities, people would use money combined with government-issued tickets distributed to urban Hukou holders. Rural people were considered self-sufficient; thus, they did not receive government-issued tickets. This type of ration system made it very difficult for people from rural areas to survive in urban cities.

After 1978, China opened its economy and started its economic reform. As China's private sector started to grow rapidly, demand for cheap labour in urban areas started to increase, and in the 1980s, the government started to relax its Hukou system. At the same time, the food ration system was also abolished. As a result, the migration of workers from rural to urban areas rapidly increased and China's urbanization took off. According to the World Bank, China's urban population was 20% in 1980 and it increased to 59% in 2018.

Despite changes that relaxed population movement, the Hukou system continues to differentiate urban Hukou holders and migrants in terms of job opportunities, wages, and many other aspects of life. Lee (2012) finds migrants still face significant wage discrimination and receive less insurance entitlements. Compared with their urban counterparts, rural migrants receive little social welfare such as housing and medical subsidies. Additionally, in terms of children's education, migrant workers need to pay a higher entry fee for public school enrolment. Song (2016) finds that Hukou-based discrimination is more serious in state-owned enterprises and that females tend to suffer more. The purpose of this paper is to explore how the Hukou system differentiates urban workers and migrant workers in terms of earnings.

3.3 Data and descriptive statistics

For this study, I use the data from the 2002 China Household Income Project (CHIP2002). Five waves of household surveys were carried out by the National Bureau of Statistics (NBS). CHIP 2002 is a national survey that consists of three subsamples, each which used a unique questionnaire. I use two of the subsamples, the urban resident survey and the rural-urban migrant survey, for the purpose of this study. Both the migrant survey and the urban survey are national representatives(Démurger et al., 2009). The urban survey includes urban residents with household heads holding urban Hukou. Most respondents in this sample hold urban Hukou. They cover 12 major provinces and 77 cities. The migrant survey is designed to interview people who live in urban cities but hold rural Hukou. Both subsamples contain rich information on individuals' income, labour and demographic characteristics. Although the two questionnaires were designed similarly, there are still some differences in terms of occupation and industry, and I carefully seek concordance to make them consistent.

My sample is limited to workers who earned a positive wage and are between the ages of 16 and 60 years old. I use urban work experience for rural migrants as a measurement for the experience. There are two measurements for education: years of schooling and education level. I separate education level into six categories: no school; elementary school; junior middle school; senior middle school; junior college;

college and above. I drop individuals with missing data on the variables list in Table 3.1. The final sample includes 5576 urban workers and 3303 rural migrants.

Table 3.1 presents the means and standard deviations of the main variables for urban residents and rural migrants. The average wage for the urban population is more than 50% higher than it is for rural migrants. Urban workers have higher education levels and more years of work experience. In terms of occupation, migrants have a significantly higher share (54%) of business ownership than urban residents, which is probably due to the fact that it is more difficult for rural migrants to find stable jobs, so they tend to be self-employed and often end up as small business owners and vendors in cities. Conversely, urban residents have a higher probability of having a professional and stable job than rural migrants. While more than half of urban workers are employed as permanent staff, for migrants, this number is less than 10%. In contrast, more than 90% of migrants end up having short-term contracts or being self-employed. To further investigate the urban-migrant wage gap, in Table 3.2 I provide the monthly wage for each group according to occupation, tenure, and education level. Urban workers have a higher average monthly wage in every category except for the no school group. The overall migrant/urban wage ratio is 62%.

3.4 Methods

3.4.1 RIF-regression

To examine whether having an urban Hukou affects one's income, I start with a simple OLS model where Hukou enters the regression as a dummy variable along with other control variables. The OLS estimation yields one number for the Hukou coefficient. It represents the mean differential in earnings between urban Hukou holders and migrants but stays silent in answering questions such as which part of the distributions are most affected by Hukou status. Consequently, one may need to switch to other methods to answer such questions. Quantile regressions are popular for analysing changes in the quantiles. A standard way is to apply the following quantile regression developed by Koenker and Bassett Jr (1978),

$$q_y^\tau = q^\tau \left(y_i|x_i\right) + \varepsilon_i^\tau = D_i\delta^\tau + X_i\beta^\tau + \varepsilon_i^\tau \tag{3.1}$$

where y_i is individual income, q_w^τ is the conditional quantile of wage for quantile τ, and D is the dummy variable for urban Hukou status. The method described above is the conditional quantile regression (CQR). CQR estimates the treatment effects conditional on the mean value of included covariates, and the interpretation of the treatment effects change when different sets of covariates are entered into the regression model. The CQR is not useful for analysing the impact of Hukou status on the unconditional distribution of wage.

To study the impact of Hukou status on the unconditional distribution of wage, I use the unconditional quantile regression proposed by Firpo et al. (2009). In the recentered influence function (RIF) regression, the dependent variable is replaced with its generated RIF variable, and then an OLS regression is applied to all the covariates.

$$\widehat{RIF}\left(Y;\hat{q}_\tau\right) = D_i\widehat{\delta_{uqr}^\tau} + X\widehat{\beta_{uqr}} \tag{3.2}$$

The RIF variable is obtained by adding the influence function back to the quantile selected.

$$\text{RIF}\left(y;q_\tau,F\right) = q_\tau + \text{IF}\left(y;q_\tau,F\right) = q_\tau + \left(\frac{\tau - I\left\{y \leq q_\tau\right\}}{f_Y\left(q_\tau\right)}\right) \tag{3.3}$$

The bracket describes the influence function (IF). As its name suggests, the influence function ($\text{IF}\left(y;q_\tau,F\right)$) of a distributional statistic $v(F_Y)$ represents the influence of an individual observation on that distributional statistic. q_τ can be estimated using a sample quantile and $f_Y(.)$ can be estimated using kernel density.

Unlike the quantile regression used by Koenker and Bassett Jr (1978), the unconditional quantile regression can be directly used to evaluate the economic impact of a change of X on the corresponding quantiles of the unconditional distribution of Y, which is usually of real interest in economic applications. In this case, $\widehat{\delta_{uqr}^\tau}$ denotes the estimated unconditional partial effect of Hukou status on wage at the τ^{th} quantile.

3.4.2 Detailed decomposition

In this section, I decompose the wage differential between the two groups-urban Hukou holders and migrants-into two components: the "composition effect" and the "structure effect". The first term, also known as the "endowment effect", refers to the earning difference caused by the different labour market characteristics between the two groups. The latter term refers to the difference resulting from the different returns to those characteristics. The Oaxaca-Blinder (OB) decomposes the mean difference after running OLS (Oaxaca, 1973; Blinder, 1973). In terms of other distributional statistics, such as quantiles, OB decomposition cannot be performed directly. Fortunately, the RIF regression carries nice features as OLS, it is more general as it can apply to any distributional statistic such as quantiles. The extension of the OB decomposition applied along with the RIF regression enables the decomposition not restricted to mean differential.

$$
\begin{aligned}
\hat{q}_{ur} - \hat{q}_{m\tau} &= \widehat{RIF}\left(Y_u, \hat{q}_{m\tau}\right) - \widehat{\mathrm{RIF}}\left(Y_m, \hat{q}_{fr}\right) \\
&= \bar{X}_u \hat{\beta}_{u\tau} - \bar{X}_m \hat{\beta}_{m\tau} \\
&= \underbrace{\left(\bar{X}_u - \bar{X}_m\right) \hat{\beta}_{u\tau}}_{\Delta_X(\text{Explained })} + \underbrace{\bar{X}_m \left(\hat{\beta}_{u\tau} - \hat{\beta}_{m\tau}\right)}_{\Delta_S(\text{Unexplained })}
\end{aligned}
\tag{3.4}
$$

Equation 3.4 is the extended OB decomposition at the τth quantile,[1] where $\hat{q}_{u\tau}$ and $\hat{q}_{m\tau}$ represent the τth quantile of Y_u and Y_m and $\hat{\beta}_{u\tau}$, and $\hat{\beta}_{m\tau}$ are the RIF regression coefficients for each subgroup. The only difference between the extended quantile OB and the OB at mean is that I replace the mean wage with RIF(Y, q_r).I choose the urban population as my reference group to compute the wage structure effect.[2]

As shown in Equation 3.4,the OB decomposition provides a straightforward way of dividing up the composition effect and the structure effect at selected quantiles; however, its simplicity comes with two limitations. The first limitation is that the detailed decomposition of structure effects into each covariate is sensitive to the choice of the

[1]Equation (3.4) is the OB decomposition without reweighting.

[2]Although the decomposition could also be conducted using the migrant group as the reference group, I choose urban as the reference to align with the reweighted OB decomposition discussed next.

base group (Oaxaca and Ransom, 1999; Gardeazabal and Ugidos, 2004). Unfortunately, there is no simple solution to this issue. The second limitation of OB is the linearity assumption. That is to say, the OB estimates are consistent only if the function form of the conditional expectation of wage is linear (Barsky et al., 2002). To tackle this limitation, I will further extend the OB decomposition to incorporate a reweighting approach.

To generate a reweighed version of the OB decomposition, I follow the work by Firpo et al. (2018) and conduct a two-step procedure to decompose wage differentials at different quantiles. First, I decompose the overall difference of wage distributions between the two groups into "structure effect" and "composition effect" using the following equation:

$$\nu\left(Y_u\right)-\nu\left(Y_m\right)=\left[\nu\left(Y_u\right)-\nu\left(Y_c\right)\right]+\left[\nu\left(Y_c\right)-\nu\left(Y_m\right)\right] \tag{3.5}$$

where $v(Y)$ denotes quantiles of wage distribution, Yu denotes wage for urban Hukou holders, Y_m denotes wage for migrants, and Y_c is the counterfactual wage for migrants if they receive the same return as the urban workers. The first bracket of Equation (3.5) is the "composition effect" and the second bracket shows the "structure effect". Now, I will address how to calculate Y_c. As Firpo et al. (2018) explain, the first step is very similar to the work of DiNardo et al. (1996)'s work and Y_c can be obtained by reweighting.

$$Y_c=\psi Y_u \text{ where } \psi_i=\left[\left(1-p\left(X_i\right)\right)/p\left(X_i\right)\right]\times[p/(1-p)] \tag{3.6}$$

In the reweighting factor ψ_i, $p(X_i)$ is the probability of an worker being urban Hukou holder given individual attributes X. It can be treated as the "propensity score", and I estimate $p(X_i)$ using a logit model. p denotes the proportion of urban Hukou holders in the population.[3]

Equation 3.5 imposes two key assumptions: "overlapping support" and "ignorability" (Fortin et al., 2011). The former requires an overlap in observable characteristics across groups. Using the same dataset, Magnani and Zhu (2012) find considerable regions of overlap in the histograms of estimated propensity scores for both groups.

[3]Nicole Fortin has nice proof of why such reweighting method works on her presentation notes available through her website https://faculty.arts.ubc.ca/nfortin/research.html

Additionally, Table 3.3 shows the urban and rural Hukou holders in each wage quintile. Since the reweighting is applied to urban workers to mimic the wage of rural Hukou holders if they hold an urban Hukou, it is critical to ensure there are enough observations for urban workers; thus, my study is not concerned with the common support. The ignorability assumption states that the distribution of error term given X is the same for both groups.

In the second step of the reweighted OB decomposition, I further decompose the "structure effect" and the "composition effect" into contributions of each covariate using the extended OB described in Fortin et al. (2011). Previously, I reweighed urban distribution to look like migrants using Equation 3.6, and sample of reweighed urban (Y_u) and sample of reweighed urban (Y_c)to get the pure composition effect; OB2) with sample of migrant (Y_m) and sample of reweighed urban (Y_c) to get the pure wage structure effect.

$$\begin{aligned}
\overline{Y}_u - \overline{Y}_m &= \left(\overline{Y}_u - \overline{Y}_c\right) + \left(\overline{Y}_c - \overline{Y}_m\right) \\
&= \left(\overline{X}_u\hat{\beta}_u - \overline{X}_c\hat{\beta}_c\right) + \left(\overline{X}_c\hat{\beta}_c - \overline{X}_m\hat{\beta}_m\right) \\
&= \left(\overline{X}_u - \overline{X}_c\right)\hat{\beta}_u + \overline{X}_c\left(\hat{\beta}_u - \hat{\beta}_c\right) + \overline{X}_m\left(\hat{\beta}_c - \hat{\beta}_m\right) + \left(\overline{X}_c - \overline{X}_m\right)\hat{\beta}_c \\
&\quad \text{Composition Effect } + \text{ Spec. Error} \qquad \text{Wage Structure } + \text{ Reweighting error}
\end{aligned} \tag{3.7}$$

3.5 Results

3.5.1 Hukou premium in a single indicator

To evaluate whether having an urban Hukou will generate any wage premium, the dummy variable of urban Hukou status enters the wage regression as the single indicator of the Hukou premium. Table 3.4 displays results using OLS, conditional, and unconditional quantile regressions for selected quantiles. The OLS regression yields a Hukou premium of 105 RMB per month on average and it is statistically significant at the 1% significance level. Considering that the average monthly income is 794 RMB for migrant workers, this premium accounts for 13% of their income.

To understand how Hukou status benefits urban Hukou holders at different quantiles of the distribution, Figure 3.1 and Columns (2)-(4) in Table 3.4 report the detailed conditional quantile estimates (using equation 3.1) for selected quantiles along with bootstrapped standard errors. Unlike the OLS estimate, which is constant across the distribution, the Hukou premium becomes larger when moving towards the end of the wage distribution. Figure 3.2 and columns (5)-(7) in Table 3.4 report the same kind of information using the unconditional quantile regressions (see equation (3.2)) along with the bootstrapped standard errors. Different from the CQR estimates, the unconditional quantile Hukou effect is highly non-monotonic. As can be seen from the graph, the Hukou premium increases from 0 at the 10th quantile to around 200RMB at the 40th quantile and reaches the plateau from the 40th to around the 65th quantile, after which, it starts to decrease and completely vanishes at the top quantile. From Figure 3.2, I do not find the "glass ceiling" or the "sticky floor" effect for the migrant workers. Instead, they seem to be worse off in the middle part of the wage distribution.[4]

To further investigate the inverse U-shaped Hukou premium in different job categories, I reproduce the Hukou premium shown in Figure 3.2 using different subsamples. Figure 3.3 shows the Hukou premium in different occupations. In the subgroups of workers whose occupations are business owners, directors, and clerks, the Hukou premium did not differ from zero across the entire distribution. Even more interesting is that migrant business owners (a subgroup that accounts for the largest share for migrant workers at 54.2%) seem to enjoy a better return at the top quantiles, even though the estimates are not statistically significant. Both professional occupations and manufacturing occupations have the inverse U-shaped Hukou premium. For service workers, urban Hukou holders enjoy premiums at the bottom half distribution and migrant workers face the sticky floor effect; however, only 11% of urban workers fall into this category and this could have a minor impact on the overall distribution. Next, I reproduce unconditional quantile estimates for Hukou premium using different job tenures. For permanent staff, having an urban Hukou does not provide extra wage

[4]Keep in mind that there are enough observations from both rural and urban sectors (see table 3.3), which ensures there are enough comparable workers and an adequate sample size across the whole distribution.

returns across the entire distribution. For short-term contract workers, a positive Hukou premium is observed and the pattern shows a clear inverse U shape. For long-term contract workers, a positive Hukou premium is obtained from the 20th to the 60th quantile. Overall, I observe no glass ceiling effect in any type of job tenure or occupation. For the migrant workers, a "sticky floor effect" exists within limited occupations and job tenures, but the number of workers in those types of jobs only accounts for a small proportion, and therefore, has minimal impact on the overall Hukou premium.

3.5.2 Separate RIF regression for urban and migrant workers

In the previous subsection, I depict the Hukou premium in a single indicator using Equation 3.2; however, Equation (3.2) explicitly restricts the returns to other control variables to be equal for both migrant and urban workers ($\widehat{\beta_{uqr}}$ does not differ by groups). In reality, the labour market rewards system for the two groups of workers could be substantially different from each other. Borrowing the idea from the Chow test, I allow the effect of each covariate to vary with the Hukou dummy, then I test the joint significance of all the interaction terms. The null hypothesis that the coefficient estimates are the same for both groups is rejected, which indicates there are fundamental differences in the estimated coefficients for the two groups.

Table 3.5 separates the unconditional quantile regression results for rural migrant workers and urban workers at selected quantiles. The coefficients exhibit different patterns for the two groups. For better visualization, Figure 3.5shows the unconditional quantile regression coefficients for selected labour market characters from the 5th to the 95th quantiles. The solid line represents the coefficients for the urban group, and the dashed line represents the coefficients for the migrant group. The upper and lower 95% confidence intervals generated by bootstrap standard errors are also shown in the graph. Panel (a) shows the RIF regression coefficient for years of schooling. The effect of education increases monotonically as a function of percentile for both groups and the coefficient is always greater in the urban group. In other words, education has a greater impact on higher quantiles than it does on lower quantiles and the return to education is greater for urban workers than for migrant workers throughout the entire distribution. It is worth noting that although the urban coefficients are larger than the migrant coefficients at the top quantiles, the slope of education for migrant workers is steeper than for their urban counterparts. This means that at the top quantile, the return to education for migrant workers starts to catch up and the gap between them closes (as can be seen the overlap of confidence intervals in the top percentile). Panel (b) shows the experience coefficient patterns for urban and migrant workers. Unlike for returning to education, migrants receive higher pay for their experience and this pattern starts to increase moving towards the end of the quantile. In other words, the incomes of higher-paid migrants increase based on their experience. Conversely, urban workers did not receive much return on their experience throughout the entire distribution. Panel (c) shows the gender wage gap for both groups. For both groups, the gender wage gap is constant and positive up until the 80th percentile, and the gender wage gap starts to increase at the top quantile for both groups with a steeper increase occurring for migrant workers. This provides evidence for both the sticky floor and glass ceiling effects on gender. Furthermore, the glass ceiling effect on gender is more pronounced among migrant workers. To sum up, all the covariates discussed in Figure 3.5 exhibit the fundamental differences between the migrant workers and the urban workers.

3.5.3 Counterfactual distribution and decomposition

As shown in Table 3.1 and Table 3.5, urban workers and migrant workers have different labour market characteristics and also differences in the return on their characteristics. Next, I decompose the overall differences between urban and migrant earning distributions into the composition effect and the structure effect. Moreover, in order to find which variables matter more in generating the composition and wage structure effect, I turn to the Oaxaca-Binder decomposition method. I use two types of OB for the decomposition at different quantiles: (1) the unweighted OB decomposition and (2) the reweighted OB decomposition.

The unweighted OB decomposition is just like the conventional two-fold OB decomposition, except that instead of decomposing at the mean, I decompose at different quantiles. Table 3.6 shows the results for the unweighted OB decomposition at the 10th, 50th, and 90th quantiles using Equation (3.4). I find that the urban-migrant wage gap can mostly be explained by the composition effect at all the selected quantiles. The structure effect is not statistically significant at the middle and top quantiles. In terms of the contribution of each covariate, years of schooling stands out since it accounts for over two thirds of the composition effect at the 50th quantile and more than three quarters at the 90th quantile.

The reweighted OB requires the construction of a counterfactual wage distribution using a reweighting method described in Equation 3.6.As a refresher, this counterfactual distribution captures the distribution of earnings that migrant workers could have earned had they received the same return on the labour market characteristics as urban workers received. Figure 3.6 shows the wage distributions for urban, migrant and migrant counterfactual earnings. As shown in the graph, some migrant workers would move to higher wage positions if they did not face discrimination for their rural Hukou status. Figure 3.7 shows the inverse cumulative distribution function (CDF) of wage distribution for the three groups. The gap between the top line and the bottom line represents the raw urbanmigrant wage gap. The differences between the urban workers' actual earnings and the migrants' counterfactual earnings represent the earning gap resulting from the "composition effect". The differences between the counterfactual earnings and the migrants' actual distribution indicate the "structure effect". The "structure effect" can be treated as the Hukou premium that urban workers enjoy or the Hukou discrimination that migrant workers face. As shown in the graph, there is no Hukou premium in the top 20% or the bottom 20% of the distribution. The Hukou premium starts to widen at the 20th quantile and reaches a maximum around the 60th quantile before it starts to decrease. This inverse U-shaped Hukou premium is consistent with my finding in Figure 3.2.

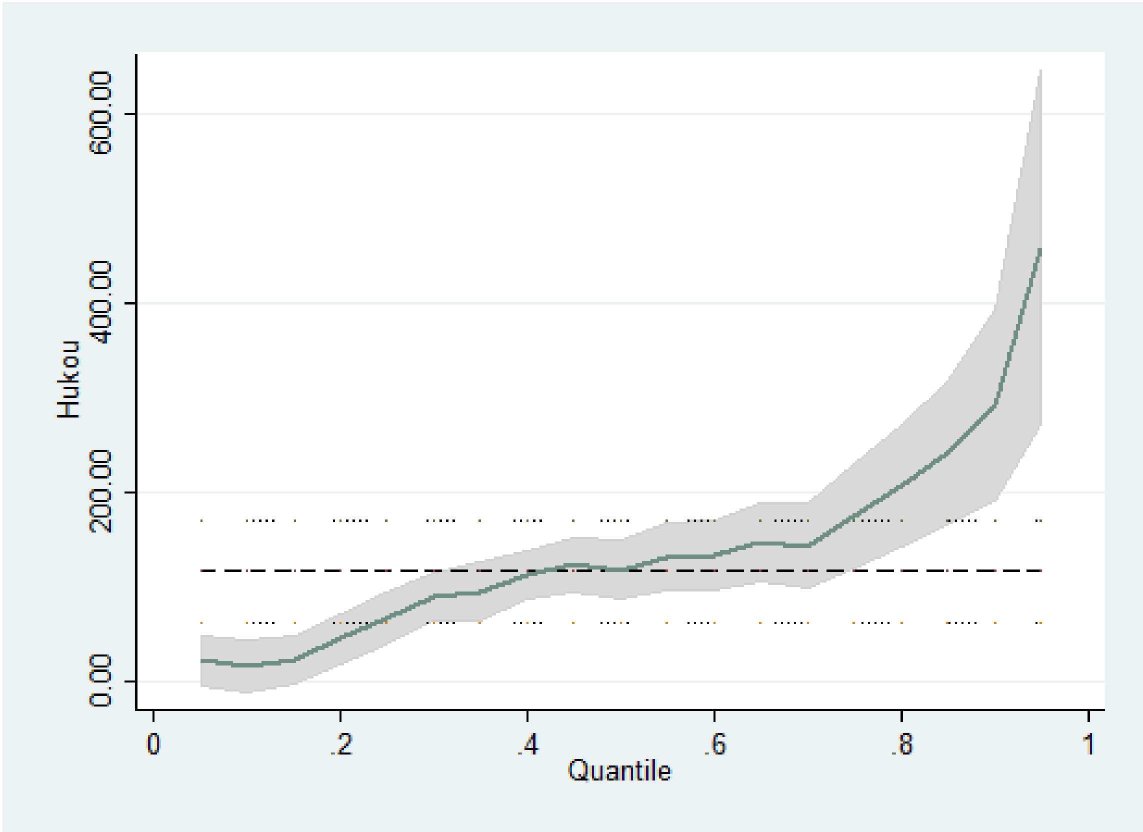
To find which variable matters more in generating the composition and wage structure effect, Table 3.7 displays the reweighted OB decompositions at the 10th, 60th and 90th quantiles. The wage structure effect is insignificant at both the top and bottom quantiles. Only in the middle of the wage distribution does the wage structure effect explain half of the total difference between urban workers and migrant workers. Among the composition effects, years of schooling is the only significant variable in all quantiles. This is consistent with the findings in Table 3.1 that urban workers, on average, have 3.6 more years of schooling than migrant workers. Among the structure effects, estimates for experience are negative at all quantiles. This indicates that migrant workers are rewarded more for their experiences than urban workers. Figure 3.8 plots the structure effects as well as the confidence intervals for the distribution. Again, using the reweighted OB decomposition, I do not find "glass ceiling" or "sticky floor" effects for migrant workers. Instead, the structure effect becomes significant in the middle part of the distribution, which explains the 200 RMB difference.

3.6 Conclusion

As the number of migrant workers has increased over the last three decades in China, the inequality between urban and migrant workers has become an important social phenomenon. This paper explores the urban-migrant wage differentials by implementing newly developed quantile methods. Using the 2002 CHIP survey data, I find the main difference can be explained by the composition effect at the top and bottom quantiles. That is to say, there is no "glass ceiling" or "sticky floor" effect for migrant workers; however, using multiple methods, I consistently find a structure effect exists at the middle part of the wage distribution for migrant workers. The inverse U-shaped Hukou premium exists in professional and manufacturing occupations. It also tends to appear in short-term contract jobs.

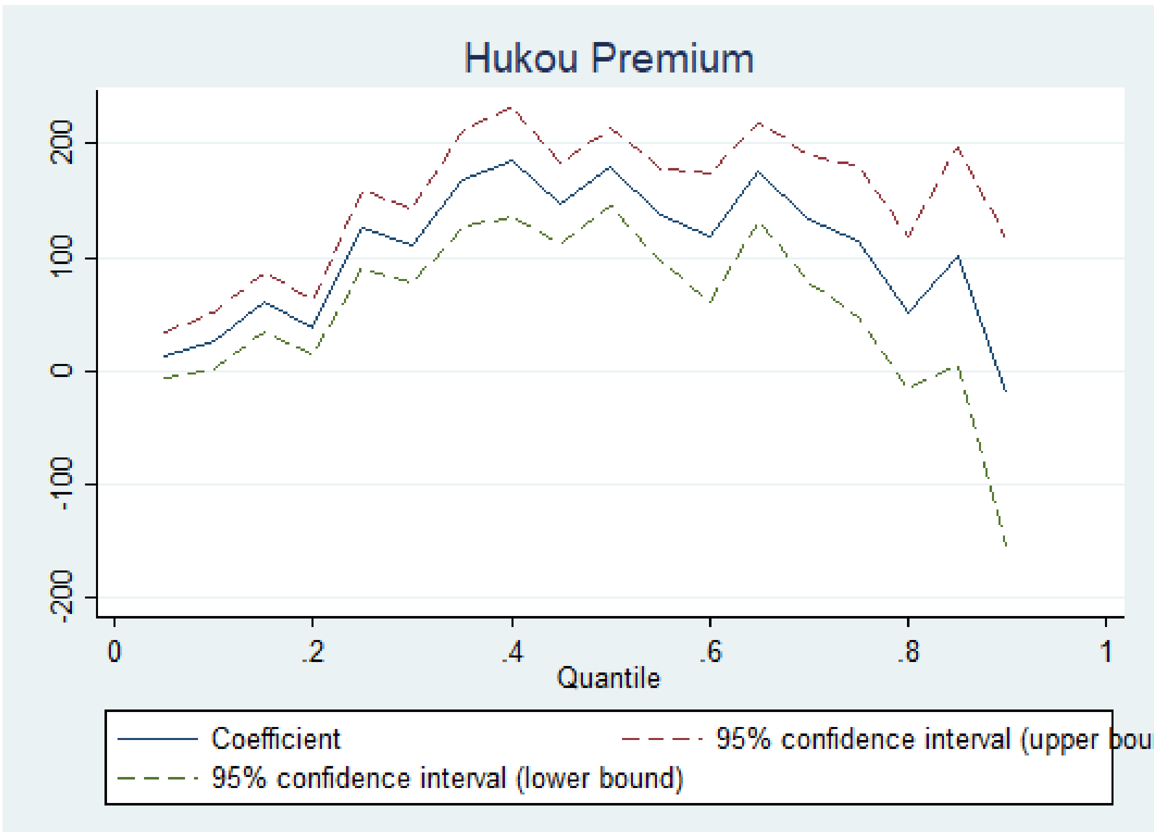
The evidence presented here provides several new insights for policy makers. Since the composition effect still plays the most important role in determining the wage gap between urban and migrant workers, the Chinese government should invest more into education in rural areas. In terms of wage discrimination, special attention should be given to middle-income migrant workers in short-term contract jobs and manufacturing jobs.

Figure 3.1: Hukou estimate from OLS and conditional quantile regssion



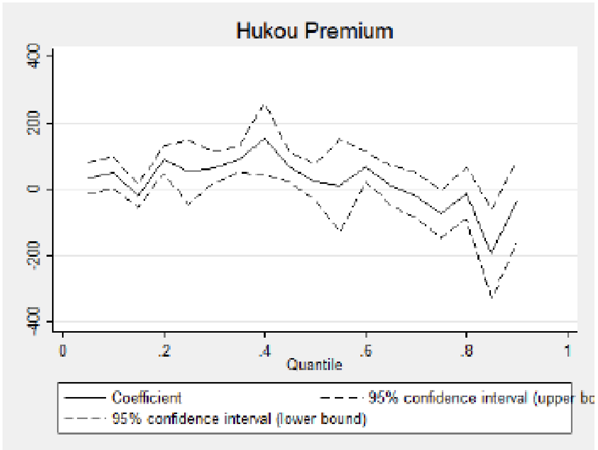
This figure shows estimates as well as confidence intervals for Hukou variable by quantile in both OLS regression (dash line) and conditional quantile regression (solid line) using equation 3.1. As shown in the figure, OLS estimate is constant across all quantiles and it represents the average effects of Hukou premium.

Figure 3.2: Hukou estimate from unconditional quantile regssion

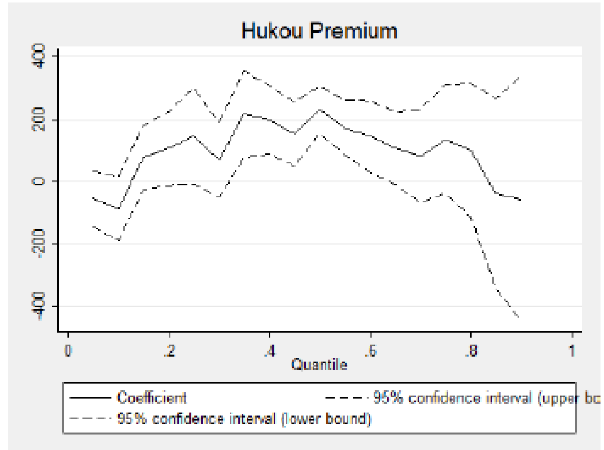


This figure presents estimates for Hukou variable in equation 3.2. As shown in the figure, the Hukou premium enlarges in the middle of wage distribution, and disappears at both the top and the bottom quantiles.

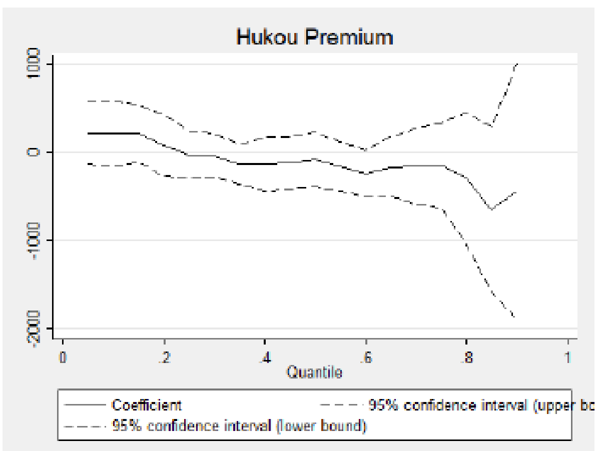
Figure 3.3: Hukou premium by occupations



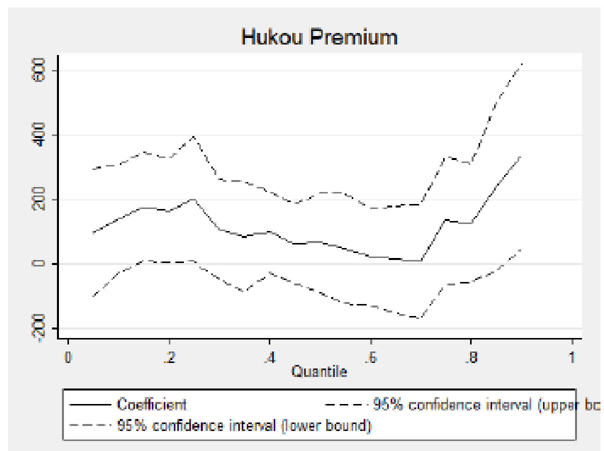
(a) Private business owner



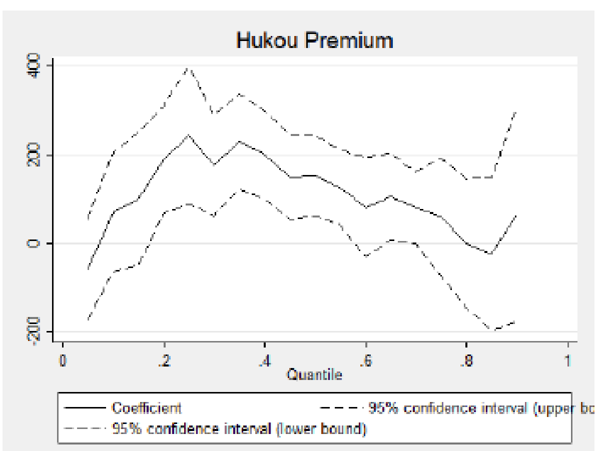
(b) Professional



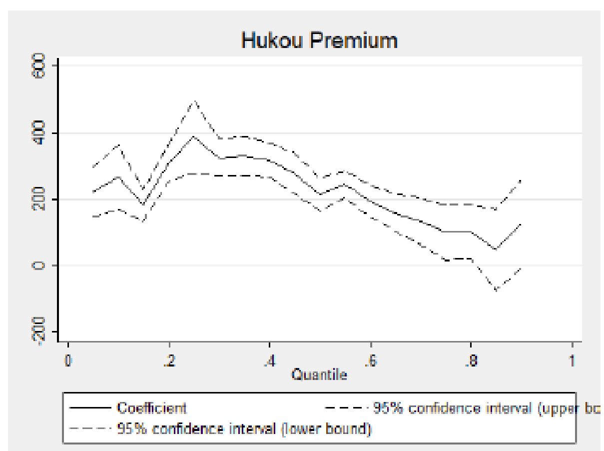
(c) Director



(d) Clerk



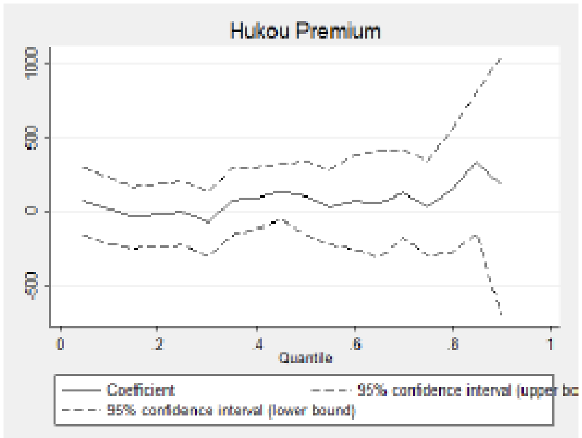
(e) Manufacturing woker



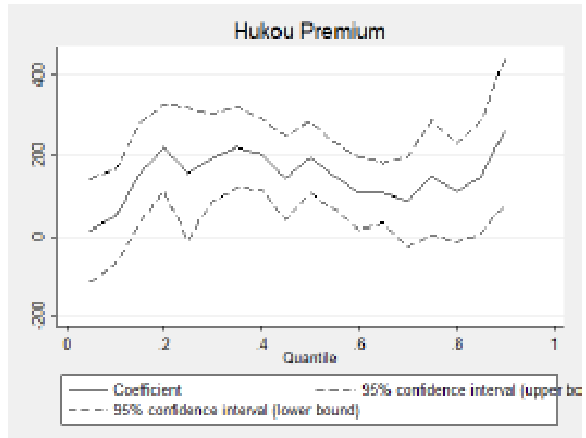
(f) Service

This figure displays Hukou premiums in different occupations. Estimates are from unconditional quantile analysis using equation 3.2. As shown in the figure, different occupation exhibit different patterns for Hukou premiums.

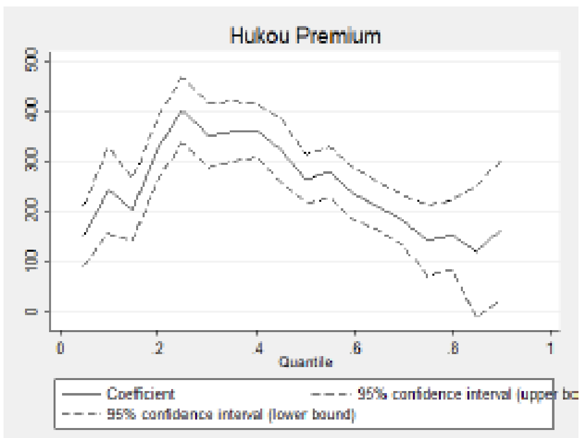
Figure 3.4: Hukou premium by job tenure



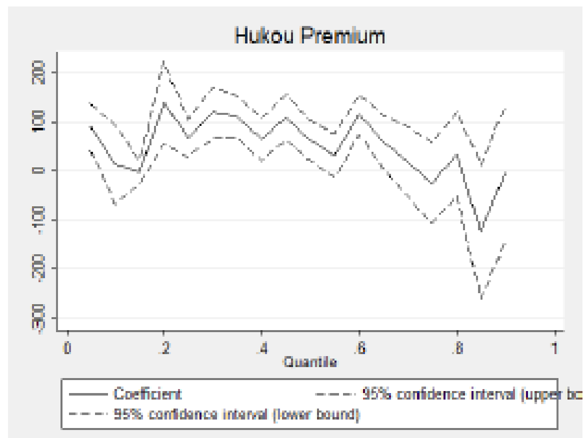
(a) Permanent staff



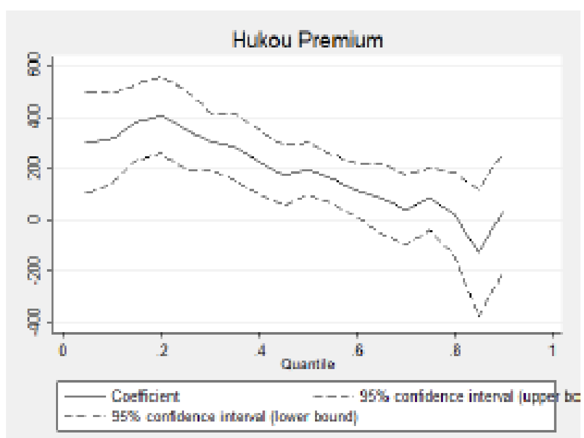
(b) Long term contract



(c) Short term contract



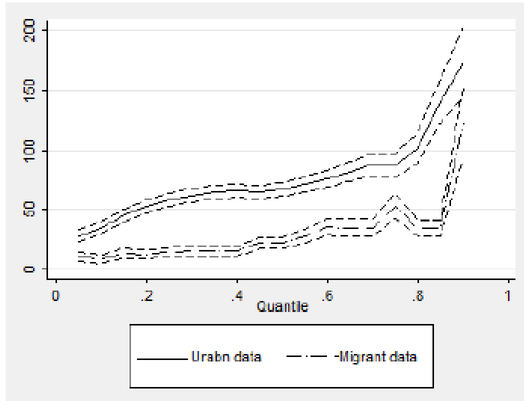
(d) Self employed



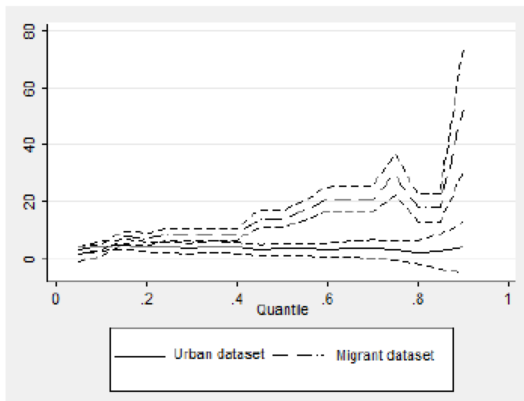
(e) Other

This figure displays Hukou premiums in different tenure types. Estimates are from unconditional quantile analysis using equation 3.2. As shown in the figure, different tenures exhibit different patterns for Hukou premiums.

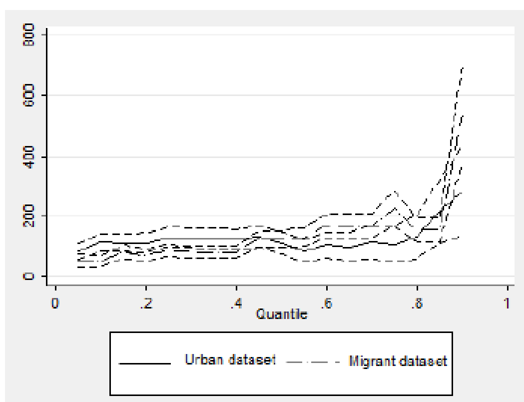
Figure 3.5: Unconditional Quantile Coefficients



(a) Years of schooling



(b) Experience



(c) Male

This figure shows the unconditional quantile regression coefficients for selected labour market characters from the 5th to the 95th quantiles. The solid line represents the coefficients for the urban group and the dashed line represents that for the migrant group. The upper and lower 95% confidence intervals generated by bootstrap standard errors are also shown in the graph. Panel (a) shows the rif-regression coefficient for years of schooling. Panel (b) shows the experience coefficient patterns for urban and migrant workers. Panel (c) shows the gender wage gap for both groups.

Figure 3.6: Monthly Wage Raw density for Urbans, Migrants and Conterfectual

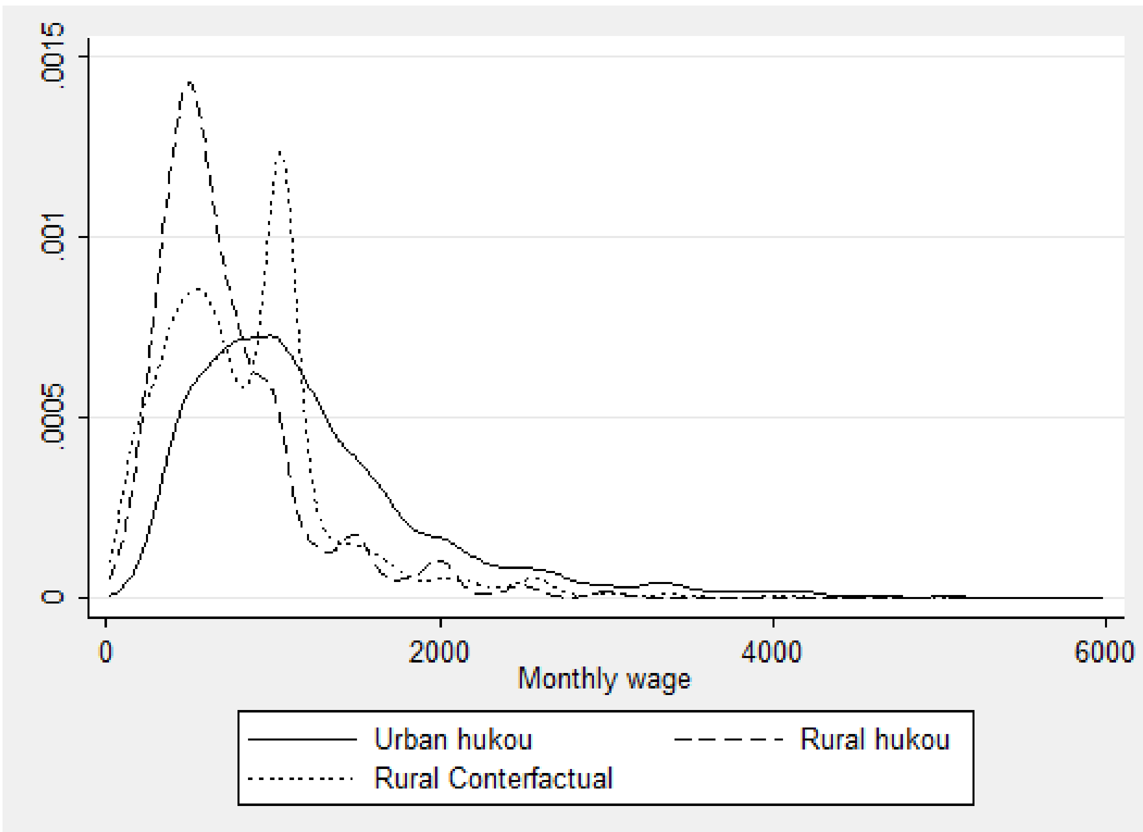


Figure 3.6 shows the wage distributions for urban, migrant, and migrant counterfactual earnings. The counterfactual earnings is constructed using equation 3.6. This counterfactual distribution tries to mimic the earnings that migrants would have earned had they received the same returns to their labour market characteristics as urban workers.

Figure 3.7: Inverse CDF of Monthly wage

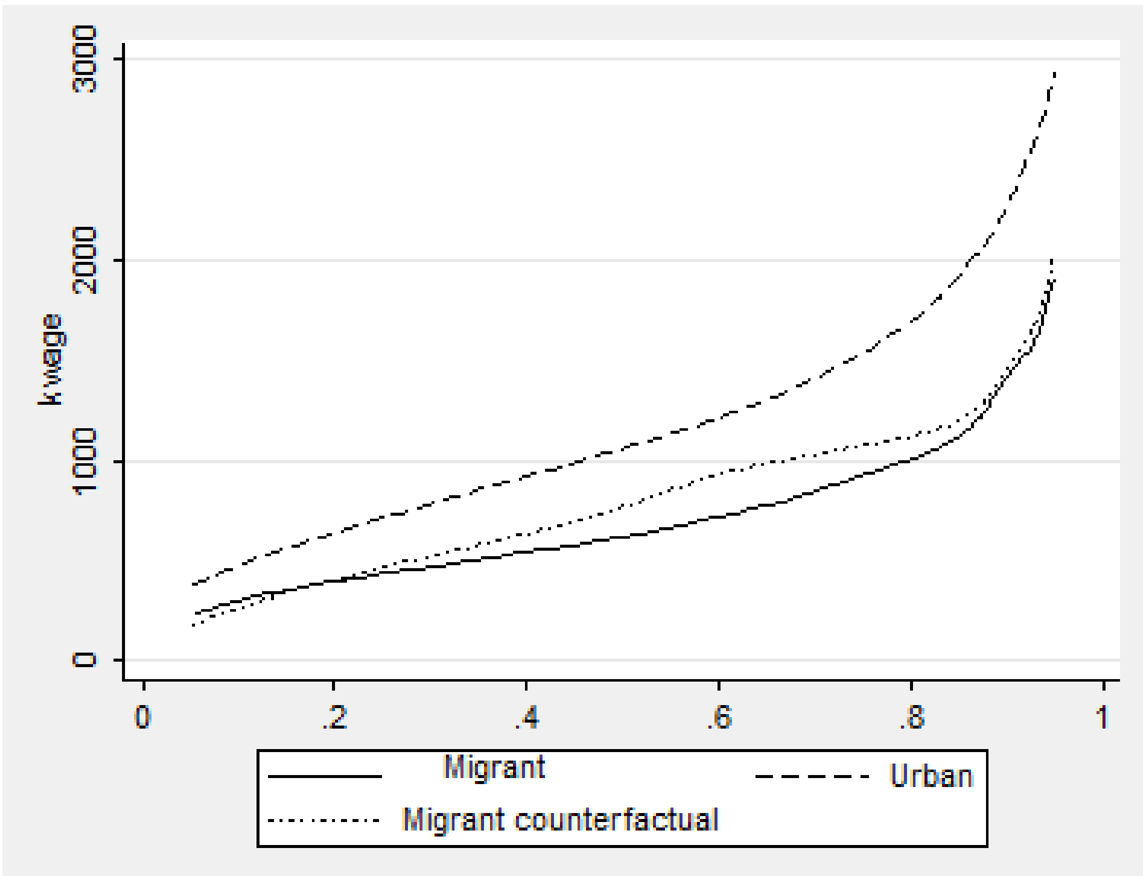
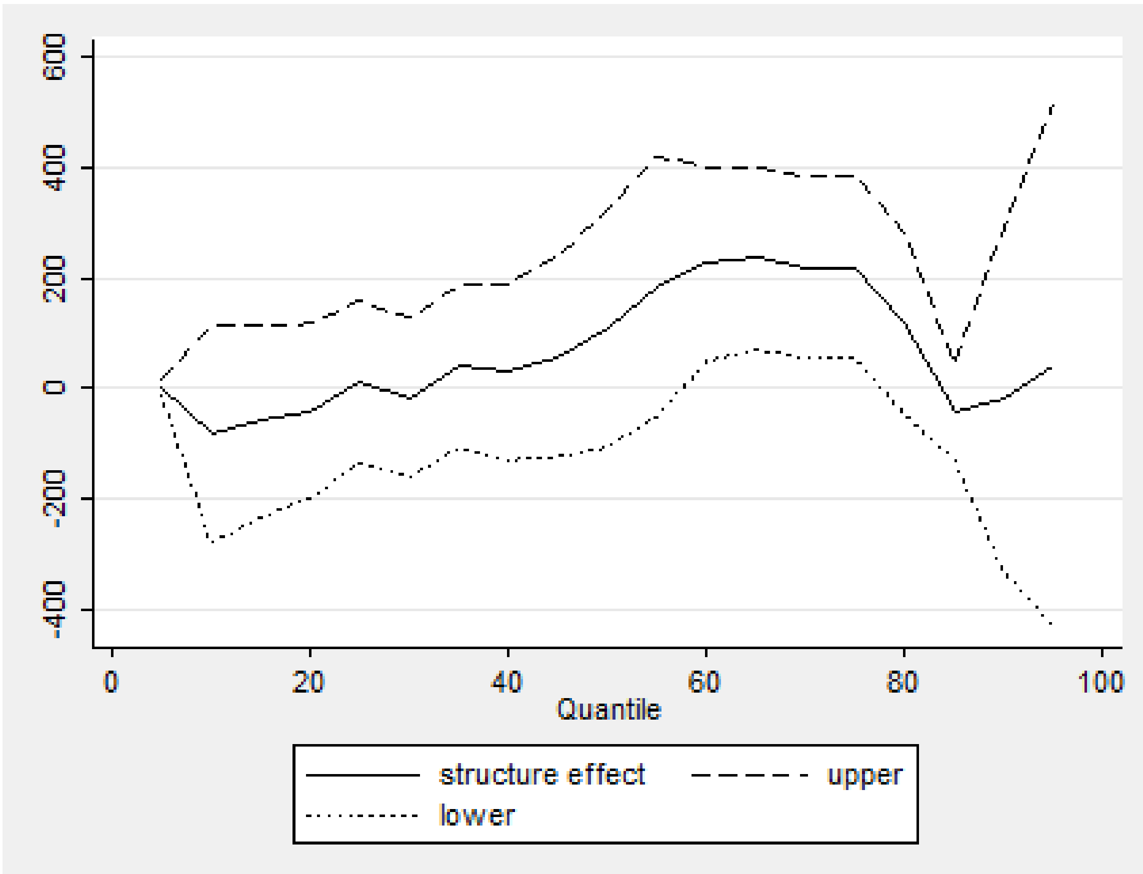


Figure 3.7 shows the inverse cumulative distribution function(CDF) of wage distribution for the three groups. The gap between the top line and the bottom line represents the raw urban-migrant wage gap; the differences between the urban workers' actual earnings and the migrants' counterfactual represent the earning gap due to the "composition effect"; the differences between the counterfactual and the migrants' actual distribution indicate the "structure effect".

Figure 3.8: Structure effects



This figure plots the structure effects as well as its confidence intervals for the distribution. The structure effects are generated from the reweighted OB decomposition. The wage structure effect is insignificant at both the top and bottom quantiles. Only in the middle part of the wage distribution, structure effects become significant.

Table 3.1: Data summary

	Urban resident		Rural migrant	
	mean	sd	mean	sd
Monthly income	1280.066	976.693	793.814	917.928
Male	0.548	0.498	0.566	0.496
Age	40.751	8.889	34.512	8.274
Experience	14.968	9.859	5.193	4.349
Years of schooling	11.630	2.897	7.908	2.732
Education level				
No school	0.001	0.038	0.097	0.296
Elementary	0.020	0.139	0.227	0.419
Junior middle	0.212	0.409	0.497	0.500
Senior middle	0.411	0.492	0.160	0.367
Junior college	0.241	0.428	0.015	0.120
College & above	0.115	0.319	0.004	0.065
Occupation				
Business owner	0.032	0.177	0.542	0.498
Professional	0.229	0.420	0.042	0.200
Director	0.110	0.313	0.006	0.079
Clerk	0.210	0.407	0.025	0.156
Worker	0.281	0.450	0.042	0.200
Service	0.112	0.316	0.277	0.448
Other	0.026	0.158	0.066	0.248
Employment type				
Permanent staff	0.527	0.499	0.009	0.093
Long term contract	0.228	0.419	0.049	0.216
Short term contract	0.177	0.381	0.255	0.436
Self-employed	0.046	0.210	0.661	0.473
Other	0.023	0.150	0.026	0.160
Observations	5576		3303	

Notes: Table shows the means, standard deviations of variables used in the analyses. The sample consists of respondents from 12 major provinces and 77 cities in China. All variables are extracted from 2002 China Household Income Project (CHIP2002).

Table 3.2: Descriptive average monthly wage by category

	Rural migrant		Urban resident		M/U
	N	$\overline{Wage}$	N	$\overline{Wage}$	%
Occupation					
Business owner	1734	885.123	180	1333.403	66.38%
Professional	133	907.567	1274	1497.407	60.61%
Director	20	1126.480	612	1690.277	66.64%
Clerk	80	820.653	1165	1318.122	62.26%
Worker	134	800.986	1562	1050.251	76.27%
Service	887	624.599	623	1006.703	62.04%
Other	211	594.001	142	924.177	64.27%
Tenure					
Permenant staff	29	1024.459	2931	1352.383	75.75%
Long term contract	161	764.573	1266	1246.611	61.33%
Short term contract	838	635.911	982	1133.187	56.12%
Self-employed	2175	859.877	256	1243.688	69.14%
Other	86	639.628	128	1183.453	54.05%
Education level					
No school	320	578.679	8	530.275	109.13%
Ellementary	749	685.383	110	867.087	79.04%
Junior middle school	1642	842.120	1182	1018.359	82.69%
Senior middle school	528	911.880	2288	1193.324	76.42%
Junior college	48	892.515	1341	1442.316	61.88%
College and above	14	1118.917	639	1816.250	61.61%
Overall	3303	793.81	5576	1280.06	62%

Notes: Table shows the number of observations and average wage level, and migrant share for different groups of respondents based on their occupation, tenure type, and education level.

Table 3.3: Hukou distribution by wage quintiles

Quintile	Rural migrant	Urban workers	Proportion of urban workers
Lowest quintile	1377	657	32.3%
Second quintile	677	841	55.4%
Middle quintile	755	1118	59.69
Fourth quintile	276	1522	84.7%
Top quintile	218	1438	86.8%

Notes: Table shows Hukou distribution by wage quintiles. The reweighting is applied to urban workers to mimic wage distribution of migrant workers. Considerable observations of urban workers in each quintile ensures the "overlapping support" assumption is valid across all quintiles.

Table 3.4: Hukou prerium at different quantiles

	OLS	Conditional Quantile			Unconditional Quantile		
	(1)	(2) 10th	(3) 50th	(4) 90th	(5) 10th	(6) 50th	(7) 90th
Hukou	105.0***	15.18	110.7***	267.4***	21.84	173.7***	-38.00
	(27.71)	(11.97)	(17.99)	(62.56)	(14.90)	(19.35)	(68.93)
Male	166.9***	80.68***	108.7***	277.7***	77.26***	137.3***	224.7***
	(18.93)	(7.960)	(10.81)	(35.17)	(9.226)	(17.55)	(42.31)
Experience	4.093**	6.333***	7.782***	7.228**	3.762***	7.974***	6.019
	(1.600)	(0.604)	(0.770)	(2.890)	(0.559)	(1.176)	(3.124)
Age	35.66***	17.71***	21.35***	61.18***	28.05***	41.18***	18.11
	(6.866)	(3.681)	(4.308)	(12.79)	(3.201)	(5.387)	(18.09)
Agesq	-0.294**	-0.208***	-0.175**	-0.588***	-0.357***	-0.424***	0.0430
	(0.0946)	(0.0521)	(0.0596)	(0.170)	(0.0393)	(0.0685)	(0.243)
Years of schooling	70.67***	27.95***	48.58***	102.4***	18.79***	59.60***	121.5***
	(3.371)	(2.005)	(2.142)	(4.780)	(1.593)	(2.983)	(9.350)
Constant	-740.8***	-306.3***	-361.8***	-1005.9***	-396.2***	-934.2***	-135.7
	(126.3)	(63.09)	(81.52)	(236.1)	(68.89)	(110.0)	(324.4)
N	8879	8879	8879	8879	8879	8879	8879
adj. R^2	0.115				0.073	0.205	0.055

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table shows estimates for Hukou premiums using different methods. Column (1) uses OLS method. Columns (2)-(4) use Conditional quantile method at selected quantiles. Columns(5)-(7) use unconditional quantile method at selected quantiles.

Table 3.5: Unconditional quantile regression by Huko status

	Rural migrant			Urban resident		
	10th	50th	90th	10th	50th	90th
Male	49.12***	127.2***	551.4***	115.8***	113.8***	277.2**
	(10.52)	(12.47)	(146.3)	(18.29)	(21.70)	(95.77)
Exerience	14.00***	29.40***	142.2**	12.78***	13.27***	-12.59
	(2.711)	(4.311)	(46.64)	(2.303)	(3.206)	(13.81)
Age	-0.400	-2.472**	9.687	4.969***	16.19***	31.76***
	(0.987)	(0.841)	(5.167)	(0.952)	(1.213)	(5.441)
Agesq	-0.569***	-0.815***	-5.170*	-0.253***	-0.322***	0.425
	(0.156)	(0.215)	(2.130)	(0.0692)	(0.0964)	(0.455)
Years of schooling	7.808***	22.15***	121.4***	34.55***	67.20***	176.3***
	(2.167)	(2.685)	(32.21)	(2.387)	(3.595)	(19.02)
Constant	231.3***	369.7***	-659.2	-293.3***	-545.5***	-1184.5***
	(42.50)	(40.28)	(639.7)	(60.34)	(72.27)	(344.6)
N	3303	3303	3303	5576	5576	5576
adj. R^2	0.026	0.089	0.047	0.063	0.109	0.036

Standard errors in arentheses

$^{*} < 0.05$, $^{**} < 0.01$, *** $p < 0.01$

Notes: Table show results using unconditional regression at selected quantiles for rural migrants and urban residents separately. All variables exhibit different returns for rural and urban workers.

Table 3.6: Oaxaca-Blinder decomposition without reweighting

	(1)	(2)	(3)
	10th	50th	90th
Overall			
Urban	484.5***	1053.3***	2259.7***
	(7.576)	(13.48)	(37.22)
Migrant	355.0***	648.1***	1439.5***
	(5.295)	(8.625)	(55.81)
Difference	129.5***	405.2***	820.2***
	(9.539)	(15.57)	(69.36)
Composition	211.3***	385.8***	846.0***
	(14.52)	(21.71)	(96.76)
Wage Stucture	-81.79***	19.44	-25.82
	(19.03)	(23.07)	(99.07)
Composition Effects			
Male	-2.121	-2.021	-5.026
	(1.423)	(1.073)	(3.357)
Experience	45.60***	29.10***	6.268
	(8.675)	(11.23)	(41.26)
Age	148.2***	184.4***	277.2
	(42.78)	(40.16)	(172.6)
Agesq	-115.4***	-82.82**	-74.61
	(40.39)	(37.43)	(169.5)
Years of schooling	134.9***	257.2***	642.2***
	(10.49)	(17.86)	(72.04)
Wage Structure Effects			
Male	38.93***	-9.772	-94.48
	(10.17)	(13.63)	(58.30)
Experience	8.441	-57.43***	-212.7***
	(7.218)	(11.62)	(55.43)
Age	-240.1	-393.2	-1717.1
	(280.5)	(311.8)	(1404.4)
Agesq	229.7*	526.3***	1278.0**
	(130.6)	(140.2)	(651.9)
Years of schooling	221.5***	363.6***	577.2***
	(25.53)	(39.69)	(174.4)
N	8879	8879	8879

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results for the unweighted OB decomposition at the 10th, 50th, and 90th quantiles using equation 3.4. The he urban-migrant wage gap can be explained mostly by the composition effect at all the selected quantiles. The structure effect is not statistically significant at the middle and top quantiles. In terms of the contribution of each covariate, years of schooling stands out since it accounts for over 2/3 of the composition effect at the 50th quantile and more than 3/4 at the 90th quantile.

Table 3.7: Oaxaca-Blinder decomposition with reweighting

	(1) 10th	(2) 60th	(3) 90th
Overall			
Urban	484.3***	1201.4***	2261.6***
	(7.338)	(10.99)	(37.89)
Migrant Counterfactual	271.1***	963.1***	1420.8***
	(96.45)	(86.73)	(152.7)
Migrant	355.1***	736.7***	1439.9***
	(4.697)	(8.976)	(35.50)
Total difference	129.2***	464.7***	821.6***
	(8.712)	(14.19)	(51.92)
Composition	213.2**	238.3***	840.8***
	(96.42)	(87.38)	(156.4)
Structure	-84.00	226.4**	-19.16
	(100.3)	(89.91)	(159.6)
Composition effects			
Age	87.83**	69.45	169.4
	(34.21)	(38.46)	(134.2)
Agesq	-73.22**	0.933	-54.17
	(32.12)	(37.97)	(136.5)
Years of schooling	201.5***	429.9***	961.1***
	(43.83)	(89.21)	(213.3)
Experience	51.61***	26.96	12.16
	(11.70)	(16.43)	(57.60)
Male	-16.91**	-14.80	-40.80
	(8.071)	(7.602)	(22.27)
Specific error	-37.60	-274.1	-206.9
	(93.90)	(144.5)	(120.3)
Structure effects			
Age	-1310.4	1333.8	-194.6
	(696.0)	(949.5)	(2460.4)
Agesq	564.6	-744.6	190.3
	(370.1)	(501.4)	(1163.3)
Years of schooling	72.77	-365.6**	399.2**
	(168.0)	(178.7)	(167.0)
Experience	-22.06	-117.5***	-94.58
	(21.80)	(34.28)	(79.21)
Male	-68.09	91.41	35.27
	(70.82)	(51.69)	(81.74)
Reweight_err	-52.58	67.15	-192.1
	(65.89)	(69.29)	(140.0)
N			
adj. R^2			

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table displays the reweighted OB decompositions at 10th, 60th, and 90th quantiles. The wage structure effect is insignificant at both the top and bottom quantiles. Only in the middle part of the wage distribution does the wage structure effect explains half of the total difference between urban workers and migrant workers.

Chapter 4

Impact of the Railway on the Urban-Rural Income Gap in China

4.1 Introduction

It has been over four decades since China opened its economy to the global market and started its economic reform. During this period, China has experienced high economic growth, and over 500 million people have risen above the poverty level. Although these gains are quite impressive, they have been accompanied by a rise in income inequality, and a high level of inequality creates an unfavourable environment for economic growth and is bad for political stability. China is known as the world's largest socialist country and has set a goal of becoming a "Socialist New Country" without inequality; however, instead of achieving this goal it has become one of the countries with the largest income inequality. In fact, there is significant evidence that China's income inequality surpasses that of the United States, the largest capitalist economy in the world (Xie and Zhou, 2014). Comparing China's income inequality level to that of other middle-income countries like Thailand and Malaysia, reveals that the problem in China is much worse (Adams, 2009). China's income inequality is reflected in the increase of the Gini coefficient from 0.28 in the early stages of the economic reform to 0.42 in 2009 (Word Bank). Also interesting, is the fact that during the last decade, income inequality experienced a clear downward trend (see Figure 4.1).

Decomposition of China's income inequality reveals that the urban rural income gap is the main contributor to overall inequality in China (Sicular et al., 2007; Li, 2010; Benjamin et al., 2007; Wu and Perloff, 2005). In 2002, the urban-rural income gap contributed to 45% of the overall income gap and in 2007, the proportion increased to

51% (Li et al., 2013). Similar to the Gini index, the urban-rural income gap during this study period also shows an inverse U shape. During the period from 1997 to 2009, the income gap rose from 2.5 to 3.3, when it reached a maximum and started to decline. The most recent gap was 2.8 in 2018 (see Figure 4.2). Thus, the extensive contribution of the increasing urban-rural income gap to income inequality suggests that it is worth studying what has driven the downward trend of the urban-rural income gap in China over the past decade.

Economists have suggested a correlation between public infrastructure and inequality (Li and DaCosta, 2013; Démurger, 2001; Chatterjee and Turnovsky, 2012). Over the past 10 years, China's urban-rural income gap has exhibited a clear downward trend. Strikingly, during this period China also experienced a large expansion of its high-speed railway network (see Figure 4.2). Due to the productivity increase in the agricultural sector, a large workforce is now available. These available rural workers tend to move to the manufacturing and service sectors, which are located in the urban areas. Consequently, the surplus migrant workers have increased the labour supply in urban areas and reduced the wage levels. This influx of workers has boosted the industrial economy. Although an increasing number of rural workers are moving to urban areas for work, they still require access to their families in rural areas; therefore, transportation plays a very important role in China's labour migration wave.

This study tries to identify the effects of China's railway expansion on the urban rural income gap. I use provincial panel data from 1993 to 2018 obtained from China Statistical Yearbook. Additionally, I exploit the railway province-by-year variation by conducting a difference-in-difference design. The dependent variable is constructed by comparing the disposable income ratio of urban households to the net income of rural households. The empirical results show the railway network expansion within a province is associated with a decrease in the urban-rural income gap. The estimates account for province and year fixed effects, which allows me to control for any fixed provincial characteristics and time-specific factors that might be related to railway expansion and the income gap. Furthermore, I show that the estimates are robust to arbitrary region-specific time trends. Importantly, I account for other time-varying provincial characteristics in order to demonstrate that the estimated effects of the railway are unchanged by these time-varying controls.

To address the potential spillover effects associated with the economic integration that resulted from the railway expansion, I conduct a spatial econometric analysis in addition to the DID design. After carefully addressing the spillover effects, I continue to find that the railway expansion has a positive impact on reducing income inequality. Additionally, I find the spillover effects, known as the indirect effects, are more significant than the direct effects.

This paper makes several contributions. First, it contributes to the body of literature examining the impacts of public infrastructure. Public infrastructure can strengthen political accountability (Akbulut-Yuksel et al., 2020), create economic prosperity (Banerjee et al., 2020; Donaldson and Hornbeck, 2016), promote urbanization (Atack et al., 2009), and increase migration (Sequeira et al., 2017). Recent studies also show that better transportation decentralizes urban cities in terms of population and industrial GDP (Baum-Snow et al., 2017). My argument that the improved factor (labour and capital) mobility, which stems from better access to transportation, can drive wages and incomes toward equalization between urban and rural areas is closely related to the claims of Baum-Snow et al. (2017).

Second, this study also contributes to the growing body of literature on income inequality. There are a number of factors that influence income inequality including GDP (Kuznets, 1955), trade (David et al., 2013; Autor et al., 2016; Feenstra and Sasahara, 2018), and human capital (Acemoglu and Autor, 2011). This study benefited from the previous literature by including these factors as control variables.

Third, this study adds to the literature about China's railway expansion over the past decade. Many recent studies have focused on the various impacts of high-speed rail (HSR). For example, Chen and Haynes (2015) find HSR-generated large effects on housing values in medium and small cities but had a negligible impact in larger capital cities. Other papers look at the impacts on the environment (Chen et al., 2016); regional tourism development (Wang et al., 2012; Chen and Haynes, 2015) and domestic air transportation (Chen, 2017). Chen and Haynes (2017) investigate the impact of HSR on regional disparity and find HSR has a positive impact on promoting regional economic convergence in China; however, the impacts of railway expansion on urban-rural income inequality remains unexplored. Consequently, this paper tries to close this gap by specifically targeting the urban-rural income gap.

The remainder of the paper is organized as follows. Section 4.2 reviews and summarizes previous literature on key contributors to the urban-rural income gap. Section 4.3 describes the estimation methodologies. Section 4.4 introduces the data and the variables used in this research. Section 4.5 analyses the main results. Section 4.6 presents robustness checks and is followed by a discussion of mechanisms and related empirical evidence in Section 4.7. Section 4.8 concludes.

4.2 Literature Review

For the last three decades, China has invested heavily in public infrastructure such as the railway, which has experienced a drastic increase in investment since 2008. To minimize the impact of the financial crisis, the Chinese government came up with a 4-trillion-dollar stimulus package. Transport and power infrastructure accounted for the largest proportion of the stimulus package (37.5% of total spending) (Wong, 2011), and this policy move led to a steady increase in the length of the railway.

Globally, there is a growing body of research that focuses on the economic performance of infrastructure projects in developing and developed countries. In Europe, many studies show that high-speed rail (HSR) has a positive impact on economic growth, job creation and the reduction of commuting time (Ahlfeldt and Feddersen, 2018; Chen and e Silva, 2014; Heuermann and Schmieder, 2019). In the U.S., transportation infrastructure favours greater price convergence, increased land price and urbanization (Michaels, 2008; Atack et al., 2009; Donaldson and Hornbeck, 2016). In India, the vast railroad network increased welfare by reducing trade cost and increasing income levels (Donaldson, 2018; Alder, 2016). In Japan, Sasaki et al. (1997) reveal that the first HSR, the Shinkansen in Japan, has resulted in employment growth in Osaka and Tokyo but has led to a reduction in employment in Nagoya.

Turning the focus to China, an emerging country that has been expanding its railway network over the last decade, the existing literature has yet to reach a consensus on the influence of transportation infrastructure. On one side, the development of public transportation has led to improved connectivity and economic growth (Chong et al., 2019; Chen et al., 2016; Jin et al., 2020). Furthermore, the development of public transportation greatly promotes migration and cargo flow, decentralization of the population and industrial activities (Baum-Snow et al., 2017) which would have a large impact on the income gap. On the other hand, better transportation infrastructure would enhance economic agglomeration, producing a mixed spatial distribution of economic activity. Rather than diffusing industrial production, reductions in trade costs between regions due to better road networks favour core regions at the expense of peripheral regions (Faber, 2014; Baum-Snow et al., 2020). More specifically, with better regional highways, core areas specialize more in manufacturing and services, while peripheral areas lose manufacturing but gain agriculture. Investing in local transportation infrastructure to promote the growth of hinterland prefectures has the opposite effect, causing them to specialize more in agriculture and lose economic activity (Baum-Snow et al., 2020). Compared to non-connected regions, connected peripheral regions experienced a reduction in industrial and total output growth based on falling trade costs between peripheral and metropolitan regions Banerjee et al. (2020) present a simple model where labour is immobile and capital is less mobile than goods and this causes remote areas to have less inequality because better connected regions lose more of their capital.

Before reconciling the different views from the previous literature. I will first lay out some comments on the differences between this study and the study by Banerjee et al. (2020). First, the timeline of their study is 1986 to 2003, whereas this study covers the much more recent period from 1993 to 2018. Second, labour mobility has improved greatly in recent years due to the relaxation of the Hukou system and improved public transportation. The assumption stated by Banerjee et al. that labour is immobile should not apply in this study. Third, they focus more on GDP and GDP growth whereas this study focuses on the urbanrural income gap. To reconcile the different views about public transportation, Zheng and Kuroda (2013)) first confirm there is a trade-off between spatial equity (more even spatial distribution of economic activities) and spatial efficiency (higher growth rate). However, they also found knowledge infrastructure that refers to public infrastructure that facilitates interregional transactions on ideas, which simultaneously reduces trade costs on ideas, increases growth and decreases the income gap and industrial agglomeration. Knowledge, skills and technology spillovers resulting from the connectivity improvement could potentially reduce regional disparities.

This study contributes to the existing literature in a number of ways. First, this paper studies one of the largest expansions in public transportation over the past 30 years. China is much larger than Japan and the European countries, and its size has contributed to the extensive and rapid development of HSR networks (Jin et al., 2020). Second, this paper looks at the impacts on income inequality, especially the urban-rural income gap. Most studies explore the regional or prefecture differences in gains or losses from public transportation (Faber, 2014; Baum-Snow et al., 2020); however, the most significant income inequality in China can be attributed to urban-rural income inequality. Third, this paper examines both the direct and indirect spillover effects of railway expansion on the urban-rural income gap. Specifically, the difference-in-difference model uses the variations within provinces to evaluate its direct impact, whereas the spatial econometric model takes the surrounding railway network into consideration.

4.3 Empirical Framework

Inspired by Akbulut-Yuksel et al. (2020), my primary identification strategy exploits province-by-year variations in the length of the railway within a province using the DID method. In addition, I include a spatial econometric model as a robustness check to address spillover effects of railway expansion.

4.3.1 Difference-in-Difference Model

This paper utilizes province-by-year variations in the length of railway within a province, and it is inspired by Akbulut-Yuksel et al. (2020). Specifically, I estimate a difference-in-difference model using the two-way fixed effects model shown below:

$$IncomeGap_{prt} = \beta \log(Rail_{prt}) + \delta_p + \gamma_t + \Pi' X_{prt} + \tau_{rt} + \epsilon_{pt} \tag{4.1}$$

where the dependent variable, $IncomeGap_{prt}$, is the ratio between per capita annual disposable income of urban households and per capita annual net income of rural households in province, p, region r, and time t. The reason for using $IncomeGap_{prt}$ as a proxy of income inequality is that data is readily available at the provincial level.[1] My main variable of interest, $\log(Rail_{prt})$, is the (log) of total railway, measured in km. The log transformation captures the dynamic evolution of the stock of railway within provinces overtime. The model controls for the province and the time fixed effects, δ_p, γ_t, time-varying provincial characteristics, X_{prt}, and region-specific time trends– τ_{rt}.[2] I cluster standard errors at the province level.

There are multiple regions in China (see Figure 4.3) and economic development exhibits different patterns in each region. Figures 4.4 and 4.5 illustrate the variations between regions in terms of income inequality and railway stock. Since China has different regional classification systems, I check regional time trends using multiple regional classification methods.

Central to the DID design is the parallel trends assumption. That is, conditional on province, year fixed effects, and time trends, which may vary at the regional level, the inequality pattern would have evolved similarly in provinces with and without growth in the length of the railway network; however, the parallel trends might fail when the railway expansion correlates with other province-specific changes that also influence the urban-rural income gap. To address the potential threat to the parallel assumption, Table 4.2 shows the balance test for the construction of the railway. In column (3), all predictors are insignificant once controlled for province and year fixed effects, and the joint F test is unable to reject the null hypothesis of joint significance of all predictors. This provides evidence that the growth of the railway is mainly driven by fixed effects captured by the province and year dummies. Nevertheless, I include variables from Table 4.2, the province, and the year fixed effects in order to flexibly deal with systematic differences in railway stock.

[1] Other inequality indexes, such as GINI, are only available at the national level.

[2] In some specifications, I control for a one-year lag of total railway length to capture conditions in the previous year.

4.3.2 Spatial Model

Since railway infrastructure affects both the local income inequality in a region and the inequality in neighbouring provinces, this study uses the spatial econometric model to evaluate the total effects and potential spatial spillover effects of the railway network. Specifically, I adopted the spatial panel auto correlation model[3] shown below to evaluate the spatial spillover effects:

$$\begin{gathered} IncomeGap_{pt} = \alpha\rho\mathbf{W} * IncomeGap_{pt} + \eta Rail_{pt} + \delta_p + \gamma_t + \Pi'\mathbf{X_{pt}} + e_{pt}, \\ \text{where } e_{pt} = \lambda\mathbf{W}e + \epsilon_{pt} \end{gathered} \tag{4.2}$$

Equation 4.2 is a Spatial Auto Correlation (SAC) model. **W** is the spatial weight matrix, which contains pairwise location information between any two provinces. $\mathbf{W} * IncomeGap$ is the spatial lag dependent variable. **Rail** denotes the $N \times 1$ vector of provincial railway stock in log forms. δ_p and γ_t denote the province and the time fixed effects respectively. **X** denotes the vectors of control variables. λ allows the error term to contain a spatial pattern. I use maximum likelihood estimation to estimate Equation 4.2. The spatial analysis is conducted using stata software.

4.4 Data Source and Descriptive Statistics

All the data in this study comes from the annual China Statistical Yearbooks, which are produced by the National Bureau of Statistic China (NBS). I construct a panel data that consists of 31 provinces from 1993-2018. Hong Kong, Macau and Taiwan are omitted from my sample due to an absence of data.

For my dependent variable, the urban-rural income gap, I used the ratio between per capita annual disposable income of urban households and per capita annual net income of rural households. I then transform this gap into a percentage, so a 200% income gap means the average per capita urban household makes two times that of the per capita rural household.

Data on railway construction were also provided by the NBS. I extracted information

[3]The detailed derivation of the SAC model can be found in Appendix B.2

on the total length of the railway in each province. Figure 4.2 shows the growth of the railway is steeper during last decade. Detailed region-specific growth can be found in Figure 4.5.

The confounding factors included in this study are: level of openness, human capital, and real GDP and its square. The influence of trade and globalization play an important role in economic disparities in China (Fujita and Hu, 2001; Liao and Wei, 2012; Hu and Wang, 1996). I use the ratio of imports and exports to total GDP as a measurement of the degree of openness in each province. To measure human capital in each province, I calculate average years in school by province.[4] I also control for GDP because of its relation to inequality known as Kuznets Curve (Kuznets, 1955). Real GDP per capita is calculated from nominal GDP per capita and CPI using 1978 as the base year.

Table 4.1 is the summary statistic of all variables in this study. The table is categorized into three columns. Column (1) contains the means and standard deviations for all observations (31 provinces across 26 years (1993 to 2018)). Column (2) shows the means and standard deviations in 1993[5] and the last column shows the means and standard deviations for 2018. As demonstrated in Table 2, the mean of railway length increased from 1881km in 1993 to 4247km in 2018, more than doubling over the last 26 years. Relatedly, the volume of railway passengers increased by almost three-fold and the volume of cargo travelling by railway increased two-fold. Additionally, China's other major investment (i.e., the highway) also expanded rapidly during this same time period. Although the urban-rural income gap decreased over the last two decades, the size of the income gap is still considerable, at an average of 255% in 2018. During the study period, GDP per capita, the urbanization rate and income all experienced rapid increases in China.

---

[4] Elementary school accounts for 6 years, the middle school diploma accounts for 9 years, and a high school diploma accounts for 12 years. People with university degrees or higher are considered to have 16 years in school.

[5] For certain variables, if data is not available in 1993, then I use the earliest available data.

4.5 Estimation Results

Table 4.3 is the baseline effects of the railway expansion on the urban-rural income gap using difference-in-difference model. All columns control for province fixed effects and time fixed effects. In column (1), I find that the urban-rural income gap decreased in areas where there was a greater expansion in the railway network. Specifically, a 10% increase in railway stock decreases the urban-rural income gap by 1.7 percentage points within the same province. To put this into perspective, if the railway stock doubled in that province, the urban-rural income gap would decrease by 17 percentage points. Railway stock almost doubled (1.7-fold) since 2008, which means railway expansion over the last decade has brought down the urban-rural income gap by 12 percentage points. The urban-rural income gap decreased by 62 percentage points during the last decade, and according to my estimate, 20% of the total decrease can be attributed to the railway expansion in China.

To argue the above findings are causal instead of correlated, I included several provincial time-varying controls. The rest of the columns in Table 4.3 control for province time-varying variables, which capture their economic and social conditions. These include GDP and its square, average years in school and degree of openness. The neighbouring provinces' railway stock might also contribute to the urban-rural income disparity. Column (3) adds additional control for railway growth in the neighbouring provinces. In addition, column (4) adds railway stock in the previous year to capture the previously existing conditions of the railway stock. I evaluate the robustness to violations of parallel trends in columns (5) and (6). I relax the parallel trends assumption and allow trends to vary across regions by including region-specific trends. Since there are different regional classification systems, I use both to further confirm the results are robust to different regional classifications. Columns (5) uses an eight-region classification system and column (6) uses a three-region classification system. Coefficients in all specifications are consistent and around -17 in value, which means that a 10% increase in railway stock decreases the urban-rural income gap by 1.7 percentage points.

To sum up, Table 4.3 shows that the urban-rural income gap decreased significantly in provinces where more railway was constructed. Using a different regional classification did not alter estimates for my main variable of interest, though adjusted R^2 increased by using more detailed regional classifications (see columns 5 and 6 in Table 4.3). This might be due to the fact that the railway expansions are not associated with regional time trends and there is no systematic increase in the growth of railway stock (see Table 4.2). It also provides evidence the expansion was driven by more than economic reasons and the network increased in areas beyond those close to the main metropolises. Furthermore, the goal of railway expansion was not preferentially targeted at provinces with high income inequality. Additionally, Figure 4.7 provides further evidence that the railway expansion was not clustered/centred around certain provinces since 2008.

4.6 Robustness Checks

4.6.1 Pre-Existing Trends or Anticipatory Effects

The question I wish to address here is whether there were already trends in the urban-rural income gap in provinces where the railway was increased later on. To demonstrate that the railway was not built in places where the income gap was already decreasing, I perform a falsification test by running a placebo test. Specifically, I replace my main independent variable in Equation 4.1 with three-year leads of railway growth, controlling for time and province fixed effects in all specifications and controlling time-varying variables in columns (2) to (6) of Table 4.4. The last two columns allow differential trends for provinces in different regions. Thus, the overall structure of 4.4 is similar to the baseline models in Table 4.3.

Results in Table 4.4 show that there were no anticipatory effects of pre-existing trends in income inequality related to the railway expansion. Points estimates for a three-year lead of changes in railway length are insignificant across all specifications. Hence, there is no evidence railways were built in provinces where the urban-rural income gap was expected to decrease or was already decreasing. Next, I provide further evidence to demonstrate that other major public investments, like highways, did not confound railway estimates.

4.6.2 Does the highway drive the inequality trend?

In this subsection, I investigate whether the trend in the urban-rural income gap is driven by the highway instead of the railway. To examine the potential confounding factor, I replicate Table 4.3 by adding changes in highway length.

Table 4.5 presents estimates of the adjusted baseline models by adding highway as a confounding factor. Estimates for changes in highway length in all specifications are all insignificant indicating that the highway is not the main factor driving the decreasing income gap. The estimates for the railway are still significant. It is interesting that when controlling for the highway, magnitudes of railway estimates are still quite consistent with what I found in Table 4.3. In short, the results continue to show that the expansion of the railway network is associated with a decreased urban-rural income gap, and I do not find such a trend driven by the highway.

4.6.3 The spatial spillover of Railway network

In this subsection, I revisit the problem by using alternative models that consider the spatial spillover effects of the railway network. The premise of using a spatial econometric model is that a significant spatial autocorrelation exists in the dependent variable (Anselin, 2001). Moran's I, which was developed by Moran (1950),measures spatial autocorrelation. The range for Moran's I is between -1 and 1. Negative values indicate negative spatial autocorrelation, which indicates dispersion of the geographic units. In the extreme situation where Moran's I is -1, it indicates the income gap is perfectly dispersed. If Moran's I equals +1, it means there is a perfect correlation of the income gaps. Zero indicates a random spatial pattern. As Moran's I is the most popular test for spatial autocorrelation, I compute Moran's I for the urban-rural income gap to provide preliminary evidence for the spatial correlation of my dependent variable (See Appendix B.1). Figure 4.6 shows the Moran's I for my dependent variable in the last two decades. Note that regions with a higher income gap tend to cluster before 2009, that trend that has been completely reversed over the last decade, and consequently, regions with high income inequality now tend to be randomly distributed compared to previous trend. Nevertheless, the Moran's I in my sample are all above zero, which provides evidence of positive spatial autocorrelation of income inequality.[6]

Results from the spatial econometric models are shown in Table 4.6. The first two columns use the 0-1 spatial weight matrix and the last two columns use the inverse distance weight matrix. All estimates for railway growth are negative, providing further evidence that railway expansion helps alleviate the urban-rural income gap. Additionally, when compared with Table 4.3, there is an increase in the significance level. Estimates from the DID model are significant under the 5% level, whereas estimates using spatial models are significant under the 1% level. The LR test, which tests the coefficient for the spatial lag, is significant in all columns and suggests the existence of a spatial pattern.

4.7 Mechanisms

The previous section demonstrated that the railway expansion alleviated urban-rural income inequality but the highway did not. Why did the construction of the railway lead to a decrease in the urban-rural income gap but not highways? What makes the railway network so special compared to the highway? To reconcile the difference, I draw some insight from the international trade theory. On the one hand, improving transportation is similar to free trade in that it promotes the flow of goods; therefore, it is likely to lead to industrial specialization and agglomeration (Baum-Snow et al., 2020; Ge, 2006). On the other hand, unlike free trade or globalization, improving transportation boosts labour mobility (the labour market is not so free in the context of international trade due to low and imperfect interregional worker mobility). With greater labour mobility, rural workers can access labour markets in cities, which

[6]It is interesting that Moran's I for railway stock shows a decline trend after 2009, and the interpretation for that is that the railway was built in regions which cluster together, and over the last decade, the railway has expanded to almost everywhere. Even more interesting is that Moran's I for GDP also shows an inverse U shape with a peak in 2010. The recent downward trend provides evidence of a reduction in regional economic gaps.

increases their probability of receiving higher wages, leading to a decrease in the urban-rural income gap (Zhigang and Shunfeng, 2006; Zhang and Shunfeng, 2003; Xu and Xie, 2015). Thus, it is possible that the railway and highway play different roles in the flow of passenger relative to the flow of cargo, which makes the railway unique in reducing urban-rural income gaps. For example, if transportation development accelerates capital flow more than the flow of labour, then well-connected places might face the risk of losing more of their capital (Banerjee et al., 2020). In this section, I extract data from the China Statistical Yearbooks and address this question by looking at the impacts of the railway and the highway on urbanization, internal migration, passenger and cargo flow, and rural incomes from different income sources.

4.7.1 Urbanization and Proportion of Migrants

Since 1978, China has experienced rapid urbanization, and studies show the rural-urban migration was the dominant contributor to Chinese urban population growth (Zhang and Shunfeng, 2003). The question I wish to address here is whether the railway or highway expansions caused China's urbanization.

Table 4.7 presents estimates of the urbanization effects of the transportation length (log) within a province using the difference-in-difference method. The top panel estimates only consider changes in railway length, whereas the bottom panel looks at both railway and highway growth. The first two columns examine the effects of changes in railway length on the urban population controlling for total population and other economic indicators. The last two columns look at the impacts on the urbanization rate. In Table 4.7, I do not find the railway expansion causes urbanization since points estimates in all specifications are insignificant. The bottom panel does not show evidence from columns (1) and (4) that highway growth contributes to urbanization; however, the results are likely to suffer from reverse causality, which means with rapid urbanization, there is a tendency to build more highways.

The urban population and the urbanization rate do not reflect where the urban population originated, which means it cannot tell whether members of the population are locals or migrants, and neither can it tell whether the migrants came from within the province or from other provinces since there is a significant flow of rural migrant workers both within and across provinces. To deal with the migrant population, I look at how the railway and the highway affect the percentage of migrants.

Table 4.8 presents the impacts of the railway and the highway on the migrants where the dependent variable is the percentage of migrants in that province. All estimates control for province and time fixed effects. Columns (2) and (4) control for provincial time-varying variables. Results show the railway has a positive impact on the proportion of migrants whereas the highway shows no effects. To sum up, in this section I do not find the railway causes urbanization in general; however, railway expansion does increase the percentage of migrants.

4.7.2 Passengers, cargo and rural incomes

The impacts of public transportation on the flow of goods and people might be different for railways and highways. For example, one might be more sensitive to the flow of people and the other might be more sensitive to the flow of goods/cargo. Furthermore, the flow of goods and people may impact rural households' income differently. This section attempts to address these issues by looking at how the railway and highway influence the passenger-cargo ratio. It then examines how passenger and cargo volumes affect rural household income using detailed income sources.

Table 4.9 examines the sensitivity of the passenger-cargo ratio to the railway and highway expansions. Specifically, I regress the passenger-cargo ratio on (log) railway length and (log) highway length. All specifications control for time and province fixed effects as well as provincial time-varying variables. I also include different regional-specific time trends. Results show railway expansion is associated with an increase in the passenger-cargo ratio, which means it boosts the flow of people relative to goods. Conversely, the expansion of the highway boosted the flow of goods.

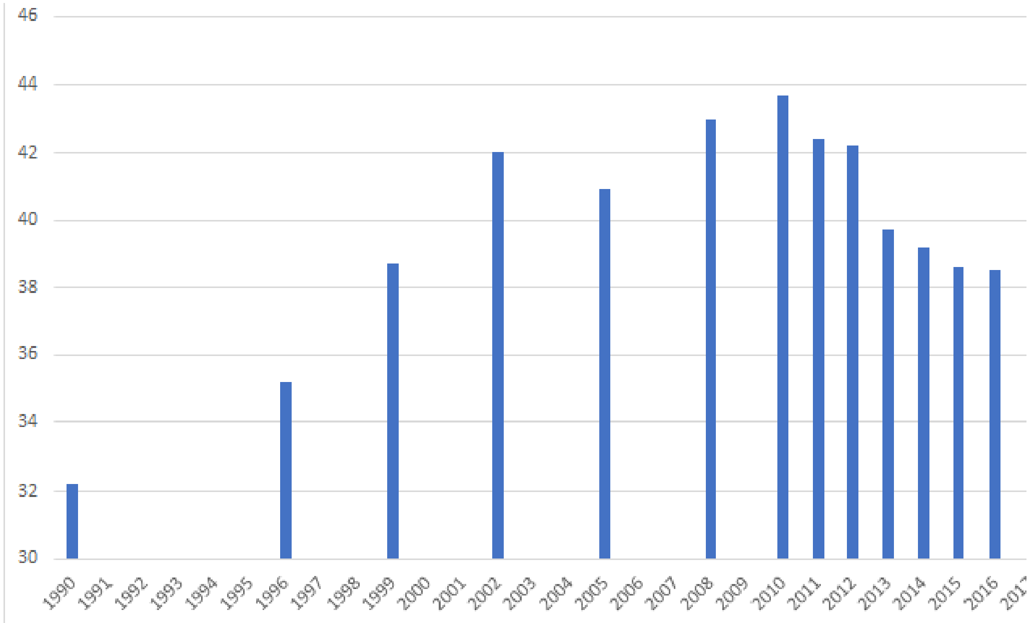
Table 4.10 investigates the impacts of passenger and cargo flow on the rural household income using income sources. In general, rural household income can be separated into four categories: transfer income, household business income, property income and wage income. The top panel presents an analysis of the railway and the bottom panel presents and analysis of both the railway and the highway. I found an association between an increase in railway passenger volume and an increase in rural household transfer income as well as wage income, which is likely a result of rural people being are able to easily take the railway to work in urban areas, thus increasing their wage. At the same time, when they make money in cities, they might send part of their income back home, which would increase rural household transfer income. I do not find a similar pattern in terms of highways. Although the estimate for highway passengers in the column (4) bottom panel is also significant, its magnitude is very mild compared to that of the railway. Overall, the flow of people, measured by the volume of railway passengers, boosted rural households' wage incomes as well as their transfer incomes, and therefore, it could potentially contribute to the decreasing trend of the urban-rural income gap.

4.8 Conclusion

Income inequality is one of the most challenging issues in China; however, on the bright side, during the last decade, China has shown a clear decreasing trend in inequality. In this paper, I focus on studying the effects of public infrastructure, specifically the railway expansion, on the urban-rural income gap in China. I explore the province-by-year variation in the railway growth by conducting a difference-in-difference design. To account for spatial spillover effects, I also use spatial econometric models. I found that up to 20% of the total income gap decrease can be explained by railway growth over the last 10 years.

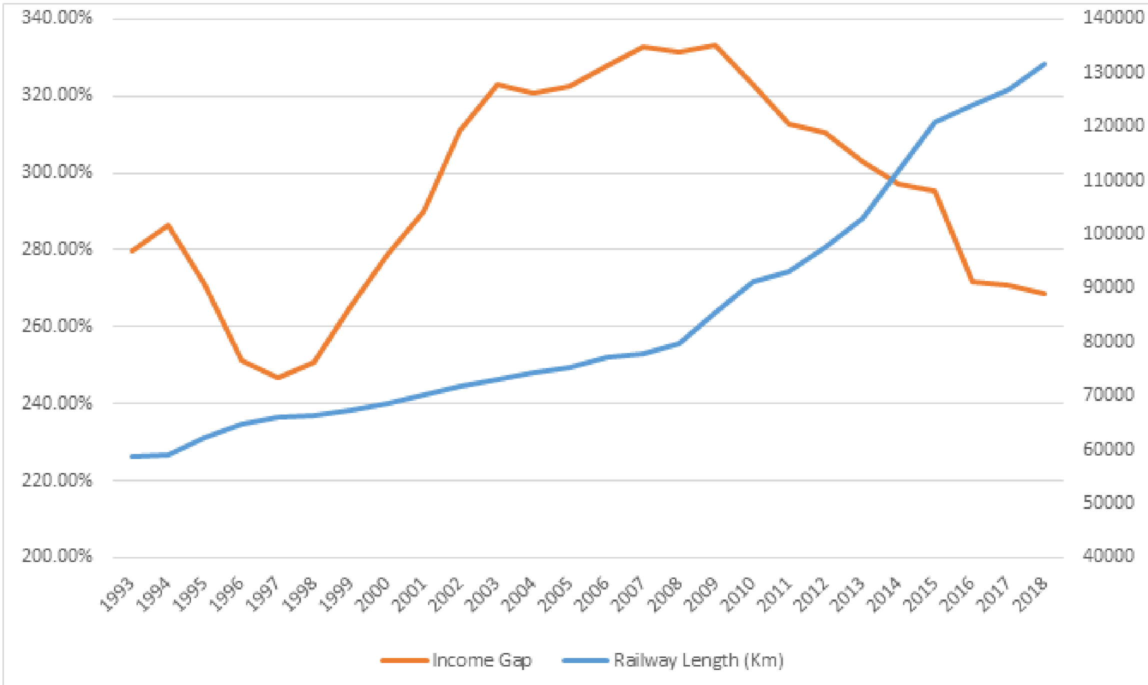
While exploring different causal channels, I find the railway expansion boosted the wage of rural households, leading to a decrease in the urban-rural income gap. Results also show that railways play a more critical role than highways in this process. Overall, the expansion of public transportation binds cities together as integrated regional areas and helps close the gaps between urban and rural households. Given the importance of railway expansion in enhancing accessibility and improving income inequality, it is important for policy makers to consider multi-criteria impacts when conducting a railway expansion policy.

Figure 4.1: China Gini Index - World Bank Estimate



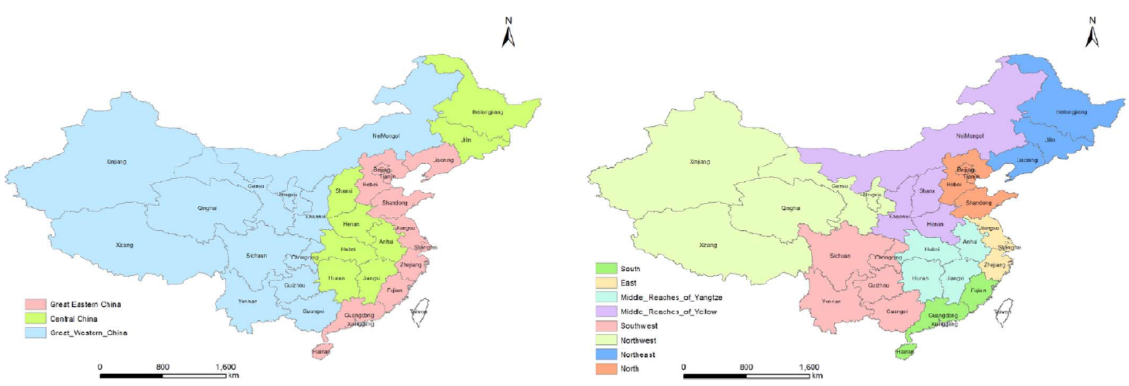
Source: World Bank

Figure 4.2: Urban-Rural Income Gap vs Total Railway Length



Source: Author's calculation based on data from NBS

Figure 4.3: Difference regional claasifications of China



(a) The Three-Region Classification

(b) The Eight-Region Classification

Source: Chen and Haynes (2017)

Figure 4.4: Change of Urban-Rural Income Gap by region

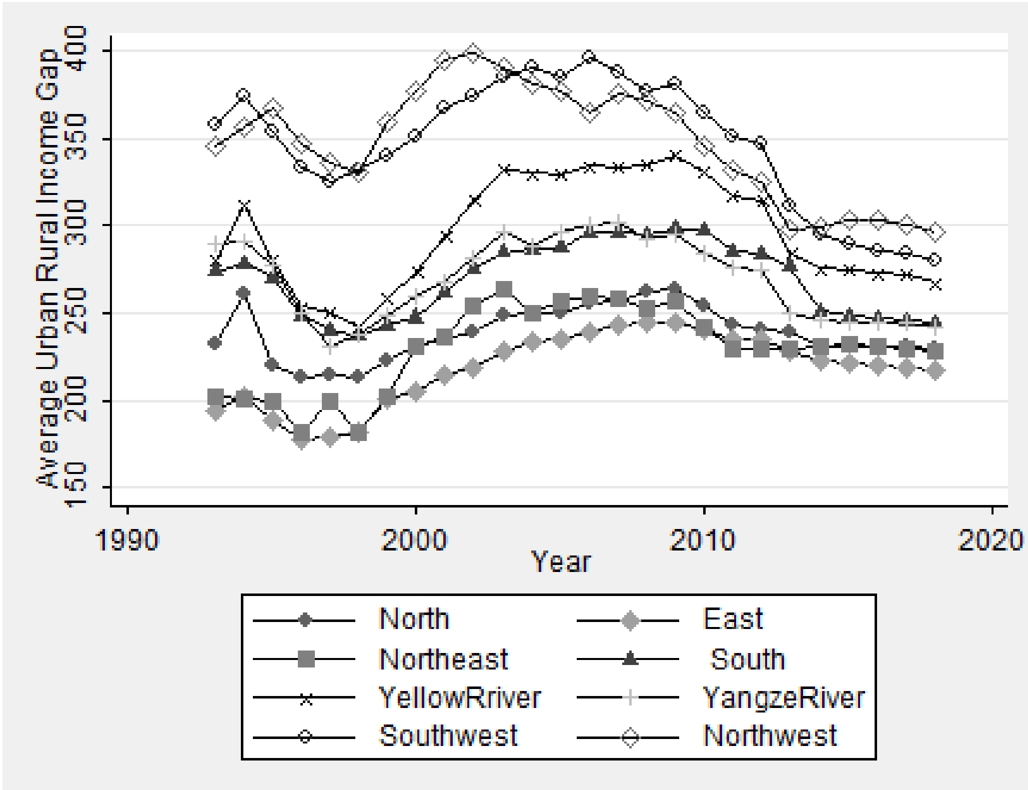


Figure 4.5: Change of Chinese railway length by region

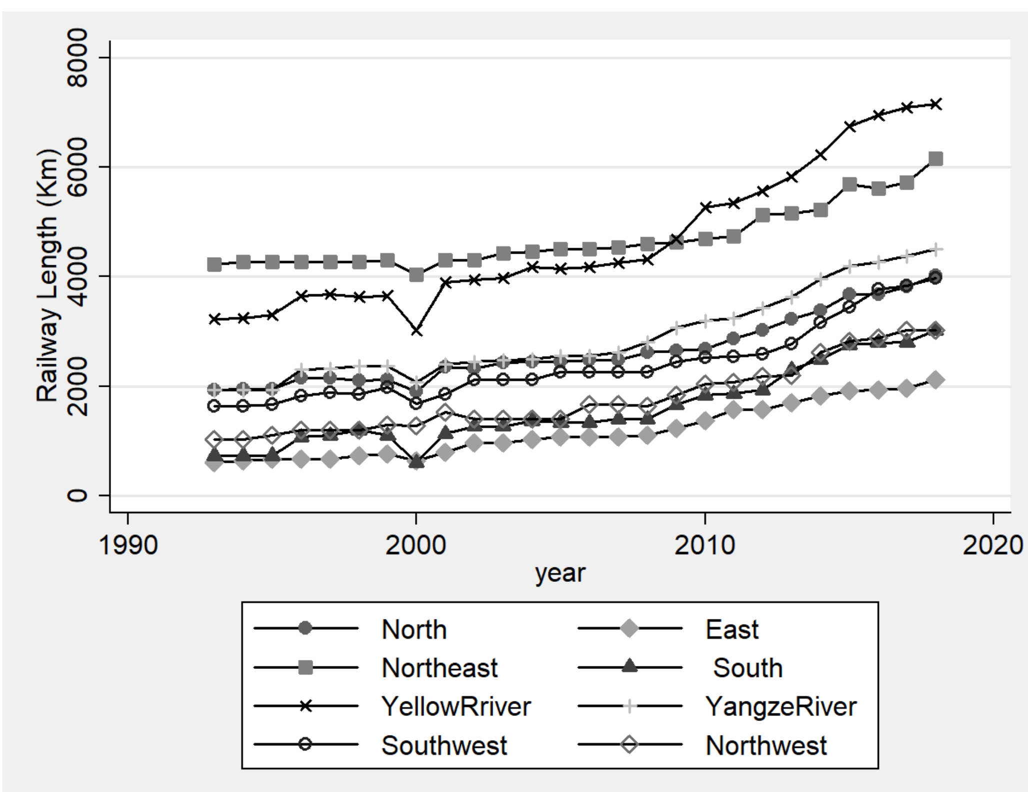


Figure 4.6: Moran's I for Urban-Rural Income Gap

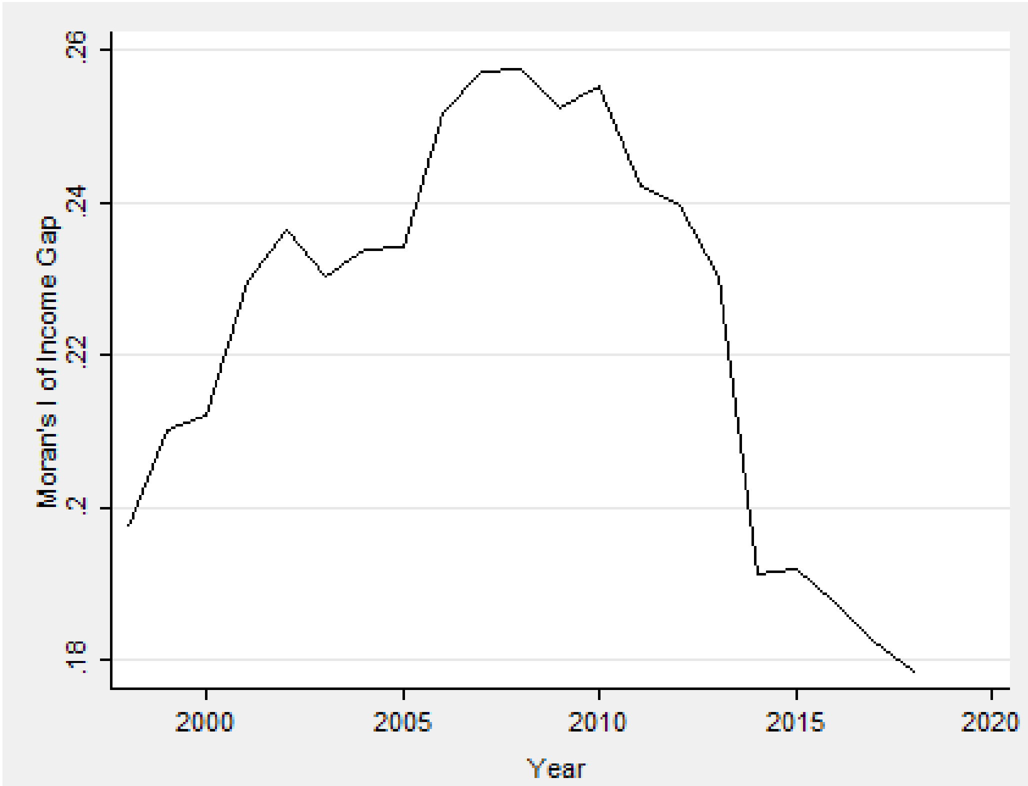


Figure 4.7: Moran's I for Railway

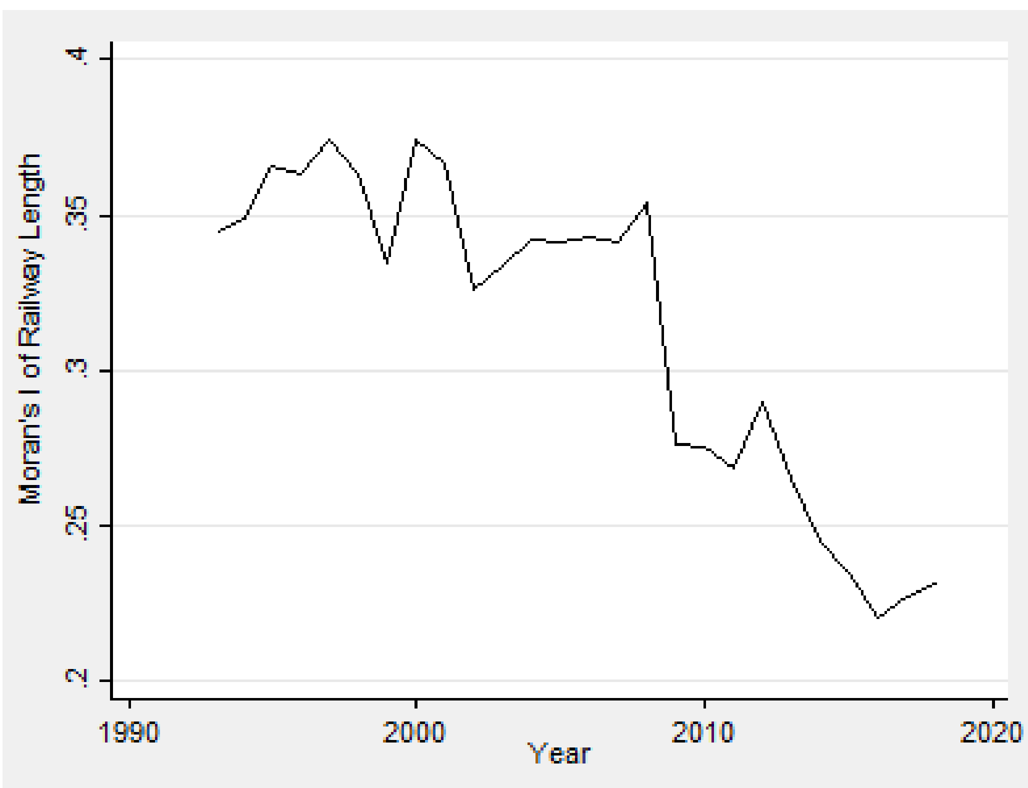


Table 4.1: Descriptive Statistics for Province-Level Data

	Total	1993[7]	2018
Urban-Rural Income Gap (%)	285.18	281.94	255.38
	(65.17)	(66.68)	(35.41)
Railway (Length, Km)	2714.27	1880.65	4246.82
	(1855.62)	(1412.90)	(2472.18)
Highway (Length, Km)	91655.04	36113.33	156339.73
	(71312.65)	(19979.43)	(82910.64)
GDP per Capita (1,000RMB)	4.58	1.18	10.03
	(3.97)	(0.76)	(4.47)
Average Years in School	7.84	6.31	8.74
	(1.39)	(1.21)	(1.00)
Degree of Openness (%)	0.29	0.21	0.24
	(0.37)	(0.25)	(0.26)
# Railway Workers	64623.70	75689.66	59154.84
	(86256.48)	(50614.16)	(35558.56)
# Highway Workers	68911.14	49793.10	117515.16
	(60946.11)	(28867.16)	(86960.27)
% of Migrants	13.31	5.68	21.80
	(11.25)	(3.32)	(11.25)
Urbanization rate	51.86	18.48	59.99
	(15.10)	(.)	(11.78)
Railway Cargo volume (10,000 ton)	8971.42	5609.14	12988.09
	(12047.54)	(5407.09)	(19540.75)
Highway Cargo volume (10,000 ton)	61982.89	28002.07	127640.99
	(58938.32)	(19217.58)	(87461.83)
Railway Passenger volume (10,000 person)	5145.20	3636.55	10886.92
	(4335.79)	(3336.27)	(7059.31)
Highway Passenger volume (10,000 person)	57002.88	28689.97	44102.27
	(59292.9)	(26545.01)	(3155.42)
Transfer Income	717.92	50.23	2978.57
	(999.36)	(29.6)	(1138.40)
Wage Income	2511.87	444	6627.64
	(3046.28)	(572.22)	(4688.10)
Household-business Income	2570.79	1125.27	5191.92
	(1535.23)	(272.80)	(1494.03)
Property Income	187.32	60.44	430.09
	(251.33)	(44.68)	(351.52)
Observations (Max)	806	31	31

Notes: Table shows the means, standard deviations of variables used in the analyses. The sample consists of 31 Provinces in China with data from 1993 to 2018, hence a maximum of 806 province-year observations. All variables are extracted from Annual China Statistical Year books.

Table 4.2: Balance Test for Construction of Railway

Dependent Variable : (Log) Length of Railway	(1)	(2)	(3)
Years in School	0.322***	0.0588*	0.0281
	(0.0813)	(0.0286)	(0.0499)
Degree of Openness	-1.129***	-0.187**	-0.0870
	(0.142)	(0.0932)	(0.0997)
GDP per Capita	-0.00447	0.134***	0.0331
	(0.0448)	(0.0152)	(0.0261)
GDP per Capita Square	-0.00532***	-0.00480***	-0.00167
	(0.00160)	(0.000713)	(0.000973)
Road Works#	0.00000571***	0.000000522	-0.000000167
	(0.000000519)	(0.000000366)	(0.000000423)
Railway Workers #	0.00000160	6.71e-08	3.50e-08
	(0.00000131)	(0.000000157)	(0.000000158)
Joint Significance F-Test			0.92
Joint Significance P-Values			0.481
Observations	806	806	806
Province FE	No	Yes	Yess
Year Fe	Yes	No	Yes
adj. R^2	0.473	0.413	0.438

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors clustered at the province level (31) in parenthesis. Table shows how changes in various measures of economic development and performance are related to year-to-year changes in the construction of railway for the 31 provinces of China. When including province fixed effects in column (3), most of the relationship disappears and all time-varying factors are jointly insignificant predictors of the growth in the length of railway. This indicates that the growth of railway is largely driven by fixed province characteristics captured by the province fixed effects.

Table 4.3: Effects of Railway Expansion on Urban-Rural Income Gap

Dependent Variable : Urban-Rural Income Gap						
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Railway	-17.79**	-16.64**	-16.64**	-17.70**	-17.65**	-17.35**
	(8.138)	(7.629)	(7.635)	(8.355)	(8.535)	(8.263)
Log of Railway in Neighbour provinces			0.209	1.416	0.375	7.193
			(20.27)	(21.63)	(19.66)	(22.87)
1-year lag of Railway				-1.567	0.330	-0.453
				(1.586)	(1.311)	(1.635)
Observations	806	806	806	775	775	775
Time-Varying Conrtols	No	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
8 Region-specific time trends	No	No	No	No	Yes	No
3 Region-specific time trends	No	No	No	No	No	Yes
Adj. R^2	0.520	0.573	0.573	0.602	0.644	0.615

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table shows the estimated effects of changes in the length of railway on the urban-rural income gap, using data form 31 Chinese provinces from 1993-2018. All estimates control for province fixed effects and time fixed effects. Column (3) includes railway stock in the neighbouring provinces. Column (4) controls 1-year lag of log railway length to capture conditions in the previous year. Column (5) and (6) controls for region specific time trends. The difference between the last two column is that (5) uses the 8 region classification and column (6) uses the three region classification. Time-Varying Controls refer to annual controls for various other measures of economic and social conditions. These include GDP per capita and its square, average years in school and degree of openness. The estimated coefficients for the main variable of interest are consistent (around -17) in all specifications.

Table 4.4: Placebo Test: Effects of Railway on Urban-Rural Income Gap (3-year Treatment Leads)

Dependent Variable : Urban-Rural Income Gap	(1)	(2)	(3)	(4)	(5)	(6)
Log of Railway Length	-7.453	-5.481	-4.438	-9.668	-15.24	-11.39
(3-year Lead)	(11.07)	(9.192)	(9.841)	(7.139)	(9.083)	(7.345)
Log of Railway in Neighbour provinces			13.35	12.53	-0.488	19.59
(3-year Lead)			(24.02)	(26.10)	(22.94)	(25.98)
Log of Railway Length				1.298	-1.20	2.487
(1-year Lag)				(14.05)	(13.84)	(12.93)
Observations	713	713	713	682	682	682
Time-Varying Conrtols	No	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
8 Region-specific time trends	No	No	No	No	Yes	No
3 Region-specific time trends	No	No	No	No	No	Yes
Adj. R^2	0.509	0.557	0.557	0.597	0.648	0.610

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors clustered at the province level (31) in parenthesis. Table shows results of a placebo test of future changes in the length of railway on Urban-Rural income gap, using data from 31 Chinese provinces from 1993 to 2018. All estimates control for province and time fixed effects except column (1). Time-Varying Controls refer to annual controls for various other measures of economic development. These include GDP per capita and its square, average years in school and an indicator for openness.

Table 4.5: Effects of Railway and Highway on Urban-Rural Income Gap

Dependent Variable : Urban-Rural Income Gap	(1)	(2)	(3)	(4)	(5)	(6)
Log of Railway	-17.87**	-16.44**	-16.44**	-17.58**	-17.31**	-17.06**
	(8.312)	(7.544)	(7.535)	(7.977)	(7.867)	(7.423)
Log of Highway	-0.686	1.314	1.331	1.865	3.351**	3.784**
	(1.879)	(1.654)	(1.628)	(1.598)	(1.647)	(1.815)
Log of Railway in Neighbour provinces			-1.926	-0.816	1.455	4.831
			(19.62)	(21.07)	(17.91)	(21.69)
1-year lag of Railway				-1.389	0.954	0.241
				(1.535)	(1.512)	(1.612)
Observations	806	806	806	775	775	775
Time-Varying Conrtols	No	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
8 Region-specific time trends	No	No	No	No	Yes	No
3 Region-specific time trends	No	No	No	No	No	Yes
Adj. R^2	0.520	0.574	0.574	0.605	0.652	0.625

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the province level (31) in parenthesis. This table is a replica of Table 4.3 and adding the changes in highway length as a robustness check. Table shows the estimated effects of changes in the length of railway and changes in the length of highway on the urban-rural income gap, using data form 31 Chinese provinces from 1993-2018. All estimates control for province fixed effects and time fixed effects. Column (3) includes railway stock in the neighbouring provinces. Column (4) controls 1-year lag of log railway length to capture conditions in the previous year. Column (5) and (6) controls for region specific time trends. The difference between the last two column is that (5) uses the 8 region classification and column (6) uses the three region classification. Time-Varying Controls refer to annual controls for various other measures of economic and social conditions. These include GDP per capita and its square, average years in school and degree of openness. The estimated coefficients for (log) railway are consistent (around -17) in all specifications. The estimated effects for (log) highway are not significant except for the last two columns.

Table 4.6: Estimation Results of Spillover of Railway

Dependent Variable : Urban-Rural Income Gap	0-1 weight		inverse distance weight	
	(1)	(2)	(3)	(4)
Log of Railway	-13.799***	-11.066***	-14.356***	-8.599***
	(1.129)	(1.103)	(1.533)	(1.291)
ρ	0.765***	0.628***	15.726***	14.121***
	(0.021)	(0.027)	(0.855)	(1.032)
λ	-0.662***	-0.5025***	-13.628***	-12.843***
	(0.059)	(0.057)	(1.394)	(1.575)
LR Test (Rho=0)	1337.936	508.656	338.572	187.142
P-Value	0.000	0.000	0.000	0.000
LR Test (Lambda=0)	124.305	76.974	95.516	66.480
P-Value	0.000	0.000	0.000	0.000
LR Test SAC vs OLS (Rho+Lambda=0)	2563.84	1143.659	504.068	352.064
P-Value	0.000	0.000	0.000	0.000
Observations	806	806	806	806
Time-Varying Conrtols	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year Fe	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Standard errors clustered at the province level (31) in parenthesis. Table shows the estimated effects of changes in the length of railway on the urban-rural income gap, using data form 31 Chinese provinces from 1993-2018 using spatial autocorrelation models (SAC). The spatial weight matrix used in columns (1) (2) are 0-1 weight matrix, the column (3) & (4) uses the inverse distance spatial weight matrix. All estimates control for province fixed effects. Colloum (2)-(4) also control for time fixed effects. Time-Varying Controls refer to annual controls for various other measures of economic and social conditions. These include GDP per capita and its square, average years in school and degree of openness.

Table 4.7: Urbanization and Public transportation

(a) Railway Only

Dependent Var	Urban Population		Urbanization rate	
	(1)	(2)	(3)	(4)
Log Railway Length	366.5	-39.92	3.327	1.091
	(455.2)	(293.1)	(2.718)	(1.964)
N	733	733	446	446
Time-Varying Conrtols	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
adj. R^2	0.403	0.595	0.891	0.947

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(b) Railway & Highway

Dependent Var	Urban Population		Urbanization rate	
	(1)	(2)	(3)	(4)
Log Railway Length	397.6	8.997	3.345	0.440
	(452.3)	(290.2)	(2.683)	(1.992)
Log Highway Length	-108.6	-2.010	1.337	-0.732
	(100.6)	(92.99)	(1.275)	(0.649)
N	734	733	446	446
Time-Varying Conrtols	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
Adj. R^2	0.486	0.634	0.895	0.950

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors clustered at the province level (31) in parenthesis. Table shows results of sensitivity of urban population/urbanization to the railway and highway, using data from 31 Chinese provinces from 1993 to 2018. All estimates control for province and time fixed effects. Time-Varying Controls refer to annual controls for various other measures of economic development. These include GDP per capita and its square, average years in school, population, and an indicator for openness. Results did not provide evidence transportation lead to urbanization. However, the results could suffer from reverse causality.

Table 4.8: Transportation and Percentatage of Migrants

Dependent Variable: Percentage of Migrants				
	(1)	(2)	(3)	(4)
Railway density	4.554**	4.872**	4.680**	5.265***
	(1.869)	(1.847)	(1.775)	(1.803)
Highway density			-0.00613	-0.0179
			(0.0281)	(0.0262)
N	619	619	619	619
Time-Varying Controls	No	Yes	No	Yes
Province FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
adj. R^2	0.724	0.731	0.723	0.732

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors clustered at the province level (31) in parenthesis. Table shows results of sensitivity of percentage of migrants to the railway and highway density, using data from 31 Chinese provinces from 1996 to 2018 (2000, 2001, and 2010 are ommited due to missing data). All estimates control for province and time fixed effects. Columns (2) and (4) controls for time-varying variables which include average years in school, total population, and an indicator for openness. Results show there is a positive impact of railway on migrants proportion but highway shows no effects.

Table 4.9: Passenger/cargo ratio and public transportation

Dependent Variable : Passenger-cargo ratio				
	(1)	(2)	(3)	(4)
Log of Railway Length	0.348***		0.374***	
	(0.0412)		(0.0402)	
Log of Highway Length	-0.822***		-0.844***	
	(0.147)		(0.145)	
Railway Lenth		0.000110**		0.0000497
		(0.0000545)		(0.0000545)
Highway Length		-0.00000596***		-0.00000492***
		(0.00000103)		(0.00000109)
N	802	802	802	802
Time-Varying Conrtols	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
3 Region-specific time trends	Yes	Yes	No	No
8 Region-specific time trends	No	No	Yes	Yes
adj. R^2	0.293	0.221	0.400	0.308

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Standard errors clustered at the province level (31) in parenthesis. Table shows results of sensitivity of passenger-cargo ratio to the railway and highway, using data from 31 Chinese provinces from 1993 to 2018. All estimates control for province and time fixed effects. Time-Varying Controls refer to annual controls for various other measures of economic development. These include GDP per capita and its square, average years in school, population, and an indicator for openness. Results show there is a positive impact of railway on passenger-cargo ratio whereas highway expansion contributes negatively to the passenger-cargo ratio.

Table 4.10: Impacts of Transportation on Rural Income by Income Source

(a) Railway Only

Dependent Var:	Transfer (1)	Household Business (2)	Property (3)	Wage (4)
Railway Passenger	0.0615***	-0.0543	0.00923	0.299*
	(0.0143)	(0.0368)	(0.00862)	(0.116)
Railway Cargo	-0.00153	-0.0000798	-0.00186	-0.0266
	(0.00567)	(0.0161)	(0.00279)	(0.0149)
N	731	731	731	731
Time-Varying Conrtols	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
adj. R^2	0.894	0.898	0.746	0.932

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(b) Railway and Highway

Dependent Var:	Transfer (1)	Household Business (2)	Property (3)	Wage (4)
Railway Passenger	0.0789***	-0.0914	0.0259**	0.452***
	(0.0218)	(0.0457)	(0.0122)	(0.131)
Railway Cargo	-0.000205	-0.00453	-0.000154	-0.0106
	(0.00527)	(0.0143)	(0.00279)	(0.00859)
Highway Passenger	-0.000577	-0.00305**	0.000622	0.00665**
	(0.000630)	(0.00119)	(0.000525)	(0.00278)
Highway Cargo	-0.00245	0.00491	-0.00225**	-0.0205**
	(0.00189)	(0.00315)	(0.00100)	(0.00834)
N	731	731	731	731
Time-Varying Conrtols	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
adj. R^2	0.875	0.868	0.537	0.786

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard errors clustered at the province level (31) in parenthesis. Top panel shows impact of railway passenger and cargo on rural household income by income source, using data from 31 Chinese provinces from 1995 to 2018. Bottom panel show the same analyse including highway passenger and highway cargo volume. All estimates control for province and time fixed effects. All estimates control for time-varying variables which include average years in school, GDP and its squre, and an indicator for openness. Results show increasing railway passenger volumes boost transfer income received by rural household and it also increased rural wage. I do not observe same effects in highway.

Chapter 5

Conclusion

In this dissertation, I examine three public policies implemented in China from 1970 to 2018, focusing on the how these policies impact inequality in vulnerable populations such as children, migrant workers and rural households. These vulnerable populations require special attention because they are underrepresented in the literature, and I intend to address this gap, at least in part. Evaluating these public policies is challenging due to the great heterogeneities in the policy-targeted population. Furthermore, a universal policy is likely to produce different results for different population subgroups, which is especially true for the identification of unintended consequences both negative and positive.

The first essay examines a family control policy implemented half a century ago. Even though various forms of strict family control policies were gradually abandoned by the Chinese government, the policy still had great impacts on the well-being of Chinese families today. With fewer children per family, parents have been more focused on child-rearing and have been able to provide better opportunities and resources for their children. As a result of the family planning policies, we saw great improvements in the average number of years that children spend in school. Furthermore, smaller-sized families have been the social norm for decades. Even after the One Child Policy was lifted, China's fertility rates remained low, leaving the country with a population that was aging too rapidly and a workforce that was shrinking. One implication resulting from this is that it may become difficult for China to keep relying on cheap labour for future development; however, the end of cheap labour in China does not mean the end of Chinese economic growth. Rising productivity and increased education mean that China's comparative advantage is shifting. China could gain sustainable growth by moving up the technological ladder and becoming a force in high value-added manufacturing and innovation (Li et al., 2012).

The second and third essay study the inequalities of the vulnerable rural population in China. The Hukou system creates institutional barriers to migration and has favoured the urban population in terms of social security and economic prosperity for decades. In the second essay, I examine the wage gaps between urban Hukou holders and rural migrant workers and conduct a decomposition analysis of the social determinants on labour market output. The results show an inverse U-shaped Hukou premium, which indicates that if rural migrants hold an urban Hukou, the wage gap could be greatly reduced for those who are from the middle part of the wage distribution. The composition effects still play the most important role in determining wage gaps for people who are in the top and bottom quantiles. Since 2005, many local governments have gradually begun to abolish the official distinction between urban Hukou and non-urban Hukou holders. In order to mitigate income inequalities between rural migrant workers and urban workers, it is critical to ensure that the Hukou reform can offer welfare entitlements including education, job opportunities and social securities, to people from rural areas.

The barriers between the urban and rural sectors originated from both the institutional system and poor public transportation. In the past, migration to distant cities for work was not an option for most rural workers; however, the development of railway networks has accelerated labour relocation. In the third essay, I examine the impact of railway expansion on the urban-rural income gap. I find railway expansion negatively contributes to these income gaps and the decreasing trend in the urban-rural income gap has been especially evident in the most recent decade. My results indicate that the improved labour mobility caused by the railway expansion boosted the wages of rural households, which lead to a decrease in the urban-rural income gap.

Over the past few decades, China has gone through fundamental transitions in terms of demographics, social norms, and inequality patterns. The three essays presented in this paper explore the role of public policies in those transitions, each focusing on a different aspect. The results show how the policies introduced several decades ago could affect the well-being and economic inequality of current individuals. Finally, this paper sheds light on the important path to understanding China's current economic outcomes and perhaps the origins of its social conflicts as well.

Bibliography

Acemoglu, D. and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, Volume 4, pp. 1043–1171. Elsevier.

Adams, A. V. (2009). Economic growth, spatial income inequality, and the role of education and training in china. Technical report, The World Bank.

Ahlfeldt, G. M. and A. Feddersen (2018). From periphery to core: measuring agglomeration effects using high-speed rail. *Journal of Economic Geography 18*(2), 355–390.

Akbulut-Yuksel, M., D. Okoye, and B. Turan (2020). Expressway to power: Infrastructure projects and political support. Technical report, IZA Discussion Papers.

Alder, S. (2016). Chinese roads in india: The effect of transport infrastructure on economic development. *Available at SSRN 2856050*.

Anselin, L. (2001). Spatial econometrics. *A companion to theoretical econometrics 310330*.

Atack, J., F. Bateman, M. Haines, and R. A. Margo (2009). Did railroads induce or follow economic growth? urbanization and population growth in the american midwest, 1850-60. Technical report, National Bureau of Economic Research.

Autor, D. H., D. Dorn, and G. H. Hanson (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics 8*, 205–240.

Babiarz, K. S., P. Ma, G. Miller, and S. Song (2018). The limits (and human costs) of population policy: Fertility decline and sex selection in china under mao. Technical report, National Bureau of Economic Research.

Banerjee, A., E. Duflo, and N. Qian (2020). On the road: Access to transportation infrastructure and economic growth in china. *Journal of Development Economics*, 102442.

Banerjee, A., X. Meng, and N. Qian (2010). The life cycle model and household savings: Micro evidence from urban china. *National Bureau of Demographic Dividends Revisited 21*.

Banister, J. (1987). *China's changing population*. Stanford University Press.

Barsky, R., J. Bound, K. K. Charles, and J. P. Lupton (2002). Accounting for the black–white wealth gap: a nonparametric approach. *Journal of the American statistical Association 97*(459), 663–673.

Baum-Snow, N., L. Brandt, J. V. Henderson, M. A. Turner, and Q. Zhang (2017). Roads, railroads, and decentralization of chinese cities. *Review of Economics and Statistics 99*(3), 435–448.

Baum-Snow, N., J. V. Henderson, M. A. Turner, Q. Zhang, and L. Brandt (2020). Does investment in national highways help or hurt hinterland city growth? *Journal of Urban Economics 115*, 103124.

Behrman, J. R. and M. R. Rosenzweig (2004). Returns to birthweight. *Review of Economics and Statistics 86*(2), 586–601.

Benjamin, D., L. Brandt, J. Giles, and S. Wang (2007). Inequality and poverty in china during reform.

Bernstein, T. P. (1977). Up to the mountains and down to the villages: the transfer of youth from urban to rural china.

Bhalotra, S. and D. Clarke (2019). Twin birth and maternal condition. *Review of Economics and Statistics 101*(5), 853–864.

Black, S. E., P. J. Devereux, and K. G. Salvanes (2005). The more the merrier? the effect of family size and birth order on children's education. *The Quarterly Journal of Economics 120*(2), 669–700.

Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources*, 436–455.

Bonnin, M. (2009). The lost generation: The sent-down movement in china, 1968-1980.

Chatterjee, S. and S. J. Turnovsky (2012). Infrastructure and inequality. *European Economic Review 56*(8), 1730–1745.

Chen, C. and C. C. Fan (2016). China's hukou puzzle: Why don't rural migrants want urban hukou? *China Review 16*(3), 9–39.

Chen, G. and J. d. A. e Silva (2014). Estimating the provincial economic impacts of high-speed rail in spain: An application of structural equation modeling. *Procedia-Social and Behavioral Sciences 111*, 157–165.

Chen, Y., Z. Fan, X. Gu, and L.-A. Zhou (2018). Arrival of young talents: The send-down movement and rural education in china. *Available at SSRN 3102716*.

Chen, Y. and H. Fang (2018). The long-term consequences of having fewer children in old age: Evidence from chinas later, longer, fewer campaign. Technical report, National Bureau of Economic Research.

Chen, Y. and Y. Huang (2018). The power of the government: China's family planning leading. group and the fertility decline since 1970. Technical report, GLO Discussion Paper.

Chen, Z. (2017). Impacts of high-speed rail on domestic air transportation in china. *Journal of Transport Geography 62*, 184–196.

Chen, Z. and K. E. Haynes (2015). Impact of high-speed rail on international tourism demand in china. *Applied Economics Letters 22*(1), 57–60.

Chen, Z. and K. E. Haynes (2017). Impact of high-speed rail on regional economic disparity in china. *Journal of Transport Geography 65*, 80–91.

Chen, Z., J. Xue, A. Z. Rose, and K. E. Haynes (2016). The impact of high-speed rail investment on economic and environmental change in china: A dynamic cge analysis. *Transportation Research Part A: Policy and Practice 92*, 232–245.

Chong, Z., Z. Chen, and C. Qin (2019). Estimating the economic benefits of high-speed rail in china. *Journal of Transport and Land Use 12*(1), 287–302.

Coale, A. J. and S. L. Chen (1987). Basic data on fertility in the provinces of china. *Honolulu: East-West Center*.

David, H., D. Dorn, and G. H. Hanson (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review 103*(6), 2121–68.

Démurger, S. (2001). Infrastructure development and economic growth: an explanation for regional disparities in china? *Journal of Comparative economics 29*(1), 95–117.

Démurger, S., M. Gurgand, S. Li, and X. Yue (2009). Migrants as second-class workers in urban china? a decomposition analysis. *Journal of Comparative Economics 37*(4), 610–628.

Derviş, K. and Z. Qureshi (2016). Income distribution within countries: Rising inequality.

DiNardo, J., N. M. Fortin, and T. Lemieux (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica 64*(5), 1001–1044.

Donaldson, D. (2018). Railroads of the raj: Estimating the impact of transportation infrastructure. *American Economic Review 108*(4-5), 899–934.

Donaldson, D. and R. Hornbeck (2016). Railroads and american economic growth: A market access approach. *The Quarterly Journal of Economics 131*(2), 799–858.

Elhorst, J. P. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*, Volume 479. Springer.

Faber, B. (2014). Trade integration, market size, and industrialization: evidence from china's national trunk highway system. *Review of Economic Studies 81*(3), 1046–1070.

Feenstra, R. C. and A. Sasahara (2018). The china shock,exports and us employment: A global input–output analysis. *Review of International Economics 26*(5), 1053–1083.

Firpo, S., N. Fortin, and T. Lemieux (2018). Decomposing wage distributions using recentered influence function regressions. *Econometrics 6*(2), 28.

Firpo, S., N. M. Fortin, and T. Lemieux (2009). Unconditional quantile regressions. *Econometrica 77*(3), 953–973.

Fortin, N., T. Lemieux, and S. Firpo (2011). Decomposition methods in economics. In *Handbook of labor economics*, Volume 4, pp. 1–102. Elsevier.

Fujita, M. and D. Hu (2001). Regional disparity in china 1985–1994: The effects of globalization and economic liberalization. *The annals of regional science 35*(1), 3–37.

Gardeazabal, J. and A. Ugidos (2004). More on identification in detailed wage decompositions. *Review of Economics and Statistics 86*(4), 1034–1036.

Ge, Y. (2006). *Regional inequality, industry agglomeration and foreign trade: the case of China*. Number 2006/105. WIDER Research Paper.

Hammar, O. and D. Waldenström (2020). Global earnings inequality, 1970–2018. *The Economic Journal 130*(632), 2526–2545.

Hannum, E. (1999). Political change and the urban-rural gap in basic education in china, 1949-1990. *Comparative education review 43*(2), 193–211.

Heuermann, D. F. and J. F. Schmieder (2019). The effect of infrastructure on worker mobility: evidence from high-speed rail expansion in germany. *Journal of economic geography 19*(2), 335–372.

Holtz-Eakin, D. and A. E. Schwartz (1995). Spatial productivity spillovers from public infrastructure: Evidence from state highways. *International Tax and Public Finance 2*(3), 459–468.

Hu, A. and S. Wang (1996). *Changes in China's regional disparities*. Washington Center for Chinese Studies.

Huang, W. and Y. Zhou (2015). One-child policy, marriage distortion, and welfare loss.

Jin, M., K.-C. Lin, W. Shi, P. T. Lee, and K. X. Li (2020). Impacts of high-speed railways on economic growth and disparity in china. *Transportation Research Part A: Policy and Practice 138*, 158–171.

Koenker, R. and G. Bassett Jr (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, 33–50.

Kuznets, S. (1955). Economic growth and income inequality. *The American economic review 45*(1), 1–28.

Lee, L. (2012). Decomposing wage differentials between migrant workers and urban workers in urban china's labor markets. *China Economic Review 23*(2), 461–470.

Li, B. and H. Zhang (2017). Does population control lead to better child quality? evidence from chinas one-child policy enforcement. *Journal of Comparative Economics 45*(2), 246–260.

Li, H., L. Li, B. Wu, and Y. Xiong (2012). The end of cheap chinese labor. *Journal of Economic Perspectives 26*(4), 57–74.

Li, H., J. Zhang, and Y. Zhu (2008). The quantity-quality trade-off of children in a developing country: Identification using chinese twins. *Demography 45*(1), 223–243.

Li, S., H. Sato, and T. Sicular (2013). *Rising inequality in China: Challenges to a harmonious society*. Cambridge University Press.

Li, Y. (2010). Analysis on the disparity in economic growth and consumption between urban sector and rural sector of china: 1978–2008. *Frontiers of Economics in China 5*(4), 559–581.

Li, Y. and M. N. DaCosta (2013). Transportation and income inequality in china: 1978–2007. *Transportation Research Part A: Policy and Practice 55*, 56–71.

Liao, F. H. and Y. D. Wei (2012). Dynamics, space, and regional inequality in provincial china: A case study of guangdong province. *Applied Geography 35*(1-2), 71–83.

Liu, H. (2014). The quality–quantity trade-off: evidence from the relaxation of chinas one-child policy. *Journal of Population Economics 27*(2), 565–602.

Magnani, E. and R. Zhu (2012). Gender wage differentials among rural–urban migrants in china. *Regional Science and Urban Economics 42*(5), 779–793.

Michaels, G. (2008). The effect of trade on the demand for skill: Evidence from the interstate highway system. *The Review of Economics and Statistics 90*(4), 683–701.

Moran, P. A. (1950). Notes on continuous stochastic phenomena. *Biometrika 37*(1/2), 17–23.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International economic review*, 693–709.

Oaxaca, R. L. and M. R. Ransom (1999). Identification in detailed wage decompositions. *Review of Economics and Statistics 81*(1), 154–157.

Parish, W. L. and M. K. Whyte (1980). *Village and family in contemporary China*. University of Chicago Press.

Rosenzweig, M. R. and J. Zhang (2009). Do population control policies induce more human capital investment? twins, birth weight and china's one-child policy. *The Review of Economic Studies 76*(3), 1149–1174.

Sasaki, K., T. Ohashi, and A. Ando (1997). High-speed rail transit impact on regional systems: does the shinkansen contribute to dispersion? *The annals of regional science 31*(1), 77–98.

Sequeira, S., N. Nunn, and N. Qian (2017). Migrants and the making of america: The short-and long-run effects of immigration during the age of mass migration. Technical report, National Bureau of Economic Research.

Sicular, T., Y. Ximing, B. Gustafsson, and L. Shi (2007). The urban–rural income gap and inequality in china. *Review of Income and Wealth 53*(1), 93–126.

Song, Y. (2016). Hukou-based labour market discrimination and ownership structure in urban china. *Urban Studies 53*(8), 1657–1673.

Wang, F. (2014). *Essays on family planning policies*. University of Southern California.

Wang, F., L. Zhao, and Z. Zhao (2017). Chinas family planning policies and their labor market consequences. *Journal of Population Economics 30*(1), 31–68.

Wang, X., S. Huang, T. Zou, and H. Yan (2012). Effects of the high speed rail network on china's regional tourism development. *Tourism Management Perspectives 1*, 34–38.

Whyte, M. K., W. Feng, and Y. Cai (2015). Challenging myths about chinas one-child policy. *The China Journal* (74), 144–159.

Whyte, M. K. and W. L. Parish (1985). *Urban life in contemporary China*. University of Chicago Press.

Wong, C. (2011). The fiscal stimulus programme and public governance issues in china. *OECD Journal on Budgeting 11*(3), 1–22.

Wu, X. and J. M. Perloff (2005). China's income distribution, 1985–2001. *Review of Economics and Statistics 87*(4), 763–775.

Xie, Y. and X. Zhou (2014). Income inequality in todays china. *Proceedings of the National Academy of Sciences 111*(19), 6928–6933.

Xu, H. and Y. Xie (2015). The causal effects of rural-to-urban migration on childrens well-being in china. *European sociological review 31*(4), 502–519.

Zhang, K. H. and S. Shunfeng (2003). Rural–urban migration and urbanization in china: Evidence from time-series and cross-section analyses. *China Economic Review 14*(4), 386–400.

Zheng, D. and T. Kuroda (2013). The role of public infrastructure in c hina's regional inequality and growth: A simultaneous equations approach. *The Developing Economies 51*(1), 79–109.

Zhigang, L. and S. Shunfeng (2006). Rural–urban migration and wage determination: The case of tianjin, china. *China Economic Review 17*(3), 337–345.

Zhou, X. and L. Hou (1999). Children of the cultural revolution: The state and the life course in the people's republic of china. *American Sociological Review*, 12–36.

Appendix A

Supplementary Material for Chapter 2

Table A.1: Total number of sent and received SDY by province, 1962-1979

Province	SDY Sent (Thousand)			SDY Received (Thousand)		
	Total	Inside	Outside	Total	Inside	Outside
Beijing	636.3	384.2	252.1	384.2	384.2	0.0
Tianjin	465.1	193.6	271.5	193.6	193.6	0.0
Hebei	384.4	377.8	6.6	510.5	377.8	132.7
Shanxi	264.3	264.3	0.0	312.9	264.3	48.6
Inner Mongolia	193.8	193.8	0.0	299.3	193.8	105.5
Liaoning	2013.4	2013.4	0.0	2018.0	2013.4	4.6
Jilin	991.4	991.4	0.0	1052.6	991.4	61.2
Heilongjiang	1519.2	1519.2	0.0	1922.2	1519.2	403.0
Shanghai	1259.2	532.3	719.9	532.3	532.3	0.0
Jiangsu	828.4	810.2	18.2	861.2	810.2	51.0
Zhejiang	646.2	563.9	82.3	595.9	563.9	32.0
Anhui	576.5	576.5	0.0	725.5	576.5	149.0
Fujian	372.3	372.3	0.0	372.3	372.3	0.0
Jiangxi	504.5	504.5	0.0	622.5	504.5	118.0
Shandong	512.9	492.7	20.2	492.7	492.7	0.0
Henan	673.0	673.0	0.0	673.0	673.0	0.0
Hubei	886.6	878.6	8.0	878.6	878.6	0.0
Hunan	635.8	635.8	0.0	635.8	635.8	0.0
Guangdong	973.2	973.2	0.0	973.2	973.2	0.0
Guangxi	434.8	434.8	0.0	434.8	434.8	0.0
Sichuan	1472.4	1427.4	45.0	1427.4	1427.4	0.0
Guizhou	213.5	213.5	0.0	224.1	213.5	10.6
Yunnan	232.5	232.5	0.0	339.1	232.5	106.6
Tibet	3.4	3.4	0.0	3.4	3.4	0.0
Shaanxi	463.1	463.1	0.0	490.3	463.1	27.2
Gansu	245.2	245.2	0.0	264.3	245.2	19.1
Qinghai	43.6	43.6	0.0	51.0	43.6	7.4
Ningxia	49.2	49.2	0.0	57.5	49.2	8.3
Xinjiang	277.6	277.6	0.0	416.6	277.6	139.0
Total	17771.8	16341.0	1423.8	17764.8	16341.0	1423.8

Note: Data source is Gu (2009) "Chinese Educated City Youth: The Whole Story."

Source: (Chen et al., 2018)

Appendix B

Supplementary Material for Chapter 4

B.1 Moran's I of Urban-Rural Income Gap

Table B.1: Moran's I of Urban-Rural Income Gap

Year	Moran's I	z	P-value
1993	0.264	7.267	0.000
1994	0.189	5.445	0.000
1995	0.277	7.604	0.000
1996	0.232	6.651	0.000
1997	0.213	6.346	0.000
1998	0.197	6.017	0.000
1999	0.210	6.289	0.000
2000	0.212	6.415	0.000
2001	0.230	6.755	0.000
2002	0.236	6.858	0.000
2003	0.230	6.598	0.000
2004	0.234	6.642	0.000
2005	0.234	6.595	0.000
2006	0.252	7.032	0.000
2007	0.257	7.150	0.000
2008	0.258	7.133	0.000
2009	0.252	7.014	0.000
2010	0.255	7.085	0.000
2011	0.242	6.777	0.000
2012	0.240	6.722	0.000
2013	0.230	6.482	0.000
2014	0.191	5.563	0.000
2015	0.191	5.562	0.000
2016	0.187	5.458	0.000
2017	0.182	5.336	0.000
2018	0.178	5.249	0.000

B.2 Spatial model derivation

The starting point of spatial analysis is very similar to the baseline model (Equation 4.1) with justification to my variable of interest.

$$IncomeGap_{prt} = \beta \log \left(Rail^{e}_{prt} \right) + \delta_p + \gamma_t + \Pi' X_{prt} + \epsilon_{pt} \tag{B.1}$$

Compared with Equation 4.1, I replace the main explanatory variable -$Rail_{prt}$ - with $Rail^{e}_{prt}$ which represents effective railway stock in province p, region r, at time t. The approach of "effective stock of railway" comes from Holtz-Eakin and Schwartz (1995). The effective stock of provincial railway capitals differs from the physical stock of railways within that province's borders. That is to say, access to the railways in other provinces also contributes to the effective stock of public transportation in a given province, which will lead to the effective stock exceeding the physical stock within the province's borders (Holtz-Eakin and Schwartz, 1995). Specifically, the effective capital stock of a province(province i) is the sum of physical railway stock in that province and the effective railway stock in its neighbouring province (province j), expressed by equation:

$$Rail^{e}_{it} = Rail_{it} + \rho Rail^{e}_{jt} \tag{B.2}$$

$Rail_{it}$ is the physical stock of railway in province i. $Rail^{e}_{jt}$ represents the effective stock of railway in the neibour province j. ρ is the spill over rate. If there are no inter-provincial spillovers, $\rho = 0$ and the effective and actual transportation stock measures will coincide ($Rail^{e}_{it} = Rail_{it}$). If $0 < \rho < 1$, it means that part of neighbouring effect transfers to province i. If $= 1$, it means that all of the neighbouring province's effective capital spills over to the effective railway stock of province i.

Considering province i has more than one neighbouring provinces, Equation B.2 becomes:

$$Rail^{e}_{it} = Rail_{it} + \rho \sum_{j=1}^{N} Rail^{e}_{jt} * w_{ij} \tag{B.3}$$

N is the total number of provinces in the data set. w_{ij} is the weight assigned to province j. I create a spatial weight matrix that is a 31×31 "neighbors" matrix containing weights for each province's transportation capital. There are two types of spatial weight matrices (W): 0-1 spatial matrices and inverse-distance spatial weight matrices. w_{ij} are elements of W. If W is a 0-1 spatial matrix, then

$$w_{ij} = \begin{cases} 1 & \text{if i and j are neighbors;} \\ 0 & \text{if i and j are not neighbors.} \end{cases} \tag{B.4}$$

In an inverse-distance spatial matrix:

$$w_{ij} = \begin{cases} 1/d_{ij} & \text{if i} \neq \text{j;} \\ 0 & \text{if i} = \text{j.} \end{cases} \tag{B.5}$$

where d_{ij} is the distance between the capital cities of provinces i and j. Normalizing the spatial weight matrix requires that every row in the matrix adds up to one. According to Holtz-Eakin and Schwartz (1995), the physical railway stock in province i not only contributes to its own province's effective transportation stock, but also contributes to its neighbouring provinces through a rate ρ. In addition, it contributes to the subsequent surrounding ring of provinces at a rate ρ^2 and so on to ρ^3 etc. If ρ is high, closer to 1, it means slow decay of the spillover effect, and vice versa.

If turning Equation (4) into matrix expression, we now have:

$$R^e = R + \rho * WR^e \tag{B.6}$$

where R denotes the $N \times 1$ vector of provincial railway stock in log forms; W is the normalized spatial weight matrix. Solving EquationB.6 for R^e yields:

$$R^e = (I - \rho W)^{-1} R \tag{B.7}$$

The substituting Equation B.6 to B.1 I get:

$$\mathbf{IncomeGap} = \beta(\mathbf{I} - \rho\mathbf{W})^{\mathbf{-1}}\mathbf{R} + \delta_\mathbf{p} + \gamma_\mathbf{t} + \mathbf{\Pi}'\mathbf{X} + \epsilon \tag{B.8}$$

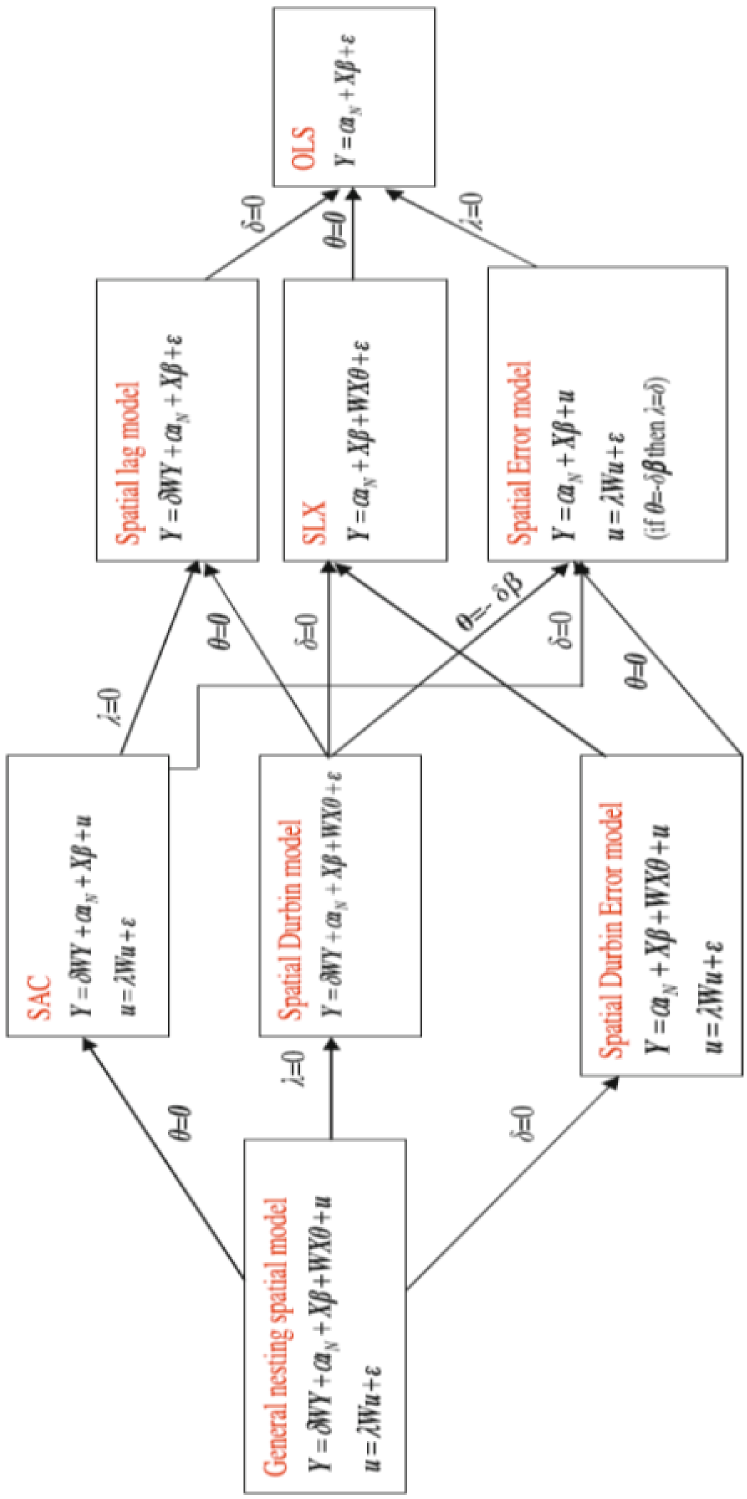
Equation B.8 takes care of spatial spillover effects of railway however the coefficient for my main dependent variable is non-linear. To solve that, I times both sides by $(I - \rho W)$ and rearrange the left hand side which yields:

$$\mathbf{IncomeGap} = \alpha\rho\mathbf{W} * \mathbf{IncomeGap} + \eta\mathbf{R} + \delta_\mathbf{p} + \gamma_\mathbf{t} + \mathbf{\Pi}'\mathbf{X} + \mathbf{e}, where\mathbf{e} = \lambda\mathbf{W}\mathbf{e} + \epsilon \tag{B.9}$$

Equation B.9 is a Spatial Auto Correlation (SAC) model. $W * IncomeGap$ is spatial lag dependent variable. λ allows error term contains a spatial pattern. I use maximum likelihood estimation to estimate Equation B.9.[1]

[1] For more spatial models please refer to Figure B1.

Figure B.1: The relationship between Different Spatial Dependence Models



Source: Elhorst (2014)