# Intergenerational Mobility and Inequality in China: Evidence from the Chinese Household Income Project

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## Abstract

We document intergenerational mobility in the income distribution in China, using Chinese Household Income Project survey data from the 1990s till 2013. To obtain a robust picture of mobility, we use several measures of mobility: from the most commonly used intergenerational income elasticity to the innovative rank mobility measures. We then estimate quantile regressions to capture variation along the income distribution. Conclusively, our results suggest higher dependence of children's income on parental income for lower income generational pairs, indicating challenges to promote upward mobility and reducing inequality.



**Keywords:** Intergenerational Mobility; Inequality; Quantile Regressions; Rank Mobility; China

**JEL Classification:** C31, D31, D63, J62, J68

## 1. Introduction

Intergenerational mobility is a fundamental cornerstone of our understanding of inequality and vulnerability. Mobility, or the lack of it, within the income distribution over time is a reliable indicator of rising and falling temporal inequality. Indeed, intergenerational mobility may co-exist with stagnant or even rising inequality.

Concerns about intergenerational mobility are particularly relevant to the recent East Asian experience, not surprisingly because of family success being considered more important than individual achievements in countries such as China, Japan, and Korea.

In this paper, using novel data and methods, we study intergenerational mobility in China, whose rapid economic growth and fast-changing income conditions in recent decades provide a perfect laboratory to uncover the dynamics of intergenerational mobility and across different stages of growth.

Much of the intergenerational mobility empirical literature is based on the experience of advanced economies (Becker and Tomes, 1979; Solon, 1992; Black and Devereux, 2011; Chetty et al, 2014a; Chetty et al, 2014b; Chetty et al, 2020a; Chetty et al, 2020b). The rich empirical literature and accompanying innovations in the estimation methodology has largely developed due to high quality income data being available. Like many other developing countries, the literature on intergenerational mobility in China is relatively under developed due to the lack of rich income data. Extant empirical studies on China draw upon a variety of microeconomic datasets and measurement models, thus resulting in highly different and often conflicting results (Gong et al, 2012; Chen et al, 2015; Jia and Li, 2017; Y. Fan et al, 2021).

Our paper has two main contributions to the Chinese empirical literature on intergenerational mobility. In addition to the standard estimates of intergenerational mobility, we document variations in mobility along the income distribution, from the parental quantile to the children's quantile, using a quantile regression approach. Apart from the commonly addressed discussion on intergenerational mobility estimation and the mechanism of changes in mobility, there is surprisingly limited documentation of intergenerational mobility variation along the income distribution in the existing literature. Chetty et al (2014a) addresses the possibility of children's generations moving out of extreme poverty or the bottom quantile of the income distribution, but the comparison is based on mobility defined as "moving from a lower quantile to a higher quantile", instead of "levels of mobility" for children's generations located in different quantiles.

Another contribution of our paper to the existing literature on intergenerational mobility is the discussion on income growth across different income percentiles. We draw the first elephant curve (also known as the growth incidence curve) in China, and show a totally different picture for the rural-urban divide. Previous literature would usually focus on either rural or urban households for the discussion, and a comparison between the two is thus important, especially if we consider that the rural areas in China are a less developed version of urban story.

Our results using several novel estimators, namely a range of elasticity and mobility estimators and quantile regressions, reveal a relatively high income association between generations in China for three measures: intergenerational income elasticity, the rank mobility measure, and the quantile estimator. We also find intergenerational income persistence in China, particularly pronounced in urban areas. An "elephant curve" to visualise income growth across different income percentiles in China reveals a significant urban-rural divide in inter-generational mobility. We observe higher income growth in higher percentiles in cities, and the opposite in rural areas.

The remainder of this paper is arranged as follows. Section 2 presents the data used in our analysis. Section 3 presents the main results based on the estimation of several measures of intergenerational mobility and the quantile regression estimates. Here we provide a comparative discussion of advantages and limitations of each set of estimations. Section 4 concludes.

## 2. Data

In this paper, we use Chinese Household Income Project (CHIP) survey data to address our research question. CHIP survey is conducted by the China Institute for Income Distribution with assistance from the National Bureau of Statistics of China. It is thus widely accepted as a highly representative source of income information for China especially during the period of China's economic reforms.

CHIP was conducted in seven waves in 1989, 1996, 2000, 2003, 2008, 2009, and 2014. The income data was collected for the years 1988, 1995, 1999, 2002, 2007, 2008, and 2013. In these seven waves, the CHIP1999 dataset was only conducted in urban areas. In all other years, both urban and rural areas were sampled. The CHIP2007 and CHIP2008 datasets form a longitudinal survey series as a part of the larger RUMiC (Rural Urban Migration in China) project. In CHIP1999 (urban) and CHIP2002, a series of five-year annual incomes were recorded for both survey waves, for 1995-1999 and 1998-2002 respectively. Therefore, a total of eleven-year annual incomes can be obtained from CHIP survey data, spanning nearly two decades from 1995 to 2013, well suiting our research needs. Data on individual characteristics such as gender, age, education, and employment-related information such as occupation, industry and wages are available from the survey data, along with household composition data, which have been used to construct our mobility measure estimates.

To construct parent-child pairs, we use the “relationship to household head” variable in the questionnaire. We first use only information on household heads and their spouses to construct the “parent” sample, then use those with a “child” relationship to household head to construct the “child” sample, and match them using their household ID. The data only contains information on the relationship with household head and no other relationships. We also look at “parents” of the household head, but the sample tends to be relatively small with the majority having reached retirement age at the time of the survey. Thus, we exclude these observations from the analysis.

Due to the nature of household survey data, we can only include members still living in the household, and data on children who have formed their own households is not included in the analysis.

All our data comes from individual questionnaire with an emphasis on wage income. From this perspective, the co-habitation bias does not lead to severe problem in our analysis, as we focus on wage income, and co-habitation only causes biases to household income as co-habiting members are closely related in terms of household assets, debt, and expenditures[1].

Our data sample results in 14,032 child-parent pairs in total. For CHIP1999 (urban) and CHIP2002, for our analysis, we construct an average annual income of five years to address the bias arising from treating the annual income of a single year as a proxy for lifetime income. CHIP1999 income data is constructed using the annual incomes in years 1995-1999. CHIP2002 income data is constructed using the annual incomes in years 1998-2002.

[1] We use wage income, rather than a more wholistic definition of income (which includes household assets, debt and expenditures). Wage income is less prone to suffer from co-habitation bias compared with household income, which is composed of several income components that are characteristic of household use and thus subject to co-habitation bias. Recent analysis shows that the estimates from co-resident sample are biased downward (see Emran, Greene, Shilpi (2018).

### 2.1 Income distribution for parents and children

To gain a general overview of the data, we plot the income distribution for both generations in Figure 1 and Figure 2. Note here that CHIP1999 only contains an urban sample, so we used data combined from CHIP2007 and CHIP2008 together for the figure plot. We omit extreme values by truncating the data such that it has a maximum at 60,000 RMB per annum. More details on income distribution are also summarised in Table 1.

Figure 1 and Figure 2 present income distributions for the parental generation and the childrens' generations, respectively. In Figure 1, we observe both CHIP1999 and CHIP2002 income distributions have greater mass at lower income levels, with the majority of the distribution within the interval below 20,000 RMB per annum. From 2007, however, the income distributions are more evenly distributed, spreading over the interval below 60,000 RMB per annum. The distributional characteristics of the children's generation (Figure 2) are very similar to that of parental generation (Figure 1), except that after 2007, the children's income distribution experienced a significant shift towards higher incomes than parental incomes. This is consistent with the fact that children's generation enter the survey at a younger age, at a time where their income growth experiences have been more rapid than that of their parents[2].

### 2.2 Descriptive Statistics

We provide descriptive statistics on demographic characteristics of our sample in Table 1. In Table 1, we observe that the average income of children's generation is quite close to average parental income, despite significant deviation in average ages. We also

[2] We are aware that the children's age in the study are quite young, compared with other studies where they are older (35-40), to observe the intergenerational effects. For this we are constrained by the dataset at hand.

observe an alarming gender bias: female children constitute only 36% of the whole sample. This gender bias is due to cultural preference where parents live with the male child, rather than the female child. Thus, the "disappearing" female child should be present in the survey with their parents-in-law, if they are married, rather than with their own parents. Mothers only represent 18% of the whole sample when we use household head income to proxy for parental impact on children's income. This reflects the fact that during the period of analysis, the majority of Chinese households still have male bread earners.

The last item in Table 1 reports residential status of the surveyed sample. Note here that the residential status differs by definition from the Hukou status, which relates to birth registration due to parental Hukou status. Residential status refers to whether the household resides in an urban area or rural area when the survey was conducted. For convenience of reporting, rural-urban migrants are categorised in the urban cohort as they mainly work and live in urban area and earn urban wages. More precisely, urban households constitute 38.08% of the whole sample, rural households constitute 57.65%, while rural-urban migrants constitute merely 4.28%. It is generally acknowledged that tracking rural-urban migrants who are fairly mobile is of great difficulty in surveys like CHIP.

## 3. Results

In this section, we present our estimations using measures of intergenerational mobility and some quantile regressions results. For the measures of mobility, we will include four widely used approaches to measure of intergenerational mobility: intergenerational income elasticity, rank mobility, quantile estimator, and the elephant curve. The intergenerational income elasticity (IGE) is a widely adopted measure in the literature, with a novel measure of intergenerational rank mobility being popular in recent years. Due to the skewed nature of the income distribution we further implement quantile regression estimates to obtain a detailed view at different quantiles of the distribution. Furthermore, we propose a novel representation – the elephant curve – to show income growth at different quantiles, which can measure within-generation mobility. All four approaches can reveal intergenerational mobility variation to some extent, with limitations of each measure discussed in detail in the following analysis.

Intergenerational income elasticity (IGE) is estimated by regressing the log income of the child on the log income of the parent. The log-log correlation has a straightforward interpretation – the coefficient on logged parental income represents the incremental percentage increase in the child's income in response to a 1% increase in the parent's income. It has certain disadvantages, such as combining both the effect from the joint distribution of income of the two generations, and the lack of information to examine the relative position in income distribution, since it only incorporates absolute income levels.

An alternative tool, intergenerational rank mobility is estimated by regressing the child's income rank on the parent's income rank. Popularised by Chetty et al (2014a, 2014b), the rank mobility measure provides new information on intergenerational income distributions and complements the observations made by IGE measures. While the IGE captures income associations between two generations, rank mobility places greater emphasis on the information on relative income positions of the two generations. The IGE measure records two types of information - one of the change in income ranks, the other of the distance between different ranks. The latter element is also referred to as the change in marginal income distributions.

Our concern with the rank measure is that while it records information on relative income positions, absolute income levels continue to matter for developing economies like China. This is especially so for the following reasons: first, China's anti-poverty campaign still defines poverty according to absolute income levels instead of ranks, thus making absolute measures an essential metric for a study on China. Second, while individuals care about relative income positions (captured by ranks) absolute levels of living quality are of greater importance to households, captured by income levels. In this light, quantile regressions are an ideal statistical tool: they provide information on both the relative position in the income distribution, and the income levels' association between the two generations.

The quantile regressions are estimated by splitting the whole sample into several income quantiles and estimating regressions for each of these selected subsamples. In our analysis we split the income distribution into five quantiles and a regression is estimated for each quantile.

### 3.1 Intergenerational Income Elasticity

Following Solon (1992), estimating intergenerational income elasticity (IGE) has been one of the most popular measures for intergenerational mobility. IGE defined as the marginal effect of parental income on children's income, is estimated as follows:

$$ln(y_{i,t}) = \alpha + \beta ln(y_{i,t-1}) + \varepsilon_{i,t} \qquad (1)$$

where $y_{i,t}$ refers to child's income of household $i$, $y_{i,t-1}$ refers to the corresponding parental income, and $\beta$ provides the linear estimate of IGE.

Table 2 summarises the IGE estimates from merging all CHIP waves. The whole sample has an elasticity of 0.51, significant at the 99% level. It indicates that a 1% increase in parental income is associated with a 0.51% increase in children's income. This result is significantly higher than estimates of IGEs in western countries (Blanden, 2009). To obtain a detailed view, we split the sample by children's birth cohorts. In Table 2, further columns present estimates of intergenerational income elasticity for four birth cohorts: children born in the 1960s, 1970s, 1980s, and 1990s, respectively. The only cohort that reports a higher than overall intergenerational income elasticity is the 1980 cohort: on average, for children born in the 1980s, one percent increase in parental income results in 0.56% increase in income. It was also in the 1980s, that China's major reforms had commenced resulting in record high economic growth.

Down from 0.38 for the 1960s, (close to the estimates for the US in the 1960s (see Chetty et al, 2014a; 2014b), the 1990s birth cohort has IGE estimates of 0.51. The observed worsening of upward mobility is in agreement with other papers documenting a similar trend (Fan et al. 2021).

### 3.2 Rank Mobility

The rank estimator, popularised by Chetty et al. (2014) is conceptually similar to IGE except that percentiles of incomes are used instead of log transformations of incomes. More specifically,

$$rank(y_{i,t}) = \gamma + \theta rank(y_{i,t-1}) + u_{i,t} \qquad (2)$$

where both parental and children's incomes are ranked within the survey year, and θ is the rank estimator of intergenerational mobility. Chetty et al (2014a) show that the rank estimator is more robust than the linear estimator, and the rank specification has become popular ever since.

Table 3 summarises the rank-rank estimation. The overall estimate of rank mobility (0.32) is very close to that of the United States as obtained in Chetty (2014b). On average, a 10 percent increase in parental income rank is associated with a 3.2 percent increase in child's income rank in China, compared to a 3.4 percent increase in the United States.

Rank mobility measures are also estimated for separate survey years to reflect the changing trend over time. The estimation results vary significantly across survey years. In 1999, China's rank mobility measures are estimated at 2.3, rising significantly to 4.1 in 2002, declining to 3.3 and 3.7 in years 2007 and 2008 respectively, and finally reaching 2.5 in 2013. The estimates are significantly lower than rank correlation estimates in Y. Fan et al (2021) who use more recent survey data in China. The difference in results is attributable to the computed income used in their estimation, and the higher correlation between parental and children's education attainment (as education attainment plays a significant role in computing income). We should interpret these results with some caution to consider the sampling differences across different survey waves.

To further capture the urban-rural divide in China, Tables 4 and 5 present estimates for urban and rural areas. The rank-rank specification estimates vary significantly. Urban correlation between parental and child's income rankings is much higher in the CHIP data. On average, a 10 percentile increase in parental income ranking is associated with a 0.6 percentile difference in ranking increases of child's income for urban and rural area.

The time trend of urban rank-rank mobility interestingly appears to follow the trend of

GDP growth of that period. In 2007, China's GDP growth peaked, reaching 14.23% in constant prices. At the same time, rank-rank correlation between parental and child's income peaked at 3.9 percentile increase response of child's income ranking to a 10 percentile increase of parental income ranking (Table 4). This points to a short-run trade-off between economic growth and income (in)equality.

Rural rank-rank mobility, however, displays a different story. In the first wave of the study, CHIP2002, the estimated rank-rank mobility measure peaked at 0.40, and thereafter follows a decreasing trend all the way to 2013. The results thus tell a story of a huge urban-rural divide – urban residents experienced overall worsened intergenerational mobility, while rural residents experienced improved mobility. This can be explained as a developing economy experience, where rural and urban areas have different modes of development.

Chetty (2014a) also distinguishes between absolute mobility and relative mobility. Our discussion in the earlier part of this section is based upon definitions of relative mobility.[3] On estimating absolute mobility, we find that on average, the children of the poorest parents are richer than 31% of the urban Chinese population (or 0.69 in terms of percentile ranking from highest to lowest), while the children of the poorest parents in rural China are richer than 39% of the rural population. Thus, the picture obtained using absolute mobility measures also suggests that rural China has less inequality compared with urban China as obtained with the relative measures.

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[3] The analysis conducted here constructs income rankings in a slightly different way from Chetty (2014a). A lower percentile refers to a higher position in income distribution (due to the nature of the dataset). Thus, when the intercept estimates refer to absolute mobility in Chetty (2014a), the sum of the intercept and coefficient refers to absolute mobility in this paper (where we set parental rank to 1).

### 3.3 Quantile Estimator

Due to the highly skewed nature of the income distribution, we estimate quantile regressions to generate more specific estimates of income associations across the two generations at different parts of the income distributions. Quantile regressions provide estimates of the associations for specific quantiles in the distribution, thus providing a close-up view of the associations at different parts of the distribution rather than the entire distribution. We adopt a five-quantile specification at cut-off points 20%, 40%, 60%, and 80% percentiles in the distribution.

$$ln(y_{i,t}) = \alpha(\theta) + \beta(\theta)ln(y_{i,t-1}) + \varepsilon_{i,t}, \theta = 0.2, 0.4, 0.6, 0.8 \qquad (3)$$

where $\beta(\theta)$ is the coefficient of the $\theta$-quantile regression. The estimated results are reported in Tables 6 and 7.

Estimates obtained in Tables 6 and 7 reveal that the quantile estimates of inter-generational mobility, for all quantiles estimated, are lower compared with the estimates obtained from the full distribution (observed in Table 2). Notably, we observe that that low-income children have a stronger income association with that of their parents, compared with children from high income parts of the distribution.

To distinguish between rural and urban effects, we conduct a subsample analysis by splitting the sample into urban and rural areas. The results are presented in Table 6, Columns 2-3. Compared to results from the full distribution presented in Column 1, we observe that urban areas have coefficients ranging between values 0.64-0.89 and rural areas have coefficient values ranging between 0.28-0.6. Thus, urban areas always have higher coefficients compared with rural areas, implying more persistence in outcomes for urban areas compared with rural areas. This result seems to conform with a general finding that poverty (and this is also often the case for inequality) tends to persist more in urban than in rural areas.

Furthermore, we categorise children by birth cohorts, results for which are presented in Table 7, Columns 2-5. For children born in the 1960s, in Column 2, we observe that the coefficient is almost the same for all quantiles. This implies that the association between incomes of parents' and children do not vary across the income distribution. This result however does not hold for the birth cohorts of later years. For all other cohorts, especially for the later years, we find that children born in the lower income quantiles have a much stronger association with their parents' incomes (0.77, for example) than those born in higher income groups, (0.39, for example). Interestingly, children born in the 1980s experienced highest income associations with their parents, (with coefficient values at 0.39-0.77) while those born in the 1960s experienced the lowest (with coefficient values at 0.32-0.39). Those who were born in the 1970s and 1990s have similar coefficients, but for the 1990-birth cohort, the range of income associations is significantly larger (at values 0.24-0.62 across five quantiles).

To complement the analysis of quantile regressions, some further estimations of IGEs using parental income quantiles are provided in Table 8. For this, we generate parent's income percentiles by the children's birth cohort, and then estimate IGEs for each cohort (and for the whole sample) for each of the selected quantiles. Table 8 reveals that for the whole sample, children from low-income families (indicated by lower income percentiles) closely follow their parents' incomes. This suggests a worrying finding – that of the persistence of poverty across generations. The two sets of estimations (quantile regressions and the IGE measures) reveal that children's income association with their parents is non-linear over the income distribution and that most children who are born to poorer families follow their parents' incomes, which is evidence of persistence of poverty over time.

### 3.4 Elephant Curve

The growth incidence curve proposed by Lakner and Milanovic (2013), often referred to as the elephant curve, presents income growth by quantiles in an economy to document changes in the income distribution for a specific economy/quantile in a specific period of time[4].

We plot, to our knowledge, the first growth incidence curve for China using CHIP data from 1999 to 2013 (rural area from 2002 to 2013).[5] Figure 3 plots income growth at percentiles in urban China from 1999 to 2013. At real prices, income increased by 215.65% on average across all percentiles. Except for the values at the lowest percentiles, the overall trend of income growth is relatively flat for the majority of middle-income population. The 10% to 80% income percentiles experienced similar growth rates during 2000-2010, between 190.36% to 234.57%. However, for the richest population earning top 20% incomes, the growth rate is significantly higher. The top 1% percentile experienced income growth as high as 272.26%, thus contributing to widening income inequality.

The average annual income growth during the 14 years examined was 21.57%. In comparison, GDP growth during the same period averaged at 9.80% annually.

A further point worth noting is the amount of variation in growth rates for the lowest 10% income levels. While the lowest 1% income population experienced high-income

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[4] They propose two different methods to record income distribution changes across time: the anonymous growth incidence curve and the non-anonymous growth incidence curve. The anonymous growth incidence curve uses different quantiles of the income distribution to compute growth, without specifying quantiles to refer to the same cohort. The non-anonymous growth incidence curve uses the income quantiles of the same cohort, taking into account the entire time period of analysis. In other words, the anonymous growth incidence curve plots growth of all quantiles, instead of the growth of family incomes at a certain quantile.

[5] The closest representation to an elephant curve that has been estimated using Chinese data is the Great Gatsby Curve in Fan et al (2021), which presents the relationship between the Gini coefficient and intergenerational mobility.

growth similar to richer groups, individuals belonging to the lowest 2-6% income percentiles experienced dramatically low growth. More specifically, none of percentiles above 12% have grown at a level lower than 20% per year. One possible explanation for the higher growth rate for the lowest 1% income percentile could be due to receipt of public funds. This, however, is not the case for the percentile groups just above the 'extreme poor' quantiles, which may explain their low growth rates. The sudden drop in growth rates, however, calls for further research and casual inference methods such as regression discontinuity design which could uncover explanations.

Figure 3 compares gender differences in growth incidence curves in urban China. We observe some salient features of the female and male growth curves: first of all, the average income growth of females in 1999-2013 is significantly lower than that of males. Specifically, females experienced 205% growth in income, or equivalently 20.50% annually on average, as opposed to males experiencing a 215.68% increase of income, or equivalently 21.57% annually on average. This difference is statistically significant at 99% level.

The second gender difference of the growth incidence curves lies in the upper half of income distribution, namely, for the population located at percentiles higher than the 50th percentile. All percentiles above the 50% threshold have higher income growth for males than for females. At the upper end, income growth at the 86% percentile for males is nearly 50 percentage points higher than that for females. This is significant if we also consider the low starting point for females – in 1999 the median income for males was a third higher than that for females.

The third gender difference in growth incidence curves emerges in the upper tail. Beyond the 80th percentile, the male-female gap in income growth widens consistently. Further investigations on the different growth patterns for highest income cohorts relies on the ability to classify income into wage income and property income. However, this is beyond the current research scope due to lack of data.

China's urban-rural growth differences can also be observed in Figures 3 and 4. The growth incidence curve in rural China during this period goes down, implying higher (lower) income is associated with lower (higher) growth for the decade. Evidently, this result is largely dependent on the fact that base income levels in rural area were considerably low back in 2002. More specifically, the lower 20% of population by income earned an annual level lower than 100 dollars, compared to the 20% percentile that earned more than 500 dollars in 1999. Nevertheless, the decreasing growth incidence curve suggests more equally distributed incomes in rural areas.

The average income growth rate across percentiles for the rural areas, presented in Figure 4 takes a maximum value of 659.15%. The high values clustered in low percentiles may be concerning, but the average decreases to 623.39% for a greater number of quantiles (20), and further decreases to 598.58% for 10 quantiles. In addition, the lowest growth rate across the distribution is 227.08%, which is still higher than the average growth rate for urban area.

The gender specific elephant curves presented in the bottom panels of Figures 3 and 4 are also different when comparing rural and urban areas. Although a steady drop in values remains the most typical characteristic, income growth for male percentiles is above female percentiles at all data points. Moreover, while gender difference remains significant, the growth gap becomes even larger at 261.04 percentage points (502.45% growth for females and 763.49% growth for males).

While a prominent gender gap is present at the upper tail for the urban curves, this gender gap is observed at the lower tail for the rural curves. The gender difference in income growth rates is also almost always monotonically decreasing. At the highest percentiles, female income growth is almost the same as male income growth.

A closer look reveals that income growth was not significantly lower for females in rural area in 2002 for most of the income distribution – at least until 80% percentile. Females earned an equal median income compared with that of males. However, by 2013, the gender gap in income growth is prominent for almost all percentiles. The median income for females was 80% of that for males, and the female highest average growth rate was at 70% of the male highest growth rate.

To summarise, the growth incidence curves suggest that the urban income distribution was increasingly unequal over time particularly for the period 2000-2013, while the reverse is observed for the rural income distribution (i.e., inequality decreased over time). In addition, we find that the gender gap in incomes in urban areas increased, while it is less obvious in rural areas, especially for the high income cohorts.

## 4. Conclusion

This paper documents intergenerational income mobility in China using several novel estimators. We find a relatively high income association between generations in China for the three measures of intergenerational income elasticity, the rank mobility measure, and the quantile estimator. We also oberve an increasing trend for intergenerational income persistence in China, and this is more pronounced for lower income groups and in urban areas.

We also estimate the first elephant curves for China, to present income growth across different income percentiles in China. We observe a significant urban-rural divide, with higher income growth for the higher percentiles in urban areas, and the reverse in rural areas. This finding is in line with the association between high income growth and low income mobility discussed in the literature on income mobility.

The observed trade-off between economic growth and income mobility that we observe in our analysis is typical of emerging economies and developing countries – the results are thus not atypical. However, it strongly indicates that policies to enhance social mobility are put in place by the Chinese policymakers to contain the extent of inequality that we observe for rural and urban areas and for the female population.

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## Tables and Figures

Table 1. Summary Statistics

| | Mean (Standard deviation) |
|---|---|
| Children's income | 14,170.70 |
| | (14,283.44) |
| log children's income | 9.29 |
| | (1.19) |
| Parental income | 14,276.04 |
| | (18,296.67) |
| log parental income | 9.31 |
| | (1.11) |
| Children's age | 24.06 |
| | (5.79) |
| Parents' age | 51.27 |
| | (7.18) |
| Children's gender (female = 1) | 0.36 |
| | (0.48) |
| Parents' gender (female = 1) | 0.18 |
| | (0.38) |
| Residence (urban = 1) | 0.42 |
| | (0.49) |
| Observations | 14,032 |

*Notes:* Income-related variables have been adjusted for inflation and are based on 1999 price levels. Residential status treats urban residents as 1 and rural residents as 0, and automatically categorise rural-urban migrants as urban residents.

*Source:* Chinese Household Income Project, CHIP1999 – CHIP2013. CPI data is from OECD Main Economic Indicators and National Bureau of Statistics of China.

Table 2. Linear Regression Results by Birth Cohorts

| | Overall | 1960s | 1970s | 1980s | 1990s |
|---|---|---|---|---|---|
| log income | 0.51*** | 0.38*** | 0.43*** | 0.56*** | 0.51*** |
| | (0.01) | (0.05) | (0.03) | (0.01) | (0.03) |
| Intercept | 4.42*** | 5.46*** | 5.10*** | 4.12*** | 4.33*** |
| | (0.10) | (0.42) | (0.25) | (0.12) | (0.33) |
| N | 14,032 | 482 | 3,074 | 7,959 | 2,392 |
| R-squared | 0.23 | 0.15 | 0.22 | 0.27 | 0.11 |

Table 3. Rank Mobility Estimates across Survey Years

| | Overall | 1999 | 2002 | 2007 | 2008 | 2013 |
|---|---|---|---|---|---|---|
| Parental rank | 0.32*** | 0.23*** | 0.41*** | 0.33*** | 0.37*** | 0.25*** |
| | (0.01) | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) |
| Intercept | 0.34*** | 0.39*** | 0.30*** | 0.33*** | 0.32*** | 0.38*** |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| N | 14,032 | 1,228 | 3,419 | 2,427 | 2,499 | 4,459 |
| R-squared | 0.10 | 0.05 | 0.16 | 0.11 | 0.13 | 0.06 |

Table 4. Rank Mobility Estimates across Survey Years, Urban Area

| | Overall | 1999 | 2002 | 2007 | 2008 | 2013 |
|---|---|---|---|---|---|---|
| Parental rank | 0.32*** | 0.23*** | 0.33*** | 0.39*** | 0.34*** | 0.35*** |
| | (0.01) | (0.03) | (0.03) | (0.04) | (0.04) | (0.03) |
| Intercept | 0.37*** | 0.39*** | 0.35*** | 0.38*** | 0.46*** | 0.32*** |
| | (0.01) | (0.01) | (0.02) | (0.03) | (0.03) | (0.02) |
| N | 5,343 | 1,228 | 1,770 | 605 | 631 | 1,109 |
| R-squared | 0.09 | 0.05 | 0.06 | 0.14 | 0.12 | 0.11 |

Table 5. Rank Mobility Estimates across Survey Years, Rural Area

| | Overall | 2002 | 2007 | 2008 | 2013 |
|---|---|---|---|---|---|
| Parental rank | 0.26*** | 0.40*** | 0.22*** | 0.28*** | 0.20*** |
| | (0.01) | (0.03) | (0.02) | (0.02) | (0.02) |
| Intercept | 0.35*** | 0.29*** | 0.36*** | 0.32*** | 0.39*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| N | 8,089 | 1,503 | 1,607 | 1,748 | 3,231 |
| R-squared | 0.07 | 0.12 | 0.05 | 0.08 | 0.04 |

Table 6. Quantile Regression by Urban/Rural Area

| | Overall | Urban | Rural |
|---|---|---|---|
| 20% | 0.73*** | 0.89*** | 0.68*** |
| | (0.01) | (0.03) | (0.01) |
| 40% | 0.62*** | 0.80*** | 0.54*** |
| | (0.01) | (0.01) | (0.01) |
| 60% | 0.51*** | 0.74*** | 0.42*** |
| | (0.01) | (0.01) | (0.01) |
| 80% | 0.36*** | 0.64*** | 0.28*** |
| | (0.01) | (0.02) | (0.01) |
| 100% | 0.21*** | 0.38*** | 0.15*** |
| | (0.03) | (0.04) | (0.03) |
| N | 14,032 | 5,343 | 8,098 |

Table 7. Quantile Regression by Birth Cohorts

| | Overall | 1960s | 1970s | 1980s | 1990s |
|---|---|---|---|---|---|
| 20% | 0.73*** | 0.39*** | 0.62*** | 0.77*** | 0.62*** |
| | (0.01) | (0.08) | (0.03) | (0.02) | (0.04) |
| 40% | 0.62*** | 0.39*** | 0.57*** | 0.63*** | 0.45*** |
| | (0.01) | (0.05) | (0.03) | (0.01) | (0.03) |
| 60% | 0.51*** | 0.40*** | 0.48*** | 0.51*** | 0.36*** |
| | (0.01) | (0.06) | (0.03) | (0.01) | (0.03) |
| 80% | 0.36*** | 0.32*** | 0.32*** | 0.39*** | 0.24*** |
| | (0.01) | (0.06) | (0.04) | (0.01) | (0.02) |
| 100% | 0.21*** | -0.11 | 0.20*** | 0.26*** | 0.19*** |
| | (0.03) | (0.29) | (0.04) | (0.04) | (0.05) |
| N | 14,032 | 482 | 3,074 | 7,959 | 2,392 |

| | | Urban | Rural |
|---|---|---|---|
| 20% | | 0.89*** | 0.68*** |
| | | (0.03) | (0.01) |
| 40% | | 0.80*** | 0.54*** |
| | | (0.01) | (0.01) |
| 60% | | 0.74*** | 0.42*** |
| | (0.01) | (0.01) | (0.01) |
| 80% | 0.36*** | 0.64*** | 0.28*** |
| | (0.01) | (0.02) | (0.01) |
| N | 14,032 | 5,343 | 8,098 |

Table 8. Quantile Regression by Birth Cohorts, Parent's Quantiles

| | Overall | 1960s | 1970s | 1980s | 1990s |
|---|---|---|---|---|---|
| 20% | 0.33*** | 0.22*** | 0.17*** | 0.45*** | 0.12 |
| | (0.03) | (0.07) | (0.06) | (0.04) | (0.12) |
| 40% | 0.77*** | 1.54** | 1.08*** | 1.32*** | 1.29*** |
| | (0.06) | (0.61) | (0.21) | (0.23) | (0.40) |
| 60% | 0.98*** | 0.29 | 1.74*** | 0.24** | 0.57 |
| | (0.04) | (0.77) | (0.27) | (0.10) | (0.50) |
| 80% | 0.89*** | 0.89 | 0.41 | 0.02 | 0.46 |
| | (0.04) | (0.74) | (0.33) | (0.16) | (0.28) |
| 100% | 0.89*** | 0.98*** | 0.71*** | 0.30*** | 0.33*** |
| | (0.04) | (0.24) | (0.07) | (0.05) | (0.12) |
| N | 13,889 | 572 | 3,305 | 7,653 | 2,359 |

Figure 1. Parental Income Distribution 1999-2013

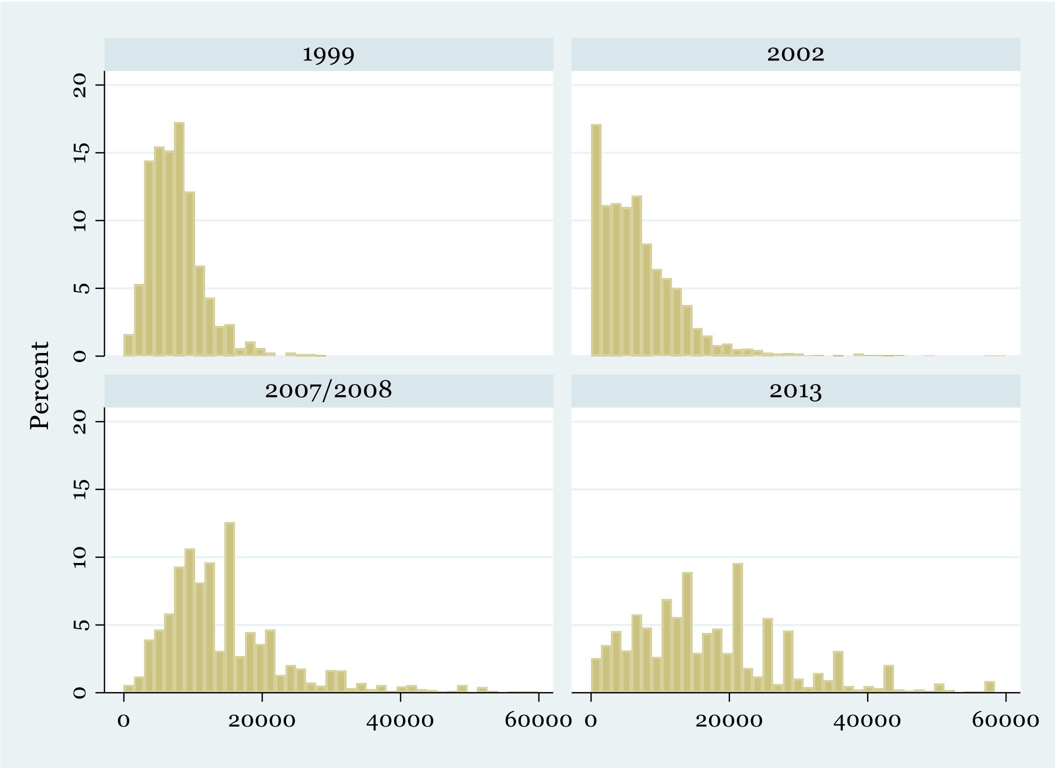


Figure 2. Children's Income Distribution 1999-2013

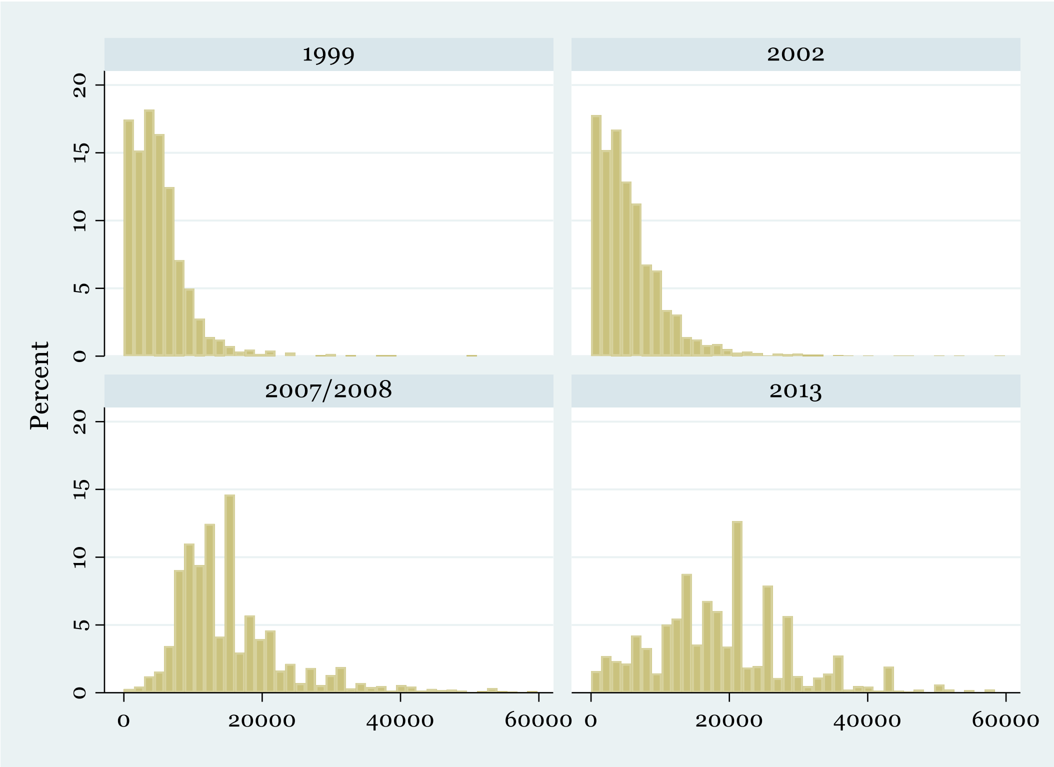
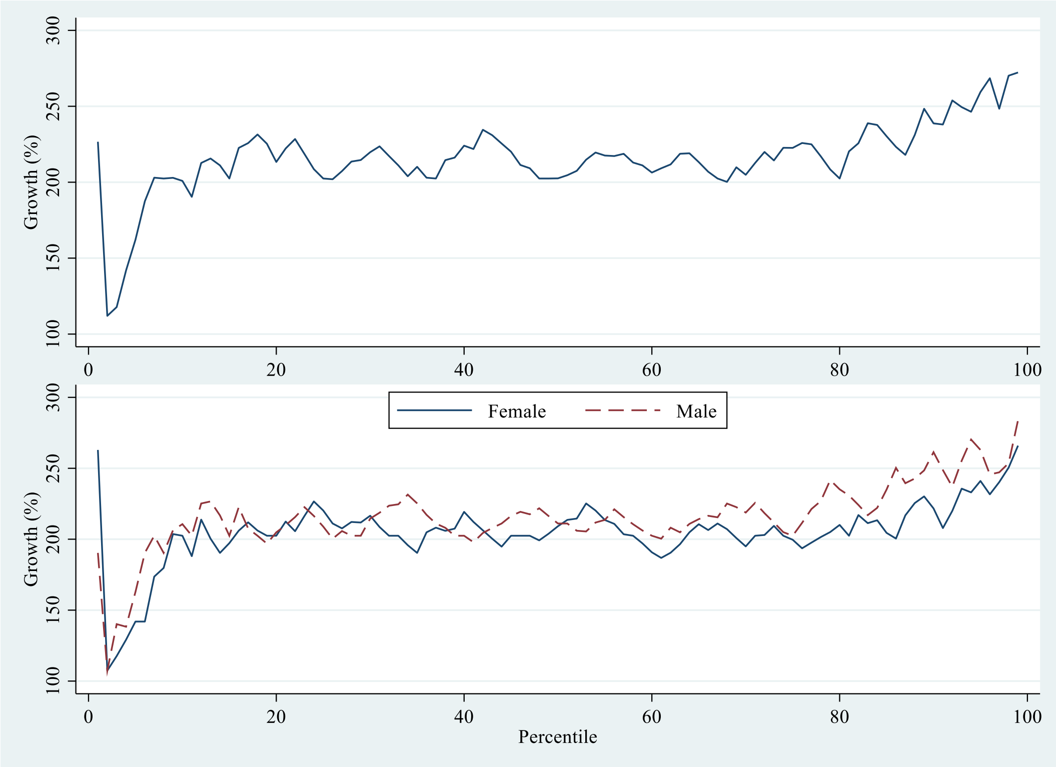
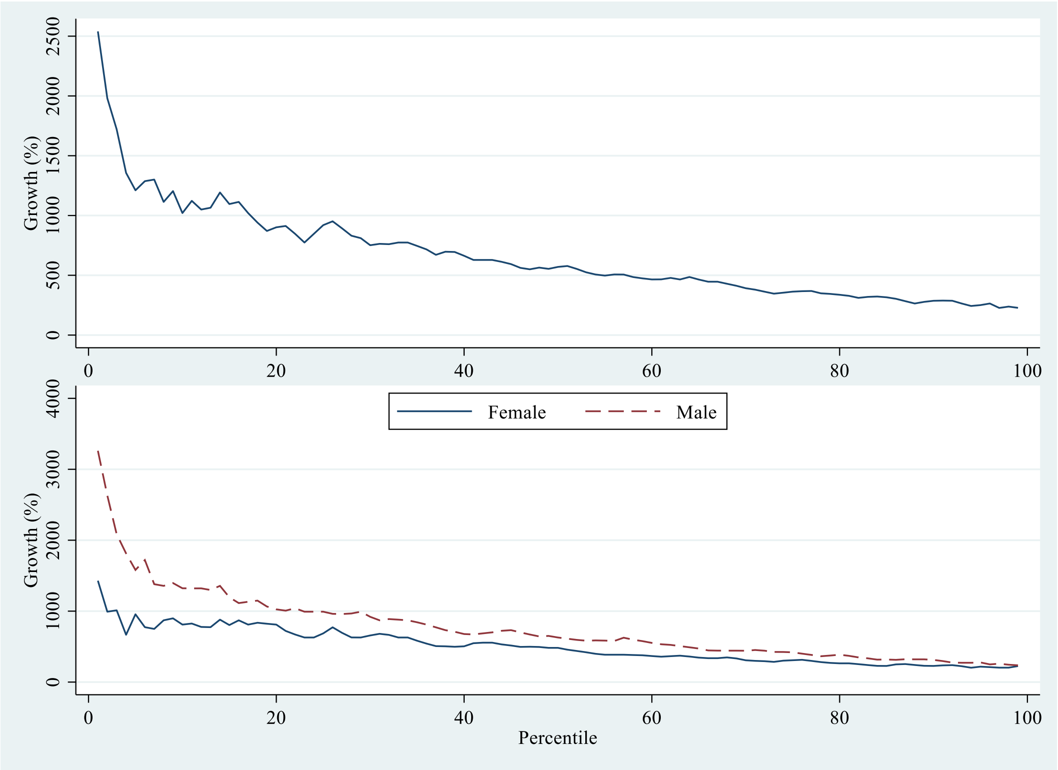


Figure 3. Growth Incidence Curve in Urban China 1999-2013




*Notes:* Income adjusted for inflation to 1999 price levels. Only household members aged 16 to 65 (included) are counted.

Figure 4. Growth Incidence Curve in Rural China 2002-2013




*Notes:* Income adjusted for inflation to 2002 price levels. Only household members aged 16 to 65 (included) are counted.