A Tale of Transition: An Empirical Analysis of Economic Inequality in Urban China, 1986–2009*

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Abstract

This paper is the first comprehensive empirical study of earnings, income, and consumption inequality in urban China from 1986 to 2009, conducted using micro-level data from the Urban Household Survey (UHS). We document a drastic increase in economic inequality for the sample period. We find that consumption inequality closely tracks with income inequality, both over time and over the life cycle. We believe that the main driver of this co-movement could be the dramatic increase in uninsurable permanent income shocks that occurred after the early 1990s, a result of the economic transition in urban China.

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1 Introduction

Over the past three decades, the world witnessed a fast-growing and changing Chinese economy. Against the backdrop of the tremendous economic growth, there is an increasing concern among policymakers and the public over the widening economic inequality in China. Compared to our knowledge on China's growth miracle, we know much less about the trend of economic inequality. This paper aims to bridge the gap by providing the first comprehensive look at rising economic inequality in China for the period 1986–2009.

Employing the micro-level annual Urban Household Survey (UHS) data from 1986 to 2009, this paper empirically investigates the evolution of inequalities in earnings, income, and consumption in urban China for this time period. To make the analysis consistent with the literature and also comparable to other country studies, we closely follow the special issue of the *Review of Economic Dynamics* (RED) 2010 ("Cross-Sectional Facts for Macroeconomists") in our sample selection and data processing.

We find that, just as the public has speculated, economic inequality has been increasing drastically in China. For example, the variance of log household disposable income in China increased from 0.14 in 1986 to 0.41 in 2006–almost threefold–over 20 years. The speed of increase is far higher than in any country covered in the RED special issue.[1] We also find that total consumption inequality is higher than disposable income inequality for most of the period. Nondurable consumption inequality, however, is slightly lower than disposable income inequality. This implies that durable consumption inequality is much higher than disposable income inequality.

What surprises us most is that consumption inequality, whether total consumption or nondurable consumption, closely tracks with disposable income inequality over time. The strong co-movement between income inequality and consumption inequality is robust even after using an alternative definition of income and consumption, as in Krueger and Perri (2006), correcting well-known measurement error problems in consumption data (Attanasio, Hurst, and Pistaferri, 2012), using an alternative dataset, and conducting other robustness checks. This pattern con-

[1] For comparison, variance of log of household disposable income increased from 0.48 in 1986 to 0.54 in 2006 in the United States (see Figure 13 in Heathcote, Perri, and Violante 2010). For Japan, the same statistics increased from 0.18 in 1986 to 0.21 in 2006 (see Figure 4.9 in Lise et al. 2014).

trasts sharply with what others have found in the United States and other advanced economies. In those countries, consumption inequality has been increasing much more slowly than income inequality. Also, the level of consumption inequality is usually significantly lower than that of income inequality. This pattern is viewed as compelling evidence of consumption smoothing (Krueger and Perri, 2006). Russia is the only country studied in the RED 2010 special issue shows that consumption inequality is higher than income inequality during the time period that it was investigated (Gorodnichenko, Peter, and Stolyarov, 2010). However, even in the Russian case, consumption inequality does not track as closely with income inequality as it does in China.

We also look at the evolution of inequality over the life cycle, following the method employed in Deaton and Paxson (1994). We find that the variances of log household earnings, disposable income, and nondurable consumption all rise over the life cycle, consistent with the pattern observed in the U.S. data (see Heathcote, Perri, and Violante, 2010). However, the variance of log of disposable income closely tracks with that of nondurable consumption over the entire life cycle, which is consistent with the time-series pattern mentioned previously in this section. At the same time, in the U.S. data, we observe a divergence between disposable income and nondurable consumption inequality over the life cycle.

This unique phenomenon of a strong co-movement between income inequality and consumption inequality over both time and the life cycle probably indicates limited consumption smoothing across individuals over time. We investigate two possible explanations for this co-movement. First, it could be an indication of the prevailing existence of "hand-to-mouth" (HtM) consumers (or more precisely, the "rule-of-thumb" consumers described in Campbell and Mankiw 1989).[2] HtM consumers are individuals who simply consume what they earn. With consumption being roughly equal to income, their variances are also roughly equal. This theory implies that the saving rate should be close to zero across households. However, in the data, only the lowest income quintile of households has average saving rates close to zero. For other income quintiles, we observe significantly positive saving rates. More importantly, the household saving rate rises over time for all other income quintiles. We thus conclude that except in the lowest income quintile, little evidence supports the existence of hand-to-mouth consumers in urban China.

Our second explanation lies in the changes of underlying income shocks structure. The literature shows that it is much more difficult for households to insure against

[2] See Kaplan, Violante, and Weinder (2014) for a survey of HtM consumers. They report that HtM consumers (both wealthy and poor HtMs) have significantly higher marginal propensities to consume in response to transitory income shocks than non-hand-to-mouth consumers do.

idiosyncratic permanent income shocks than against transitory income shocks (Blundell, Pistaferri, and Preston, 2008). Therefore, a possible explanation for why consumption inequality closely tracks with income inequality in urban China is that rising permanent income shocks dominate the transitory income shocks over time. It makes the uninsurable part of idiosyncratic income shocks increase over time, and thereby impeding a household's ability to smooth consumption. To test this hypothesis, we estimate labor income dynamics following the literature (Heathcote, Perri, and Violante, 2010). We explore the panel structure of the UHS to construct a two- or three-period short panel at the household level. As in Heathcote, Perri, and Violante (2010), we use a method with moments based on income growth rates ("difference") and a method with moments based on log income levels ("level"). As found in Heathcote, Perri, and Violante (2010) and other articles in the RED special issue, we find that there is a substantial divergence between the average transitory and permanent variances obtained by the two methods. Compared to the level method, the difference method gives us a much less volatile estimation of the income process. We therefore choose to focus on the difference method for the analysis of the income process in China.

The estimation done using the difference method shows that permanent income shocks have been increasing significantly relative to transitory income shocks since the mid-1990s. From 1994 to 2005, permanent income variance in urban China increased from 0.012 to 0.095, that is, by about eight times. By contrast, transitory income variance decreased from 0.04 to 0.017 for the same time period. Taking into account the fact that individuals can only partially insure against permanent income shocks, and almost fully insure against transitory income shocks (Blundell, Pistaferri, and Preston, 2008), the underlying change in the composition of income shocks implies that sharing risks across individuals over time is becoming more difficult. This leads to a stronger synchronization between consumption inequality and income inequality. We believe that this could be a plausible explanation for the observed co-movement of income and consumption inequalities.

We make a further effort to investigate what has been causing the substantial increase in income inequality and permanent income shocks in urban China since the mid-1990s. As is discussed in the next section, the tremendous economic transformation pushing the economy towards a more market-oriented trend has been taking place since mid-1990s. A large number of state-owned enterprises (SOEs) have been either privatized or simply shut down. Employment has been shifted rapidly towards privately-owned enterprises (POEs). During the economic transition, evidence shows that less educated, relatively older workers face higher chances of being laid off (Appleton and others 2002). Motivated by these facts, we further decompose the income inequality and income process estimation along three dimensions: sector, worker age, and education. Our results show that older, less educated workers employed by POEs tend to have higher income inequality, higher "within-group" income inequality, and higher permanent income variances. These findings indicate that economic transformation might be an important driving force behind the dramatic increase in income inequality, and the fundamental change in the underlying income shocks structure. In that sense, we believe the co-movement of income and consumption inequalities in China could be a tale of transition. The transition in urban China has created tremendous uncertainty, and led to an increase in income inequality and uninsurable income shocks, which passes on to rising consumption inequality.

The paper is organized as follows. Section 2 discusses two closely related papers. Section 3 provides a brief historical background on the Chinese economy over the past three decades. Section 4 describes our dataset and sample selection criteria. Section 5 shows the trend of economic inequality over time. Section 6 investigates the economic inequality over the life cycle. Section 7 estimates income dynamics using the panel structure in the UHS dataset and further investigates the possible cause of the substantial increase in income inequality and permanent income shocks. Section 8 concludes.

2 Related Literature

This paper is closely related to Cai, Chen, and Zhou (2010) and Santaeulalia-Llopis and Zheng (2016). In this section, we discuss the position of our paper in the literature and the consistency of the findings across papers.

Cai, Chen, and Zhou (2010) examine the changes in income inequality and consumption inequality in urban China using the UHS data for the period 1992–2003. Their access to the UHS data covers all provinces for that time period. They find a striking co-movement between income inequality and consumption inequality over time. They then construct a panel data set at the provincial level and conduct an empirical analysis to detect the correlation between the rising income inequality and three major structural changes during the period: SOE reforms, urbanization, and globalization. They attribute the most important driving force behind the rising urban inequality to the SOE reforms.

Our paper differs from Cai, Chen, and Zhou (2010), in that our focus is to provide a systematic examination of stylized facts on earnings, income, consumption, and wealth inequality in urban China. Providing these kinds of cross-sectional facts is important for macroeconomists who are interested in the rapidly growing Chinese economy. To achieve this goal, we closely follow the methodology in the RED 2010 special issue to make sure our results are comparable to those in the issue. We not only study the evolution of different dimensions of inequality over time but also over the life cycle. Along the way, we confirm the main findings in Cai, Chen, and Zhou (2010), namely, the strong co-movement between income and consumption inequalities in China, though for a much longer time period (1986–2009). The results of the decomposition exercise for "between-group" versus "within-group" inequalities are also consistent across the two papers. In addition, we demonstrate that this co-movement shows up not only over time but also over the life cycle. To dig deeper into what caused the rising inequality and the strong co-movement between income and consumption inequalities, we further investigate the residual income and decompose it into permanent versus transitory shocks. We find that the changing nature of income shocks, possibly due to the economic transition, could be the driving force behind the strong co-movement. This echoes the finding in Cai, Chen, and Zhou (2010) that the SOE reform is the largest contributor to rising income inequality from a different perspective.

Santaeulalia-Llopis and Zheng (2016) apply the methodology in Blundell, Pistaferri, and Preston (2008) to the Chinese Health and Nutrition Survey (CHNS) data, and estimate the partial insurance coefficient of income shocks in China from 1989 to 2009. They find that consumption insurance in China deteriorated dramatically with a transmission of permanent income shocks to consumption, and that it tripled from 1989 to 2009. Their findings are consistent with our conjecture on the implications of risk sharing based on the changing nature of income shocks we found. In fact, Santaeulalia-Llopis and Zheng (2016) also use CHNS data to decompose permanent and transitory income shocks based on the same methodology employed in Section 7 of our paper. Our findings are consistent with those of Santaeulalia-Llopis and Zheng's: Permanent income shocks increased by more than three times from the early 1990s to the early 2000s then decreased slightly in urban China. However, our paper differs from theirs not only in terms of dataset (CHNS is a Chinese version of the Panel Study of Income Dynamics (PSID) with limited data on consumption), but also in the focus. Again, we aim to provide a systematic view of inequality in urban China, which could be used to reveal cross-sectional facts when studying China's macro economy. By contrast, their goal is to estimate the extent of risk sharing on consumption in China, and to discuss its welfare implications.

3 Background of China's Economic Transformation

In this section, we provide a brief historical background of the Chinese economy over the past three decades, with particular concentration on the economic reforms that took place in urban China.

In 1978, Chinese leader Deng Xiaoping initiated the "Open Door" policy and economic reform after the end of the devastating Cultural Revolution. After the successful household responsibility reform in rural areas, the focus of economic reform shifted to cities in 1984. The state's control of industry was relaxed. POEs were allowed to operate and compete with SOEs, and POEs gradually expanded their market share at the expense of SOEs. However, corruption and rising inflation led to political turmoil in 1989, which halted the market-oriented reform and triggered an economic crisis.

In 1992, during his famous tour to south China, Deng Xiaoping pushed for further radical reform toward a market economy in urban areas. Privatization began to accelerate afterwards. The private sector surpassed the state sector in terms of the share of GDP for the first time in the mid-1990s. The economic troubles ensuing from the inefficiency of money-losing SOEs finally prompted the Chinese government to initiate a large-scale privatization of SOEs in 1997 under the slogan "Grasp the Big, Let Go of the Small" (see Hsieh and Song 2015 for details). Except for large SOEs in strategic sectors (energy, electricity, telecommunications, and banking), the majority of the small- to medium-sized SOEs were either privatized or allowed to go bankrupt. Accompanying the SOE reform, a series of reforms regarding the privatization of social security, education, health care, and housing were enacted. During the time of the large-scale restructuring reform from 1997 to 2002, more than 35 million SOE workers were laid off (He et al. 2017). The landscape of the Chinese urban economy had changed forever.

After the SOE reform, growth accelerated. China's accession to World Trade Organization (WTO) in 2001 further boosted growth. The annual real GDP growth rate exceeded 10 percent on average from 2002 to 2011. The private sector accounted for more than 60 percent of GDP in 2012. China's economy had been transformed into a market-oriented dynamic economy.

4 Data

In this section, we describe the two micro-level household survey datasets used. Our main dataset is the annual UHS. We also use the Chinese Household Income Project (CHIP) to measure wealth inequality.

4.1 Urban Household Survey (UHS)

The UHS is conducted by the National Bureau of Statistics (NBS) of China. The UHS is based on a multi-stage probabilistic sample and stratified design, similar to the design used in the Current Population Surveys (CPS) in the U.S. The UHS provides detailed information about income, consumption expenditure, and the demographic characteristics of household members at the household and individual levels. In that sense, it can be viewed as the Chinese counterpart of a combination of the CPS and Consumer Expenditure Survey (CEX) in the U.S. The UHS has begun to gain attention in the research community.[3]

The NBS draws from a first-stage sample (called the "big sample") of households randomly from selected cities and towns in each province every three years. A final sample (the "small sample") is then randomly selected from the big sample for recurrent interviews and diary-keeping (detailed consumption expenditures per month). From 1986 to 2006, every year one-third of the households in the final sample are replaced by other households from the first-stage sample. Since 2007, each year half of the households in the small sample are replaced.[4] The UHS's design enables the construction of a short panel (two- or three-year period), on the household and individual levels, using this rotation structure. The survey questionnaires have been updated several times since 1986. Two major changes were made in 1992 and 2002, and minor changes were made in 1997 and 2007.

UHS is not publicly available. The portion to which we have access covers the time period from 1986 to 2009. The number of provinces and households covered varies across years. For the period 1986–1992, we have, on average, more than 12,000 households per year from 28 provinces. For 1993–1997, we have data for just under 6,000 households from 10 provinces (Beijing, Shanxi, Liaoning, Jiangsu, Anhui,

[3]Researchers have used the UHS to study the Chinese saving rate (Song and Yang 2010, and Chamon and Prasad 2010), wage structure (Ge and Yang 2014), and income and consumption inequalities (Cai, Chen, and Zhou 2010), among others.

[4]As pointed out by Feng, Hu, and Moffitt (2015), this rotation design has not always been strictly enforced. Probably because of budget constraints, the rotation ratio is always lower than what it was originally designed to be, as we document in Section 7 and Appendix D (Tables 8 and 9).

Table 1: Sample Size of UHS

Year	**# of Obs**	**Provinces**
1986	11660	28
1987	12365	28
1988	12901	28
1989	12374	28
1990	12827	28
1991	12890	28
1992	15835	28
1993	5751	10
1994	5899	10
1995-97	5907	10
1998-01	5450	9
2002	26990h, 109326p	16
2003	30384h, 120845p	16
2004	31832h, 127157p	16
2005	33360h, 132453p	16
2006	33441h, 131690p	16
2007	34462h, 131616p	16
2008	38944h, 154400p	16
2009	37480h, 146205p	16

Hubei, Guangdong, Chongqing, Sichuan, Gansu) per year. For 1998–2001, we have access to the data covering nine provinces (Beijing, Liaoning, Zhejiang, Anhui, Hubei, Guangdong, Sichuan, Shanxi, Gansu) with 5,450 households per year. For the period 2002–2009, UHS reports household and individual data separately.[5] We have access to the data for more than 30,000 households and more than 120,000 individuals per year (except for 2002, for which we have 26,990 households and 109,326 individuals). These data cover 16 provinces (Beijing, Shanxi, Liaoning, Heilongjiang, Shanghai, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Guangdong, Chongqing, Sichuan, Yunnan, Gansu).

Table 1 summarizes the sample size of our access to UHS for different years.

[5] Before 2002, the UHS does not separate household and individual variables into two sets of tables. However, each household member does have an ID that we can use to track individuals across years.

4.2 Chinese Household Income Project Survey (CHIP)

Our second dataset is derived from the Chinese Household Income Project (CHIP) surveys. The surveys are conducted by the Chinese Academy of Social Science (CASS) and the NBS through a series of questionnaire-based interviews, conducted in rural and urban areas in China, during four different years: 1988, 1995, 2002, and 2007.[6] The households in each survey are randomly selected following a strict sampling process so that they are nationally representative. The surveys cover a sample of about 15,000 to 20,000 households in 10 provinces in China. The surveys contain detailed data on the households' economic statuses, employment, levels of education, sources of income, household compositions, household expenditures, and wealth. CHIP data have been widely used in the empirical literature.[7]

4.3 Sample Selection

Following the methodology in Heathcote, Perri, and Violante (2010), we construct three different data samples from the UHS and label them A, B, and C.

In Sample A, we drop records from the dataset only if there is no information on the age of the household head. We will use this sample to compare micro level data from the UHS to macro aggregates and check the consistency with macro data.

Sample B is more restricted than Sample A. First, we keep records only if the household head is between the ages of 25 and 60. Then, we exclude records with negative values in household earnings, disposable income, and consumption in each year. Sample B is the main sample used for our household-level estimation.

Sample C is our individual-level sample. To construct it, we first select all individuals aged 25–60 from Sample B. We then further restrict the sample by only including individuals who report nonnegative earnings.

We deflate every nominal variable by the urban consumer price index (base year = 2000).

We summarize major household characteristics statistics based on Sample A in Table 2. Several important demographic trends are observed here. First, household size has substantially declined over time. The average household size decreased from 3.84 in 1986 to 2.85 in 2009. The strict implementation of the "one-child policy" since the early 1980s may have contributed to that dramatic decline. Second, the share of households headed by males in total households increased from 61.4 percent in 1986 to 70 percent in 2009, possibly because declining female labor force participation.

[6] So far only CHIP 2007 is not publicly available.

[7] See Wei and Zhang (2011) and He et al. (2017).

Table 2: Summary Statistics of Demographic Characteristics in UHS

	1986	**1990**	**1995**	**2000**	**2005**	**2009**
Household size	3.84	3.48	3.19	3.08	2.93	2.85
Male HH head (%)	61.4	67.6	66.6	68.1	70.7	70.0
# of children	N.A.	1.37	1.05	0.95	0.86	0.74
Age of HH head	42.3	44.6	45.6	47.7	48.9	49.4
SOE workers (%)	72.0	70.3	66.3	56.3	43.7	35.7
Above HS (%)	10.1	15.1	21.8	26.1	30.1	32.3
# of obs	11660	12827	5907	5450	33359	37462

Third, as a direct evidence of the one-child policy, the average number of children in one household declined from 1.37 in 1990 to 0.74 in 2009. Fourth, the average age of household heads increased quite significantly, from 42.3 in 1986 to 49.4 in 2009, reflecting the trend of rapid aging in urban China. Fifth, the percentage of household heads working for SOEs decreased by almost 100 percent, from 72.0 percent in 1986 to 35.7 percent in 2009. This reflects the economic transition described in Section 3. Finally, educational attainment has been improved significantly over the past three decades. The share of household heads who had degrees higher than high school diplomas more than tripled, from 10.1 percent in 1986 to 32.3 percent in 2009.[8]

4.4 Consistency with Macro Data

Before we begin to use the UHS to analyze inequalities in urban China, we would like to check whether the micro data from the UHS are consistent with the macro data from the *China Statistical Yearbook* provided by NBS.

Figure 1 reports this consistency check. Panel A shows the log of real disposable income per capita in both UHS and NBS macro data. Before 2001, the two data series were nearly identical. However, starting in 2002, log real disposable income per capita has decreased in the UHS, and has differed from the NBS data since then. This shift is possibly due to the fact that the UHS began including migrated workers (mostly from rural areas) into the sample in 2002, and migrated workers without urban household registration statuses (the so-called *hukou*) typically have significantly lower income and consumption than urban residents. Despite this discrepancy, the trend of real disposable income in the UHS after 2002 was still closely aligned with that of the macro data.

[8]For comparison, the share of households with a college degree or above increased from 7.7 percent in 1995 to 13.6 percent in 2009.

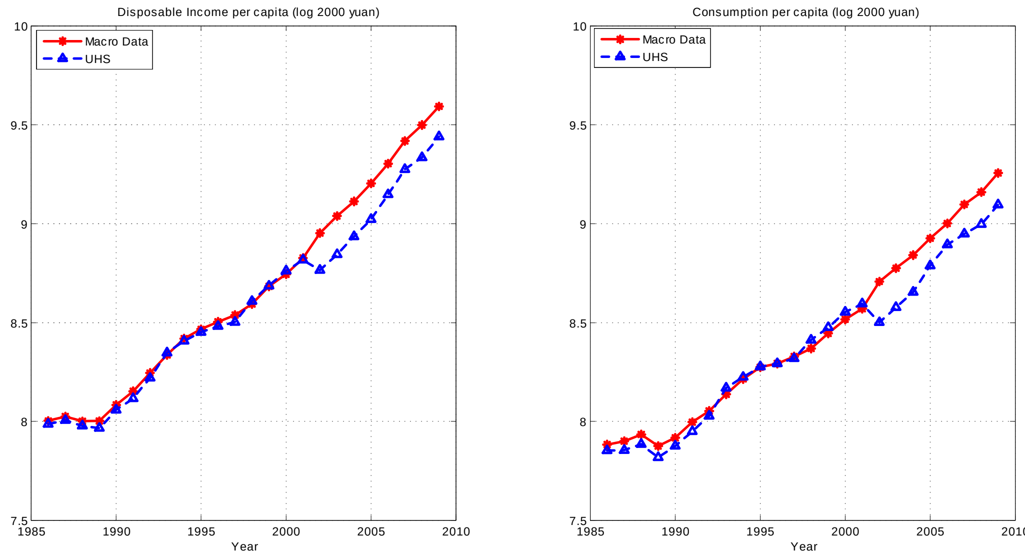

Figure 1: Comparison between UHS and Macro Data

Panel B in Figure 1 compares log of real consumption per capita in the UHS and NBS macro data. It shows a pattern similar to that of disposable income. The two data series aligned remarkably well before 2001. They diverged in 2002 but maintained the same trend afterwards.

The comparison verifies that the UHS is a reliable dataset, broadly consistent with the official macro data reported by the NBS. Therefore, we may confidently proceed with our empirical analysis based on the UHS data.

5 Inequality over Time

In this section, we report the evolutions of earnings, income, consumption, and wealth inequalities in urban China over the past three decades based on UHS and CHIP data. Following the literature, we adopt four measures of inequality throughout the paper: the Gini coefficient, variance of log, P90/50 ratio, and P50/10 ratio.

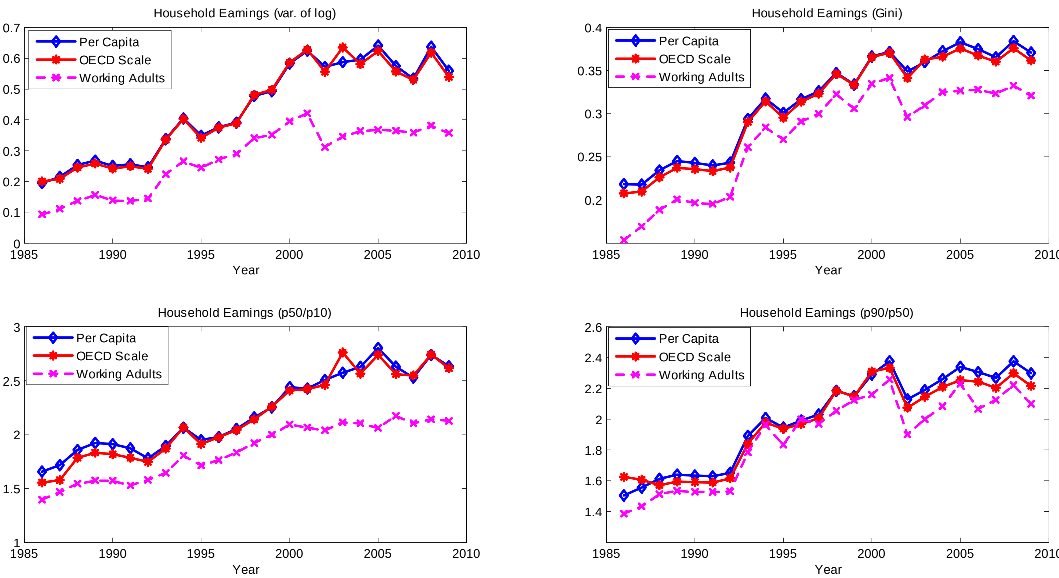

Figure 2: Various Measures of Household Earnings Inequality

5.1 Household-level Inequality

5.1.1 Earnings

We start with household-level inequality based on Sample B.[9] Figure 2 reports the four measures of dispersion of household earnings on per capita bases (lines labeled "Per Capita"). Each of the four measures shows a dramatically increasing pattern. For example, variance of log earnings had roughly tripled, from about 0.2 in 1986 to about 0.55 in 2009. Notice that variance of log household earnings in the top left panel closely resembles the P50/P10 ratio in the bottom left panel. The similarity reflects the sensitivity of the variance of log to the shape of the bottom portion of the earnings distribution. By contrast, the Gini coefficient in the top right panel looks similar to the P90/P50 ratio in bottom right panel. This confirms that the Gini coefficient is sensitive to the upper portion of the earnings distribution (Heathcote, Perri, and Violante, 2010).

Figure 2 shows that all four of the inequality measures of household earnings

[9]Following Cai, Chen, and Zhou (2010), all of the household-level measures are adjusted for household size simply by dividing each variable by household size.

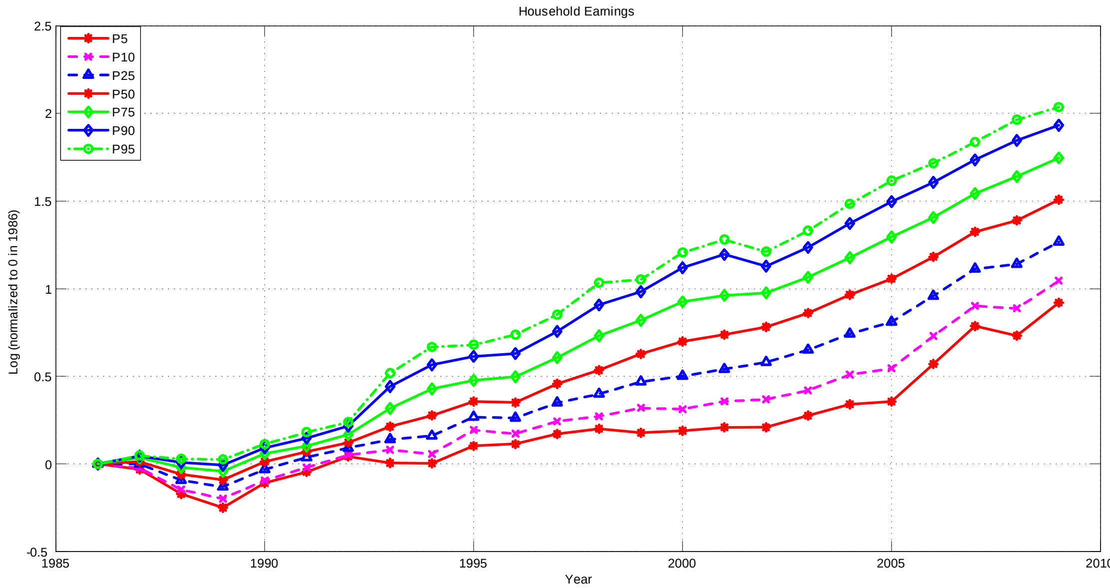

Figure 3: Percentiles of the Household Earnings Distribution

had increased significantly from 1986 to 2009. But is this because the poor are becoming poorer and the rich are becoming richer over time? Figure 3 plots the log level of household earnings by different percentiles over time (all normalized to zero in 1986). Consistent with the message in Figure 2, Figure 3 shows that the gaps between different percentiles of household earnings have been widening over time. However, even in the bottom 5th and 10th percentiles, household earnings increased about 100 log points (or in absolute level, increased about 2.72 times) between 1986 and 2009. This sharp increase in household earnings, even in the bottom income percentiles, reflects the rapid growth of China's economy. Therefore, the answer to the question is that all percentiles of earnings distribution have seen dramatic increases over time. However, the rich have gained much more from the economic growth than the poor.

To further control the possible effect of changing household composition over time, we also adjust household earnings to a per-adult-equivalent basis using the OECD equivalence scale, assigning a weight of 1.0 to the first adult, 0.7 to each additional adult, and 0.5 to each child, following the literature (see RED 2010 special issue). The line labeled "OECD Scale" in Figure 2 shows the four dispersion measures of OECD scale equivalized household earnings. As one can see, it is similar to our benchmark (per capita) measure of household earnings although with a slightly lower magnitude for most years. This is mainly due to the fact that the poor tend to have more children than rich in urban China. Therefore, given the same household size, the OECD scale is smaller for the poor than the rich.

An alternative equivalence scale would be to equivalize earnings by dividing them by number of working adults, since only they contribute to the earnings. The number of children should not affect the income measure. Equivalizing consumption using the OECD scale is reasonable, since the OECD scale is designed to account for economies of scale, which are involved in consumption. UHS does have data on the number of working adults in households. We thus conduct this alternative equivalization on earnings and report the results in the lines labeled "Working Adults" in Figure 2.[10] In so doing, we see that earnings inequality still increases significantly over time. However, the magnitude decreases compared to the other two equivalization methods because Chinese households often have two-earners (Figure 4). The rich and the poor do not see much difference in terms of that ratio. Yet, as pointed out before, the poor on average do have more children than the rich, thereby amplifying the inequality when one uses either household size or the OECD scale to equivalize earnings.

To impart a sense of how the equivalizing is shaping cross-section inequality, we plot some indicators of household composition and an associated inequality measure (variance of log) in Figure 4. The top left panel shows the fraction of two-adult households among all of the households.[11] In the UHS, the fraction is very close to 100 percent. In the top right panel, we plot the variances of log for one-adult household earnings and two-adult household earnings. Within this limited sample, one-adult households show a significantly higher inequalities in earnings than two-adult households, confirming the notion that income pooling among two-adult households reduces inequality.

The middle left panel in Figure 4 shows the fraction of two-earner households among all two-adult households. The ratio had stabilized at around 90 percent until 1995, and then declined drastically to below 70 percent after 2004, possibly due to the massive lay-offs of SOE workers during the period (see He et al. 2017). Declining female labor force participation in urban China also possibly contributed to the decline. The middle right panel shows the variances of log of one-earner versus two-earner households. It is not surprising that risk sharing within two-earner households

[10] We exclude the observations reporting negative or zero number of working adults for the line.

[11] UHS does not have data on marital status until 2002. We therefore use two-adult households to approximate the statistics of married couples.

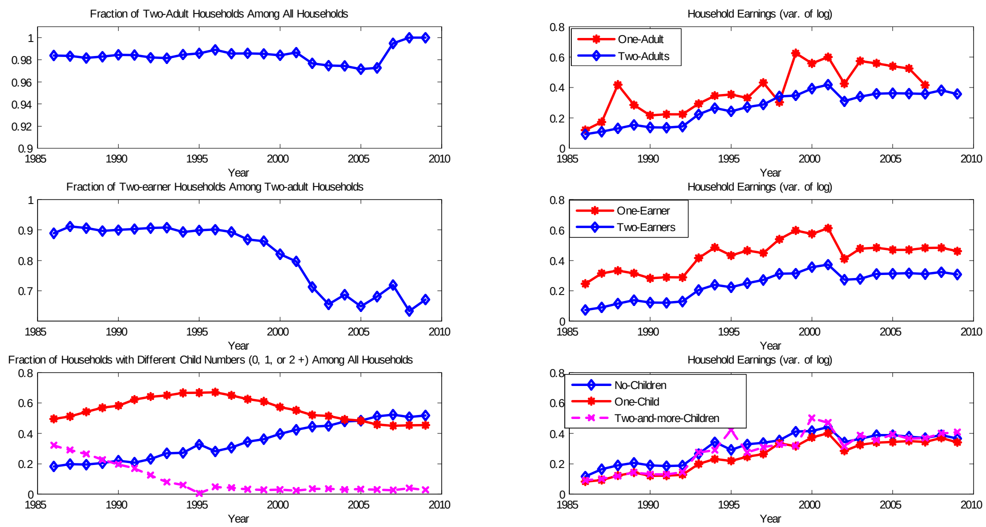

Figure 4: Household Composition and Earnings Inequality

is much stronger than it is for their one-earner counterparts. Therefore, the earning inequality is lower for the former group.

Finally, the bottom left panel plots the fractions of non-children, one-child, and two-or-more children households. Due to the one-child policy, the fraction of one-child families had been steadily increasing since the mid-1980s. Meanwhile, the fraction of two-or-more children families declined to almost zero. However, after the mid-1990s, the fraction of non-children families increased quite astonishingly, possibly reflecting the rapidly rising costs of raising children in urban China (see Choukhmane, Coeurdacier, and Jin, 2016). The trends in variances of log among the three types of household earnings in the bottom right panel, however, are very similar, with the notable exception that the variance of log earnings of two-or-more children households is higher than the other two in several years. Since the variance of log mostly captures the bottom half of income distribution, it is consistent with the fact that poor households tend to have more children and, therefore, more likely the poor is more visible for the two-or-more children group. That increases the dispersion in the group.

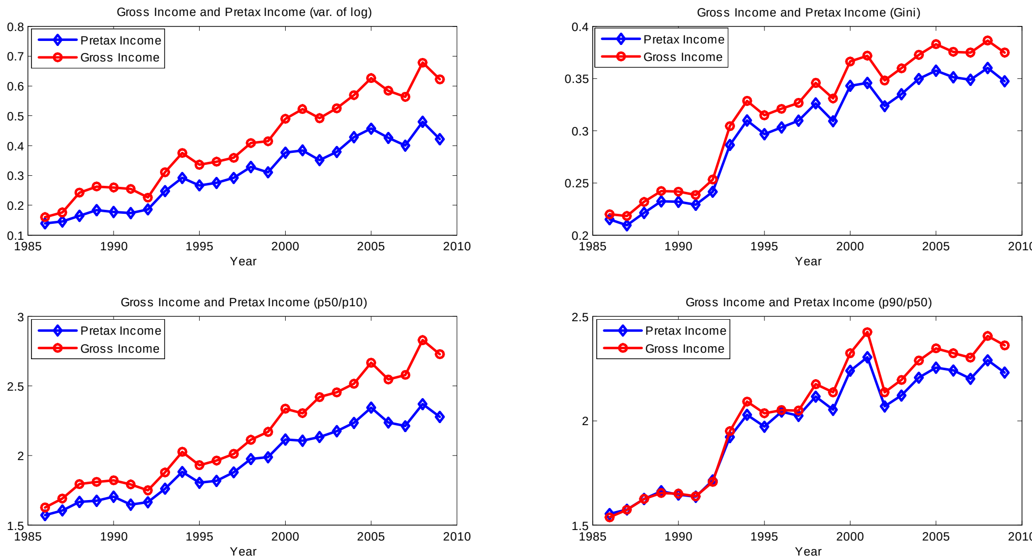

Figure 5: The Role of Government in Income Inequality

5.1.2 Income and Government Redistribution

What did the Chinese government do to reduce rising income inequality? Figures 5–9 answer the question. Figure 5 shows the evolutions of both gross income (household earnings + private transfers + asset income) and pretax income (gross income + public pension benefits + unemployment insurance (UI) benefits + other social security/welfare benefits) inequality at the household level. The difference between gross income and pretax income is public pension benefits and other social security benefits (see Appendix A). The growing gap between gross income inequality and pretax income inequality seems to suggest that government transfers contribute to the reduction of income equality for each year during the period 1986–2009.

To further understand which type of government transfers contributes to the growing gap between gross and pretax income inequality, we decompose different sources of government transfers and examine their impacts on income inequality one by one. Starting with gross income, we first add public pension benefits, then UI. Finally, on top of pension benefits and UI, we add other social welfare such as subsidy of economic hardship, to reach the pretax income. Figure 6 shows the results. It is clear that the public pension contributes the most to reducing income inequality,

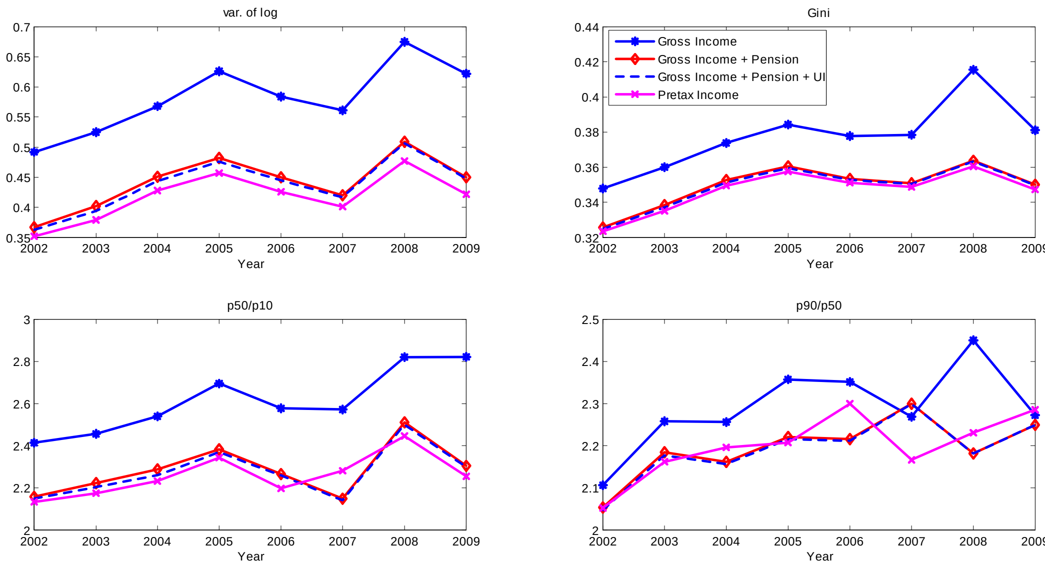

Figure 6: Decomposing the Role of Government in Reducing Income Inequality

especially so for the bottom portion of the income distribution. Social welfare also has some sizable impact on reducing inequality. By contrast, UI contributions are negligible with regard to the growing gap between gross income and pretax income inequalities.

Since retirees receive government transfers mostly via public pension, we also run an additional test to compare the difference between gross and pretax income inequalities using two samples: one includes retirees in the households, and another excludes them. The results for households with retirees are reported in Figure 7. And Figure 8 shows that the gross income inequality and pretax income inequality based on the sample only includes households without retirees. Pretax household income inequality is significantly reduced when retirees are included in household statistics. By contrast, we do not see a significant reduction in pretax household income inequality when a household does not include any retirees. This confirms the notion that public pension does, indeed, contribute the most to the growing gap between household gross income inequality and pretax income inequality.

Figure 9 shows the evolution of pretax income and disposable income inequalities. Disposable income, by definition, is pretax income minus taxes (see Appendix A). Here we see a much smaller difference between inequalities in pretax and disposable

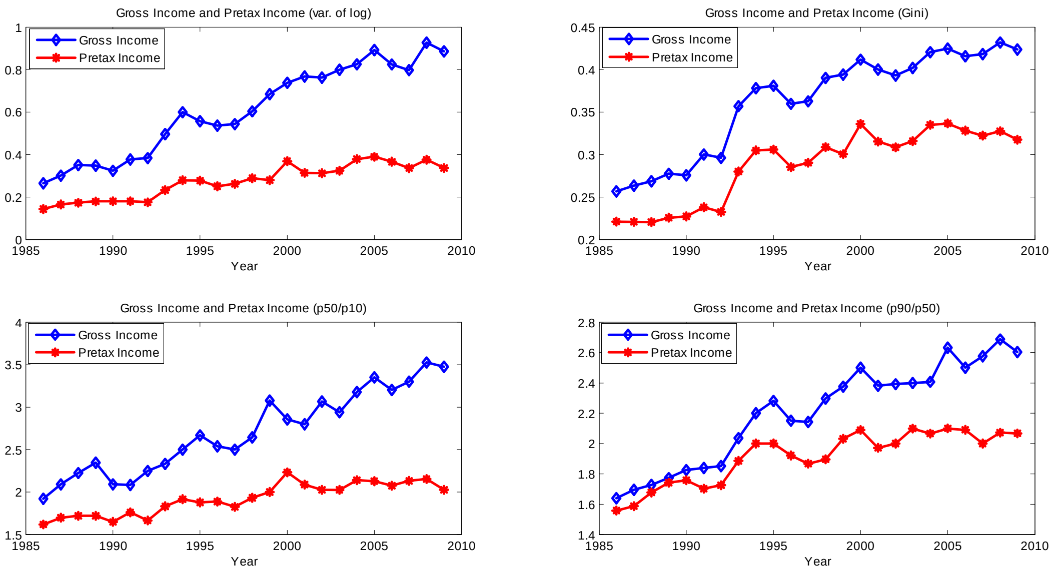

Figure 7: Income Inequality for Households with Retirees

incomes than between inequalities in gross income and pretax income in Figure 5. In fact, the difference was almost negligible before 2000. This pattern differs from the one in countries like Japan. Japan shows a much larger reduction in inequality by taxes than by transfers (see Figure 4.8 in Lise et al. 2014). The reason is that, unlike the case in advanced economies, labor income tax only accounts for a small fraction of Chinese government revenue, and is not quite progressive. Therefore, in China, income tax plays a much less important role in income redistribution than public pensions do.

5.1.3 From Disposable Income to Consumption

For most of the countries documented in the RED special issue, a common feature is that income inequality has been increasing much faster than consumption inequality, and consumption inequality is often significantly lower than income inequality (except in Russia). This pattern reflects the possible improvement in risk sharing resulting from financial development. Consumers thus can smooth consumption relatively easily, which leads to the divergence of income inequality and consumption inequality.

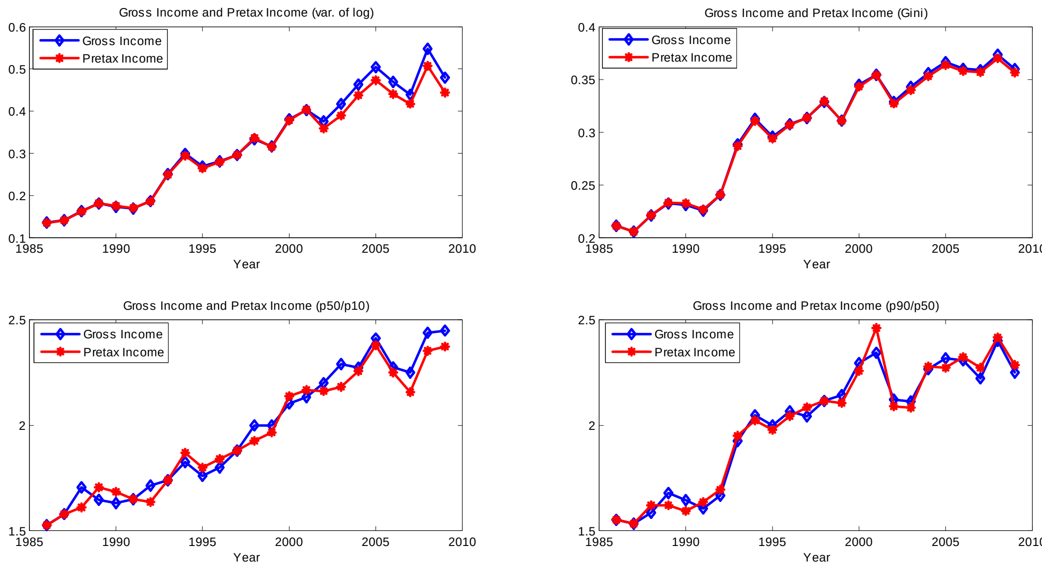

Figure 8: Income Inequality for Households without Retirees

Figure 10 shows the evolutions of household-level disposable income inequality and total consumption inequality for the period 1986–2009. China, however, shows a surprising pattern that contrasts with most countries. The Gini index of total consumption is uniformly higher than that of disposable income throughout the entire period. And the Gini indexes of disposable income and total consumption closely track each other (especially after 1993). Other measures show a somewhat consistent story, although the differences between income inequality and consumption inequality levels became less significant than they are under the Gini measure. In all four measures, however, consumption inequality closely tracks with income inequality.[12]

Because the UHS covers a broad range of consumption variables, we explore the consumption data by dividing it into durable versus nondurable consumption, and plot their respective inequalities in Figure 11. We see that the the Gini index of durable consumption is about two to three times higher than that of nondurable consumption. We then further differentiate nondurable consumption into “necessary nondurable consumption” and “social status nondurable consumption” (see Appendix A for the definitions). We find that the Gini coefficient of social status consump-

[12] Cai, Chen, and Zhou (2010) use the UHS and document a similar pattern of income inequality and consumption inequality for 1992–2003.

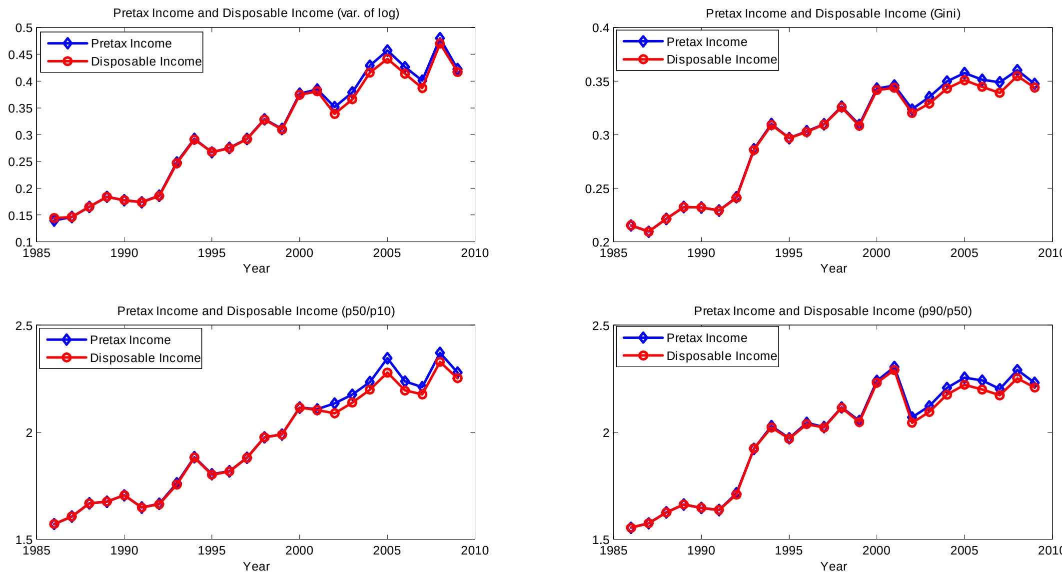

Figure 9: From Pretax to Disposable Income

tion is much higher than nondurable consumption, which, in turn, is slightly higher than necessary nondurable consumption.[13]

Motivated by the findings in Figure 11, we then revisit Figure 10 by replacing total consumption with nondurable consumption. Figure 12 shows the results.

We see that nondurable consumption inequality is very close to income inequality from 1986 to 1992. This might be due to the fact that, under the centrally planned economy, workers had a very generous social safety net (the so-called iron rice bowl). In exchange, workers received low wages and used almost all of their incomes on consumption. After 1992, as the urban economic reform began speeding up, and households had higher wages and hence, increased their saving rate, nondurable consumption inequality began diverging from income inequality. However, a surprising finding is that nondurable consumption inequality still closely tracks with income inequality. This is very different from the pattern in the U.S. as documented in Krueger and Perri (2006), and Heathcote, Perri, and Violante (2010), as well as the pattern in other countries, documented in the RED 2010 special issue.[14]

[13] We suspect that the significant jumps in 1992 and 2002 for variance of log and the P50/10 ratio are due to the changes in the UHS questionnaire for those years.

[14] Probably the only country that has a similar relationship between disposable income inequality

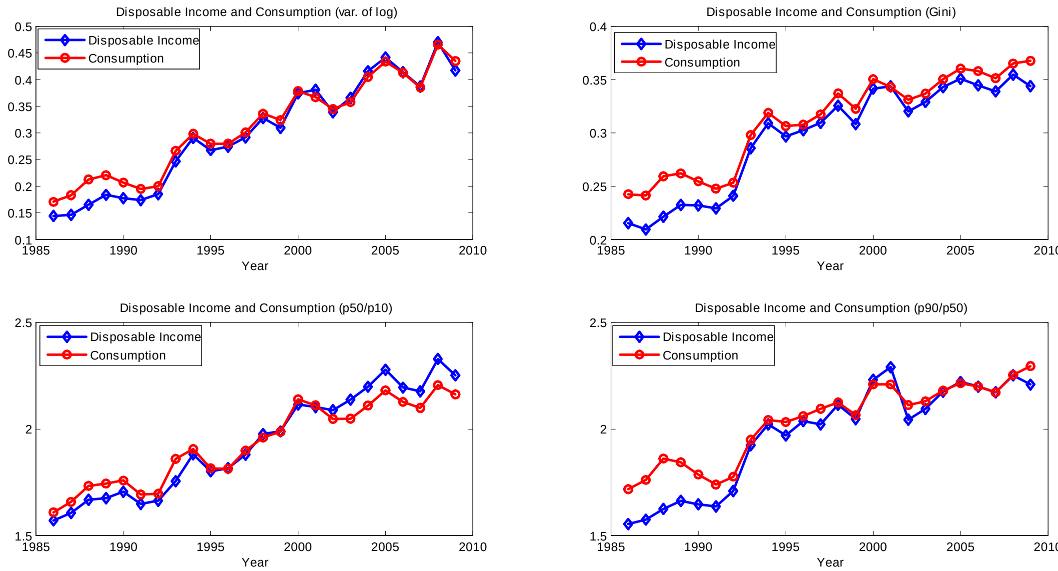

Figure 10: From Disposable Income to Consumption

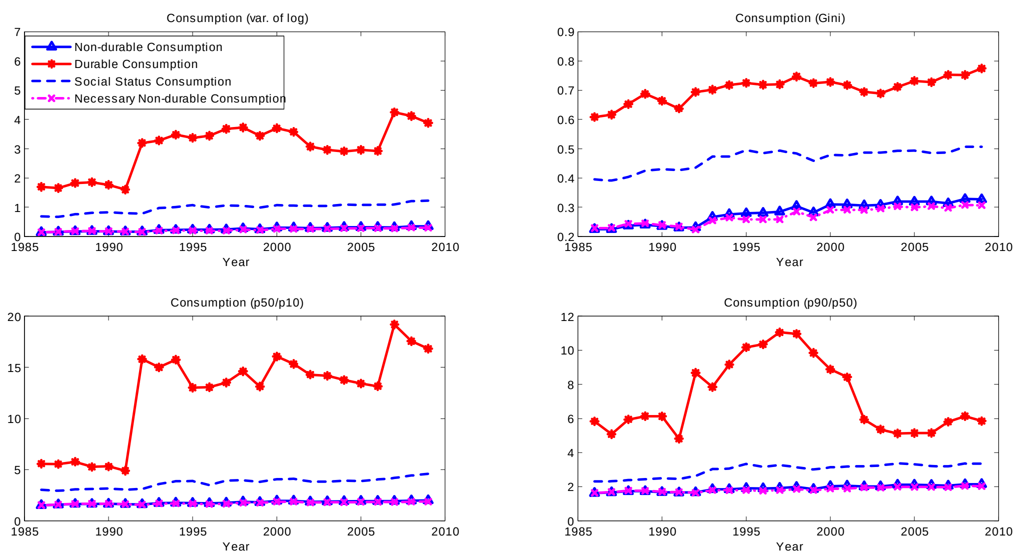

Figure 11: Consumption Inequality by Category

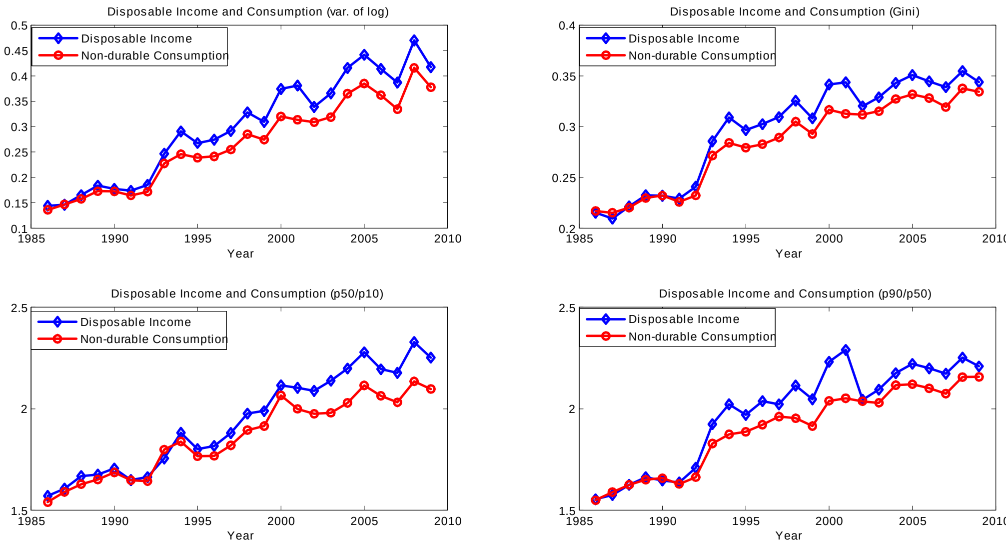

Figure 12: From Disposable Income to Nondurable Consumption

Comparison to Krueger and Perri (2006) The close co-movement between income and consumption inequalities found in Figures 10 and 12 contrasts sharply with the large, increasing gap between income and consumption inequalities in the U.S. data documented in Krueger and Perri (2006). Notice that our definition of income and consumption follows the one in Heathcote, Perri, and Violante (2010) closely, and is slightly different from the one used in Krueger and Perri (2006), especially in dealing with imputing service flow from housing and vehicles. To make the comparison meaningful, we follow exactly the same procedure as Krueger and Perri (2006) for measuring income and consumption. Appendix B describes the details of our procedure.

Figure 13 now can be compared directly to Figure 1 in Krueger and Perri (2006).[15] Compared to Figure 10, following the definition of income and consumption in

and nondurable consumption inequality in China is Japan (see Lise et al. 2014). However, even in Japan, the level of nondurable consumption inequality is substantially lower than income inequality, not as close as in the Chinese data. In fact, the Japanese data actually show negative co-movement between income inequality and consumption inequality since the early 1990s (see Figure 4.9 in Lise et al. 2014).

[15]Same as in Krueger and Perri (2006), the standard errors are computed using a bootstrap procedure with 100 repetitions in Figure 13.

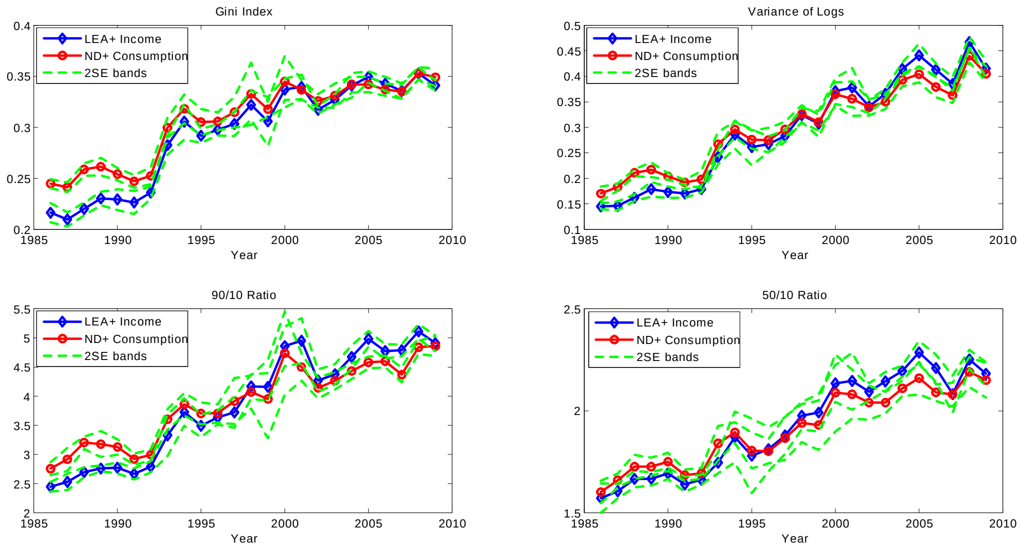

Figure 13: The Evolution of Income and Consumption Inequality: Krueger-Perri Procedure

Krueger and Perri (2006) does not significantly change the pattern of income inequality and consumption inequality observed earlier. From 1986 to 2009, the UHS data show that the variance of log after-tax labor earnings (LEA+ in Krueger and Perri 2006) increased from 0.145 in 1986 to 0.415 in 2009, about 286 percent, while the variance of log consumption (ND+ in Krueger and Perri 2006) increased about 238 percent from 0.17 in 1986 to 0.405 in 2009 (a similar magnitude). In fact, except earlier years, the differences between income and consumption inequalities in Figure 13 are not statistically significant. In sharp contrast, Krueger and Perri (2006) showed that variance of log income increased about 21.4 percent from 1980 to 2003 in the U.S., while the variance of log consumption only increased about 5.3 percent. More importantly, the income inequality and consumption inequality in Figure 13 are highly co-moved, while in Krueger and Perri (2006) the income inequality and consumption inequality in the U.S. are far less synchronized.

We also measure nondurable consumption (ND) following the definition in Krueger and Perri (2006). See Appendix B for details. Using the new definition of ND, variance of log nondurable consumption increased about 263 percent from 0.135 in 1986 to 0.355 in 2009 in urban China. The increase is surprisingly close to those of income and total conumption inequalities. By contrast, Krueger and Perri (2006) reported that the variance of log nondurable consumption only increased about 3.3 percent from 1980 to 2003 in the US.

Correcting the Measurement Error of Consumption Data For household survey data, it is likely that measurement errors exist in both income and consumption data. Recent literature has shown that measurement error in consumption might be larger than that in the income data. Therefore, correcting measurement errors in the consumption data must be completed before seriously considering any results from household survey data (Attanasio and Pistaferri, 2016).

Attanasio, Hurst, and Pistaferri (2012) have developed different methods for overcoming the measurement error problems in the Consumer Expenditure Survey (CEX). Following them, we have executed two experiments to correct the possible measurement errors in the UHS.

First, similar to the food data in the diary survey in the CEX, the food consumption data in the UHS are documented well in the diary component of the UHS in a comprehensive fashion. Therefore, it is believed that the food expenditure data in the UHS is subject to fewer measurement errors. We calculate the variance of log household food expenditure at home on a per capita basis in the UHS for the period 1986–2009. It increased from 0.1529 in 1986 to 0.2683 in 2009. We then follow Aguiar and Bils (2015) to estimate the expenditure elasticity of food consumption at home according to the specification

$$\ln x_{hjt} - \ln \bar{x}_{hjt} = \alpha_{jt} + \beta_j \ln X_{ht} + \Gamma_j Z_h + u_{hjt}$$

where x_{hjt} denotes reported expenditure on good j (here, food at home) at time t by household h, and $\bar{x}_{hjt}$ is the average across households. X_{ht} denotes total expenditure at time t by household h, $X_{ht} = \sum_{j=1}^{J} x_{hjt}$. Z_h is the vector of characteristics of household h, and β_j measures expenditure elasticity of food expenditure at home. The average of this elasticity over the period 1986–2009 is 0.6896 (Aguiar and Bils 2015 found that this elasticity is, on average, 0.37 in the CEX). A simple back-of-the-envelope calculation in the spirit of Aguiar and Bils (2015) and Attanasio, Hurst, and Pistaferri (2012) implies that the variance of log total consumption should increase $(0.2683 - 0.1529)/(0.6896^2) = 0.2428$ from 1986 to 2009. The data in Figure 10 shows that the variance of log total consumption in the UHS increased from 0.1706 in 1986 to 0.4347 in 2009. The increase was 0.2642. Our first method of correcting measurement errors comes surprisingly close to the increase in the consumption inequality using the original UHS data. More importantly, the correlation between the time series of variance of log total consumption corrected the measurement error, and the variance of log household disposable income in Figure 10 is 0.9230, meaning the two series are still highly co-moved.

Second, Attanasio, Hurst, and Pistaferri (2012) developed another method to deal with measurement error problems in the consumption data, namely, to focus on components of consumption for which the measurement issues are less severe and possibly stable over time. The two such measures they focus on are expenditure on entertainment goods and services (excluding durable goods) as a luxury consumption, and food at home as a necessary consumption. Under certain assumptions, Attanasio, Hurst, and Pistaferri (2012) show that the variance of log total "true" consumption for household h at time t could be inferred from the variance of log of the ratio of two goods as follows:

$$Var(\log(C_{ht})) = \frac{Var(\log(q^1_{ht}) - \log(q^2_{ht}))}{(\alpha_1 - \alpha_2)^2}$$

where q^1 is the expenditure on a luxury commodity, and q^2 is the expenditure on a necessary commodity, and α_1 and α_2 denote their elasticities with respect to total expenditure C. We expect that $\alpha_1 > 1$ and $\alpha_2 < 1$.

Using the UHS data, which contain detailed consumption categories, we perform the exercise. As mentioned above, the average elasticity α_2 for food at home for 1986–2009 is 0.6896. The average elasticity α_1 for entertainment goods and service for the same time period is 1.4475. The difference is 0.76.[16] UHS data show that the variance of log of the ratio of nondurable entertainment and food at home was 0.98 in 1986, and increased dramatically to 2.47 in 2009. Translated into the corrected measure of total consumption, this indicates an increase in the variance of log of total consumption at a factor of 2.6, much higher than that of the consumption inequality shown in Figure 10. However, more importantly, the correlation between the time series of variance of log total consumption corrected the measurement error, and the variance of log household disposable income is still high at 0.89.

In summary, despite serious efforts to correct the possible measurement error problems in the UHS consumption data, the tight co-movement between income and consumption inequalities (Figures 10 and 12) persists.

In addition, we have done a series of other robustness checks for this striking co-movement relationship between income inequality and total/nondurable consumption inequality (Figures 10 and 12) along several dimensions (see Appendix C). We used alternative equivalization methods, studied different regions, compared local residents with migrated workers, focused the sample only on the same nine provinces

[16] Aguiar and Bils (2015) use the CEX data to obtain $\alpha_1 = 1.74$ and $\alpha_2 = 0.37$ for the US. The difference is 1.37.

for the whole sample period (1986–2009), and used an alternative dataset (CHIP). No matter which dimension we observe, the co-movement between income inequality and consumption inequality stands.

Decomposing Income and Consumption Inequality Following the methodology in Krueger and Perri (2006), we decompose the inequality (more precisely, variance of log) of disposable income, total consumption, and nondurable consumption into between-group inequality and within-group inequality. Between-group inequality captures the portion of inequality that can be explained by observable household characteristics. Within-group inequality is the residual variance.

For between-group inequality, we follow the estimation specification in Cai, Chen, and Zhou (2010) to run the following regressions for our interested variables: log of disposable income, consumption, and nondurable consumption at the household level y_{it} against observable household characteristics x_{it} including age, age^2, education, occupation, industry, ownership of firms worked, and provincial dummies for each year t:

$$y_{it} = \alpha_t + \beta_t x_{it} + \varepsilon_{it}. \tag{1}$$

The between-group inequality is the cross-section variance of y_{it} multiplied by the R^2 of equation (1). The within-group inequality is the residual variance, i.e., the cross-section variance of y_{it} multiplied by the $(1 - R^2)$.

For presentation purposes, Table 3 shows the estimation of some key household characteristics for three dependent variables: log disposable income, log consumption, and log nondurable consumption in 2009.[17] All three dependent variables are negatively associated with age, and positively associated with education and SOE employment. And all coefficients are significant at 1 percent. To help us visualize these coefficients and understand the sources of the rise in income and consumption inequalities, we plot income and consumption premia along three important dimensions of household characteristics in Figure 14. We define the college premium as the ratio of our interested variables between the education level of "above high school" and "high school and below." The experience premium is the ratio of the interested variables between ages 40–60 and ages 25–39. Finally, the SOE premium is the ratio of the interested variables between SOE and non-SOE workers. Figure 14 shows that the college premia in disposable income, consumption, and nondurable consumption was relatively stable before 1999. They incrased significantly since then. The experience premia in three variables increased before 1995, but have declined quite substantially since then, possibly reflecting the fact that the SOE reform that has

[17]Estimations for other controls are suppressed to save space.

Table 3: Between-Group Inequality in 2009: Estimation

	Dependent Variables		
Regressors	**log(Dis Inc)**	**log(Cons)**	**log(ND Cons)**
age	-0.0526	-0.0279	-0.0264
	(0.0039)	(0.0041)	(0.0039)
age^2	0.0007	0.0004	0.0004
	(0.00004)	(0.00004)	(0.00004)
college	0.3537	0.3340	0.3195
	(0.0080)	(0.0085)	(0.0081)
SOE	0.1522	0.1305	0.1209
	(0.0075)	(0.0079)	(0.0075)
R^2	0.2506	0.1862	0.1897

Source: UHS 2009.
Note: Standard errors are in parentheses.

been taking place since 1995 hurt older workers more than younger workers. Older workers faced a higher probability of being laid off (see Appleton et al., 2002) and, therefore, the accumulated experience premium became obsolete. Finally, the SOE premium was fairly stable before 1999, and has increased since then. This finding is consistent with that of Ge and Yang (2014). A plausible explanation behind the rising SOE premium is that the SOE reform raised the labor productivity and total factor productivity of SOEs, so SOEs were able to pay workers a higher premium (see Ge and Yang, 2014 and Hsieh and Song, 2015).

Figure 15 shows the evolutions of between-group and within-group inequalities of disposable income, consumption, and nondurable consumption. We have several findings. First, between-group inequality is dwarfed by within-group inequality in terms of magnitude. For example, the between-group variance of log for disposable income increased from around 0.04 in 1986 to about 0.12 in 2009, while within-group inequality increased significantly from slightly above 0.1 in 1986 to 0.3 in 2009. Therefore, the increase in income and consumption inequalities is mainly driven by within-group inequality. Second, in terms of inequality level, between-group inequality has the highest variance of disposable income. Next is total consumption. Nondurable consumption is the lowest. However, matters are quite different for within-group inequality. Variance of log total consumption is uniformly higher than that of disposable income, while variance of log nondurable consumption is quite close to that of disposable income, although it is lower than that of income most of the time. Third, in terms of the co-movement between income inequality and consumption inequal-

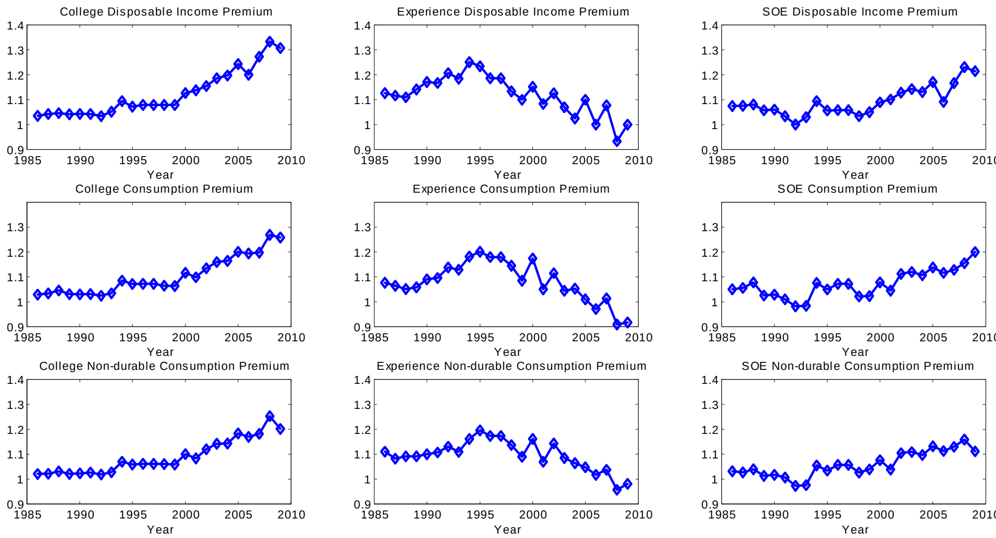

Figure 14: Income and Consumption Premia

ity, both between-group and within-group inequality exhibit strong co-movements, with the co-movement being even stronger in the within-group decomposition. Overall, the decomposition shows that the relationship between income and consumption inequalities is mainly determined by within-group effect, not between-group effect.

The increasing within-group consumption inequality speaks against a complete market model, as emphasized in Krueger and Perri (2006). The close tracking of within-group consumption inequality to within-group income inequality is also a clear sign of severe lack of within-group consumption smoothing. That said, to understand the driving force behind the co-movement of income inequality and consumption inequality, we have to look at residual income, which is not captured by observable household characteristics.

5.1.4 Wealth Inequality

Finally, we would like to illustrate the evolution of wealth inequality in urban China. Unfortunately the UHS does not contain wealth data. We therefore turn to the CHIP data for the analysis. The CHIP only has wealth data in its 1995 and 2002 waves. We use different measures of wealth which are summarized in Appendix A. Panel A in Table 4 shows the composition of the wealth. In 1995, financial

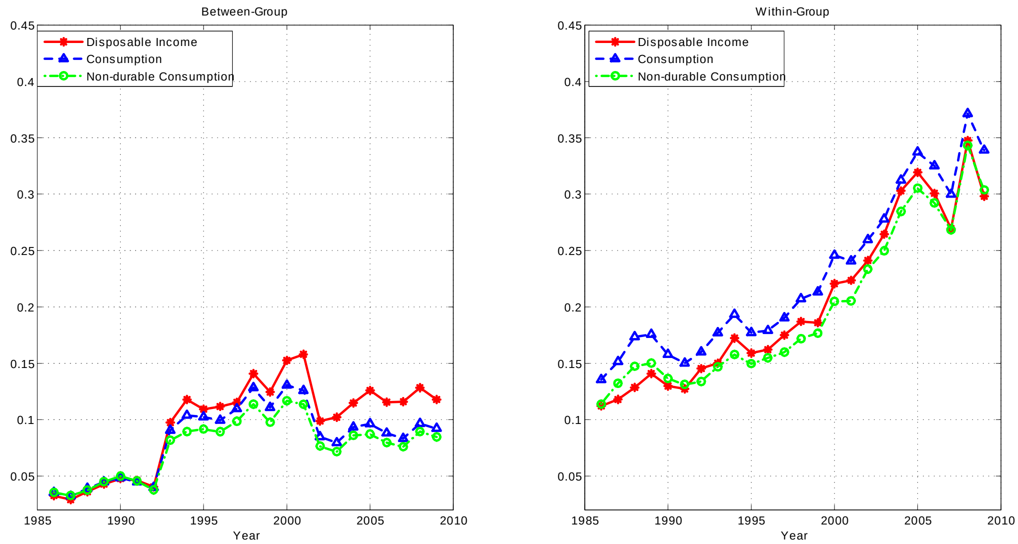

Figure 15: Between-group versus Within-group Inequality

wealth accounted for about 38.2 percent of total wealth in urban China. The ratio decreased to 35.7 percent in 2002. By contrast, housing wealth only accounted for 22.7 percent of households' wealth in 1995. However, it rose drastically to 60.2 percent in 2002. Before the housing reform in the late 1990s, most SOE workers rented houses from the state without paying, or paying only a small amount of rent. This was among the benefits included in the "iron rice bowl." As reflected in the CHIP data, there were quite frequent zeros in the 1995 CHIP statistics on housing wealth. Accompanying the SOE reform, the housing reform aimed to privatize the housing market. SOE workers could pay substantial amounts of money to buy the houses they were currently inhabiting. The housing market has also been developed, and housing transactions were allowed. Positive housing wealth appeared much more frequently in 2002 CHIP and the number of zero housing wealth reduced rapidly. This is probably the reason the housing wealth fraction jumped.

In terms of wealth inequality measures, differing wealth measures offer vastly different pictures of inequality evolution. Financial wealth Gini stabilized between 1995 and 2002. Housing wealth Gini decreased significantly from 0.82 in 1995 to 0.55 in 2002, possibly due to the aforementioned housing reform. Because of the dramatic reduction in housing inequality, total wealth Gini also declined between

Table 4: Wealth Inequality in Urban China

	1995	**2002**
Composition (% of total wealth)		
financial wealth	38.2	35.7
housing wealth	22.7	60.2
others	39.1	4.1
Gini		
financial wealth	0.613	0.617
housing wealth	0.821	0.547
total wealth	0.547	0.490
financial net worth	0.706	0.812
total net worth	0.558	0.508

Source: CHIP 1995, 2002.

1995 to 2002. Finally, excluding housing wealth, financial net worth, which is total financial wealth minus total household debt, increased from 0.71 in 1995 to 0.81 in 2002. However, once we include housing wealth, the Gini of total net worth actually decreased from 0.558 in 1995 to 0.508 in 2002, largely due to the drop in housing wealth inequality.

5.2 Individual-level Inequality

We now turn our attention to individual-level inequality. All empirical results for individual-level inequality are based on Sample C. The only available individual-level variable in the UHS is earnings. Figure 16 shows the evolution of individual earnings as a whole, and also by gender. Individual earnings data in the UHS are only available starting from 1992. As shown in panel B in Figure 16, earnings Gini has been increasing quite significantly from about 0.25 in 1992 to about 0.40 in 2009. The magnitude is about the same as that of the household level, as shown in Figure 2.[18]

[18] Notice that both variance of log and the P50/10 ratio show dramatic drops in 2002 and significant jumps in 2007. The Gini coefficient and P90/50 ratio also show smaller drops in 2002. We suspect that these shifts are due to changes in the sample and questionnaire that occurred during those two years.

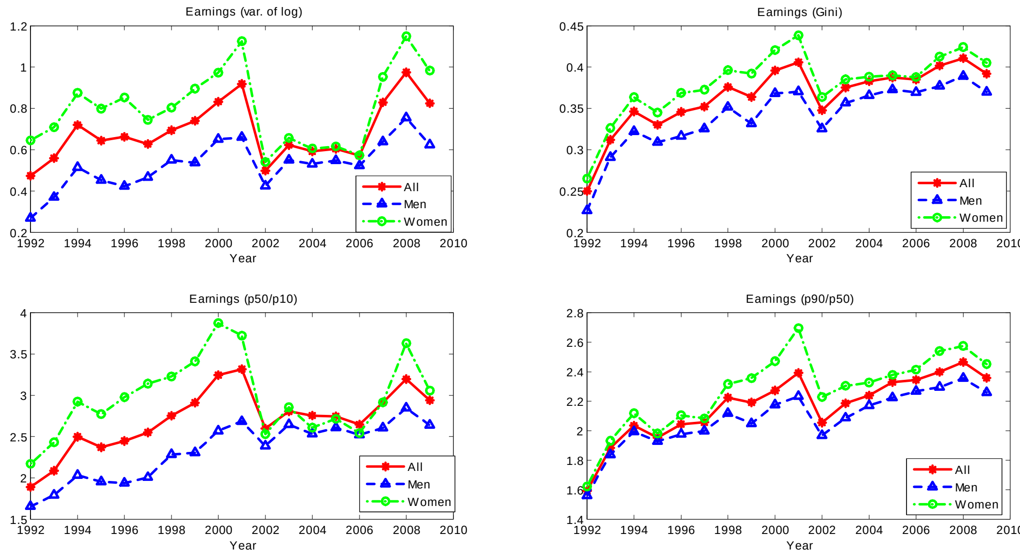

Figure 16: Individual Earnings Inequality

6 Inequality over Life Cycle

The previous section focuses on the evolution of cross-sectional economic inequality over time. We can draw conclusions regarding consumption smoothing across individuals, and also across time from the data pattern we found. How does inequality over the life cycle look like in China? How would the Chinese insure against income shocks over the life cycle? To answer these questions, we use the methodology in Deaton and Paxson (1994) to estimate the age profiles for inequalities in earnings, income, and consumption, based on Sample B in the UHS data.

Following Heathcote, Perri, and Violante (2010), we denote $m_{a,c,t}$ as a cross-sectional moment of interest (e.g., the variance of log per capita income) for the group of household heads, with age a belonging to birth cohort c at year t. We run the following two regressions separately to control for year effects and cohort effects respectively:

$$m_{a,c,t} = \beta_a' D_a + \beta_t' D_t + \varepsilon_{a,c,t} \quad (2)$$
$$m_{a,c,t} = \beta_a' D_a + \beta_c' D_c + v_{a,c,t} \quad (3)$$

where D_a, D_t, and D_c are vectors with entries corresponding to age, year, and cohort dummies, respectively.

Panel A in Figure 17 reports β_a for all ages in equation (2), which controls for year effects.[19] Panel B reports β_a for all ages in equation (3), which controls for cohort effects. The results in Figure 17 are worth discussing. First, we find that in the Chinese data, the magnitude of increases in life cycle inequality is sensitive to the particular effect that is being controlled. For example, the variance of log household earnings increases about two times faster over the entire life cycle under the cohort view than under the year view. This is quite different to the findings in the U.S. data (see Figure 14 in Heathcote, Perri, and Violante 2010) that variance of log household earnings is fiarly close under the cohort view and the year view. The increase of disposable income and nondurable consumption inequalities over the life cycle is also much smaller under the year view. Second, the order of rising inequality over the life cycle is similar to that found in the U.S. data, as we see in Heathcote, Perri, and Violante (2010). The variance of log household earnings rises over the life cycle far more significantly than that of disposable income, which, in turn, rises more than the variance of log nondurable consumption (especially so under the cohort view). However, the main difference between the pattern in Figure 17 and the one shown in the U.S. data (Figure 14 in Heathcote, Perri, and Violante 2010) is that nondurable consumption inequality still closely tracks with income inequality over the life cycle in urban China. In the U.S., on the other hand, consumption inequality and income inequality diverge as an individual ages. In other words, unlike the U.S. data, which show that the consumption inequality profile is concave over the life cycle, the Chinese data show a convex consumption inequality profile, similar to that of income. The co-movement of income inequality and consumption inequality also appears over the life cycle. This indicates that the ability to insure against idiosyncratic income shocks over the life cycle is also quite limited for Chinese households.

As pointed out in Heathcote, Perri, and Violante (2010), if one takes the pure cohort view, cross-sectional inequality can increase only if each successive cohort starts out with a more unequal income. By contrast, under the pure time (year) view, cross-sectional inequality can increase only if each cohort sees faster growth in within-cohort inequality over time. The results in Figure 17 show that there was not much of a general (applied to all cohorts) increase in earnings inequality over time, but rather successive birth cohorts see rapid increases in their within-cohort inequalities. In our opinion, this is a symptom of rapid economic transition. Earlier cohorts still enjoyed the legacy of socialism when they entered the labor market. Most

[19] Following Heathcote, Perri, and Violante (2010), we group observations in five-year age bins. Therefore, the data start at age 27, which is the midpoint of the first five-year age group (25–29). We also normalize the data at zero for the first age group.

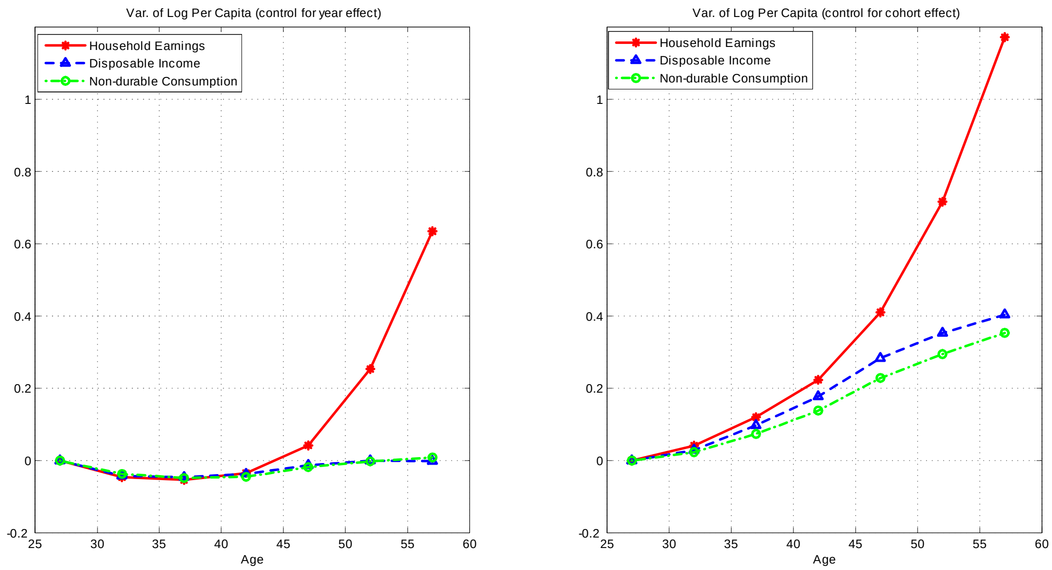

Figure 17: Inequality over the Life Cycle

of them were employed by SOEs with compressed wages and enjoyed job security. The SOE reform that started in the mid-1990s significantly shook job security and the associated benefits of being an SOE worker. Facing much higher uncertainty, and a higher chance of working for POEs, cohorts that entered the labor market after the SOE reform would have to start with much higher within-cohort inequalities than their earlier counterparts.

To check the robustness of the results in Figure 17, we also redo the figure using the OECD scale. Figure 18 shows that the main pattern in Figure 17 remains the same when controlling for the OECD equivalent household scale.

7 Income Dynamics

The most striking fact about inequality in urban China that we have found so far is that *over time*, consumption inequality closely tracks with income inequality. In addition, this co-movement also exists *over the life cycle*.

What could be the reason behind the surprising co-movement between income inequality and consumption inequality in China? One possible explanation could

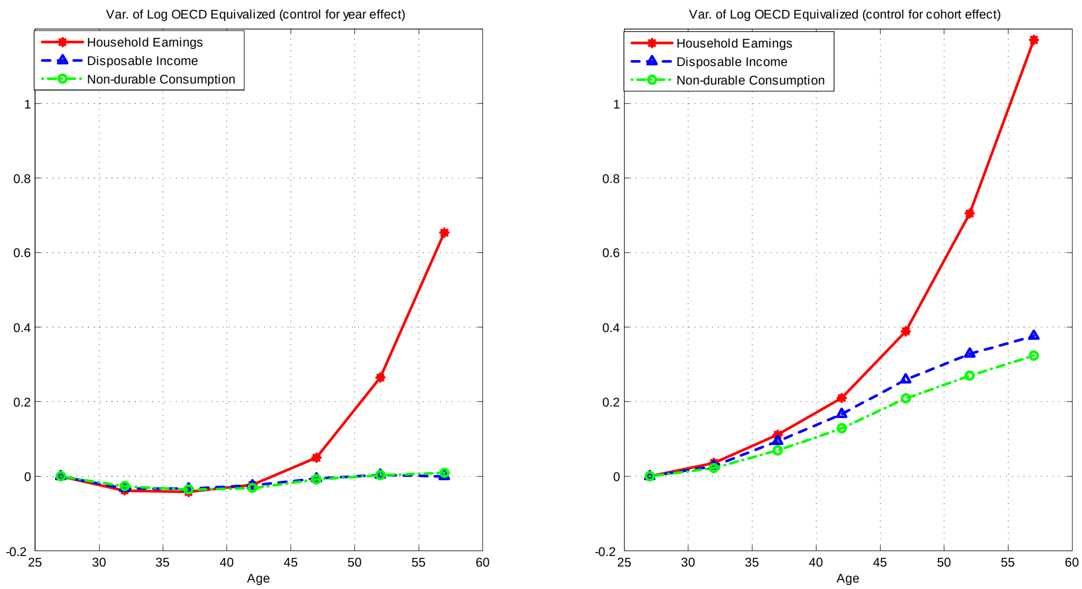

Figure 18: Inequality over the Life Cycle: OECD Equivalent Household Scale

be that it is a sign of the prevailing existence of hand-to-mouth consumers. In other words, a large share of consumers in the population simply consume what they earn. In this case, consumption would be roughly equal to income. Therefore, their variances are also roughly equal.

This theory obviously implies that the saving rate should be close to zero across households. The average household saving rate in the UHS data, however, is close to 20 percent over time. We tend to reject the theory at large. To look further into the story, we plot the changes in the household saving rate over time, by income quintiles, as shown in Figure 19.[20] Except in the lowest income quintile, we see that the household saving rate is significantly positive across all income quintiles. The saving rate increases as the income quintile moves up. More importantly, for all other income quintiles, the saving rates have been increasing over time.[21] Therefore, at most, we can only claim that there is probably some evidence supporting the existence of hand-to-mouth consumers in the lowest income quintile.[22] However, we reject this explanation as the main driving force behind the co-movement of income inequality and consumption inequality among the majority of individuals in the society.

On average, high-income households have higher saving rates. Higher saving rates should allow them to conduct better consumption smoothing, and presumably compresses consumption inequality. However, in Table 5, we delve deeper into each income quintile, revealing the standard deviation of household saving rates over time. For each year, especially after 1995, we see that the dispersion of household saving rates exhibits a "U" shape, with a significantly higher dispersion in the bottom and top quintiles. Over time, except in the bottom quintile (which may involve public transfer in consumption, leading to potentially negative saving rates), in general, each income quintile sees an increase in the dispersion of saving rates. The mes-

[20] Household saving rate = 1 - household consumption/household disposable income.

[21] A related possible explanation for the co-movement is the "target saving rate" hypothesis. In other words, the Chinese might target their saving rates at constant levels. Once they earn their incomes, they first save constant fractions of their incomes, and then use the remaining portions for consumption. In such case, their consumption is a constant fraction (call it α) of income as well. $C = \alpha Y$ then implies $Var(C) = \alpha^2 Var(Y)$. This implies that consumption inequality is lower than income inequality, but both co-move. Figure 19 obviously refutes this theory, as well, because we observe that the saving rates in all income quintiles (except the bottom one) increase significantly over time. Therefore α declines over time, which should make consumption inequality and income inequality less connected over time, a fact that is not reflected in the data.

[22] Unfortunately, the UHS does not have wealth data to help us differentiate between wealthy HtM and poor HtM consumers, as investigated in Kaplan, Violante, and Weidner (2014). However, because we control the income quintiles in Figure 19, our guess is that the HtM consumers in the lowest income quintile are most likely poor ones.

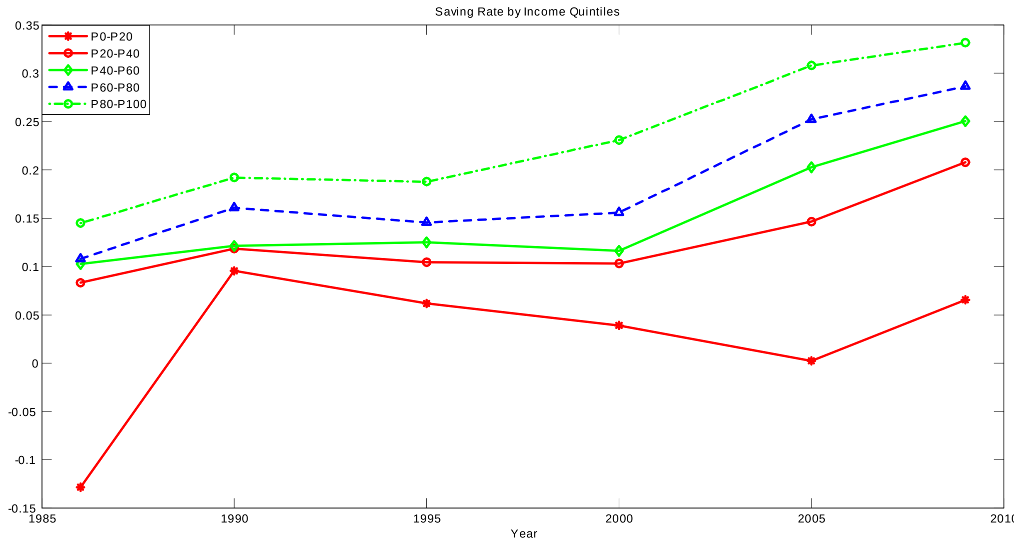

Figure 19: Household Saving Rate by Income Quintiles

sage here is that although, on average, higher-income households have higher saving rates, the dispersion of saving rates within the high-income group is also higher, and is increasing over time. On the first-order aspect, consumption smoothing is improving. However, on the second-order aspect, savings/consumption is becoming more dispersed. Consumption inequality should be determined by both aspects, hence, its evolution is not that straightforward.

Our second explanation lies in the changes in the underlying income shocks structure and its interaction with the changes in the financial market. The literature shows that it is much harder for households to insure against idiosyncratic permanent income shocks than against transitory income shocks (Blundell, Pistaferri, and Preston, 2008). Access to the financial market provides a tool for smoothing consumption. Therefore, a possible explanation for why consumption inequality closely tracks with income inequality is that rising permanent income shocks dominate transitory income shocks over time. Meanwhile, due to the financial system reform, access to the financial market has been improving over time, as well. On one hand, the uninsurable part of idiosyncratic income shocks increases over time, which impedes the ability of households to smooth consumption, leading to a tighter co-movement between income inequality and consumption inequality. On the other hand, in earlier

Table 5: Standard Deviation of Household Saving Rates

Year\Quintile	Bottom 20%	P20-40	P40-60	P60-80	Top 20%
1986	8.202	0.262	0.214	0.232	0.241
1990	0.249	0.249	0.249	0.226	0.229
1995	0.536	0.209	0.214	0.273	0.261
2000	0.358	0.328	0.313	0.314	0.426
2005	2.518	0.338	0.336	0.313	0.384
2009	0.658	0.316	0.36	0.352	0.400

Source: UHS.

years (late 1980s to early 1990s), when the insurable part of idiosyncratic income shocks dominated, the financial market was underdeveloped, and could not provide much consumption smoothing, either. The changing nature of income shocks and its interaction with the changing nature of the financial market lead to very limited consumption smoothing and, consequently to a tight co-movement between income inequality and consumption inequality throughout the entire time period.

To test this theory, we first explore the rotating panel structure of the UHS as described in Section 4.1, to construct short panels of data at the household level. Appendix D provides the details of the construction. We then use the constructed data to estimate a permanent-transitory earnings dynamic model.

7.1 Model

We estimate a simple statistical model following Heathcote, Perri, and Violante (2010). First, we run a Mincerian regression to regress log earnings from the data against household characteristics, such as age, age^2, education, employment status, and provincial dummies. We run this regression year by year. Let $w_{i,c,t}$ be the residual earnings for individual i of cohort c at year t from the regressions. We then estimate a permanent-transitory wage dynamic model as follows:

$$\begin{aligned} w_{i,c,t} &= z_{i,c,t} + \varepsilon_{i,c,t} \\ z_{i,c,t} &= z_{i,c,t-1} + \eta_{i,c,t} \end{aligned}$$

where $z_{i,c,t}$ is the permanent component of income process and $\varepsilon_{i,c,t}$ is the transitory income shocks. $\eta_{i,c,t}$ is the innovation to the permanent income process. We assume that $\varepsilon_{i,c,t}$ and $\eta_{i,c,t}$ are uncorrelated over time and independent and identically distributed across individuals, with zero mean and variances $\sigma_{\varepsilon,t}$ and $\sigma_{\eta,t}$. By assumption, these variances are time-varying, but not cohort-dependent.

We follow the literature for estimating two specifications of the model. One uses moments based on income *growth rate*: these are the first-differences in log earnings. The other uses moments in the log earnings *level*. Appendix E provides a detailed description of the estimation strategy for the two methods. We refer readers to Heathcote, Perri, and Violante (2010) for more details about these methods.

7.2 Findings

We plot the estimated variances of permanent and transitory income shocks (that is, $\sigma_{\eta,t}$ and $\sigma_{\varepsilon,t}$) based on both methods in Figure 20. As we explain in Appendix D, we focus on the time period from 1992 to 2007 because of our data limitations.[23,24,25]

There are some similarities and some dissimilarities in income shocks between China and advanced economies, like the U.S. Similar to the U.S., the variance of transitory shocks is higher (for most of the time period) than that of permanent shocks under the level method, while it is exactly opposite under the difference method. We also find that estimates based on the level method differ significantly from those based on the difference method, which is a common problem for the countries examined in the RED special issue, as emphasized in Heathcote, Perri, and Violante (2010).

We also notice that, as is the case with the U.S. data, the level-based estimates of variance of permanent income shocks are negative in some years. However, in contrast to the U.S. data, permanent income shocks estimated using the level method is far more volatile. The difference method gives us a much less volatile estimation than the level method (see Figure 20). In addition, the difference method of estimating the income process is commonly used in labor economics research (see, for example, Blundell, Pistaferri, and Preston 2008). We therefore decide to focus on the difference

[23] To test the robustness of our results in Figure 20 on the sample selection, we also rerun the estimation for two methods using the panels that relax age restriction. See Appendix D for the construction of this relaxed age restriction sample and the associated results. We find that our results are largely robust to relaxing age restriction.

[24] Because we cannot have a three-year panel for 2001–2003, due to the major changes made to the questionnaires in 2002, any term that involves $\triangle w_{i,c,2002}$ and $\triangle w_{i,c,2003}$ in estimation equations (4) and (5) becomes unavailable. Therefore we cannot estimate $\sigma_{\eta,t}$ for the years 2001, 2002, and 2003 and we cannot estimate $\sigma_{\varepsilon,t}$ for years 2001 and 2002 using the difference method. Similarly, because we do not have the three-year panel for the 1991–1993 period because of the changes made to the questionnaires in 1992, we are unable to estimate $\sigma_{\eta,t}$ for 1993 and we cannot estimate $\sigma_{\varepsilon,t}$ for 1992 using the difference method. We refer our readers to Appendix D for more details.

[25] Because we cannot have a two-year panel for 2001–2002, any term involving $cov(w_{i,c,2002},w_{i,c,2003})$ in estimation equations (6) and (7) becomes unavailable. Therefore, we cannot estimate $\sigma_{\eta,t}$ for 2001 and 2002, and we cannot estimate $\sigma_{\varepsilon,t}$ for 2001 using the level method.

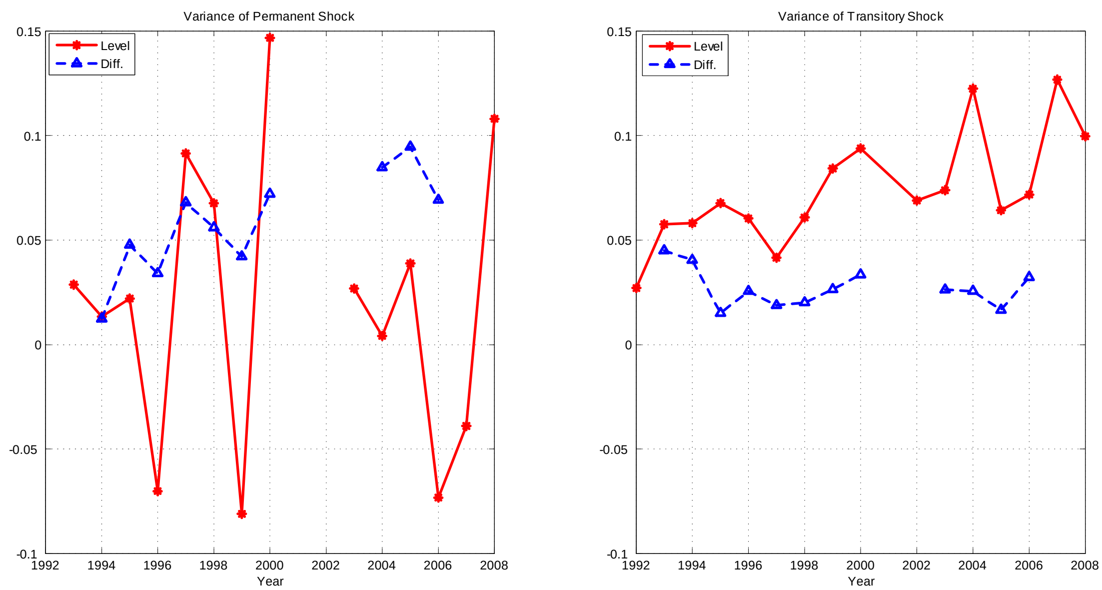

Figure 20: Transitory versus Permanent Income Shocks

method for the analysis of the income process in China.

By looking at the results of the difference method, we notice that the biggest difference in income shocks between China and the U.S. (also Japan) is that we observe a dramatic increase in the variance of permanent income shocks. As shown in panel A in Figure 20, the difference method tells us that σ_η has increased from 0.012 in 1994 to 0.095 in 2005; that is, by almost eight times. We have never seen an increase of this size in σ_η in any advanced economy covered by the RED special issue and Japan (see Figure 6.1 in Lise et al. 2014). Although permanent income shocks show a dramatic increase after the early 1990s in China, transitory income shocks do not show any secular change (although we did note that there is a slight declining trend). Owing to the drastic increase in the permanent income shocks, the composition of the income process has been fundamentally changed. In 1994, transitory income variance was 0.04, about three times larger than permanent income variance. However, by 2005, transitory income variance was only 0.017, five-and-a-half times smaller than permanent income variance.

As shown in Panel A in Table 6, for the period 1994-2006, the average variance of permanent income shocks is 0.058. By contrast, the average variance of transitory income shocks is 0.026. This pattern is in sharp contrast to the magnitude of average permanent and transitory income shocks in the U.S. (Figure 18 in Heathcote, Perri, and Violante 2010) and Japan (Figure 6.1 in Lise et al. 2014). In both U.S. and Japan, transitory income shocks on average are much larger than permanent income shocks. Whether permanent or transitory income shocks dominate of course has an important implication on the relationship between income and consumption inequalities, which we are going to explore in the next subsection.

7.3 Blaming Transition?

Taking into account the fact that that individuals can only partially insure against permanent income shocks, and almost fully insure against transitory income shocks (Blundell, Pistaferri, and Preston, 2008), the underlying change in the composition of the income shocks implies that it is becoming more difficult to share risk across individuals over time, which might lead to a synchronization between consumption inequality and income inequality. We believe that this could be a plausible explanation for the observed co-movement of income and consumption inequalities.[26]

[26] Santaeulalia-Llopis and Zheng (2016) apply the Blundell, Pistaferri, and Preston (2008) methodology to the CHNS data, and estimate the partial insurance coefficient of the permanent income shocks. They find that consumption insurance in urban China did deteriorate dramatically from 1989 to 2009.

But what caused such a dramatic increase in permanent income variance? As shown in Section 3, a vast effort to push the economy toward market orientation has been taking place since the mid-1990s. A large number of SOEs have been either privatized or simply shut down. As employment shifted towards POEs, workers faced tremendous, systematic uncertainty. In addition, during the economic transition, disadvantaged groups, such as less educated and relatively older workers, faced higher chances of being laid off and, thus, were hurt more severely by the transition (Appleton et al., 2002). Therefore, a natural question would be to what extent rising inequality and permanent income variance have to do with the economic transition. Figure 14 shows the premia of income and consumption across the different groups affected by the transition. Here, we would like to dig deeper to further decompose income inequality along those dimensions.

Figure 21 shows the decomposition. First, the variance of log disposable income among SOE workers is significantly lower than that of POE workers over time. The gap between them widened after the late 1990s. Second, except for a few years, on average, workers with above high school education attainment face lower income inequality than those with education levels of high school or below. Again, the gap has widened since the late 1990s. Finally, the relatively older group (ages 40–60), on average, faces higher income inequality than the younger group (ages 25–39), without a clear trend in terms of the gap.[27]

We then perform the between-group and within-group inequality (variance of log) decomposition, as in Section 5.1.3, along these three dimensions. Figure 22 reports the results. Consistent with what we observed earlier on for income inequality in Figure 15, an increase in within-group inequality captures the majority of the increase in disposable income inequality across different groups. We see a divergence of rising within-group income inequality between SOE vs. POE workers, and between high-skilled and low-skilled workers after the late 1990s.[28]

Motivated by the findings in Figure 22, to understand the driving force behind rising income inequality, and determine whether the economic transition played a role in it, we turn our attention to residual income. We thus redo the decomposition exercise of income shocks in Section 7.1 along the three dimensions, using the difference method. Table 6 shows the results and compares the mean of variance

[27] T-tests are conducted to test the statistic significance of the difference between average income inequalities of two opposite groups along each dimension. For SOEs vs. POEs, it is 1% significant. While the differences along the other two dimensions are not significant.

[28] T-tests are conducted to test the statistic significance of the difference between average between-group and within-group income inequalities of two opposite groups along each dimension. For SOEs vs. POEs, it is 5% significant for both between-group and within-group inequalities. While the differences along the other two dimensions are not significant.

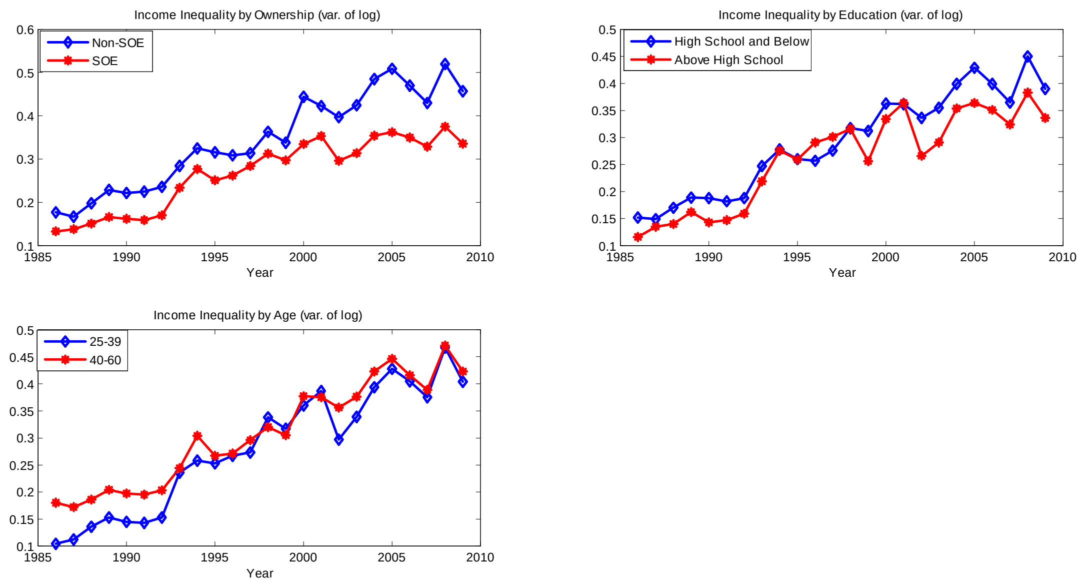

Figure 21: Income Inequality by Sector, Education, and Age

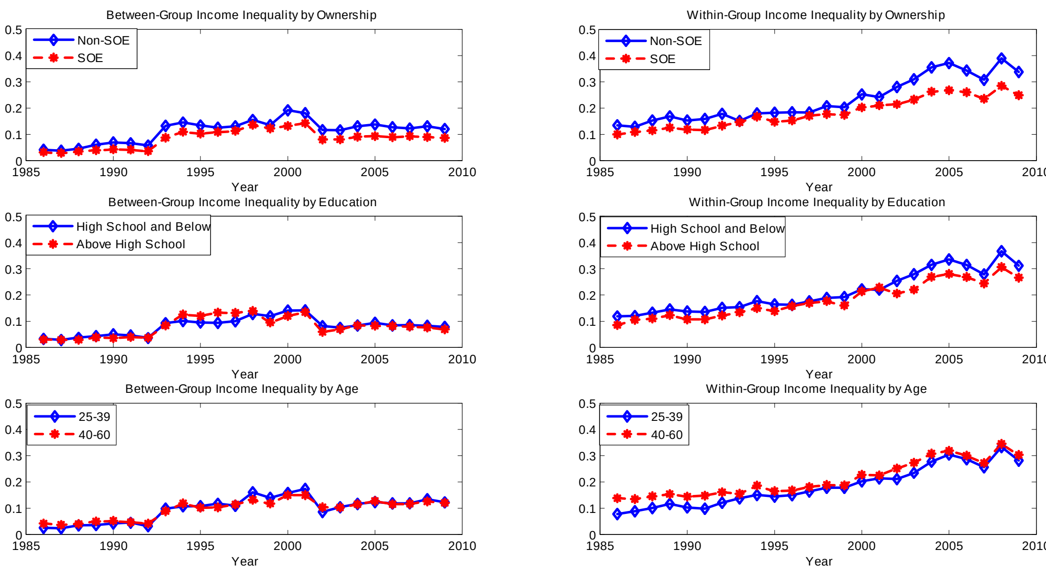

Figure 22: Between-group versus Within-group Inequality by Sector, Education, and Age

Table 6: Economic Transition and Income Shocks

	Perm. Income shocks			**Trans. Income shocks**		
	93-06	**Pre 97**	**Post 97**	**93-06**	**Pre 97**	**Post 97**
	Whole Sample					
	0.058 (0.005)	0.031 (0.007)	0.070 (0.006)	0.026 (0.003)	0.027 (0.007)	0.025 (0.003)
	Sector					
SOE	0.042 (0.005)	0.015 (0.011)	0.053 (0.006)	0.015 (0.003)	0.025 (0.006)	0.010 (0.002)
Non-SOE	0.073 (0.023)	0.047 (0.066)	0.084 (0.018)	0.067 (0.015)	0.089 (0.038)	0.055 (0.012)
	Education					
Above HS	0.046 (0.010)	0.021 (0.022)	0.057 (0.011)	0.011 (0.004)	0.009 (0.010)	0.012 (0.004)
HS or below	0.061 (0.007))	0.030 (0.016)	0.075 (0.008)	0.031 (0.004)	0.037 (0.009)	0.027 (0.005)
	Age					
25-39	0.052 (0.008)	0.021 (0.015)	0.065 (0.009)	0.020 (0.004)	0.027 (0.009)	0.017 (0.003)
40-60	0.057 (0.008)	0.038 (0.017)	0.066 (0.008)	0.032 (0.004)	0.026 (0.009)	0.035 (0.005)

Source: UHS 1992-2007.

Note: All variables are the means for the period. Pre-1997 does not include 1997. Post-1997 includes 1997. Standard errors are computed using a bootstrap procedure with 100 repetitions and displayed in parentheses.

of permanent and transitory income shocks, before and after 1997 (starting of the massive SOE reform), along the three dimensions.

Several key messages are conveyed in Table 6. First, the vulnerable groups hurt by the economic transition face higher permanent and transitory income shocks (more significant for POE workers and unskilled laborers, less significant for older workers). Second, all groups face dramatic increases in permanent income shocks after 1997. Relatively speaking, SOE workers and unskilled laborers face significantly higher increases in their permanent income shocks after the SOE reform, reflecting the impact of the massive lay-off resulting from the reform. Finally, all groups face declining transitory income shocks after 1997 (except older workers at ages 40–60). Overall, the table tells us that the uninsurable part of income shocks has been dominant since the SOE reform.

In summary, the decomposition not only offers a robust check for the main message in Figure 20, but also further identifies the groups who bear higher income risks during the economic transformation. The estimation shows that non-SOE, less-educated, and older workers, on average, bear higher income risks and have higher income inequality. They, in particular, face increasing permanent income shocks over time and are being hurt most during the economic transition in urban China. The decomposition exercise thus helps us to establish a link between the economic transition and changing income inequality.

Linking all findings together provides a big picture to help us understand the cause of rising income inequality in urban China. Suggestive evidence shows that the economic transformation might be an important driver of that fundamental change in the underlying income shocks structure, namely, a dramatic increase in permanent income shocks, which leads to rising income inequality. In that sense, we believe the co-movement of income inequality and consumption inequality in China could be a tale of transition. The transition in urban China created tremendous uncertainty, and led to a significant increase in uninsurable income shocks, which could contribute to the rising consumption inequality resulting from the lack of insurance against permanent income shocks, as emphasized in Blundell, Pistaferri, and Preston (2008). Testing how quantitatively important this potential channel is in explaining the pattern observed in Figure 10 goes beyond the scope of the current paper. It is, however, the next step in our research agenda.

8 Conclusion

This paper provides a comprehensive empirical study of earnings, income, and consumption inequalities in urban China from 1986 to 2009, using the micro-level data from the UHS. We document a drastic increase in economic inequality for the sample period. For example, the variance of log household disposable income in China increased from about 0.14 in 1986 to about 0.43 in 2009, that is, threefold, over 24 years. We also uncover a striking fact: consumption inequality closely tracks with income inequality over time, which seems to oppose the standard consumption smoothing theory. Following the literature, we estimate inequalities over the life cycle and find that the co-movement between income and consumption inequalities also exists over the life cycle. This unique fact has not been found in the study of other countries (see, for example, RED 2010 special issue).

Why does consumption inequality closely track with income inequality over time in urban China? One possible explanation is that individuals are just hand-to-mouth consumers, that is, they merely consume their income. Looking at the changes in the household saving rates by income quintiles over time, we only find vague supporting evidence in the lowest income quintile. Therefore, we largely tend to reject this hypothesis. Another possible explanation is that, on one hand, there is a fundamental change in the income shocks structure, which makes it more difficult for individuals to insure against income shocks. On the other hand, during earlier years, when the insurable part of idiosyncratic income shocks (i.e., transitory shocks) dominated, the financial market was underdeveloped and could not provide much consumption smoothing. Together, the changing nature of income shocks and its interaction with the changing nature of the financial market lead to very limited consumption smoothing and, therefore, to a tight co-movement between income and consumption inequalities throughout the entire period.

To test this theory, we estimate the income process in China and find that there is a dramatic increase in permanent income shocks after the mid-1990s. The increasing uninsurable permanent income shocks dominate the insurable transitory income shocks as time goes by. We make further efforts to investigate the causes of the substantial increase in permanent income shocks. We find that in general the vulnerable groups that were more severely affected by the urban economic transition faced higher within-group inequality and more volatile permanent income variance. Therefore, we link the economic transition to the changing income shocks structure. We believe that this changing income shocks structure, and the effects of the economic transition, could be the main driving forces behind the seemingly puzzling co-movement between income and consumption inequalities.

The lesson we learn from our investigation of economic inequality in urban China is that economic transition and structural transformation could tremendously change the underlying structure of idiosyncratic income shocks and severely limit consumption smoothing among individuals. The rising economic inequality could be the price paid for economic transition.

9 Appendix

9.1 A. Variable Definition

1. Household (HH) earnings: regular earnings, temporary earnings and bonuses of HH head, spouse, and other HH members.

2. Gross income: HH earnings + private transfers + asset income.

3. Pretax income: gross income + public pension benefits + UI benefits + other social security/welfare benefits.

4. Disposable income: pretax income - taxes.

5. Consumption: food, clothing, HH appliances, health, transportation and communications, education and entertainment, housing rent and utilities, etc.[29]

6. Durable consumption: durable goods for HH appliances, transportation tools, communication tools, and durable goods for entertainment.

7. Nondurable consumption = consumption - durable consumption - housing rent.

8. Social status nondurable consumption = food away from home, education, entertainment, and miscellaneous expense and service (jewelry and gold, watch, cosmetics and associated services such as cosmetology, hairdressing, lodging, etc)

9. Necessary nondurable consumption = nondurable consumption - social status nondurable consumption.

10. Financial wealth = balances in checking accounts, saving accounts, stocks, bonds, contributions to employer funds, and loans to others.

11. Total wealth = financial wealth + housing wealth + other wealth (estimated market value of durable goods, fixed assets, and other assets).

12. Financial net worth = financial wealth - debt.

13. Total net worth = total wealth - debt.

9.2 B. Krueger-Perri Procedure

In order to compare our results for income and consumption inequalities in Figure 10 to the ones shown in Figure 1 in Krueger and Perri (2006), we follow exactly the same procedure found in Krueger and Perri (2006) for measuring income and consumption as a robustness check.

Krueger and Perri (2006) define income as after-tax labor earnings plus transfers (LEA+ income). This is equivalent to disposable income - asset income in our definition (see Appendix A).

[29] For housing rent, if the home is an owner-occupied house, we take the "imputed" rent variable from the UHS. If the house is rented, we take the actual rent.

The measure of consumption (ND+) in Krueger and Perri (2006) aims to capture the flow of consumption services. For nondurable consumption and small semidurable goods, consumption expenditure is a good approximation for that flow. However, dealing with service flow from large durable goods, such as cars and housing, is less trivial. We therefore follow their procedure precisely in order to impute service flows from cars and housing.

9.2.1 Service Flows from Vehicles

From 2002 to 2009, UHS reports expenditures for purchases of new and used vehicles for each household. The UHS also reports the number of cars owned by the household in that year. Following Krueger and Perri (2006), for each year, we first select all observations that report positive expenditures for vehicle purchases. Then we run a regression of these expenditures on quadratics in income and total non-vehicle consumption expenditures, expenditure on gasoline, expenditures on public transportation, vehicle maintenance, the number of cars owned, and a complete set of household head characteristics (including age, education, region of residence, and household size).These regressions have an R^2 ranging from 22 percent to 65 percent in our sample period (2002–2009), which is much lower than the ones reported in Krueger and Perri (2006). We think the reason for a much lower R^2 is that car ownership was much lower in urban China for the sample period than that it is in the U.S. Krueger and Perri (2006) report that a little more than 10 percent of households report positive expenditures on vehicles in every year in CEX. The average number for 2002–2009 in the UHS is only 0.65 percent, ranging from 0.15 percent in 2002 to 1.48 percent in 2009. Therefore the data sample in the UHS is much more limited.

Next, we use the estimated regression coefficients to predict expenditures for all of the households (who own or do not own vehicles) in that year. Our measure of consumption services from vehicles, then, is the predicted expenditures on vehicles, times the number of cars that the household owns, times 1/8 (reflecting the assumption of average complete depreciation of a vehicle after eight years).

The UHS does not report the number of cars owned by households during 1986–2001. It is safe to assume that during those years, households rarely owned cars. We therefore do not measure consumption service flows from vehicles for 1986–2001.

9.2.2 Services Flows from Primary Residence

The UHS provides information on whether a household rents or owns its primary residence. If the household rents, we measure housing services as the actual rent paid. For an owner-occupied house, we impute the rent. For the period 2002–2009, the UHS contains the variable of self-reported rents by households that own their primary residences. This variable is not available for the years 1986–2001. We therefore use the self-reported rents to approximate service flows for owner-occupied housing for 2002–2009. For 1986-2001, we follow Krueger and Perri (2006) to use an imputation procedure similar to the one for vehicles in order to impute rents for owner-occupied housing.

For 1986–2001, for each year, we regress reported market rents for households who rent on a complete set of housing condition variables (house square meters, number of rooms, water/sewer, sanitary equipment, heating, housing ownership, etc.), quadratics in income and total nonhousing consumption expenditures, and a complete set of household characteristics (including age, education, region of residence, and household size).[30] These regressions have an R^2 ranging from 7.3 percent to 38.9 percent in the sample years 1986–2001. We then use estimated regression coefficients to predict the rental values of owned properties for all of the homeowners in that year.

9.2.3 Nondurable Consumption

We also measure nondurable consumption (ND) following the definition in Krueger and Perri (2006). The main difference between the nondurable consumption in our text (see Appendix A) and the definition of Krueger and Perri (2006), is that we further deduct entertainment and other vehicle expenses.

9.3 C. Robustness Check for the Co-movement between Income and Consumption Inequalities

We have done a series of robustness checks for this striking co-movement relationship between income and total/nondurable consumption inequalities.

First, we redo Figures 10 and 12 using the OECD scale to equivalize household disposable income and consumption (total and nondurable) for the period 1986–2009. Figure 23 shows the results. We still observe a strong co-movement between income and total/nondurable consumption inequalities. The most striking fact is robust to controlling for household composition.

Second, we also use the alternative equivalized scale for income to divide disposable income by the number of working adults, while keeping the OECD scale for total/nondurable consumption (see Section 5.1.1). Figure 24 reports the results.

[30] Krueger and Perri (2006) use self-reported property values in the regressions. The UHS does not have such data. Instead the UHS has detailed information about housing conditions. We thus choose to include the housing condition variables in the regressions.

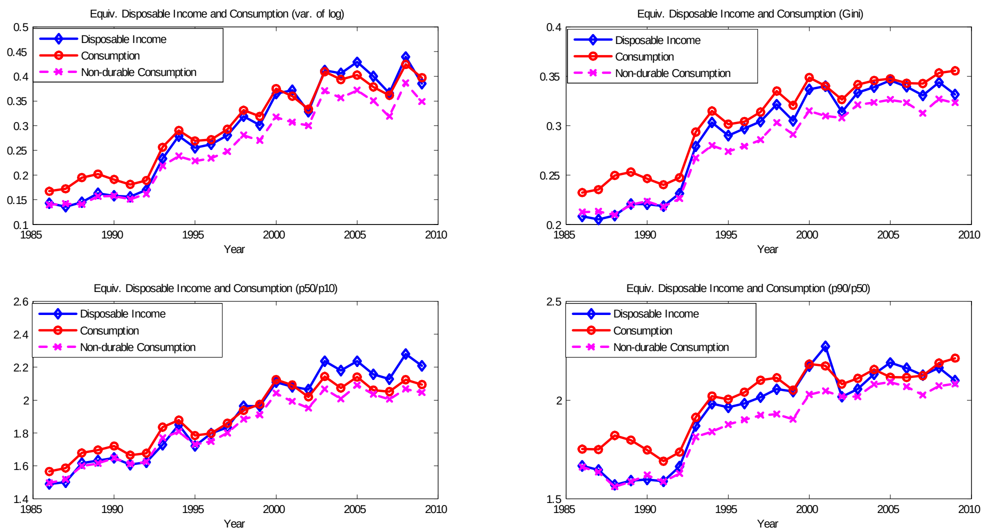

Figure 23: From Disposable Income to Nondurable Consumption: OECD Equivalized Scale

Despite a now lower disposable income inequality, the strong co-movement between income and consumption inequalities is still evident.

Third, we check the evolution of disposable income and total/nondurable consumption inequalities in different regions of China (Figure 25), and for different residence statuses (*hukou* versus migrated workers, see Figure 26).[31] The relationship between income and consumption inequalities remains largely unchanged for all of these checks.

Fourth, to check that the relationship between income and consumption inequalities is not driven by the changes in the number of provinces over time, due to our limited access to the UHS data, we redo Figures 10 and 12 using the data for the nine provinces for which we do have data access (1986–2009).[32] The results are shown in Figure 27. Again, we see that the results are largely similar to those in Figures 10 and 12.

Finally, we check the relationship between income and total consumption inequal-

[31] In the UHS hukou information is available only for the years 2002–2009. Migrated workers are severely undersampled in the survey.

[32] The nine provinces are Beijing, Liaoning, Zhejiang, Anhui, Hubei, Guangdong, Sichuan, Shanxi, and Gansu.

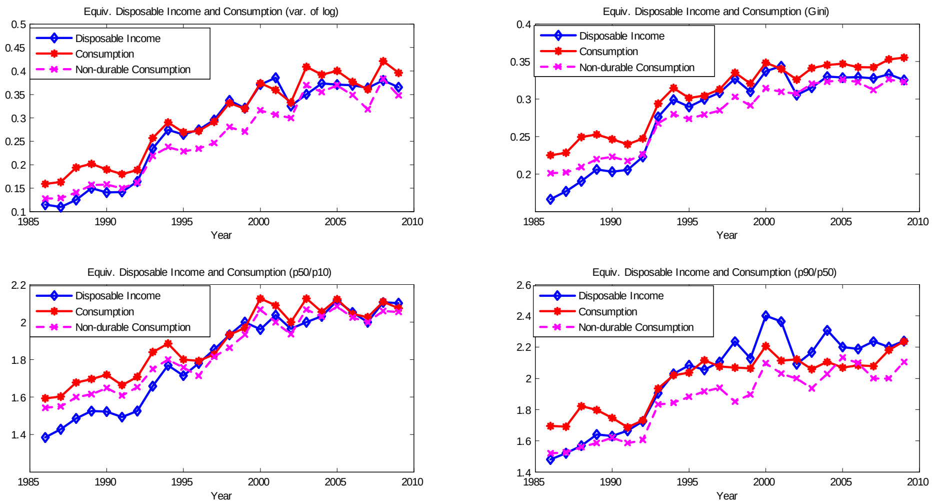

Figure 24: From Disposable Income to Nondurable Consumption: the Alternative Equivalized Scale

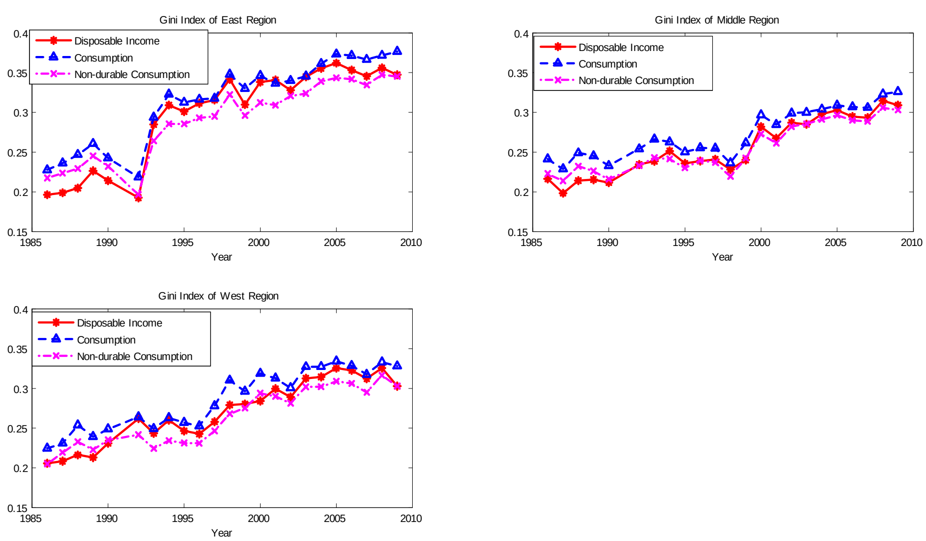

Figure 25: Income and Consumption Inequality by Region

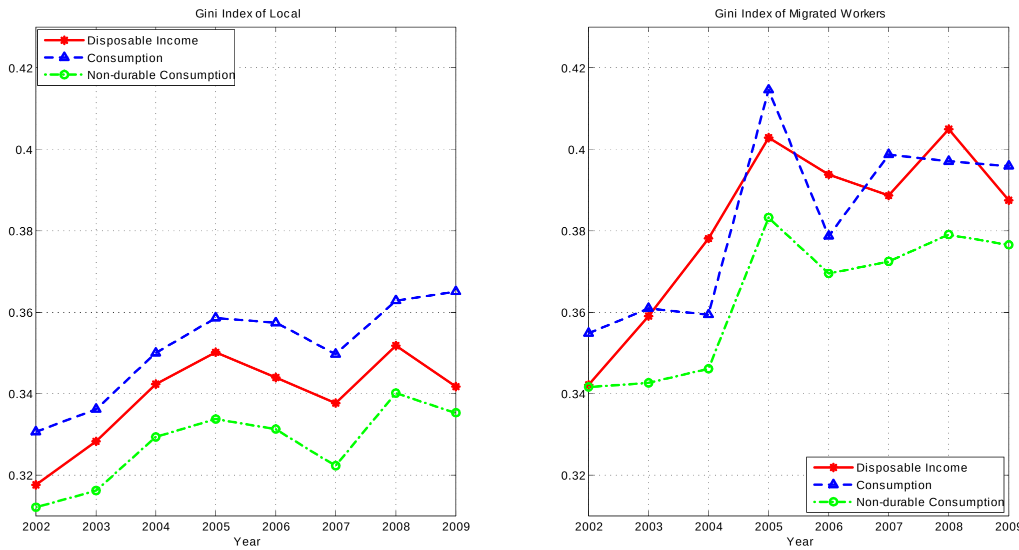

Figure 26: Income and Consumption Inequality: Hukou vs. Migrated Workers

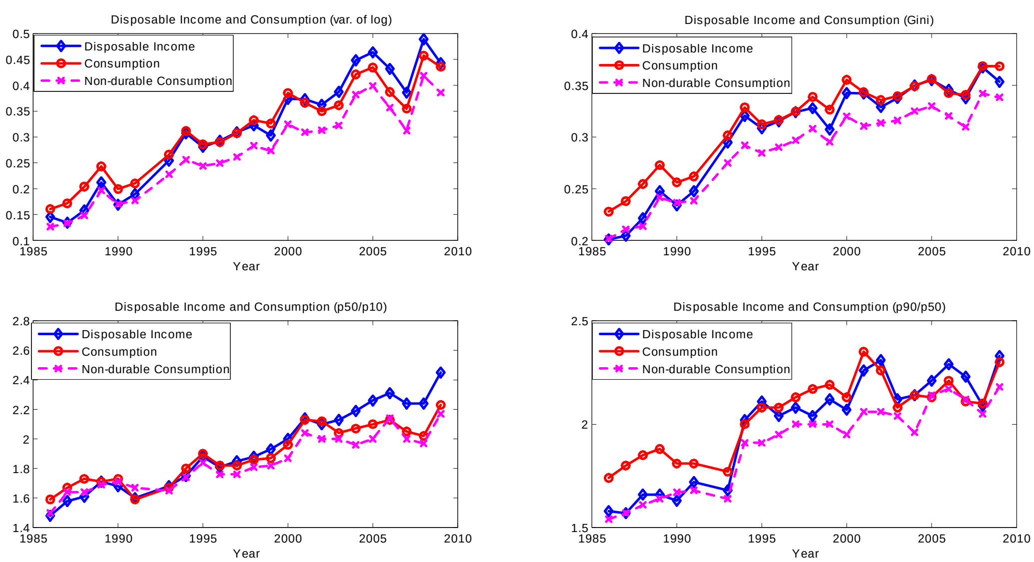

Figure 27: Income and Consumption Inequality: Nine Provinces for 1986–2009

Table 7: Inequality Measures in CHIP

Variables	**Disposable Income**				**Consumption**			
Year\Measure	Var Log	Gini	P90/50	P50/10	Var Log	Gini	P90/50	P50/10
1995	0.207	0.256	1.818	1.692	0.301	0.312	2.067	1.875
2002	0.341	0.318	2.070	2.122	0.348	0.329	2.114	2.064
2007	0.394	0.340	2.167	2.283	0.400	0.363	2.145	2.109

Source: CHIP 1995, 2002, 2007.

ities using the CHIP dataset.[33] Following the measures in Figure 10, we compute the four measures of household disposable income and consumption inequalities, and present the results in Table 7. The pattern in Table 7 is similar to the one shown in Figure 10. The variance of log and Gini coefficient of consumption are higher than that of disposable income for all survey years, while the gap is narrowing over time. The P90/P50 and P50/P10 ratios show similar patterns to those in Figure 10, as well. The strong co-movement between income and consumption inequalities is still evident even when using a different household survey.

9.4 D. Panel Construction from the UHS

The trackable household IDs provide the basis for constructing short panels from the UHS data. We merge the UHS every two years and keep the household IDs which show up in both years in the combined data. We then check the household head's age in the combined data to see whether it increases once the year increases. For example, we merge the 1986 and 1987 UHS into a combined dataset. We only keep those households whose IDs appear in both 1986 and 1987. We then check to confirm that, for example, if a household head's age is 25 in 1986, his age has increased to 26 in 1987. We eliminate observations that do not satisfy this criterion. After the age check, we also go to the remaining sample to check each observation visually to see if its variables make sense (for example, making sure that a househead's gender does not change over the sample).

For the UHS data before 2007, we have a three-year rotation structure. Therefore, we can further merge those two-year combined data into the three-year short panel that we use for the difference method when estimating income process. For example, we merge 1986–87 data with 1987–88 data to form a 1986–1988 three-year panel.

[33] Due to the lack of data availability, we cannot differentiate nondurable consumption from total consumption in the CHIP. In addition, 1988 CHIP does not cover all consumption categories, and it is subject to severe missing data issues. We therefore do not report the results for 1988.

Again, we only retain those households in the data whose IDs show up in all three years. We also check the ages of household heads to make sure they are consistent across three years. For the UHS data after 2007, we only have a two-year rotation panel structure. Therefore, we do not further merge data into the three-year panel.

The second column in Table 8 shows the sample size of the three-year panel constructed through the procedure above, which we use for the difference method.[34] The second column in Table 9 shows the sample size of the two-year panel constructed for the estimation using the level method.

To ensure that the panel data sample we constructed is nationally representative, and also consistent with the original data, we report the sample means of the key characteristic variables of the constructed three-year panel, as well as sample A, in Table 10.[35] As we can see, the sample means of variables are broadly consistent with the sample means of the original UHS data.

To mitigate possible measurement errors caused by the age restriction, and to increase the sample size of the constructed panels, we relax the age restriction by allowing ages for the next year to fall into the ± 1 range. For example, a household head aged 25 in 1986 is now assigned the age of either 25 or 26, or 27 in 1987 for the relaxed age restriction panels. As shown in the third columns of Tables 8 and 9, the sample size of each short panel significantly increases.

Using the panels with the relaxed age restrictions, we rerun the estimation for both the difference and level method. We report the estimations of $\sigma_{\eta,t}$ and $\sigma_{\varepsilon,t}$ in Figure 28. As one can see, the results are largely similar to the ones in Figure 20.

9.5 E. Methodology of Income Dynamics Estimation

Following Heathcote, Perri, and Violante (2010), we estimate the variances of the permanent and transitory income shocks ($\sigma_{\eta,t}$ and $\sigma_{\varepsilon,t}$) using either the difference or level methods.

For the difference method, we need a panel with a range of at least three years.

[34] The household ID is misidentified in 1991. Therefore, we cannot construct a three-year panel for 1989–1991, 1990–1992, or 1991–1993. There is a change in the household ID definition after 2001. Therefore, we cannot match household ID in a three-year panel for the periods 2000–2002 and 2001–2003. The sample size of the constructed three-year panel is strictly limited before 1992. For example, the periods 1986–1988 and 1987–1989 only have 33 observations in each panel. Therefore, for the analysis, we restrict our three-year panel to the years 1992–2007.

[35] The UHS categorizes education attainment on a scale of 1–9, where 1 means no schooling, 3 corresponds with an elementary school educational level, 5 corresponds with a high school educational level, 8 refers to the college graduate level, and 9 refers to the postgraduate level.

Table 8: Panel Construction from UHS: Three-Year Panel for Difference Method

Year	**# of HHs**	**# of HHs relaxed age rest.**
1992 – 94	140	387
1993 – 95	263	526
1994 – 96	162	1176
1995 – 97	152	437
1996 – 98	137	346
1997 – 99	506	841
1998 – 2000	293	515
1999 – 2001	401	657
2002 – 2004	8636	8975
2003 – 2005	3780	4030
2004 – 2006	4120	4374
2005 – 2007	1187	2355

Table 9: Panel Construction from UHS: Two-year Panel for Level Method

Year	**# of HHs**	**# of HHs relaxed age rest.**
1992 – 93	1109	1631
1993 – 94	684	1174
1994 – 95	1289	1912
1995 – 96	1648	2418
1996 – 97	475	891
1997 – 98	1118	1478
1998 – 99	1731	2218
1999 – 00	791	1095
2000 – 01	2098	2434
2002 – 03	12133	12397
2003 – 04	15939	16150
2004 – 05	7629	7940
2005 – 06	17011	17252
2006 – 07	1382	2736

Table 10: Sample Mean of Constructed Three-Year Panel and Original UHS: Comparison

Year\Var	Age		% Male		% Married		Education		% SOE worker		HH Size	
	Panel	UHS	Panel	UHS	Panel	UHS	Panel	UHS	Panel	UHS	Panel	UHS
1993 − 95	46.6	45.6	67.7	68.0			3.7	3.9	73.5	66.1	3.2	3.2
1994 − 96	46.7	45.8	67.2	66.6			3.9	3.9	61.3	65.8	3.2	3.2
1995 − 97	45.3	46.0	69.3	66.2			3.9	3.9	68.3	65.8	3.1	3.2
1996 − 98	43.8	46.3	64.1	65.1			3.9	3.9	74.3	64.7	3.1	3.2
1997 − 99	45.5	46.5	62.0	64.1			3.9	3.8	63.5	63.1	3.1	3.1
1998 − 00	46.9	47.0	62.6	64.6			3.9	3.8	64.0	60.0	3.2	3.1
1999 − 01	47.7	47.4	69.0	66.3			3.8	3.8	59.1	57.4	3.1	3.1
2002 − 04	48.2	48.5	70.9	70.5	95.1	94.2	5.4	5.3	54.1	50.1	3.0	2.9
2003 − 05	48.4	48.7	67.6	70.7	94.9	93.8	5.4	5.4	52.3	47.1	3.0	2.9
2004 − 06	49.5	49.0	63.3	70.5	94.0	93.6	5.4	5.4	47.3	45.2	2.9	2.9
2005 − 07	47.1	49.1	74.4	70.2	94.6	93.5	5.5	5.5	43.5	43.6	3.0	2.9

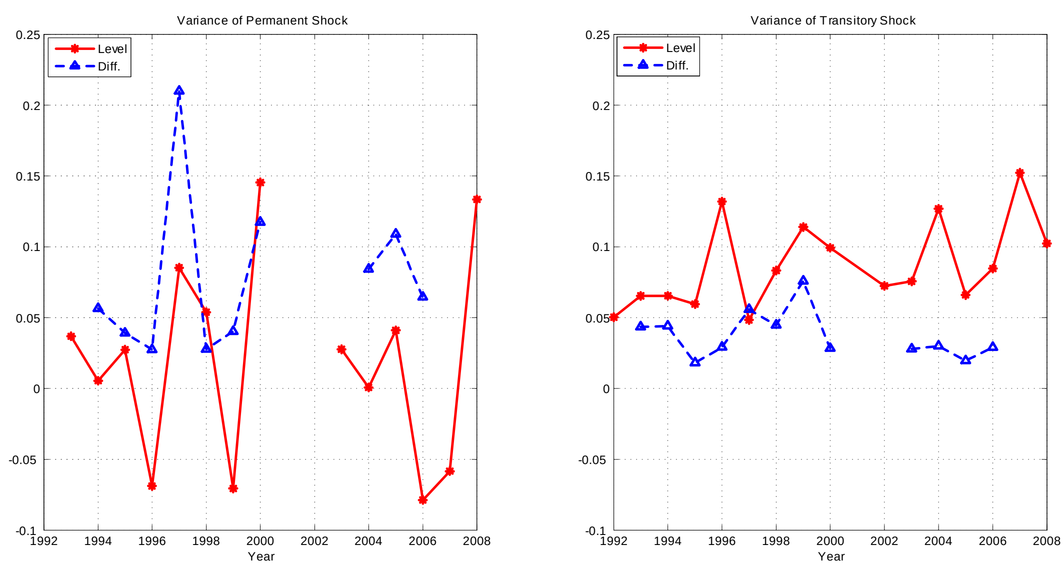

Figure 28: Transitory versus Permanent Income Shocks: Relaxed Age Restriction

We first define a first-difference

$$\triangle w_{i,c,t} \equiv w_{i,c,t} - w_{i,c,t-1} = \eta_{i,c,t} + \varepsilon_{i,c,t} - \varepsilon_{i,c,t-1}$$

Following this expression, we have

$$cov_c(\triangle w_{i,c,t+1}, \triangle w_{i,c,t}) = -\sigma_{\varepsilon,c,t} \tag{4}$$
$$var_c(\triangle w_{i,c,t}) = \sigma_{\eta,c,t} + \sigma_{\varepsilon,c,t} + \sigma_{\varepsilon,c,t-1} \tag{5}$$

We then identify $\sigma_{\varepsilon,c,t}$ $\forall t$ from equation (4) for different years. Knowing $\sigma_{\varepsilon,c,t}$ for all t, we can then identify $\sigma_{\eta,c,t}$ from equation (5). Finally, we average out $\sigma_{\varepsilon,c,t}$ and $\sigma_{\eta,c,t}$ across all cohorts c at year t to obtain $\sigma_{\varepsilon,t}$ and $\sigma_{\eta,t}$.

For the level method, we need a panel with a range of at least two years. We first form the level moment

$$w_{i,c,t+1} = z_{i,c,t} + \eta_{i,c,t+1} + \varepsilon_{i,c,t+1}$$

Based on this expression, we have

$$var_c(w_{i,c,t}) - cov_c(w_{i,c,t+1}, w_{i,c,t}) = \sigma_{\varepsilon,c,t} \tag{6}$$
$$var_c(w_{i,c,t}) - cov_c(w_{i,c,t}, w_{i,c,t-1}) = \sigma_{\eta,c,t} + \sigma_{\varepsilon,c,t} \tag{7}$$

We then identify $\sigma_{\varepsilon,c,t}$ from (6). Based on that identification, we can further identify $\sigma_{\eta,c,t}$ from (7). Finally, we average out $\sigma_{\varepsilon,c,t}$ and $\sigma_{\eta,c,t}$ across all cohorts c at year t.

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