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Income Inequality in Urban China, 1978-2005

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**ABSTRACT**

The aims of this paper are twofold: (1) identifying the “winners” and “losers” in China’s economic transition via regression analyses on income using repeated cross-sectional data at individual levels over the entire period of economic reform, and (2) linking the “winners” and “losers” categories to the income inequality at the aggregate level by decomposing the trend in overall income inequality with respect to some key characteristics of these categories. Based on individual level analyses of 11 waves of survey data collected in urban China from 1978 to 2005, we found that (1) returns to schooling have been increasing over time; (2) returns to party membership did increase, but when distinguishing between ordinary party members and cadre members, the increase in income returns to ordinary members seemed to be non-substantive and there is no temporal trend in returns to cadre members; (3) workers in the private sector and the self-employed (getihu) are –looking at the entire period 1978 – 2005- among the “losers” of the economic transition; (4) the unemployed, although profiting from the transition during the first half of the 80s, also turned out to be among the “losers”; and (5) the employers in the private sector were among the “winners”. Results from the decomposition analyses showed similar effects on China’s overall income inequality. A link between the “winners” and “losers” on the micro-level and changes in the explained income inequality at the macro-level could be established.
INTRODUCTION

The transformation from state socialist to market economies in former state socialist countries has provided a unique opportunity for scholars to study the impact of institutional changes on stratification outcomes, namely, the patterns of social stratification emerging from the new social order (Gerber and Hout, 1998; Nee, 1989; Nee and Cao, 2002; Rona-Tas, 1994, 1998; Stark, 1996; Stark and Bruszt, 1998, 2001; Szelenyi and Szelenyi, 1995; Walder, 1995, 1996). Empirical analysis was typically focused on income distribution. To address the effects of institutional transition on income inequality (Stark, 1992, 1996; Verhoeven et al., 2008a), researchers in sociology and economics have examined changes in the determinants of individual and household incomes (Cao and Nee, 2005; Nee, 1989, 1991, 1992, 1996; Vecernik, 1996; Verhoeven et al., 2005, 2008a, 2008b, 2009) and trends in overall income inequality (Alam et al., 2005; Heyns, 2005; Flemming and Micklewright, 2000; Milanovic, 1998; World Bank, 2000). The first line of literature, organized under the heading of “market transition debate”, attempts to answer who have benefited in the process of transition from a planned to a market economy. Scholars have debated on whether returns to individuals’ political capital, human capital, and entrepreneurship have increased over time (e.g., Bian and Logan, 1996; Nee, 1989; Rona-Tas 1994; Wu and Xie, 2003; Zhou, 2000). The second line of literature attempts to describe the trend in income inequality at the macro-level and link it to institutional changes or policy episodes (Atkinson and Micklewright, 1992; Heyns, 2005; Ivaschenko, 2002; Kaasa, 2003; Wang, 2008).

Among the above literature, research on China has been a special focus, not only because the phenomenal growth in prosperity is accompanied by sharp increases in economic inequality (e.g., Griffin and Zhao, 1993; Hauser and Xie, 2005; Zhao and Zhou, 2002), but also because such a high degree of income inequality did not lead to social instability, as many social commentators expected (Whyte, 2010; Wu, 2009a). Economists have made a
great effort in documenting the trends in income inequality in China, which can be traced back as early as the 1950’s, albeit mostly with aggregated data, and investigating the causes of the trends. In Figure 1, we plot the trend of per capita income Gini’s, reported by Zhang, Liu and Yao (2001), supplemented by the per capita family disposable income Gini’s from Wu and Perloff (2005), the personal equivalent gross income Gini’s from Ying (1995), and the per capita household consumption inequality entropy measures, reported by Bhalla, Yao and Zhang (2003).

Figure 1. Income Inequality China, 1952 – 2001

The trends in income inequality display in Figure 1 are often linked to policy episodes in the history of People Republic of China (Jian et al., 1996; Qian, 2000; Zhou, 2004, pp. 36-39). For instance, the increasing inequality during the 1952-1960, the period of rapid economic growth, peaked in ‘the Great Leap Forward’, was followed by declining inequality during the economic disaster period from 1961-1965. During the earlier years of the ‘Cultural Revolution’, a stable pattern of moderate income inequality can be observed, followed by a decline. In the post-Mao era, market reforms were introduced from 1978 on. The early years
of the reform has witnessed a decline in income inequality, but the trend has been reversed since the mid-1980s. After some retreat and revival of reform in the period 1989-1993, income inequality has been rising dramatically during the radical market reforms period from 1994 onward.

In this paper, we focus our analysis on the post-Mao period of market reforms. Scholars often relate the trend in income inequality during this period to the government development strategies and re-distributional policies. The period from 1981 to 1984 is described as “growth with equity”, during which real income increased by 12.6 percent annually while the Gini index rose only marginally, as the market reform initially benefited those from the bottom of the socialist hierarchy, such as peasants and workers (or “direct producers” in Victor Nee’s term). The period 1984-1989 is characterized as “income inequality with little growth”, during which the overall real mean income increased by less than 1 percent annually while the growth was very unevenly distributed. The stagnant economy and rising inequality had caused popular discontents that led to the Tiananmen Incident in 1989. After a brief setback following the Tiananmen Incident, the paramount leader Deng Xiaoping launched a new stage of reform that pushed Chinese economy to further marketization without loosening political controls. The period from 1990 onwards, especially since 1992 when Deng made his tour to southern China to call for further reform, is labelled “growth with income inequality”, as both the overall real mean income and the inequality grew rapidly (Qin et al., 2009, p. 70). Gini coefficients increased from 0.357 in 1990 to 0.449 in 2005, while GDP per capita increased from 1,643 yuan to 14,040 yuan in the same period (Wu, 2010b, Table 1).

Previous studies have revealed that income inequality in urban China is much less than in rural China (shown in Figure 2) and that the overall income inequality for a large part is caused by the urban– rural income inequality gap (Bramall, 2001; Chang, 2002; Chen and Zhou, 2005; Gustafsson, Li, and Sicular, 2008; Ravaillon and Chen, 2007; Tian et al., 2003; Wu and Perloff, 2005, and Zhang, 2003). For instance, Qin et al. (2009, p. 71) found that the rural–
urban income gap explains one-third of the total inequality in 1995 and one-half of the increase in inequality since 1985. Such an inequality structure is largely the result of government policies during the reform era. As Yao and Zhu put it (1998, p. 148), “there has been a continuous social policy that favours urban residents. In the early years of reforms (1978-84), massive growth in agricultural production and rural incomes was unleashed by the household production responsibility system and a great improvement in agriculture’s terms of trade.

The following decade (1985-94), however, witnessed government’s unhelpful attitude towards rural prosperity. State policies were geared towards supporting the urban economy and subsidizing state-owned enterprises.” As a consequence, rural economic growth was stagnant and rural-urban inequality was enlarged. Statistical data show the urban – rural ratio of income per capita, after an initial decline from 2.35 in 1978 to 2.14 in 1985, increased dramatically since then, to 2.51 in 1990, 2.79 in 1995, 3.10 in 2000 and 3.22 in 2005 (see Wu 2010b Table 1).
In addition to the rural-urban divide, other analyses have shown that macro-economic variables could have affected income inequality in China (e.g., Wang, 2008). For instance, educational opportunities are unequally distributed in China, leading to an increasing effect on income inequality, measured by Gini coefficients (Wang, 2008, p.29). The fiscal transfer and social security systems are found to contribute to higher inequality, ironically, due to the inefficient use of the transfer payment and low coverage of the social security systems for the poor (Wang, 2008, p. 26).

While economic analyses tend to focus on the impact of institutional transition and policy changes on income inequality at societal (aggregated) levels, sociological analyses are more concerned about the changing inequality among individuals of different social groups (difference in mean income) in the course of transition, and pose the question - “who are the winners and who are the losers?” Few studies, nevertheless, have been able to bridge the two lines of literatures to answer how the inequality pertaining to relevant social groups has contributed to the change in overall income inequality at societal level. For economists, it may be that they are unaware of waves of individual-level survey data to be used in a decomposition analysis of income inequality (Gustafsson, Li, and Sicular, 2008). For sociologists, individual-level regression models conventionally employed are unable to link the group mean difference to the dynamic picture of overall income inequality.

Against this context, some puzzling questions emerged from time to time in the market transition debate among sociologists. Indeed, some scholars have pointed out internal inconsistencies in the market transition theory and the related literature (Nee, 1989, 1992). As Szelenyi and Kostello (1996, p. 1089) put it, “it is implausible to argue that returns to human capital increase at the same time that the degree of inequality declines.” On the other hand, with regard to changing income advantages of communist cadres in economic transition, Cao and Nee (2000, p. 1180) contended that, even cadres’ advantage as suggested by the power-conversion hypothesis is “theoretically interesting and also likely to manifest itself through statistically significant coefficients in empirical analysis, its overall importance is
questionable” (italics are the authors’). Because cadre-converted entrepreneurs accounted for only a tiny proportion of the population, their higher income would not have substantive significance (albeit statistically significant) in affecting overall inequality structure.

In this paper, by employing a decomposition method that incorporates both categorical variables and covariates, we aim to identify the “winners” and “losers” of the economic transition, and then to link the changing effects of individual characteristics on income to overall inequality in China from 1978 to 2005. Due to the fact that most of our individual-level datasets do not have comparable information on income between rural and urban individuals, we are unable to incorporate the urban–rural divide and therefore focus on urban samples only.

Following previous sociological literature on the market transition (Cao and Nee, 2002; Nee, 1989, 1991, 1992, 1996; Vecernik, 1996; Verhoeven et al., 2005, 2008a, 2008b, 2009) and economic studies on China (Gustafsson and Li, 2001; Gustafsson and Sai, 2009; Sicular et al., 2007; Wang, 2008; Zhou, 2004), we employ education, employment status, employment sector, and political status as explanatory variables. Gender and age (as a proxy for work experience) are also added to the analyses as controls. In so doing we are able to identify “winners” and “losers” in economic transition and how they contribute to the overall changing income inequality in China.

**DATA AND VARIABLES**

We use waves of survey data collected in urban China. There were few national representative sampling surveys conducted in China before the 1990s. We employ the data from a life history survey in 20 Chinese cities with retrospective information on income and other related variables in 1978, 1984, 1987, 1991, 1992, 1993, and 1994. This survey was led by Xueguang Zhou and the fieldwork was implemented in 1994, covering a variety of geographic locations and different types of urban economies in the country (Zhou 2000, 2004). The second data sources we use are from the China Household Income Project, 1995 and
2002 (CHIP95 and CHIP02). The project started in 1988 by a group of economists in the Chinese Academy of Social Science in cooperation with China National Bureau of Statistics, with a sample of both rural and urban household covering large parts of China. The survey was repeated in 1995 and 2002, respectively (see Khan and Riskin, 1998; Gustafsson, Li, and Sicular, 2008).

Finally, we use the available data from the China General Social Surveys in 2003 and 2005 (hereafter CGSS03 and CGSS05). The Chinese General Social Survey is an annual survey of a national representative sample of the adult population aged 18 or above in urban China in 2003, and in both rural and urban China (except for Tibet) in 2005. Again, we restrict the analysis to the urban sample only.

As a result, we are able to obtain repeated information in 1978, 1984, 1987, 1991, 1993, 1994, 1995, 2002, 2003, and 2005. To our knowledge, this is the first project that systematically analyzes many repeated cross-sectional survey data covering most period of the reform era of China, given the lack of longitudinal data on income inequality in China.

Variables were coded consistently to facilitate the examination of the temporal trend of overall income inequality and income returns to different individual characteristics. One may be concerned that the sample distributions vary from survey to survey. We present the descriptive statistics in the Appendix and show that the distributions are quite similar to each other across years.

In the following analyses, income, our dependent variable, refers to the total amount of income an individual received from work. Based on previous literature and discussion, we

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1 We did not use the CHIP88 data because the standard deviation of the income variable is much smaller than for all other data sets, leading to exceptional results in the decomposition analyses. There is no obvious reason for such a small standard deviation and no outliers can be found. Data are available upon request.
2 Both the data and sampling documents of the above surveys are available in the Interuniversity Consortium for Political and Social Research (ICPSR), University of Michigan, Ann Arbor.
3 The data are available at [http://www.chinagss.org](http://www.chinagss.org).
include explanatory variables such as gender, age, education, employment status, party membership and employment sector. Gender is coded as a dummy variable (female=1), education is measured by years of schooling, whereas employment status is coded into 5 categories (1=employed, 2=employer, 3=self-employed, 4=unemployed, 5=not in the labour force). Party membership is coded into 3 categories (1=no member, 2=ordinary member, 3=cadre member); employment sector also is coded by three categories (1= private, 2=collective, and 3=state). To capture the nonlinear effect of age, a squared term is also included. Descriptive statistics for all variables in 11 survey years are presented in the Appendix.

“WINNERS” AND “LOSERS” IN CHINA’S ECONOMIC TRANSITION

In this section, we present results from regression analyses on the individual data from the repeated cross-section surveys. The total amount of income will be regressed on a set of key explanatory variables of interest to scholars involved in the market transition debate (Cao and Nee, 2000; Nee, 1989; Verhoeven et al., 2005, 2009): years of schooling, employment status and sector, and party membership. Female, age and $age^2$ are included as control variables. A lognormal distribution has been defined for the income variable. It is impossible to include the dummy variables for employment status and those for employment sector in one single model, because all employers and the self-employed are in the private sector, and the information on sector is necessarily missing for the unemployed and those not in the labour force. Hence, we construct a new variable, combining employment status and sector in a new variable status_sector with 5 categories: (1) employees in the private sector, (2) employees in the collective and state sectors, (3) employers, (4) self-employed, and (5) unemployed. In evaluating the interactions of the explanatory variables with survey year, we are able to identify the “winners” and “losers” in China’s economic transition.
Model 1 in Table 1 presents an additive model. We use schooling and age as well as its square term to measure human capital. Gender, survey year, employment sector and political status are also included in the model.

Table 1. Individual Level Regression Analyses (streg) Results, China 1978-2005.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of schooling</td>
<td>0.06 (0.002)</td>
<td>0.02 (0.003)</td>
</tr>
<tr>
<td>Age</td>
<td>0.06 (0.002)</td>
<td>0.06 (0.002)</td>
</tr>
<tr>
<td>(Age)^2/100</td>
<td>-0.06 (0.003)</td>
<td>-0.06 (0.003)</td>
</tr>
<tr>
<td>Female</td>
<td>-0.17 (0.006)</td>
<td>-0.19 (0.02)</td>
</tr>
<tr>
<td>Year (1978 = 0; 2005 = 27)</td>
<td>0.10 (0.000)</td>
<td>0.08 (0.002)</td>
</tr>
<tr>
<td>Employee in collective/state sector (reference)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employer in private sector</td>
<td>-0.05 (0.01)</td>
<td>0.41 (0.04)</td>
</tr>
<tr>
<td>Self-employed (getihu)</td>
<td>-0.04 (0.02)</td>
<td>0.31 (0.06)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>-0.75 (0.01)</td>
<td>0.35 (0.04)</td>
</tr>
<tr>
<td>Non-member party (reference)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Party member</td>
<td>0.11 (0.008)</td>
<td>0.04 (0.02)</td>
</tr>
<tr>
<td>divided among:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ordinary member</td>
<td>0.05 (0.01)</td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>cadre member</td>
<td>0.17 (0.01)</td>
<td>0.16 (0.03)</td>
</tr>
<tr>
<td>Years of schooling * year</td>
<td></td>
<td>0.002 (0.000)</td>
</tr>
<tr>
<td>Female * year</td>
<td></td>
<td>0.001 (0.001)</td>
</tr>
<tr>
<td>Employee in private sector * year</td>
<td>-0.02 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Employer in private sector * year</td>
<td>-0.01 (0.006)</td>
<td></td>
</tr>
<tr>
<td>Self-employment * year</td>
<td>-0.02 (0.003)</td>
<td></td>
</tr>
<tr>
<td>Unemployment * year</td>
<td>-0.05 (0.002)</td>
<td></td>
</tr>
<tr>
<td>Membership * year</td>
<td>0.003 (0.001)</td>
<td></td>
</tr>
<tr>
<td>divided among:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ordinary member * year</td>
<td></td>
<td>0.004 (0.002)</td>
</tr>
<tr>
<td>cadre member * year</td>
<td></td>
<td>-0.001 (0.002)</td>
</tr>
</tbody>
</table>

N = 48,069
R^2 = 0.58
LR chi^2(11) = 41,899
-2LL = 24,052

N = 48,069
R^2 = 0.59
LR chi^2(19) = 43,115
-2LL = 28,748

The model 2 coefficients have been compared with those from the same model having ln(income) as the dependent variable (reg). A Hausman test of the H0: “differences in the coefficients between (streg) and (reg) are not systematic” shows that differences are systematic: \(\chi^2(19) = 398.53; p < .001\). Largest differences are found in the coefficients of the status_sector categories: employer in the private sector (diff. = .04); unemployed (diff. = .04).

Figures in the parentheses are standard errors.

As expected, years of schooling has positive effect on income. One year increase in education brings about 6.2 percent increase in earnings \(e^{0.06} - 1\), net of others, and the effect is statistically significant (p<.01). The effect of age on income is curvilinear, first increasing
and then decreasing at the peak of 50 years old. Women receive 16 percent \((e^{-0.17-1})\) less than men do, controlling for other factors. Consistent with the trajectory of China’s economy, income has been growing about 10.5 percent \((e^{0.10-1})\) every year since 1978.

Moreover, results show that, compared to those working in the state/collective sector, only employers in the private sector enjoyed income advantages, by 52.2 percent \((e^{0.42-1})\) (also see Lin and Wu 2009). Self-employed and employees in the private sector earn slightly less, by 4 percent and 5 percent \((e^{-0.04-1} \text{ and } e^{-0.05-1})\), respectively. The unemployed are doing much worse, and with their incomes only 47 percent \((e^{-0.75-1})\) of those working in the state/collective sector, net of other factors. All the factors above are statistically significant at .05.

On the other hand, political capital (measured by party membership and cadre status) continues to play an important role in income determination. Compared to nonparty members, party members enjoy a net advantage in income by 12 percent \((e^{0.11-1})\). Distinguishing between ordinary party members and cadre members, we find that ordinary party members enjoy a slight, but non-significant, net advantage in income, by 5 percent \((e^{-0.05-1})\), but cadre members, notably, enjoy 18.5 percent higher income \((e^{0.17-1})\), controlling for over factors (p<.01).

To examine the temporal trend in income distribution to find out the winners and losers in process of transition in late stage of reform, based on previous literature on the market transition debate and findings from Lin and Wu (2009), we include interaction terms of all independent variables with survey year except for age. Regression results are presented in Model 2 of Table 1.

Consistently with the findings reported by Hauser and Xie (2005) (also Bian and Logan 1996; Zhou 2000), both returns to schooling and returns to party membership have been increasing over time from 1978 to 2005. For instance, one additional year of schooling brings about 2 percent \((e^{0.02-1})\) net increase in income in 1978, 3.5 percent \((e^{0.02+0.002*(1985-1978)-1})\) in 1985, 4.5 percent \((e^{0.02+0.002*(1990-1978)-1})\) in 1990, 5.5 percent \((e^{0.02+0.002*(1995-1978)-1})\) in 1995, 6.6 percent \((e^{0.02+0.002*(2000-1978)-1})\) in 2000, and 7.7 percent \((e^{0.02+0.002*(2005-1978)-1})\) in 2005. The differences are highly significant (p<.001). Although at the start of the period examined, no differences between members and non-members were found, cadre members,
relative to non-members and ordinary party member, earn significantly more. During the time period, income returns to party membership are increasing, but only in a non-substantial way (some 3 percent in 10 years), and only limited to ordinary members. For cadre members, there is no trend in the advantages they enjoyed over time.

Workers in the private sector and the self-employed (getihu) were among the “winners” at the start of the period studied (the positive coefficient of the main effect). This is exactly what the market transition theory predicted based on the data in the 1980s (Nee, 1989, 1991). However, they gradually lost their advantages, as shown by the negative coefficient of the interaction effect. Overall, they are the “losers” in the course of economic transition from 1978 to 2005. The economic situations of the unemployed are getting even worse over time, decreasing by 5 percent every year ($e^{-0.05}\times1$) ($p<.001$). The employers in the private sector were also among the “winners” but seem to have been maintained their status over time compared to employees in the state/collective sector.

How do the changes in winners and losers contribute to overall income inequality trend for China in the period 1978-2005? In the following section, we will present the links by decomposing the income inequality. Before doing that, we would like to introduce a new method of decomposition.

**A NEW METHOD OF DECOMPOSING INCOME INEQUALITY**

Economists and sociologists have been using a range of index to measure income inequality, among which most popular are the Gini coefficient, the members of the Generalized Entropy (GE) class of indices (such as the Theil and Atkinson coefficients), and the percentile ratios (e.g., P90/P10 and P75/P25) (Allison, 1978; Liao, 2006).

The Gini coefficient is based on the differences in incomes of all possible pairs of individuals

$$Gini = \{1/(2n^2)\Sigma_i \Sigma_j |Y_i - Y_j|\}/(1/n)\Sigma_i Y_i$$

($n = \text{number of individuals}; i = 1, \ldots, n; j = 1, \ldots, n; i \neq j; Y_i = \text{income of individual } i; Y_j = \text{income of individual } j$), whereas the Theil coefficient for non-weighted data is defined as
\[
GE_T = \Sigma_i\{(1/n)(Y_i/m)(\log(Y_i/m))\}
\]

\(T =\) Theil; \(n =\) number of individuals; \(i = 1, \ldots, n; Y_i =\) income of individual \(i; m =\) arithmetic mean income.

As all members of the GE class, the Theil coefficient can be additively decomposed by subgroup into a within-group inequality and a between-group inequality part. The between-group inequality can provide “explained” inequality profiles at fixed points in time and trends in “explained” inequality by population subgroup using overtime data. The Gini coefficient cannot be properly decomposed by population subgroup into a within and a between part, because the decomposition would result in:

\[
\text{Gini(total)} = \text{Gini(within)} + \text{Gini(between)} + \text{Gini(overlap)},
\]

in which the between part accounts for the differences in mean incomes between the subgroups, and the within part depends on the Gini coefficients within each subgroup. The between part would be the only component if there was no variation in income within the subgroups. The overlap part would be zero if there was no overlap between the income ranges of the various subgroups, an unrealistic assumption in most cases.

For the decomposition analysis of income inequality, there are two Stata macros currently available. One is INEQDECO (Jenkins, 2001), which estimates a range of inequality indices and provides decompositions for a subset of these indices by population subgroups. The decomposition part of the macro focuses on the Generalized Entropy class of inequality indices \(\text{GE}(a)\) with \(a = -1, 0, 1, 2\). The other macro is GINIDESC (Aliaga and Montoya, 1999), which provides the Gini coefficient for the whole population, for each subgroup defined, and decomposes Gini coefficients into between, within, and overlap parts, based on the algorithm written by Pyatt (1976).

Both existing methods of decomposition have several limitations. First, one can handle just only one population grouping variable in the decomposition, as done by many economists...
(e.g., Gustafsson, Li and Sicular, 2008). Of course, several grouping variables could be combined, but this will lead to an increasingly large number of subgroups and difficulty for group comparisons and interpretations. Second, only categorical variables can be used as population grouping variables and it is impossible to incorporate covariates in the analysis. Finally, trends in the within and between parts of the inequality index may be attributable to a variety of sources: (1) differential changes in the group means, (2) changes in within-group inequalities, and (3) changes in group composition, which are hardly identifiable with the existing decomposition methods.

In this paper we propose a solution to remedy some of the above limitations. We use the \textit{streg} module in Stata, define a lognormal distribution for the dependent variable, which is the individual income ($Y$), and simultaneously model the average subgroup income ($E(Y|X)$) and the inequality ($\text{Var}(Y|X)$), where the $X$’s can be both categorical and continuous variables. This method takes into account changes in the group means and in the within group distributions but cannot provide a solution for changes in group composition.\textsuperscript{4}

A different approach has been followed in Xie and Hannum (1996), Hauser and Xie (2005), and Xie and Wu (2008). Income inequality has been decomposed by modeling the error variance that is left from regressing ln(income) on a set of predictors. However, the homoscedasticity assumption in this regression analysis may be questioned, as is shown in the bottom section of Table 1. In particular, for the status-sector categories, the homoscedasticity assumption in the ln(income) regression seems to be violated. In our analyses, we explicitly model the variance of income in a lognormal distribution, and compare our parameter estimates with those from a regression analysis on ln(income), using a Hausman test on the consistency of the estimates.

\textsuperscript{4} To give an example, in an Analysis of Variance with hourly income as the dependent variable, and gender as the fixed factor, where doubling the number of women (changing the composition radically) does not affect the income means, but disproportionally affects the mean square error (unexplained) part and mean square between (explained) part of the variance.
DECOMPOSITION RESULTS

In Figure 3, we first calculate Gini coefficients on personal income for all survey datasets and plot them together with the most comparable coefficients from official statistical data (Bramall, 2001). The Gini coefficients from the survey data are always larger, because they have been computed from individual data and not from grouped data as used by Bramall (2001, p. 692), a typical practice in economic research. The grouped data used by Bramall originate from the National Statistical Bureau.

Figure 3. Income Inequality Urban China, 1978 – 2005.

As shown in the figure, the trends in the overlapping period (1978-1995) are strikingly similar, even though the survey data include retrospective ones for the period 1978-1994 from Xueguang Zhou (2000, 2004). These retrospective data show a surprisingly high quality (Zhou 2000). The correlation between the Zhou-based Ginis and those from Bramall is 0.90. The decrease from 1993 (in both the survey Gini’s and the “official” ones) may be explained
by the 1989-1993 period of “retreat and revival”, following the Tiananmen Incident in 1989, as described in the beginning of this paper. The retreat may become visible in the income inequality figures after some delay. In the new millennium the inequality rose to 45.5 in 2003 and 45.7 in 2005, which is in line with the overall Gini (46.9) reported for 2004 by the World Bank (UNU-WIDER, 2008).

We then decompose the inequality according to the variables mentioned above: gender (female), party membership, status_sector, and the covariates age, age squared, and years of schooling. Each decomposition will result in a total inequality part, a between (“explained” by the explanatory variables) component, and a within (“unexplained”) component. The results of the first decomposition, using all explanatory variables, are plotted in Figure 4 as the trend in the relative between (“explained”) part.

Figure 4. Inequality Decomposition in Urban China, 1978 – 2005.
As displayed in Figure 4, from 1978 to 1984, the part of the inequality that could be explained by the explanatory variables decreased, almost reaching 5 percent in 1984; from 1984 onward it steadily increased, to almost 30 percent in 2002. This is consistent with the U-shape trend of income inequality in post-socialist transition economies which has been well documented (Szelenyi and Kostello, 1996). Interestingly, in more recent years, this trend is levelling off. The trends up to 2002 are in line with the periods (1981-1984, 1984-1989 and 1990-2002), as described by Qin et al. (2009) and also in the introduction section of this paper. The rising level of explained inequality during the period 1990-2002 coincides with the “growth with income inequality” period in which exponential economic growth was accompanied by worsening income inequality.

What part of the between-component can be explained by human capital, by political capital, and by the status_sector variable? To answer this question, we run a set of decomposition models, in which years of schooling, the dummies for party membership and the status_sector dummies have been removed from the full model, with all other explanatory variables included. The results are presented in Models 1-5 in Table 2.

Differential returns to human capital (education) started to affect overall income inequality from the 1990s, as can be inferred from comparing Model 2 (without years of schooling) with the full model 1 (with all explanatory variables). Comparing the full model with and without party membership (Models 1 and 3 in Table 2), we notice that party membership does not affect overall income inequality, despite the fact that party members may enjoy advantages in mean income over non-party members in urban China (Appleton et al., 2009; Hauser and Xie, 2005; Li et al., 2007), and such an advantage increases slightly over time, and in a different way for ordinary party members and cadre members, as reported in Section 3. The different effects for ordinary party members and cadre members, found in the individual level analysis may explain the absence of the party membership effect on the aggregate level.
Table 2. Trends in the explained part of income inequality (relative between component) for various models, China 1978-2005.

<table>
<thead>
<tr>
<th>Year</th>
<th>Model 1: full model</th>
<th>Model 2: without years of schooling</th>
<th>Model 3: without party membership</th>
<th>Model 4: without status_1,2,5,6</th>
<th>Model 5: without status_1,2,3,4,6</th>
<th>Model 6: full model B</th>
<th>Model 7: without private sector</th>
<th>Model 8: without collective and state sectors</th>
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<td>7.9</td>
<td>7.5</td>
<td>8.7</td>
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<td>1991</td>
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<td>20.1</td>
<td>20.2</td>
<td>25.8</td>
<td>21.9</td>
<td>20.1</td>
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<tr>
<td>2005</td>
<td>31.7</td>
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<td>28.8</td>
<td>30.7</td>
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Full model A: female, age, age squared, education, party membership categories, status _sector categories (1=employee in private sector; 2=employee in collective or state sector; 3=employer; 4=self-employed; 5=unemployed; 6=not in the labour force).

Full model B: female, age, age squared, education, party membership categories, sector categories (1=private sector; 2=collective sector; 3=state sector; 4=not in the labor force)

Figures in bold for models 4-5: more than 10% decrease relative to model 3; for model 2: more than 10% decrease relative to model 1; for models 7-8: more than 10% decrease relative to model 6.

Comparing Model 3 with the next two models, we find that the employers/self-employed categories started to affect overall income inequality from 1995 onward, while the same is true for the unemployed in 1994 and again from 2003. Deleting the employers and self-employed from Model 3 gives a decrease in the explained inequality from 1995 in Model 4, and deleting the unemployed from Model 3 leads to a decrease in the explained inequality in 1994, and from 2003 in Model 5. From these results we can reasonably infer that employers probably belong to the “winners” of the economic marketization and contribute to overall income inequality, based on the fact that including them with high average incomes in the decomposition raises the explained part of the income inequality, and that the unemployed belong to the “losers”, because including them in the decomposition would raise the explained part of the income inequality, given the fact that they receive much lower incomes than workers in the state/collective sector. These findings confirmed that, among the recent market entrants, those who were forced to leave the state sector might possess less human and

5 Because of data limitation, we cannot separate the self-employed from the employers.
political capital or other unobserved characteristics negatively associated with potential earnings, whereas those who were self-selected into the market sector to become entrepreneurs might possess certain observable or unobservable characteristics that are positively associated with potential earnings. The workers, who entered the market through these two mechanisms, fared differently, and contributed to the sharply rising labor market inequality in contemporary China (Wu, 2010).

Previous research pointed out the importance of danwei ownership in social stratification (Bian 1994; Wu 2002; Xie and Wu 2008). To evaluate the effects of the income differentials among different employment sectors on the overall income inequality, we present the results of the decomposition in Models 6-8 in Table 2. Model 6 is a slightly different version of the full Model 1, replacing the status_sector dummy variables with the employment sector categories. In Model 7, the private sector has been excluded; in model 8 the collective and state sectors. Comparing Models 7 and 8 with model 6, it is clear that from 1994 both the private sector and the collective/state sectors started to affect the explained part of the income inequality. Here the decrease in the explained part may be also explained by different mechanisms. The employers in the private sector moved to the higher end of the income distribution and will belong to the “winners” of China’s economic transformation, but in the mid-1990s the employees in the private sector lost their advantages relative to those in the collective and state sectors, and may eventually be among the “losers” in the transformation process.

SUMMARY AND CONCLUSION

Previous research on the changing income inequality during China’s economic transition tends to either document the trend at the macro-level or to identify “winners” and “losers” in the market transition via individual-level regression analysis. In this paper, we identify the “winners” and “losers” in China’s economic transition using a regression analysis on individual data, propose a method to decompose trends in overall income inequality with respect to some key variables of interests in the literature, both categorical and continuous,
and link the changing effects of individual characteristics on income to overall inequality in urban China from 1978 to 2005.

Based on the literature of the market transition debate and subsequent studies we selected some individual-level variables for both the regression analysis at the individual level and the decomposition of income inequality at the macro level: education, party membership, employment status categories, and employment sector categories, as well as age and gender. Both the individual level analysis and the aggregate analysis showed that human capital affected individual income and the overall income inequality. On the individual level, income returns to each additional year of schooling increased from 2 percent in 1978 to 8 percent in 2005. On the aggregate level, the adding of the human capital variable to the decomposition model increased the explained part of the income inequality, and increasingly so from 1987 to 2005. The regression analysis showed that party members, compared to non-members, did not gain from marketization at the start of the period studied. Looking at the different categories of membership, the effect of cadre membership seems to cancel that of ordinary party membership. Where cadre members earn in 1978 about 17 percent more than non-members, there is no difference between ordinary party members and non-members. The effect of ordinary party membership increased over time (but only 3 percent in 10 years); that of cadre membership did not change. This is consistent with the findings from the macro level analysis. Decomposition analysis of 11 waves of survey data collected in urban China from 1978 to 2005 suggested that, party membership does not explain part of the overall income inequality.

From the decomposition findings as well as the results from the regression analysis, the “entrepreneurs” (employers in the private sector and self-employed) seem to be among the “winners” of the marketization. From the decomposition results, the “entrepreneurs” are among the “winners” from 1995, when China started turning to a stage of rapid economic市场化 and private ownership gained more legitimacy.

Regression results also show that employees in the private sector were among the winners during the first part of the period studied, but gradually lost their position relative to
those in the collective and state sectors. The unemployed had an increasing effect on the income inequality during the period studied; the effect has become even stronger since 1994, after Deng Xiaoping made his political tour to southern China to push the further marketization of China’s economies. State–owned enterprises were allowed to lay off workers and many became unemployed (Wu, 2010). The unemployed were among the “losers” of marketization and the growing rate of unemployment would lead to high inequality, but this trend probably may have been alleviated by welfare transfers in recent years since the Chinese government, under the leadership of Chinese President Hu Jintao and Premier Wen Jiabao, has launched a new social policy on construction of a harmonious society (Fan, 2006).
REFERENCES


### Appendix. Descriptive Statistics

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<td>52.8% (1,843)</td>
<td>52.9% (1,984)</td>
<td>53.6% (2,092)</td>
<td>53.6% (2,056)</td>
<td>53.7% (2,019)</td>
<td>53.8% (1,980)</td>
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<td>Female</td>
<td>48.5% (1,367)</td>
<td>47.2% (1,651)</td>
<td>47.1% (1,767)</td>
<td>46.4% (1,809)</td>
<td>46.4% (1,778)</td>
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<td>12.9% (298)</td>
<td>6.9% (197)</td>
<td>6.7% (203)</td>
<td>7.5% (237)</td>
<td>8.8% (275)</td>
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<td>16.3% (377)</td>
<td>18.1% (519)</td>
<td>17.5% (528)</td>
<td>16.0% (506)</td>
<td>15.6% (486)</td>
<td>15.0% (460)</td>
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<td>70.8% (1,636)</td>
<td>75.0% (2,143)</td>
<td>75.8% (2,295)</td>
<td>76.5% (2,425)</td>
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<td>75.5% (2,314)</td>
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<td>78.1% (2,728)</td>
<td>77.5% (2,907)</td>
<td>77.8% (3,036)</td>
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<td>0.9% (33)</td>
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<td>3.4% (120)</td>
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<td>2.6% (102)</td>
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<td>13.3% (519)</td>
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<td>86.1% (3,007)</td>
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<td>85.4% (3,333)</td>
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<td>84.9% (3,126)</td>
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<td>4.5% (159)</td>
<td>5.3% (197)</td>
<td>5.0% (194)</td>
<td>5.2% (199)</td>
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<td>11152.4/8597.7 (12,794)</td>
<td>11459.3/13563.9 (3,826)</td>
<td>13408.9/16677.4 (4,399)</td>
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<td></td>
</tr>
<tr>
<td>Age</td>
<td>Mean/Std. Dev.</td>
<td>39.9/10.6 (14,261)</td>
<td>41.2/10.3 (14,230)</td>
<td>40.8/10.4 (5,015)</td>
<td>40.0/10.8 (4,850)</td>
<td>39.7/10.7 (63,601)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age squared</td>
<td>Mean/Std. Dev.</td>
<td>1705.8/853.2 (14,261)</td>
<td>1804.7/828.2 (14,230)</td>
<td>1771.2/849.3 (5,015)</td>
<td>1713.2/872.8 (4,850)</td>
<td>1686.4/856.3 (63,601)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(yearinc.)</td>
<td>Mean/Std. Dev.</td>
<td>8.58/0.69 (9,06/0.79)</td>
<td>8.96/0.91 (8,96/0.91)</td>
<td>9.11/0.90 (9,11/0.90)</td>
<td>8.43/1.02 (8,43/1.02)</td>
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</tr>
</tbody>
</table>
The Population Studies Center (PSC) at the University of Michigan is one of the oldest population centers in the United States. Established in 1961 with a grant from the Ford Foundation, the Center has a rich history as the main workplace for an interdisciplinary community of scholars in the field of population studies.

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