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Income Inequality, Family Formation and Generational Mobility in Urban China

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Abstract

Income inequality has increased in most developed and developing economies in the world in the last 30 years and China is exemplary in this regard. Many analyses of its strident growth in income inequality have focused on the effects of policies relating to Urban-Rural and Inland-Coastal distinctions. Yet income inequality growth has prevailed on both sides of those respective divides as though there is something more fundamental underlying the phenomenon. Here, by showing how specific types of change in family formation and specific types of human capital transfer engender increases in inequality measures, growth in urban inequality is rationalized as a consequence of the changing nature of the family and the structure of the human capital augmentation process that has been a feature of the last 70 years in China. Influenced by such events as the Cultural Revolution, the One Child Policy and the Economic Reforms, people changed the way they chose a marriage partner, invested in children and passed on human capital endowments. Social class designations became less important and educational class designations became more important. Using a unique data set linking grandparents, parents and children, such changes can be observed empirically.

Keywords: Inequality, Intergenerational Mobility, Education, Social Classs

Introduction

The rapid economic growth in China since the Economic Reforms of the early 80's has been attended by an equally strident increase in inequality with National Gini coefficients below 0.3 in the early 1980's rising to values above 0.5 in the first decade of the 21st century (Xie and Zhou 2014). The rise has been uneven, Li (2015) reports rural Gini's of 0.24 and 0.37 in 1981 and 2011 respectively and urban Gini's of 0.15 to 0.34 in those same years. That the National Gini is somewhat higher than its urban and rural counterparts is accounted for by rural–urban disparities which are not a component of the "within" urban and "within" rural statistics[1]. In addition, due to the extensive urbanization process in China over the last 3 decades[2], the weight attached to the "rural" component has diminished substantially placing much greater emphasis on the urban component of inequality.

With urban and rural inequalities trending disproportionately there has been no shortage of stories as to sources of the trends. Researchers have looked to urban – rural and inland – coastal disparities in social and economic structure and policy treatment (Yang 1999, Kanbur and Zhang 1999, Gustafsson and Li 2002, Meng et al. 2005, Wu 2005, Hertel and Fan 2006, Ravallion and Chen 2007, Benjamin et al. 2008). Population aging, access to and disparities in education, the rise of rural industrial enterprises, increases in the returns to education and the shift of employment into secondary and tertiary sectors have also been cited as sources of the rise in inequality (Yang 1999, Meng 2004, Wan 2004 Goh, Luo and Zhu 2009, Zhong 2011). Many researchers have studied urban income inequality using the household survey (Knight and Song (2003), Meng (2004), Hauser and Xie (2004), Fang, Zhang and Fan (2002)). Typically they suggest that the sharp increase in the urban area Gini coefficient in the reform era is exacerbated

[1]Gini is a mean normalized average of income differences within the urban society, within the rural society and between the urban and rural societies and the latter component only appears in the national measure. Yang (1999) concludes that the rural-urban disparity accounts for most of the inequality among rural, urban and rural-urban disparity inequalities, whereas urban inequality accounts for 11% of the overall inequality. However, Ravallion and Chen (2007) emphasize that, although relative inequality is higher in rural than urban areas, there has been steeper inequality gradient over time in urban areas. Moreover, after accounting for higher living cost in urban, absolute inequality is higher in urban areas.

[2]In 1981 the urban population accounted for about 20% of a 1.001 billion Chinese population, by 2011 it had risen to about 51% of the 1.347 billion people living in the country (NBS 2014 (National Bureau of Statistics of China).

by growing regional wage dispersion pointing out that large-scale unemployment due to labor reallocation reduced income at the lower end of distribution thus increasing urban income inequality. However many of these rationales characterize symptoms rather than sources of the steady incessant increase in disparity, and when both urban and rural sectors have similar trends, an explanation based upon fundamental ongoing structural change that is fueling the trending inequality in all sectors is required.

Here, it will be argued that the ubiquitous growth in inequality also has roots in the changing nature of the family and class system in China. Specifically the roots lay in changes in the way families are formed and changes in the way that the stock of human capital is augmented over generations, namely the generational transition of educational status mechanism and the transition from a social class based to an education class based society. These changes were shaped by certain historical events, the Cultural Revolution, the One Child Policy and the Economic Reforms. Household income generation will be seen to be heavily dependent upon the educational levels of the parents, education levels that over the second half of the last century were to some degree governed by their class origins. These education levels were also influenced by certain policies embarked upon during the Cultural Revolution that were at once equalizing in the present and dis-equalizing for the future. The One Child Policy changed the way families were formed in obvious and less obvious ways and also changed investment in children and their education. Finally the Economic Reforms had a profound effect on incomes especially in urban China. The Chinese Household Income Project (Li, Luo, Wei and Yue 2008), which is a rich dataset providing information on grandparent's social class designation, parent's educational status and child's (grandchildren's) educational status as well as other household characteristics, will be employed to explore these possibilities. In summary a source of increased urban inequality was found to be the increased dependency of household incomes on household human capital and diminished dependency on social class. Increased positive assortative matching in the One Child Policy–Economic Reform Era increased the disparities in household human capital which in turn increased the disparities in household incomes and concomitantly the disparities in the circumstances of children whose educational outcomes were themselves highly dependent upon their parental circumstances.

Background

Historical events such as the Cultural Revolution, the One Child Policy and the Economic Reforms changed fundamentally the nature of the family class and educational transmission processes. In 1949, when the country was founded, in order to eliminate "political opponents" as much as half of the farmland was seized from the landlord class and redistributed to the formerly landless peasants (Walder and Hu 2009, Clark 2014). In this very early stage of the Chinese agrarian revolution (the late 1940's and early 1950's) the entire urban and rural population (the "grandparents" in this study) was classified into ordered social classes according to family employment status, income sources and political loyalties at the time of the "liberation". The classes, 12 in number, ranged from landless peasants through landlord classes to the aristocracy of the revolution, the revolutionary "fighters". The class label was assigned to the entire household and inherited through the male line regardless of the offspring's political stance or behavior, it was the main criteria when an individual looked for a job or promotion etc.

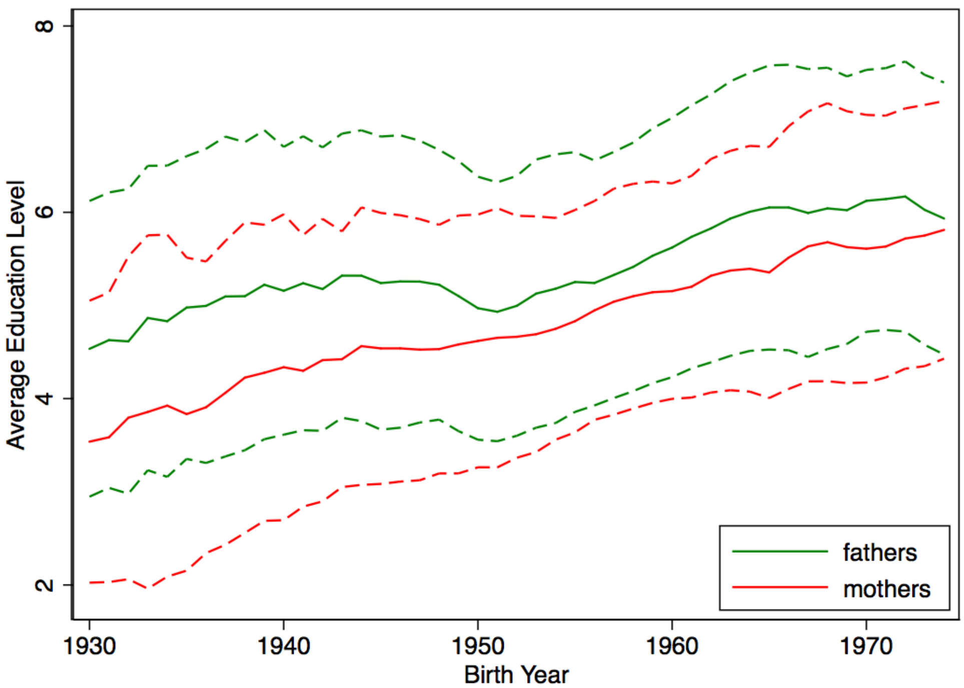
The Cultural Revolution 1966-76 (the educational period of some of the parents in this study) saw mass school closures (Gregory and Meng 2002, Deng and Treiman 1997) and a "class enemy" purge of "elites", a relatively small portion of the population. At the time one slogan of the Communist party was *"eliminate the distinction between town and country, industry and agriculture, physical and mental labor"*. Policies were designed to curtail "elites" and intellectuals from passing on social status and educational advantage to their next generation. Teachers and professors were ostracized and all levels of schools were closed. When higher education institutions reopened after 1972, children from formerly lower social designations were given more opportunities for education and occupational attainment than those from higher social designations. Higher education institutions did not resume recruiting based on merit until the Cultural Revolution ended (Clark 2014)[3].

Post 1980 saw the profound growth spurt precipitated by the Economic Reforms and the effects of the One Child Policy which increased investment in child education (Anderson and Leo 2009). Often these children would have been born into families

[3] However Gregory and Meng (2002) suggest that the largest negative impact was faced by children from lower educational achievement and lower social class families.

headed by parents who had suffered the effects of the Cultural Revolution. The loss of schooling effects of the Cultural Revolution may be seen in the average number of years of schooling and average level of schooling profiles experienced by the birth cohorts who would have been educated in the period of the Cultural Revolution. Essentially the cohort born between 1948-1955 possibly missed senior high school due to the Cultural Revolution and the cohort born between 1956-1963 who missed part of primary school and junior high school or experienced a lower quality of school in the Cultural Revolution.

Diagram. 1: Average Education Level by Birth Year



*The dash lines are 1 standard deviation.

From Diagram 1 the effects may be seen to have predominantly impinged upon educational growth trends in males, the growth trends in education for both genders diminished but for males it became negative over the 1945–1952 period so the male–female education gap was narrowed significantly. Over the same time period variations in educational attainment levels and education years across both genders diminished greatly, a consequence of the Cultural Revolution, it represents an equalization of circumstances for future generations.

There is also evidence that the One Child Policy embarked upon in 1978 changed the way people chose partners (Anderson and Leo, 2013). With procreation, child rearing and family income production all being part of household production, under a regime which constrains one of the marital outputs (procreation and child rearing) relative to other outputs, potential partners with specialized procreation and child rearing skills become less attractive relative to partners with specialized income generating skills. This will result in an increase in the extent to which people chose partners similar to themselves in income generating dimensions relative to choosing partners on the basis of other dimensions such as social class (Becker, 1993).

The relationship between Income inequality, human capital transmission and family formation

Generational transition matrices may be construed as blueprints of the way in which human capital qualities are passed on through generations changing the anatomy of the arrival (inheritors) distribution from that of the departure (parents) distribution by moving agents into new positions relative to their ancestors position in the departure distribution. Anderson (2016) characterized such transition matrices as polarizing, converging or static matrices, when respectively the net transfer of mass is from the center of the departure distribution to the peripheries of the arrival distribution, or from the peripheries of the departure to the center of the arrival distribution or not transferring mass at all. When incomes have a monotonic non decreasing dependency upon human capital qualities, polarizing transitions can be seen to make future generations' income distributions more unequal and converging transition matrices can be seen to be making future generations' income distributions more equal, static transition matrices result in no change in the income distribution over time.

In considering the potential impact of changes in the way human capital is transferred and augmented over the generations, changes in the nature of the transition matrix are considered, in particular interest focuses on the extent to which transitions exhibit dependencies that are converging or polarizing in nature. The extent of dependency of outcomes in a transition matrix is reflected in the mobility it characterizes.

Mobility indices for square matrices abound (Shorrocks (1978), Fields and Ok (1996), Formby, Smith and Zheng (2004), Fields (2008), Ramos and Van de Gaer (2014)), but here some of the matrices are not square as they reflect transitions between conceptually different paradigms (e.g. social class to educational class or social class to income class). Complete mobility exists when all conditional outcome distributions of given circumstance classes are identical. As such, complete mobility is characterized by the transition matrix T having common columns which all sum to 1. Letting $t_{i.}$ be the i'th row of the n_r x n_c transition matrix T and $MAXR(t_{i.})$ and $MINR(t_{i.})$ operators which return the maximum and minimum value in the row vector respectively, TM, an index of mobility, may be written as:

$$TM(T) = 1 - \frac{\sum_{i=1}^{n_c}(MAXR(t_{i.}) - MINR(t_{i.}))}{n_c}$$

TM is one minus an n_c distribution version of Gini's two distribution dissimilarity or "transvariation" index (Gini, 1915)[4] rescaled by the number of distributions being compared. When columns of T are identical, the Outcome distributions emerging from the n_c Initial States will overlap perfectly, the sum of maximums will equal the sum of minimums and $TM = 1$. If on the other hand the Final State Outcome distributions are orthogonal as in the Perfect Immobility case the intersections of the overlaps will be null (the sum of minimums will be 0) and the sum of maximums will equal n_c, the number of conditional distributions so that $TM = 0$ so that in the square T case $TM(T)$ will be 0 when $T = I$. $1 - TM(T)$ has the interpretation of an inequality of distribution index, a distributional GINI index as it were. For inference purposes TM can be shown to be asymptotically normal.

The extent to which a transition matrix is polarizing/converging may be examined by assessing the extent to which it transfers mass to the peripheries of the arrival state distribution relative to it transferring mass from the peripheries to the center. This can be measured by considering the balance of probabilities BP where:

$$\begin{aligned}\text{BP} = {} & P(\text{Arrival State Peripheries} \mid \text{Departure State Center}) \\ & - P(\text{Arrival State Center} \mid \text{Departure State Peripheries})\end{aligned}$$

[4]It could be based on the discrete multivariate distribution Overlap measure of Anderson and Leo (2011) the continuous version of which is given in Anderson, Linton and Wang (2012).

In a similar fashion the extent to which a transition matrix represents predominantly upward or downward transitions may be examined by assessing the extent to which it transfers mass from relatively lower departure states to relatively higher arrival states versus transferring mass from relatively higher departure states to relatively lower arrival states. This can be measured by considering the balance of probabilities BP where:

$$\begin{aligned}\text{BP} = {} & P(\text{Higher Arrival State} \mid \text{Lower Departure State}) \\ & - P(\text{Lower Arrival State} \mid \text{Higher Departure State})\end{aligned}$$

Noting that $-1 < \text{BP} < 1$, $\text{IP} = 0.5 + 0.5\text{BP}$ constitutes an upward transference index that obeys all of the usual axioms for ordinal comparisons and under the null of no net transference IT is asymptotically N(0.5, 0.25/n) (see Anderson 2016).

Explicit analysis of the effects of such transfers on inequality is facilitated by considering a rearrangement of the Gini coefficient interpreted as the average over all agents of a "relative to the mean" distance measure of each agent from all other agents. From equation (1a) and (1b) in Appendix 2 for grouped data (where π_i is the proportion of the population receiving income X_i, i=1 to K) and for continuous data the respective Gini's may be written as:

$$\sum_{i=1}^{n} \pi_i \left|\frac{X_i}{\bar{X}} - 1\right|; \big(\text{ where } \bar{X} = \sum_{i=1}^{n} \pi_i X_i\big) \text{ and } E_{f(y)}\big(\left|1 - \frac{y}{\mu}\right|\big); (\text{ where } \mu = E(y)) \tag{1}$$

Now consider the effect on these formulations of the Gini coefficients[5] in the context of generational transition matrices with respect to educational attainments or income which are polarizing.

Proposition1: Any net transfer of mass from the center to the peripheries of a distribution will increase the Gini coefficient.

Demonstration: In terms of the grouped Gini for convenience suppose that n is odd and that X_m is the mean of the distribution where $m = (n+1)/2$ and consider a shift of mass such that $\pi^*_m = \pi_m - \delta_{k1} - \delta_{k2}$, $\pi^*_{m+k1} = \pi_{m+k1} + \delta_{k1}$ and $\pi^*_{m-k2} = \pi_{m-k2} + \delta_{k2}$ for all δ_{k1}, δ_{k2} positive. Letting GINI* and GINI be the respective grouped Gini coefficients

[5]These exercises can be performed with other inequality measures to similar effect.

after and before the transfer, then from equation (1)

$$
\begin{aligned}
&GINI^* - GINI \\
&= \sum_{i=m-1}^{m+1} (\pi_i^* - \pi_i)|\frac{X_i}{X_m} - 1| = \delta_{k2}|\frac{X_{m-1}}{X_m} - 1| + \delta_{k1}|\frac{X_{m+1}}{X_m} - 1| > 0
\end{aligned}
$$

In the continuous distribution context, consider a distribution $f(x)$ for $x \in [a, b]$ where $0 < a < b$ and $E(x) = \int x f(x)dx = \mu$ and contemplate another distribution $f^*(x)$ where mass has been transferred in $f(x)$ from the center to the peripheries in the following fashion:

$$
\begin{aligned}
f^* &\leq f(x) \text{ for } x \in [\mu \pm \delta] \text{ (stritly < somewhere)} \\
f^* &\geq f(x) \text{ for } x \notin [\mu \pm \delta] \text{ (stritly > somewhere)}
\end{aligned}
$$

Noting that:

$$
\begin{aligned}
&-\int_{\mu-\delta}^{\mu+\delta} (f^*(x) - f(x))dx \\
&= \Big\{ \int_a^{\mu-\delta} (f^*(x) - f(x))dx + \int_{\mu+\delta}^b (f^*(x) - f(x))dx \Big\} > 0
\end{aligned}
$$

and

$$
0 < |1 - \frac{x}{\mu}|_{x \in [\mu \pm \delta]} < |1 - \frac{x}{\mu}|_{x \notin [\mu \pm \delta]}
$$

so that

$$
\begin{aligned}
&-\int_{\mu-\delta}^{\mu+\delta} (f^*(x) - f(x))|1 - \frac{x}{\mu}|dx \\
&= \Big\{ \int_a^{\mu-\delta} (f^*(x) - f(x))|1 - \frac{x}{\mu}|dx + \int_{\mu+\delta}^b (f^*(x) - f(x))|1 - \frac{x}{\mu}|dx \Big\}
\end{aligned}
$$

From equation (1) GINI*-GINI is given by:

$$\int_{\mu-\delta}^{\mu+\delta}(f^*(x)-f(x))|1-\frac{x}{\mu}|dx+\int_{a}^{\mu-\delta}(f^*(x)-f(x))|1-\frac{x}{\mu}|dx \\ +\int_{\mu+\delta}^{b}(f^*(x)-f(x))|1-\frac{x}{\mu}|dx>0$$

Effectively the resultant income or educational attainment distributions become more unequal. By a simple reversal of the demonstration the following corollary to Proposition 1 can be obtained:

Corollary 1. Any net transfer of mass from the peripheries to the center of a distribution will reduce the Gini coefficient and a static transition matrix will leave the Gini coefficient unaltered.

It is perhaps less clear how increased positive assortative matching increases inequality, to see why, consider the marginal effect of an increased positive correlation coefficient (or rank correlation) between husband and wives incomes (educational attainments) on a Gini coefficient of the household aggregate income (educational attainment).

Proposition 2. Increased positive correlation or rank correlation between husbands and wives incomes/educational attainments increases the corresponding Gini (Grouped Gini) coefficient for household incomes or educational attainments.

Demonstration: Let z be the ordered vector of husbands incomes (education levels) and y be the associated wives incomes (education levels) so that the vector of household incomes (education levels) $x = z+y$. Let r_z and r_y be the vectors of corresponding ranks of z and y. Note that $\mu_x = \mu_z+\mu_y$. Suppose the element $x_m = \mu_z+y_m$ i.e. the husband in the m'th household has the average husbands' income and, for convenience suppose $z_{m-1} < z_m < z_{m+1}$. so that $r_{zm+1} = r_{zm-1} + 2$, and suppose further $y_{m-1} = y_{m+1} + \delta$ so that $r_{ym-1} = r_{ym+1} + K$ where K is an integer ≥ 1. In essence husband and wife rankings are negatively correlated around the m'th observation. When husbands and wives in the $m-1$ and $m+1$ observations swap partners there will be increased positive assortative matching in terms of increased positive association in the correlation (for incomes) and rank correlation (for educational status) of husbands and wives. Consider RN, the numerator of correlation coefficient (before) and RN^*, the numerator of the correlation coefficient after the swap.

$$
\begin{aligned}
\sqrt{RN} &= \sum_{i=1}^{n}(X_i - \bar{X})Y_i \text{ and} \\
\sqrt{RN^*} &= \sum_{i=1}^{n}(X_i - \bar{X})Y_i - (X_{m+1} - \bar{X})Y_{m+1} - (X_{m-1} - \bar{X})Y_{m-1} + (X_{m+1} - \bar{X})Y_{m-1} \\
&\quad + (X_{m-1} - \bar{X})Y_{m+1} \\
&= \sqrt{RN} - (X_{m+1} - \bar{X})(Y_{m-1} - \delta) - (X_{m-1} - \bar{X})Y_{m-1} + (X_{m+1} - \bar{X})Y_{m-1} \\
&\quad + (X_{m-1} - \bar{X})(Y_{m-1} - \delta) \\
&= \sqrt{RN} + \delta\{(X_{m+1} - \bar{X}) - \ (X_{m-1} - \bar{X})\} > \sqrt{RN}
\end{aligned}
$$

To examine the effects of matching on educational status ranks where income distance measures do not apply assume for simplicity there are no ties in either husbands or wives incomes and consider Spearman's Rank Coefficient before (SR) and after (SR^*) the swap.

$$
\text{Since } SR = 1 - \left(\frac{6\sum_{i=1}^{n}(r_{zi} - r_{yi})^2}{n(n^2-1)}\right)
$$

Note that

$$
SR^* - SR = \frac{6}{n(n^2-1)}(r_{zm+1} - r_{ym+1})^2 + (r_{zm-1} - r_{ym-1})^2 - (r_{zm+1} - r_{ym-1})^2 - (r_{zm-1} - r_{ym+1})^2
$$

Recall $(r_{zm+1} - r_{zm-1}) = 2$ and $(r_{ym-1} - r_{ym+1}) = k \geq 1$
substitution yields:

$$
SR^* - SR = \frac{6}{n(n^2-1)}4K > 0
$$

For convenience write $GINI$ (before) and $GINI^*$ (after the swap) then, since from Appendix 2:

$$
GINI = \frac{1}{n}\sum_{i=1}^{n}|\frac{x_i}{\mu} - 1|
$$

Note that:

$$GINI^* - GINI = |\frac{x_{m+1} + \delta}{\mu} - 1| - |\frac{x_{m+1}}{\mu} - 1| + |\frac{x_{m-1} - \delta}{\mu} - 1| - |\frac{x_{m-1} - \delta}{\mu} - 1|$$

Since $\frac{x_{m+1}}{\mu} > 1$ and $\frac{x_{m-1}}{\mu} < 1$, $GINI^* - GINI = \frac{2\delta}{\mu} > 0$.

By a simple reversal of the demonstration the following corollary to Proposition 2 can be obtained:

Corollary 2. Reduced positive correlation or rank correlation between husbands and wives incomes/educational attainments reduces the corresponding Gini (Grouped Gini) coefficient for household incomes or educational attainments.

The influence of social class and education on a households location in the income distribution can be examined by studying the way that class or education translates to a place in the income distribution via a transition matrix which describes the arrival or outcome state distribution given a departure or initial state class. In a perfectly mobile world all such conditional outcome distributions are identical essentially relaying the idea that the initial state has no effect on the outcome class. When they are not identical the departure class has an impact on the arrival state.

Empirical Analysis

Following the analysis of the impact of positive assortative matching in marriage and generational transition effects have on household income inequality, the propensity for changes in the structure of marriage matching and transitional patterns examined using data from The Chinese Household Income Project (Li et al. 2008) in models of household income generation and formation. It is a rich dataset providing information on grandparent's social class designation given in the late 1940s, parent's educational status and child's (grandchildren's) educational status facilitating measurement of the transition from Grandparents Social class to parent's educational status and ultimately a child's educational status. Grandparent social classification (*Chengfen*) was C1: Poor Peasant or Landless (53.96%), C2: Lower Middle Peasant (14.14%), C3: Upper Middle Peasant (4.81%), C4 : Rich Peasant (2.01%), C5: Landlord (2.82%), C6: Manual Worker (8.21%), C7: Office Worker (3.30%), C8: Enterprise Owner (0.43%), C9 : Petty Proprietor (3.75%), C10: Revolutionary Cadre (1.38%), C11: Revolutionary Army Man

(1.03%), C12: Other (4.16%). To simplify analysis, and because some cells were very small this categorization was condensed to 5 social classes. SC1 = {C1}, SC2 = {C2, C6}, SC3 = {C3, C9, C12}, SC4 = {C4, C7, C11}, SC5 = {C5, C8, C10}. The first group SC1 is poor peasant or landless persons, which accounts for roughly half of the population. SC2 is comprised of lower middle peasant and manual workers because they each have low social status. SC3 is made up of self-sufficient upper middle peasants and petty proprietors, also included in this group is the unidentified "other" because their education label is similar to the other 2 member classes. SC4 is comprised of is rich peasant, office worker and revolutionary army man who have relatively more resources and typically has less manual labor obligations. SC5 is made up of Landlords, Enterprise owners and Revolutionary Cadres.

The educational categories were 0 no category, 1 if never schooled, 2 if classes for eliminating illiteracy, 3 elementary school, 4 if junior middle school, 5 if senior middle school (including professional middle school), 6 if technical secondary school, 7 if junior college, 8 if college/university, 9 if graduate. Educational categories 0 through 9 were condensed to EDC1 = {0,1,2,3}, EDC2 = {4}, EDC3 = {5}, EDC4 = {6}, EDC5 = {7}, EDC6 = {8}, EDC7 = {9}. Information was available on 6610 parent - grandparent pairings and 1514 parent–child pairings (only children over 22 years old were used under the assumption they would have completed their education). Family cohort membership is determined by the age of the household head (father) at the time of the survey. Those whose household heads are older than 48 are deemed to be the Pre Cultural Revolution Cohort of households (the education of these heads would not have been influenced by the vagaries of the Cultural Revolution). Those households whose heads are of age 39 to 48 are deemed the Cultural Revolution Cohort households and those younger than 39 are deemed the Post Cultural Revolution cohort, these household heads would have completed their education after the Cultural Revolution and made their marriage choices after the implementation of the one child policy.

Household Income Generation and Household Size Equations

A sense of the influence on household income production of the nature of the family is provided by a simple regression of Adult Equivalized Household Income[6] on a variety

[6]Adult Equivalization uses the square root rule (Brady and Barber 1948) essentially it is household income divided by the square root of the number of people in the household.

of factors, the equation is reported in Table1. The household income regression reveals strong cohort effects (F test for no cohort effects 2.9157, $P(f > 2.9157) = 0.00013$) and a strong dependence on the educational status of both parents throughout the eras.

In the Pre Cultural Revolution cohort mother's educational status has a bigger impact than fathers educational status on household income. The difference disappears in the Cultural Revolution era and is re-established in the post Cultural Revolution era. There does appear to be some substitutability of parental education in income production with respect to education with a significantly negative cross partial derivative (suggesting that the propensity for positive assortative matching may not be as strong as would otherwise be the case (Becker 1993) but recall income production is not the only household objective). Absolute differences in mother father education levels, reflecting the positive assortative matching effect, appears to have little impact on income generation in this era.

Household income is a weakly increasing concave function of household vintage (head of household's age) a life cycle income pattern which is positive for all households whose head is < 75. Equivalized Household income is decreasing in household size, (not surprising given adult equivalization) however in the Cultural Revolution and Post Cultural Revolution eras the value of the parameter diminishes somewhat to the point where its effect is eliminated for the youngest households. Having a head who was potentially affected by the cultural revolutions educational exigencies and the social class of the family do not appear to significantly affect household income except through the fathers social class. The interaction of class and the Cultural Revolution dummy is significantly positive indicating that the higher social class of a family head (who potentially missed years of education), the higher household income would be similarly the post Cultural Revolution dummy and social class interaction appears to enhance the income generation prospects of a household.

Family formation was studied by way of a household size equation. The size of a household was a concave function of vintage (age of household head) and negative in the relevant range, it switched to a convex function for vintages in the range that were affected by the Cultural Revolution, so generally older households were larger. Higher social class families were significantly smaller with an implied elasticity of -0.01. The overall effect of education is to engender slightly smaller families though the larger the father-mother educational gap the larger the family size, an effect which outweighs

Table 1: The Structure of Household Income Generation

VARIABLES	Coefficient	t-statistics
vintage	0.0265***	(3.376)
vintage2	-0.000170**	(-2.296)
Mother edu	0.194***	(7.353)
Father edu	0.154***	(5.441)
family size	-0.181***	(-14.38)
Father edu*Mother edu	-0.0131***	(-2.646)
Father-Mother edu difference	0.0341**	(2.082)
Social Class	-0.00901	(-0.784)
CR	0.106	(0.500)
postCR	-0.555***	(-3.150)
Mother edu*CR	-0.0664	(-1.636)
Father edu*CR	-0.0401	(-0.956)
family size*CR	0.0505***	(2.669)
Father edu*Mother edu*CR	0.0111	(1.519)
Father-Mother edu difference*CR	-0.00526	(-0.264)
Social Class*CR	0.0391***	(2.833)
Mother edu*postCR	0.00504	(0.553)
Father edu*postCR	0.000408	(0.0109)
family size*postCR	0.156***	(5.414)
Father edu*Mother edu*postCR	0.00184	(0.423)
Father-Mother edu difference*postCR	-0.0283	(-1.133)
Social Class*postCR	0.0365**	(2.027)
Constant	7.451***	(31.30)
Observations	6,137	
R-squared	0.265	

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

CR is Cultural Revolution Dummy, postCR is post Cultural Revolution Dummy

Table 2: Household size equation ($\ln(\sqrt{\text{household size}})$ dependent variable) reparametrized

VARIABLES	Coefficient	t-statistics
vintage	0.0221**	(2.158)
vintage2	-0.000296***	(-2.904)
Father edu	-0.0412**	(-2.035)
Father edu*Mother edu	-0.00180	(-0.844)
edu difference	0.0415***	(3.746)
Social Class	-0.0391***	(-3.086)
CR	3.846***	(2.649)
Father edu*CR	0.0152	(0.606)
Father edu*Mother edu*CR	-0.000747	(-0.271)
Social Class*CR	0.0342**	(2.034)
vintage*CR	-0.165***	(-2.625)
vintage2*CR	0.00166**	(2.449)
Constant	3.030***	(12.42)
Observations	6,599	
R-squared	0.022	

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

CR is Cultural Revolution Dummy, postCR is post Cultural Revolution Dummy the positive effect in the income equation so the net effect is negative which is consistent with the idea of parental complementarity in family production which would predict positive assortative matching in income. Although the household income equation suggests some substitutability in household income production positive assortative matching appears to prevail and increases in extent for younger cohorts. A simple regression reflects the extent to which positive assortative matching intensified over the period in question.

Table 3: Absolute Education Class Difference

VARIABLES	Coefficient	t-statistics
vintage	0.0229**	(2.408)
vintage2	-0.000163*	(-1.711)
Constant	0.215	(0.936)
Observations	6,684	
R-squared	0.005	

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

The absolute differences in husband and wives educational class were regressed on the husband age (essentially household vintage) and husband's age squared. As may be seen younger cohorts of couples are much more closely matched than older cohorts. Differences in matching patterns over the 3 Eras in terms of social class and education class are compared by employing Spearman's Rank Correlation Coefficient (Spearman (1904)) of husbands and wives education or social classes as a positive assortative matching index. In a balanced marriage market with effective market clearing under positive assortative matching, the rank correlation coefficient will be 1. However there may be a slight cause for concern with the use of the statistic as a matching index since it could understate the extent of positive assortative matching. If the marriage market was unbalanced, i.e. insufficient numbers of a particular type on one side of the market to match with those on the other side of the market then the correlation coefficient would record less than perfect matching even though the market cleared perfectly according to the positive assortative matching rule (Becker 1993). One way around this is to rescale the rank correlation coefficient by its maximum possible value based upon everyone having matched with their best feasible match [7]. It would then

[7]The maximum value can be obtained by separately sorting husbands and wives matching index,

record a value of 1 if market clearing was effective. Table 4 reports the corresponding matching indices.

Husband and wife scaled educational and social status correlations did not change significantly between the Pre Cultural Revolution and Cultural Revolution eras. The significance of the unscaled Spearman statistic and non-significance of the scaled Spearman statistic suggests that the Pre Cultural Revolution-Cultural Revolution change in educational matching had more to do with the increased capacity for matching. However both scaled and non-scaled the educational class correlations increased substantially in the post Cultural Revolution period whereas the corresponding Social Class correlations diminished significantly suggesting education matching and social class matching behaviors reflect different objectives or different responses in the Post Cultural Revolution era. If, as the household income equation in Table 1 suggests, Educational classification more closely reflects income objectives relative to Social class (which more closely reflects procreative and child rearing objectives), this would be consistent with the theoretical reasoning in Anderson and Leo (2013) which predicts intensified positive assortative matching on Education relative to Social Status when household production of children is rationed, as was the case in the Post Cultural Revolution era.

Human Capital Transition Effects

Changes in transitional structures affect the income distribution both indirectly and directly. Social class may affect incomes both directly and through its effect on Educational classification. Educational classification cannot affect social class since the latter is predetermined and formally exogenous but it can affect income class. The study of the direct effect of Social Class to Income Class and Education Class to Income Class transitions is facilitated by a semi-parametric decomposition of the household income distribution from which individual probabilities of income class membership for each household and income group can be developed (Anderson et. al. 2016) details of which are confined to the appendix, ultimately 5 household income classes were determined. Details of the transition matrices for the overall population and the various cohorts for social class to education, social class to income and education to income are reported in this section.

pair husbands and wives according to rank and calculate the Spearman rank correlation index for such a pairing.

Table 4: Positive Assortative Matching Indices

	Spearman Rank Correlation Coefficients			
	Education	Social Class	Scaled Education	Scaled Social Class
All Cohorts	0.5514	0.2800	0.5855	0.2823
(Variance)	(6.4629e-005)	(6.4629e-005)	(7.2874e-005)	(6.5697e-005)
[Maximal Value]	[0.9417]	[0.9918]		
Pre Cultural Revolution Cohort	0.5042	0.2854	0.5398	0.2880
(Variance)	(0.000267)	(0.000267)	(0.000306)	(0.000272)
[Maximal Value]	[0.9342]	[0.9910]		
Cultural Revolution Cohort	0.5058	0.2818	0.5341	0.2848
(Variance)	(0.000114)	(0.000114)	(0.000127)	(0.000116)
[Maximal Value]	[0.9470]	[0.9895]		
Post Cultural Revolution Cohort	0.6200	0.2350	0.6536	0.2377
(Variance)	(0.000338)	(0.000338)	(0.000376)	(0.000346)
[Maximal Value]	[0.9486]	[0.9886]		

Table 5: Spearman Rank Correlation difference analysis

Comparison	Matching Index	Spearman Difference	Standard Deviation	t-stat t-stat
PanelA: Spearman Rank Correlation difference analysis				
Post Cultural Revolution Cohort *vs*	Education	0.1158	0.0235	4.9277
Pre Cultural Revolution Cohort	Social Class	-0.0504	0.0237	5.8550
Post Cultural Revolution Cohort *vs*	Education	0.1142	0.0206	5.5437
Cultural Revolution Cohort	Social Class	-0.0468	0.0207	-2.2609
Cultural Revolution Cohort *vs*	Education	0.0016	0.0865	4.8962
Pre Cultural Revolution Cohort	Social Class	-0.0036	0.0187	-0.1925
PanelB: Scaled Spearman Rank Correlation difference analysis				
Post Cultural Revolution Cohort *vs*	Education	0.1138	0.0235	4.8426
Pre Cultural Revolution Cohort	Social Class	-0.0503	0.0237	-2.1224
Post Cultural Revolution Cohort *vs*	Education	0.1195	0.0206	5.8010
Cultural Revolution Cohort	Social Class	-0.0471	0.0207	-2.2754
Cultural Revolution Cohort *vs*	Education	-0.0057	0.0185	-0.3081
Pre Cultural Revolution Cohort	Social Class	-0.0032	0.0187	-0.1711

*The standard error for Spearman's Rank Correlation is $0.6325/\sqrt{n-1}$ and for the differences it is $\sqrt{0.4001 * (\frac{1}{n_1-1} + \frac{1}{n_2-1})}$ where nk is sample size for the k'th cohort. For the Scaled coefficient the standard error is scaled by the corresponding scaling factor.

Table 6: Parent Social Class-Educational Transitions

Pre CR Fathers(N=1672)	SocClass1	SocClass2	SocClass3	SocClass4	SocClass5
Education Class 1	0.2040	0.1311	0.1056	0.0891	0.0899
Education Class 2	0.3511	0.2674	0.3310	0.2574	0.2472
Education Class 3	0.1508	0.1568	0.1690	0.1485	0.2135
Education Class 4	0.1248	0.1799	0.1549	0.1386	0.1685
Education Class 5	0.1088	0.1671	0.1127	0.2079	0.1011
Education Class 6	0.0581	0.0951	0.1232	0.1485	0.1798
Education Class 7	0.0025	0.0026	0.0035	0.0099	0.0000
CR Fathers(N=3680)					
Education Class 1	0.0439	0.0481	0.0557	0.0119	0.0229
Education Class 2	0.3366	0.2861	0.3559	0.2460	0.2114
Education Class 3	0.2937	0.3058	0.1864	0.2579	0.2743
Education Class 4	0.0828	0.0937	0.1162	0.0913	0.1200
Education Class 5	0.1740	0.1936	0.1816	0.2579	0.2457
Education Class 6	0.0611	0.0641	0.1017	0.1190	0.0857
Education Class 7	0.0079	0.0086	0.0024	0.0159	0.0400
Post CR Fathers(N=1258)					
Education Class 1	0.0099	0.0081	0.0238	0.0000	0.0192
Education Class 2	0.2133	0.1707	0.1190	0.2000	0.0385
Education Class 3	0.2219	0.2358	0.2024	0.2308	0.2115
Education Class 4	0.1110	0.0894	0.1667	0.0923	0.1154
Education Class 5	0.2552	0.2724	0.3333	0.2769	0.3077
Education Class 6	0.1800	0.2154	0.1310	0.1692	0.2885
Education Class 7	0.0086	0.0081	0.0238	0.0308	0.0192

Table 6b: Social Class-Education Transition Indices

Cohort	Mobility	Upward	Polarize
Pre CR	0.7853967	0.4892344	0.3560291
CR	0.9073940	0.5875000	0.3319542
Post CR	0.6947007	0.7428458	0.3893200

Observe from Table 6, that social class to education class mobility was at its highest for the cultural revolution cohort, a direct effect of the Cultural Revolution, mobility was significantly progressively upward over the 3 cohorts but the transitions were never polarizing indeed they were significantly convergent or equalizing. Turning to the Social Class–Income Class transitions, Table 8 indicates that mobility was invariably quite high implying that income distributions of the various social classes was very similar, put another way social class had little impact on the shape of the income distribution over all cohorts. Transitions were invariably upward and progressively so over the cohorts, though they were never polarizing, and none of the differences were profoundly significant.

A very different story emerges for Education class to Income class transitions reported in Table 7. Transition matrices characterize a very immobile society (and increasingly so over the cohorts) suggesting that a households place in the income distribution is very much governed by its educational status and increasingly so. Transitions are typically upward but to a diminishing extent. Most significantly for present purposes transitions are always polarizing and increasingly so over more recent cohorts. In effect Social Class appears to have a weaker direct effect on household incomes than does educational classifications. However educational outcomes are dependent on Social Class and changes in the way social class translates to educational class influences the income distribution indirectly.

Lefranc, Pistolesi and Trannoy (2008, 2009) propose evaluating the presence of equality of opportunity by evaluating the extent of second order dominance relationships between the various conditional outcome distributions with absence of dominance relationships supporting the equality of opportunity hypothesis. Strictly speaking that is not possible here because only outcome classes are being considered and only first order dominance comparisons can be made. However some insight on the differences across regimes can be gleaned from examining the first order comparisons and noting

Table 7: Social Class-Income Transition of father

	SocClass1	SocClass2	SocClass3	SocClass4	SocClass5
Overall					
IncomeClass1	0.00742	0.00544	0.00693	0.00324	0.00670
IncomeClass2	0.0160	0.0147	0.0110	0.0146	0.00876
IncomeClass3	0.256	0.231	0.236	0.199	0.198
IncomeClass4	0.354	0.344	0.349	0.340	0.335
IncomeClass5	0.367	0.404	0.398	0.444	0.451
PreCR					
IncomeClass1	0.0120	0.00350	0.00815	0.00312	0.0217
IncomeClass2	0.0246	0.0116	0.0171	0.0296	0.00442
IncomeClass3	0.268	0.223	0.242	0.231	0.201
IncomeClass4	0.349	0.352	0.341	0.335	0.349
IncomeClass5	0.346	0.410	0.392	0.402	0.424
CR					
IncomeClass1	0.00722	0.00505	0.00574	0.00343	0.00127
IncomeClass2	0.0143	0.0175	0.00872	0.00628	0.0126
IncomeClass3	0.252	0.230	0.233	0.178	0.207
IncomeClass4	0.355	0.340	0.351	0.337	0.330
IncomeClass5	0.372	0.407	0.402	0.475	0.449
PostCR					
IncomeClass1	0.00359	0.00959	0.00902	0.00274	0.000330
IncomeClass2	0.0120	0.00985	0.00273	0.0230	0.00316
IncomeClass3	0.253	0.248	0.227	0.229	0.163
IncomeClass4	0.358	0.347	0.366	0.356	0.331
IncomeClass5	0.373	0.386	0.396	0.390	0.503

Table 7b: Social Class-Income Transition indices

Cohort	Mobility	Upward	Polarize
Pre CR	0.8793059	0.6654964	0.3145048
CR	0.8280157	0.6948723	0.3072642
Post CR	0.8475474	0.7265366	0.2834459

that dominance at the first order implies dominance at the second order. Turning to the Cumulative household distributions conditioned on social class and education class of the household in Tables 7c and 8c respectively, note that income distributions for higher Social Classes do not always dominate those of lower social classes both overall and across the three cohorts. Indeed the high value of the overlap measure of the extreme distribution comparison indicates small differences between the income distributions of various social classes. On the other hand income distributions for higher education classes always dominate lower education classes for all conditional distributions in all cohorts (except for the lowest educational class in the Post Cultural revolution cohort) and overall, that is to say there is a strict ordering of income class outcomes by educational class. Furthermore the overlap between the extreme income distributions conditional on educational classes is much lower indicating greater variation in the conditional income distributions by educational class. This reflects the lack of mobility indicated in Table 8 which is characteristic of a society where educational rather than social status governs income status.

Conclusion

The strident growth in Chinese household income inequality has been ubiquitous in the last 35 years. Rural, urban, central and coastal regions have all had similar inequality growth experiences so that differences between them are unlikely to provide a rationale for it, something equally ubiquitous and ongoing has to be the root source. Here the changing nature of family formation and changes in the way that human capital is passed on through the generations, are examined as a source of growing urban household income disparities. Shaped by historical events, the Cultural Revolution, The One Child Policy and the Economic Reforms, people changed the way they chose partners and invested in children, consequently changing the structure of generational relationships

Table 8: Educational-Income Transition of Fathers

	EduClass1	EduClass2	EduClass3	EduClass4	EduClass5	EduClass6	EduClass7
Overall							
IncomeClass1	0.0276	0.0111	0.00581	0.00145	0.000802	6.68e-05	1.06e-05
IncomeClass2	0.0588	0.0223	0.0142	0.0100	0.00181	9.86e-06	0
IncomeClass3	0.368	0.310	0.253	0.220	0.170	0.121	0.0663
IncomeClass4	0.331	0.362	0.361	0.358	0.343	0.310	0.256
IncomeClass5	0.214	0.295	0.366	0.410	0.484	0.569	0.678
PreCR							
IncomeClass1	0.0359	0.00799	0.00668	0.00111	0.000268	7.89e-05	2.08e-06
IncomeClass2	0.0683	0.0222	0.00772	0.00790	0.00237	7.69e-06	0
IncomeClass3	0.366	0.286	0.231	0.217	0.159	0.126	0.0381
IncomeClass4	0.323	0.367	0.361	0.361	0.329	0.308	0.222
IncomeClass5	0.207	0.317	0.394	0.413	0.509	0.567	0.739
CR							
IncomeClass1	0.0158	0.0119	0.00476	0.00122	0.00122	6.45e-05	9.94e-06
IncomeClass2	0.0466	0.0203	0.0153	0.0113	0.00200	1.72e-05	5.22e-11
IncomeClass3	0.362	0.304	0.252	0.207	0.160	0.111	0.0553
IncomeClass4	0.342	0.362	0.358	0.351	0.337	0.298	0.231
IncomeClass5	0.233	0.302	0.370	0.429	0.499	0.592	0.714
PostCR							
IncomeClass1	0.00225	0.0139	0.00887	0.00263	0.000278	6.18e-05	1.54e-05
IncomeClass2	0.0155	0.0323	0.0165	0.0104	0.00109	3.10e-06	0
IncomeClass3	0.485	0.386	0.281	0.260	0.198	0.129	0.104
IncomeClass4	0.377	0.355	0.368	0.370	0.363	0.325	0.330
IncomeClass5	0.120	0.213	0.326	0.357	0.438	0.546	0.566

Table 8b: Educational-Income Transition Indices

Cohort	Mobility	Upward	Polarize
Pre CR	0.4276802	0.7327413	0.6351860
CR	0.4189770	0.6771935	0.6824907
Post CR	0.3871865	0.5284033	0.7040519

and the social order.

It was demonstrated that ceteris paribus certain types of transition structure and intensified marital matching behavior engender increases in income inequality. A study of social class to education, social class to income and education to income transition patterns and marital matching patterns using data linking Grandparents, Parents and Children across cohorts determined by Pre Cultural Revolution, the Cultural Revolution and the One Child Policy and Economic Reform Eras revealed that these structures prevailed and changed over the Era's in such a way as to promote increased income inequality. For example, increased positive assortative matching and polarizing education class to income transitions in the post Cultural Revolution era promoted increases in inequality. In essence a source of increased urban inequality was an increased dependency of household incomes on household human capital and a diminished dependency on social class. Increased positive assortative matching increased the disparities in household human capital, which in turn increased the disparities in household incomes and concomitantly the disparities in the circumstances of children whose educational outcomes were highly dependent upon their parental circumstances. An interesting sidebar was that, although educational polarization persists throughout the time, there was a substantial narrowing of the educational status in the Cultural Revolution equalizing the circumstances of later generations. In addition the middle social class is elevated after the Cultural Revolution and ends up dominating both the lower and upper social classes in its education and income outcome distributions.

Table 7c: Income Class Cumulative densities conditional on social class

	SocClass1	SocClass2	SocClass3	SocClass4	SocClass5
Overall Social Class CDF, overlap of extreme pdf's=0.91558					
IncomeClass1	0.00742	0.00544	0.00693	0.00324	0.00670
IncomeClass2	0.02339	0.02012	0.01792	0.01785	0.01546
IncomeClass3	0.27918	0.25156	0.25346	0.21674	0.21362
IncomeClass4	0.63340	0.59580	0.60248	0.55624	0.54897
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000
Pre CR Social Class CDF, overlap of extreme pdf's= 0.91292					
IncomeClass1	0.01196	0.00350	0.00815	0.00312	0.02170
IncomeClass2	0.03654	0.01510	0.02523	0.03268	0.02612
IncomeClass3	0.30473	0.23841	0.26691	0.26354	0.22754
IncomeClass4	0.65379	0.59005	0.60832	0.59835	0.57645
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000
CR Social Class CDF, overlap of extreme pdf's=0.92304					
IncomeClass1	0.00722	0.00505	0.00574	0.00343	0.00127
IncomeClass2	0.02150	0.02257	0.01446	0.00971	0.01386
IncomeClass3	0.27360	0.25271	0.24772	0.18765	0.22107
IncomeClass4	0.62811	0.59284	0.59839	0.52483	0.55115
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000
Post CR Social Class CDF, overlap of extreme pdf's=0.87024					
IncomeClass1	0.00359	0.00959	0.00902	0.00274	0.00033
IncomeClass2	0.01561	0.01944	0.01175	0.02576	0.00349
IncomeClass3	0.26880	0.26725	0.23881	0.25457	0.16665
IncomeClass4	0.62720	0.61414	0.60447	0.61010	0.49743
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000

Table 8c: Income Class Cumulative densities conditional on education class

	EduClass1	EduClass2	EduClass3	EduClass4	EduClass5	EduClass6	EduClass7
Overall Education Class CDF, overlap of extreme pdf's=0.53582							
IncomeClass1	0.02761	0.01112	0.00581	0.00145	0.00080	0.00007	0.00001
IncomeClass2	0.08638	0.03340	0.02004	0.01149	0.00262	0.00008	0.00001
IncomeClass3	0.45476	0.34297	0.27345	0.23179	0.17293	0.12105	0.06631
IncomeClass4	0.78617	0.70510	0.63396	0.58970	0.51581	0.43084	0.32199
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
Pre CR Education Class CDF, overlap of extreme pdf's=0.46773							
IncomeClass1	0.03594	0.00799	0.00668	0.00111	0.00027	0.00008	0.00000
IncomeClass2	0.10423	0.03022	0.01440	0.00901	0.00263	0.00009	0.00000
IncomeClass3	0.47020	0.31607	0.24551	0.22636	0.16152	0.12582	0.03815
IncomeClass4	0.79279	0.68277	0.60617	0.58718	0.49091	0.43336	0.26052
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
CR Education Class CDF, overlap of extreme pdf's=0.51889							
IncomeClass1	0.01585	0.01194	0.00476	0.00122	0.00122	0.00006	0.00001
IncomeClass2	0.06242	0.03220	0.02005	0.01256	0.00321	0.00008	0.00001
IncomeClass3	0.42486	0.33665	0.27177	0.21929	0.16361	0.11070	0.05532
IncomeClass4	0.76706	0.69823	0.63024	0.57064	0.50095	0.40841	0.28595
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
Post CR Education Class CDF, overlap of extreme pdf's=0.55406							
IncomeClass1	0.00225	0.01390	0.00887	0.00263	0.00028	0.00006	0.00002
IncomeClass2	0.01773	0.04618	0.02532	0.01299	0.00137	0.00006	0.00002
IncomeClass3	0.50266	0.43227	0.30591	0.27287	0.19946	0.12954	0.10387
IncomeClass4	0.87995	0.78718	0.67380	0.64254	0.56234	0.45409	0.43402
IncomeClass5	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000

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Appendix 1

Table A1: Household Adult Equivalized Income data.

N=6226	Mean	Std. Dev.	Min	Max
Household Equivalized Income(1)	12911.67	8406.592	0.00	113968.90
Household vintage (2)	48.23863	10.62279	27.00	75.00
Household vintage^2	2439.792	1079.848	729.00	5625.00
Father edu	5.375504	1.538859	1.00	9.00
Mother edu	4.964889	1.445191	1.00	9.00
Social Class (3)	1.836103	1.151939	1.00	5.00
Family Size	3.023266	0.7778607	1.00	9.00
CR Dummy (4)	0.5551081	0.4969909	0.00	1.00
vintage*CR	25.7648	23.30947	0.00	54.00
vintage^2*CR	1207.075	1124.387	0.00	2916.00
Father edu*CR	2.952801	2.851391	0.00	9.00
Mother edu*CR	2.789631	2.671376	0.00	9.00
Social Class*CR	1.025227	1.258468	0.00	5.00
Family Size*CR	1.680089	1.578344	0.00	8.00

(1) Brady Barber square root rule.
(2) Age of Household Head.
(3) Sum of fathers parents social class ranks and mothers parents social class ranks)/4.
(4) Household heads between ages 38 and 52 at the time of the survey would have been affected by the shut-down of schools in the Cultural Revolution, D is an indicator of heads of this age.

Determination of Mixture Components:

To study the various direct transition effects on the income distribution, following Anderson et. al (2016), the distribution of adult equivalized household income y was modeled as a K component mixture distribution of $ln(y)$ of the form:

$$f(lny) = \sum_{k=1}^{K} w_k f_k(\ln y, \mu_k, \delta_k^2)$$

$$\text{where } f_k(\ln y, \mu_k, \delta_k^2) = \frac{1}{\sqrt{2\pi\delta_k^2}} e^{-\frac{(\ln\ y-\mu_k)^2}{2\delta^2}}$$

The preferred specification had 5 components details of which are reported in Table

6. The structure can be seen to be primarily a 3 class model of roughly similar sizes with 2 components representing the poorest 2% of the sample.

Component	μ_k	δ_k	w_k
1	7.491525332	0.595191821	0.004187388
2	7.970963519	0.177103563	0.018043197
3	8.859922538	0.457431763	0.257995935
4	9.220069174	0.457684671	0.352934957
5	9.617802324	0.43377088	0.366838523

Transitions to an income distribution class can be explored by computing $P(I \in \text{Class}k|y_i)$ the probability that a household with ln income y_i is in class k by using the formula:

$$P(\text{household } i \in \text{ Class } k|y_i)\frac{w_k f_k(\ln\, y, \mu_k, \delta_k^2)}{\sum_{k=1}^{K} w_k f_k(\ln\, y, \mu_k, \delta_k^2)} \text{ for } k = 1, ..., K \quad (2)$$

A regression of these probabilities on social or educational class membership dummies will yield the corresponding transition matrix.

To determine the optimal number of mixture components in the mixture distribution the comparison of each mixture with a kernel estimate of the distribution using versions of Gini's Transvariation Statistic with and without importance weighting and with and without parsimony penalization. Closer proximity of the mixture distribution $fM(x)$ to the kernel estimate of the distribution $fK(x)$ is the objective function here and GINI's Transvariation and importance weighted measures measure that proximity in terms of:

$$GINIIT = \int_0^\infty |f_M(x) - f_K(x)|dx = \int_0^\infty |\frac{f_M(x)}{f_K(x)} - 1|f_K(x)dx$$
$$= E_{f_x}\big(|\frac{f_M(x)}{f_K(x)} - 1|\big) = \frac{1}{n}\sum_{i=1}^{n}|\frac{f_M(x_i)}{f_K(x_i)} - 1|$$
$$GINITIM = \int_0^\infty |f_M(x) - f_K(x)|f_k(x)^{-0.5}dx = \int_0^\infty |\frac{f_M(x)}{f_K(x)} - 1|f_k(x)^{-0.5}f_K(x)dx$$
$$= E_{f_x}\big(|\frac{f_M(x)}{f_K(x)} - 1|f_k(x)^{-0.5}\big) = \frac{1}{n}\sum_{i=1}^{n}|\frac{f_M(x_i)}{f_K(x_i)} - 1|f_k(x)^{-0.5}$$

The parsimony penalization factor was + $3n(k)$ where $n(k)$ is the number of parameters estimated in the k component mixture. The results are reported in Table A2. In all cases the 5 component mixture minimized the statistic.

Table 15: Transvariation statistics for the mixture–kernel distribution comparisons.

Num of Components	GINIT	GINIT Penalized	GINITIMP	GINITIMP Penalized
1	0.10904065	0.10993805	65.379380	65.380278
2	0.022838910	0.024633705	1.5981538	1.5999486
3	0.030588285	0.033280477	3.5404273	3.5431195
4	0.022758709	0.026348299	0.15000316	0.15359275
5	0.018226032	0.022713020	0.061861663	0.066348651
6	0.018332401	0.023716786	0.50103731	0.50642169

Appendix 2

$$\frac{1}{X_m}\sum_{i=1}^{n}\sum_{j=1}^{n}\pi_i\pi_j|X_i-X_j| = \sum_{i=1}^{n}\pi_i\sum_{j=1}^{n}\pi_j\Big(\frac{|X_i-X_j|}{X_m}\Big) = \sum_{i=1}^{n}\pi_i\frac{|\sum_{j=1}^{n}\pi_j X_i - X_m|}{X_m} = \sum_{i=1}^{n}\pi_i|\frac{X_i}{X_m}-1| \tag{1a}$$

For a continuous income distribution f(x), GINI may be written as:

$$\frac{1}{\mu}\int_a^b f(x)\int_a^b f(y)|x-y|dxdy = \int_a^b f(y)|\frac{E_{f(y)}(x)-y}{\mu}|dy = \int_a^b f(y)|1=\frac{y}{\mu}|dy = E_{f(y)}\Big(|1-\frac{y}{\mu}|\Big) \tag{1b}$$

Note for n equal sized groups:

$$GINI = \frac{1}{\mu n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i-x_j| = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{n}\sum_{j=1}^{n}\frac{|x_i-x_j|}{\mu} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{n}\frac{|nx_i-\sum_{j=1}^{n}x_j|}{\mu} = \frac{1}{n}\sum_{i=1}^{n}|\frac{x_i}{\mu}-1|$$

Table 6c: Education Class Cumulative Densities Conditional on Social Class

Pre CR Fathers	SocClass1	SocClass2	SocClass3	SocClass4	SocClass5
Education Class 1	0.2040	0.1311	0.1056	0.0891	0.0899
Education Class 2	0.5550	0.3985	0.4366	0.3465	0.3371
Education Class 3	0.7058	0.5553	0.6056	0.4950	0.5506
Education Class 4	0.8307	0.7352	0.7606	0.6337	0.7191
Education Class 5	0.9394	0.9023	0.8732	0.8416	0.8202
Education Class 6	0.9975	0.9974	0.9965	0.9901	1.0000
Education Class 7	1.0000	1.0000	1.0000	1.0000	1.0000
Post CR Fathers					
Education Class 1	0.0439	0.0481	0.0557	0.0119	0.0229
Education Class 2	0.3805	0.3342	0.4116	0.2579	0.2343
Education Class 3	0.6742	0.6400	0.5981	0.5159	0.5086
Education Class 4	0.7570	0.7337	0.7143	0.6071	0.6286
Education Class 5	0.9310	0.9273	0.8959	0.8651	0.8743
Education Class 6	0.9921	0.9914	0.9976	0.9841	0.9600
Education Class 7	1.0000	1.0000	1.0000	1.0000	1.0000
Post CR Fathers					
Education Class 1	0.0099	0.0081	0.0238	0.0000	0.0192
Education Class 2	0.2232	0.1789	0.1429	0.2000	0.0577
Education Class 3	0.4451	0.4146	0.3452	0.4308	0.2692
Education Class 4	0.5561	0.5041	0.5119	0.5231	0.3846
Education Class 5	0.8113	0.7764	0.8452	0.8000	0.6923
Education Class 6	0.9914	0.9919	0.9762	0.9692	0.9808
Education Class 7	1.0000	1.0000	1.0000	1.0000	1.0000