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THE SINS OF THE FATHERS: INTERGENERATIONAL INCOME MOBILITY IN CHINA

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This paper aims to obtain an accurate estimate of China's intergenerational income mobility and to present evidence on its distributional pattern. Using panel data from the China Health and Nutrition Survey (CHNS) over the period 1989–2009, I find that China is less mobile than most developed countries. Then, I employ five different approaches to investigate the distributional pattern of China's intergenerational mobility across income levels. The results suggest that poor families have relatively high mobility, indicating opportunities for the poor children to escape poverty. Finally, I show that while wealthy fathers are likely to pass on their favorable economic status to their sons, rich sons come from a very wide range of family economic backgrounds.

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1. Introduction and Literature

Income inequality has always been a major concern for both economists and politicians. One way to measure inequality is to examine the income distribution at a given point in time, typically using cross-sectional data. On the other hand, intergenerational income mobility deals with the way current inequality is passed to the next generation.

There is a large body of literature exploring intergenerational mobility, much of which focuses on fathers and sons in the USA. The conventional approach is to estimate the intergenerational income elasticity (IGE) which gives an answer to the question: If the father's lifetime income is one percent higher than the average of his generation, by how many percentage points will his son's lifetime income exceed the average of the second generation. The IGE is a mirror image of the intergenerational income mobility. They are inversely related to each other. In the following paper, both of these terms will be used.

Most of the early papers find the IGE in the USA to be about 0.2. However, in later research, people point out that the single-year measure of father's earnings induces an attenuation bias given that it is a poor proxy for the permanent income. As a result, they use better data such as Panel Study of Income Dynamics (Solon, 1992) and National Longitudinal Surveys of Labor Market Experience (Zimmerman, 1992) and replace the single-year father's earnings with averages of father's earnings taken over three to five years. They conclude that the IGE in the

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USA over the long run is around 0.4. More recently, Mazumder (2005) argues that even 0.4 has been biased down by 30 percent due to the persistent transitory income fluctuations and that the USA is substantially less mobile than people have thought.

Compared with the research on the USA, many studies find higher mobility in other OECD countries such as Sweden, Germany, Finland, Norway, Spain, and Canada.[1] But there are two exceptions: Great Britain's IGE almost reaches 0.6 when IV regression is employed (Dearden *et al.*, 1997); and the IGE in Italy is estimated to be 0.55 or 0.44, depending on the definition of income used (Piraino, 2007).

However, only a very limited number of papers focus on the less developed countries due to the paucity of data. According to these studies, mobility appears to be lower on average in developing countries such as Brazil, Ecuador and Peru (Andrade *et al.*, 2004; Grawe, 2004; Dunn, 2007; Gong *et al.*, 2012). Table B.1 in the online Appendix provides the main findings of relevant papers.[2]

In recent years, there have been a number of works regarding China's intergenerational mobility, but as of yet there is no consensus. The estimates of China's IGE range from around 0.3 to 0.63 (Guo and Min, 2008; Gong *et al.*, 2012; Fan *et al.*, 2013; Yuan and Lin, 2013). The broad range of IGE estimates probably result from different samples, sample selection rules, econometric model specifications and definitions of income.

Aside from obtaining estimates of the IGE in each country, researchers are also interested in the distributional pattern of intergenerational mobility across income levels. However, the literature on this topic is still very small. To my knowledge, only five papers carefully examine the issue econometrically.[3] In these studies, Eide and Showalter (1999) and Andrade *et al.* (2004) perform quantile regressions. Interestingly, The USA is found to have a generally decreasing IGE while Brazil is almost the opposite. Corak and Heisz (1999) use a nonparametric model and find that income mobility in Canada is higher at the lower end of the income distribution than on the top and in the middle. Finally, Bjorklund *et al.* (2012) use linear spline regressions to show that for the 0.1-percent richest Swedish families, fathers' economic status is highly transmissible to their sons. Figure 1 summarizes these findings.[4]

My paper is the first one to study in depth how intergenerational mobility varies across income levels in China. Using a diversity of methods, I find that poor families enjoy higher mobility, which may give people more confidence in China's poverty reduction. On the other hand, whereas wealthy fathers tend to give rise to wealthy sons, wealthy sons can come from a broad range of family economic backgrounds.

The remainder of this paper will be organized as follows: Section 2 introduces the data and sample selection rules, Section 3 estimates China's overall IGE, Section 4 investigates its distributional pattern, and Section 5 concludes the paper.

[1]See Bjorklund and Jantti, 1997; Couch and Dunn, 1997; Corak and Heisz, 1999; Osterbacka, 2001; Bratberg *et al.*, 2005 and Pascual, 2009.

[2]All tables and figures with the prefix "B" can be found in the online Appendix.

[3]Although there are many papers approaching the distributional pattern problem using transition matrices, they all reach similar conclusions due to an innate flaw of the matrix. I will discuss and correct the flaw in section 4.

[4]Grawe (2004) applies two-sample-two-stage-least-squares (TS2SLS) quantile regressions and estimated the IGE distribution patterns for several countries. Since most of their samples are quite small, I do not show the graphs.

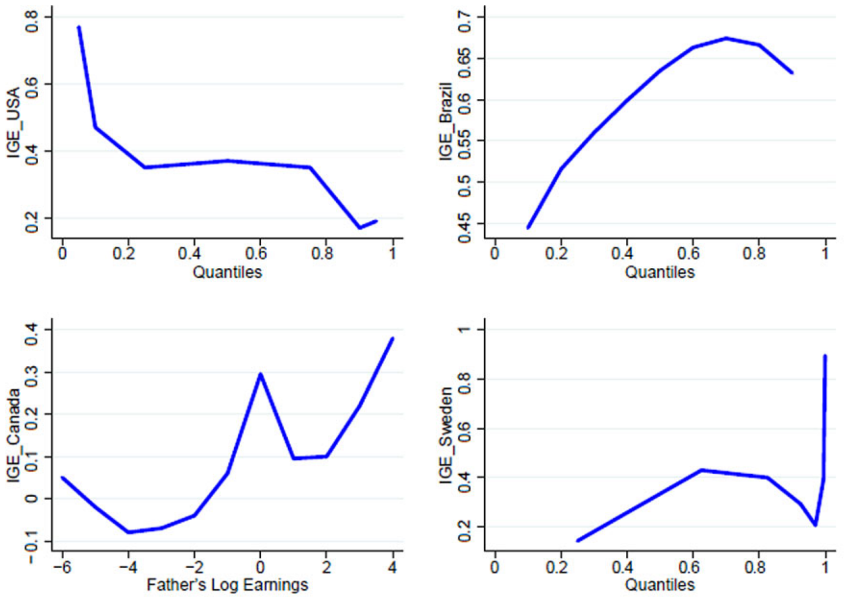

Figure 1. Distributional patterns of the IGE in other countries

2. Data and Sample Selection

The data are from the China Health and Nutrition Survey (CHNS), which was conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill and the Chinese National Institute of Nutrition and Food Safety. The survey covers a total of nine provinces in China including Heilongjiang, Jiangsu, Shandong Liaoning, Henan, Hubei, Hunan, Guangxi and Guizhou, and has had eight waves, collected in 1989, 1991, 1993, 1997, 2000, 2004, 2006 and 2009 respectively. In each wave of the survey, approximately 200 communities, 4000 households, and 26,000 individuals were interviewed. The participants were asked about health and nutrition conditions, medical care, family planning, demography, education, socioeconomic status, among other things. This micro longitudinal data set has proven to be representative and reliable (Wang, 2007), and is regarded as one of the best resources to investigate Chinese households and communities.

There are advantages and limitations regarding the data. The advantages are: first, it is a longitudinal data set that spans 20 years. If a person takes the survey in multiple years, researchers will be able to have a better knowledge of that person's income trend and lifetime income. Second, it collects information on individuals whether or not they are still residing in the same household with their families. Therefore, it does not suffer from the co-residing bias. The biggest shortcoming of the data, however, is that not every household participates in the survey from 1989 to 2009. Households may exit the survey for reasons that researchers may not know although the data do tell researchers when an individual leaves the sample due to death. New households will enter to replace the old ones so that the total number of families and individuals interviewed is similar in each wave. Thus, the sample includes households whose survey years may be different. To address this issue, I only use the households that stay in the survey for more than 16 years so that they are from roughly the same period.

I utilize the family member relationship file and individual's gender information to identify all the father-son cases. Sons who are enrolled in school and fathers who have retired are excluded from the sample. When calculating permanent incomes, years with negative or zero incomes are not considered. This step is justified by more than a computational issue. Reports of abnormally low incomes are most likely to be a result of measurement errors and using these values could incorrectly assign the corresponding individuals a very low lifetime income. The problems regarding missing values are always salient when dealing with survey data. In this study, I do not exclude individuals who fail to have a complete income series. For example, if one out of eight years is missing when calculating the eight-wave average, I use the average of the remaining seven years. This exercise is consistent with Osterberg (2000) and Bratberg *et al.* (2005). However, I drop fathers who have fewer than five income observations to ensure that the average incomes can approximate the lifetime incomes. Finally, following Couch and Dunn (1997) and Mazumder (2005), if more than one son is matched to a father, all sons who satisfy the screening rules are retained to have a larger sample size.[5] After all the restrictions are imposed on the data, the final sample size is reduced to 1407 father-son pairs, which is fairly small compared with the raw data. I acknowledge that there might be a representativeness issue associated with the small final sample used in the regressions. Table B.2 reports the summary statistics of the key variables. Here, the concept "Income" is defined as incomes from all sources including job earnings (calculated as the product of monthly earnings and the number of months a person worked in a given year), annual bonus and other cash or non-cash incomes. It is then adjusted to the 2009 price level using the consumer price indices. It shows that the sons earn more than the fathers on average. Sons are much better educated than fathers, probably due to the nine-year compulsory education since 1986 and the increasing return on human capital in the last decades (Yuan and Lin, 2013). The average age is about 24 for the sons and 53 for the fathers in 2000.

3. China's Overall Mobility

3.1. *Empirical Model*

I use a Galton-Becker-Solon equation as the baseline regression model. It is a conventional specification in the literature (Solon, 1992; Solon, 2002):

$$Y_i^{son} = \alpha + \beta \cdot Y_i^{father} + \varepsilon_i. \tag{1}$$

In equation (1), Y denotes the natural logarithm of mean income. As commonly done by other studies, I also control for the son's and father's age and age squared to account for their different stages in the life cycle. The coefficient of interest β is the IGE, which indicates the extent to which father's permanent income level affects his son's. The higher the β, the more likely sons will inherit father's

[5]The standard errors are adjusted for within-household correlation. If the sample is restricted to the oldest son in the household, there are fewer observations, but the results are largely unchanged.

economic position and the lower the intergenerational mobility. In the extreme, when β equals zero, father's income has no bearing on the son's and there exists perfect income mobility. In contrast, if β is greater than or equal to one, not only economic status tends to be passed down to the next generation, but the income distribution fails to regress to the mean.

The regression investigates the net effect of father's income on the son's through any possible channels, obviating the need to include other control variables on the right-hand side without incurring the missing variable bias. But researchers have been trying different ways to handle the attenuation bias caused by the measurement error in father's permanent income. Single-year income is not a good proxy as it consists of both permanent income and transitory fluctuations (Solon, 1992; Solon, 2002; Mazumder, 2005). Three methods to mitigate the bias have been recommended. One is to take the average of the incomes across several years (usually three to five years) to get a more accurate measure of permanent income (Solon, 1992; Zimmerman, 1992; Bjorklund *et al*., 2012). However, Mazumder (2005) argues that the five-year average income still suffers from large measurement error, as transitory fluctuations are probably persistent. Second, if longitudinal income data are not available, instrumental variable regressions can be used. Among the most well-known IVs are a father's education (Solon, 1992; Dearden *et al*., 1997) and a father's social or economic status (Zimmerman, 1992; Dearden *et al*., 1997). These two instruments have fewer transitory fluctuations than the current incomes. Using them as the IVs alleviates the downward bias. IV regression, however, is also problematic in that the IV may be invalid. Take the father's education level as an example: if a father's education is somehow positively correlated with his son's income after controlling for his own income, the IGE will be overestimated. The third method uses the two-sample two-stage least squares (TS2SLS) procedure (Bjorklund and Jantti, 1997; Dunn, 2007). Three steps are taken. First, the relationship between permanent income and personal characteristics is established using a complementary data set. Then, with the estimated relationship, father's lifetime income can be predicted using characteristics in the primary data set. Finally, the child's income is regressed on the predicted father's income.

The measurement error in the son's income does not in and of itself cause biases, but many researchers still choose to average their incomes across years to gain greater efficiency (Gustafsson, 1994; Couch and Dunn, 1997; Mazumder, 2005). Another issue regarding the regression is that the IGE tends to be biased downwards when the sons are at the beginning stage of their career (Solon, 2002; Haider and Solon, 2006). The correction of this problem is to only use sons within a specific range of age, typically from their late 20s to early 40s, or to average their earnings only in their latest years in the data such that the current income is close to the lifetime income (Gustafsson, 1994; Jantti and Osterbacka, 1999; Bjorklund and Jantti, 1997).

I follow the literature and use the average income across all available years as a measure of father's lifetime income. For the sons, I take the average of their incomes between 25 and 40 years old. I also run regressions using sons of all ages to take advantage of the larger sample size.

Additionally, I perform IV regressions for comparison. The instrumental variables I use are father's years of education and the average income within father's occupation. The former IV is the most commonly used in the literature. The rationale for the latter one is that fathers' incomes are highly correlated with their occupations, but the occupation itself does not directly affect their sons' income. As such, the exclusion condition is well satisfied. However, note that if father's occupation has predicting power of son's occupation, which affects son's income, the result will be biased upwards. In this sense, the IV regressions provide an upper bound of β. The first-stage regression shown in Table B.3 indicates that the IV is very strong.

3.2. *Results*

Table 1 presents all of the results. OLS using sons of all ages indicates that China's IGE is approximately 0.5. Restricting the sample to older sons reduces the estimate to about 0.4. As has been found in the literature, using IV regressions increases the estimates substantially, to between 0.59 and 0.80. Given that OLS tends to underestimate and IV regression tends to overestimate the IGE, the true value may lie between 0.5 and 0.6. In addition, since the majority of the fathers have income observations in seven or eight waves out of a total of eight waves, the average income should be quite representative of their long-run incomes and the measurement error is supposed to be effectively wiped out.[6] As such, China's IGE is likely to lean toward the OLS end, and settle near 0.5. By comparing the results from OLS and IV regressions with the corresponding estimates in Table B.1, I find that China's IGE is greater than those of most developed nations, especially the Scandinavian countries. The implied low mobility might be due to more nepotism and rent-seeking in recent years in China (Yuan and Lin, 2013).

There are big differences between China's urban economy and rural economy in many aspects. To explore whether it is true for income mobility, I split the sample into urban subsample and rural subsample according to father's residence and estimate the IGE for these two areas respectively. Since the number of observations (especially for the urban areas) is fairly small, I use sons of all ages in the regressions to maintain a reasonable sample size. Table 2 reports the OLS results. It turns out that the urban households have a much higher IGE than the rural ones. It is not unexpected given that tens of millions of Chinese rural people, most of whom are young men (second generation), have migrated into cities to work in the manufacturing industry during the past two decades, which improved their earnings and weakened the link between father's and son's incomes. A further investigation into the data confirms this phenomenon: 84 percent of the urban working sons live at home while the number for rural working sons is only 62 percent.

4. The Distributional Pattern of Income Mobility

One interesting question concerning mobility is whether rich parents and poor parents have an equal effect on their children's future incomes. If not, the mean IGE misses a lot of information.

[6]On average, fathers report their incomes 6.65 times, with the survey waves spanning 17.71 years. About 60 percent of fathers have seven or eight income observations.

TABLE 1

Estimates of China's Overall IGE

Covariates	Ages of Sons: All ages: OLS	All ages: IV: Father's Years of Education	All ages: IV: Occupational Income	25–40 years old: OLS	25–40 years old: IV: Father's Years of Education	25–40 years old: IV: Occupational Income
Ln (Father's mean income)	0.498***	0.800***	0.717***	0.382***	0.594*	0.682***
	(0.051)	(0.227)	(0.188)	(0.071)	(0.327)	(0.230)
Age_{son}	–0.001	–0.012	–0.009	–0.214***	–0.186**	–0.174**
	(0.030)	(0.032)	(0.031)	(0.073)	(0.076)	(0.083)
Age^2_{son}	0.000	0.001	0.001	0.003**	0.003**	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age_{father}	–0.073	–0.062	–0.065	0.097	0.096	0.095
	(0.045)	(0.046)	(0.045)	(0.067)	(0.068)	(0.070)
Age^2_{father}	0.001	0.001	0.001	–0.001	–0.001	–0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
F-statistic	29.32	11.01	11.65	20.87	13.51	15.67
R^2	0.108	0.081	0.094	0.237	0.217	0.196
Observations	1407	1407	1407	442	442	442

Notes:
1 The sample is from the China Health and Nutrition Survey (CHNS) 1989–2009.
2 Dependant variable: Ln (son's mean income).
3 Robust standard errors adjusted for within-household correlation are in brackets. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

TABLE 2
Difference Between the Urban and Rural Areas

Covariates	Rural	Urban
Ln (Father's mean income)	0.407***	0.694***
	(0.059)	(0.099)
Age_{son}	–0.016	0.062
	(0.040)	(0.059)
Age^2_{son}	0.001	–0.001
	(0.001)	(0.001)
Age_{father}	–0.053	–0.188*
	(0.049)	(0.107)
Age^2_{father}	0.004	0.002*
	(0.004)	(0.001)
F-statistic	17.19	12.17
R^2	0.075	0.262
Observations	1189	218

Notes:
1 OLS is employed. The dependant variable is the natural logarithm of son's mean income.
2 Sons of all ages are used.
3 Rural/urban is defined by parents' residence.
4 Robust standard errors adjusted for within-household correlation are in brackets. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Previous papers have adopted five different approaches (transition matrix, linear spline regression, nonparametric regression, quantile regression and instrumental quantile regression) to examine the distributional pattern of mobility in other countries. In the following section, I apply all these methods to study this question in China. It is important to maintain a relatively large sample size because all of these methods allow mobility to vary across cohorts. Thus, I do not impose restrictions on son's ages. It may bias the estimates of mobility upwards, but to the extent that every cohort is similarly affected, it will not change its distribution pattern.

4.1. *Transition Matrix*

One of the most popular methods of addressing this question is with the use of a transition matrix (Jarvis and Jenkins, 1998; Corak and Heisz, 1999; Bratberg *et al.*, 2005; Shi *et al.*, 2010). Using my data, I construct the following quintile matrix:

TABLE 3
5 × 5 Father-Son Income Transition Matrix

		Son's Income				
		Bottom	Second	Third	Fourth	Top
Father's Income	Bottom	0.326	0.259	0.216	0.135	0.064
	Second	0.212	0.283	0.226	0.155	0.124
	Third	0.196	0.206	0.210	0.221	0.167
	Fourth	0.159	0.155	0.223	0.244	0.219
	Top	0.107	0.096	0.125	0.246	0.427

It is notable that for the richest and poorest parents, their children are more likely to maintain the same income level while children with parents who fall in the middle groups enjoy much more income mobility. For example, about 43 percent ((5, 5) entry of the matrix) of the sons born to top rich fathers will end up being the richest as well. On the contrary, for the three middle-income cohorts, the probability of children having the same income status as their parents is well below 30 percent.

However, people are concerned that the way the matrix is constructed guarantees higher numbers at the end points and smaller numbers in the middle (Atkinson *et al.*, 1983; Corak and Heisz, 1999).[7] This ceiling/floor problem is recognized in the early 1980s; unfortunately, researchers keep using the matrix without trying to address this flaw.

In this paper, to address this concern, I take two steps to modify the matrix. First, I divide parents and children into ten groups respectively and expand the matrix to a 10×10 one. The transition matrix becomes:

TABLE 4
10×10 FATHER-SON INCOME TRANSITION MATRIX

		Son's Income									
		Bottom	2nd	3rd	4th	5th	6th	7th	8th	9th	Top
Father's Income	Bottom	0.170	0.170	0.128	0.099	0.170	0.064	0.050	0.078	0.035	0.035
	2nd	0.128	0.184	0.156	0.135	0.071	0.128	0.085	0.057	0.043	0.014
	3rd	0.098	0.098	0.140	0.147	0.112	0.112	0.091	0.077	0.070	0.056
	4th	0.107	0.121	0.136	0.143	0.064	0.164	0.079	0.064	0.064	0.057
	5th	0.136	0.114	0.143	0.100	0.100	0.064	0.114	0.071	0.050	0.107
	6th	0.071	0.071	0.078	0.092	0.142	0.113	0.135	0.121	0.092	0.085
	7th	0.077	0.092	0.085	0.056	0.113	0.092	0.134	0.134	0.162	0.099
	8th	0.085	0.064	0.071	0.099	0.106	0.113	0.106	0.085	0.121	0.149
	9th	0.057	0.043	0.057	0.071	0.093	0.064	0.100	0.171	0.193	0.150
	Top	0.071	0.043	0.007	0.057	0.050	0.043	0.106	0.113	0.234	0.277

It is conspicuous that the top decile (the (10, 10) entry) has an exceptionally large number, much larger than its bottom counterpart, indicating a lower mobility for the richest families than the poorest families. As a second step, I define a new concept called "relatively stable". It means that the son's income either stays in the same decile as his father's income or moves to the neighboring deciles. For instance, the probability that a father in the bottom 10 percent stays "relatively stable" is the sum of the (1, 1) and (1, 2) entries whereas the chance of a "second to poorest" father (10 percent–20 percent) remaining "relatively stable" is the sum of the (2, 1), (2, 2) and (2, 3) entries of the matrix. As such, the ceiling/floor effect associated with the richest and poorest families is counteracted by only adding up two numbers as opposed to three. Table 5 and Figure B.1 summarize these probabilities for all the ten subgroups.

[7]Consider a father in the lowest quintile. If his son's income improves substantially, this father-son observation will wind up in a position of (1, 2), (1, 3), (1, 4) or (1, 5) entry in the matrix, depending on the extent of the enhancement. In contrast, if the son has a worsened income compared to other children, no matter how poor the situation is, he will still stay in (1, 1) of the matrix. The situation is different for a middle-class family because they will not stay on the diagonal of the matrix whenever the son has a considerable change in his income, either richer or poorer. For example, a son with third-grade parents could move to (3, 4) or (3, 5) if he enjoys a higher earning, or switch to (3, 1) or (3, 2) if he makes less money. In other words, the poorest and the richest have only one direction of change while people in between can go either way.

TABLE 5

Probabilities of Being "Relatively Stable"

0–10%	10–20%	20–30%	30–40%	40–50%	50–60%	60–70%	70–80%	80–90%	90–100%
0.340	0.468	0.385	0.343	0.264	0.390	0.430	0.312	0.514	0.511

TABLE 6

Linear Spline Regression Results

Quantiles	0–20%	20–40%	40–60%	60–80%	80–100%
Estimates of the IGE	0.277	0.443	0.720	0.700	0.559
F-statistic	19.46				
R2	0.112				
Observations	1406				

The large numbers for the top 20 percent families imply that sons with rich fathers can easily inherit their favorable economic status. It should not be surprising as wealthy parents have more power and resources to transmit their income advantages. On the other hand, people in the left tail (lowest decile) of the income distribution enjoy relatively high mobility. This pattern comes as a consolation since it means that the moving up mechanism is not blocked for children from poor families. Given that the rural areas are typically poorer than the urban areas, this distributional pattern is also consistent with the previous finding that mobility in the rural areas is higher than in the urban areas.

4.2. *Linear Spline Regression*

The second method I use is linear spline regression. It allows the slope of the regression line to change at each pre-defined breakpoint (called knot), which can be designated arbitrarily. The regression yields a series of coefficients in each interval created by any two neighboring knots. By observing these coefficients, one is able to know how the coefficient of interest varies across the quantiles of the explanatory variable. Mathematically, suppose we separate the regressor into two pieces connected at z, and y is piecewise regressed on x, the regression equation would be:

$$y_i = \alpha + \beta \cdot x_i + \gamma \cdot (x_i - z) + \varepsilon_i. \tag{2}$$

In this paper, I define the knots as the 20th, 40th, 60th and 80th percentiles of father's log average income. I do not divide it into finer pieces because the coefficients will become overly volatile when the sections are small. The results are presented in Table 6 and Figure B.2. Generally speaking, the IGE is the lowest for the bottom 20 percent fathers and rises to about 0.7 before declining slightly to 0.56 for the top 20 percent. This pattern also indicates greater mobility for the poor families than the wealthy families as is suggested by the transition matrix.

4.3. *Nonparametric Regression*

Nonparametric technique allows very flexible coefficients throughout. It does not make assumptions about the functional form of the relationship between the dependent and independent variables.

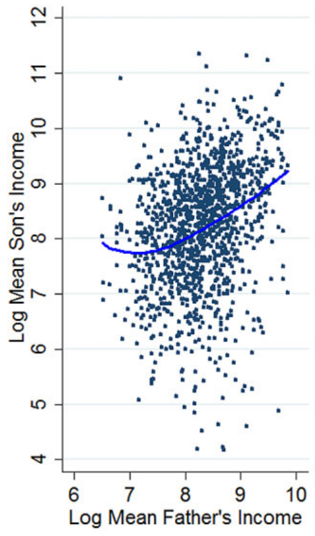

Figure 2. Results of the nonparametric regression

There are various specifications for nonparametric regressions. In this work, I adopt kernel weighted local polynomial smoothing, set the degree of the polynomial equal to 3 for the functional form, choose Epanechnikov kernel, set the bandwidth equal to 0.8 and abandon the outliers at the left tail as they are not likely to represent people's lifetime income.[8] The result is shown in Figure 2 where the blue line is the fitted line. Since the horizontal axis and vertical axis represent log mean father's income and log mean son's income respectively, the slope of the fitted line (which is also the derivative of log mean son's income with respect to log mean father's income), is the estimated IGE. It is obvious that the slope starts being zero or even negative in the first place. Then it turns positive and grows monotonically until around the midpoint. After that, the slope keeps roughly constant. It implies that the poor families are more mobile than the rich ones. This pattern further corroborates the findings in 4.1 and 4.2.

Summing up the results so far, the transition matrix, the linear spline regression, and the nonparametric regression all suggest considerably higher income mobility for the poor than for the rich. However, the implications for the middle-income families are not consistent across methods. The transition matrix shows that the IGE for the middle class is somewhat lower than for the poorest and much lower than for the richest group; the nonparametric regression indicates a higher IGE for the middle class than for the poorest, but there does not seem to be much difference between the rich and the middle class; finally, the spline regression shows that the IGE for the middle class is much higher than the poor and is even slightly higher than the richest group. The noise in the middle-income cohort could come from different econometric models and from the fact that the sample is not

[8]I have also used other nonparametric regressions such as locally weighted scatterplot smoothing (Lowess), and experimented with other bandwidths and kernels. The results are similar.

TABLE 7
Quantile Regression Results

Quantile	Regular Quantile regression	IV Quantile Regressions: IV: Father's Years of Education	IV Quantile Regressions: IV: Mean Occupational Income
0.1	0.390***	0.387***	0.839***
0.2	0.574***	0.870***	0.826***
0.3	0.527***	0.759***	0.970***
0.4	0.569***	0.886***	0.863***
0.5	0.536***	0.973***	0.924***
0.6	0.485***	0.782***	0.670***
0.7	0.443***	0.760***	0.546***
0.8	0.437***	0.589***	0.587***
0.9	0.415***	0.665***	0.670***

Note: ***denotes significance at the 1% level.

particularly large. The only conclusion that can be safely drawn from all three methods is that there is greater mobility for the poor than for the rich.

4.4. *Quantile Regression*

The remaining two methods to explore the distributional pattern of mobility are Quantile Regression and Instrumental Quantile Regression. Quantile regression has a few favorable properties compared with least squares. It does not require any distributional assumption of the error term and is robust to extreme values and outliers. This attribute is especially important for handling survey data since unusually large or small incomes are not rare. Another advantage is that it utilizes all the observations when computing the coefficients for each quantile without diminishing the sample size. This property is particularly useful for studying the distribution pattern of the IGE as people do not need to worry about the subsamples being too small.

The results of the quantile regression and IV quantile regressions are reported in Table 7 and Figure B.3. A common feature these regressions share is that the richest sons happen to have low IGE and hence high mobility. The generally growing mobility across son's incomes (except for the lowest decile) is in accordance with Eide and Showalter (1999) who find a similar pattern in the USA.

4.5. *Reconciliation of Different Results*

Quantile regressions demonstrate that rich families end up with low intergenerational elasticity, which is at odds with what is implied by the transition matrix, the linear spline regression, and the nonparametric regression. To reconcile these results, first note that quantile regressions group people according to son's income whereas other methods are all based on father's income. They look at the problem from different perspectives.

Figure B.4 provides a technical explanation of why decreasing IGE from quantile regressions and increasing IGE from a non-quantile regression can actually coexist. Suppose the observations are evenly distributed like a right triangle in the graph. According to the definition of quantile regression, the fitted line of a

TABLE 8
The Variation of Father's Income for Different Groups of Sons

Percentile of Son's Income	0–10%	10–20%	20–30%	30–40%	40–50%	50–60%	60–70%	70–80%	80–90%	90–100%
Standard deviation of Log Father's Income	0.75	0.64	0.54	0.63	0.69	0.60	0.64	0.63	0.74	0.69

particular quantile in this case is simply a straight line that connects the series of points associated with a given quantile value for the dependent variable at each value of the independent variable. At the rightmost point of the triangle, every quantile value clusters there. Thus, all quantile regression lines must cross that point. It can be shown that the slope of the regression line decreases as the quantile gets higher (in the graph, the 80th percentile line must be flatter than the 20th percentile line. When the quantile reaches the upper bound 100th percentile, the slope is zero). By contrast, if the sample is divided conditional on the independent variable, and OLS is conducted in each subsample, the fitted line will start from being flat (in the left extreme, the slope is zero) and becomes steeper as the independent variable increases. Actually, Figure 2 depicts the distribution of the observations, which does look somewhat like the triangle described above.

A potential economic reason for the high income mobility associated with the wealthiest sons is that they may come from a broad range of economic backgrounds, such that the father's income does not have large explanatory power in regards to son's income. To test whether this is the case, I calculate the standard deviation of log father's average income for sons of different income levels. Note that taking the natural log takes care of heteroscedasticity in the father's income. Table 8 shows that fathers of the richest sons (top 2 deciles) indeed have a broader range of incomes than other fathers except for the poorest cohort. This should come as no surprise because China's opening-up and reform policy, the adoption of the market economy and the compulsory education have given Chinese young men a great number of opportunities to build wealth, even if they do not come from rich families.

Finally, integrating the results from all these econometric techniques, one may conclude that: on one hand, rich parents can easily pass wealth to the next generation (according to the non-quantile regression methods); on the other hand, young men have various ways other than being born into an affluent family to become wealthy (according to the quantile regressions).

4.6. *Comparing the Methods*

There is no answer as to which method should be used when studying the distributional pattern of the IGE. However, it helps to keep in mind the shortcomings of each method.

Transition matrix suffers from two drawbacks. One is the ceiling/floor effect as is mentioned above. The second is missing information on ages of both fathers and sons, which can be problematic. Solon (2002) and Haider and Solon (2006) show that the IGE tends to be underestimated if sons are very young while Grawe (2004) illustrates that estimates of IGE are negatively correlated to father's age.

Linear spline regression allows people to choose the knots (specifying intervals) arbitrarily. However, the result is very sensitive to the choice of the knots. Poorly selected knots can result in exceptionally large coefficients at the cost of unusually small or even negative coefficients for the neighboring intervals.

Nonparametric regression also fails to directly control for ages. Besides, the best-fitting line may be affected by the outliers in the tails of the distribution. Finally, setting parameters may be challenging.

Quantile regression approaches a problem from the angle of the dependent variable, making it seemingly contradictory to other methods sometimes.

In sum, every method has its own drawbacks. Even with the same data, different methods can generate very different results. In the absence of theories, one should be very careful about putting too much weight on any single result; robustness checks are necessary. It may be worthwhile to adopt multiple methods to get a range of coefficients before making conclusions.

5. Concluding Remarks

This paper explores intergenerational income mobility and its distributional pattern in China using a longitudinal sample. I find that China's IGE is likely to be between 0.5 and 0.6, which hints that China has less mobility than most of the developed countries. This conclusion is in line with the conjecture that developing countries provide people with less equal opportunity and are thus less mobile. Additionally, I adopt a variety of strategies to investigate the distribution of income mobility across income levels. It turns out that the modified transition matrix, the linear spline regression, and the nonparametric regression end up telling a fairly consistent story that the poor households in China are much more mobile than the rich, which implies opportunities for the poor children to escape poverty. However, quantile regression uncovers a different pattern that rich sons are actually a highly mobile cohort. Combining all the information I conclude that in China, while wealthy parents can easily make their children wealthy, there are plenty of ways for a child to become rich. Being born into an affluent family is not the only one.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web-site:

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