Essays on Intergenerational Mobility in China

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Dedication

This thesis is dedicated to the past.

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Chapter 1

Introduction

Intergenerational mobility has triggered widespread interest in both the academic and political arenas. At the heart of it, it is about whether individual effort can lead to improvements in wellbeing beyond that of your progenitors. Can society provide an environment beneficial to achieve self-worth? The Great Gatsby Curve links intergenerational mobility to income inequality. It describes the positive correlation between inequality and intergenerational immobility. In other words, if you live in a society with high income inequality, it becomes harder for you to climb the social ladder.

In many cases, economic development is accompanied by increasing inequality. A high concentration of wealth may prevent parents from carrying out the human capital investments that allow their offspring to enjoy economic opportunity. Jerrim and Macmillan (2015) shows education attainment plays a significant role in intergenerational mobility and income inequality in most OECD countries and suggests diminishing the education disparities might be crucial for the next generation to gain more equal opportunities. A Chinese study from J. Yang and Qiu (2016) demonstrates that a direct subsidy from the government can effectively alleviate budgetary constraints on investments in children's early education and therefore enable them to acquire higher education and reduce intergenerational income inequality.

This is a relatively broad topic in academia, with different studies in economics and social disciplines. Becker and Tomes (1979) incorporate the human capital model into the analysis framework of intergenerational income inheritance inequality, establish the equilibrium theory of income and intergenerational mobility distribution, and further analyze the relationship between children's income and father's income, education and government public expenditure. This is regarded as the starting point for the study of intergenerational mobility in economics. First of all, we need to understand the intergenerational mobility situation in a country. We usually start with empirical research, look for reliable data, and apply econometric methods to analyse it. A country's intergenerational mobility situation is meaningful when compared with its own past, rather than making broad international comparisons. I want to understand what intergenerational mobility has been like in China in recent decades. Therefore, I employ the longest micropanel data - the China Health and Nutrition Survey (CHNS) database - to estimate the intergenerational income mobility effect between parents and children. After gaining a certain understanding of the data, I then try to build a theoretical model that is consistent with China's situation to explain my empirical findings. The overlapping generations model is widely used to consider intergenerational problems. By taking into account the cash transfer program and redistribution taxation, I focus on adjusting the value of the policy parameter in the model to better promote intergenerational mobility and economic development. Finally, based on this theoretical model, from the government's perspective, I consider what optimal policies to adopt to promote economic development and improve mobility to maximize social welfare. More specifically, it examines the optimal government policy, where the government is assumed to design the best cash transfer program that maximizes overall economic welfare, while considering the optimization behavior of private agents. This issue is commonly known as the Ramsey problem of government under commitment.

China's rapid economic transformation over the past few decades has had profound effects on both individual and societal outcomes, including income distribution and social mobility. The nation's institutional backdrop, characterized by a unique blend of market reforms and state control, provides essential context for understanding intergenerational income mobility. For example, institutional reforms have alleviated poverty and transformed China from a planned, agrarian economy into a market-oriented, industrial one. The relaxation of the household registration (hukou) system has spurred significant domestic temporary rural-to-urban migration (Zhu 2012). Additionally, the expansion of higher education in 1999 was aimed at enhancing the supply of skilled labour to some extent.

In the second chapter, I carry out empirical research to investigate the heterogeneous intergenerational mobility in China. Specifically, by applying the semiparametric quantile (SQR) model to analyse the relationship between children's income, parent's income, and children's years of education using the China Health and Nutrition Survey (CHNS) dataset. My contribution is to document some key empirical features of intergenerational income mobility using the novel econometric method and the longest panel data. The main findings show there is a rising intergenerational income persistence within different income groups. Importantly, the low-income group from rural areas and female group have relatively lower income persistence, implying a higher degree of income mobility. In addition, I found children's years of education has a positive impact on their income, in particular for the low-income group. I also conduct the robustness check using the nonparametric quantile model to verify the semiparametric method.

Based on these empirical findings, I build a two-period overlapping generations model to examine the effects of the government's cash transfer program and redistributive taxation on intergenerational mobility and economic growth in my third chapter. Then I calibrate the model to the recent Chinese economy for the quantitative analysis, showing the cash transfer program has a great impact on economic growth and upward mobility, especially, when the government provides more cash transfers to individuals with low abilities which can further promote economic growth and upward mobility. Moreover, when I implement a tax reform by increasing the tax rate for the educated workers and lowering the tax rate for the uneducated workers, highlighting the beneficial effect on the economic development and intergenerational mobility.

In the following chapter, I extend my overlapping generations model by taking into account the government to seek the optimal cash transfer policy in order to foster intergenerational income mobility and to reduce skill premium. The model is calibrated to the Chinese economy to match some significant empirical characteristics in the data. Then, I study the optimal policy when the government maximizes the aggregate welfare. My results indicate that the government is expected to provide more cash transfers to children with low abilities. This policy can encourage more children to acquire higher education and become skilled labour force. Therefore, the number of skilled worker greatly increases and the skill premium between skilled and unskilled workers decreases accordingly when the government implements the optimal policy. At the end, the social welfare improves as well under this optimal policy.

Chapter 2

Heterogeneous Intergenerational Mobility in China

Abstract

Using the China Health and Nutrition Survey, I conduct an investigation into the relationship between offspring's income, parental income, and years of education from 1989 to 2015. I allow for heterogeneity in intergenerational mobility using a semiparametric quantile additive model. My findings indicate the presence of rising intergenerational income persistence during this period among different income groups. Additionally, I discover significant heterogeneity within various subgroups. Notably, the level of education is found to have a substantial impact on income, particularly among low-income groups. To ensure the robustness of our results, I conduct additional tests using a nonparametric quantile additive model, which confirms the validity of the semiparametric approach.

2.1 Introduction

In recent years, the issue of intergenerational mobility has garnered significant public attention. At its core, intergenerational mobility addresses the issue of how economic outcomes and opportunities are transmitted between different generations within society. It focuses on understanding the extent to which individuals' socioeconomic status is influenced by the economic position of their parents. If one's family origins have a substantial influence on their future prospects, individuals from disadvantaged families may be deprived of the chance to succeed in adulthood. This situation leads to the underutilization of human capital and undermines social stability. Since individuals have no control over their birth background, a fair society should strive to minimize the impact of family background on adult outcomes. China's rapid economic development, industrialization, and urbanization have resulted in substantial improvements in living standards. Since the late 1970s, China has transitioned from a centrally planned economy to a more market-oriented system through a series of reforms, commonly known as "Reform and Opening-Up". These reforms, initiated under Deng Xiaoping, have led to significant increases in income levels, but they have also introduced varying degrees of inequality across regions and population groups. The shift toward market-driven growth has created opportunities for upward mobility, but it has also magnified the disparities in wealth and access to resources, particularly between urban and rural areas. As of 2021, China's GDP per capita stands at $12,720.2, which marks an almost 80-fold increase since the initiation of economic reforms in 1978. However, alongside these advancements, income inequality in China has also risen significantly. The Gini index reached its highest level in 2010 and, although it has since decreased, it remains around 0.4[1]. This growing income inequality has implications for the structure of the labour market and the extent to which parents invest in their children's human capital. One of the most significant institutional features affecting intergenerational mobility in China is the hukou system, a household registration system that restricts internal migration and access to public services based on an individual's registered location, typically urban or rural. The hukou system has historically played a central role in limiting the mobility of rural populations, restricting access to better education, healthcare, and employment opportunities in urban areas. As a result, the system has contributed to persistent income gaps and has implications for both intra- and intergenerational mobility. Moreover, education plays a critical role in shaping intergenerational income mobility, and in China, the government has made significant strides in improving access to education, particularly in the post-reform era. However, disparities remain, especially in rural regions where the quality of education lags behind urban areas. The 9-year compulsory education system has created more equal opportunities in primary and middle school education, but access to higher education - an essential factor in income mobility - remains uneven. The competitiveness of university admissions, the urban bias in educational

[1]Data sources: World Bank.

resources, and differences in family investment in education contribute to varying degrees of mobility across generations (Heckman 2005; Heckman and Yi 2014). Therefore, it is essential to delve into the underlying mechanisms of this seemingly perplexing phenomenon from the perspective of intergenerational mobility. By doing so, I can gain a better understanding of the factors contributing to income inequality and its effects on social and economic dynamics in China.

The standard empirical approach to measuring intergenerational mobility is through the regression of offspring income on parental income, which yields the intergenerational income elasticity (IGE). In China, various studies using different datasets and time periods have produced a wide range of estimates for intergenerational income elasticity, ranging from 0.2 to 0.8 (Fan et al. 2021; Fan 2016; Deng et al. 2013; Gong et al. 2012; Yuan 2017; Jin et al. 2019; Chen and T. Li 2019). Consequently, it is contentious to draw definitive conclusions about China being either a highly mobile society or one characterized by rigid intergenerational income distribution based solely on intergenerational income elasticity measurements. Chen and T. Li (2019) and M. Yang and Wang (2022) use the same dataset as me to estimate the IGE among different income groups. The OLS estimation yields the pooled IGE 0.549 for the rural residents, which means the intergenerational income mobility is relatively low in rural China (Chen and T. Li 2019). The limitation of their paper is they only focus on the rural area and do the pooled linear regression rather than the longitudinal analysis. M. Yang and Wang (2022) found intergenerational income mobility increases after 2004, but there is more persistence among the high- and low-income groups. Fan (2016), Deng et al. (2013), and Gong et al. (2012) only examine mobility in urban China, while in this chapter, I consider urban and rural areas together, providing a more complete picture with regards to this issue in China.

Additionally, many prominent studies in the field have specifically addressed nonlinearity using rank-rank estimation because they think rank-rank estimation is more robust than IGE estimation (Dahl and DeLeire 2008; Bhattacharya and Mazumder 2011; Mazumder 2014; Chetty, Hendren, Kline, and Saez 2014; Chetty, Hendren, Kline, Saez, and Turner 2014). While in studies on China, Fan et al. (2021) and M. Yang and Wang (2022) found the results of rank-rank estimation are consistent with IGE. Therefore, it is crucial to find a way to overcome the limitations of nonparametric methods while addressing heterogeneity and nonlinearity in intergenerational mobility research. It is important to note that my study focuses on examining heterogeneous effects in intergenerational mobility rather than summarizing changes in intergenerational income elasticity. Moreover, my research data spans a longer time period, allowing for a more comprehensive understanding of intergenerational mobility.

Following the approach of Carneiro et al. (2021), who utilized semiparametric regression models to estimate various human capital outcomes of children such as years of education, dropout rates, and earnings at age 30, this chapter also adopts a semiparametric methodology. My primary focus lies in examining the offspring's income at around age 30. Furthermore, a significant contribution of this chapter is the incorporation of quantile regression within the semiparametric model. By incorporating quantile regression, I aim to analyse the relationship between parental income, education, and offspring's income across different income groups, providing valuable insights into intergenerational income mobility and its heterogeneity.

In this chapter, I propose the use of a semiparametric quantile regression (SQR) model that allows for heterogeneity in intergenerational income persistence and is robust to these limitations. The SQR model has the advantage of considering both linear and nonlinear aspects of the variables, providing a comprehensive understanding of the relationship between parental income, offspring's education, and offspring's income. Utilizing data from the China Health and Nutrition Survey (CHNS) spanning the years 1989 to 2015, this chapter investigates the longitudinal distribution and characteristics of intergenerational income mobility in China. It analyses the heterogeneous effects within three subgroups: male/female, urban/rural areas, and eastern/central/western regions. Additionally, it examines the contribution of various factors to changes in offspring's income at different quantile points.

My objective is to gain insights into the income distribution among different income groups in China, which can shed light on the effectiveness of social and economic policies aimed at promoting equal opportunities and reducing inequality. This chapter is notable as it utilizes the longest panel data available to document intergenerational income mobility. The key findings underscore the increasing intergenerational income persistence over the studied period, particularly among the low-income group. Additionally, the analysis reveals significant heterogeneity across subgroups, such as females and individuals in the eastern region. The importance of offspring's education years in determining their income is emphasized, particularly for individuals in the low-income group.

The rest of this chapter is organized as follows: Section 2.2 provides the methodology that I use; Section 2.3 describes the data; Section 2.4 analyses data and regression results; Section 2.5 discusses the robustness check; Section 2.6 concludes this chapter.

2.2 Methodology

In the study of intergenerational income distribution, combining parametric and nonparametric methods can be advantageous when estimating the income distribution quantile model. Semiparametric methods offer the benefit of considering both linear and nonlinear information of the relevant variables. The linear component of the estimation converges more quickly and requires relatively fewer sample data. This approach can address issues such as heavy-tailed distributions and outliers in the data, providing flexibility and wide applicability in researching economic problems. Quantile regression, on the other hand, focuses on regressing the conditional quantile of the dependent variable Y on the independent variable X. It quantifies the relationship between X and different quantiles of the conditional distribution of Y. Unlike traditional regression that primarily examines the mean, quantile regression enables a comprehensive understanding of the changing characteristics of the research object at different quantile levels. The quantile regression estimator, proposed by Koenker and Bassett (1978), allows for estimating the relationship between any conditional percentiles of X and Y. Overall, quantile regression provides a means to visualize the shape of the entire joint distribution of X and Y, capturing a more nuanced perspective beyond the mean.

According to the earlier discussion, the model structure can be specified:

$$Y_i(\tau|x_i, z_i) = \theta x_i + \sum_{d=1}^{D} g_d(z_{id}) \tag{2.2.1}$$

In this case, Y_i represents the offspring i's log income, τ is the quantile, x_i is the education years of offspring i, z_i is the nonparametric factor, g_d is unknown nonparametric functions, there are two nonparametric factors: father's log income[2] and offspring's age [3]. From (2.2.1), I can obtain the estimated coefficient, θ, of the parametric term which is the offspring's education years, and the nonparametric effect of the father's income and offspring's age on the offspring's income. The estimation allows me to analyse the relationship between these variables and the quantile of interest. In Section 2.4 of the chapter, the coefficients of education years from 2000 to 2015 will be presented as a table. This table will provide insights

[2] I proxy the head of household's income as father's income, since in China, the head of household is usually the father, and the father's income is often the main source of income for the household.

[3] Parental income might affect children's education years, I missed to estimate the relationship between parental income and children education years.

into the impact of education on offspring's income across different years. Moreover, the nonparametric effect of father's income on offspring's income will be visualized through graphs. Specifically, the nonparametric effect of father's income will be depicted in separate graphs for the years 2000, 2004, 2011, and 2015. These graphs will allow for a clearer understanding of the relationship between father's income and offspring's income at different quantiles, highlighting any variations across the selected years.

2.3 Data Description

Accurately capturing the income relationship between parents and children requires high-quality micro-survey data. Two crucial requirements for such data are a sufficiently long time span and a large sample size. Among the available micro databases in China, the chosen dataset for this study is the China Health and Nutrition Survey (CHNS) database. The CHNS database, conducted collaboratively by the University of North Carolina Population Research Center, the U.S. National Institute of Nutrition and Food Safety, and the Chinese Center for Disease Control and Prevention, stands out as the longest-running micropanel data in China. The purpose of this survey is to examine the effectiveness of national and local government health, nutrition, and population planning policies and to verify how China's socioeconomic transition affects the health and nutritional status of the population. The collection of CHNS data began in 1989 and has been supplemented and improved every 2-4 years since then.

Since 1989, CHNS has been conducted for 10 rounds, respectively in 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015. The years to which the survey data belongs are the year before the survey year. The survey covered 8 provinces in previous years, expanded to 12 provinces in 2011, and expanded to 15 provinces in 2015, including major provinces and municipalities[4]. These 15 provinces and municipalities cover about 58% of China's population, and there are huge differences in these provinces and regions in terms of geographical location, economic development, public resources, and health indicators, which are specifically reflected in income, employment, education, modernization level, and related aspects of health, nutrition and population measurement. Hence, this data provides unique benefits for studying intergenerational changes and correlations between variables.

Therefore, I screen CHNS data to some extent based on the existing literature on the solutions of some measurement errors. The sample generation process is as follows:

First, according to the relation, only the relationship between the father and the father-son or the father-daughter is retained, so the sample selected includes the origin family with multiple children and the son from his origin family in the newly formed family with his own children which avoids the sample cohabitation bias.

Second, according to Solon and Haider (2006), in order to solve the problem of life cycle bias, the average age of the children and the father

[4]There are 34 province-level administrative units in China.

in the sample should be controlled as far as possible in the early 30s and the middle 40s, so that the current income observed by the children and father in this age group is the closest to the lifetime income. In order to meet the above requirements, the original sample must be processed as follows. First, when measuring the intergenerational income mobility in a certain year, samples with offspring older than 25 years old and below 35 years old should be included to ensure that the average age of offspring is controlled at around 30 years old. For example, to estimate intergenerational income mobility in 2015, samples of children aged between 25 and 35 in the CHNS2015 database were selected. Although the lifetime income of the offspring can be replaced by the current income observed in 2015, I cannot choose the father's current income in 2015 as his lifetime income. Instead, the current income of the years about 14 years before the year of observation of the current income of the offspring should be selected, that is, the current income of 2000, so as to better reflect the family's economic resources in the growth process of the offspring sample. From the above two steps, it can be obtained that, if you want to estimate the intergenerational income mobility in 2015, you are supposed to select the sample of the children in the CHNS2015 between 25 and 35 years old, and the matching father sample should come from CHNS2000. Similarly, in the intergenerational mobility measurement samples of 2000, 2004, 2009, and 2011, the children samples should be selected from the ages of 25 to 35 in CHNS2000, CHNS2004, CHNS2009, and CHNS2011. As for the selection of the matching father sample, on the one hand, from the selected year, it should be pushed forward from 2000, 2004, 2009, and 2011 respectively for about 14 years. On the other hand, from the average age of the father sample, based on the previous discussion, it should be controlled in the middle of 40s. Therefore, based on the above two aspects, I believe that the father samples matched with the offspring in 2000, 2004, 2009, 2011, and 2015 should come from CHNS1989, CHNS1991, CHNS1993, CHNS1997, and CHNS2000 respectively[5]. By implementing these steps, the study ensures that the selected samples control for the appropriate age range and provide a more accurate representation of intergenerational income mobility.

Third, according to Solon (1992) and Mazumder (2001), in order to avoid temporary income bias, the multi-year average of father's income should be used to measure intergenerational income mobility. Therefore, the intergenerational income mobility in 2015 can be calculated by using the offspring income of CHNS2015[6] and the average father income of CHNS1997, CHNS2000, and CHNS2004.

In terms of the variable description, the income of the offspring and the income of the father are the total income level of the offspring and the total income of the father respectively[7]. For those their incomes are zero, I reassign the value of 1 for them to do the log transformation when doing

[5]The reasons that I do not choose CHNS2006 wave are as follows: on the one hand, there is no corresponding survey wave for the father sample, on the other hand, if I choose CHNS2006 instead of CHNS2004, that would be some time gap from the previous wave of CHNS2000.

[6]The literature generally assumes that measurement errors in the dependent variable do not lead to bias (Lee and Solon 2009), even though the offspring's one-year income may experience a transitory shock in a given year. And my study focuses on longitudinal changes rather than analysing one specific year's results.

[7]Specifically, according to the design of total personal income in CHNS adult questionnaire, total personal income of urban residents includes wages, bonuses, subsidies and other incomes of the first and second jobs. The total income of rural residents is composed of individual income from agriculture, forestry, animal husbandry, fishery, handicraft, and other income.

the estimation. Due to the large span of variable years, in order to avoid the effect of inflation on real income, this chapter adopts the income of CHNS which is uniformly converted into 2015 after considering inflation. The education year of offspring is from the measurement of the degree of education and I translate the proxy variable into the specific education years. For example, in the process of data investigation, the number "1" represents the highest education degree for respondents who graduated from primary school, "2" on behalf of the highest education degree for respondents who graduated from junior school, and so on, graduated from high school, technical college, bachelor degree and master degree and higher. Next, I assign a value of 6 to the education degree of 1, that is, the highest education qualification for primary school is 6 years. Similarly, the junior school graduation is assigned a value of 9, the high school graduation is assigned a value of 12, the technical college graduation is assigned a value of 15, the undergraduate graduation is assigned a value of 16, and the postgraduate graduation is assigned a value of 19. The descriptive statistics of variables of five waves can be found in the Appendix A.1.

2.4 Data Analysis and Results

I estimate the semiparametric model at three quantile points: P10, P50, and P90, so as to clearly explore and compare the differences between low-income, middle-income, and high-income groups respectively. The results of the data analysis are as follows.

The statistical description in Table A.2 presents the changes in quantiles for different variables, specifically focusing on child's income and father's income. The unit of offspring and father income is CNY (Chinese Yuan Renminbi) in the text and tables. In the past two decades, the income of residents has not increased simultaneously among different classes. It shows that the changes in child's income differ across quantiles, with a greater increase observed in the low quantile compared to the high quantile. For example, at P10, it has increased from 1045.82 in 2000 to 11818.55 in 2015, an increase of 10 times, while at P90, it has increased from 17881.72 in 2000 to 74226.80 in 2015, an increase of 3 times. In contrast, the increase in father's income is not substantial across different quantiles. At both the P10 and P90 quantiles, the increase is relatively small, with values of 0.83 and 1.18 times respectively. This could be attributed to the matching father sample being sourced from the 1989 to 2000 survey waves, indicating that over time, individuals have had more opportunities to increase their incomes, resulting in more dynamic income growth for their children compared to themselves. The changing characteristics of quantiles suggest that income growth among residents in China has been uneven across different income groups over the past two decades. The growth rate of low-income earners has been higher than that of high-income earners, indicating a reduction in income inequality and a narrowing of the income gap. These observations support the hypothesis that intergenerational income mobility has likely been enhanced during this period. To further examine this hypothesis, the semiparametric model can be assessed by evaluating the estimated coefficients and their significance levels, as well as exploring the relationships between education years, father's income, and offspring's income at different quantiles. This analysis will provide insights into the factors influencing intergenerational income mobility and shed light on the dynamics of income distribution in China.

I also show the descriptive statistics of different quantiles of some sub-samples in Table A.3, Table A.4 and Table A.5, which give me a comprehensive understanding of the data. In Table A.3, I can observe that the increase in income in rural area is greater than that in urban area, both for children and their fathers [8]. Throughout these years, the number of years of education for children also increase. In terms of the male and female sub-sample in Table A.4, it is worth mentioning that, at the P10 quantile of child income, females experienced a much higher increase in income compared to males. The income of females from lower income groups increased by 14 times, while for males, the increase was 8 times. This suggests that women from low-income backgrounds have made significant strides in income growth, surpassing their male counterparts in relative terms. Table A.5 reveals that in terms of child income at the P10 quantile, the increase in income is greater in the eastern region compared to the central and western regions. Notably, the number of years of education in the western region shows no increase at the P50 quantiles, suggesting that children from middle-income groups in the western region still face lim-

[8] The urban or rural status is based on the current hukou status, the hukou status at birth or during childhood is not recorded in the dataset. Therefore, I cannot look into the impact of rural-to-urban migration.

ited access to education. Overall, there is substantial heterogeneity among these sub-groups, with women from low-income groups, individuals in rural areas, and individuals in the eastern region experiencing significant income growth. These findings highlight the need to consider the diverse characteristics and dynamics of different sub-groups when analyzing intergenerational income mobility and income distribution.

Combining the analysis in the previous part, based on the empirical data in this chapter, among the selected three independent variable factors, the offspring's education year is treated as a parametric factor, and the father's income and offspring's age are assigned as nonparametric factors to construct a semiparametric quantile additive regression model together.

Figure 2.1 visually represents the relationship between father's income and offspring's income at different quantile levels in the selected survey waves (2000, 2004, 2011, and 2015)[9]. The x-axis represents the father's log income, while the y-axis represents the offspring's log income. The colored curves (red, green, and purple) correspond to the high, medium, and low child income groups, respectively. The figure reveals several key findings. First, there has been a notable increase in intergenerational income persistence over the surveyed years, indicating that the influence of fathers' income on their children's income has strengthened. This trend is consistent with previous research by Fan et al. (2021). A comparison of the sub-figure from 2000 and 2015 shows a general upward shift in the position of the curves, particularly for the 10th percentile (P10), suggesting that in-

[9]The estimated effect of father's income on child's income in 2009 survey wave is in the Appendix A.1.

tergenerational income persistence is more pronounced among low-income groups. Moreover, the lack of intersections between the three curves, along with their consistent ordering over the years, highlights the persistence of income distribution patterns across generations. The low-income group consistently remains at the bottom, the middle-income group occupies the middle, and the high-income group stays at the top. In conclusion, these findings suggest a decline in intergenerational income mobility in China over time.

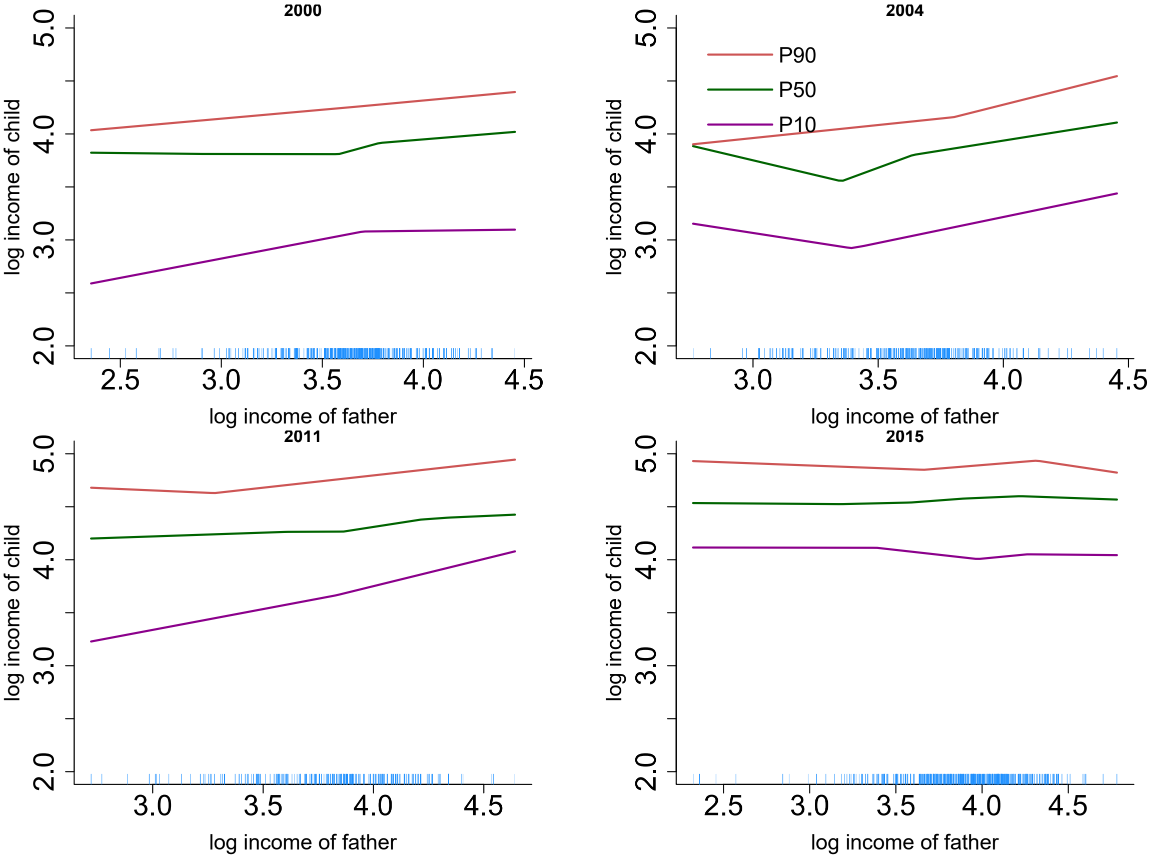

Figure 2.1: Estimated Effect of Father's Income on Child's Income of SQR in 2000, 2004, 2011, 2015

Table 2.1 summarizes the estimated coefficients of offspring's years of education from 2000 to 2015, illustrating longitudinal changes across different quantiles and offering insights into the role of education in shaping future income. Across all three quantile regressions, the coefficients for children's years of education are positive, indicating that higher educational attainment positively impacts future income. Notably, for the 10th percentile (P10) quantile regression, the coefficient increases from 0.055 in 2000 to 0.086 in 2015, with some fluctuations. This means that, in 2015, an additional year of education is associated with an 8.6% increase in income. This growth in the coefficient is the highest among the three quantile regressions, suggesting that education plays an especially crucial role in boosting income for individuals in low-income groups. Additionally, the impact of education on income appears to strengthen over time, signaling the increasing importance of educational attainment in determining income outcomes. Interestingly, the influence of education on high-income groups is less pronounced compared to low-income groups. For instance, in 2015, the coefficient for the 90th percentile (P90) is 0.024, compared to 0.086 for P10. This indicates that, for the high-income group, additional years of education have a relatively smaller effect on income growth. Instead, as shown in Figure 2.1, their fathers' income may exert a greater influence on their income outcomes.

Next, I do some sub-sample analysis to see how changes in heterogeneous intergenerational income mobility vary by rural/urban areas, male/female, and eastern/central/western regions in China[10]. I mainly present figures about the effect of father's income on offspring's income and tables of the estimated coefficients of education years of these sub-samples.

[10]It has some sample bias among sub-groups in the CHNS. For example, two-thirds of survey samples

Wave	P10	P50	P90
2000	0.055***	0.023*	0.026**
	(0.013)	(0.010)	(0.009)
2004	0.099***	0.031*	0.005
	(0.018)	(0.125)	(0.011)
2009	0.076***	0.027**	0.009
	(0.015)	(0.010)	(0.012)
2011	0.056***	0.017	0.003
	(0.016)	(0.012)	(0.011)
2015	0.086***	0.012*	0.024***
	(0.016)	(0.006)	(0.007)

Significant codes: "∗∗∗", 0.001; "∗∗", 0.01; "∗", 0.05; ".", 0.1.

Table 2.1: Estimated Coefficients of Child's Education Years from 2000 to 2015

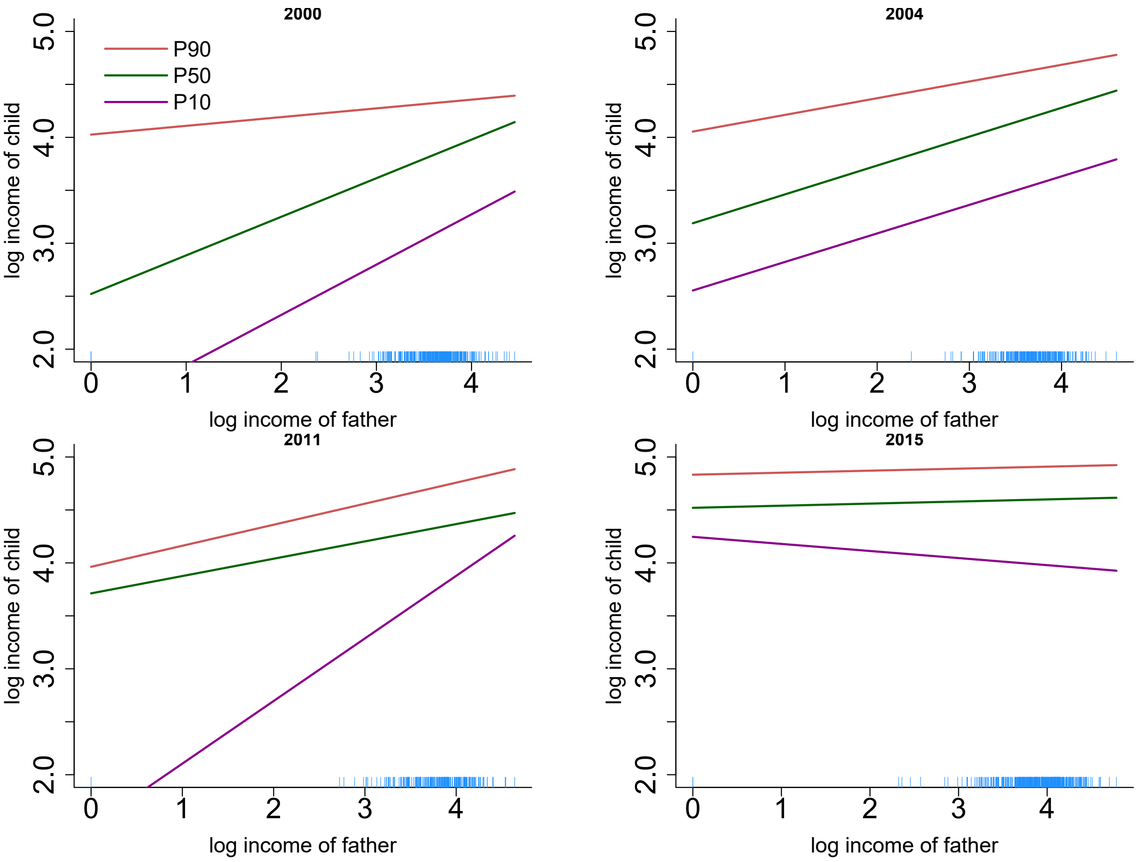

Figure 2.2: Estimated Effect of Father's Income on Child's Income of SQR in Rural Area in 2000, 2004, 2011, 2015

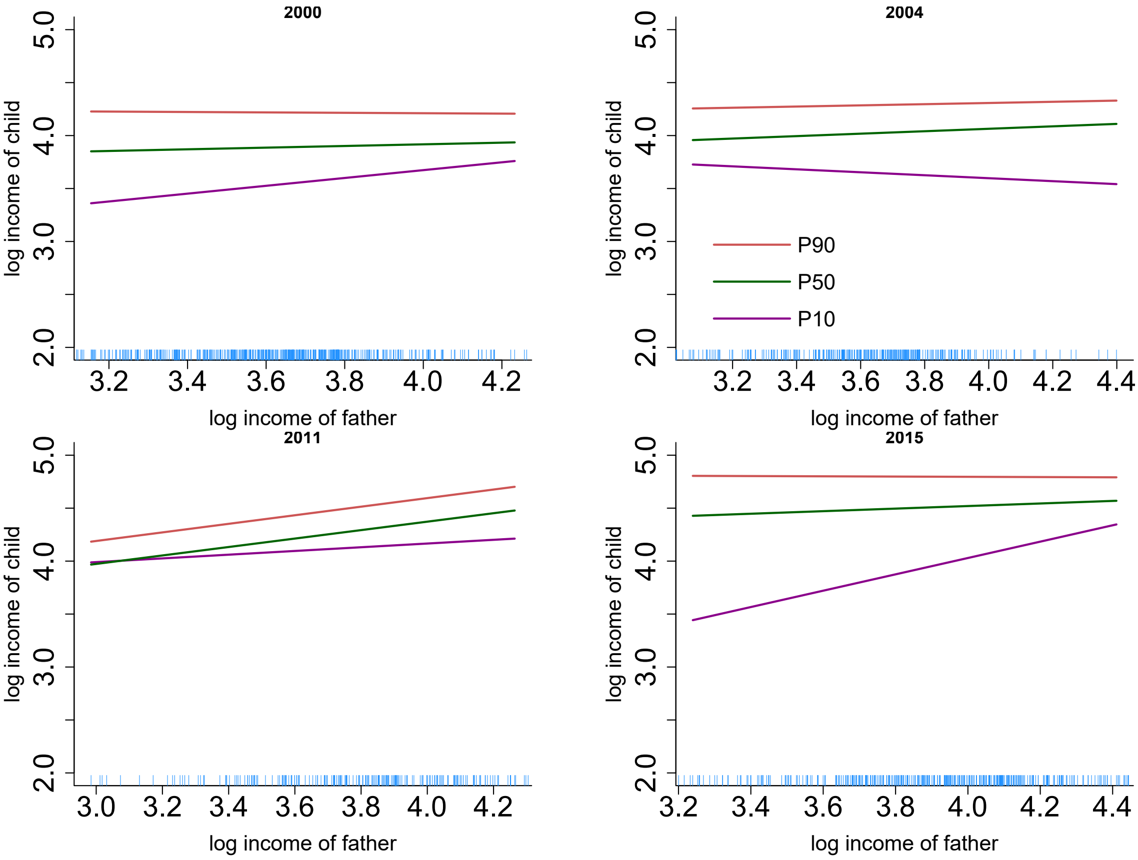

Figure 2.3: Estimated Effect of Father's Income on Child's Income of SQR in Urban Area in 2000, 2004, 2011, 2015

Rural Area	P10	P50	P90
2000	0.033***	0.032*	0.031***
	(0.008)	(0.012)	(0.008)
2004	0.089***	0.056**	0.009
	(0.021)	(0.017)	(0.015)
2009	0.081***	0.018	0.011
	(0.021)	(0.012)	(0.013)
2011	0.079*	0.033*	0.021.
	(0.031)	(0.016)	(0.012)
2015	0.095***	0.013.	0.030***
	(0.017)	(0.007)	(0.008)
Urban Area	**P10**	**P50**	**P90**
2000	0.047	0.029*	0.024**
	(0.041)	(0.123)	(0.009)
2004	−0.015	0.021	0.022
	(0.025)	(0.018)	(0.023)
2009	0.075	0.026	0.027
	(0.056)	(0.038)	(0.053)
2011	0.016	0.040*	0.018
	(0.026)	(0.017)	(0.026)
2015	0.068	0.017	0.035
	(0.047)	(0.028)	(0.022)

Significant codes: "$***$", 0.001; "$**$", 0.01; "$*$", 0.05; ".", 0.1.

Table 2.2: Rural and Urban Area Estimated Coefficients of Child's Education Years from 2000 to 2015

Comparing the rural and urban sub-samples in 2000, 2004, 2011, and 2015, as illustrated in Figure 2.2 and 2.3 respectively, I observe a rising trend in intergenerational income persistence across the three income groups. Notably, the persistence of low-income groups in urban areas is higher than that in rural areas, suggesting that individuals from rural areas experience greater intergenerational income mobility. Furthermore, the coefficients for children's years of education in both rural and urban areas, as shown in Table 2.2, reveal a positive impact of education on children's future income. Focusing on the P10 regression for rural areas, the coefficient rises from 0.033 in 2000 to 0.095 in 2015, indicating that each additional year of education is associated with an increase in income from 3.3% in 2000 to 9.5% in 2015. This demonstrates the growing importance of education in enhancing future income for low-income groups in rural areas. Moreover, it highlights that rural children from low-income backgrounds are likely to improve their income prospects through education. This finding aligns with previous research by Chen and T. Li (2019) and Z. Tang (2023), who also used the same dataset to show that education is a crucial factor in raising children's income in rural areas. These observations suggest that expanding educational opportunities in rural regions can be a key strategy for promoting intergenerational income mobility.

The analysis of intergenerational income mobility between males and females reveals interesting patterns. Over time, the impact of intergenerational income persistence has increased for both genders. However, as

are from rural areas.

shown in Figure 2.4, the persistence is more pronounced among males compared to females, whose intergenerational income persistence is illustrated in Figure 2.5. This indicates that for women, the influence of fathers' income on their own income is weaker than it is for men. Table 2.3 presents the estimated coefficients for years of education among males and females from 2000 to 2015. For low-income male groups, education plays an increasingly significant role in raising income, as the coefficient rises from 0.055 in 2000 to 0.072 in 2015, despite some fluctuations. This suggests that, over time, education has become more crucial in improving income prospects for low-income males.

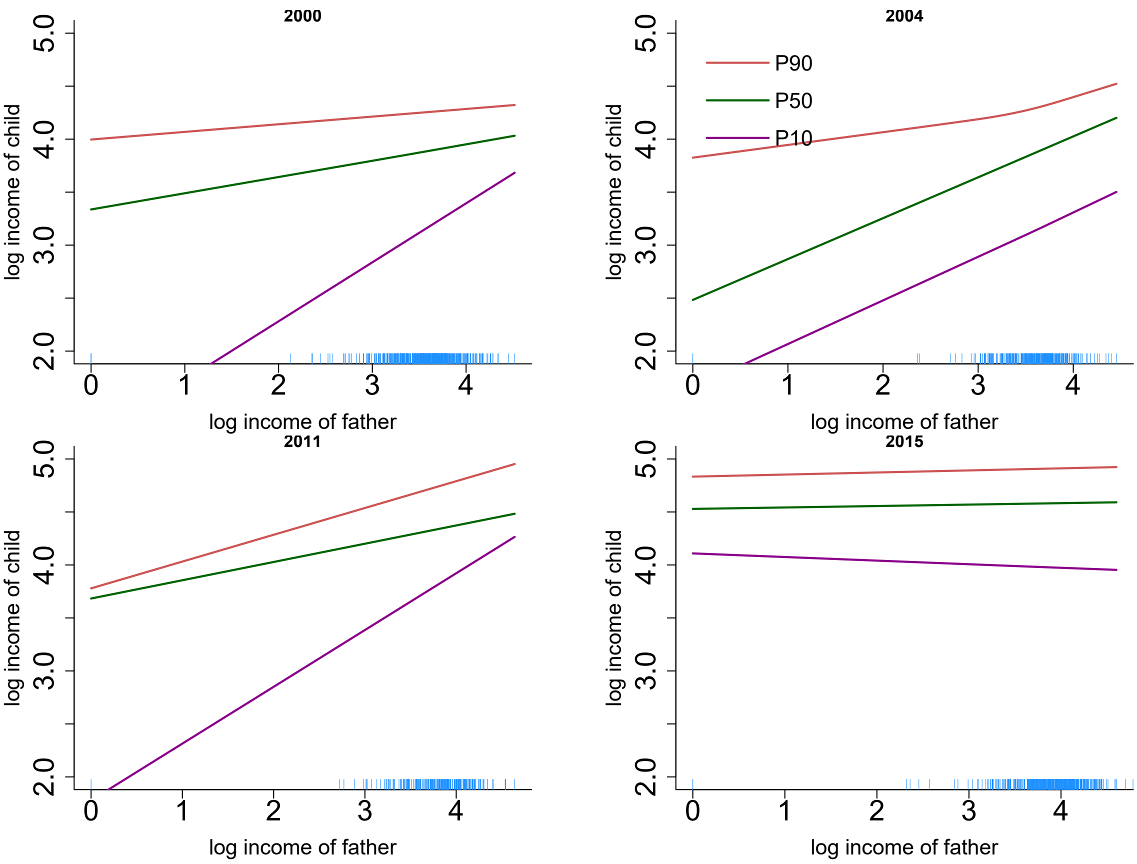

Figure 2.4: Estimated Effect of Father's Income on Child's Income of SQR of Male in 2000, 2004, 2011, 2015

The last but not least, I point out the results of different regions in

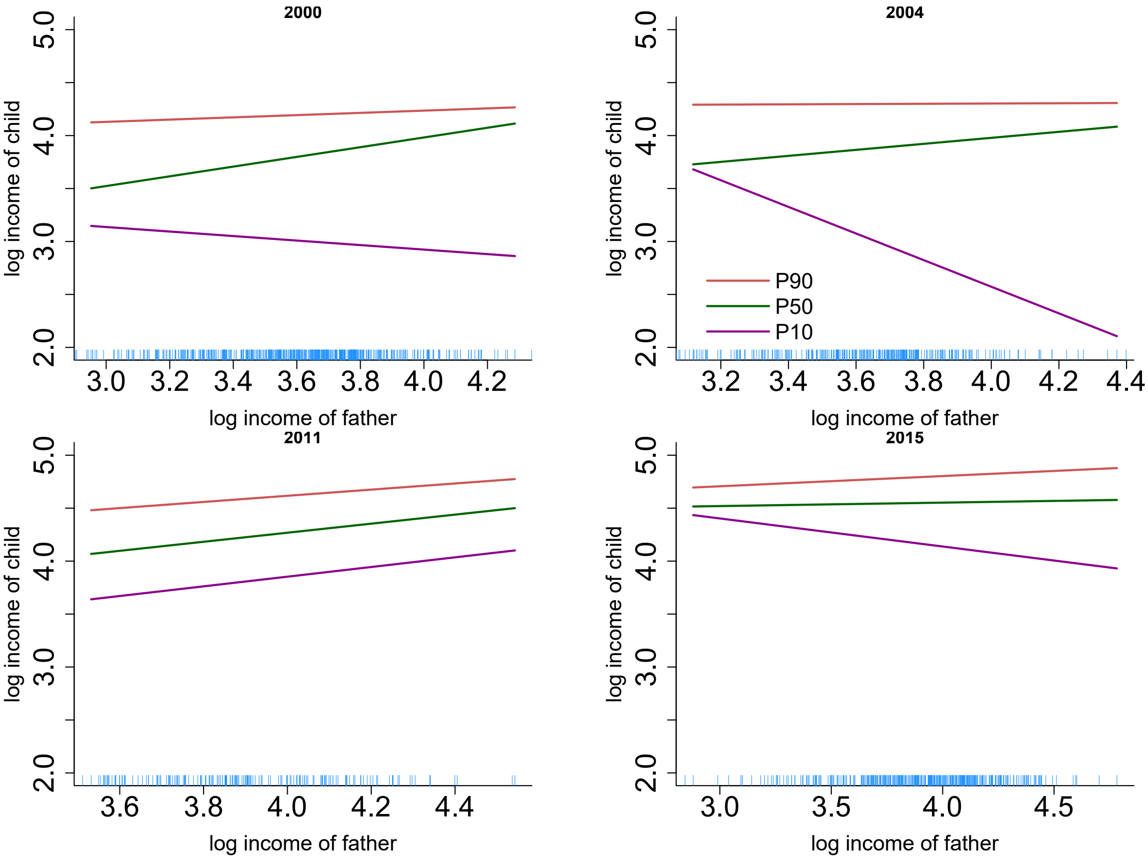

Figure 2.5: Estimated Effect of Father's Income on Child's Income of SQR of Female in 2000, 2004, 2011, 2015

Male	P10	P50	P90
2000	0.055**	0.032*	0.019*
	(0.018)	(0.010)	(0.009)
2004	0.108***	0.040**	0.016
	(0.020)	(0.015)	(0.013)
2009	0.091***	0.037**	0.009
	(0.018)	(0.012)	(0.012)
2011	0.046*	0.015	0.001
	(0.021)	(0.013)	(0.012)
2015	0.072***	0.010	0.029***
	(0.016)	(0.008)	(0.008)
Female	P10	P50	P90
2000	0.115**	0.028	0.014
	(0.042)	(0.025)	(0.021)
2004	0.188*	0.029	0.009
	(0.082)	(0.038)	(0.041)
2009	0.130*	0.043	0.056.
	(0.053)	(0.027)	(0.030)
2011	0.124	0.051.	0.034
	(0.010)	(0.030)	(0.030)
2015	0.089.	0.018	0.039**
	(0.048)	(0.014)	(0.014)

Significant codes: “$***$”, 0.001; “$**$”, 0.01; “$*$”, 0.05; “.”, 0.1.

Table 2.3: Male and Female Estimated Coefficients of Child’s Education Years from 2000 to 2015

China. As can be seen from the Figure 2.6, 2.7, and 2.8 are the effect of father's income on offspring's income at P10, P50 and P90 quantile regressions in central, eastern, and western regions respectively. A similar pattern of rising intergenerational income persistence is evident across all regions. Notably, the persistence is stronger in the eastern region compared to the central and western regions, suggesting lower income mobility in the east.

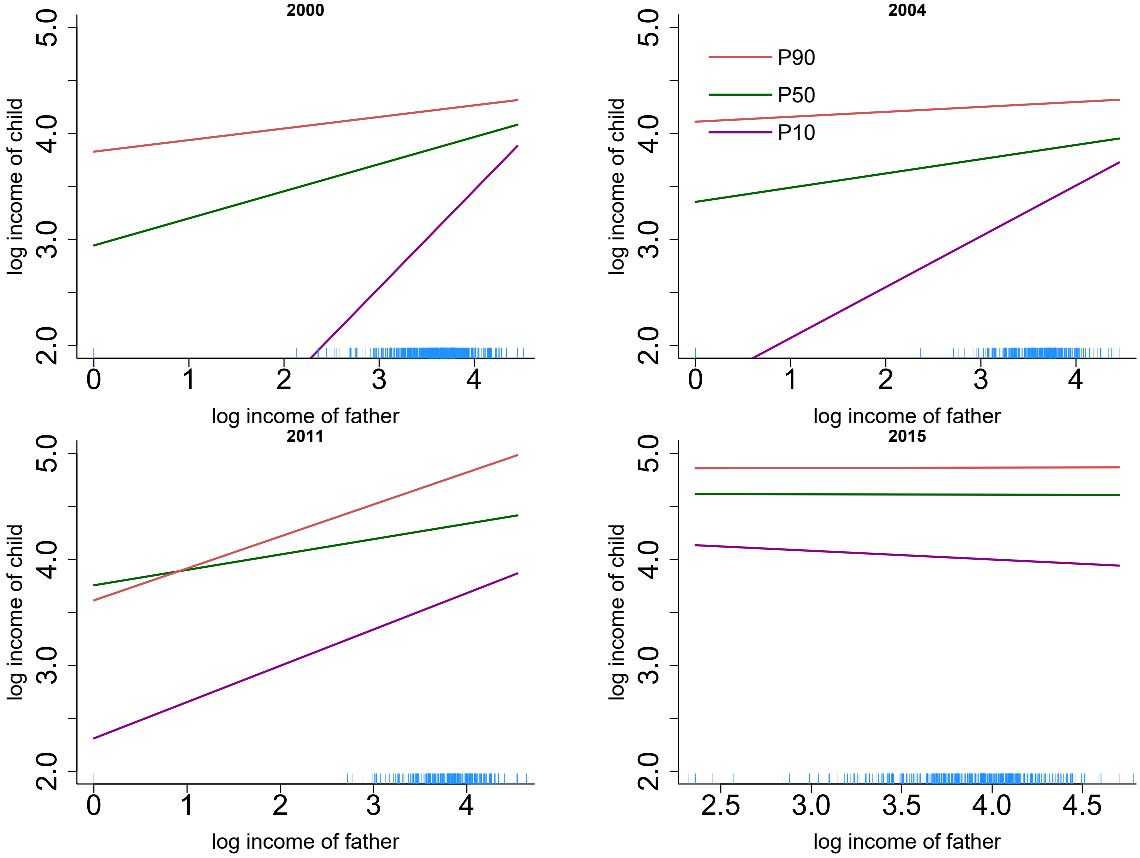

Figure 2.6: Estimated Effect of Father's Income on Child's Income of SQR in Central Region in 2000, 2004, 2011, 2015

Table 2.4 summarizes the changes in the estimated coefficients of children's years of education over the study period for the three regions. For low-income groups, increasing educational attainment has a substantial impact on future income, regardless of the region. However, education

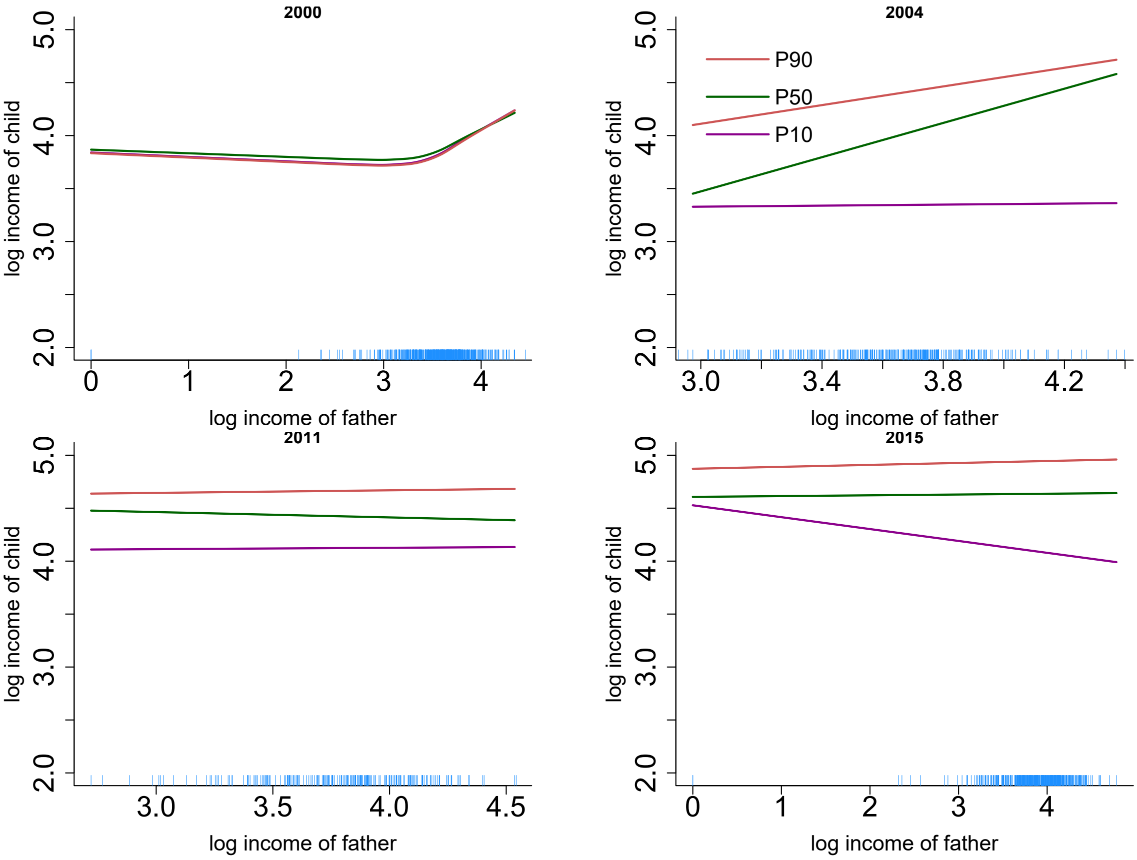

Figure 2.7: Estimated Effect of Father's Income on Child's Income of SQR in Eastern Region in 2000, 2004, 2011, 2015

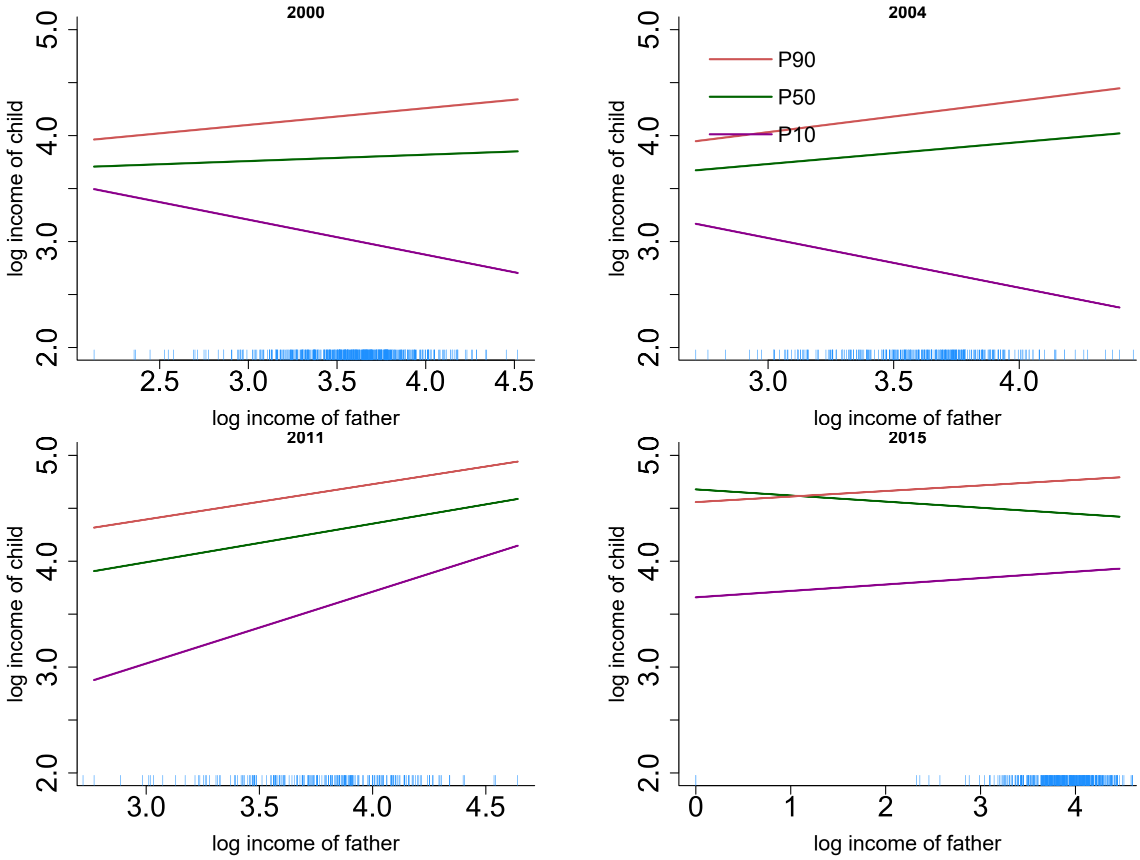

Figure 2.8: Estimated Effect of Father's Income on Child's Income of SQR in Western Region in 2000, 2004, 2011, 2015

appears to be more crucial for individuals from the central and western regions than for those from the eastern region. This is evidenced by the fact that the P10 coefficients for the central region are consistently higher than those for the eastern region.

Eastern Region	P10	P50	P95
2000	0.052**	0.015	0.010
	(0.019)	(0.015)	(0.013)
2004	0.111**	0.018	0.005
	(0.033)	(0.022)	(0.021)
2009	0.044.	0.029	0.021
	(0.022)	(0.020)	(0.019)
2011	0.056**	0.020	0.014
	(0.020)	(0.020)	(0.017)
2015	0.062**	0.012	0.030*
	(0.019)	(0.014)	(0.015)
Central Region	**P10**	**P50**	**P90**
2000	0.072**	0.025	0.015
	(0.027)	(0.025)	(0.018)
2004	0.092**	0.047.	0.017
	(0.027)	(0.028)	(0.023)
2009	0.135***	0.048*	0.005
	(0.032)	(0.021)	(0.018)
2011	0.062*	0.020	0.005
	(0.031)	(0.020)	(0.020)
2015	0.070***	0.018	0.028**
	(0.018)	(0.011)	(0.009)
Western Region	**P10**	**P50**	**P90**
2000	0.010***	0.016	0.019
	(0.025)	(0.017)	(0.013)
2004	0.167***	0.052.	0.021
	(0.043)	(0.031)	(0.022)
2009	0.028	0.030	0.056*
	(0.032)	(0.026)	(0.027)
2011	0.126*	−0.001	0.015
	(0.048)	(0.031)	(0.027)
2015	0.020	0.002	−0.015
	(0.019)	(0.014)	(0.015)

Significant codes: "∗∗∗", 0.001; "∗∗", 0.01; "∗", 0.05; ".", 0.1.

Table 2.4: Estimated Coefficients of Child's Education Years from 2000 to 2015 by Regions

2.5 Robustness Check

In this section, I apply the nonparametric quantile regression (NQR) model as a robustness check. The nonparametric model assumes that the functional relationship between economic variables is unknown, and the whole regression function should be estimated in advance.

For simplicity, first ignore the quantile regression, and only consider the nonparametric additive model, which is represented by the matrix

$$Y = c + \sum_{d=1}^{D} g_d(X_d) + \varepsilon, \tag{2.5.1}$$

where $E(\varepsilon|X) = 0$. Here, g_d is a one-dimensional nonparametric estimation of a predictive variable, there are D such nonparametric functions, which is the number of nonparametric factors, here there are three nonparametric factors: father income, child education years, and child age.

In this model, $g_d(X_d), d = 1, \cdots, D$ is the nonparametric function of $X_d, d = 1, \cdots, D$. X_1 affects explained variable Y through the function $g_1(X_1)$, X_2 affects explained variable Y through the function $g_2(X_2)$, $\cdots$, X_D affects explained variable Y through the function $g_D(X_D)$, which Y is the sum of these nonparametric functions. And each function $g_d(X_d)$ is only affected by its own independent variable X_d. In this way, the influence of X_d on the dependent variable Y can be decomposed into the influence of each X_d on its nonparametric function to $g_d(X_d)$. Since each nonparametric function is relatively independent of each other, it will not fall into the so-called "curse of dimensionality".

Figure 2.9 shows the nonparametric effects of child education years on the child's income at three different quantiles in 2000, 2004, 2011, 2015 respectively. The curves representing these effects show relatively little variation, suggesting that the relationship between child education years and income can be approximated as linear. Therefore, it is reasonable to consider offspring's education years as a parametric term in the analysis, implying that the effect of education years on income can be adequately captured by a linear relationship.

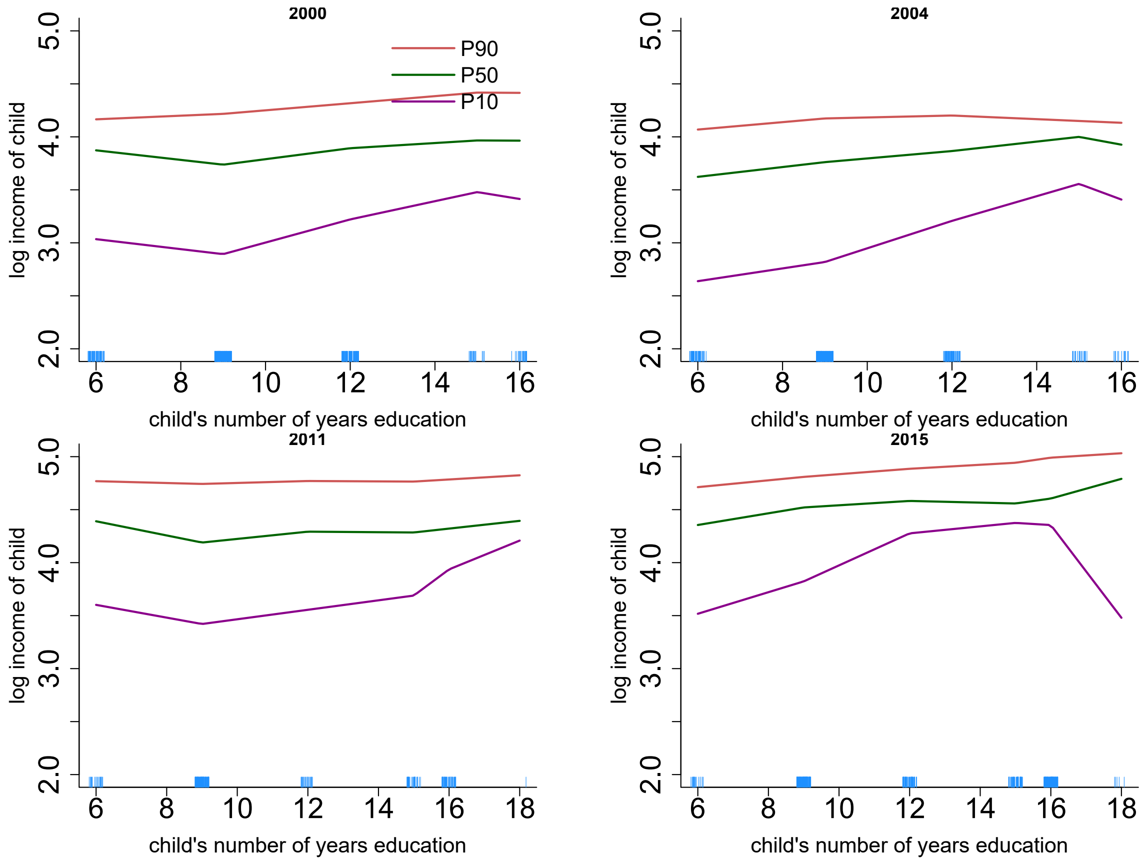

Figure 2.9: Estimated Effect of Child's Education Years on Child's Income of NQR in 2000, 2004, 2011, 2015

Therefore, this finding supports the use of a semiparametric quantile additive regression model, where offspring's education years are included as a parametric factor alongside the nonparametric factors of father's income and offspring's age. By incorporating both parametric and nonparametric terms, the model can effectively capture the complex relationship between these variables and provide insights into intergenerational income mobility.

2.6 Policy Implications and Conclusion

This chapter presents a semiparametric additive quantile regression model that investigates the relationship between the offspring's income, their father's income, and offspring's years of education. This model is constructed by integrating the characteristics of parametric estimation, nonparametric estimation, and quantile regression. I conduct regression at three quantile points, P10, P50, and P90, in order to better understand the effect of different income groups on intergenerational mobility.

My findings provide valuable insights into intergenerational income mobility in China. The observed rising intergenerational income persistence aligns with the economic growth and development in the country. The sub-sample analyses uncover significant heterogeneity in mobility patterns. The lower intergenerational income persistence among females suggests that women from lower-income groups have experienced greater income gains compared to men, highlighting potential for improved income mobility and reduced gender-based income disparities. The results for rural and urban areas indicate that the impact of education on income has become more pronounced in rural regions over time. This underscores the importance of expanding educational opportunities in rural areas to promote greater income mobility and help bridge the urban-rural income gap. Additionally, the increasing significance of education in the eastern region reflects the influence of regional development disparities. For low-income individuals in the central and western regions, enhancing education provides more opportunities to boost income, reinforcing the critical role education plays in fostering upward mobility. Therefore, the Chinese government should launch some projects to help children get more access to higher education, such as cash transfers program, especially for children from rural and undeveloped regions. The inclusion of the nonparametric quantile regression model as a robustness check enhances the reliability of my analysis. Overall, my research contributes to the understanding of intergenerational income mobility in China, highlighting the importance of education, the influence of gender and regional disparities.

Chapter 3

Intergenerational Mobility with Cash Transfer and Redistributive Taxation in China

Abstract

In this chapter, I construct an overlapping generations model to analyse the effects of cash transfers and redistributive taxation on intergenerational mobility and economic growth. For numerical exercise, I calibrate the model for the Chinese economy and conduct the quantitative analysis. My findings reveal that the government's cash transfer initiatives exert a positive influence on economic growth and upward mobility. Specifically, when the policy parameter is set below 1, I observe a greater prevalence of upward mobility and enhanced economic expansion. This phenomenon is attributed to increased accessibility to education for children in the future, facilitated by greater cash transfers to those with lower abilities, enabling them to invest in their education. Additionally, I explore the effects of

different tax reforms and find that they promote economic growth and mobility.

3.1 Introduction

In recent decades, the intergenerational mobility has attracted attention to both economists and policymakers widely. It has not only affected the social welfare but also economic growth. Policymakers have been focusing on designing economic policies that can promote intergenerational mobility and therefore reduce income inequality. It is widely recognized that individuals' decisions regarding educational investment can be influenced by the release of budget constraints. For instance, J. Yang and Qiu (2016) conduct a study using a calibrated model based on Chinese data and find that direct subsidies from the government to poor parents are the most effective and efficient policies for alleviating budgetary constraints on investments in children's early education. These subsidies enable children to access higher levels of education, leading to higher future earnings and therefore reducing intergenerational income inequality. As a result, intergenerational income mobility is significantly increased. Similar findings have been confirmed in the United States and Norway by Herrington (2015). James J. Heckman and his collaborators examine the effect of high-quality early education on disadvantaged children, particularly through initiatives like the Perry Preschool Project and the ABC/CARE program. For instance, the Perry Preschool Project tracked disadvantaged children who attended a high-quality preschool and compared their outcomes to a control group. Findings indicate that participants had higher educational attainment, increased lifetime earnings, and lower rates of crime. The study also noted intergenerational benefits: children of Perry Preschool participants displayed better social and economic outcomes than those of non-participants, breaking the poverty cycle. This evidence underscores the intergenerational effects of early childhood education on both participants and their offspring (Garcia et al. 2023; Garcia et al. 2016). Jerrim and Macmillan (2015) highlight the importance of education in driving the relationship between intergenerational mobility and income inequality. They suggest that policies aimed at redistributing financial resources and reducing the education gap between rich and poor are crucial for ensuring equal opportunities for the next generation. Another policy experiment conducted by Zheng and Graham (2022) using a four-period overlapping generations model with neighborhood choice and human capital accumulation demonstrated that redistributing property tax revenues equally among schools improves mobility and welfare. Schneider (2010) analyses the impact of education subsidies and redistributive taxation on the proportion of educated individuals, social mobility, and inequality at the aggregate level. Their findings show that education subsidies in the form of conditional transfer payments to households investing in education can increase social mobility and reduce inequality under certain circumstances. Additionally, their study reveals that redistributive tax policies involving unconditional transfers from skilled to unskilled workers can only achieve the goal of increasing social mobility. Hanushek et al. (2014) utilize a dynamic general equilibrium model within a three-period overlapping generations framework to examine how different college aid schemes influence educational decisions, income distribution, and intergenerational mobility. They find that need-based aid programs generally result in the best combination of overall economic performance and a more equal income distribution. Hassler et al. (2007) demonstrate a negative correlation between inequality and mobility when education subsidies are implemented. In China, there are many forms of education subsidies from the government, such as The National Student Loan Program, The National Scholarship, and the National Endeavor Scholarship Program. In this chapter, I employ an overlapping generations model to investigate the effects of redistribution taxation and cash transfers on the number of educated workers, intergenerational mobility, and economic growth. My study builds on the work of Maoz and Moav (2001), with the addition of two new elements: redistributive taxation and government cash transfers. Unlike Maoz and Moav (2001), I tax all workers, regardless of their educational background, which aligns with the actual situation. Moreover, I assume that the income tax rate for educated workers is higher than that for uneducated workers. In my setting, although taxes have a negative impact on incentives to invest in education, they also alleviate mobility constraints for certain individuals in the economy. Inspired by Murayama (2019) and Sano and Tomoda (2010), I extend my model by incorporating a government cash transfer program based on children's abilities, taking into account different values of the policy parameter, λ. This means that high ability individuals may receive more or less cash transfers depending on the value of λ, which in turn affects the decision of education investment and the share of educated people in the future. Conditional cash transfer programs, commonly known as scholarships or stipends, have been evaluated in African, Latin American, and Caribbean countries, demonstrating positive impacts on school enrollment, grade attainment in primary and secondary education (ICAI 2017; Fiszbein et al. 2009; Evans et al. 2023), and even higher education attainment (Patel-Campillo and García 2022a; Barrera-Osorio et al. 2019). In my model, the cash transfer provided by the government is unconditional. This means that all children, regardless of their parents' type, are eligible to receive the cash transfer, which can be utilized for either consumption or education. An important insight from my model is that economic growth is driven by the improvement of human capital, primarily through the upward mobility of children whose parents lack education but acquire it themselves. It is worth noting that my research focuses on identifying the optimal cash transfer program that the government can implement to promote economic development and intergenerational mobility through adjusting the value of the policy parameter, rather than looking for the effects on poverty and vulnerability, which is also one of my main contributions.

For the quantitative analysis, I calibrate the model to the Chinese economy. In the baseline scenario, where the policy parameter is set to 1, indicating that individuals receive equal amounts of cash transfers regardless of their initial abilities, I find that this program has positive effects on economic growth and upward mobility. Subsequently, I compare the outcomes across various values of the policy parameter, including those less than and greater than 1. Remarkably, all scenarios demonstrate positive impacts on economic growth and upward mobility, underscoring the considerable benefits of the government's cash transfer program. Notably, when the policy parameter is less than 1, signifying that individuals with lower abilities receive more cash transfers, there is a pronounced incentive for them to pursue education and eventually transition into skilled workers. Consequently, this fosters robust economic growth and broadens opportunities for upward mobility among the populace. In addition, I propose a policy reform involving an increased tax rate for educated individuals and a decreased tax rate for uneducated individuals to explore its effects within the model. My findings have important policy implications, as they highlight the significance of government intervention in implementing education policies that can promote economic development and intergenerational mobility.

The chapter is organized as follows. Section 3.2 presents the model; Section 3.3 calibrates the model to the Chinese economy; Section 3.4 conducts the quantitative analysis; Section 3.5 investigates the effects of some tax changes and discusses further implications of my results; Section 3.6 concludes.

3.2 The Model

I employ an overlapping generations model with two periods. Each period involves the production of a single homogeneous good, which can be allocated for either consumption or investment in education by both educated and uneducated workers. It is assumed that the total number of individuals engaged in labour is normalized to one, and they pay labour income tax based on their labour types [1]. The number of educated workers is endogenously determined in my model. Following Maoz and Moav (2001) and Owen and Weil (1998), I rule out educational loans from my model. In other words, individuals do not have access to the borrowing to receive education.

3.2.1 Production and Factor Prices

$$Y_t = A_t E_t^{1-\alpha} U_t^{\alpha}, \tag{3.2.1}$$

where E_t is the number of educated workers, U_t is the number of uneducated workers, A_t is defined as the total factor productivity, α represents the elasticity of uneducated workers. Since $E_t + U_t = 1$, I re-write the production function as : $Y_t = A_t E_t^{1-\alpha}(1 - E_t)^{\alpha}$.

Because the economy is competitive, production factors are paid at their marginal products. I define w_t^e and w_t^u as the wages of an educated and an uneducated worker respectively in period t:[2]

[1] In the model, I assume the labour market is in a competitive economy, but in the Chinese context, the hukou system might prevent the free flow of labour between rural and urban areas.

[2] $w_t^u < w_t^e$ iff $E_t < 1 - \alpha$.

$$w_t^e = \frac{\partial Y_t}{\partial E_t} = (1-\alpha)A_t(E_t)^{-\alpha}(U_t)^{\alpha} = (1-\alpha)A_t\big(\frac{U_t}{E_t}\big)^{\alpha} = (1-\alpha)A_t\big(\frac{1-E_t}{E_t}\big)^{\alpha};$$
$$w_t^u = \frac{\partial Y_t}{\partial U_t} = \alpha A_t(E_t)^{1-\alpha}(U_t)^{\alpha-1} = \alpha A_t\big(\frac{U_t}{E_t}\big)^{\alpha-1} = \alpha A_t\big(\frac{1-E_t}{E_t}\big)^{\alpha-1}. \tag{3.2.2}$$

Then, I assume the tax rates of educated and uneducated workers are τ_t^e and τ_t^u respectively, and $\tau_t^e > \tau_T^u$. Therefore, the after tax wages in period t are as follows:

$$\begin{aligned} \widetilde{w}_t^e &= (1-\tau_t^e)w_t^e = (1-\tau_t^e)(1-\alpha)A_t(1-E_t)^{\alpha}(E_t)^{-\alpha}; \\ \widetilde{w}_t^u &= (1-\tau_t^u)w_t^u = (1-\tau_t^u)\alpha A_t(1-E_t)^{\alpha-1}(E_t)^{1-\alpha}. \end{aligned} \tag{3.2.3}$$

3.2.2 Individuals

The economy is made up of two periods overlapping generations of individuals, each with a single parent and a single child. In the first period, the individual does not work and decides whether to acquire education based on the transfers he receives from his parent and the government. The transfer received from the parent represents a bequest intended for the individual and also his own educational costs, while the transfer from the government takes the form of a cash transfer program that allocates the funds collected by the tax revenue to children according to their abilities. In the second period, the individual works and divides his income between his consumption and a transfer to his child. An individual's labour type is by default uneducated at the beginning, if he received education in the first period, then his type would become educated.

The decision to pursue education or not may vary from person to person because of the individual's abilities and transfers received. The budget constraints of individual i at time periods t and $t+1$ are:

$$c_t^i + \delta^i h_t^i = x_t^i + s_t^i, \tag{3.2.4a}$$

$$c_{t+1}^i + x_{t+1}^i = \widetilde{w}_{t+1}^i, \tag{3.2.4b}$$

where

$$\delta^i = \begin{cases} 1, & \text{individual } i \text{ acquires education} \\ 0, & \text{otherwise ,} \end{cases}$$

hence,

$$\widetilde{w}_{t+1}^i = \begin{cases} \widetilde{w}_{t+1}^e, & \delta^i = 1 \\ \widetilde{w}_{t+1}^u, & \delta^i = 0. \end{cases}$$

x_t^i is the transfer that individual i of generation t (i.e. born in period t) receives from his parent, s_t^i is the cash transfer he receives from the government, and x_{t+1}^i is the transfer this individual makes to his child.

In this model, differences in abilities are expressed as differences in individual education costs. h_t^i denotes the education cost of individual i who was born in period t and I further assume the higher is h_t^i, the lower is i's ability [3], and the government is able to recognize individual's

[3]Higher-ability individuals might enter the education system with a stronger foundational knowledge or learning efficiency, enabling them to complete degrees faster or at lower costs (e.g., by earning credits in high school or placing out of introductory classes). This leads to a reduced cost of obtaining higher education compared to individuals who need more time or additional support (e.g., private tutoring) to

ability through the non-tertiary education[4]. It is remarkable that the cash transfer here is unconditional, that is, it is not conditional on the children's predetermined investment in education. Regardless of the parents' income level, all children can get the cash transfer and use it for consumption and education (Murayama 2019). The cash transfer s_t^i is supposed to have the following form:

$$s_t^i = (1-\lambda)(h_t^i - h_t^{0.5}) + \tilde{s}_t, \tag{3.2.5}$$

where $\tilde{s}_t$ is the budget for cash transfers since $\tilde{s}_t = \tau_t^e w_t^e E_t + \tau_t^u w_t^u (1-E_t)$, $h_t^{0.5}$ is the mean of h_t^i, and λ is a policy parameter. In the spirit of Sano and Tomoda (2010), if $\lambda = 1$, then $s_t^i = \tilde{s}_t$, meaning all children receive the same cash transfer regardless of their abilities. $\lambda < 1$ shows individual with lower (high) ability receives larger (smaller) transfers than $\tilde{s}_t$, while $\lambda > 1$ indicates that individual with higher (lower) ability receives larger (smaller) transfers than $\tilde{s}_t$.

Individuals gain utility from consumption in both periods and from transfer to their children. Thus, I have the additively separable utility function:

$$u_t^i = \log c_t^i + \log c_{t+1}^i + \log x_{t+1}^i, \tag{3.2.6}$$

where c_t^i and c_{t+1}^i are the consumption of an individual born in period t in two periods of his life and x_{t+1}^i is the transfer to his offspring.

Since I assume the capital market is imperfect and the utility function is separable. The individual optimization problem can be achieved whether

reach the same level.

[4] China's college entrance examination scores are a good proxy for abilities of individuals.

to purchase education after deciding how to allocate income between consumption and bequest in the second period. Therefore, the allocation of second period income decision means solving:

$$z(\widetilde{w}^i_{t+1}) \equiv \max_{\{c^i_{t+1}, x^i_{t+1}\}} (\log c^i_{t+1} + \log x^i_{t+1})$$
$$s.t.(3.2.4b).$$

The maximization gives the optimal allocations:

$$\mathcal{L} = \log c^i_{t+1} + \log x^i_{t+1} - \lambda^i_{t+1}\big[c^i_{t+1} + x^i_{t+1} - \widetilde{w}^i_{t+1}\big]$$
$$\frac{\partial \mathcal{L}}{\partial c^i_{t+1}} = \frac{1}{c^i_{t+1}} - \lambda^i_{t+1} = 0 \Rightarrow c^i_{t+1} = \frac{1}{\lambda^i_{t+1}}$$
$$\frac{\partial \mathcal{L}}{\partial x^i_{t+1}} = \frac{1}{x^i_{t+1}} - \lambda^i_{t+1} = 0 \Rightarrow x^i_{t+1} = \frac{1}{\lambda^i_{t+1}}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda^i_{t+1}} = c^i_{t+1} + x^i_{t+1} - \widetilde{w}^i_{t+1} = 0 \Rightarrow c^i_{t+1} + x^i_{t+1} = \widetilde{w}^i_{t+1}$$

$$x^i_{t+1} = \widetilde{w}^i_{t+1}/2. \tag{3.2.7}$$

From (3.2.4b) I can get $c^i_{t+1} = \widetilde{w}^i_{t+1} - x^i_{t+1}$, then substituting it into $z(\widetilde{w}^i_{t+1})$, I get

$$z(\widetilde{w}^i_{t+1}) \equiv max\big[\log(\widetilde{w}^i_{t+1} - x^i_{t+1}) + \log x^i_{t+1}\big] \tag{3.2.8}$$

Then substitute (3.2.7) into (3.2.8), I get

$$\begin{aligned} z(\widetilde{w}^i_{t+1}) &= \log\big(\widetilde{w}^i_{t+1} - \frac{\widetilde{w}^i_{t+1}}{2}\big) + \log\frac{\widetilde{w}^i_{t+1}}{2} \\ &= \log\frac{\widetilde{w}^i_{t+1}}{2} + \log\frac{\widetilde{w}^i_{t+1}}{2} \\ &= \log\widetilde{w}^i_{t+1} - \log 2 + \log\widetilde{w}^i_{t+1} - \log 2 \\ &= 2\log\widetilde{w}^i_{t+1} - 2\log 2. \end{aligned} \tag{3.2.9}$$

Hence, individuals will choose to invest in education if and only if:

$$\log(x^i_t + s^i_t - h^i_t) + z(\widetilde{w}^e_{t+1}) \geq \log(x^i_t + s^i_t) + z(\widetilde{w}^u_{t+1}). \tag{3.2.10}$$

From (3.2.10) it follows that given the transfer from parents, x^i_t, and cash transfer from the government, s^i_t, an individual received, he will invest in education if the cost, h^i_t, is small enough.

Substituting (3.2.9) into (3.2.10), I get

$$\log(x^i_t + s^i_t - h^i_t) + 2\log\widetilde{w}^e_{t+1} - 2\log 2 \geq \log(x^i_t + s^i_t) + 2\log\widetilde{w}^u_{t+1} - 2\log 2$$

$$\begin{aligned} \log(x^i_t + s^i_t - h^i_t) - \log(x^i_t + s^i_t) &\geq 2\log\widetilde{w}^u_{t+1} - 2\log\widetilde{w}^e_{t+1} \\ \log\big(\frac{x^i_t + s^i_t - h^i_t}{x^i_t + s^i_t}\big) &\geq \log\big(\widetilde{w}^u_{t+1}\big)^2 - \log\big(\widetilde{w}^e_{t+1}\big)^2 \\ \log\big(1 - \frac{h^i_t}{x^i_t + s^i_t}\big) &\geq \log\big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2 \\ 1 - \frac{h^i_t}{x^i_t + s^i_t} &\geq \big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2 \\ h^i_t &\leq (x^i_t + s^i_t)\big[1 - \big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2\big] \end{aligned} \tag{3.2.11}$$

Substituting (3.2.5) into (3.2.11), I can get

$$h_t^i \leq \left[x_t^i + (1-\lambda)(h_t^i - h_t^{0.5}) + \tilde{s}_t\right]\left[1 - \left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2\right], \tag{3.2.12}$$

Rearranging it I get

$$h_t^i \leq \frac{1 - \left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2}{1 - (1-\lambda)\left[1 - \left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2\right]}\left[x_t^i - (1-\lambda)h_t^{0.5} + \tilde{s}_t\right] \tag{3.2.13}$$

Let $\hat{h}_t^i$ be the critical value of the education cost for individual i so that he will invest in education iff: $h_t^i \leq \hat{h}_t^i$. $\hat{h}_t^i$ is the largest value of h_t^i where (3.2.10) and (3.2.4) hold, and it can be expressed as a function of future wages and transfers received by individual i:

$$\hat{h}_t^i = \frac{1 - \left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2}{1 - (1-\lambda)\left[1 - \left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2\right]}\left[x_t^i - (1-\lambda)h_t^{0.5} + \tilde{s}_t\right] \tag{3.2.14}$$

It follows that $\frac{\partial \hat{h}_t^i}{\partial\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)} < 0$, $\frac{\partial \hat{h}_t^i}{\partial x_t^i} > 0$, and $\frac{\partial \hat{h}_t^i}{\partial \tilde{s}_t} > 0$. The negative sign of the derivation of $\hat{h}_t^i$ with respect to $\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}$ shows that higher wage inequality affects education cost negatively. The positive signs of the derivative of $\hat{h}_t^i$ in terms of parent transfers and government cash transfers suggest that the more transfers received, the more likely an individual is to invest in education.

From equation (3.2.4b) I know that workers belonging to the same group (educated or uneducated) have the same second-period income. So, their consumption and transfer to their children, and also their children's critical values are the same. Therefore, the individual index i in the transfer notation can be replaced by an index describing the parent type: e or u. Also, substitute (3.2.7) into the critical values function (3.2.14), which can take the following form:

$$\begin{aligned}\hat{h}_t^e &= \frac{1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2}{1-(1-\lambda)\left[1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2\right]}\left[\frac{\widetilde{w}_t^e}{2}-(1-\lambda)h_t^{0.5}+\tilde{s}_t\right];\\ \hat{h}_t^u &= \frac{1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2}{1-(1-\lambda)\left[1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2\right]}\left[\frac{\widetilde{w}_t^u}{2}-(1-\lambda)h_t^{0.5}+\tilde{s}_t\right],\end{aligned} \tag{3.2.15}$$

where

$$\tilde{s}_t = \tau_t^e w_t^e E_t + \tau_t^u w_t^u (1-E_t) \tag{3.2.16}$$

Following Maoz and Moav (2001), I further assume education cost of individual i at period t is:

$$h_t^i = \theta_t^i (a + b\overline{w}_t), \tag{3.2.17}$$

where $a \geq 0$, $b \in [0,1]$, $\overline{w}_t$ denotes the average wage in period t, θ_t^i is the individual i's education cost parameter and the higher is i's ability, the lower is θ_t^i, so the lower h_t^i as well. The average wage in period t is a weighted average of educated and uneducated wages which can be expressed as: $\overline{w}_t = E_t\widetilde{w}_t^e + (1-E_t)\widetilde{w}_t^u = Y_t$, meaning that an individual's cost of education is not based on the type of labour of his parents, but on his own ability and level of economic output. With regards to the education cost parameter, θ_t^i, is independent of the type of his parent and is uniformly distributed over the interval $(\underline{\theta}, \overline{\theta})$ with $\underline{\theta} \geq 0$. Hence, h_t^i is uniformly distributed over the interval $(\underline{h}_t, \overline{h}_t)$.

3.2.3 The Dynamic System

Let me denote the c.d.f. of $\hat{h}_t^e$ and $\hat{h}_t^u$ as $F_t(\hat{h}_t^e)$ and $F_t(\hat{h}_t^u)$ respectively[5]. Therefore, $F_t(\hat{h}_t^e)$ represents the proportion of children whose parents are educated and choose to invest in education in period t, while $F_t(\hat{h}_t^u)$ is the proportion of children whose parents are uneducated and choose to invest in education in period t. Then, the dynamic behavior equation of the number of educated workers can be written as:

$$E_{t+1} = E_t F_t(\hat{h}_t^e) + (1 - E_t) F_t(\hat{h}_t^u), \tag{3.2.18}$$

where, the first term $E_t F_t(\hat{h}_t^e)$ is the number of children who have educated parents and invest in education in period t, the second term $(1 - E_t)F_t(\hat{h}_t^u)$ is the number of children who have uneducated parents and invest in education in period t. It shows that E_t uniquely determines E_{t+1}. In each period, economic growth is characterized by the share of the educated population. The dynamics of the number of educated workers in the economy is the result of mobility from one type of labour to another. I define upward mobility as individuals with uneducated parents acquiring education, and downward mobility as individuals with educated parents who do not receive education.

[5] $F_t(\hat{h}_t^e) = \frac{\hat{h}_t^e - \underline{\theta}(a+bY_t)}{\overline{\theta}(a+bY_t) - \underline{\theta}(a+bY_t)}$, $F_t(\hat{h}_t^u) = \frac{\hat{h}_t^u - \underline{\theta}(a+bY_t)}{\overline{\theta}(a+bY_t) - \underline{\theta}(a+bY_t)}$

3.3 Calibration

Table 3.1 reports the numerical values of the model parameters for the Chinese economy for the time period of 2010 to 2019 based on an annual calibration. The table also indicates how each parameter is obtained from various sources.

I assume some values for A, $\overline{\theta}$, and $\underline{\theta}$ in the model. Fleisher et al. (2011) investigate the role of education on worker productivity and a firm's total factor productivity using a panel of firm-level data from China for the period of 1998 - 2000. Given their estimation of the production function, I get the value of α [6]. Following Maoz and Moav (2001), the intercept of the education cost function, a, is assumed to be 0.05. The coefficient of the average wage in the education cost function, b, is estimated using the China Institute for Educational Finance Research-Household Survey (CHIEFR-HS) database which the first round of the survey was conducted in 2017. I extract a few survey variables including tuition fees, various expenditures in school, etc. from the database to calculate the total education expenditure of one of the interviewed household's children in elementary, middle, and high schools, another survey variable I extract is the total income of the household. Then, I take the linear regression between the education expenditure and total income (log(education expenditure)$\sim$ log(total in-

[6] Fleisher et al. (2011) specify the value-added production function: $Y_{it} = A_i K_{it}^{\beta_k} L_{sit}^{\beta_s} L_{pit}^{\beta_p} e^{u_{it}}$, where Y is output measured by value-added, K is capital, L_s is the number of highly educated workers, L_p is the number of workers with less education, and u is a disturbance term for firms $i = 1, 2, \ldots, n$ and from year $t = 1, 2, \ldots, T$. The parameters β_k, β_s, and β_p are the output elasticises of the corresponding inputs. Given the estimation of the production function, they get $\beta_s = 0.538$, $\beta_p = 0.344$. Then, I re-calculate the elasticity of uneducated workers: $\alpha = \frac{0.344}{0.538+0.344} = 0.390$.

come)) with sample size is 111. Therefore, I get the estimated coefficient, $b = 0.20$. I use China Household Finance Survey (CHFS) database to calculate the tax rates of educated and uneducated workers. First, I choose a few variables from the survey: educational level, individual tax amount, individual weight, and after-tax income. According to the measurement of educational level, I define people who have bachelor's, master's, or doctorate degree as educated workers, while people who hold college/vocational degree and below is uneducated workers. Secondly, the tax rates are calculated through the following equation: individual tax/(individual tax + after-tax income) with weight and controlling the education. Since CHFS has five survey waves which are 2011, 2013, 2015, 2017, and 2019, finally I take the average of five tax rates for the educated and uneducated workers respectively, and I get $\tau^e = 10.28\%$, $\tau^u = 6.25\%$.

Parameter	Value	Definition	Source
A	1.20	total factor productivity	assumption
α	0.39	elasticity of uneducated workers	literature
$\overline{\theta}$	1.20	the highest bound of education cost parameter	assumption
$\underline{\theta}$	0.90	the lowest bound of education cost parameter	assumption
a	0.05	intercept of education cost function	literature
b	0.20	coefficient of education cost function	estimate
τ^e	0.1028	tax rate of educated workers	data
τ^u	0.0625	tax rate of uneducated workers	data

Table 3.1: Model Parameters

3.4 Numerical Exercises with λ

3.4.1 Benchmark Value of $\lambda = 1.0$

I apply the values presented in Table 3.1 to derive the numerical results for the model considering different values of the policy parameter λ. Beginning with the baseline case, which corresponds to $\lambda = 1$, it implies that all children receive an equal amount of cash transfer from the government regardless of their abilities. Figure 3.1 illustrates the relationship between the number of educated workers in period $t + 1$ (E_{t+1}) and the initial number of educated workers in period t (E_t) under the influence of the cash transfer program. The black line represents the 45-degree line, and it is evident that the dynamic behavior function consistently lies above it. This signifies that the cash transfer program facilitates the growth of the educated population in the subsequent period. Furthermore, the program fosters upward mobility and economic growth. Consequently, individuals with uneducated parents, irrespective of their abilities, are inclined to invest in education upon receiving cash transfers from the government, thereby transitioning into educated individuals and generating upward mobility.

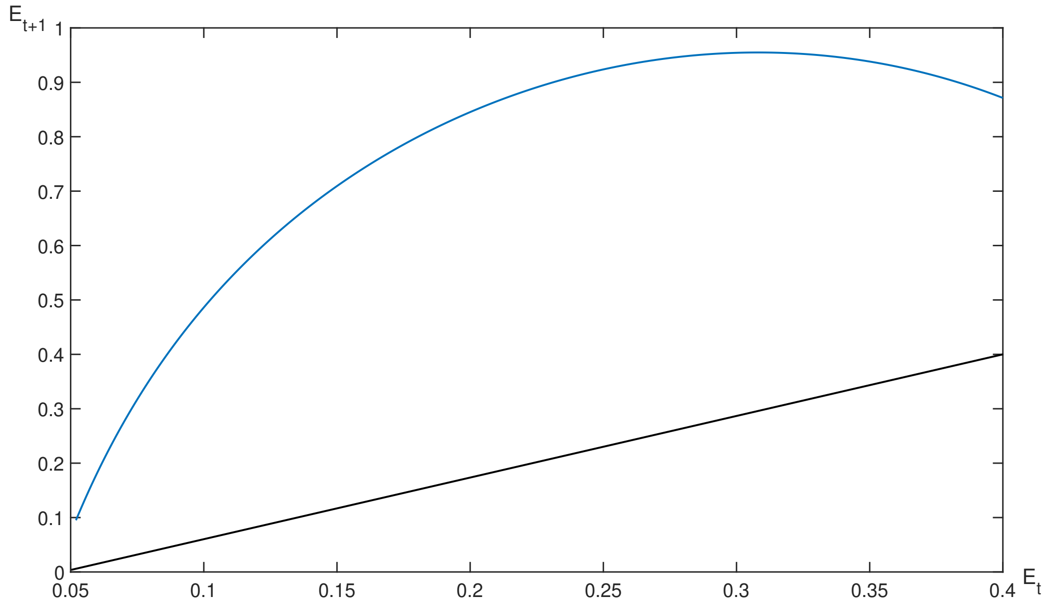

Figure 3.1: The Evolution of Education and Mobility in the Economy: $\lambda = 1.0$

3.4.2 Varying Values of λ

In the subsequent analysis, I compare the evolution of education and mobility with different values of λ as illustrated in Figure 3.2. It is evident that the government's cash transfer program profoundly influences the educated population and economic growth. However, varying values of the policy parameter λ yield distinct effects. Let us recall the different transfer strategies of the government of different values of λ. When $\lambda < 1$, it means that the government is supposed to provide more cash transfers for children with low abilities. In contrast, $\lambda > 1$ implies high abilities children will receive more transfers from the government. In Zone 1, characterized by a relatively small educated population in period t and consequently a low supply of skilled labour in the economy, allocating more transfers to children with high abilities proves more advantageous for both the educated population and economic growth, as indicated by the dominance of the yellow curve. When the skilled population is limited, children inherit fewer transfers from their parents due to the majority of the population being unskilled, thereby restricting their ability to transfer substantial amounts. Additionally, given my model's setting where the cost of education for high-ability children is low, governmental support towards these individuals becomes imperative to foster their transition into skilled labour. At point A, the three curves intersect, suggesting that regardless of the value of λ - whether the government allocates more or fewer cash transfers to children with higher or lower abilities - the number of educated individuals in the subsequent period remains constant. Transitioning to Zone 2, where an increasing number of individuals are educated in the current period, additional cash transfers from the government to children with low abilities will continue to enhance their access to education, consequently fostering upward mobility and economic development. This is evident from the consistent positioning of the orange curve above the other two. As a country's economy progresses, its supply of skilled labour expands. During this phase, it becomes imperative to allocate more educational expenditure towards children with limited access to education, thereby elevating the overall educational attainment of the population to a significant degree. Next, I focus on the case when $\lambda = 0.9$. Figure 3.3 provides insights into the dynamics of critical and boundary values ($\hat{h}_t^e$, $\hat{h}_t^u$, $\underline{h}_t$, $\overline{h}_t$) and the upward mobility is observed. $\hat{h}_t^u$ evolves between $\underline{h}_t$ and $\overline{h}_t$, hence, the children with uneducated parents will choose to get educated and become skilled workers, this is the upward mobility. At the same time, the wage gap between educated and uneducated workers diminishes due to the supply of educated workers raises, acting as a motivating factor for individuals to pursue education, as depicted in Figure 3.4.

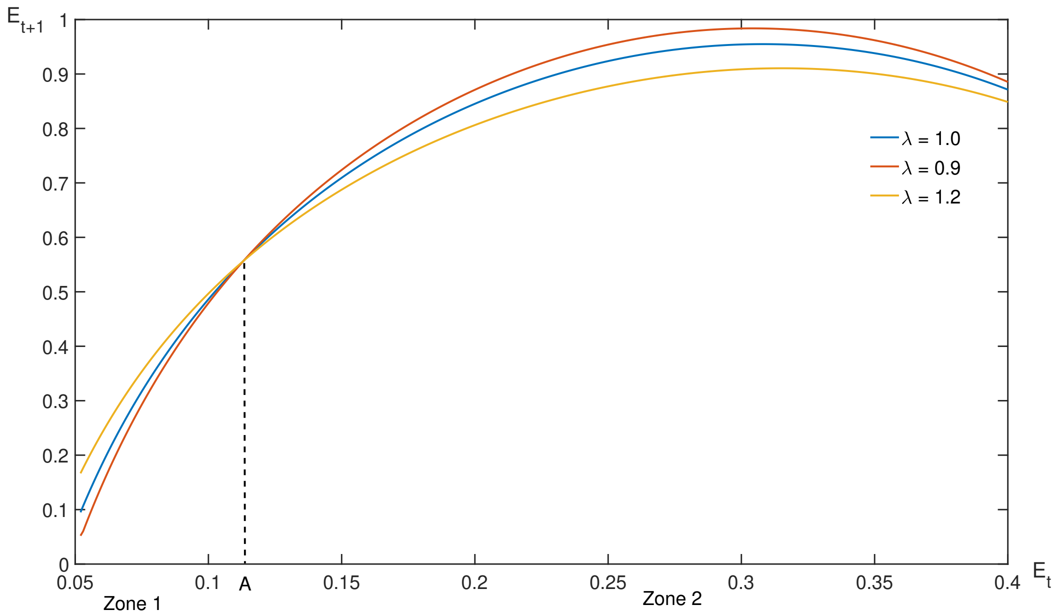

Figure 3.2: The Evolution of Education and Mobility in the Economy with different λ

3.5 Policy Exercises

In previous sections, I have calibrated the model to the Chinese economy and conducted the quantitative analysis. I found that when the government provides equal cash transfers to all children regardless of their abilities, it generally promotes economic growth and upward intergenerational mobility. Furthermore, my analysis revealed that adjusting cash transfers based on individual abilities can lead to varying magnitudes of impact. Specifically, when children with low abilities receive larger transfers, they

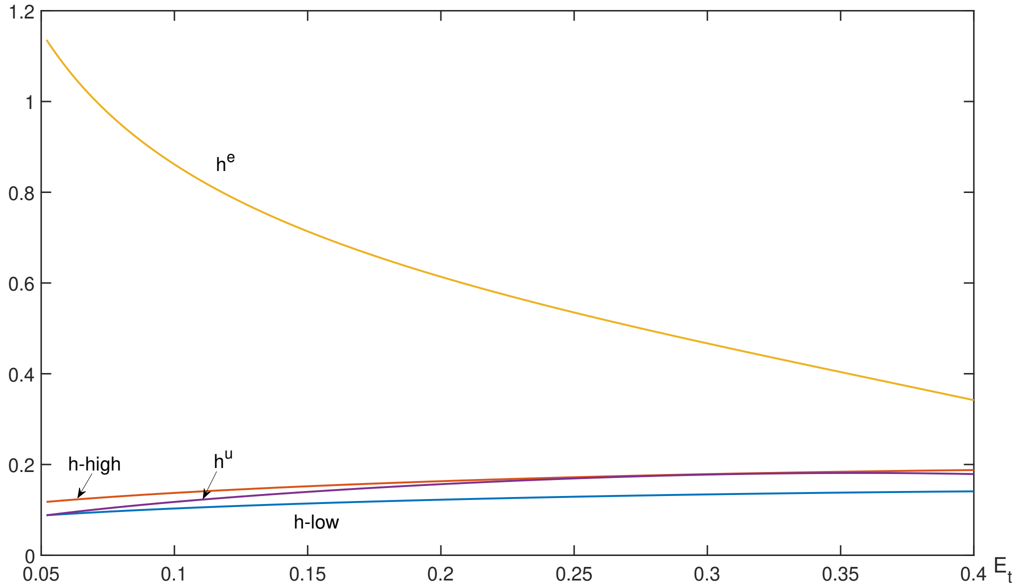

Figure 3.3: The Evolution of the Critical Values: $\lambda = 0.9$

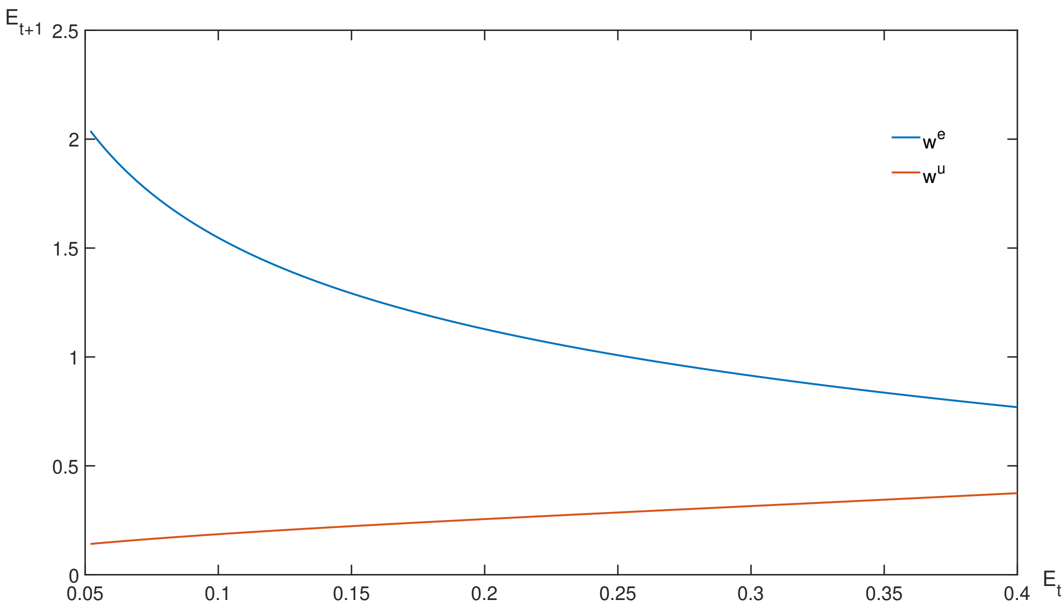

Figure 3.4: The Evolution of the wages: $\lambda = 0.9$

are more incentivized to invest in education. This, in turn, stimulates economic growth and fosters upward mobility, as more individuals are inclined to pursue education. The increase in the educated population is most pronounced in this scenario. Therefore, based on my findings, it would be beneficial for the government to adjust the policy parameter to be less than 1, indicating that more transfers should be allocated to children with low abilities. Such a policy adjustment not only better promotes economic growth but also facilitates upward intergenerational mobility.

Now I examine the effects of different tax reforms from the perspective of the government, that is, raise the tax rate for educated workers to 11%, lower the tax rate for uneducated workers to 5.5%, and then see how the numerical results change. I presume the policy parameter, λ, of 0.9, which means that children with lower abilities will receive larger cash transfers compared to those with higher abilities. This choice is based on my previous discussions, where I found that when λ is less than 1, the economy experiences healthy growth and intergenerational mobility effectively. In Figure 3.5, I observe a consistent overall trend, albeit with slight magnitude differences. In Zone 1, characterized by a limited supply of educated labour, I note a pronounced increase in upward mobility. This suggests that more children from uneducated backgrounds, particularly those with low abilities, opt to pursue education. At this juncture, the relatively high income for skilled workers, driven by the scarcity of skilled labour in the market, acts as an incentive for individuals to attain education and transition into skilled roles. Moreover, the larger cash transfers provided by the government serve as additional motivation for investing in education. Consequently, despite the higher tax rate imposed on their income, the number of educated workers in the subsequent period experiences a notable increase. However, if the economy starts with a sufficiently large supply of educated workers, such as in Zone 2, I observe a different pattern. Given the same number of educated workers in period t compared to the previous unadjusted policy, fewer individuals are willing to pursue education in period $t+1$. I attribute this to the higher tax rate for educated workers and the lower tax rate for the uneducated. As the supply of skilled people increases, their wages also decrease, which discourages individuals from acquiring education.

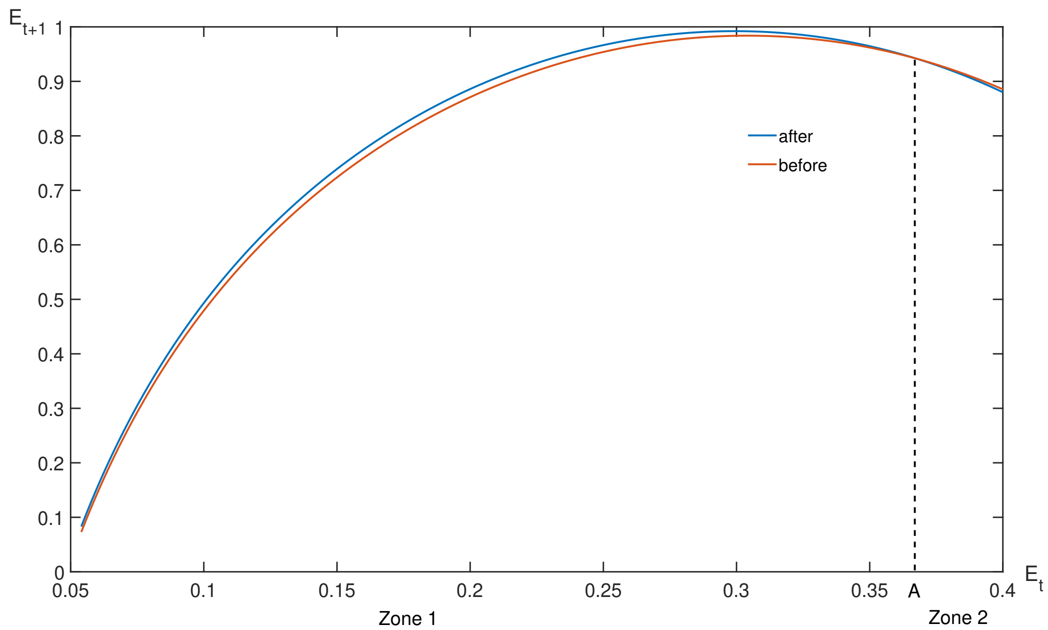

Figure 3.5: Compare The Evolution of Education and Mobility in the Economy before and after Tax Reforms: $\lambda = 0.9$

From the results of the tax reform policy, I can conclude that initially, imposing higher taxes on educated individuals and lower taxes on uneducated individuals, based on the existing tax rates, can have positive effects on economic development and intergenerational mobility. This policy encourages people, particularly those with low abilities, to pursue education by providing them with larger cash transfers. As a result, the number of educated workers increases more, leading to economic growth and upward mobility in the early stages. Nevertheless, as the population of educated workers continues to grow, I observe a decline in the willingness of individuals to pursue education. This can be attributed to the higher tax burden placed on educated workers and the lower tax burden on the uneducated, and at the same time, the income of skilled workers falls due to the increase in skilled labour supply. Therefore, while the initial impact of the tax reform policy seems beneficial in promoting economic development and upward mobility, the long-term consequences suggest the need for careful consideration and evaluation of the tax structure to maintain a balance between incentivizing education and sustaining economic growth.

3.6 Conclusion

This chapter employs an overlapping generations model to investigate the effects of government's cash transfers and redistributive taxation on intergenerational mobility and economic growth for the Chinese economy. By calibrating the model to the Chinese economy and conducting quantitative analysis, the study demonstrates that when the government offers more cash transfers to the low ability children, the number of educated workers increases more in the subsequent period. This will effectively promote intergenerational mobility and therefore economic growth. Furthermore, this chapter examines the effects of tax reforms in terms of increasing the tax on educated workers to make up for the tax loss from reducing tax on uneducated workers. The findings reveal that initially, individuals still choose to receive education despite the higher tax. However, this result does not persist and later on, fewer choose to get educated. This suggests the existence of potential trade-offs in determining tax rates between educated and uneducated individuals. Higher tax rates may discourage them from investing in education in the long run, while lower tax rates for uneducated individuals may lead to a reduced future population of educated workers, potentially hindering economic development. Achieving an optimal taxation policy can ensure the promotion of education, maintain a growing educated population, and support sustainable economic development from the government's perspective.

Chapter 4

Intergenerational Income Mobility and Skill Premium: Investigating the Optimal Government Education Expenditure in China

Abstract

I use an overlapping generations model to study the optimal government education expenditure in the form of cash transfers to school children in order to boost intergenerational income mobility and reduce skill premium in the labour force. To quantify the results, the model is calibrated to the recent Chinese economy to match the key empirical features in the data. Then, I study the optimal policy when the government maximises the aggregate welfare. The optimal policy suggests that the government should make more cash transfers to the kids with low abilities as their educational costs (efforts) are higher. This is consistent with China's nationwide higher

education expansion program implemented since 1999. This policy will encourage more children to enrol in higher education and become skilled workers later on. The numerical results suggest that the policy can generate upward mobility by about 56% and therefore reduce skill premium by about 58%. The aggregate welfare is improved by about 13%.

4.1 Introduction

Income inequality has been an economic and social concern over the last decades in many countries. The income inequality has increased with the economic development in major economies, especially during the COVID-19 pandemic. There has been a huge literature studying the reasons behind this, see e.g. Bardhan et al. (2007) and Turnovsky (2015). Empirical evidence has suggested that intergenerational mobility across generations has a big impact on income inequality. Countries with higher intergenerational income mobility have more even income distribution and smaller income inequality (so called the 'Great Gatsby curve'), see e.g. Fisher et al. (2016) and Corak (2020). A social system characterised by high concentration of wealth ('inequality of outcomes') can be economically effective and politically acceptable only when the social mobility ('equality of opportunity') is high, see Kanbur and Stiglitz (2016).

This has also attracted attention to the policymakers. It has not only affected the social welfare but also economic growth. Policymakers have been focusing on designing economic policies that can promote intergenerational mobility and therefore reduce income inequality. It's important for the government to strike a balance between fiscal considerations and investments in human capital of the population. Human capital investment help to promote intergenerational mobility and therefore increase the supply of skilled labour. This reduces the wage gap between skilled and unskilled labour. Hanushek et al. (2014) used a three-period overlapping generations model to investigate how the government's different college aim schemes can influence individuals' decision on receiving education and therefore intergenerational mobility. They found that a need-based approach can help promote the intergenerational mobility to achieve a more equal income distribution for the society. Also, Hanushek et al. (2023) measured the returns to skills over the period of 2007-2018. They have found that the college wage premium has been decreasing over time. This suggests the dominant influence of the surge in the supply of college-educated workers although the restructure of the economy may raise the demand for skilled workers. This result has emphasised the importance of higher education attainment in reducing wage premium in labour markets.

The government expenditure in helping education attainment takes the form of cash transfer programs[1]. This can increase the overall human capital of the population. Specifically, the government cash transfer programs have been evaluated in African, Latin American, and Caribbean countries, demonstrating positive impacts on higher education attainment, see e.g. Patel-Campillo and García (2022b), Barrera-Osorio et al. (2019). Similar

[1]The government cash transfer program is one of the policies in helping education attainment, there are many other policies implemented such as Compulsory Education Policies in 1986.

findings have been confirmed in the US by Herrington (2015) and in Norway by Jerrim and Macmillan (2015). The cash transfer of government also plays an important role in the Chinese economy since late 1990s. China witnessed dramatic surges in the supply of college-educated labour due to China's nationwide higher education expansion program implemented in 1999 [2]. Since the expansion of college enrollment, China's higher education has achieved full development. As of the end of 2018, over 28 million students were enlisted in 2,663 colleges and universities throughout the country. As a result of its accession to the World Trade Organization in 2001, China has experienced increasing openness and trade during this period, which is likely to increase the demand for a college-educated workforce. This is the so-called "race between education and technology"[3](Goldin and Katz 2008). As a result, the government education expenditure can reduce the investment gap between poor and rich parents in their children's education. This plays a crucial role in generating upward intergenerational mobility, see e.g. Huang et al. (2021). J. Yang and Qiu (2016) used a calibrated model based on Chinese data and found that direct subsidies from the government to poor parents are the most effective and efficient policies for alleviating budgetary constraints on investments in children's early education. L. Tang et al. (2021) also found the importance of government

[2] In 1986, China implemented the Compulsory Education Law, marking a major reform aimed at making nine years of education mandatory for all children, typically covering primary school (six years) and junior secondary school (three years). This policy was introduced to improve literacy, bridge regional education gaps, and promote human capital development across the country. Therefore, the nine-year compulsory education reform has also increased the supply of skilled labor to some extent.

[3] Human capital investment increases the supply of such educated labour. When the relative demand for college-educated labour moves outward faster than does the relative supply, the wage gap between college- and high shcool-educated labour widens; and vice versa when supply outpaces demand. This is the so-called "race between education and technology".

spending in increasing the intergenerational mobility of underdeveloped families and improving equality of opportunity in China.

In this chapter, I employ an overlapping generations model to investigate the optimal government education expenditure in the form of cash transfers to children and how this affects their decision-making regarding education. My study builds on the work of Maoz and Moav (2001) and Murayama (2019), incorporating a government cash transfer program based on children's abilities. Specifically, children with varying abilities may receive different amounts of cash transfers from the government, depending on the political parameter, which influences their decisions on education investment and the future educated population's share. In my model, the cash transfer provided by the government is unconditional, meaning that all children, regardless of their parents' type, are eligible to receive the transfer, which can be used for either consumption or education. It is worth noting that my chapter considers the optimal government policy in the sense that the government is assumed to choose the optimal cash transfer program to maximise the aggregate welfare of the economy, taking into account the optimisation of private agents. The model with exogenous policy instruments is calibrated so that its steady state can reflect the main empirical characteristics of the current Chinese economy, with particular focus on its popular shares of educated and uneducated, and the wage premium between two groups. The main findings can be summarised as follows. The government should make more cash transfers to the kids with low abilities as their educational costs (efforts) are higher. This is consistent with China's nationwide higher education expansion program implemented since 1999. This policy will encourage more children to enrol in higher education and become skilled workers later on. The numerical results suggest that the policy can generate upward mobility by about 56% and therefore reduce skill premium by about 58%. The aggregate welfare is improved by about 13%. The rest of the chapter is organised as follows: Section 4.2 sets out the model structure. Section 4.3 discusses the calibration and steady state of the model given exogenous policy. Section 4.4 studies the Ramsey problem of the government and the optimal policy at the steady state. Section 4.5 concludes.

4.2 Model

4.2.1 Production and Factor Prices

Aggregate output Y in period t is given by constant returns to scale production function:

$$Y_t = A_t (n_t^e)^{1-\alpha} (n_t^u)^{\alpha}, \tag{4.2.1}$$

where n_t^e is the number of educated workers, n_t^u is the number of uneducated workers, A_t is defined as the total factor productivity, α represents the elasticity of uneducated workers. Since $n_t^e + n_t^u = 1$, I re-write the production function as : $Y_t = A_t(n_t^e)^{1-\alpha}(1 - n_t^e)^{\alpha}$.

Because the economy is competitive, production factors are paid at their marginal products. I define w_t^e and w_t^u as the wages of an educated and an uneducated worker respectively in period t:

$$
\begin{aligned}
w_t^e &= A_t(1-\alpha)(n_t^e)^{-\alpha}(n_t^u)^{\alpha}; \\
w_t^u &= A_t\alpha(n_t^e)^{1-\alpha}(n_t^u)^{\alpha-1}.
\end{aligned} \tag{4.2.2}
$$

Then, I assume the tax rates of educated and uneducated workers are τ_t^e and τ_t^u respectively, and $\tau_t^e > \tau_t^u$. Therefore, the after tax wages in period $t+1$ are as follows:

$$\widetilde{w}_{t+1}^e = (1-\tau_{t+1}^e)w_{t+1}^e; \tag{4.2.3a}$$

$$\widetilde{w}_{t+1}^u = (1-\tau_{t+1}^u)w_{t+1}^u. \tag{4.2.3b}$$

4.2.2 Individuals

The economy is made up of two periods overlapping generations of individuals, each with a single parent and a single child. In the first period, the individual does not work and decide whether to acquire education based on the transfers he receives from his parent and the government. The transfer from his parent is a bequest for him, while the transfer from the government is the cash transfer program in the form of allocating the funds collected by the tax revenue to children according to their abilities. In the second period, the individual works and divides his wealth between his own consumption and a transfer to his child. An individual's labour type is by default uneducated at the beginning, if he received education in the first period, then his type becomes educated.

The decision to pursue education or not may vary from person to person because of the individual's abilities and transfers received. The budget constraints of individual i are:

$$c_t^i + \delta^i h_t^i = x_t^i + s_t^i, \tag{4.2.4a}$$

$$c_{t+1}^i + x_{t+1}^i = \widetilde{w}_{t+1}^i, \tag{4.2.4b}$$

where

$$\delta^i = \begin{cases} 1, & \text{individual } i \text{ acquires education} \\ 0, & \text{otherwise }, \end{cases}$$

hence,

$$\widetilde{w}_{t+1}^i = \begin{cases} \widetilde{w}_{t+1}^e, & \delta^i = 1 \\ \widetilde{w}_{t+1}^u, & \delta^i = 0. \end{cases}$$

x_t^i is the transfer that individual i of generation t (i.e. born in period t) receives from his parent, s_t^i is he receives the cash transfer from the government, and x_{t+1}^i is the transfer this individual makes to his children.

In this model, differences in abilities are expressed as differences in individual education costs. h_t^i denotes the education cost of individual i who was born in period t and I further assume the higher is h_t^i, the lower is i's ability[4]. It is remarkable that the cash transfer here is unconditional,

[4]Higher-ability individuals might enter the education system with a stronger foundational knowledge or learning efficiency, enabling them to complete degrees faster or at lower costs (e.g., by earning credits in high school or placing out of introductory classes). This leads to a reduced cost of obtaining higher education compared to individuals who need more time or additional support (e.g., private tutoring) to reach the same level.

that is, it is not conditional on the children's predetermined investment in education. Regardless of the parent's income level, all children can get the cash transfer and use it for consumption and education (Murayama 2019). The cash transfer s_t^i is presumed to have the following form:

$$s_t^i = (1 - \lambda_t)(h_t^i - h_t^{0.5}) + \tilde{s}_t, \tag{4.2.5}$$

where $\tilde{s}_t$ is the budget for cash transfers since $\tilde{s}_t = \tau_t^e w_t^e n_t^e + \tau_t^u w_t^u n_t^u - g_t$, $h_t^{0.5}$ is the mean of h_t^i, and λ_t is a political parameter. In the spirit of Sano and Tomoda (2010), if $\lambda = 1$, then $s_t^i = \tilde{s}_t$, meaning all children receive the same cash transfer regardless of their abilities. $\lambda < 1$ shows individual with lower (high) ability receives larger (smaller) transfers than $\tilde{s}_t$, while $\lambda > 1$ indicates that individual with higher (lower) ability receives larger (smaller) transfers than $\tilde{s}_t$.

Individuals gain utility from consumption in both periods and from transfer to their children. Thus, I have the utility function:

$$u_t^i = \log c_t^i + \log c_{t+1}^i + \log x_{t+1}^i, \tag{4.2.6}$$

where c_t^i and c_{t+1}^i are the consumption of an individual born in period t in the two periods of his life and x_{t+1}^i is the transfer to his offspring.

Since I assume the capital market is imperfect and the utility function is separable. The individual optimization problem can be achieved whether to purchase education after deciding how to allocate income between consumption and bequest in the second period. Therefore, the allocation of second period income decision means solving:

$$z(\widetilde{w}^i_{t+1}) \equiv \max(\log c^i_{t+1} + \log x^i_{t+1})$$

$$s.t.(4.2.4b).$$

The maximization gives the optimal allocations:

$$\mathcal{L} = \log c^i_{t+1} + \log x^i_{t+1} - \lambda^i_{t+1}[c^i_{t+1} + x^i_{t+1} - \widetilde{w}^i_{t+1}]$$

$$\frac{\partial \mathcal{L}}{\partial c^i_{t+1}} = \frac{1}{c^i_{t+1}} - \lambda^i_{t+1} = 0 \Rightarrow \lambda^i_{t+1} = \frac{1}{c^i_{t+1}} \tag{4.2.7a}$$

$$\frac{\partial \mathcal{L}}{\partial x^i_{t+1}} = \frac{1}{x^i_{t+1}} - \lambda^i_{t+1} = 0 \Rightarrow \lambda^i_{t+1} = \frac{1}{x^i_{t+1}} \tag{4.2.7b}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda^i_{t+1}} = c^i_{t+1} + x^i_{t+1} - \widetilde{w}^i_{t+1} = 0 \Rightarrow c^i_{t+1} + x^i_{t+1} = \widetilde{w}^i_{t+1} \tag{4.2.7c}$$

From (4.2.7a) and (4.2.7b), I can get

$$\frac{1}{c^i_{t+1}} = \frac{1}{x^i_{t+1}} \tag{4.2.8}$$

Together with (4.2.7c), I can get

$$x^i_{t+1} = \widetilde{w}^i_{t+1}/2. \tag{4.2.9}$$

From (4.2.4b) I can get $c^i_{t+1} = \widetilde{w}^i_{t+1} - x^i_{t+1}$, then substituting it into $z(\widetilde{w}^i_{t+1})$, I get

$$z(\widetilde{w}^i_{t+1}) \equiv max[\log(\widetilde{w}^i_{t+1} - x^i_{t+1}) + \log x^i_{t+1}] \tag{4.2.10}$$

Then substitute (4.2.9) into (4.2.10), I get

$$
\begin{aligned}
z(\widetilde{w}_{t+1}^{i}) &= \log\big(\widetilde{w}_{t+1}^{i} - \frac{\widetilde{w}_{t+1}^{i}}{2}\big) + \log\frac{\widetilde{w}_{t+1}^{i}}{2} \\
&= \log\frac{\widetilde{w}_{t+1}^{i}}{2} + \log\frac{\widetilde{w}_{t+1}^{i}}{2} \\
&= \log\widetilde{w}_{t+1}^{i} - \log 2 + \log\widetilde{w}_{t+1}^{i} - \log 2 \\
&= 2\log\widetilde{w}_{t+1}^{i} - 2\log 2.
\end{aligned} \tag{4.2.11}
$$

Hence, individual will choose to invest in human capital if and only if:

$$
\log(x_t^i + s_t^i - h_t^i) + z(\widetilde{w}_{t+1}^{e}) \geq \log(x_t^i + s_t^i) + z(\widetilde{w}_{t+1}^{u}). \tag{4.2.12}
$$

From (4.2.12) it follows that given the transfer from parents, x_t^i, and cash transfer from the government, s_t^i, an individual received, he will invest in education if the cost, h_t^i, is small enough.

Substituting (4.2.11) into (4.2.12), I get

$$
\log(x_t^i + s_t^i - h_t^i) + 2\log\widetilde{w}_{t+1}^{e} - 2\log 2 \geq \log(x_t^i + s_t^i) + 2\log\widetilde{w}_{t+1}^{u} - 2\log 2
$$

$$
\begin{aligned}
\log(x_t^i + s_t^i - h_t^i) - \log(x_t^i + s_t^i) &\geq 2\log\widetilde{w}_{t+1}^{u} - 2\log\widetilde{w}_{t+1}^{e} \\
\log\big(\frac{x_t^i + s_t^i - h_t^i}{x_t^i + s_t^i}\big) &\geq \log\big(\widetilde{w}_{t+1}^{u}\big)^2 - \log\big(\widetilde{w}_{t+1}^{e}\big)^2 \\
\log\big(1 - \frac{h_t^i}{x_t^i + s_t^i}\big) &\geq \log\big(\frac{\widetilde{w}_{t+1}^{u}}{\widetilde{w}_{t+1}^{e}}\big)^2 \\
1 - \frac{h_t^i}{x_t^i + s_t^i} &\geq \big(\frac{\widetilde{w}_{t+1}^{u}}{\widetilde{w}_{t+1}^{e}}\big)^2 \\
h_t^i &\leq (x_t^i + s_t^i)\big[1 - \big(\frac{\widetilde{w}_{t+1}^{u}}{\widetilde{w}_{t+1}^{e}}\big)^2\big]
\end{aligned} \tag{4.2.13}
$$

Substituting (4.2.5) into (4.2.13), I can get

$$h_t^i \leq \big[x_t^i + (1-\lambda_t)(h_t^i - h_t^{0.5}) + \tilde{s}_t\big]\big[1 - \big(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\big)^2\big], \tag{4.2.14}$$

Rearranging it I get

$$h_t^i \leq \frac{1 - \big(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\big)^2}{1-(1-\lambda_t)\big[1 - \big(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\big)^2\big]}\big[x_t^i - (1-\lambda_t)h_t^{0.5} + \tilde{s}_t\big] \tag{4.2.15}$$

Let $\hat{h}_t^i$ be the critical value of the education cost for individual i so that he will invest education iff: $h_t^i \leq \hat{h}_t^i$. $\hat{h}_t^i$ is calculated as the largest value of h_t^i where (4.2.12) and (4.2.4) hold, and it can be expressed as a function of future wages and transfers received by individual i:

$$\hat{h}_t^i = \frac{1 - \big(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\big)^2}{1-(1-\lambda_t)\big[1 - \big(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\big)^2\big]}\big[x_t^i - (1-\lambda_t)h_t^{0.5} + \tilde{s}_t\big] \tag{4.2.16}$$

It follows that $\frac{\partial \hat{h}_t^i}{\partial\big(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\big)} < 0$, $\frac{\partial \hat{h}_t^i}{\partial x_t^i} > 0$, and $\frac{\partial \hat{h}_t^i}{\partial \tilde{s}_t} > 0$. The negative sign of the derivation of $\hat{h}_t^i$ with respect to $\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}$ shows that higher wage inequality affects education cost negatively. The positive signs of the derivative of $\hat{h}_t^i$ in terms of parent transfers and government cash transfers suggest that the more transfers received, the more likely an individual is to invest in education.

From equation (4.2.4b) I know that workers belonging to the same group (educated or uneducated) have the same second-period income. So, their consumption and transfer to their children, and also their children's critical values are the same. Therefore, the individual index i in the transfer notation can be replaced by an index describing the parent type: e or u. Therefore, from (4.2.16):

$$\hat{h}_t^e = \frac{1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2}{1-(1-\lambda_t)\left[1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2\right]}\left[\frac{\widetilde{w}_t^e}{2}-(1-\lambda_t)h_t^{0.5}+\tilde{s}_t\right]; \tag{4.2.17a}$$

$$\hat{h}_t^u = \frac{1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2}{1-(1-\lambda_t)\left[1-\left(\frac{\widetilde{w}_{t+1}^u}{\widetilde{w}_{t+1}^e}\right)^2\right]}\left[\frac{\widetilde{w}_t^u}{2}-(1-\lambda_t)h_t^{0.5}+\tilde{s}_t\right], \tag{4.2.17b}$$

where

$$\tilde{s}_t = \tau_t^e w_t^e n_t^e + \tau_t^u w_t^u n_t^u - g_t \tag{4.2.18}$$

Following Maoz and Moav (2001), I further assume education cost of individual i at period t is:

$$h_t^i = \theta_t^i(a + b\overline{w}_t), \tag{4.2.19}$$

where $a \geq 0$, $b \in [0,1]$, $\overline{w}_t$ denotes the average wage in period t, θ_t^i is the individual i's education cost parameter and the higher is i's ability, the lower is θ_t^i. The average wage in period t is a weighted average of educated and uneducated wages which can be expressed as: $\overline{w}_t = n_t^e\widetilde{w}_t^e + n_t^u\widetilde{w}_t^u$. With regards to the education cost parameter, θ_t^i, is independent of the parent's labour type and is uniformly distributed over the interval $(\underline{\theta}, \overline{\theta})$ with $\underline{\theta} \geq 0$. Hence, h_t^i is uniformly distributed over the interval $(\underline{h}_t, \overline{h}_t)$, where $\underline{h}_t = \underline{\theta}(a + b\overline{w}_t)$, $\overline{h}_t = \overline{\theta}(a + b\overline{w}_t)$.

4.2.3 Government

The government finances its stream of purchases $\{g_t\}_{t=0}^{\infty}$ by levying flat-rate, time-varying taxed on earnings from educated workers τ_t^e and uneducated workers τ_t^u. The government also conducts the cash transfer program for the educated s_t^e and uneducated workers s_t^u. The government's budget constraint is

$$g_t = \tau_t^e w_t^e n_t^e + \tau_t^u w_t^u n_t^u - s_t^e n_t^e - s_t^u n_t^u, \tag{4.2.20}$$

where $s_t^e = (1-\lambda_t)(\hat{h}_t^e - h_t^{0.5}) + \tilde{s}_t$ and $s_t^u = (1-\lambda_t)(\hat{h}_t^u - h_t^{0.5}) + \tilde{s}_t$.

4.2.4 Resource Constraint

The aggregate resource constraint

$$Y_t = c_t^e n_t^e + c_t^u n_t^u + g_t. \tag{4.2.21}$$

4.3 Calibration and Steady State for the Exogenous Policy

I now summarize the decentralized competitive equilibrium (DCE) conditions in the model. The DCE consists of the budget constraint for the educated and uneducated workers, i.e. BC_{t+1}^e, BC_{t+1}^u; the first order conditions, i.e. FOC_{t+1}^e, FOC_{t+1}^u; government budget constraint, i.e. GBC_t, the aggregate resource constraint, i.e. ARC_t[5].

Table 4.1 reports the values of the model parameters with Chinese data,

[5] The full DCE conditions are provided in the Appendix A.2.1.

indicating how each parameter is obtained by referring to various sources.

Parameter	Value	Definition	Source
$A > 0$	1.20	total factor productivity	calibration
$0 < \alpha < 1$	0.39	elasticity of uneducated workers	estimate
$a \geq 0$	0.05	intercept of education cost function	calibration
$0 \leq b \leq 1$	0.20	coefficient of education cost function	estimate
$\overline{\theta} > 0$	0.02	the highest bound of education cost parameter	calibration
$\underline{\theta} > 0$	0.01	the lowest bound of education cost parameter	calibration
$\lambda > 0$	1.00	political parameter	calibration
$0 < \tau^e < 1$	0.1028	tax rate of educated workers	data
$0 < \tau^u < 1$	0.0625	tax rate of uneducated workers	data

Table 4.1: Model Calibration

A is calibrated to the number of educated workers to be in line with data. Fleisher et al. (2011) investigate the role of education on worker productivity and a firm's total factor productivity using a panel of firm-level data from China for the period of 1998 - 2000. Given their estimation of the production function, I get the value of α [6].

The coefficient of the average wage in the education cost function, b, is estimated using the China Institute for Educational Finance Research-Household Survey (CHIEFR-HS) database in 2017. I extract two survey variables from it, one is the total education expenses of one of the interviewed household's children in elementary, middle, and high schools, the other is the total household income. After filtering the data, I take the linear regression between the education expenditure and total income

[6] Fleisher et al. (2011) specify the value-added production function: $Y_{it} = A_i K_{it}^{\beta_k} L_{sit}^{\beta_s} L_{pit}^{\beta_p} e^{u_{it}}$, where Y is output measured by value-added, K is capital, L_s is the number of highly educated workers, L_p is the number of workers with less education, and u is a disturbance term for firms $i = 1, 2, \ldots, n$ and from year $t = 1, 2, \ldots, T$. The parameters β_k, β_s, and β_p are the output elasticises of the corresponding inputs. Given the estimation of the production function, they get $\beta_s = 0.538$, $\beta_p = 0.344$. Then, I re-calculate the elasticity of uneducated workers: $\alpha = \frac{0.344}{0.538+0.344} = 0.390$.

(log(education expenditure) $\sim$ log(total income)) with the sample size is 111 [7]. Therefore, I get the estimated coefficient, $b = 0.20$. I use China Household Finance Survey (CHFS) database to calculate the tax rates of educated and uneducated workers. First, I choose three variables from the survey: educational level, individual tax amount, and after-tax wages. According to the measurement of educational level, I define people who have bachelor's, master's, or doctorate degree as educated workers, while people who hold college/vocational degree and below are uneducated workers. Secondly, the tax rates are calculated through the following equation: individual tax/(individual tax + after-tax money wages) controlling the education and considering the weight. Since CHFS has five survey waves which are 2011, 2013, 2015, 2017, and 2019, finally I take the average of these five tax rates for the educated and uneducated workers respectively, and I get $\tau^e = 0.1025$, $\tau^u = 0.0628$.

Variable	Data average	Model
C^e/Y	0.2587	0.2737
C^u/Y	0.2377	0.1828
C/Y	0.4964	0.4564
G/Y	0.5036	0.5435
N^e	0.3835	0.3850
$(w^e * N^e)/Y$	0.6297	0.6100
w^e/w^u	2.4748	2.4985

Table 4.2: Data Averages and Model's Steady State Values

Below is how the data average gets. By making use of the data from the China Household Income Project (CHIP) in 2013 and 2018[8], I cal-

[7] I match the education expenditure and total income through the household ID to get the sample size.

[8] The data quality of previous survey waves is not good, so I didn't expand the period.

culate the consumption rate of educated and uneducated people[9]. Since the consumption variable in this project is household level, I filter the samples with only one household member which is the household head, so the consumption of this household just belongs to this household head[10]. After controlling the age between 16 and 64, education level, and matching the GDP per capita of different provinces, then I can get the average consumption over GDP of educated and uneducated people[11]. Because my model does not have separate investment and net export terms, they are added to government spending. Therefore, I can get $G/Y = 1 - C^e/Y - C^u/Y = 1 - 0.2587 - 0.2377 = 0.5036$ from above data average. Following W. Li et al. (2019), after they revise and correct the data on the Chinese consumption rate in terms of both residents' own housing consumption and grey consumption, the average consumption rate between 2010 and 2012 is 0.4303, which is quite matched with the calibrated result: $C/Y = C^e/Y + C^u/Y = 0.2736 + 0.1828 = 0.4564$. With regards to N^e, I choose the gross enrollment rate of higher education[12] from 2010 to 2019, then the average is 0.3835. w^e is calculated from five waves of CHFS, I get $w^e = 86027.222$, then the output Y is the average GDP of those years [13], $Y = 71,853,252,000,000$, therefore I can get the educated labour in-

[9] Since the Chinese Bureau of Statistics does not have data on consumption by education level, and the existing literature does not have such data, I can only use the survey data to calculate.

[10] I exclude the housing expenditure from the consumption expenses.

[11] The consumption over GDP of educated and uneducated people from CHIP is 0.6747 and 0.3855 respectively, then multiple the share of educated and uneducated people, 0.3835 and 0.6165, finally I get $C^e/Y = 0.2587$, $C^u/Y = 0.2377$

[12] According to the "China Education Monitoring and Evaluation Statistical Index System", the formula for calculating the gross enrollment rate of higher education is: gross enrollment rate of higher education (%) = The total number of students in higher education / the population in the age group of 18 to 22 * 100%.

[13] China Statistical Yearbook 2020, average GDP of 2011, 2013, 2015, 2017, 2019, keep consistent with

come share $(w^e * N^e)/Y = 0.6297$. The skill premium $w^e/w^u = 2.4748$ is calculated from the CHIP in 2018[14].

Table 4.2 compares the data with the calibrated results and I can see the model's steady solution matches most of the data averages well.

4.4 Optimal Policy with Commitment

4.4.1 Ramsey Problem

In the commitment framework, the government considers that both educated and uneducated individuals will act in their own best interest, taking all variables as given. Each applicable cash transfer program leads to a feasible equilibrium allocation that fully reflects the optimal behavioral response to resource distribution. Given a welfare criterion, the government's optimization problem is to select the best cash transfer program that can produce an equilibrium allocation, thereby yielding the highest aggregate welfare. To avoid the general issue of time inconsistency in policy-making, it is assumed that the government commits to a once-and-for-all cash transfer program, which is announced during the initial period and never re-optimized. This problem is commonly referred to as the Ramsey problem of government under commitment.

The government now optimally chooses the policy instrument while simultaneously determining the allocation of individuals. This method is known as the dual approach to the Ramsey problem. The government's

the waves of CHFS.

[14] Average the rural and urban data.

objective is to maximize the present discounted value of a weighted average of the welfare of both educated and uneducated workers:

$$\sum_{t=0}^{\infty} \beta^t [n^e_{t+1}(\log c^e_{t+1} + \log x^e_{t+1}) + (1 - n^e_{t+1})(\log c^u_{t+1} + \log x^u_{t+1})] \quad (4.4.1)$$

The optimal policy approach emphasizes the constraints under which the government must operate. These are summarized within the DCE conditions. To simplify the government optimization problem, it is requisite to decrease the number of government choice variables, I substitute out, s^e_t, s^u_t, by making use of the expressions of $\hat{h}^e_t$, $\hat{h}^u_t$, $h^{0.5}_t$, $\tilde{s}_t$[15]. To summarize, the choice variables for the government are six allocation variables, $\{c^e_{t+1}, x^e_{t+1}, c^u_{t+1}, x^u_{t+1}, n^e_t, g_t\}^{\infty}_{t=0}$ and the policy parameter $\{\lambda_t\}^{\infty}_{t=0}$. The optimization problem can thus be summarized as follows:

$$\max_{\{c^e_{t+1}, x^e_{t+1}, c^u_{t+1}, x^u_{t+1}, n^e_t, g_t, \lambda_t\}^{\infty}_{t=0}} \sum_{t=0}^{\infty} \beta^t [n^e_{t+1}(\log c^e_{t+1} + \log x^e_{t+1}) + (1 - n^e_{t+1})(\log c^u_{t+1} + \log x^u_{t+1})] \quad (4.4.2)$$

[15] The simplified government budget constraint is provided in the Appendix A.2.2.

subject to the DCE conditions of

$$c^e_{t+1} + x^e_{t+1} = (1-\tau^e_{t+1})(1-\alpha)A_{t+1}(n^e_{t+1})^{-\alpha}(1-n^e_{t+1})^{\alpha} \tag{4.4.3}$$

$$c^u_{t+1} + x^u_{t+1} = (1-\tau^u_{t+1})\alpha A_{t+1}(n^e_{t+1})^{1-\alpha}(1-n^e_{t+1})^{\alpha-1} \tag{4.4.4}$$

$$\frac{1}{c^e_{t+1}} = \frac{1}{x^e_{t+1}} \tag{4.4.5}$$

$$\frac{1}{c^u_{t+1}} = \frac{1}{x^u_{t+1}} \tag{4.4.6}$$

$$\begin{aligned}
g_t &= A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}T \\
&- n^e_t\Bigg\{(1-\lambda_t)\Bigg(\frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2+\lambda_t}\Big\{\frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha} \\
&- (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T)-T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t\Big\} \\
&- \Theta\big[a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big]\Bigg) + A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}T - g_t\Bigg\} \\
&- (1-n^e_t)\Bigg\{(1-\lambda_t)\Bigg(\frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2+\lambda_t}\Big\{\frac{1}{2}(1-\tau^u_t)A_t\alpha(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1} \\
&- (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T)-T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t\Big\} \\
&- \Theta\big[a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big]\Bigg) + A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}T - g_t\Bigg\}
\end{aligned} \tag{4.4.7}$$

$$g_t = A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - c^e_t n^e_t - c^u_t(1-n^e_t) \tag{4.4.8}$$

where $\Theta = 0.5(\underline{\theta}_t + \overline{\theta}_t)$, $T = \tau^e_t - \alpha(\tau^e_t - \tau^u_t)$, $\Phi = \big[\frac{\alpha(1-\tau^u_t)}{(1-\alpha)(1-\tau^e_t)}\big]^2$.

The Lagrangian function of the government can be written as:

$$
\begin{aligned}
\mathcal{L} = \sum_{t=0}^{\infty} \beta^t \Bigg\{ & n^e_{t+1}(\log c^e_{t+1} + \log x^e_{t+1}) + (1-n^e_{t+1})(\log c^u_{t+1} + \log x^u_{t+1}) \\
& + \lambda^1_t \Bigg\{ (1-\tau^e_{t+1})(1-\alpha)A_{t+1}(n^e_{t+1})^{-\alpha}(1-n^e_{t+1})^{\alpha} - c^e_{t+1} - x^e_{t+1} \Bigg\} \\
& + \lambda^2_t \Bigg\{ (1-\tau^u_{t+1})\alpha A_{t+1}(n^e_{t+1})^{1-\alpha}(1-n^e_{t+1})^{\alpha-1} - c^u_{t+1} - x^u_{t+1} \Bigg\} \\
& + \lambda^3_t \Bigg\{ \frac{1}{x^e_{t+1}} - \frac{1}{c^e_{t+1}} \Bigg\} \\
& + \lambda^4_t \Bigg\{ \frac{1}{x^u_{t+1}} - \frac{1}{c^u_{t+1}} \Bigg\} \\
& + \lambda^5_t \Bigg\{ A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} T \\
& - n^e_t \Bigg\{ (1-\lambda_t) \Bigg(\frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t} \Bigg\{ \frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha} \\
& - (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T) - T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t \Bigg\} \\
& - \Theta\big[a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big] \Bigg) + A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} T - g_t \Bigg\} \\
& - (1-n^e_t) \Bigg\{ (1-\lambda_t) \Bigg(\frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t} \Bigg\{ \frac{1}{2}(1-\tau^u_t)A_t\alpha(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1} \\
& - (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T) - T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t \Bigg\} \\
& - \Theta\big[a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big] \Bigg) + A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} T - g_t \Bigg\} - g_t \Bigg\} \\
& + \lambda^6_t \Bigg\{ A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - c^e_t n^e_t - c^u_t(1-n^e_t) - g_t \Bigg\} \Bigg\},
\end{aligned}
$$

where λ_t (for $i = 1, 2, ..., 6$) represents the multiplier associated with each constraint in equations (4.4.3) - (4.4.8). The constraints in the Lagrangian function have been rearranged to ensure that all multipliers are nonnegative at the steady state. Additionally, the FOCs of the government should also include the constraints to the Ramsey problem, i.e. equations (4.4.3) - (4.4.8)[16].

4.4.2 Optimal Policy

Table 4.3 presents the steady state of the optimal policy along with the exogenous policy. Under the exogenous policy, the government is making the same cash transfers to all the children regardless of their ability level. However, under the optimal policy when the government aims to maximise the aggregate welfare, it chooses to bias towards the children with low abilities by offering more cash transfers to them. As a result, the educated population share has increased to 60.18% from 38.50%. This suggests that the optimal policy can generate upward mobility by about 56%. It also has a significant influence on the wage premium between those two groups. I can see that the wage premium has fallen sharply by about 58%. This means that the government is able to reduce wage inequality in the society. Both uneducated and aggregate welfare improve under the optimal policy setting. The welfare of educated population worsens but this is due to the reduced wage income as a result of more educated labour supply. The optimal policy clearly reflects the 1999 nationwide higher education expansion policy in China. This has enhanced the supply of educated labour population.

[16]The FOCs of government in the Ramsey problem are provided in the Appendix A.2.3.

Variable	Exogenous Policy	Optimal Policy
C^e	0.3943	0.2795
C^u	0.1648	0.2822
G	0.3014	0.3341
λ	1.0000	0.9220
N^e	0.3850	0.6018
$(w^e * N^e)/Y$	0.6100	0.6100
w^e/w^u	2.4985	1.0351
U^e	-1.8612	-2.5492
U^u	-3.6060	-2.5303
U	-2.9343	-2.5417

Table 4.3: Model's Steady State Values and Optimal Policy

4.5 Conclusions

This chapter employs an overlapping generations model to examine the optimal government education expenditure in the form of cash transfers to children and its impact on their educational decision-making. To analyse the quantitative results, I calibrated my model to the current Chinese economy to ensure it aligns with real data characteristics.

My findings indicate that to maximize the aggregate welfare of the economy, it is optimal for the government to offer enhanced cash transfers to children with lower abilities. This policy encourages more of these children to pursue higher education and subsequently become educated workers when they enter the labour force. Quantitative results show that this policy can achieve approximately 56% upward mobility within the population. As a result, the economy can better supply educated labour, significantly reducing the wage premium and income gap between educated and uneducated individuals. Overall, this policy enhances aggregate welfare by about 13%. Additionally, this policy supports the 1999 nationwide higher education reform.

Chapter 5

Summary and Conclusion

In this thesis, I first investigate the intergenerational mobility situation in China to give a relatively comprehensive understanding of this issue. More specifically, I use the semiparametric quantile model to examine the relationship between offspring's income, parents' income, and offspring's education years. Some key empirical findings are: I observe the increasing intergenerational income persistence among different groups; I also highlight the importance of education in increasing the income for the offspring. Then, I construct an overlapping generations model to try to explain these empirical findings. Basically, considering the government's cash transfer program and the redistribution taxation, I look at their effects on intergenerational mobility and economic growth in China. When calibrating the model to the recent Chinese economy and conducting quantitative analysis, I find that if the government provides more cash transfers to the children with low abilities, then it will promote the growth of the number of educated workers in the next period and effectively boost the upward mobility and economic growth. These effects will be more significant when the tax reforms are implemented. This suggests a need for policies that provide financial support specifically to children from low-income families, enabling them to pursue education and enhance their future earning potential. By expanding such transfers, the government could foster a more skilled workforce and promote long-term economic growth. Lastly, the government is taken into account to seek the optimal policy in order to maximize the social welfare in the overlapping generations model. With this optimal policy, the number of education population increases a lot, up to 60%, implying under the optimal policy, more children decide to receive education and become skilled workers. This significantly promotes intergenerational mobility, which generates upward mobility by about 56% and the wage premium also decreases from 2.5 to 1.04 times, reducing by about 58%. The last but not least, the aggregate welfare also improves by about 13%. The optimal policy results suggest a re-evaluation of social welfare strategies to maximize their impact on mobility and social welfare. By strategically adjusting cash transfers, tax policies, and education funding, the government can achieve significant increases in the skilled labor force, reduce wage inequality, and improve social welfare metrics substantially.

The thesis highlights the crucial role of education as a pathway for economic mobility, underscoring that policies aimed at making education more accessible can have far-reaching impacts on income inequality and social structure. This aligns with broader theories that position human capital investment as central to reducing economic disparity. One of the limitations of this thesis is the quality and completeness of the data, which may introduce some measurement errors and restrict the generalizability of the results. Despite rigorous cleaning and adjustments, the dataset has certain gaps, particularly regarding sub-sample bias. Future research with more comprehensive or high-resolution data could enhance the robustness of these findings. The overlapping generations model presented in this thesis relies on certain simplifying assumptions, such as the simplified production and utility functions as well as the distribution of ability. While these assumptions allow for a focused analysis, they may oversimplify the complexity of real-world dynamics. Relaxing these assumptions in future studies could provide a more nuanced understanding and improve the model's applicability to diverse contexts.

Intergenerational mobility is indeed a widely concern issue all over the world. Each country has a different level of development, and the severity of the problems they are concerned about are also different, but intergenerational mobility is basically encountered by all countries on their development path. All I did was explore the field of economics and use the knowledge I learned to try to solve my doubts. It can also be said that the exploration and freshness of unknown areas gave me the motivation to research.

Appendix A

A.1 Chapter 2 Appendix

Wave: 2000									
Variables	Mean	Median	Mode	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
ChildIncome	10333.70	7777.78	10000.00	15024.19	43.91	5.96	-1132.02	146166.67	563
FatherIncome	4763.30	4033.29	3789.87	3680.14	11.64	2.62	-1688.23.02	33000	563
ChildAge	28.79	28	25	2.96	-0.83	0.44	25	35	563
ChildEduYears	9.55	9	9	2.61	0.28	0.71	6	16	563
Wave: 2004									
Variables	Mean	Median	Mode	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
ChildIncome	11032.48	8401.47	11428.57	13727.59	76.28	6.74	-3870.97	184424.24	338
FatherIncome	5029.92	4374.31	1983.63	3719.00	9.98	2.51	-659.89	28434.48	338
ChildAge	29.83	30	29	3.11	-1.23	0.05	25	35	338
ChildEduYears	9.86	9	9	2.71	-0.09	0.65	6	16	338
Wave: 2009									
Variables	Mean	Median	Mode	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
ChildIncome	22640.39	17097.39	15584.42	24886.38	17.24	3.61	-261.44	193811.98	305
FatherIncome	5931.87	4924.85	6193.27	4426.37	14.23	2.87	-880.32	39386.89	305
ChildAge	30.31	30	34	3.18	-1.17	-0.07	25	35	305
ChildEduYears	10.32	9	9	3.04	-0.62	0.63	6	16	305
Wave: 2011									
Variables	Mean	Median	Mode	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
ChildIncome	26055.04	22500	30000	18638.58	2.61	1.41	-1538.46	102857.14	222
FatherIncome	8204.16	6907.44	13773.94	6236.00	6.54	1.99	-745.46	43723.08	222
ChildAge	29.94	30	25	3.24	-1.28	-0.08	25	35	222
ChildEduYears	11.25	9	9	3.46	-1.39	0.25	6	18	222
Wave: 2015									
Variables	Mean	Median	Mode	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
ChildIncome	48678.03	38665.18	41379.31	78893.87	115.03	9.67	76.63	1149424.14	410
FatherIncome	10037.83	8603.71	2709.52	7534.33	7.56	2.04	-1196.81	60547.54	410
ChildAge	29.36	29	27	3.11	-1.11	0.35	25	35	410
ChildEduYears	12.16	12	9	3.37	-1.52	-0.04	6	18	410

*The unit of child and father income is CNY (Chinese Yuan Renminbi).

Table A.1: Description Statistics of Variables

Wave: 2000			
Quantiles	P10	P50	P90
ChildIncome	1045.82	7777.78	17881.72
FatherIncome	1448.78	4033.29	8656.07
ChildAge	25	28	33
ChildEduYears	6	9	15
Wave: 2004			
Quantiles	P10	P50	P90
ChildIncome	1093.14	8401.47	20590.48
FatherIncome	1445.07	4374.31	8596.96
ChildAge	26	30	34
ChildEduYears	6	9	15
Wave: 2009			
Quantiles	P10	P50	P90
ChildIncome	3285.70	17097.39	41791.67
FatherIncome	1992.07	4924.85	10260.57
ChildAge	26	30	35
ChildEduYears	6	9	16
Wave: 2011			
Quantiles	P10	P50	P90
ChildIncome	6053.34	22500	46915.38
FatherIncome	2372.67	6907.44	15466.91
ChildAge	25	30	34
ChildEduYears	6.3	9	16
Wave: 2015			
Quantiles	P10	P50	P90
ChildIncome	11818.55	38665.18	74226.80
FatherIncome	2688.89	8603.71	18827.88
ChildAge	25	29	34
ChildEduYears	9	12	16

Table A.2: Descriptive Statistics of Different Quantiles

Wave: 2000						
Quantiles	P10		P50		P90	
Rural/Urban	Rural	Urban	Rural	Urban	Rural	Urban
ChildIncome	898.18	4111.11	7704.92	8108.11	18281.65	16216.22
FatherIncome	1317.95	3257.55	3676.89	4977.93	8933.43	8180.86
ChildAge	25	25	28	29	33	34
ChildEduYears	6	9	9	12	12	16
Wave: 2004						
Quantiles	P10		P50		P90	
Rural/Urban	Rural	Urban	Rural	Urban	Rural	Urban
ChildIncome	957.31	4755.09	7619.06	10849.28	20857.14	19320.57
FatherIncome	1429.93	3614.02	3993.33	5139.06	8650.58	8279.56
ChildAge	26	26	30	29.5	34	34
ChildEduYears	6	9	9	12	12	16
Wave: 2009						
Quantiles	P10		P50		P90	
Rural/Urban	Rural	Urban	Rural	Urban	Rural	Urban
ChildIncome	2890.33	9125.98	16438.36	22265.82	38961.04	55100.18
FatherIncome	1882.07	3329.47	4704.09	6253.90	9955.99	12346.79
ChildAge	26	25.5	31	29	35	33.5
ChildEduYears	6	9	9	15	16	16
Wave: 2011						
Quantiles	P10		P50		P90	
Rural/Urban	Rural	Urban	Rural	Urban	Rural	Urban
ChildIncome	4894.89	12500.00	22500	21855.67	53553.11	37500.00
FatherIncome	2052.39	4723.22	6109.48	8565.97	15297.63	15374.57
ChildAge	25.6	25	31	28	34	34
ChildEduYears	6	9	9	16	16	16
Wave: 2015						
Quantiles	P10		P50		P90	
Rural/Urban	Rural	Urban	Rural	Urban	Rural	Urban
ChildIncome	10430.11	15875.36	38895.07	34615.38	74226.00	69038.46
FatherIncome	2462.11	6642.75	7552.56	12029.36	18199.01	21840.58
ChildAge	26	26	29	29	34	34
ChildEduYears	9	9	12	16	16	16

Table A.3: Descriptive Statistics of Different Quantiles of Rural and Urban Areas

Wave: 2000							
Quantiles	P10		P50			P90	
Gender	Male	Female	Male	Female		Male	Female
ChildIncome	1037.74	1514.12	7735.83	8092.51		18275.86	16162.16
FatherIncome	1367.93	2040.69	3919.08	4869.56		8272.59	10659.04
ChildAge	25	25	29	27		33	31
ChildEduYears	6	6	9	9		12	14.7
Wave: 2004							
Quantiles	P10		P50			P90	
Gender	Male	Female	Male	Female	Male		Female
ChildIncome	1107.97	1124.54	8057.97	9341.59		20386.83	21316.84
FatherIncome	1425.10	2312.46	4209.55	5211.19		8286.43	12100.45
ChildAge	26	25	30	28		34	33
ChildEduYears	6	8.1	9	9		12.3	15
Wave: 2009							
Quantiles	P10		P50			P90	
Gender	Male	Female	Male	Female		Male	Female
ChildIncome	3402.08	2953.83	17285.81	15753.99		41815.32	37833.33
FatherIncome	1824.13	3262.77	4614.42	6708.13		9293.26	17074.00
ChildAge	26	25	30	30		35	34
ChildEduYears	6	9	9	12		15	16
Wave: 2011							
Quantiles	P10		P50			P90	
Gender	Male	Female	Male	Female		Male	Female
ChildIncome	6053.34	6427.33	22674.59	19890.11		54560.44	42414.00
FatherIncome	2036.36	5214.41	6382.70	10613.46		14345.82	17917.83
ChildAge	25	25	30.5	28		34	33
ChildEduYears	6	9	9	15		16	16
Wave: 2015							
Quantiles	P10		P50			P90	
Gender	Male	Female	Male	Female		Male	Female
ChildIncome	9244.13	22706.20	38709.68	37209.68		76640.71	63851.85
FatherIncome	2486.93	3852.48	7789.84	11351.41		18202.30	21956.97
ChildAge	26	25	29	28		34	34
ChildEduYears	6	9	12	16		16	16

Table A.4: Descriptive Statistics of Different Quantiles of Gender

Wave: 2000									
Quantiles	P10			P50			P90		
Regions	Central	Eastern	Western	Central	Eastern	Western	Central	Eastern	Western
ChildIncome	776.50	2021.09	1352.23	7109.11	9762.71	6388.89	17439.23	19028.06	15790.16
FatherIncome	1429.93	1871.43	1345.82	4062.65	4467.35	3499.13	9461.94	9425.91	7625.79
ChildAge	25	25	25	28	29	28	34	33	33
ChildEduYears	6	6	6	9	9	9	12	15	12
Wave: 2004									
Quantiles	P10			P50			P90		
Regions	Central	Eastern	Western	Central	Eastern	Western	Central	Eastern	Western
ChildIncome	1622.84	1440.35	802.85	7864.00	11428.57	7272.73	19305.19	29267.86	18947.37
FatherIncome	1439.33	2277.17	1312.33	4290.52	5176.36	3587.50	8026.44	12014.62	7648.55
ChildAge	26	25	26	29	30	30	34	34	34
ChildEduYears	6	9	6	9	9	9	15	15	12
Wave: 2009									
Quantiles	P10			P50			P90		
Regions	Central	Eastern	Western	Central	Eastern	Western	Central	Eastern	Western
ChildIncome	2698.12	7619.05	2537.23	16709.67	21802.74	12626.71	32449.90	52777.78	32852.4
FatherIncome	2326.22	2373.32	1595.93	5228.21	5846.99	3898.92	11221.62	11498.00	7526.08
ChildAge	26	26	26	30	30	31	34.5	35	35
ChildEduYears	6	9	6	9	9	9	16	16	12.9
Wave: 2011									
Quantiles	P10			P50			P90		
Regions	Central	Eastern	Western	Central	Eastern	Western	Central	Eastern	Western
ChildIncome	7289.38	15000.00	2628.28	24513.99	25404.04	18653.35	53754.58	53464.65	44764.39
FatherIncome	2093.38	3441.90	1949.88	7217.18	8169.85	5715.64	14717.26	17185.06	12766.05
ChildAge	26	25	25	30	30	30	35	34	34.9
ChildEduYears	6	9	6	12	9	9	16	16	16
Wave: 2015									
Quantiles	P10			P50			P90		
Regions	Central	Eastern	Western	Central	Eastern	Western	Central	Eastern	Western
ChildIncome	13360.95	19538.06	6652.98	39130.44	41379.31	28790.89	76625.96	96192.77	58620.69
FatherIncome	3631.33	2138.38	2334.12	8958.44	10319.29	5504.65	18334.55	23479.11	13118.28
ChildAge	26	25	26	29	29	29	34	34	34
ChildEduYears	9	9	9	12	12	9	16	16	16

Table A.5: Descriptive Statistics of Different Quantiles of Regions

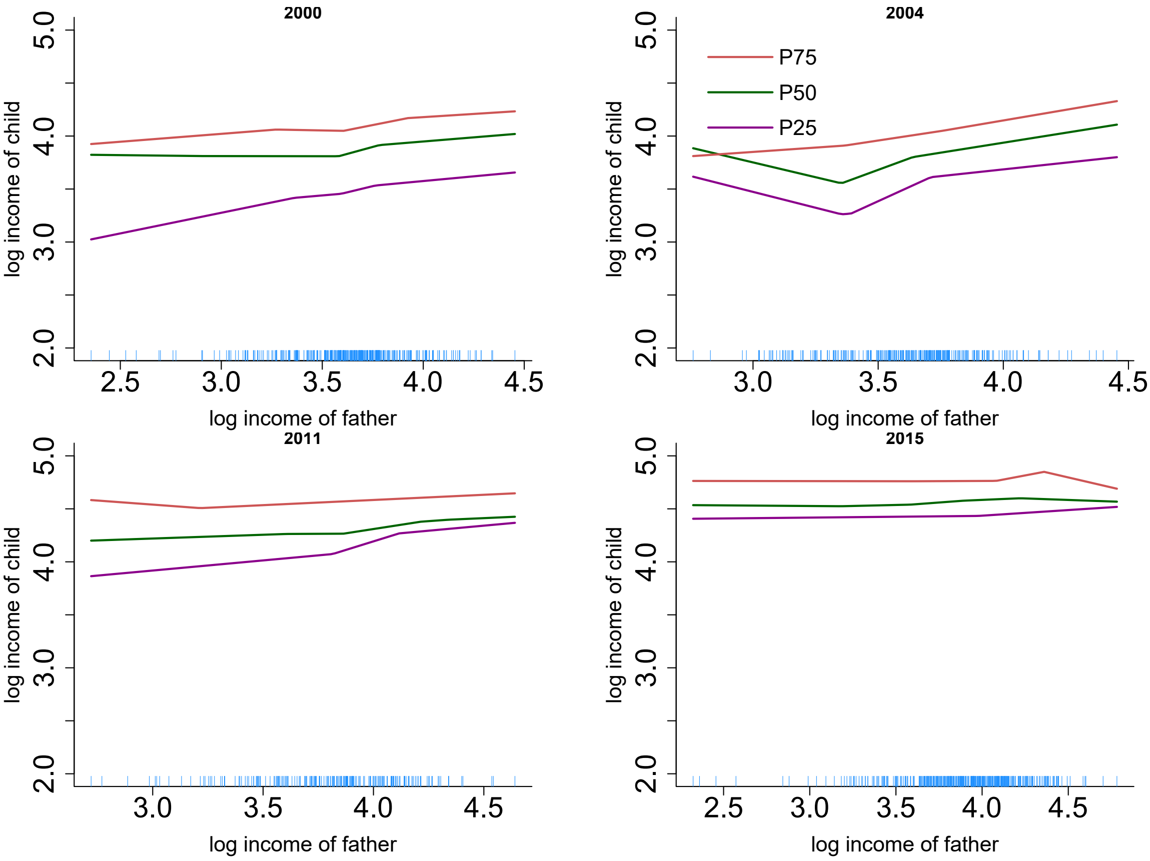

Figure A.1: Estimated Effect of Father's Income on Child's Income of SQR in 2000, 2004, 2011, and 2015

Wave	P25	P50	P75
2000	0.05***	0.023*	0.013**
	(0.011)	(0.010)	(0.008)
2004	0.064***	0.031*	0.021.
	(0.014)	(0.125)	(0.012)
2009	0.039***	0.027**	0.019.
	(0.010)	(0.010)	(0.010)
2011	0.041***	0.017	0.006
	(0.012)	(0.012)	(0.011)
2015	0.021**	0.012*	0.014*
	(0.008)	(0.006)	(0.006)

Significant codes: "$***$", 0.001; "$**$", 0.01; "$*$", 0.05; ".", 0.1.

Table A.6: Estimated Coefficients of Child's Education Years from 2000 to 2015

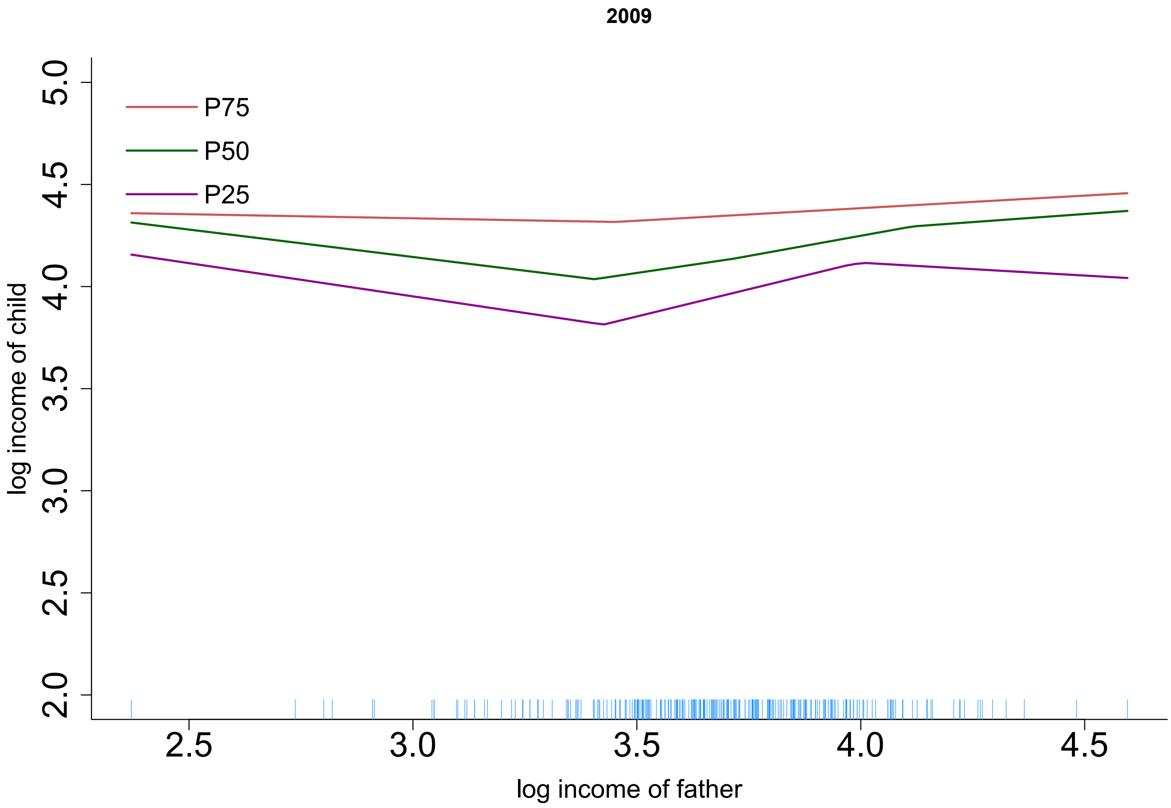

Figure A.2: Estimated Effect of Father's Income on Child's Income of SQR in 2009

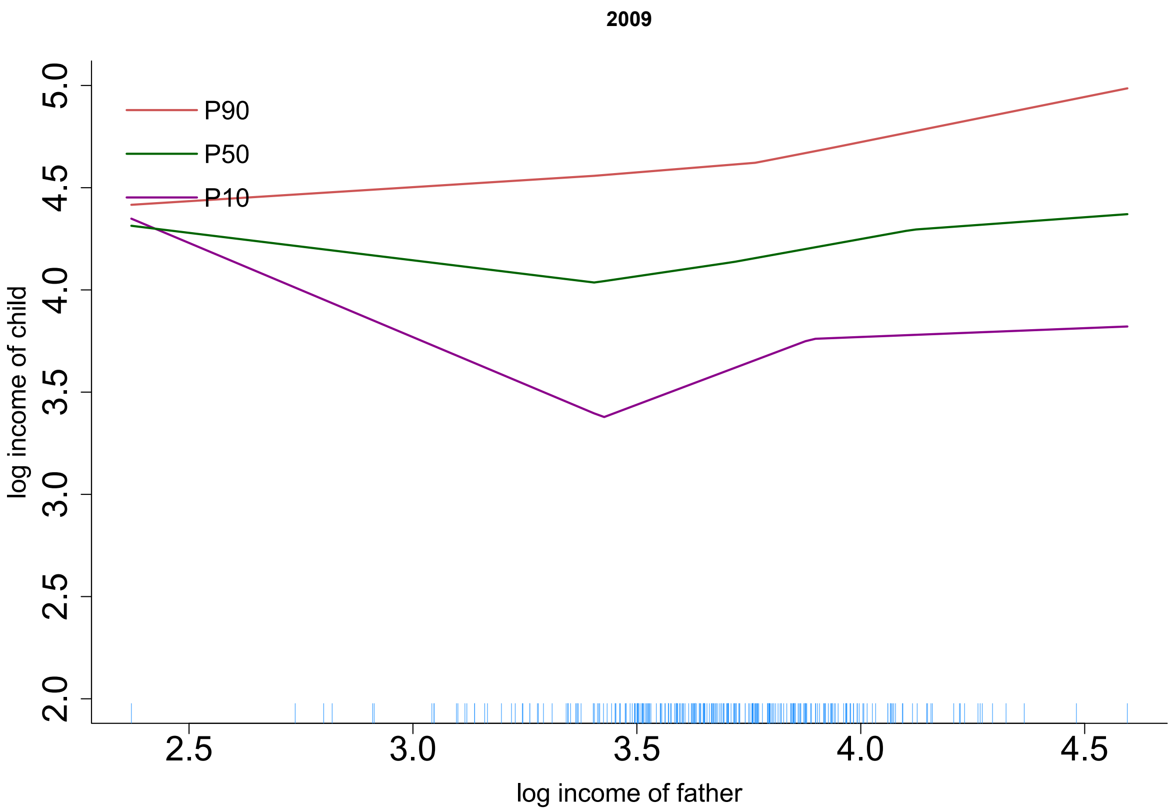

Figure A.3: Estimated Effect of Father's Income on Child's Income of SQR in 2009

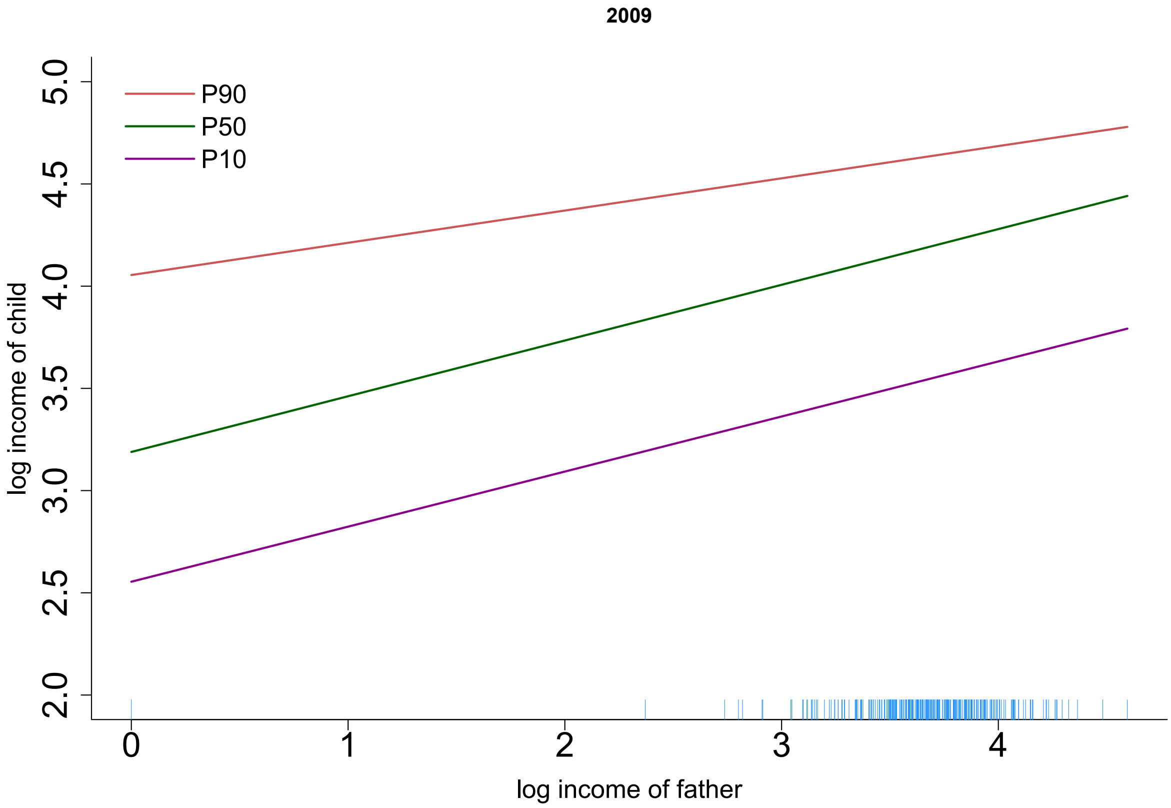

Figure A.4: Estimated Effect of Father's Income on Child's Income of SQR in Rural Area in 2009

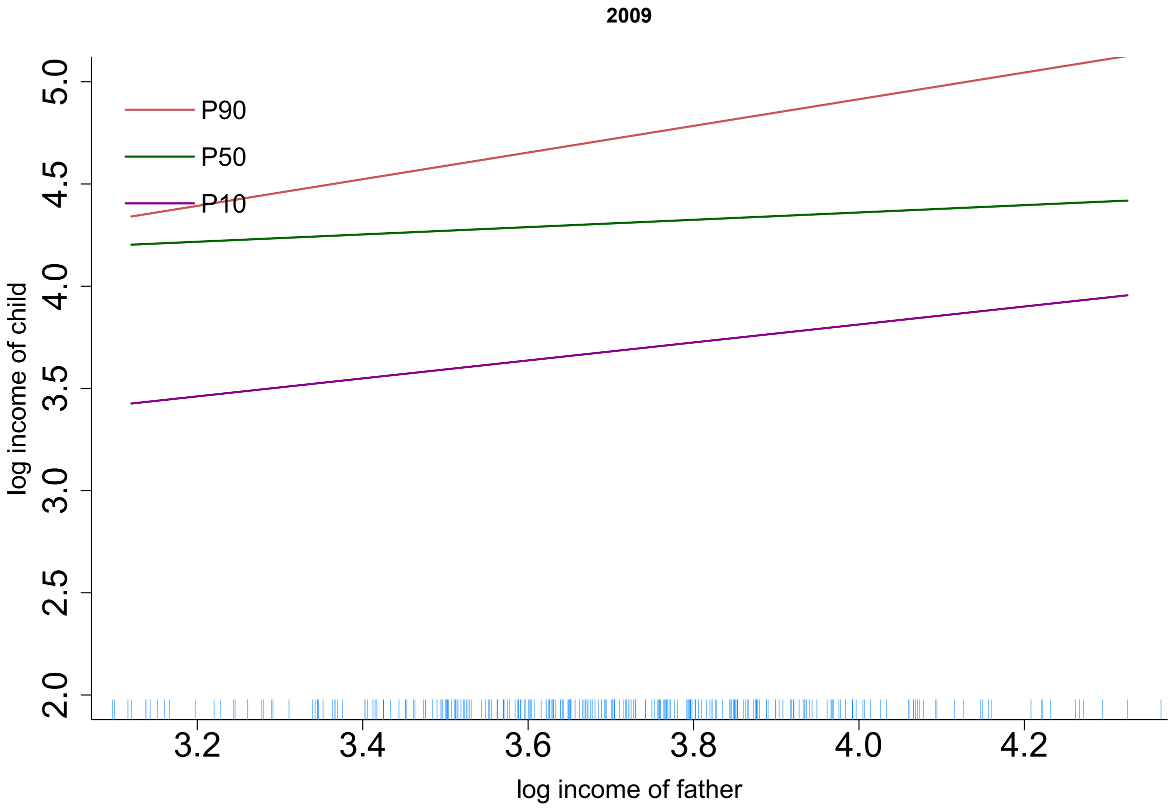

Figure A.5: Estimated Effect of Father's Income on Child's Income of SQR in Urban Area in 2009

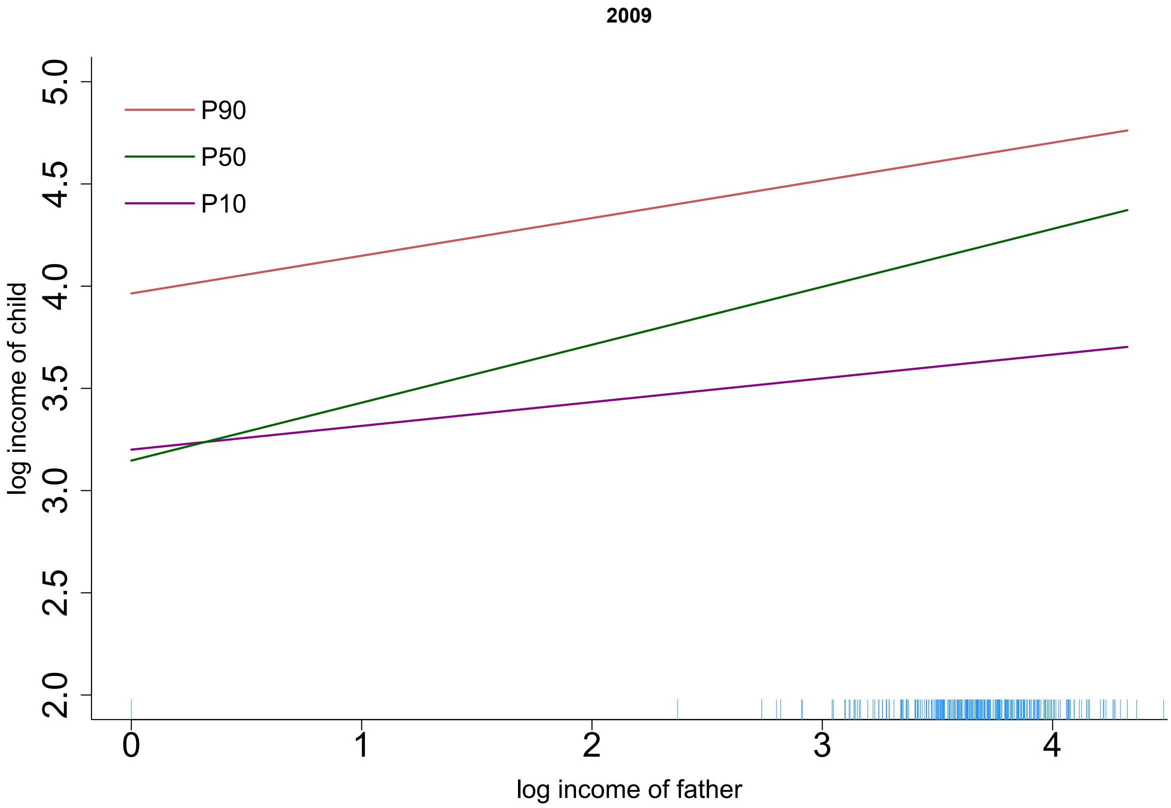

Figure A.6: Estimated Effect of Father's Income on Child's Income of SQR of Male in 2009

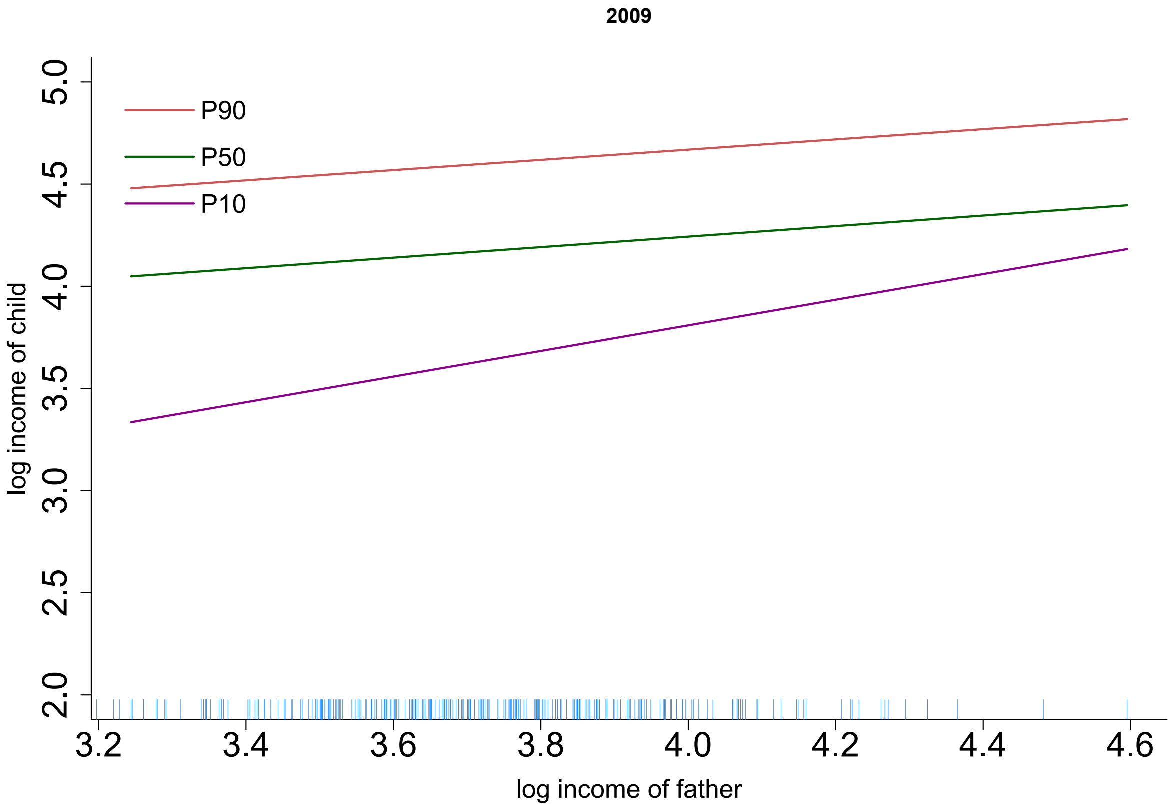

Figure A.7: Estimated Effect of Father's Income on Child's Income of SQR of Female in 2009

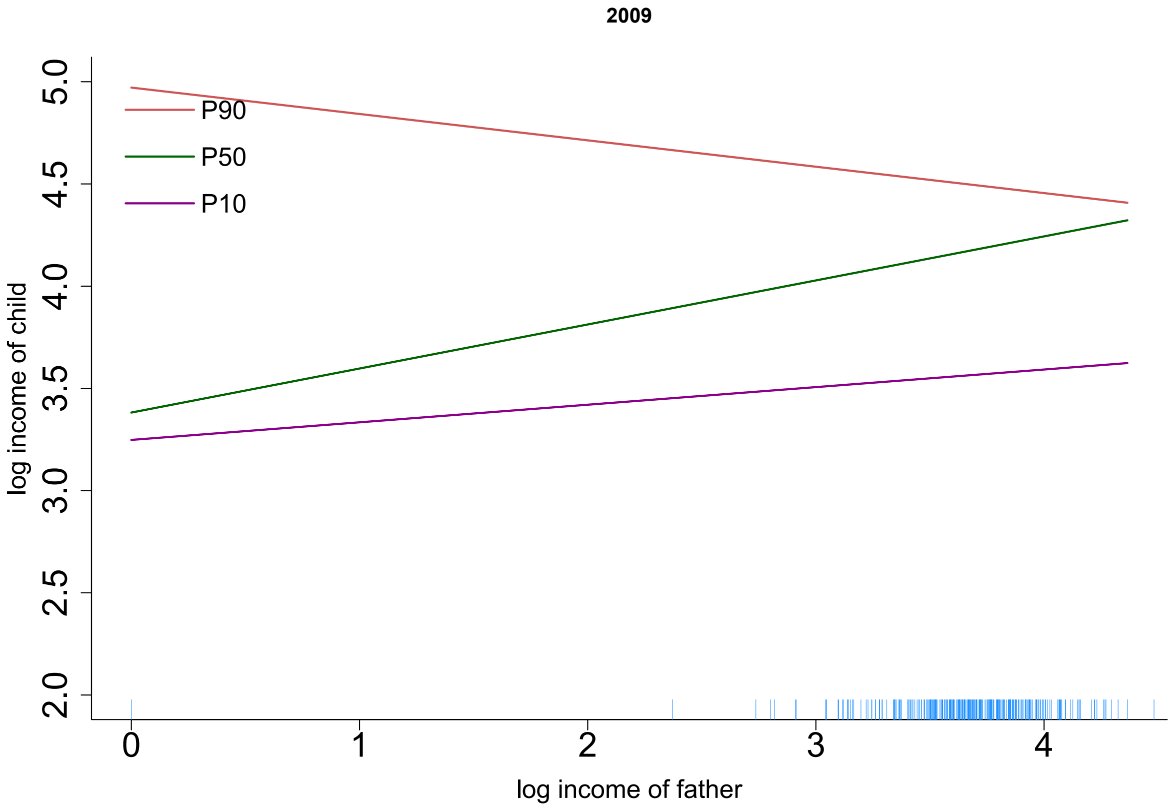

Figure A.8: Estimated Effect of Father's Income on Child's Income of SQR in Central Region in 2009

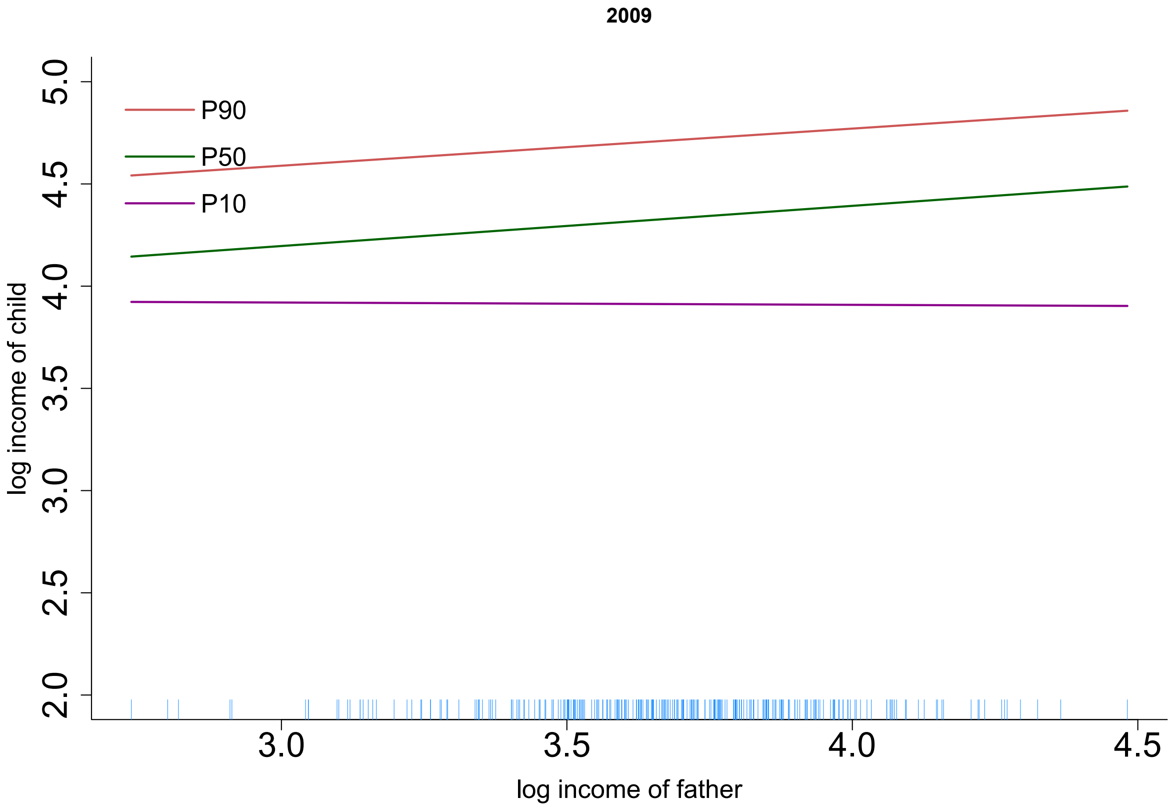

Figure A.9: Estimated Effect of Father's Income on Child's Income of SQR in Eastern Region in 2009

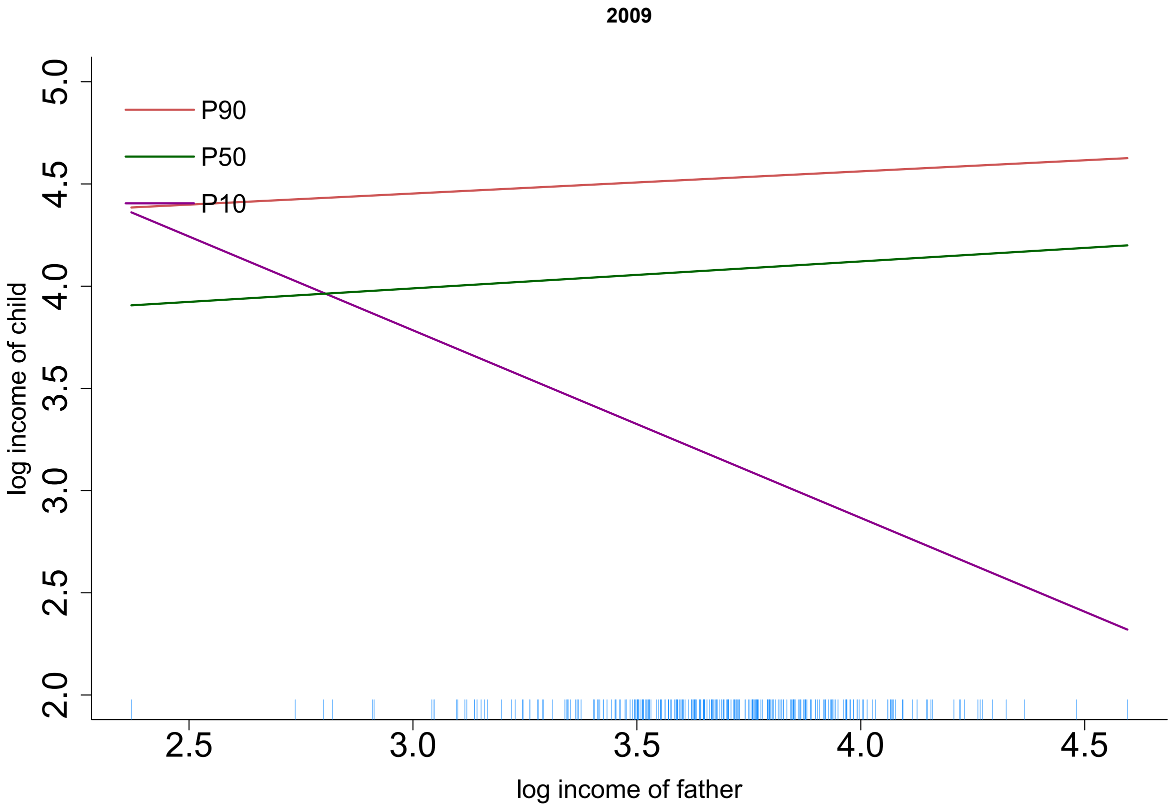

Figure A.10: Estimated Effect of Father's Income on Child's Income of SQR in Western Region in 2009

A.2 Chapter 4 Appendix

A.2.1 The DCE Conditions

The DCE conditions:

$$
\begin{aligned}
BC^e_{t+1} :& c^e_{t+1} + x^e_{t+1} = \tilde{w}^e_{t+1} \\
BC^u_{t+1} :& c^u_{t+1} + x^u_{t+1} = \tilde{w}^u_{t+1} \\
FOC^e_{t+1} :& \frac{1}{c^e_{t+1}} = \frac{1}{x^e_{t+1}} \\
FOC^u_{t+1} :& \frac{1}{c^u_{t+1}} = \frac{1}{x^u_{t+1}} \\
GBC_t :& g_t = \tau^e_t w^e_t n^e_t + \tau^u_t w^u_t (1 - n^e_t) - s^e_t n^e_t - s^u_t (1 - n^e_t) \\
ARC_t :& g_t = Y_t - c^e_t n^e_t - c^u_t (1 - n^e_t)
\end{aligned}
$$

A.2.2 The Government Budget Constraint

From (4.2.17) we know the expression of $\hat{h}^e_t$ and $\hat{h}^u_t$:

$$
\begin{aligned}
\hat{h}^e_t &= \frac{1 - \big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2}{1 - (1-\lambda_t)\big[1 - \big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2\big]} \big[\frac{\widetilde{w}^e_t}{2} - (1-\lambda_t) h^{0.5}_t + \tilde{s}_t\big], \\
\hat{h}^u_t &= \frac{1 - \big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2}{1 - (1-\lambda_t)\big[1 - \big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2\big]} \big[\frac{\widetilde{w}^u_t}{2} - (1-\lambda_t) h^{0.5}_t + \tilde{s}_t\big].
\end{aligned}
$$

where

$$
\widetilde{w}^e_t = (1 - \tau^e_t) w^e_t = (1 - \tau^e_t) A_t (1-\alpha)(n^e_t)^{-\alpha}(1 - n^e_t)^{\alpha}, \tag{A.2.1}
$$

$$
\widetilde{w}^u_t = (1 - \tau^u_t) w^u_t = (1 - \tau^u_t) A_t \alpha (n^e_t)^{1-\alpha}(1 - n^e_t)^{\alpha-1}, \tag{A.2.2}
$$

$$\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}} = \frac{n^e_{t+1}}{1-n^e_{t+1}}\Big[\frac{(1-\tau^u_t)\alpha}{(1-\tau^e_t)(1-\alpha)}\Big], \tag{A.2.3}$$

$$\begin{aligned} h^{0.5}_t &= 0.5(\underline{h}_t + \overline{h}_t) = 0.5(\underline{\theta}_t + \overline{\theta}_t)[a + b(n^e_t \tilde{w}^e_t + n^u_t \tilde{w}^u_t)] \\ &= 0.5(\underline{\theta}_t + \overline{\theta}_t)\big[a + b[A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}(1-\tau^e_t + \alpha(\tau^e_t - \tau^u_t))]\big] \\ &= \Theta\big[a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big] \end{aligned} \tag{A.2.4}$$

where $\Theta = 0.5(\underline{\theta}_t + \overline{\theta}_t)$, $T = \tau^e_t - \alpha(\tau^e_t - \tau^u_t)$.

$$\begin{aligned} \tilde{s}_t &= \tau^e_t w^e_t n^e_t + \tau^u_t w^u_t n^u_t - g_t \\ &= \tau^e_t n^e_t (1-\alpha)A_t(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha} + \tau^u_t(1-n^e_t)\alpha A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1} - g_t \\ &= (1-\alpha)\tau^e_t A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} + \alpha\tau^u_t A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t \\ &= (1-\alpha)\tau^e_t A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} + \alpha\tau^u_t A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t \\ &= A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}[\tau^e_t - \alpha(\tau^e_t - \tau^u_t)] - g_t \\ &= A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}T - g_t \end{aligned} \tag{A.2.5}$$

$$\begin{aligned} \hat{h^e_t} &= \frac{1-\big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2}{1-(1-\lambda_t)\big[1-\big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2\big]}\Big[\frac{\widetilde{w}^e_t}{2} - (1-\lambda_t)h^{0.5}_t + \tilde{s}_t\Big] \\ &= \frac{1-\big[\frac{\alpha(1-\tau^u_t)n^e_{t+1}}{(1-\alpha)(1-\tau^e_t)(1-n^e_{t+1})}\big]^2}{(1-\lambda_t)\big[\frac{\alpha(1-\tau^u_t)n^e_{t+1}}{(1-\alpha)(1-\tau^e_t)(1-n^e_{t+1})}\big]^2 + \lambda_t}\Big\{\frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha} \\ &- (1-\lambda_t)\Theta\big(a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big) + A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}T - g_t\Big\} \end{aligned}$$

$$= \frac{1 - \Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t}\Big\{\frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha} - (1-\lambda_t)\Theta a$$

$$- [\Theta b(1-T)(1-\lambda_t) - T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t\Big\}, \tag{A.2.6}$$

where $\Phi = \big[\frac{\alpha(1-\tau^u_t)}{(1-\alpha)(1-\tau^e_t)}\big]^2$.

$$\hat{h^u_t} = \frac{1 - \big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2}{1-(1-\lambda_t)\big[1-\big(\frac{\widetilde{w}^u_{t+1}}{\widetilde{w}^e_{t+1}}\big)^2\big]}\big[\frac{\widetilde{w}^u_t}{2} - (1-\lambda_t)h^{0.5}_t + \tilde{s}_t\big]$$

$$= \frac{1 - \big[\frac{\alpha(1-\tau^u_t)n^e_{t+1}}{(1-\alpha)(1-\tau^e_t)(1-n^e_{t+1})}\big]^2}{(1-\lambda_t)\big[\frac{\alpha(1-\tau^u_t)n^e_{t+1}}{(1-\alpha)(1-\tau^e_t)(1-n^e_{t+1})}\big]^2 + \lambda_t}\Big\{\frac{1}{2}(1-\tau^u_t)A_t\alpha(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1}$$

$$- (1-\lambda_t)\Theta\big(a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big) + A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}T - g_t\Big\}$$

$$= \frac{1 - \Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t}\Big\{\frac{1}{2}(1-\tau^u_t)A_t\alpha(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1} - (1-\lambda_t)\Theta a$$

$$- [\Theta b(1-T)(1-\lambda_t) - T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t\Big\}, \tag{A.2.7}$$

Then substituting them into s^e_t and s^u_t, so I can express them as:

$$s^e_t = (1-\lambda_t)(\hat{h}^e_t - h^{0.5}_t) + \tilde{s}_t$$

$$= (1-\lambda_t)\Bigg(\frac{1 - \Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t}\Big\{\frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha}$$

$$- (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T) - T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t\Big\}$$

$$- \Theta\big[a + b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\big]\Bigg) + A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}T - g_t \tag{A.2.8}$$

$$
\begin{aligned}
s_t^u &= (1-\lambda_t)(\hat{h}_t^u - h_t^{0.5}) + \tilde{s}_t \\
&= (1-\lambda_t)\left(\frac{1-\Phi\left(\frac{n_{t+1}^e}{1-n_{t+1}^e}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n_{t+1}^e}{1-n_{t+1}^e}\right)^2+\lambda_t}\left\{\frac{1}{2}(1-\tau_t^u)A_t\alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}\right.\right. \\
&\left. - (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T)-T]A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha} - g_t\right\} \\
&\left. - \Theta\big[a + b(1-T)A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}\big]\right) + A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}T - g_t
\end{aligned}
\tag{A.2.9}
$$

At the end, the government's budget constraint can be expressed as:

$$
\begin{aligned}
g_t &= \tau_t^e w_t^e n_t^e + \tau_t^u w_t^u (1-n_t^e) - s_t^e n_t^e - s_t^u(1-n_t^e) \\
&= A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}T \\
&- n_t^e\left\{(1-\lambda_t)\left(\frac{1-\Phi\left(\frac{n_{t+1}^e}{1-n_{t+1}^e}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n_{t+1}^e}{1-n_{t+1}^e}\right)^2+\lambda_t}\left\{\frac{1}{2}(1-\tau_t^e)A_t(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha}\right.\right.\right. \\
&\left. - (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T)-T]A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha} - g_t\right\} \\
&\left.\left. - \Theta\big[a + b(1-T)A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}\big]\right) + A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}T - g_t\right. \\
&- (1-n_t^e)\left\{(1-\lambda_t)\left(\frac{1-\Phi\left(\frac{n_{t+1}^e}{1-n_{t+1}^e}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n_{t+1}^e}{1-n_{t+1}^e}\right)^2+\lambda_t}\left\{\frac{1}{2}(1-\tau_t^u)A_t\alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}\right.\right.\right. \\
&\left. - (1-\lambda_t)\Theta a - [\Theta b(1-\lambda_t)(1-T)-T]A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha} - g_t\right\} \\
&\left.\left. - \Theta\big[a + b(1-T)A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}\big]\right) + A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}T - g_t\right\}
\end{aligned}
\tag{A.2.10}
$$

A.2.3 FOCs of the Government

FOCs of the government are as follow:

$$c^e_{t+1}: \frac{n^e_{t+1}}{c^e_{t+1}} - \lambda^1_t + \frac{\lambda^3_t}{(c^e_{t+1})^2} = 0 \quad \Rightarrow \quad \lambda^1_t = \frac{n^e_{t+1}}{c^e_{t+1}} + \frac{\lambda^3_t}{(c^e_{t+1})^2} \tag{A.2.11}$$

$$x^e_{t+1}: \frac{n^e_{t+1}}{x^e_{t+1}} - \lambda^1_t + \frac{\lambda^3_t}{(x^e_{t+1})^2} = 0 \quad \Rightarrow \quad \lambda^1_t = \frac{n^e_{t+1}}{x^e_{t+1}} + \frac{\lambda^3_t}{(x^e_{t+1})^2} \tag{A.2.12}$$

$$c^u_{t+1}: \frac{1-n^e_{t+1}}{c^u_{t+1}} - \lambda^2_t + \frac{\lambda^4_t}{(c^u_{t+1})^2} = 0 \quad \Rightarrow \quad \lambda^2_t = \frac{1-n^e_{t+1}}{c^u_{t+1}} + \frac{\lambda^4_t}{(c^u_{t+1})^2} \tag{A.2.13}$$

$$x^u_{t+1}: \frac{1-n^e_{t+1}}{x^u_{t+1}} - \lambda^2_t + \frac{\lambda^4_t}{(x^u_{t+1})^2} = 0 \quad \Rightarrow \quad \lambda^2_t = \frac{1-n^e_{t+1}}{x^u_{t+1}} + \frac{\lambda^4_t}{(x^u_{t+1})^2} \tag{A.2.14}$$

$$g_t: \lambda^5_t \Bigg\{ - n^e_t \Big\{ -(1-\lambda_t) \frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t} + 1 \Big\}$$

$$-(1-n^e_t)\Big\{ -(1-\lambda_t) \frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t} + 1 \Big\} - 1 \Bigg\} - \lambda^6_t = 0 \quad \Rightarrow$$

$$\lambda^5_t \Bigg\{ (1-\lambda_t) \frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t} \Bigg\} = \lambda^6_t = 0 \tag{A.2.15}$$

$$\lambda_t: \lambda^5_t \Big\{ - n^e_t \frac{\partial s^e_t}{\partial \lambda_t} - (1-n^e_t)\frac{\partial s^u_t}{\partial \lambda_t} \Big\} = 0 \quad \Rightarrow$$

$$\frac{\partial s^e_t}{\partial \lambda_t} = -(\hat{h^e_t} - h^{0.5}_t) + (1-\lambda_t)\frac{\partial \hat{h^e_t}}{\partial \lambda_t}, \quad \frac{\partial s^u_t}{\partial \lambda_t} = -(\hat{h^u_t} - h^{0.5}_t) + (1-\lambda_t)\frac{\partial \hat{h^u_t}}{\partial \lambda_t}, \quad \Rightarrow$$

$$\frac{\partial \hat{h^e_t}}{\partial \lambda_t} = \frac{\Big(1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2\Big)\Big(\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 - 1\Big)}{\Big[\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 - \lambda_t\Big(\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 - 1\Big)\Big]^2} \Big\{ \frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha}$$

$$-(1-\lambda_t)\Theta a - [\Theta b(1-T)(1-\lambda_t) - T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha} - g_t \Big\}$$

$$+ \frac{1-\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n^e_{t+1}}{1-n^e_{t+1}}\big)^2 + \lambda_t} [\Theta a + \Theta b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}],$$

$$
\begin{aligned}
\frac{\partial \hat{h_t^u}}{\partial \lambda_t} &= \frac{\left(1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2\right)\left(\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-1\right)}{\left[\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-\lambda_t\left(\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-1\right)\right]^2}\Big\{\frac{1}{2}(1-\tau^u_t)A_t\alpha(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1} \\
&- (1-\lambda_t)\Theta a - [\Theta b(1-T)(1-\lambda_t)-T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}-g_t\Big\} \\
&+ \frac{1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2+\lambda_t}[\Theta a+\Theta b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}],
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial s^e_t}{\partial \lambda_t} &= -\left\{\frac{1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2+\lambda_t}\Big\{\frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha}-(1-\lambda_t)\Theta a\right. \\
&- [\Theta b(1-T)(1-\lambda_t)-T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}-g_t\Big\} \\
&\left.- \Theta\left[a+b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\right]\right\} \\
&+ (1-\lambda_t)\left\{\frac{\left(1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2\right)\left(\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-1\right)}{\left[\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-\lambda_t\left(\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-1\right)\right]^2}\Big\{\frac{1}{2}(1-\tau^e_t)A_t(1-\alpha)(n^e_t)^{-\alpha}(1-n^e_t)^{\alpha}\right. \\
&- (1-\lambda_t)\Theta a - [\Theta b(1-T)(1-\lambda_t)-T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}-g_t\Big\} \\
&\left.+ \frac{1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2+\lambda_t}[\Theta a+\Theta b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}]\right\},
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial s^u_t}{\partial \lambda_t} &= -\left\{\frac{1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2+\lambda_t}\Big\{\frac{1}{2}(1-\tau^u_t)A_t\alpha(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1}-(1-\lambda_t)\Theta a\right. \\
&- [\Theta b(1-T)(1-\lambda_t)-T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}-g_t\Big\} \\
&\left.- \Theta\left[a+b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}\right]\right\} \\
&+ (1-\lambda_t)\left\{\frac{\left(1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2\right)\left(\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-1\right)}{\left[\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-\lambda_t\left(\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2-1\right)\right]^2}\Big\{\frac{1}{2}(1-\tau^u_t)A_t\alpha(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha-1}\right. \\
&- (1-\lambda_t)\Theta a - [\Theta b(1-T)(1-\lambda_t)-T]A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}-g_t\Big\} \\
&\left.+ \frac{1-\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2}{(1-\lambda_t)\Phi\left(\frac{n^e_{t+1}}{1-n^e_{t+1}}\right)^2+\lambda_t}[\Theta a+\Theta b(1-T)A_t(n^e_t)^{1-\alpha}(1-n^e_t)^{\alpha}]\right\}, \quad \Rightarrow
\end{aligned}
$$

$$\lambda_t^5\Bigg\{n_t^e\Bigg[\frac{1-\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2+\lambda_t}\Big\{\frac{1}{2}(1-\tau_t^e)A_t(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha}-(1-\lambda_t)\Theta a$$

$$-[\Theta b(1-T)(1-\lambda_t)-T]A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}-g_t\Big\}$$

$$-\Theta\big[a+b(1-T)A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}\big]\Bigg]$$

$$-(1-\lambda_t)\Bigg[\frac{\big(1-\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2\big)\big(\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2-1\big)}{\big[\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2-\lambda_t\big(\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2-1\big)\big]^2}\Big\{\frac{1}{2}(1-\tau_t^e)A_t(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha}$$

$$-(1-\lambda_t)\Theta a-[\Theta b(1-T)(1-\lambda_t)-T]A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}-g_t\Big\}$$

$$+\frac{1-\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2+\lambda_t}[\Theta a+\Theta b(1-T)A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}]\Bigg]$$

$$+(1-n_t^e)\Bigg[\frac{1-\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2+\lambda_t}\Big\{\frac{1}{2}(1-\tau_t^u)A_t\alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}-(1-\lambda_t)\Theta a$$

$$-[\Theta b(1-T)(1-\lambda_t)-T]A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}-g_t\Big\}$$

$$-\Theta\big[a+b(1-T)A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}\big]\Bigg]$$

$$-(1-\lambda_t)\Bigg[\frac{\big(1-\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2\big)\big(\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2-1\big)}{\big[\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2-\lambda_t\big(\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2-1\big)\big]^2}\Big\{\frac{1}{2}(1-\tau_t^u)A_t\alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}$$

$$-(1-\lambda_t)\Theta a-[\Theta b(1-T)(1-\lambda_t)-T]A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}-g_t\Big\}$$

$$+\frac{1-\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2}{(1-\lambda_t)\Phi\big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\big)^2+\lambda_t}[\Theta a+\Theta b(1-T)A_t(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha}]\Bigg]\Bigg\}=0 \tag{A.2.16}$$

$$n_t^e:\lambda_t^5\Big\{T\frac{\partial Y_t}{\partial n_t^e}-s_t^e-n_t^e\frac{\partial s_t^e}{\partial n_t^e}+s_t^u-(1-n_t^e)\frac{\partial s_t^u}{\partial n_t^e}\Big\}+\lambda_t^6\Big\{\frac{\partial Y_t}{\partial n_t^e}-c_t^e+c_t^u\Big\}=0 \quad \Rightarrow$$

$$\frac{\partial Y_t}{\partial n_t^e}=A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha}-\alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}],$$

$$\frac{\partial s_t^e}{\partial n_t^e}=(1-\lambda_t)\Big(\frac{\partial \hat{h}_t^e}{\partial n_t^e}-\frac{\partial h_t^{0.5}}{\partial n_t^e}\Big)-\frac{\partial \tilde{s}_t}{\partial n_t^e},\qquad \frac{\partial s_t^u}{\partial n_t^e}=(1-\lambda_t)\Big(\frac{\partial \hat{h}_t^u}{\partial n_t^e}-\frac{\partial h_t^{0.5}}{\partial n_t^e}\Big)-\frac{\partial \tilde{s}_t}{\partial n_t^e},$$

$$\frac{\partial \hat{h}_t^e}{\partial n_t^e} = \frac{1-\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2}{(1-\lambda_t)\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2+\lambda_t}\Big\{\frac{1}{2}\frac{\partial \tilde{w}_t^e}{\partial n_t^e} - [\Theta b(1-T)(1-\lambda_t)-T]\frac{\partial Y_t}{\partial n_t^e}\Big\},$$

$$\frac{\partial \hat{h}_t^u}{\partial n_t^e} = \frac{1-\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2}{(1-\lambda_t)\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2+\lambda_t}\Big\{\frac{1}{2}\frac{\partial \tilde{w}_t^u}{\partial n_t^e} - [\Theta b(1-T)(1-\lambda_t)-T]\frac{\partial Y_t}{\partial n_t^e}\Big\},$$

$$\frac{\partial \tilde{w}_t^e}{\partial n_t^e} = (1-\tau_t^e)(1-\alpha)(-\alpha)A_t[(n_t^e)^{-\alpha-1}(1-n_t^e)^\alpha + (n_t^e)^{-\alpha}(1-n_t^e)^{\alpha-1}],$$

$$\frac{\partial \tilde{w}_t^u}{\partial n_t^e} = (1-\tau_t^u)\alpha(1-\alpha)A_t[(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha-1} - (n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-2}],$$

$$\frac{\partial h_t^{0.5}}{\partial n_t^e} = \Theta b(1-T)\frac{\partial Y_t}{\partial n_t^e} = \Theta b(1-T)A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^\alpha - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}],$$

$$\frac{\partial \tilde{s}_t}{\partial n_t^e} = T\frac{\partial Y_t}{\partial n_t^e} = TA_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^\alpha - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}],$$

$$\frac{\partial \hat{h}_t^e}{\partial n_t^e} = \frac{1-\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2}{(1-\lambda_t)\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2+\lambda_t}$$

$$\Big\{\frac{1}{2}(1-\tau_t^e)(1-\alpha)(-\alpha)A_t[(n_t^e)^{-\alpha-1}(1-n_t^e)^\alpha + (n_t^e)^{-\alpha}(1-n_t^e)^{\alpha-1}]$$

$$-[\Theta b(1-T)(1-\lambda_t)-T]A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^\alpha - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}]\Big\},$$

$$\frac{\partial \hat{h}_t^u}{\partial n_t^e} = \frac{1-\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2}{(1-\lambda_t)\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2+\lambda_t}$$

$$\Big\{\frac{1}{2}(1-\tau_t^u)\alpha(1-\alpha)A_t[(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha-1} - (n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-2}]$$

$$-[\Theta b(1-T)(1-\lambda_t)-T]A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^\alpha - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}]\Big\},$$

$$\frac{\partial s_t^e}{\partial n_t^e} = (1-\lambda_t)\Bigg\{\frac{1-\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2}{(1-\lambda_t)\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2+\lambda_t}$$

$$\Big\{\frac{1}{2}(1-\tau_t^e)(1-\alpha)(-\alpha)A_t[(n_t^e)^{-\alpha-1}(1-n_t^e)^\alpha + (n_t^e)^{-\alpha}(1-n_t^e)^{\alpha-1}]$$

$$-[\Theta b(1-T)(1-\lambda_t)-T]A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^\alpha - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}]\Big\}$$

$$-\Theta b(1-T)A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^\alpha - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}]\Bigg\}$$

$$- TA_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha} - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}]$$

$$\frac{\partial s_t^u}{\partial n_t^e} = (1-\lambda_t)\Bigg\{\frac{1-\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2}{(1-\lambda_t)\Phi\Big(\frac{n_{t+1}^e}{1-n_{t+1}^e}\Big)^2+\lambda_t}$$

$$\Big\{\frac{1}{2}(1-\tau_t^u)\alpha(1-\alpha)A_t[(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha-1} - (n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-2}]$$

$$- [\Theta b(1-T)(1-\lambda_t) - T]A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha} - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}]\Big\}$$

$$- \Theta b(1-T)A_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha} - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}]\Bigg\}$$

$$- TA_t[(1-\alpha)(n_t^e)^{-\alpha}(1-n_t^e)^{\alpha} - \alpha(n_t^e)^{1-\alpha}(1-n_t^e)^{\alpha-1}] \tag{A.2.17}$$

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