Doctoral Dissertation

Three Essays on the Demographic and Economic Problems in China

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September 2022

Three Essays on the Demographic and Economic Problems in China

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In Partial Fulfillment of the
Requirements for the Degree of
Doctor of Philosophy
in the

Graduate School of International Social Science

Yokohama National University

Yokohama, Japan

2022

(Defended June 7, 2022)

Abstract

This dissertation consists of three chapters that study the demographic and economic problems in China during the twenty years of rapid economic growth.

The first chapter studies the phenomenon of Chinese fertility always peaking in October and finds evidence linking it to population movement during the Chinese Spring Festival. The seasonality of human births varies in different countries and regions, and this variation has been attributed to both biological and behavioral factors. The seasonality of births in mainland China is documented using data from a large sample from China's Fifth National Population Census conducted in 2000. Monthly time series birth data are decomposed into annual, seasonal, and random trends. The results show large seasonal birth fluctuations, with a salient peak in October. This seasonal birth pattern is hypothesized to be partially due to a home-bound wave of movement of people after the annual Spring Festival. Subsequent analysis of the calculated de-trended monthly births offers supportive evidence for this hypothesis. Further in-depth analysis reveals a variation in the magnitude of births based on location and family characteristics. These findings should inform researchers in the field of economics, where the seasonality of births has been previously regarded as exogenous.

To what extent does large-scale transportation infrastructure impact regional economic development in the long term? Chapter 2 examines this question using the historical event of the construction of the Eastern China Railway as a large-scale natural experiment. In the early years after the establishment of the People's Republic in 1949, Eastern China Railway transported 70% of its physical and 40% of its human capital. To address the problem of non-random placement of railroad lines, I propose an instrument variable strategy based on the connection between two Russian cities and two Chinese cities. It is plausible that much of the construction of the railroad networks is without regard to its impact on the post-2010 internal reorganization of counties. The results show that for every 1% increase in rail density, total GDP and GDP per capita increase significantly by about 0.3%, but the growth rate is not affected. I also find that the denser the railroad, the greater the number of large industrial enterprises, which provides supporting evidence for the hypothesis of agglomeration effects

In the third and final chapter, I estimate the gender-inequal resource allocation in Chinese households. The collective household model has existed for over 30 years now.

However, because expenditure data for assignable goods are inaccessible, and given the estimation methods based on nonlinear models, only one-seventh of the literature on resource shares (i.e., the fraction of each household member's expenditure to the total household's expenditure) focuses on developing countries. Applying a linear reframing of the nonlinear model and using China's nutrition expenditure data can overcome this issue. The findings confirm that nutrition data may be used as assignable goods to estimate resource shares and that the resources are unequally allocated to household members by gender.

Acknowledgement

First and foremost, I am extremely grateful to my supervisor, Prof. Yoshiaki Omori, for his invaluable advice, continuous support, and patience during my Ph.D. study. His immense knowledge and plentiful experience have encouraged me in all the time of my academic research and daily life.

I am deeply grateful to my Ph.D. committee members, Prof. Tsuruoka and Prof. Okumura, and my thesis defense committee, Prof. Furukawa and Prof. Parsons, for their support which was really influential in shaping my thesis and critiquing my results.

I would like to offer my special thanks to Prof. Junchao Zhang of Niigata University for his insightful comments and suggestions for both my research and academic career.

I would like to thank all the members in the Graduate School of International Social Science of YNU. It is their kind help and support that have made my study and life in Japan a wonderful time.

Finally, I would like to express my gratitude to my parents. Without their tremendous understanding and encouragement over the past few years, it would be impossible for me to complete my study.

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Chapter 1

Analysing the Seasonality of Births in Mainland China

1.1 Introduction

The seasonal distribution of human births has been widely studied in many countries and has been found to vary from country to country. Many demographers have focused on the United States, and have documented that the American monthly distribution of fertility has a minor peak in the spring and a major peak in the autumn. For example, Levine (1990) showed that, in Texas, approximately 60% of the population is born in the autumn and summer, while only 40% are born in the winter and spring. In Australia, the major birth-month peak occurred in September in the early 1960s, but the peak moved to February and March in the late 1970s (Mathers & Harris, 1983). Becker (1981) found that twice as many births occurred in the winter than in the summer in Matlab, Bangladesh, which is a marked pattern.

Studies based on large samples in Asian countries seem to show similar seasonal patterns of births. For example, using three waves (1992, 1998, 2005) of National Family Health Survey data with more than 100,000 observations, Loksbin and Radyakin (2012) found that, in India, most people are born in August and October, with proportions of 10% and 11%, respectively, of the number of total births in a single year, while the least number of births occur in the three months, December, January and February, accounting for approximately 9%, 6% and 8% of the total births in a single year. Abeysinghe (1991) studied the seasonality of Chinese births using data from Chinese individuals living overseas and documented that the largest proportion of Chinese births occurred in October and November. He noted that Chinese culture may be the cause of this seasonality.

As Lam and Miron (1991) concluded, the seasonality of human births cannot be due to a single reason. The possible explanations for the seasonal patterns of human births that have been put forward can be separated into biological and behavioural factors. Demographic studies have demonstrated that a fickle external environment, such as temperature (Becker, 1981) and rainfall (Philibert, 2013), can affect the seasonal distributions of births by affecting fecundity and fetal loss. Some demographers have tried to study the seasonal fluctuation of human births from a global point of view and have found that the peak month of births seems to differ across latitudes (James, 1990). Based on this phenomenon, it is natural to conclude that there is a link between human births and photoperiod. As a result, some studies have investigated this problem and have found that fertility increases with a longer photoperiod (Wehr, 1998; Bronson, 2004; Cumming, 2010). However, studies of biological factors are always limited by the trade-off between convincing results and a large sample because the effects of customs and habits must be excluded; however, when focusing on a small town in which people share the same customs, the data are not always large enough to study the effect of climate change. For this reason, data from mainland China as a whole provide a good sample for the study of biological factors. The mainland Chinese population is large and, compared with countries with the same scale of data, its customs are relatively similar throughout.

Coital frequency has been demonstrated to be influenced by behavioural factors such as festivals, marriage and the social characteristics of individuals. Cesario (2002) systematically studied the 'Christmas Effect' on human births using data from the UK. Greksa (2004) proposed the 'wedding hypothesis' using evidence in the Old Order Amish. Using data from two rural Chinese counties, Pasternak (1978) found that the main influence on birth was the reliability of the food supply, which was more important than time of marriage or the factors of temperature, rainfall or workload.

The basic method that is always used in these related studies is the analysis of monthly birth data, and this was the method used in the present study. Employing a large sample from the Chinese National Census, the study created a unique time series of monthly births in mainland China. The decomposition of the time series data allowed the extraction of a pure seasonal pattern. Finally, more detailed analyses by province and social group examined possible reasons for how the seasonal distributions of the births were formed.

From a public health perspective, research on the seasonality of births provides a reference for government policies to address certain diseases. Wellings *et al.* (1999) showed that unsafe sexual activities have a major peak around Christmas in Britain, which may increase the potential risk of HIV and abortions. The current study shows that in China, the Spring Festival is related to the main peak of conception; thus, it is reasonable to infer that more unsafe sexual activities occur during the time of the Spring Festival than during other seasons. As a result, the government can predict the peak of HIV risks, abortions and births based on the timing of domestic holidays to make better arrangements for medical resources and to avoid possible shortages of immunization medicines. Moreover, using population-based data from the Civil Registration System in Denmark, Mortensen *et al*. (1999) found that the risk of schizophrenia is significantly associated with the season of birth; in their study, the highest risk was found for births in February and March, while the lowest risk was found for births in August and September. The long-term effect of birth season on some diseases cannot be neglected in such a large country such as China. In this sense, determining the birth season patterns is necessary for making medical and health policies.

1.2 Methods

1.2.1 Data

China's Fifth National Population Census (FNPC) was organized by the Chinese National Census Office and carried out in October 2000; the respondents comprised all individuals from 31 provinces who were Chinese nationals residing in mainland China. The 1% micro-sub-sample of the FNPC was emplyed, which includes information for approximately 11 million individuals. In addition to individuals' year and month of birth, personal and family characteristics were extracted from the FNPC, including the resident's province and rural/urban classification. Using the respondents' personal ID codes, individuals could be matched with their parents to determine the effect of parental educational attainment. Information for those born far earlier than the study period was comparatively 'blurred' and unnecessary in the research, so the focus was only on individuals born between 1976 and 1995, a time span of 20 years. In this period, 3.9 million observations are used as research objects.

To compare the seasonal distribution of births in mainland China with that of the United States, which much previous research has focused on, birth-month data from the 2000 Decennial Census were employed, which was closest to the study's focus period. A total of 75 million observations were accounted for in the subsequent time series analyses.

1.2.2 Analysis

Decomposition of time series

The decomposition of time series data is a commonly used method in time series analysis. Monthly births for mainland China and the United States were decomposed into the yearly 'trend', 'seasonality' and 'remainder' using the following additive model:

$$Y_t = Trend_t + Seasonality_t + Remainder_t \tag{1}$$

where Y_t is the number of births in month t. In equation (1), the year trend is defined as a moving average of every 12 months as follows:

$$Trend_t = \frac{1}{12}\sum_{i=-6}^{6} Y_{t+j} \tag{2}$$

The seasonal pattern was estimated by the classic decomposition method, which simply calculates an average of the de-trended value for each season (here, it is each month). Finally, the 'remainder' is given by:

$$Y_t - Trend_t - Seasonality_t \tag{2}$$

Month-length-corrected birth amplitudes

Because the monthly fluctuation of births partially comes from the fluctuation of month length itself, following the methods of He and Earn (2007) and Dorelien (2016), month-length-corrected birth amplitudes were calculated using the following three equations:

$$\bar{X}_i = \frac{1}{12}\sum_{j=1}^{12} X_{ij} \tag{3}$$

$$C_{ij} = \frac{(Days\ in\ year\ i)/12}{Days\ in\ month\ i\ of\ year\ j} \tag{4}$$

$$Y_{ij} = \frac{C_{ij}X_{ij} - \bar{X}_i}{\bar{X}_i} \tag{5}$$

Employing information on the year and month of the birth observations in the FNPC database, first the number of monthly births in month j of year i, X_{ij}, was obtained. Then, equation (3) was used to calculate the average number of births in a month of average length in year i, $\bar{X}_i$. Equation (4) defines the corrected length of month j in year

i, C_{ij}. Finally, equation (5) was used to calculate a scaled, month-length-corrected

$$c(\alpha) = \sqrt{-\frac{1}{2}\ln\alpha} \tag{9}$$

monthly amplitude of month j in year i, represented by Y_{ij}.

On average, the month-length-corrected monthly amplitude in a given period can be expressed as:

$$Z_i = \frac{1}{N_{yr}} \sum_{years} Y_{ij} \tag{6}$$

The study focused on the periodic fluctuation of monthly births over the 20 years from 1976 to 1995, which was artificially divided it into two decades, 1976–1985 and 1986–1995, to study time trends $N_{yr} = 10$ To obtain the average month-length-corrected monthly amplitude in each decade, $Z_i$was set, as represented by Z_i.

Kolmogorov–Smirnov test

The Kolmogorov–Smirnov (K–S) test was used to assess whether the seasonality of births in groups with different social characteristics had the same distribution, using the formula:

$$D_{n,m} = \sup_x \left|F_{1,n}(x) - F_{2,m}(x)\right| \tag{7}$$

where $F_{1,n}(x)$ and $F_{2,m}(x)$ are the empirical distribution functions of the first sample (with a sample size of n) and the second sample (with a sample size of m), and *sup* is the *supremum* function. For large samples, the null hypothesis (i.e. that the two samples come from the same distribution) was αat the significance level α, if:

$$D_{n,m} > c(\alpha)\sqrt{\frac{n+m}{nm}} \tag{8}$$

1.3 Results

The patterns of birth seasonality and related statistics were examined from three different angles. First, country-level analysis was conducted and a cross-national comparison with the United States was made. Second, the use of a large sample allowed cross-provincial differences in the seasonal patterns of births to be analysed. Third, the distribution of monthly births by social groups was determined employing personal and family characteristics from the FNPC database.

1.3.1 Country-level results

Annual and monthly fluctuations

The results for mainland China were compared with those from the United States over the same period. Figure 1.1 shows the annual birth rate pattern from the decomposition of the Chinese monthly birth data. The number of annual births in the current sample gradually increased from approximately 1980 and then dropped sharply in 1990. The population increased in the early 1980s because there had been a baby boom in the 1960s, and those babies came of marriage and childbearing age in the 1980s.

In the late 1980s, the one-vote veto family planning system began to be implemented in all of China. This policy aimed to reinforce the one-child policy that had been implemented at the beginning of the 1980s by linking the evaluation of cadres with their performance in economic development and family planning work, with the latter being the priority. The cadres were evaluated highly when they did well in both economic development and family planning work but were punished if their performance was bad in family planning despite being good in economic development. In recent years, the one-child policy has been regarded as the culprit of the Chinese ageing population problem; however, in 1990, this problem was not imaginable under the one-vote veto family planning system, and government officers at all levels tried countless ways to control the fertility rate. Indeed, this policy significantly decreased the number of children born after 1990, as the current data show.

The births in China from 1976 to 1995 also exhibit a clear seasonal pattern. By extracting a cycle of seasonal trends from figure 1.1, a major peak in the seasonal distribution of births in China in October and a minor peak in February can be found (figure 1.3-a). The average number of births in October exceeds the average number of monthly births by more than 30%. It is rare to see such a large fluctuation in monthly birth data, especially in China, as it is a country with a large population.

Cross-national comparison

Compared with China, the seasonal pattern is greatly different in the United States. This is significant because China and the United States are at exactly the same latitude (except for Alaska, where few people live).

Using the same methods, the monthly birth data from the United States were decomposed into annual trends, seasonality and the remainder (figure 1.2). The population of the United States continued to grow until 1990 and then slowly declined after 1990. What is also interesting is that the remainder in the data of the United States looks more random, but in China, as figure 1.1 shows, the remainder is not random at all. The peaks appear approximately every 3 years. This phenomenon implies that the distribution of birth seasonality is complex and may correlate to some unobservable factors.

In the United States, birth seasonality shows peaks in August and September, while the minor peak is in February, and the trough is in January or March (figure 1.3-b). However, the magnitude of fluctuation is always smaller than 0.1, compared with a (–0.1, 0.4) magnitude in China.

The Spring Festival effect

Under the assumption that fetal loss holds constant for months or only exerts a modest effect on births, the time of birth depends on the time of conception. The lunar calendar regularly changes each year based on the perspective of the solar calendar. The FNPC investigates the birth month of individuals using the solar calendar, which makes it possible to observe the annual changes in birth months as they relate to the time of the Spring Festival (Lunar New Year). Figure 1.4 shows time series representations of the relationship between the timing of the Spring Festival and birth months from 1976 to 1995 in mainland China. The left y-axis represents the Spring Festival date in the solar calendar. A higher y value represents an earlier Spring Festival. The right y-axis represents the proportion of births from October to November. Assuming 40 weeks of pregnancy, the predicted birthdays for January conceptions are in October, and if conception occurs in February, the predicted birthday will be in November. In figure 1.4, it can be seen that although the peak of births consistently exists in October, the magnitude varies with the time of the Spring Festival. This means that the Spring Festival indeed influences the seasonality of births for a number of families.

The above finding provides a partial explanation as to why there is always a peak of Chinese births in October. The current hypothesis is that for urban residents, the Spring

Festival is a long holiday that allows them to have enough leisure time for conception. At the same time, in rural areas, because a large number of rural labourers work in cities to earn money, the Spring Festival is an important time for them to return home and be together with their families, thereby creating a chance for them to conceive a baby.

Undoubtedly, the seasonal pattern of births is a superposition of all the factors and an error term, and subsequent sections of this paper look at social factors to determine why the seasonal fluctuation of births is so large in mainland China and how it varies with other variables.

1.3.2 Province-level results

The province-level analysis provides an overview of the seasonality of Chinese births, i.e. wherever the province is located in the vast mainland Chinese territory, people living in most of the provinces have the same or similar features of their seasonal distribution of births, with only subtle differences. It is important to remember that the identical patterns are still dominant.

A geographic analysis (figure 1.5) shows the patterns in a more detailed way, as the 31 provinces are divided into four tiers by different magnitudes of peaks in their October births, represented by different colours. Based on the results shown on the map, the birth rates of almost all the provinces have peaks in October, yet subtle differences exist in the magnitude of these peaks. In general, the magnitudes of the south provinces are stronger than those of the north. Another clear pattern is that the magnitudes of the coastal areas are always stronger than those of the inland areas.

The results suggest that the direction of population flow is the main reason for these spatial patterns. In southern mainland China, a large number of farmer workers find jobs in large cities in coastal areas. In northern China, Hebei Province provides a considerable number of labourers for the Chinese capital area (the cities of Beijing and Tianjin). Gansu Province is almost the poorest province in China. Many rural residents of Gansu labour as farm workers in the nearby cities. These facts may explain why Hebei and Gansu Provinces are the provinces with the highest peaks in the north.

1.3.3 Results in different social groups

The monthly variations in Chinese births from 1976 to 1995 were compared for different social groups: rural–urban residence, highest parental education level and the father's occupation. The variation of the monthly birth amplitude was compared within different groups. A *t*-test was used to test whether the average number of births per month was significantly different within different social characteristics. The Kolmogorov–Smirnov (K–S) test was used to determine whether different social groups had significantly different distributions of births per month (see table 1.1, 1.2, and 1.3).

Both the average birth season and birth amplitude distribution across the years are significantly different in urban and rural areas (table 1.1). The rural sample shows a higher peak amplitude in October than the urban sample (figure 1.6). Of the approximately 12 million observations, 9 million represent residents in rural areas and approximately 3 million in urban areas; however, in rural areas, 33% more people were born in October than the average number of monthly births, while this number was 25% in urban areas. Meanwhile, it is also evident that fewer births occur in January and July in rural areas compared with urban areas.

Parental education also seems to have a significant effect on fertility plans (figure 1.7 and table 1.2). Highest parental educational attainment was grouped as: less than a primary education, primary education, secondary education and university education. The ‘less than a primary education’ group is significantly different from the other three groups (table 1.2). Parents with primary education have a higher October birth peak compared with the lowest education group. Parents in the ‘less than primary education’ group have a unique and flatter distribution in the monthly number of births of their children. This result is contrary to that of Warren and Tyler (1979), assuming that a lower education level represents a lower social status.

A difference in the distribution of monthly amplitude can also be found for father’s occupation (figure 1.8 and table 1.3). In figure 1.8, six types of occupations are shown with their corresponding monthly amplitudes: senior officers or managers, professionals, services and sales workers, agricultural and fishery workers, craft and trade workers, and plant and machine workers, most of which have significantly different means (except managers versus services, professionals versus services and professionals versus plants workers) and distributions (except professionals versus plants workers) (table 1.3). Within these occupations, agricultural and fishery workers have the highest peak of October births, and craft and trade workers the second-highest peak, but the differences between the groups are not large.

When comparing different family and social backgrounds, the patterns can be briefly summarized as follows: i) the birth distributions of different social groups have the same seasonal pattern, ii) the birth distributions in rural areas are higher in magnitude than those in urban areas, and iii) parents with junior high school education are more likely to given their children births in October than the parents with other degrees of education.

1.4 Discussion

The country-level, provincial-level and family-level results from this large Chinese sample show that the monthly or seasonal patterns of births (with a significant peak in October) are similar in different social groups with different social characteristics, but there are tiny differences in magnitude in all areas (except for some minority groups) and social groups.

The periodically directed migration of rural labour may partially explain the persistent peak in births in October. The annual 'Spring Festival travel rush' transports hundreds of millions of migrant workers from China's economically developed cities to their homes in rural areas – the largest-scale human migration activity in the modern world. Similar examples of population migration affecting seasonality of births can be found in sub-Saharan Africa, where migrants stay at home to plant crops during the rainy season and migrate in search of work in the dry season. Higher educated women in sub-Saharan Africa have been shown to exhibit weaker seasonal magnitudes in their birth patterns (Dorélien, 2016), and a similar result was found in the present study.

This theory can also explain the minor peak of births in February in China because the second longest holiday (of 7 days) is International Workers' Day in May (nine months from February); however, this is not a festival represented by family gatherings in China, so workers in cities are not as eager to go back home as they are for the Spring Festival.

Provincial differences can also be partially explained by rural workers' migration. The northern Chinese provinces of Henan, Hebei and Gansu have the highest October birth peaks. This is possibly because they are the provinces with the largest proportions of farmers in northern China. Moreover, Hebei surrounds Beijing and Tianjin, which are the Chinese capital and an important city, respectively; thus, a large portion of the Hebei population works in these two cities and only go back home during holidays. In the southern provinces, the peaks of births in October are much higher for the inland provinces than the coastal provinces. This is because the Chinese south-eastern coastal areas are much richer and more developed, and absorb large numbers of labourers from the inland areas. In particular, Guangdong Province contains Shenzhen and Zhuhai, which were designated special economic zones in the 1980s and became seen as the 'promised land' for people in the surrounding provinces.

Comparisons of different social groups also provide supportive evidence for the study's hypothesis. First, it is natural that the study rural sample would have larger number of births in October and February because most of the migrant workers were originally from rural areas (figure 1.6). This result cannot be explained by leisure time because urban workers and rural workers always have the same leisure time during holidays. Second, a comparison of parental education levels shows a contrasting result to those of former studies, i.e. that there was greater variation of seasonal births with lower social status. The possible reason for this outcome is shown in figure 1.7; parental education is strictly defined as their highest educational attainment, which means that those couples whose highest educational attainment was 'less than primary' may have found it hard to find a job in the cities. As a result, both of such parents remain farmers and stay together at the county home. This could explain why the seasonal distribution of births was flattest in the 'less than primary' education group.

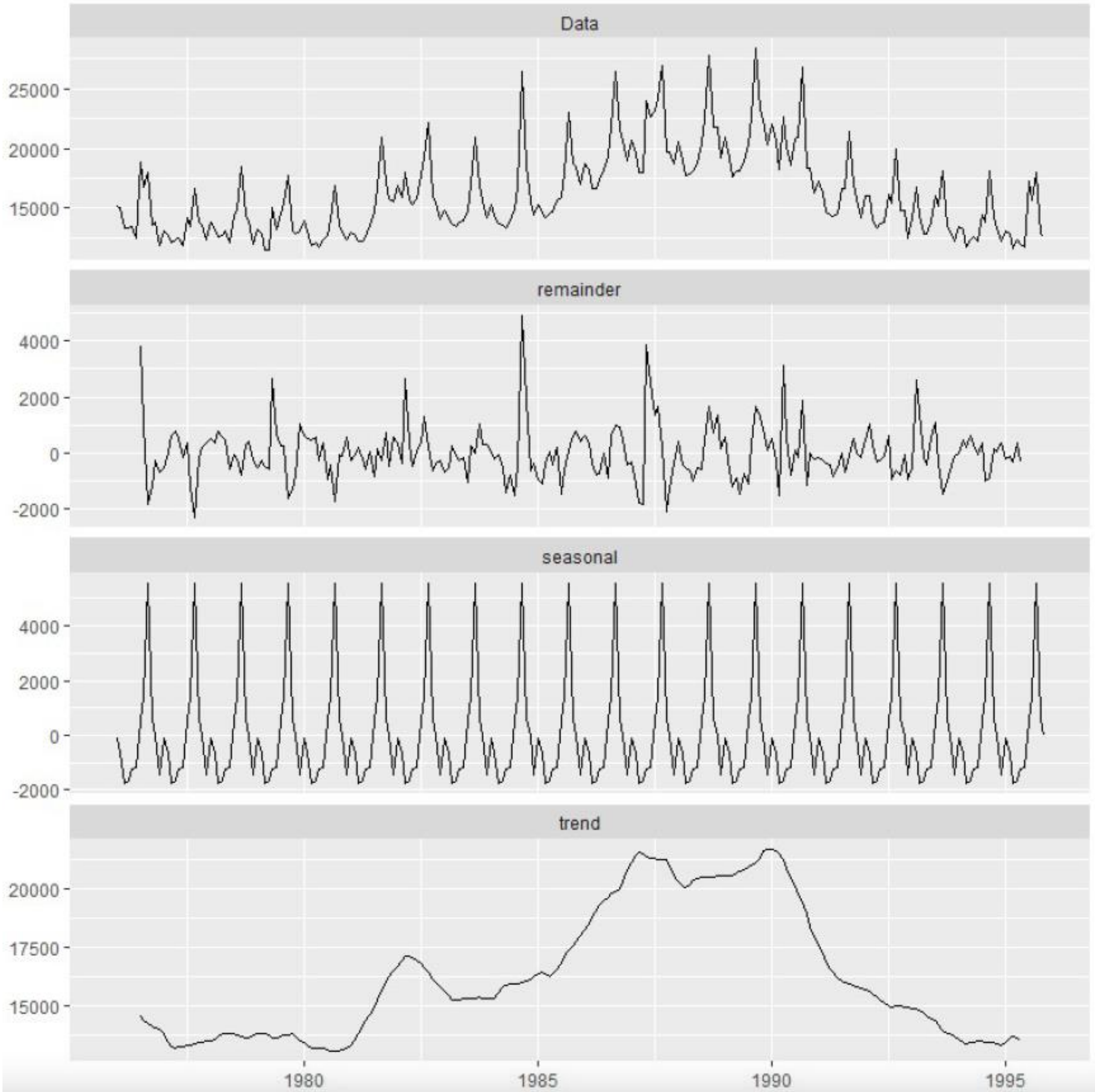
Other behavioural factors may also affect the seasonality of births. For example, marriage (Grech, 2003). In China, especially rural areas, people prefer to get married during the Spring Festival because, first, they can go back home at that time, and second, their friends and families will also go back home and they will thus earn more wedding gift money. Birth order and parental income have also been found to be related to the seasonality of births (Bobak & Gjonca, 2001; Benderlioglu & Nelson, 2004; Greksa, 2004). Unfortunately, due to the limitations of the data, this study did not provide any evidence on these factors in China.

The study results suggest that season of birth may not be a good instrument to study the economic 'return' from schooling in China, because it is significantly correlated to family location and parental education and occupation. Although controlling for these variables in the regression is possible, the unobservable variables correlated with them cannot be controlled. For example, parental education can be controlled for in the regression, but parents' education may correlate with ability level, which can be genetically inherited by their children and thus affect the children's outcomes in the future. In the case that parents' education affects children's birth season, the IV estimator will be biased and will thus fail to identify the causal effect of education.

Biological factors certainly affect the seasonality of births in mainland China. For example, agricultural and fishery workers have larger seasonal variations of births that can partially be explained by weather and rainfall. On the other hand, behavioural factors can only partially explain the seasonality of conception; fetal loss, sperm motility and menstrual periods are more relative to biological factors, including weather, rainfall and sunshine (Wehr, 1998; James, 1990; Bronson, 2004; Cumming, 2010). However, this study has demonstrated that behavioural factors are more important in mainland China. Only these can explain the uniform seasonal pattern of births in different areas of the country with different climates, and the comparison between two countries with similar area and latitudes, China and the United States.

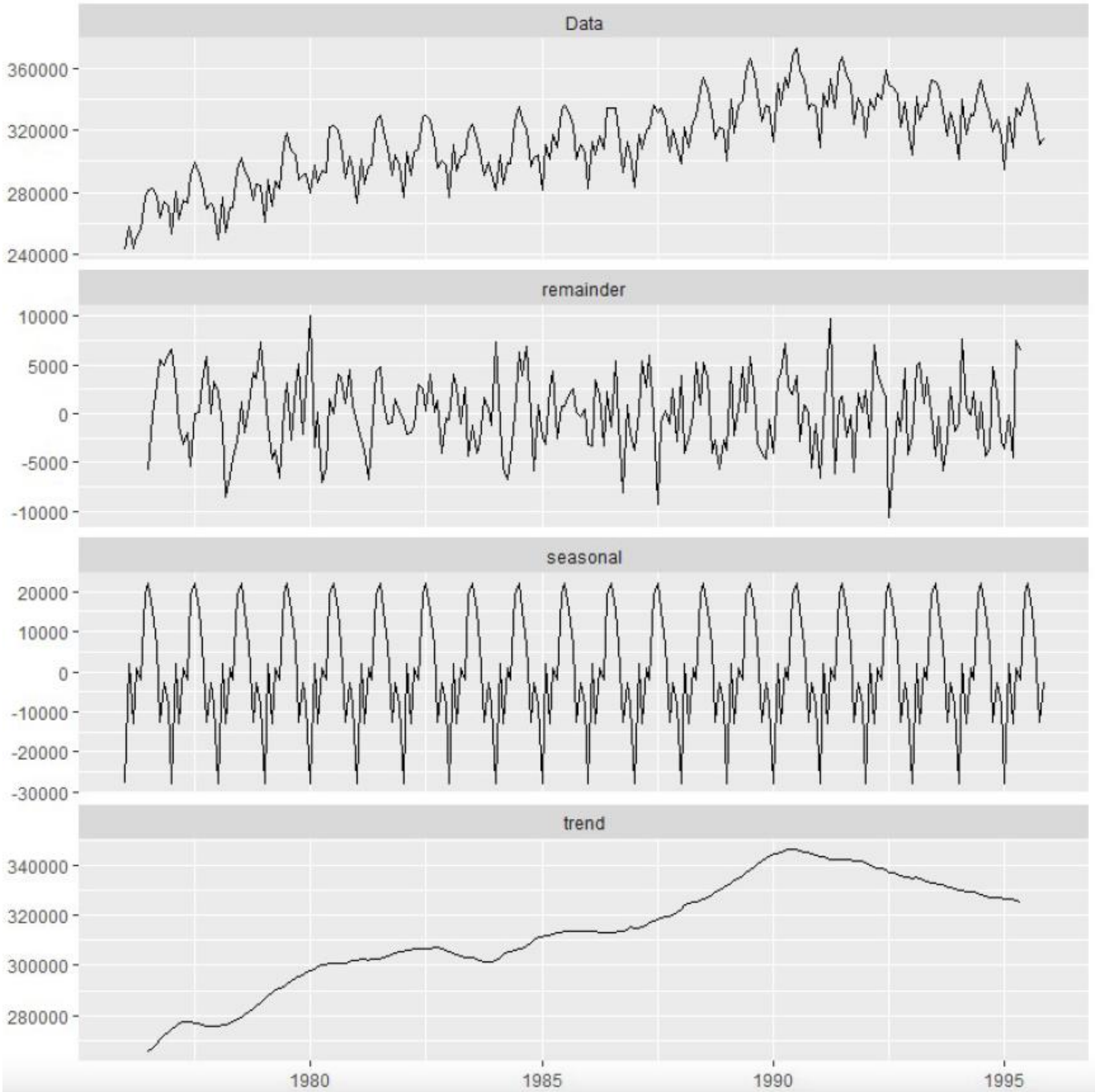
In conclusion, this study of the seasonal patterns of births in mainland China using a large sample found that Chinese migration and the ‘Spring Festival effect’ jointly determine the seasonality of births.

Figure 1.1: Decomposition of monthly births in China. The observed time series equals the sum of annual, seasonal and random trends.



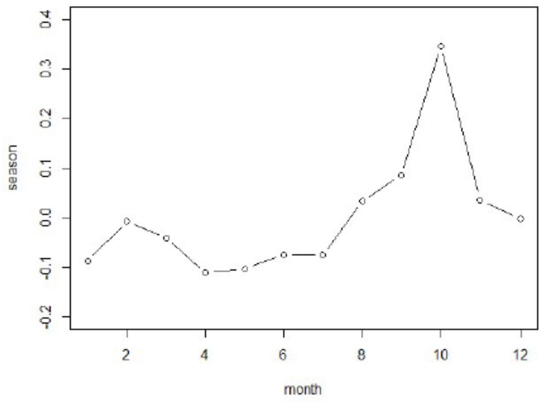
Note: Data were from the fifth National Population Census (2000) with 3,874,962 observations taken into account.

Figure 1.2: Decomposition of monthly births in the United States.

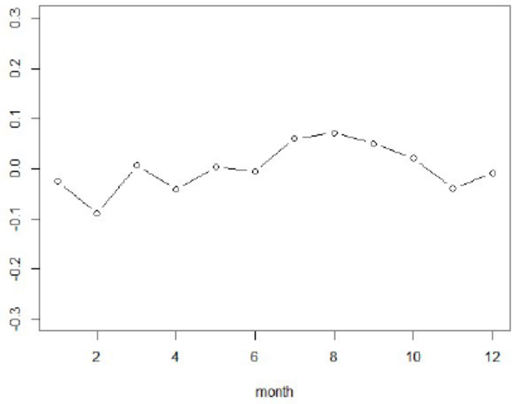


Note: The observed time series equals the sum of annual, seasonal and random trends. Data from the 2000 Decennial Census, with 75,015,903 observations taken into account.

Figure 1.3: Seasonal pattern of births in (a) China and (b) the United States.



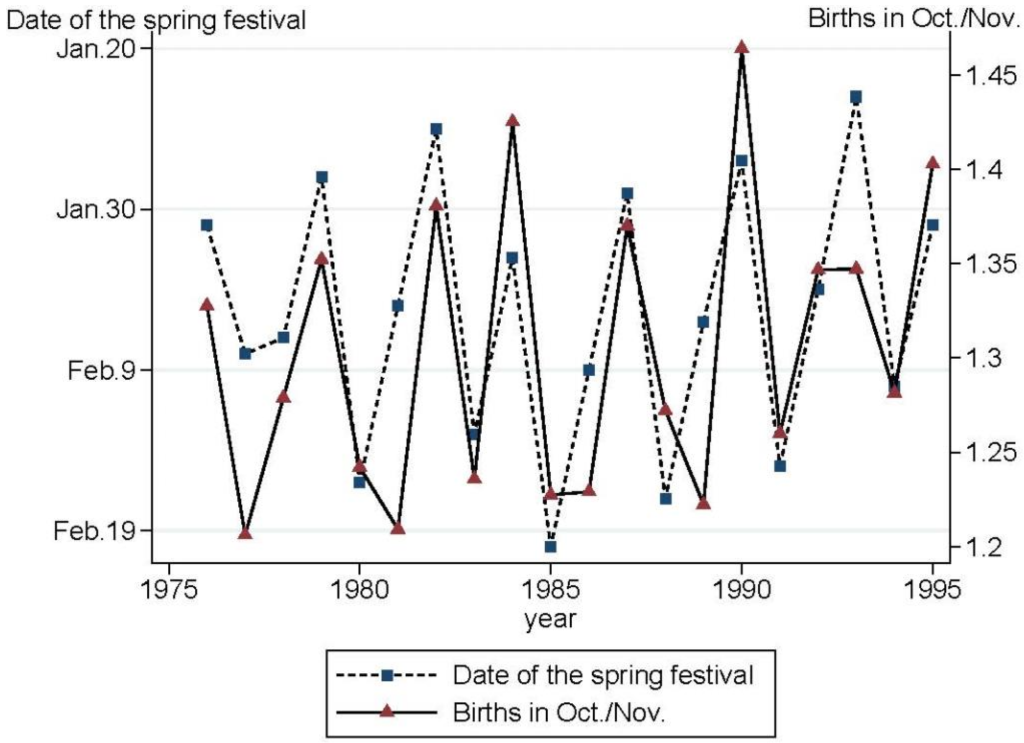
(a) China



(b) The United States

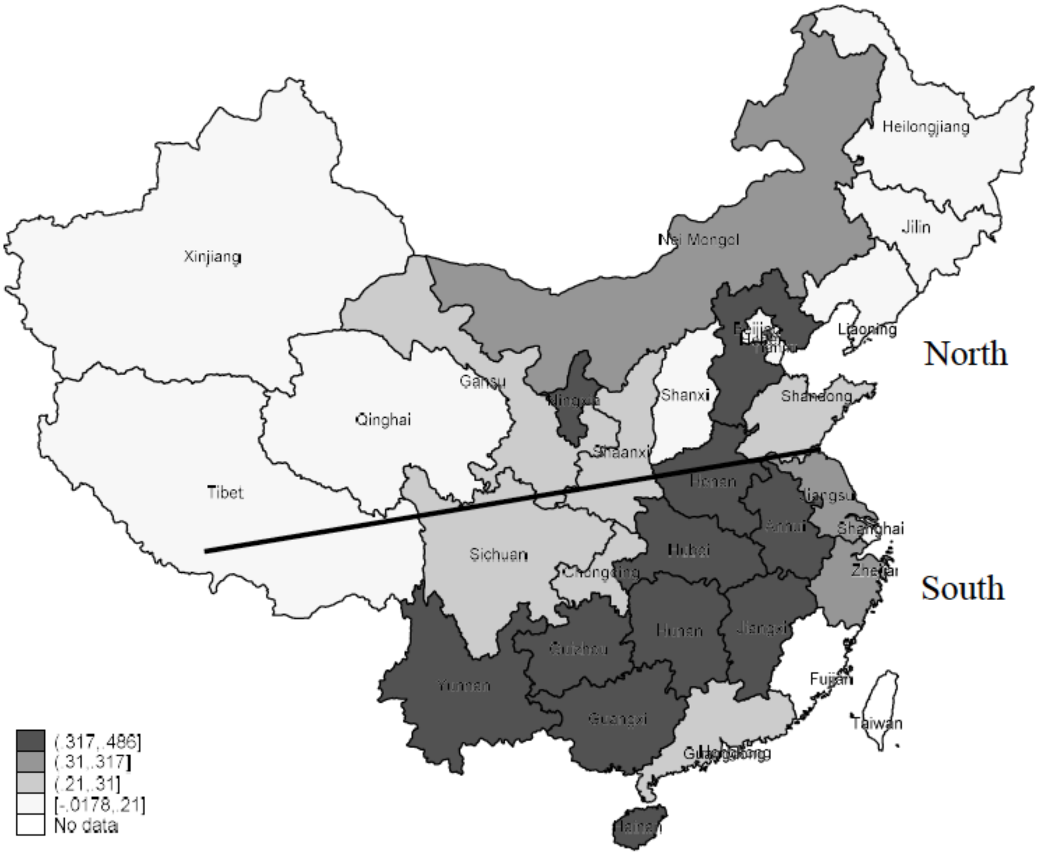
Note: The seasonal trend was extracted from the decomposition of the time series in Figs 1 and 2. The *y*-axis represents the magnitude of the fluctuation from the average.

Figure 1.4: Correlation between the timing of the Spring Festival and proportions of births in October and November.



Note: Earlier (January) Spring Festivals are correlated with higher proportions of October births relative to November births. The left-hand *y*-axis represents the solar calendar date of the Spring Festival. The right-hand *y*-axis represents the proportion of births in October relative to births in November. The *x*-axis is the time series year (1976–1995).

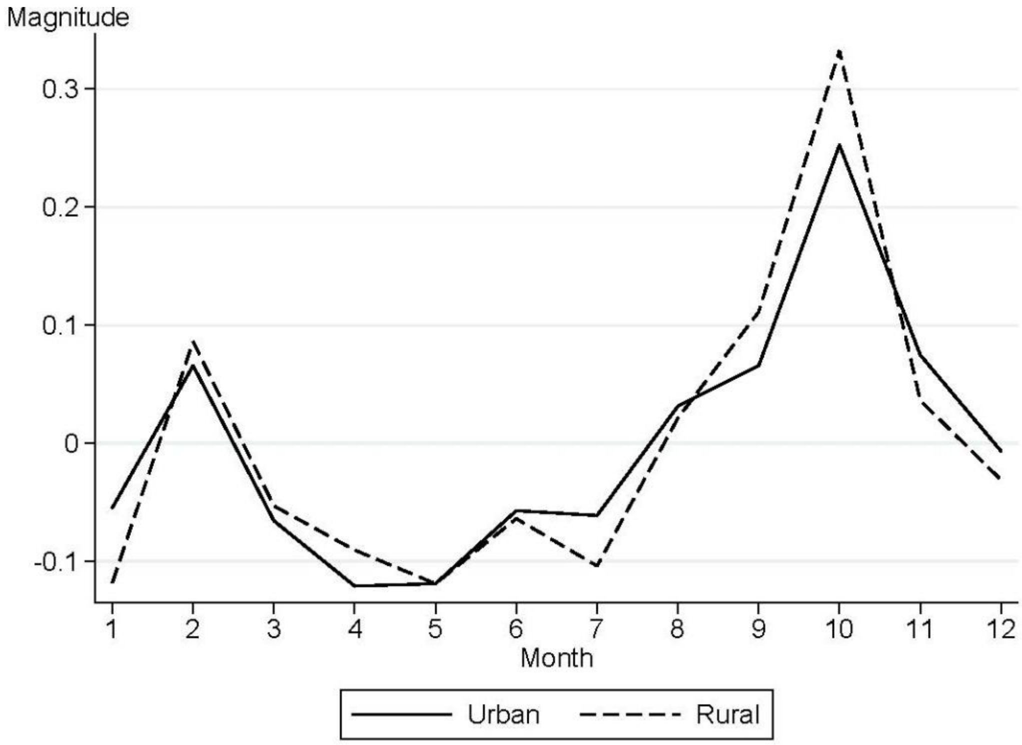
Figure 1.5: Average amplitude of births in October 1976–1995 by Chinese province, calculated using equation (6).



[1976-1995]

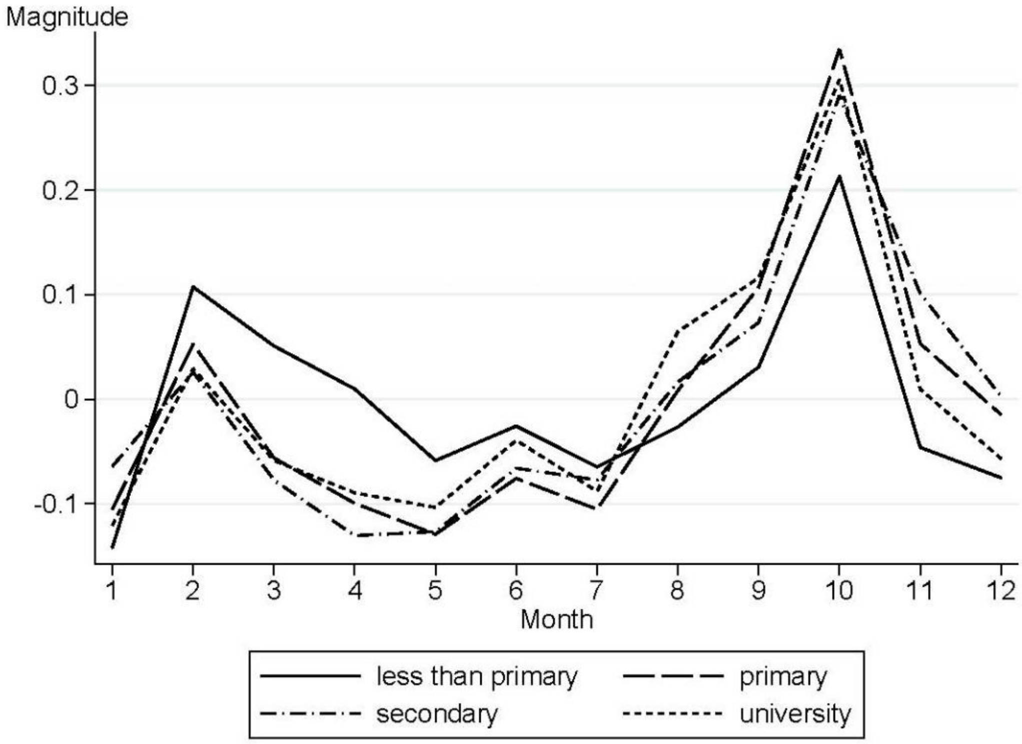
Note: The darker the shading, the more children born in October in that province than the monthly average.

Figure 1.6: Average monthly birth amplitude by urban–rural residence.



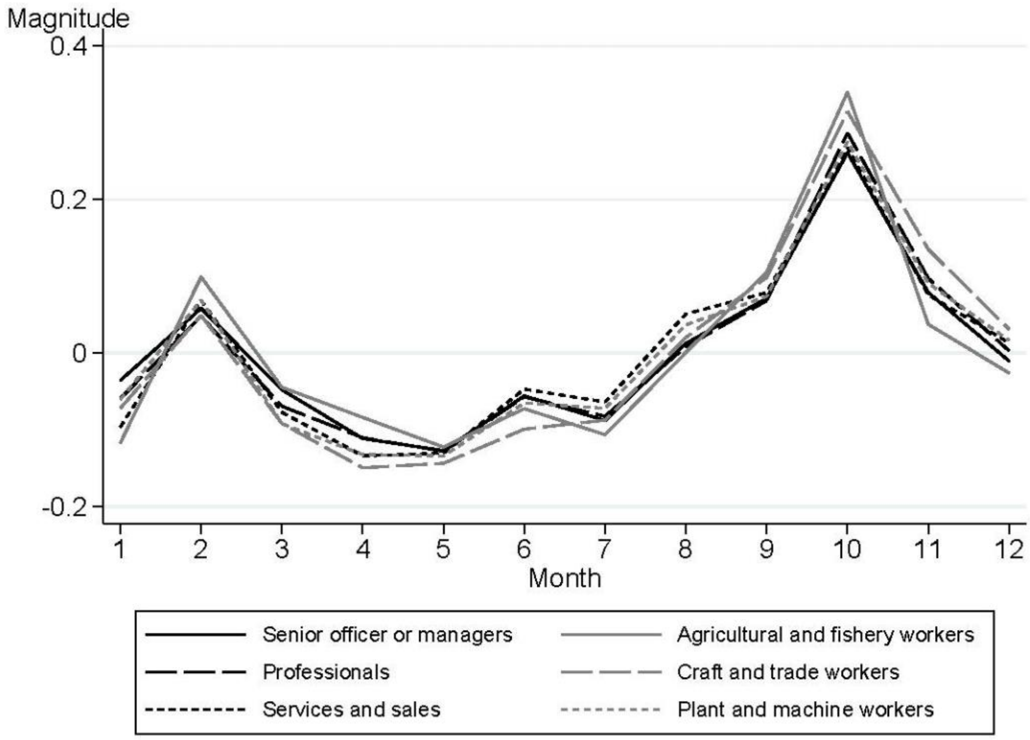
Note: The *y*-axis represents the average month-length-corrected monthly amplitude between January 1976 and December 1995.

Figure 1.7: Average monthly birth amplitude by parents' educational attainment.



Note: The *y*-axis represents the average month-length-corrected monthly amplitude between January 1976 and December 1995.

Figure 1.8: Average monthly birth amplitude by parents' educational attainment.



Note: The *y*-axis represents the average month-length-corrected monthly amplitude between January 1976 and December 1995.

Table 1.1: Comparison of monthly amplitude of births in urban and rural areas of mainland China, FNPC, 2000

	t-test	K–S test
	Rural	Rural
Urban	8.94***	0.01***

Note: The null hypothesis for the *t*-test is that the average month of birth is the same in urban and rural sample. The null hypothesis for the Kolmogorov-Smirnov (K–S) test is that the urban sample has the same distribution of monthly births as the rural sample. *$p \leq 0.1$; **$p \leq 0.05$; ***$p \leq 0.01$.

Table 1.2: Monthly amplitude of births by parents' education level, FNPC, 2000

	t-test			K–S test		
	Primary	Secondary	University	Primary	Secondary	University
Less than primary	20.29***	19.73***	7.33***	0.03***	0.03***	0.02***
Primary	—	2.07**	1.88*	—	0.01***	0.01***
Secondary	—	—	2.38**	—	—	0.01***

Note: The null hypothesis for the *t*-test is that the average month of birth is the same in two samples. The null hypothesis for the Kolmogorov–Smirnov (K–S) test is that the host sample has the same distribution of monthly births as the partner sample. *$p \leq 0.1$; **$p \leq 0.05$; ***$p \leq 0.01$.

Table 1.3: Monthly amplitude of births by father's occupation

	t-test					K–S test				
	Agriculture	Professional	Trade	Service	Plant	Agriculture	Professional	Trade	Service	Plant
Manager	1.86*	2.73***	7.48***	4.13	3.34***	0.01***	0.01**	0.02***	0.01***	0.01***
Agriculture	—	1.96*	11.97***	4.59***	3.05***	—	0.01***	0.01***	0.01***	0.01***
Profession	—	—	5.02***	1.27	0.49	—	—	0.02***	0.01***	0.00
Trade	—	—	—	4.47***	5.08***	—	—	—	0.01***	0.01***
Service	—	—	—	—	0.02***	—	—	—	—	0.00

Note: The null hypothesis for the *t*-test is that the average month of birth is the same in the two samples. The null hypothesis for the Kolmogorov–Smirnov (K–S) test is that the host sample has the same distribution of monthly births as the partner sample. *$p \leq 0.1$; **$p \leq 0.05$; ***$p \leq 0.01$.

Chapter 2

The Long-run Effect of Transportation Infrastructure on Economic Growth: Evidence from Northeastern China

2.1 Introduction

The question of whether access to transportation infrastructure promotes or discourages economic growth is a long-running and controversial debate in economics and other social sciences. Easy access to traffic lines may boost the flow of goods, labor, and information, and hence promote economic growth (Calderon and Serven, 2004; Canning and Pedroni, 2008). Yet, it may discourage economic growth by increasing corruption (Tanzi and Davoodi, 1998) and heightening the urban agglomeration effect (Glaeser and Gottlieb, 2009; Greenstone *et al.*, 2010). It is challenging to find the causal evidence that can resolve this debate, and extant findings remain ambiguous. I approach this debate by analyzing the construction of the Chinese Middle East Railway—railroads built under Tsarist Russia in Northeast China—and its consequences on the economic growth over a century later.

Before the novel coronavirus pandemic 2019, China was experiencing rapid economic development that was unhindered for over 40 years. The role of transportation infrastructure in its economic development has been a subject of intense research. The expansion of high-speed rail in China in the twenty-first century has manifested a temporal and geographic convergence with economic development. Scholars suggest that high-speed rail has had a significant stimulating effect on China's regional economic growth (Yao *et al.*, 2019; Ke *et al.*, 2017; Chen and Haynes, 2017). For fixed factor endowments, the improved access to markets and ideas should benefit all regions of the country, as evident in the United States. Indeed, in the United States, the expansion of transportation infrastructure also expanded existing cities and created new cities, which then turned into engines of growth for the whole country.

Policymakers have since considered the long-term causal effect of transportation more intensively. Devarajan *et al*. (1996) pointed out the negative or insignificant effect of transportation investment on economic growth based on evidence from developing countries. Glaeser and Gottlieb (2009) argued that transportation infrastructure has shortened distances between urban and rural areas; the flow of rural populations into cities has created an urban agglomeration effect, which has also deepened the inequalities between urban and rural areas. However, most researchers generally agree on the positive effects of infrastructure on economic output.

It is, however, challenging to identify the causal effects of transportation infrastructures because their effect on economic development is always endogenously determined. Scholars have attempted to use quasi-natural experiments to identify the effects of transportation infrastructure. Banerjee *et al*. (2020) addressed the problem of the endogenous placement of networks by examining the tendency for these networks to connect historical cities. This can be regarded as an exogenous source of variation in transportation network access. Yamasaki (2017) studied the causal effect of railroad access on technological progress by digitizing novel datasets of factories and railroad networks in the late nineteenth and early twentieth century Japan, using the cost-minimizing path between prioritized destinations as an instrument.

In this study, I use a natural experiment to estimate the causal effect of the railway on local economic growth in Northeast China. My identification strategy is based on a historical event in the late nineteenth century: The Russian Empire constructed the Chinese Eastern Railway (CER) in Northeast China, directly connecting important cities in the far east of Russia (Chita and Vladivostok) and two Chinese cities (Harbin and Dalian). I use the straight lines connecting Chita and Vladivostok (CV line) and the line connecting Harbin and Dalian (HD line) as instruments to identify the causal effect of the railway on the local economy.

The strategy employed in this study has several advantages. First, it provides us with a relatively exogenous source of variation in the access to transportation networks. Compared with some previous studies that used historical lines connecting domestic cities (e.g., Banerjee *et al*., 2020; Yamasaki, 2017), my study uses an exogenous variable originating from a foreign country as an instrument. Second, this exogenous variation was introduced at least 110 years before the commencement of this study in 2013, leaving ample time for the patterns of economic activity to relocate and establish.

We can therefore ask what the long-term level effect of being close to the line (and hence to transportation) was between 2013 and 2018.

I use the data of 180 counties in Northeast China for 2013–2018 and find that more advanced railway networks indeed promote the local economy. A 1% increase in railroad length leads to a 0.3% increase in the gross domestic product (GDP) and per capita GDP. The effect of railway networks on per capita GDP growth is insignificant. I also analyze the possibility that an advanced railway infrastructure could lead to a crowd-in effect for above scale firms, and I find that the transportation infrastructure has a significant positive effect on the number of firms.

Another concern for the rationality of the instrument used is whether the Northeast railroad network expands surrounding the CVHD line or the segment city, Harbin. In this pioneering study, I set up a series of virtual straight lines as a placebo and replaced the instrumental variables with the distance from each village to these straight lines. The results show that the coefficients of the true instrumental variable straight lines are significantly better than those of the adjacent angles. This approach strongly supports the rationality of the selected instrumental variables.

The remaining chapter is organized as follows. Section 2 describes the background of the CER and the exogeneity of the instrument. Section 3 describes the data and main variables. Section 4 presents the results and robustness checks, and section 5 concludes.

2.2 Background

2.2.1 History

The CER is the historical name for a railway system in Northeast China. After the Treaty of Aigun (1858) and the Convention of Peking (1860) were concluded between the Russian Empire and the Qing dynasty of China, the Russian Empire was granted the right to inhabit Ussuri Krai, a part of modern Primorsky Krai, including the largest city of far-eastern modern Russia, Vladivostok. To strengthen their control of the outer Xing'an Mountains and the Ussuri Krai, the Russian Empire constructed the world's longest railroad, the Trans-Siberian Railway, to connect the densely populated western area and the sparsely populated Far East. However, the eastern part of the Siberian Railway required a detour along the outer regions of China's Heilongjiang Province, which lengthened the distance and made construction difficult. Therefore, Russian engineers proposed building the railway directly from Chita to Vladivostok via Manchuria under the control of the Qing dynasty. In 1896, the Russian Empire and the Qing dynasty signed the Sino-Russian Secret Treaty, which allowed the Russian Empire to construct a railroad across the Heilongjiang province of China. The construction of the railroad, which was named the CER, started in 1897 and was completed in 1902. The original railway system linked Chita and Vladivostok in Russia, and went from Manzhouli city to Suifenhe city in China, with a branch line from Harbin to Lushun. As shown in figure 2.1, the original T-shaped railway consisted of three branches, centered in Harbin city: the western branch, from Manzhouli to Harbin; the eastern branch, from Harbin to Suifenhe; and the southern branch, from Harbin to Lushun.

Russia lost much of the South Manchurian branch to Japan after the Russo-Japanese War in 1905. The railway line from Changchun to Lushun—transferred to Japanese control—became the South Manchuria Railway. In 1932, Manchukuo (a puppet state of the Empire of Japan in Northeast China and Inner Mongolia from 1932 until 1945) was established. The Middle East Railway was jointly controlled by the Soviet Union and Manchukuo, and its name was changed to North Manchuria Railway. Eventually, in 1935, the USSR sold its rights to the railway to the Manchukuo government. The CER was unilaterally controlled by Japan until 1945, after which it came under the joint control of the USSR and China. Finally, in 1952, the USSR transferred (free of charge) all its rights to the CER to the People's Republic of China.

2.2.2 Exogeneity

This study uses the exogeneity of the straight line connecting Chita and Vladivostok to establish a link with economic development in Northeast China. This identification strategy is supported by the following evidence. First, before the construction of the CER, cities on the CV line were no different from most other cities in Northeast China. The two cities at the ends of the CER, namely, Manzhouli and Suifenhe, were very small towns, almost non-existent before the construction of the CER. Only after the construction of the CER did many people and merchants come to the two cities, thus promoting the development of the local economy.

Second, the original purpose of the railway construction was to promote Russia's development in the Far East. Initially, according to the Sino-Russian Secret Treaty, the

CER was ostensibly owned jointly by Russia and China, but the actual owner was the Russian government[1]. Thus, the development of the economy of Northeast China was not a primary goal of the CER. Except for Qiqihar and Harbin, which are on the CV line, the railway did not connect the other large cities in the Heilongjiang province.

Third, since its construction, the CER remains the centerline of railroads in Northeast China. During the period that the CER was taken over by Japan (1905–1945), the South Manchuria Railway Co. constructed many bunch railroads to connect their military towns with the main railway. The width of the CER also changed from the Russian standard to the Japanese standard. However, through all the changes, Harbin remained at the center of the T-shaped line.

In previous studies, some historical lines in China have been used to identify the causal effect of transportation infrastructure. Li *et al.* (2012) considered the construction of some highways in China to be influenced by post roads in the Ming dynasty. Banerjee (2020) also used the straight lines interconnecting China's historical cities and the new "Treaty Ports" constructed by Western colonial powers as instruments. However, the connection between domestic cities may have existed before the construction of the transportation infrastructure, leading to uncertainty about the reliability of the instrument. The CER is a special sample because it was constructed for another country. Before the construction of the CER, the cities on the CV line were small, almost non-existent towns, which ensures their exogeneity to the local economy. Additionally, since its construction, the CER has always been the main railway in that region; thus, there is no ambiguity that the main benefits of economic growth accrue from the CV line.

2.3 Data

2.3.1 Datasets

[1] In the first paragraph of the Sino-Russian Secret Treaty, the contract stipulates that the Sino-Russian Dousheng Bank will build and manage the railway, but this bank was, in fact, controlled by Russia, placing the control of the railway under Russian governance. Before signing the contract, Sino-Russian Dousheng Bank and the Russian government had reached an agreement stipulating that 70% of the railway shares should belong to the Russian government and the remaining 30% should be subscribed to by private individuals. Soon after the contract was signed, the Hua-Ru Dao Sheng Bank decided that all the shares should be controlled by the government. On December 29, 1896, the Middle East Railway Company publicly listed its shares for sale in St. Petersburg. Owing to the hasty notification and the value of each share, which was as high as 5,000 rubles, Russian and Chinese businesspeople could not subscribe, and the "provision" ended only a few minutes after it started. The 5 million rubles of shares were thus all held by the Russian Ministry of Finance, making it the sole shareholder and actual controller of the CER.

Panel data on the economic variables of the counties

The main dataset comes from the Chinese County Statistics Yearbook (CCSY), collated by the Chinese National Bureau of Statistics for the period 2000–2018. The dataset provides the main socio-economic variables for most Chinese counties. Unfortunately, county-level GDP data could only be found for 2013–2018, so this period is the focus of the main regressions.

Geographic data

This study requires precise geographic information on the distribution of railroad and highway networks, river transport facilities, and the border lines in each county. The geographic data used in this study come from the National Catalogue for Geographic Information. In this study, all geographic information is processed using ArcGIS software.

Panel data on industrial firms

The firm-level data used in this study are from the Annual Survey of Industrial Firms (ASIF) supplied by China's National Bureau of Statistics for the period 2000–2013. The survey covers all industrial state-owned enterprises (SOEs), and non-SOEs with sales above RMB 5 million. Here, "industry" includes mining, manufacturing, and public utilities. In this study, I focus on manufacturing firms only.

The dataset provides information on the address and regional codes of each firm so that it can be matched with the CCSY data. During the sample period, however, the administrative boundaries and city codes experienced some changes. Using the 1999 National Standard (GB/T 2260-1999) as the benchmark codes, I convert the city codes of all the firms into these benchmark codes to achieve consistency throughout the whole sample period.

A potential sample selection issue is that the CCSY does not cover all Chinese counties. Because the CCSY data report the total output of enterprises above the average size of each county, I can compare it with the aggregated firm data using ASIF, which covers all firms above the average size.

The annual trend of the average output of firms above the average size is shown in figure 2.2. The total revenues calculated using CCSY and ASIF data are close to each other; thus, there is no serious sample selection problem in the dataset.

2.3.2 Variables

Distance to the connection lines

The instrument variable used in this study is the distance from each county to the nearest connection line. The straight lines connecting the CV and the HD lines are where the original T-shaped CER was constructed. Two problems should be addressed: First, as county shapes are irregular and vary across counties, I use ArcGIS to calculate the center of gravity in each county, and then to calculate the distance from each center point to the CV and HD lines. Second, as shown in figure 2.3, the distance to the CV line is measured from each county to the straight line because the CV line extends across the Northeast China area; but for some counties on the upper and right side of the HD line, I use their distance to the endpoint or Harbin city as an estimation for their distance to the HD line.

In the regression analysis, the distances from the counties to the nearest ports, airports, and regional center cities (Harbin, Shenyang, Changchun, and Dalian) are also included among the control variables. These distances are also defined as the distance between the gravity centers of the objects.

Railroad length

Based on data from the National Catalogue for Geographic Information, I use ArcGIS to calculate the railroad length in each county. As shown in figure 2.1, the railways include both the central and branch railroads. This study only includes railroads that can carry passengers, and smaller railroads such as mining railroads are excluded.

Highway and traffic river length

In the regression analysis, I also control for the density of the highway and river traffic networks. The highway network may potentially affect economic development as well as the construction of the railway network (Zhu *et al.*, 2021). As shown in figure 2.4, in some directions, such as on the connecting line from Harbin to Dalian, the rail and road networks even overlap. Thus, the causal effect of railroads can only be identified when the length of roads in each county is accounted for.

For this reason, I also calculate the length of the rivers within each county because rivers can also be used for transportation in the summer seasons. In China, there are four classes of tributaries. As shown in figure 2.5, only the length of first-class rivers is used as a control variable in this study, and no other classes of rivers are included.

Because the lengths of railroads, highways, and rivers are correlated with the area of each county, the latter is controlled for in all the regression equations. The area variable is drawn from the CCSY.

Distance to the nearest ports and central city

Another concern regarding the validity of the instrument is that being closer to the traffic lines also means being closer to the central city or ports. Therefore, I calculate the distance from the center of gravity of each county to the central city and the nearest major ports in the Northeast. The central cities are the capitals of each province: Harbin, Changchun, Shenyang, and an economically developed city, Dalian. The major ports include the Dalian port and the Dandong port.

2.3.3 Discriptive statistics

Table 2.1 shows the descriptive statistics. The full sample used in this analysis covers 198 counties in Northeast China for the period 2000–2018, including 3,729 observations. However, county-level GDP data are only available from 2013 to 2018; therefore, 1,369 and 990 observations are used for variables $\ln(GDP)$ and $\ln(GDP\ per\ capita)$ and for $\ln(GDP\ per\ capita\ growth)$, respectively. The variables indicating distances or lengths do not have measurement units (i.e., meters or kilometers); therefore, I use their logarithm values.

Before performing the regression analysis, I first observe the relationship between the distribution of the rail network and the instrumental variables through the figures. In figures 2.6 and 2.7, the purple straight line represents the connecting line between CV and HD. We can see from figure 2.6 that the two major railroad traffic lines in the Northeast are located around the purple straight line. Moreover, the closer the area to the purple straight line, the denser the branch railroads are, and the area away from the purple straight line is sparser. Figure 2.7 shows a map of the rail density in different regions, with darker colors indicating greater rail density. We can clearly see that the dark black areas are concentrated around the purple line, especially on the line from

Harbin to Dalian. The northern part of the CV line and the Inner Mongolia region (left side of the image) have a lower railroad density.

2.4 Model

In the first step, I use the following model:

$$Y_{ct} = \beta lnL_c + X_{ct}\Lambda + \rho_c + \tau_t + \varepsilon_{ct} \quad (1)$$

Where Y_{ct} constitutes the outcome variables of interest for county c and year t; lnD_c is the logarithm of railroad density in county c; X_{ct} is a vector of county-specific controls; and ρ_c and τ_t are the county and year fixed effects, respectively. The standard errors are clustered at the county level. This study is interested in the local average effect of β_{ct}, the effect of railroad density on outcome Y.

When no unobservable variables included in ε simultaneously affect the railroad density and outcome Y, the ordinary least squares estimator β is estimated as a causal effect. This is obviously not the case here. Many invisible factors hinder economic development, while also affecting the construction of railways. Even though river density is controlled for, other geographical conditions such as mountains, swamps, and basins are unobservable in the model. Mountainous areas are always hard to develop owing to their remoteness and inaccessibility, which also makes the construction of railroads difficult. These omitted variables will lead to a bias in β.

To address the bias caused by omitted variables, I use the instrumental variable approach. The first stage of the two-stage least squares regression is as follows:

$$lnL_c = \gamma lnD_c + X_{ct}\Gamma + \rho_c + \tau_t + \theta_{ct} \quad (2)$$

In the proposed instrument, as discussed in section 3, L_c is the distance from the centroid of county c to the CV or HD line, depending on which one is closer. To prevent the instrument from influencing the outcome variables through other channels, X_{ct} includes a series of controls: the county area, population, the logarithm of highway and river length in each county, and the logarithm of distance from each county to the central cities and the nearest ports.

2.5 Results

Table 2.2 presents the results of the regression for estimating the effect of railroad length on the logarithm of GDP. Columns (1), (4), and (7) only control the land area and population of the county. The distance to the nearest navigated rivers and border lines may affect the traditional transportation modes, which existed before the railroads were constructed. As discussed in section 3, the railroad overlaps the highway in some areas. To exclude the effect of shipping and road transportation, columns (2), (5), and (8) control for the lengths of highways and rivers, and the distance from each centroid of the county to the nearest border line. Another concern is that, as the instrument, the virtual line should not affect economic development through channels other than railroads. In case the virtual line itself goes through some developed cities and ports, it may affect economic development through these important places. Columns (3), (6), and (9) show the result of the specification controlling the distance from the regional central cities (Shenyang, Dalian, Changchun, and Harbin) and the important ports (Dalian and Dandong). As shown in column 3 of Table 2, the ordinary least squares coefficient of $ln\,(Railroad\ Length)$ is not significant, while the instrumental variable estimator is significantly positive at the 0.3% level. This result points to the presence of an omitted variable bias. From the result of the first stage, when the distance from the virtual CVHD line increases by 1%, railroad length significantly decreases by 0.495%, controlling for the counties' area. From the second stage result, railroad length increases by 1%, and GDP increases by 0.304%.

Table 2.3 shows the results of the regression analysis of the effect of railway length on per capita GDP. From table 2.3 onward, I only report the results after controlling for all variables. The result of the ordinary least squares specification shows no significant effect of railroad length on per capita GDP. The coefficient of $ln\,(Railroad\ Length)$ at the second stage of the two-stage least squares regression is significant at the 1% level, indicating that per capita GDP is positively correlated with railroad length. A 1% increase in railroad length will increase the per capita GDP by 0.289%. Compared with the effect of railroad length on total GDP (0.304%), this similar result indicates that the mechanism causing the change in GDP is per capita GDP, and not population. Unfortunately, population data can only be accurate up to the 10,000 level; therefore, a direct result cannot be derived by regressing railroad length on the population.

In table 2.4, I examine the annual growth in per capita GDP. Column (3) shows the estimates of the effect of railroad length on per capita GDP growth. I calculate per capita GDP growth as the difference between the log per capita GDP growth for one year and the previous one, for each county, $ln(GDPpc_{c,t}) - ln(GDPpc_{c,t-1})$. The instrumental variable estimator is not statically significant. The figures are also negative and very small in magnitude, while the mean growth rates of these counties are in the range of 4 to 8%. Therefore, I conclude that railroad length does not affect per capita GDP growth. This result is consistent with Banerjee *et al.*'s (2020) finding.

The above results show that more intensive railway infrastructure will increase local GDP and per capita GDP, while the growth rate of per capita GDP was unaffected from 2013 to 2018. One potential interpretation of this result is that per capita GDP levels are higher in regions near the line and there is a possibility of displacement. For example, the placement of transportation may have a crowding-in effect, where firms relocate to be near the line. To validate this hypothesis, I examine the effect of railroad length on the number of firms above average size in each county (annual sales larger than 500 million RMB). Table 2.5 shows the results.

Column (3) of table 2.5 provides supportive evidence for the crowding-in hypothesis. The effect of railroad length on the number of firms above size is significantly positive at the 5% level. When the railroad length increases by 1%, the number of firms above scale will increase by 0.208. Another point is that the length of the highway is not significant in column (3), whereas it significantly and positively affects the annual growth of per capita GDP. This comparison indicates that railways play a more important role than highways in attracting large firms.

2.6 Robustness check

One obvious concern regarding the strategy used in this study is the relevance of the distance from the CVHD line and railroad density. Earlier in this section, I showed that proximity to the lines is positively correlated with proximity to transportation infrastructure. However, the intersection point of the CV and HD lines is located in Harbin, the provincial capital of Heilongjiang province. One may be concerned that the rail network in Northeast China is not centered on the instrumental variable (CVHD line) but rather in a radial pattern centered from Harbin city, and that the CVHD line is just one of the lines surrounding Harbin.

To check whether the rail network expands from the CVHD line or centrally exists around Harbin, I design a placebo test. With Harbin as the center, I choose 120 straight lines with angles ranging from 0 to 360 degrees, each with a difference of 3 degrees. I regress the distance from the center of gravity of each county to these straight lines on the density of the rail network within each county. In other words, I run regressions with these 120 straight lines to replace the CV line to find the correlation between the distance from these lines and the railway densities.

The result of the placebo test is shown in figure 2.8. The x-axis in figure 2.8 represents the angle of the placebo lines. The y-axis is the estimated coefficient, indicating the correlation between the distance from these lines and the railway densities, with 95% confidence intervals—the shadow area. For most placebo straight lines, the farther from such lines, the lower the railroad density in that county. The two lowest points of the coefficients, compared with the points around them, are the lines with an angle of 53 degrees and 153 degrees, corresponding to the CV line and the HD line, respectively. The coefficient of the CV line is more significantly negative than the HD line because the HD line ends in Harbin, while the CV line goes through Harbin and reaches the national border at the end. Thus, the railway network in Northeast China expands from the CVHD line, instead of Harbin city, which validates the instrument.

2.7 Concluding remarks

Using the CER as an exogenous instrument for the railway network in Northeast China, I examine the influence of the railroad on long-term regional economic development. Using panel data from a sample of 198 counties from 2013–2018, the estimation results provide strong evidence that railroad infrastructure has a significant positive long-term effect on regional GDP and per capita GDP, even over 100 years. This effect is the result of the stabilization of all short-term changes, such as the effect of infrastructure on the local labor market and direct investments. In particular, I use the connecting lines of two foreign cities as instrumental variables, as these railroads were not originally intended to facilitate domestic transportation.

However, I find no evidence that the railroad infrastructure affected income growth during this period. This result does not contradict the literature (Banerjee *et al.*, 2020). Economists argue that the effect of transportation facilities per se on regional economies is uncertain. For example, well-developed transportation facilities can facilitate the flow of goods and capital, but they can also accelerate the loss of talent in certain regions. The findings of this study on firm-level data also suggest that transportation development may have an agglomeration effect.

These results should not discourage those who believe that investment in transportation infrastructure can promote economic development. The northeastern region has been an important industrial zone in China since 1949. It was not until after the Reform and Opening that the economic center of China gradually shifted to the southern coastal cities. To this day, the Northeast region retains a well-developed railroad transportation network. As I stated at the beginning of this chapter, the epidemic has led to a renewed awareness of the important role of transportation in economic development. Further and more detailed research is needed to ensure that transportation investments play a greater role in post-epidemic economic development.

Figure 2.1: Chinese Eastern Railway and branch railways.

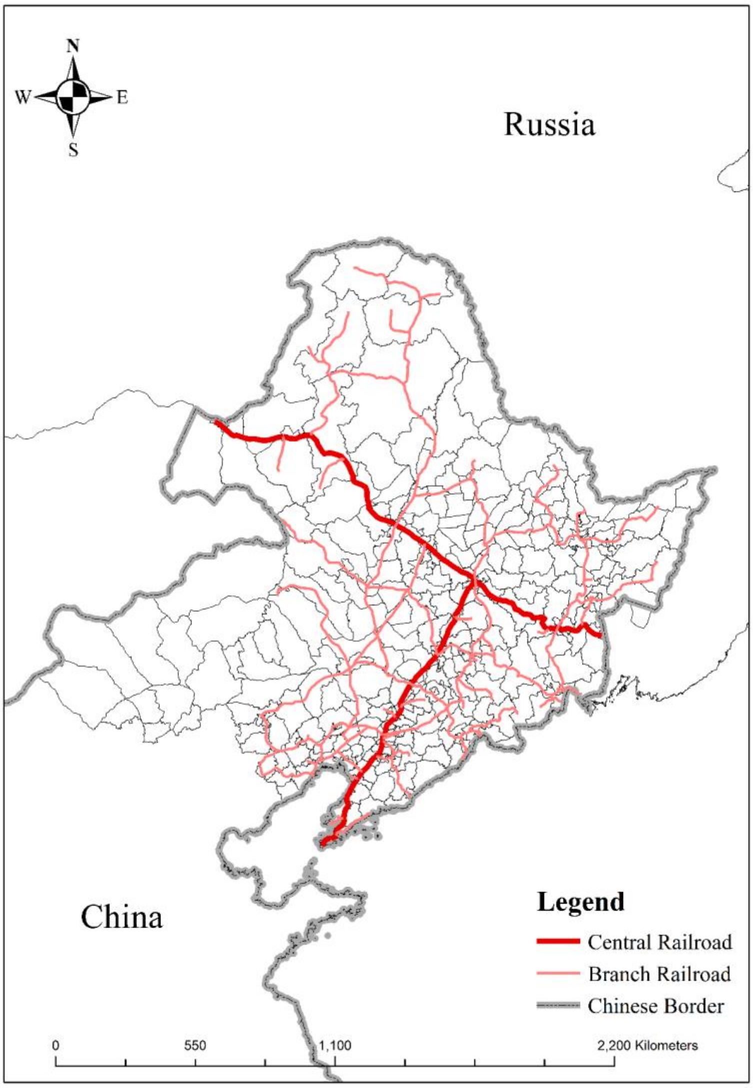


Figure 2.2: Comparison of average output from CCSY with ASIF.

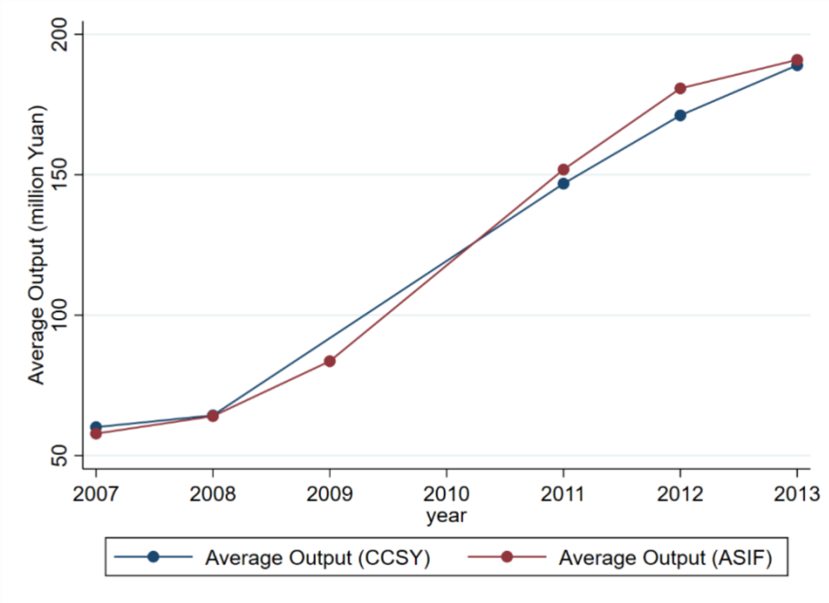


Figure 2.3: Center of gravities of the counties and the CVHD line.

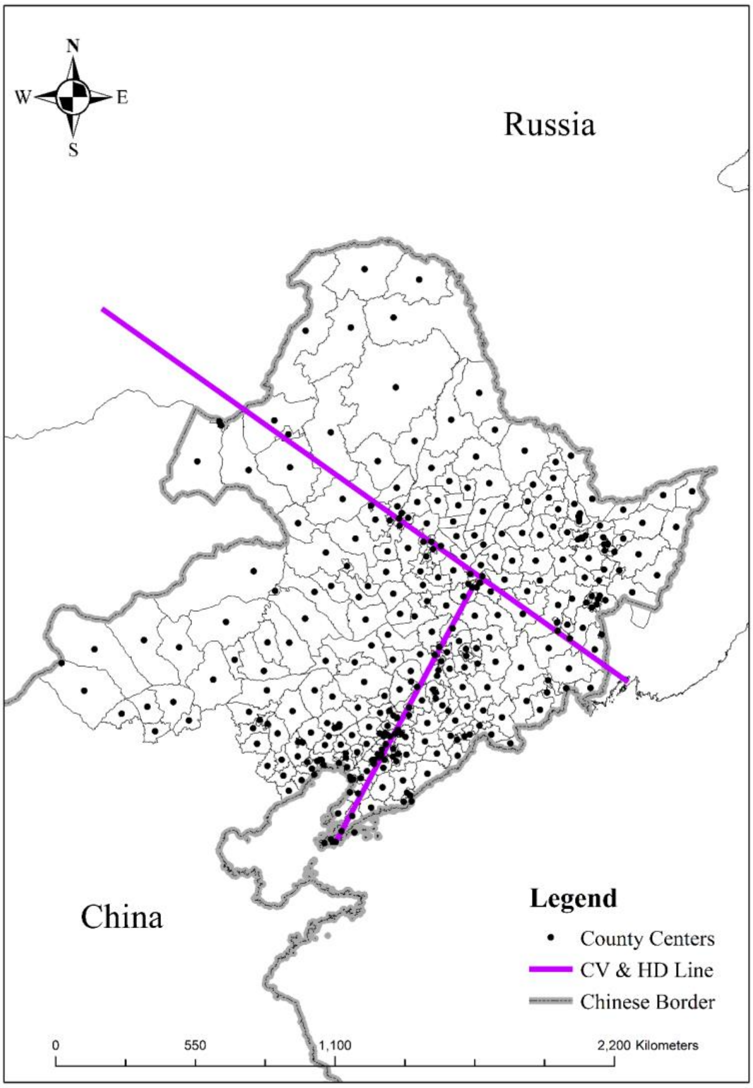


Figure 2.4: Highway network.

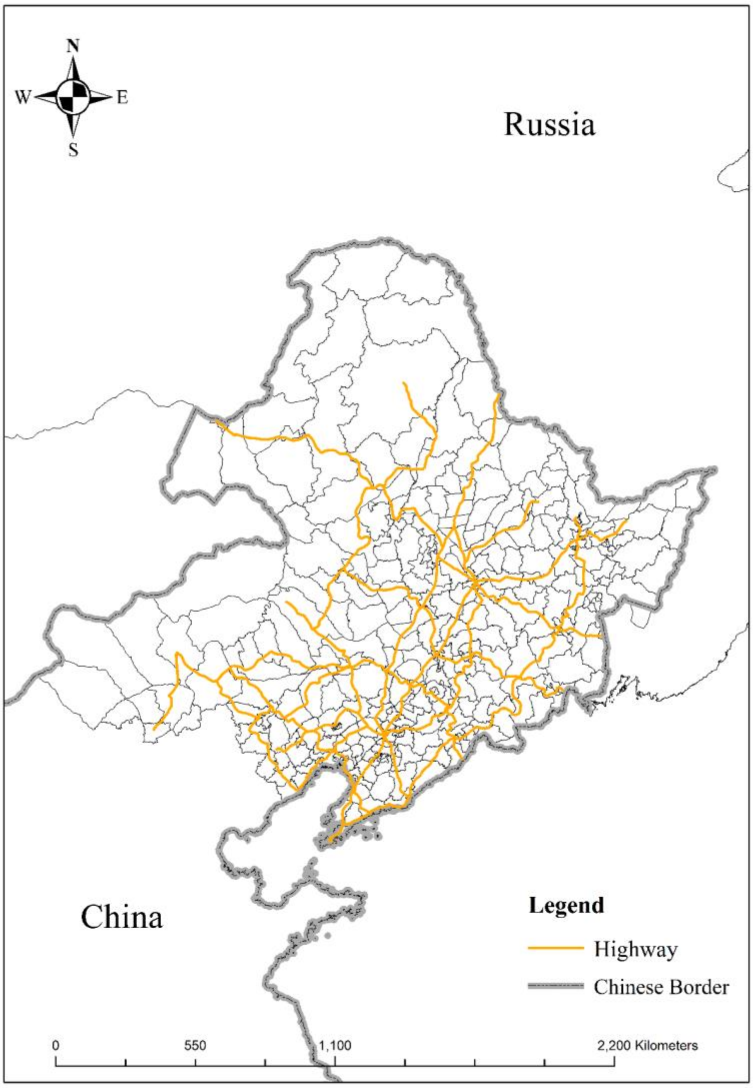


Figure 2.5: First-class river network.

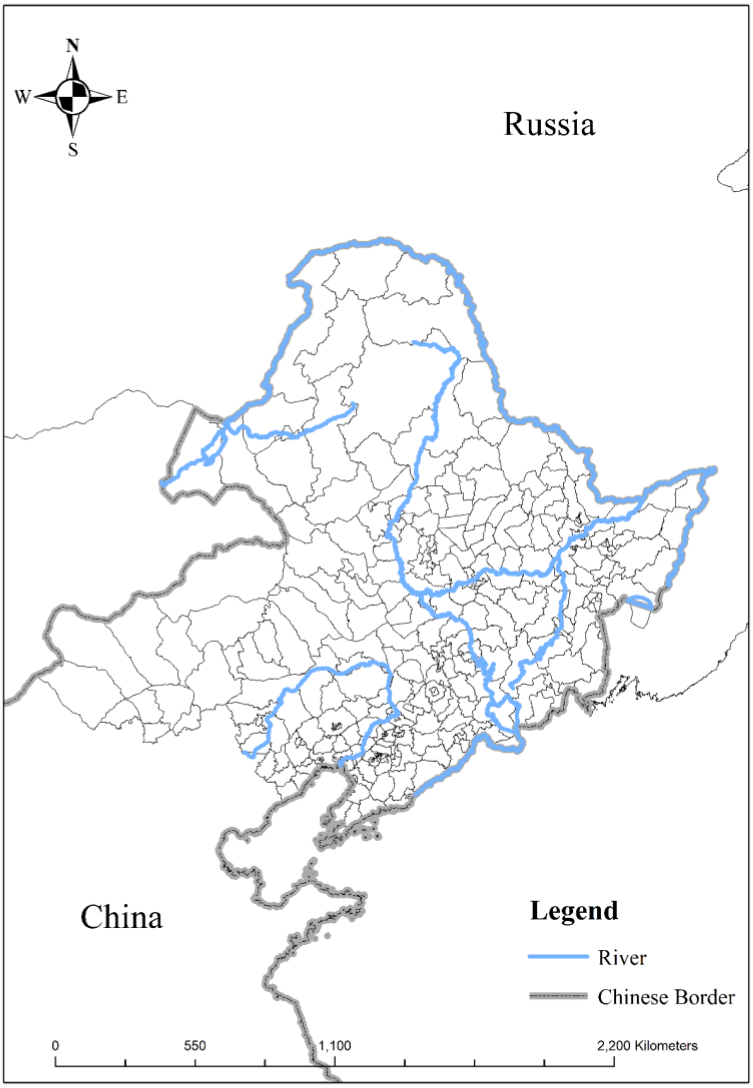


Figure 2.6: Railway network and the CVHD line.

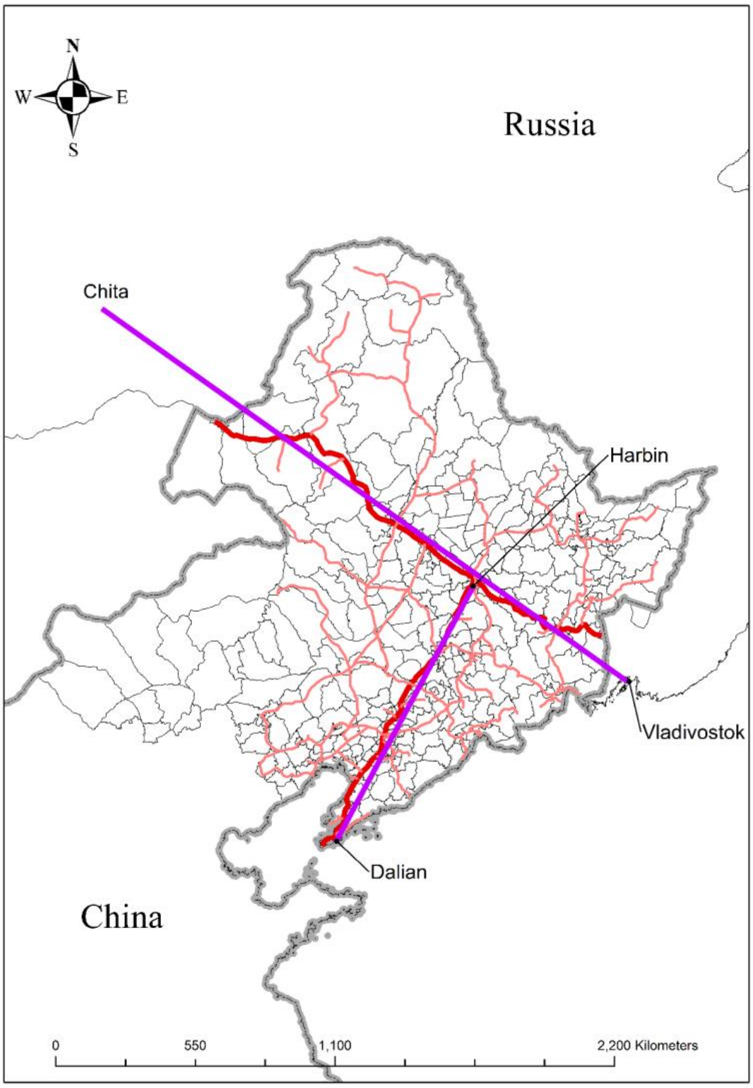


Figure 2.7: Railway density and the CVHD line.

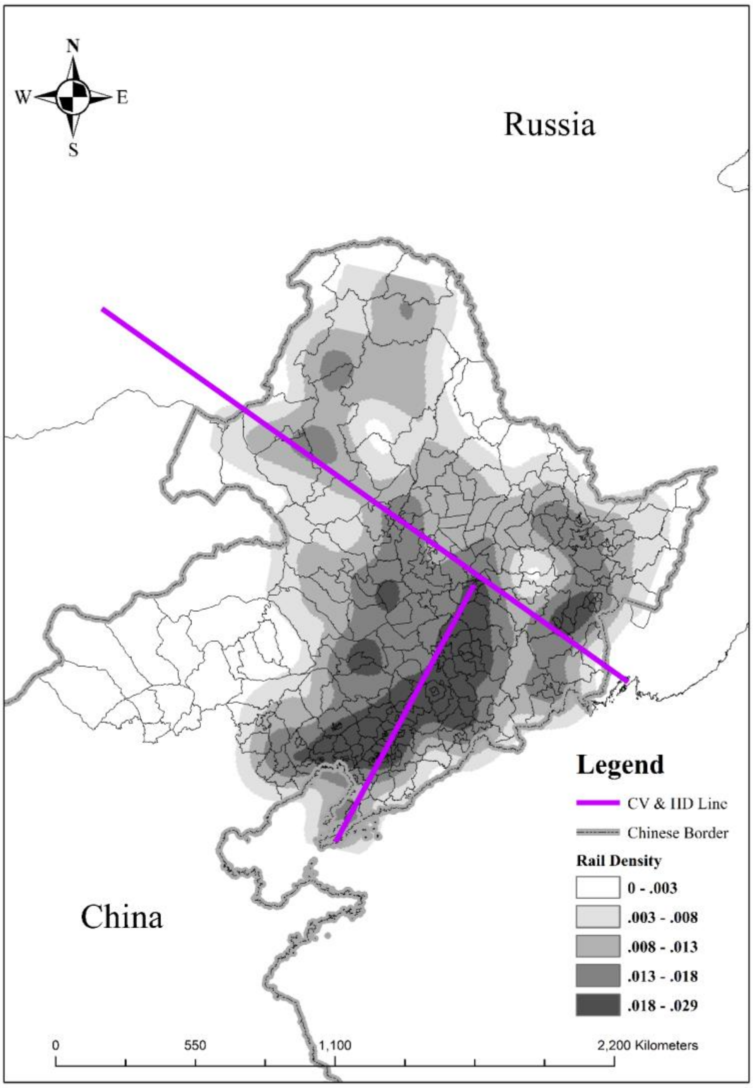
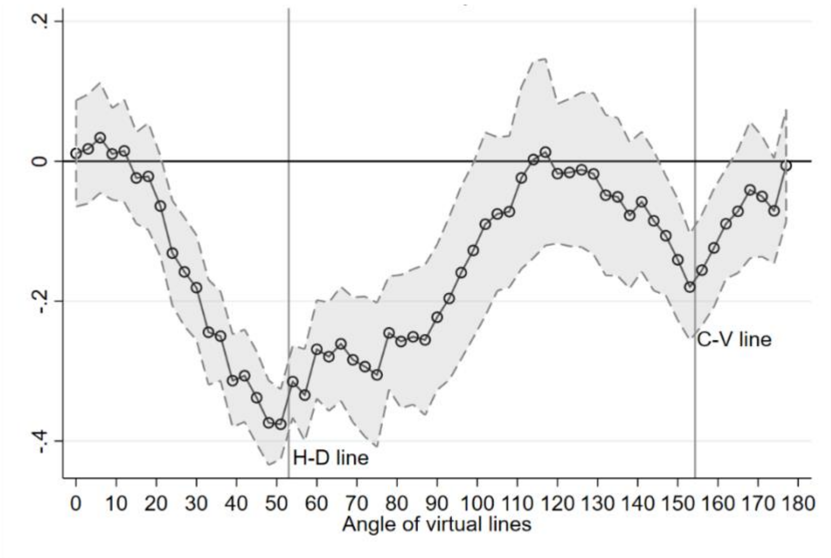


Figure 2.8: Robustness check: Distance to the placebo line on railroad density.



Note: The x-axis in represents the angle of the placebo lines. The y-axis is the estimated coefficient, indicating the correlation between the distance from these lines and railway densities. The shadow area covers the 95% confidence intervals of the coefficients.

Table 2.1: Descriptive statistics.

Variable	N	Mean	SD
ln(Distance to CVHD line)	3729	11.700	1.090
ln(Railroad Length)	3729	3.162	2.058
ln(GDP)	1369	12.190	0.873
ln(GDP per capita)	1369	6.496	0.589
ln(GDP per capita growth)	990	-0.060	0.137
ln(Area)	3729	8.436	0.868
Population	3729	390.100	243.300
ln(Distance to Dalian)	3729	6.490	0.568
ln(Distance to Shenyang)	3729	5.997	0.723
ln(Distance to Changchun)	3729	5.912	0.595
ln(Distance to Harbin)	3729	5.945	0.624
ln(Distance to Nearest Port)	3729	6.251	0.650
ln(Highway Length)	3729	3.216	2.090
ln(River Length)	3729	2.062	2.442
ln(Distance to Border Line)	3729	4.701	1.085

Table 2.2: Main result: The effect of railroad length on ln(GDP).

Indep. variable	OLS ln(GDP)			1st stage of 2SLS ln(Railroad Length)			2nd stage of 2SLS ln(GDP)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(Railroad Length)	0.016	0.006	0.013				0.485***	0.515**	0.304***
	(0.020)	(0.021)	(0.022)				(0.183)	(0.206)	(0.101)
Distance to CVHD line				-0.371***	-0.345***	-0.495***			
				(0.127)	(0.123)	(0.142)			
ln(Area)	-0.120**	-0.121**	-0.011	0.538***	0.488**	0.258	-0.325***	-0.318**	-0.081
	(0.060)	(0.061)	(0.077)	(0.203)	(0.206)	(0.199)	(0.126)	(0.131)	(0.088)
Population	0.002***	0.002***	0.002***	0.002***	0.001**	0.003***	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
ln(Highway Length)		0.040*	0.027		0.170**	0.192**		-0.054	-0.030
		(0.021)	(0.021)		(0.077)	(0.075)		(0.064)	(0.038)
ln(River Length)		0.015	0.012		0.077	0.052		-0.027	-0.002
		(0.015)	(0.015)		(0.056)	(0.057)		(0.037)	(0.023)
Distance to Border Line		-0.052	-0.144***		-0.168	-0.095		0.022	-0.074
		(0.036)	(0.050)		(0.121)	(0.182)		(0.079)	(0.080)
Distance to Nearest Port	No	No	Yes	No	No	Yes	No	No	Yes
Distance to Segment City	No	No	Yes	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N of Obs	1188	1188	1188	1188	1188	1188	1188	1188	1188
Adjusted R square	0.652	0.663	0.692	0.185	0.218	0.261	0.000	0.000	0.322

Note: Standard errors in parentheses. Year and province fixed effects are controlled in all regressions. Columns (1), (4), and (7) control for land area and population. Columns (2), (5), and (8) further control the length of the highway and river and the distance to the borderline. Columns (3), (6), and (9) further control the distance to the nearest airport and segment city. *p≤0.1; **p≤0.05; ***p≤0.01.

Table 2.3: The effect of railroad length on ln(GDP per capita).

Indep. variable	OLS ln(GDP per capita)	1st stage of 2SLS ln(Railroad Length)	2nd stage of 2SLS ln(GDP per capita)
	(1)	(2)	(3)
ln(Railroad Length)	-0.011		0.289***
	(0.020)		(0.091)
Distance to CVHD line		-0.577***	
		(0.137)	
ln(Area)	-0.005	0.429**	-0.130
	(0.078)	(0.202)	(0.098)
ln(Highway Length)	-0.031	0.257***	-0.113***
	(0.020)	(0.074)	(0.041)
ln(River Length)	0.017	0.046	0.003
	(0.015)	(0.058)	(0.025)
Distance to Border Line	-0.251***	-0.113	-0.176**
	(0.058)	(0.169)	(0.087)
Distance to Nearest Port	Yes	Yes	Yes
Distance to Segment City	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
N of Obs	1362	1362	1362
Adjusted R square	0.263	0.248	0.000

Note: Robust standard errors in parentheses. Year and province fixed effects are controlled in all regressions. *$p \leq 0.1$; **$p \leq 0.05$; ***$p \leq 0.01$.

Table 2.4: The effect of railroad length on ln(GDP per capita growth).

Indep. variable	OLS ln(GDP pc growth)	1st stage of 2SLS ln(Railroad Length)	2nd stage of 2SLS ln(GDP pc growth)
	(1)	(2)	(3)
ln(Railroad Length)	-0.004**		-0.010
	(0.002)		(0.008)
Distance to CVHD line		-0.506***	
		(0.144)	
ln(Area)	0.001	0.330	0.003
	(0.006)	(0.204)	(0.006)
ln(Highway Length)	0.003*	0.199***	0.004*
	(0.002)	(0.075)	(0.002)
ln(River Length)	-0.001	0.039	-0.001
	(0.001)	(0.057)	(0.002)
Distance to Border Line	-0.010*	-0.201	-0.011*
	(0.005)	(0.175)	(0.006)
Distance to Nearest Port	Yes	Yes	Yes
Distance to Segment City	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
N of Obs	985	985	985
Adjusted R square	0.097	0.272	0.092

Note: Robust standard errors in parentheses. Year and province fixed effects are controlled in all regressions. *$p \leq 0.1$; **$p \leq 0.05$; ***$p \leq 0.01$.

Table 2.5: The effect of railroad length on the number of firms above scale.

Indep. variable	OLS Number of firms (1)	1st stage of 2SLS ln(Railroad Length) (2)	2nd stage of 2SLS Number of firms (3)
ln(Railroad Length)	0.014		0.208**
	(0.022)		(0.094)
Distance to CVHD line		-0.481***	
		(0.141)	
ln(Area)	-0.028	0.305	-0.083
	(0.066)	(0.189)	(0.080)
Population	0.002***	0.003***	0.001**
	(0.000)	(0.001)	(0.000)
ln(Highway Length)	0.046**	0.194***	0.008
	(0.019)	(0.073)	(0.032)
ln(River Length)	0.006	0.038	-0.001
	(0.015)	(0.056)	(0.020)
Distance to Border Line	-0.068	-0.216	-0.001
	(0.048)	(0.172)	(0.064)
Distance to Nearest Port	Yes	Yes	Yes
Distance to Segment City	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
N of Obs	3710	3710	3710
Adjusted R square	0.646	0.290	0.575

Note: Robust standard errors in parentheses. Year and province fixed effects are controlled in all regressions. *$p \leq 0.1$; **$p \leq 0.05$; ***$p \leq 0.01$.

Chapter 3.

A Linear Estimation of Intrahousehold Resource Distribution: Evidence from China's Nutrition Data

3.1 Introduction

Giving female adults and female children equal rights to economic resources is one of the Sustainable Development Goals pledged to be met by 2030 and adopted by all United Nations Member States. Gender equality is seen as both a development goal and a necessary condition for sustainable development. Indeed, higher levels of economic development and gender equality are known to favor the manifestation of gender differences in preferences across countries (Falk and Hermle, 2018).

Research on the preference for a male child in China has always focused on the rapid masculinization of sex ratios at births, termed the "missing women phenomenon." China's one-child policy has further aggravated the issue of son preference, as a smaller family size forces parents to bear a son within the confines of fewer births (Zhang and Goza, 2006; Ebenstein, 2010). At the same time, the availability of technologies for sex-selective abortion enables parents to act on son preference in a way that arguably entails lower emotional costs than postnatal interventions such as the lethal neglect of female children. Li, Yi, and Zhang (2011) also attributed the imbalanced sex ratio in China to the aforementioned reasons.

Despite the literature on sex ratios at birth, only a few studies have focused on the resources accessed by male children and female children after birth in China. Since Chiappori (1992) developed a collective model thereof, a growing corpus of evidence has rejected the unitary model of intrahousehold resource allocation in developing countries (Quisumbing and Maluccio 2003; Brown 2009; Chen 2006; Park and Rukumnuaykit 2004). The collective model refers to households comprised of individual people who maximize utilities and together reach the Pareto frontier—a subject of great interest in academia (Cherchye *et al.*, 2007).

Despite its popularity, the collective model is seldom used to study household resource allocation in China. This is because, first, although expenditure data on assignable goods are available in many developed countries and through some international surveys, they are still unavailable in China. Second, using the collective model as a general framework, Browning, Chiappori, and Lewbel (2013) (hereafter, BCL) and Dunbar, Lewbel, and Pendakur (2013) (hereafter, DLP) introduced structural models that allow us to use off-the-shelf data—of the sort collected routinely by statistical agencies—to reveal the resource shares of individual household members. Both BCL and DLP propose nonlinear structural models to estimate resource shares. As Lechene *et al.* (2022) (hereinafter, LPW) stated:

> *We believe that the lack of a simple and transparent empirical methodology is the reason that structural models identifying resource shares have not been used widely in policy work, studies of gender disparities.*

Over the past two decades, the linear methods of ordinary least squares and two-stage least squares have received renewed attention from empirical economists. These linear methods are widely understood, simple to implement, computationally inexpensive, and have unique solutions. For these reasons, some scholars consider linear methods to be more transparent than more complex methods. Indeed, a commonly held view is that if one does not see the empirical result in linear regression, then it is probably not true. LPW argues that the lack of simple and transparent empirical methodologies is why structural models for determining resource shares are not widely used in policy work, gender disparity studies, and poverty assessments.

To address the above questions, I use data from the China Nutrition and Health Survey (CHNS) to estimate resource shares and gender inequality in Chinese households through a linear estimation model proposed by LPW. I extracted nutrient intakes of household members from CHNS data and calculated nutrient prices based on local food prices for grains, vegetables, and meat. In turn, I obtained the expenditure of household members on each nutrient, considered assignable goods required in the estimation of resource shares. I find that equal sharing is rejected by the data, and there is further evidence of gender gaps in resource shares. For example, adult female adults' resource shares were estimated to be 5 to 6 percentage points lower than adult men's, and female children's shares were 9 to 10 percentage points lower than male children's in China. Such a resource allocation was found to be heterogeneous across households with different incomes.

The remaining chapter is organized as follows. In section 2, I present a theoretical model following DLP and LPW. In section 3, I introduce the data and then calculate the households' expenditure on nutrition. In section 5, I report the result and conclude in section 6.

3.2 Theoretical model

Ideal data are generally unavailable, requiring one to estimate the resource share for individuals in a household. In other words, when ideal data are available, the estimation can be skipped, and one can directly make the calculations. Table 3.A1 depicts ideal data, where we can directly observe the expenditure on each good by the sample of male adults, female adults, male children, and female children in the household.

Such ideal data as in table 3.A1 directly reveal the resource shares for each household member, defined as the ratio of an individual's total expenditures to the household total expenditure. For example, the male adults' resource share is 40% (2,750 of 6,950), and those of female adults, male children, and female children are 31%, 17%, and 13%, respectively.

Following BCL, the consumption goods can be divided into sharable and non-sharable. For example, food is non-shareable because food eaten by one cannot be eaten by another. The table is fully sharable. In table 3.A1, if the total expenditure on the table is 200, then each individual's expenditure will be 50.

However, datasets, in reality, look more like in table 3.A2, where we see the total expenditures on all types of goods, but we may see only one or two goods' expenditures at the individual level. The BCL, DLP, and LPW models solve the estimation for the 40%, 31%, 17%, and 13% resource shares in table 3.A1 using the incomplete expenditure data in Table A2. In many developing countries, the dataset shown in table 3.A2 is also unavailable. In this article, I first calculate individual expenditure on nutrients as non-sharable goods. Second, I use the data to estimate the resource shares. To this effect, in the theoretical model, I describe herein, I follow LPW's model.

Let t index the types of individuals, in this study's case, m for adult male, f for adult female, and c for children. Let the household consist of N^t individuals of each type t, and let $N = \sum_t N^t$. The types are, in some sense, defined by the data, as we will see below. Let y be the observed household budget.

The *resource share* for household members of type *t*, η^t, is defined as the share of the household budget allocated to them. η^t satisfies $\sum_t \eta^t = 1$. Within each type, I assume that resources are distributed equally. Thus, the shadow budget for all people of type t in the household is $\eta^t y$ and the shadow budget for each person in type *t* is given by $\eta^t y/N^t$.

Shadow price is defined as the within-household price of consumption. If $\boldsymbol{p}$ denotes the market price vector of goods, then $\widetilde{\boldsymbol{p}}$ denotes the shadow price vector. Theoretically, because sharing of goods results in more consumption by individuals than the nominal value of what the household purchases, the shadow price of consumption of shared goods is lower than the market price. The household purchases vector *Q*:

$$Q = \boldsymbol{A} \sum_t N^t\, q^t \tag{1}$$

where $\boldsymbol{A}$ is a square matrix capturing the *consumption technology* associated with the number of individual purchases and the consumption of goods. This implies that the shadow price of consumption within the household is $\boldsymbol{Ap}$:

$$\widetilde{\boldsymbol{p}} = \boldsymbol{Ap}$$

In this analysis, all consumption of nutrition is private (there are no public goods) and non-shareable because nutrients absorbed by one person cannot be absorbed by another person. Thus, in this chapter, the shadow price equals the market price of the goods, meaning $\widetilde{\boldsymbol{p}} = \boldsymbol{p}$.

Let $q^t(p, y)$ be the scalar-valued demand function for a person of type t for their assignable goods. Individual demand within the household is evaluated at their shadow budget constraint, so q^t equals $q^t(\boldsymbol{p}, \eta^t(p, y)y/N^t)$. Substituting q^t into equation (1) we obtain

$$Q^t(p, y) = A_1^t \sum_t N^t\, q^t(\boldsymbol{p}, \eta^t(p, y)y/N^t) \tag{2}$$

Following DLP and LPW, the household Engel curve function for the assignable goods of type t, $W^t(y)$, is given by

$$W^t(y) = \bar{p}_1^t \bar{A}_1^t N^t q^t(\overline{\boldsymbol{p}}, \eta^t(p,y)y/N^t)/y$$

where $\overline{\boldsymbol{p}}$ is some vector for the constant price. Let $w^t(y) = \bar{p}_1^t \bar{A}_1^t q^t(\overline{\boldsymbol{p}}, y)/y$ be the Engel curve function at the fixed shadow price vector $\overline{\boldsymbol{p}}$ for a person of type t for their assignable goods at budget y. Finally, we obtain equation (3) of DLP:

$$W^t(y) = \eta^t(y) w^t(\eta^t(y)y/N^t) \tag{3}$$

The DLP provides sufficient constraints on the model so that resource shares can be determined from data on the Engel curve function of allocable goods for collective households facing a single price vector. Three sufficient restrictions are imposed: First, the resource shares do not depend on the household budget, and thus $\eta^t(y) = \eta^t$. Second, the individual Engel curve is linear in lny, and thus $w^t(y) = \alpha^t + \beta^t lny$ (an example of such an Engel curve is the almost ideal demand system of Deaton and Muellbauer [1980]). Third, the preferences of individuals are similar but not identical, and thus $\beta^t = \beta$. Substituting these assumptions into an equation, we obtain

$$W^t(y) = \eta^t(\alpha^t + \beta(lny + ln\eta^t - lnN^t)) \tag{4}$$

Equation (4) does not include any covariates such as some household characteristics that affect members' preference. If we let z be all variables that affect preferences and/or resource shares and add it into equation (4) we obtain

$$\begin{aligned} W^t(y,z) = \eta^t(z)\alpha^t(z) + \eta^t(z)\beta(z)lny + \eta^t(z)\beta(z)ln\eta^t(z) \\ - \eta^t(z)\beta(z)lnN^t \end{aligned} \tag{5}$$

Equation (5) defines a nonlinear model because α^t and β are multiplied by the resource shares η^t; and in this equation, η^t should be positive because of the $ln\eta^t$ term. In this analysis, I use a linear reframing of this model following LPW. Rewrite equation (5) with a subscript h (h=*1, ..., H* indicates households), and the error term ε_h^t, as the following model:

$$W_h^t = a_h^t + b_h^t ln y_h + \varepsilon_h^t \tag{6}$$

where

$$a_h^t = \eta^t(z_h)\alpha^t(z_h) + \eta^t(z_h)\beta(z_h) ln\eta^t(z_h) - \eta^t(z_h)\beta(z_h) lnN_h^t \tag{7}$$

and

$$b_h^t = \eta^t(z_h)\beta(z_h) \tag{8}$$

From equation (7) and equation (8), we can see that both a_h^t and b_h^t are functions of z_h, the conditioning variables, and a_h^t is a third-order function of z_h, and b_h^t is quadratic in z_h. Because z_h includes the number of household members of each type, that is, $N = \{N^t\}$, setting $\tilde{z}$ as some sub-vector that includes all variables excluding N, means that z can be rewritten as $z = [N\ \tilde{z}]$. This leads to a complex calculation in the estimation of the resource share. Hence, following LPW, I approximate the intercept and slope terms using the following equation:

$$\begin{cases} a_h^t = a_0^t + a_{lnN^t}^t lnN_h^t + a_z^{t\prime} z_h \\ b_h^t = b_0^t + b_z^{t\prime} z_h \end{cases} \tag{9}$$

Then, the ordinary least squares estimator $\hat{b}_h^t$ of b_h^t will be:

$$\hat{b}_h^t = \hat{b}_0^t + \hat{b}_z^{t\prime} z_h \tag{10}$$

Under the linear restriction that $\sum_t \boldsymbol{b}_{\tilde{z}}^t$=0, which implies that $\sum_t b_h^t = \sum_t (b_0^t + b_{N^f}^t N_h^f + b_{N^m}^t N_h^m + b_{N^{cf}}^t N_h^{cf} + b_{N^{cm}}^t N_h^{cm})$, I can estimate the resource share for type t:

$$\hat{\eta}^t(z_h) = \frac{\hat{b}_0^t + \hat{b}_z^{t\prime} z_h}{\sum_t (\hat{b}_0^t + \hat{b}_{N^f}^t N_h^f + \hat{b}_{N^m}^t N_h^m + \hat{b}_{N^{cf}}^t N_h^{cf} + \hat{b}_{N^{cm}}^t N_h^{cm})} \tag{11}$$

In equation (11), $\hat{b}_{N^t}^t$ indicates the ordinary least squares estimator for $b_{N^t}^t$, the multivariate polynomial over N_h^t, and can be estimated using equation (6). In the empirical analysis in the next section, I use the expenditure of four nutrients to estimate the Engel curve function as equation (6) and calculate the resource share using equation (11).

3.3 Data

The data set used in this chapter are from the 2004, 2006, 2009, and 2011 waves of the CHNS, which is conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill, the National Institute of Nutrition and Food Safety, and Chinese Center for Disease Control and Prevention. The investigated areas include nine provinces: Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou. In this analysis, I restrict the sample to 3,122 households with both husband and wife and at least one child.

In addition to nutrition intake, to calculate each household member's value of nutrition intake, I will need information on household-level food prices. CHNS provides detailed information on food consumption and local food prices. The household survey records household food consumption over three days using the following definition:

$$\begin{gathered} \textit{Actual Consumption} = \\ \textit{Initial Amount on Hand} + \textit{Total Amount Purchased or Grown} \\ - \textit{Total Amount Discarded} - \textit{Total Remaining} \end{gathered}$$

The household consumption of each type of food corresponds to a food code, which links with the food name according to the Chinese Food Composition Table (FCT). FCT provides information about the nutrient content of each food. This allows me to calculate the per gram price of nutrients for each family.

The community survey includes the local food price of eight major categories of food in free markets and supermarkets specifically. I define food prices as prices in the local free market based on Gould's (2002) study. Finally, Table 1 shows the mean and standard deviation of the prices of eight major and thirty-five minor categories of food. Compared with Gould's (2002) study, the food prices I use are not unusual. Table 3.1 also reports the rate of households with zero consumption of each type of food. The smaller zero consumption means that kind of food is more essential, such as rice, noodle, soy sauce, cabbage, and pork. Note that the CHNS community data only provide prices for the 35 common food items listed herein, but do not cover all food groups. This makes the analysis vulnerable to errors.

CHNS contains many missing data on food prices and household food consumption. The percentage of missing data on household food consumption was 5.4%. For the analysis, I delete all households that do have this data. Further, the absence of food price data will invalidate all samples in this region. Therefore, for those communities with missing food prices, I replace the missing data with the food prices of the closest neighboring communities.

Based on a household's three-day food consumption and the nutrient content of the food, I can calculate the price of each nutrient for each household and assume that that price is the shadow price. The household nutrient price is equal to the total price of foods containing this nutrient over three days divided by the sum of the amount of nutrients in those foods.

Table 3.2 provides the summary statistics for all variables used in the household-level analysis. The average number of female and male adults is 1.00 because I only include those households with at least one mother and one father. The standard deviations are not zero, because some households with young families might also have a grandparent. The average number of male children is lower than female children in the households, which may seem erroneous given China's preference for a male children. In this study, I define "children" as those family members who have parents and are aged under 18; given that male children may have likely left the household earlier, our sample has more female children. The urban households take a ratio of 34% and the deflated mean family income is RMB 38,036. In 2011, the Chinese mean personal income was RMB 6,977 for rural residents and RMB 23,979 for urban residents. Children's average age and minimum age are also controlled as covariates, based on LPW's empirical analysis. Finally, the three-day consumption of food and nutrients is also reported, along with expenditure by family member type (see table 3.3).

In table 3.3, I report the descriptive statistics of personal characteristics, including the three-day average expenditure of nutrients, average age, and average educational year. On average, adult male adults spend the highest amount of money on all four nutrients for the whole household. For children, female children spend more on carbohydrates and proteins than male children, but less on energy and fat than male children. This statistic may be explained by the different nutrient requirements of children of different genders at different stages of development.

3.4 Empirical result

I estimate the equations in section 2 via seemingly unrelated regression in Stata. The observed vector of demographic variables z_h is comprised the numbers of female adults, male adults, female children, and male children (N_h); the average ages of female adults, male adults, and children; the minimum age of the children; the average education levels of the female and male adults; and a dummy variable indicating that the household lives in an urban area. Resource shares are then computed using equation (11).

3.4.1 Resource shares

The estimated per-person resource shares of female adults, male adults, female children, and male children are shown in table 3.4. As explained in section 4, I use the expenditure for four nutrients—energy (in kcal), carbohydrates, fats, and proteins (in gram)—to estimate the resource share of household members. The two rightmost columns report the t-test of equality for male and female adults and children; the standard deviations of these estimated resource shares are 8.95, 0.33, 0.07, and 0.01, respectively, indicating high heterogeneity in resource shares driven by the sample variation in the value of energy and carbohydrates consumption. It appears that the estimated resource share using energy is unreliable.

According to the point estimates, adult males usually have the largest share of resources except for the estimated resource share using carbohydrates, which are 28, 26, 25, and 32%, respectively. Adult females obtain between 22 to 28% by different methods. The largest differences between male and female adults were estimated for proteins and carbohydrates—4.5 and 6.5%, respectively.

Further, male children have a greater share of resources than female children, except for energy-based resource shares. The differences between male and female children's resource shares are 9, 0.6, and 10.6% for carbohydrates, fats, and proteins, respectively.

It is unclear whether this result reflects the unequal distribution of resources because resource shares may be governed by the different needs of different people as well as inequality or power imbalances. Children have a smaller share of resources than adults, a result consistent with using a lower poverty line for children than for adults based on presumed low needs. Similarly, male and female children require different nutrition or resources during development owing to their innate physical differences. Therefore, the result can only indicate differences in the resource shares for male and female children, but not parents' gender preference or discrimination.

3.4.2 Bargaining power

For the estimation of the resource shares, I use household compositions that include at least one female adult, one male adult, and one child regardless of gender, which allows further analysis to determine whether there are different ways of allocating resources for different family compositions. There are three possible family compositions, (f, m, cf), (f, m, cm), and (f, m, cf, cm), indicating that individuals of the type f for adult female, m for adult male, cf for female child, and cm for male child. The estimated resource shares for the three types of households are shown in table 3.5.

When family resources are limited, the parent may sacrifice their own consumption when having an additional child. In table 3.5, the carbohydrate- and fat-based estimated resource shares for male and female adults in panel C, which are 0.20, 0.25, 0.24, and 0.24, are smaller than in panels A and B. The standard deviations of fat-based resource share are always at the level of 0.01, much smaller than the mean, indicating that the difference is significant.

For female adults in households with one male child and one female child, the protein-based resource share is smaller than that in households with one child of either gender, while for male adults, the protein-based resource share is smallest in households with one male child. As for the energy-based resource share, the comparison between different types of households seems pointless because of its large standard deviation.

The above findings contribute to the literature on intrahousehold bargaining power, a fairly straightforward concept. However, the lack of a proper measure of the relative bargaining power of female adults presents challenges when empirically examining intrahousehold resource allocation. In a patrilineal familial system, such as in China, where women, upon marriage, live with their spouse's families, giving birth to a male child guarantees respect and care from family members and relatives, especially among the in-laws. Thus, the child's gender could affect the mother's relative bargaining power in family decisions. This phenomenon is characteristic of Chinese society (Das Gupta *et al*. 2003).

In panels A and B of table 3.5, I estimate the resource shares for households with one child of either gender. In the households with one male child, the mother's resource shares estimated by energy, carbohydrate, fat, and protein are 0.42, 0.25, 0.24, and 0.26, respectively—larger than that in households with only one female child, that is, 0.41, 0.20, 0.24, and 0.25. Note that this change in the mother's share of resources may be due to differences in the family resource shares for the child based on gender. However, comparing the estimated resource share for children in panels A and B shows that the resource share for male children in families with one male child is more than that for female children in families with one female child. This result confirms that the increase in the mother's resource shares is not due to a crowding-out effect. Nevertheless, the overall results do provide evidence confirming the relationship between a female adult's status and the gender of the child.

3.4.3 Resource share and household income

The methodology I use clearly shows how resource shares depend on covariates. Figure 1 shows a scatter plot of 3,122 estimates of Chinese households' resource shares based on assignable data on fat consumption in households with at least one male adult and one female adult, plotted against the household budget measured in 2015 CNY$ (on a logged scale). I use the fat-based estimated resource share because it has the smallest standard deviation, making it more reliable.

Figure 3.1 reveals several important patterns. First, for family members of the same gender, the resource share is always more dispersed for adults than for children, suggesting that adults in control of family resources appear to have more flexibility in deciding the intrahousehold allocation of resources. Children, as recipients of resources, do not have much autonomy over the allocation of resources.

Second, the variance of resource shares among household members is greater for low-income households. Even if the household budget is right at the poverty line, there may be many poor and nonpoor members in the household.

Third, there is a weak negative correlation with total household expenditure for female adults, but a positive correlation for male adults. Recall that my identification strategy assumes that, conditional on covariates, resource shares do not vary with household budgets. The unconditional correlation we observe is driven by age and education, which are positively correlated with household budgets, but negatively correlated with resource shares.

3.5 Conclusion

In this chapter, I show that the expenditure data for nutrients can help us estimate the resource shares in a linear model. Despite its long history, the collective approach is seldom used for intrahousehold analysis to estimate the distribution of resources.

According to Donni and Molina (2018), between 2015 and 2018, 49 empirical articles used the collective model, of which only seven focused on developing countries. One reason for this gap in the literature is the lack of detailed expenditure data on intrahousehold members, especially in developing countries. In this chapter, I innovatively introduce the concept of nutrient prices to the estimation of resource shares, an approach that contributes significantly to empirical studies in developing countries. I also draw on LPW's method by using a linear model to estimate resource share, which reduces the difficulty of the empirical analysis.

The findings reveal gender inequalities in the allocation of resources within Chinese households in favor of male adults and children than female ones, respectively, and also reveal a relationship between the number of children and the distribution of family resources. The heterogeneity analysis finds that resources are not allocated in exactly the same way for households with different incomes. For example, among low-income households, household resources are more likely to be allocated toward adult males.

Nevertheless, I must also discuss a limitation of this study: The resource shares estimated herein using the four nutrients are not the same, which is not in accordance with the theoretical results. This is because nutrients, as a finely categorized consumer good, are more susceptible to personal preferences than expenditures on clothing, food, and transportation. In future, this problem must be overcome to obtain more accurate conclusions based on the available data.

Table 3.1: Food price and zero consumption rate.

Food name	Mean	S.D.	Zero consumption	Food name	Mean	S.D.	Zero consumption
Food Grains				Cabbage (per 500g)	0.645	0.591	0.515
Good rice (per 500g)	1.697	0.448	0.420	Apple (per 500g)	1.647	0.735	0.879
Rice, most commonly eaten (per 500g)	1.323	0.214	0.945	Orange (per 500g)	1.245	0.471	0.957
Bleached flour (per 500g)	1.721	1.456	0.978	*Meat and Poultry*			
Unbleached flour (per 500g)	1.359	0.875	0.828	Pork, fatty and lean (per 500g)	6.663	1.396	0.580
Noodles made of bleached flour (per 500g)	1.650	0.673	0.984	Pork, lean (per 500g)	8.286	1.589	0.875
Noodles made of unbleached flour (per 500g)	1.371	0.388	0.659	Live chicken (per 500g)	6.517	2.629	0.991
Corn flour (per 500g)	1.302	0.543	0.938	Chicken, cleaned (per 500g)	6.361	2.512	0.927
Millet (per 500g)	1.867	0.683	0.947	Beef (per 500g)	9.233	2.367	0.940
Sorghum (per 500g)	1.381	0.506	0.998	Mutton (per 500g)	9.826	3.052	0.989
Cooking Oil and Sugar				*Fresh Milk*			
Rape seed oil (per 500g)	3.954	1.132	0.811	Fresh milk (per package—250 ml)	1.706	0.866	0.951
Soybean oil (per 500g)	3.946	1.144	0.732	*Preserved Milk Products*			
Peanut oil (per 500g)	5.399	1.578	0.800	Whole, powdered (per 500g)	14.275	5.014	0.995
Cottonseed oil (per 500g)	3.551	1.306	0.987	Substitute formula, soy or rice (per 500g)	8.897	5.225	0.998
Tea oil (per 500g)	7.156	3.480	0.989	Infant formula (per 500g)	23.322	12.880	1.000
White sugar (per 500g)	2.315	0.690	0.855	*Fish*			
Eggs (per 500g)	3.366	1.159	0.569	Common carp (per 500g)	4.367	1.155	0.978
Soy sauce, most commonly used (per 500g)	1.842	1.308	0.201	Hair-tailed fish (per 500g)	5.962	2.434	0.973
Vinegar, most commonly used (per 500g)	1.453	0.771	0.666	*Bean Curd*			
Vegetables and Fruits				Bean curd, pressed (per 500g)	2.238	0.911	0.928
Green vegetables (rape) (per 500g)	0.839	0.708	0.946	Bean curd (per 500g)	1.130	0.557	0.748

Table 3.2: Descriptive of households' characteristics.

Variable	Obs	Mean	Std. dev.
2004 sample	3,122	0.34	0.47
2006 sample	3,122	0.27	0.44
2009 sample	3,122	0.23	0.42
2011 sample	3,122	0.17	0.38
Number of female adults	3,122	1.00	0.04
Number of male adults	3,122	1.00	0.05
Number of female children	3,122	0.64	0.55
Number of male children	3,122	0.54	0.57
Urban	3,122	0.34	0.47
Household income (yuan)	3,122	38036.21	44128.27
Three-days food consumption	3,122	24.34	22.62
Three-days Carbohydrate (g)	3,122	2062.73	1842.44
Three-days Fat (g)	3,122	510.44	837.78
Three-days Energy (kcal)	3,122	14327.84	12345.12
Three-days Protein (g)	3,122	386.15	316.48
Children's average age	3,122	11.99	3.52
Children's minimum age	3,122	11.38	3.70

Table 3.3: Descriptive statistics of individual characteristics.

Three-days Average Expenditure (yuan)	Female			Male			Female children			Male children		
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Energy	3,122	4.05	3.52	3,122	4.81	4.22	1,894	4.19	3.73	1,574	3.57	3.11
Carbohydrate	3,122	16.92	67.39	3,122	20.18	80.87	1,894	13.79	45.67	1,574	18.13	89.06
Fat	3,122	25.65	98.83	3,122	29.60	113.88	1,894	26.42	100.44	1,574	24.08	97.19
Protein	3,122	11.13	36.92	3,122	13.30	44.74	1,894	9.49	26.48	1,574	12.61	55.28
Average age	3,122	38.55	6.19	3,122	40.31	6.69	-	-	-	-	-	-
Average years of education	3,122	6.95	4.74	3,122	8.54	4.01	-	-	-	-	-	-

Table 3.4: Predicted resource share.

		Estimated Resource Shares				t-test	
	Obs	Female	Male	Female children	Male children	F≠M	FC≠MC
Energy	3122	0.279	0.280	0.232	0.239		
		(8.81)	(8.953)	(1.804)	(1.159)		
Carbohydrate	3122	0.217	0.262	0.254	0.344	***	***
		(0.385)	(0.326)	(1.101)	(0.167)		
Fat	3122	0.244	0.250	0.244	0.250	***	***
		(0.006)	(0.013)	(0.006)	(0.013)		
Protein	3122	0.250	0.315	0.181	0.287	***	***
		(0.034)	(0.069)	(0.031)	(0.186)		

Note: The last two columns in Table 4 report the t-test result for null hypothesis: (1) resource share of female adult ≠ resource share of male adult; and (2) resource share of female children ≠ resource share of male children, respectively. The significance levels are: * 0.1 **0.05 ***0.01.

Table 3.5: Predicted resource shares by household composition.

		Estimated Resource Shares			
	Obs	Female	Male	Female children	Male children
Panel A. Households with one female child.					
Energy	1455	0.408	0.161	0.260	
		(3.012)	(3.186)	(1.154)	
Carbohydrate	1455	0.200	0.256	0.269	
		(1.075)	(0.965)	(2.695)	
Fat	1455	0.244	0.246	0.248	
		(0.003)	(0.008)	(0.003)	
Protein	1455	0.249	0.334	0.187	
		(0.014)	(0.034)	(0.017)	
Panel B. Households with one male child.					
Energy	1156	0.424	0.129		0.215
		(2.438)	(2.35)		(0.442)
Carbohydrate	1156	0.247	0.275		0.374
		(0.037)	(0.111)		(0.329)
Fat	1156	0.244	0.258		0.261
		(0.003)	(0.007)		(0.006)
Protein	1156	0.260	0.292		0.298
		(0.014)	(0.01)		(0.022)
Panel C. Households with one female child and one male child.					
Energy	308	0.423	0.240	0.213	0.371
		(10.445)	(14.69)	(2.435)	(2.475)
Carbohydrate	308	0.203	0.253	0.223	0.319
		(0.024)	(0.026)	(0.055)	(0.016)
Fat	308	0.243	0.240	0.248	0.267
		(0.01)	(0.015)	(0.002)	(0.005)
Protein	308	0.239	0.315	0.175	0.267
		(0.012)	(0.021)	(0.008)	(0.041)

Figure 3.1: Estimated household members' resource share (fat-based).

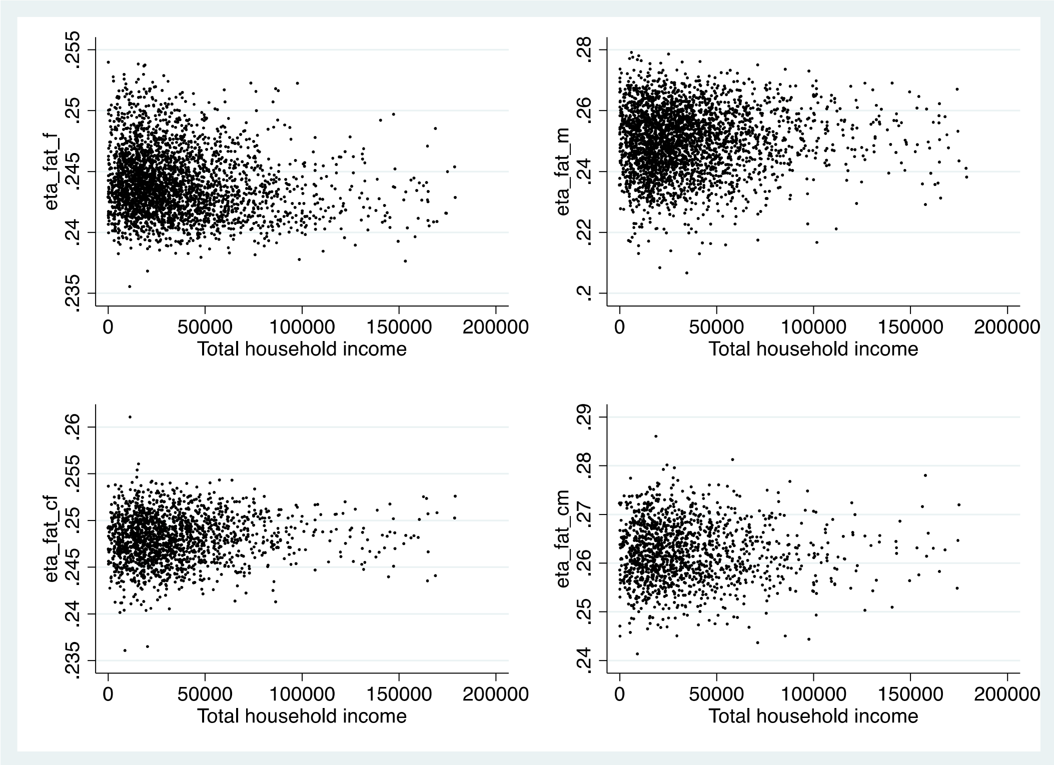


Table 3.A1: Ideal data on expenditure.

	Men	Women	Boys	Girls	Total
Food	1200	1000	800	600	3600
Clothing	500	800	200	150	1650
Table	50	50	50	50	200
Transport	1000	300	100	100	1500
Total	2750	2150	1150	900	6950
Resource shares	40%	31%	17%	13%	100%

Table 3.A2: Real data on expenditure.

	Men	Women	Boys	Girls	Total
Food	1200	1000	800	600	3600
Clothing					1650
Table					200
Transport					1500
Total					6950
Resource shares					

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