The Dynamics of Income Inequality: The Case of China in a Comparative Perspective*

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Abstract

We compare household income panel data from China, Germany, the UK, and the US. Consistent with previous research, we show that income is more unequally distributed in China than in the three Western countries. But China also has a higher level of intragenerational income mobility. Because mobility tends to have an income-equalising effect, the snapshot measures of inequality overstate the true level of inequality in China to a greater degree than they do for the other countries. But even after we have taken into account the impact of mobility, permanent income is still more unequally distributed in China than in the US, the UK, and Germany. Moreover, in the three Western countries, the lion's share of income inequality is between individuals rather than within individual. The opposite holds for China. We also show that the most important determinants of income inequality in China are those long-standing institutions that predate the market reform.

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1 Income inequality in China

Income inequality in China has exploded. Because of deliberate policies of destratification, urban China under Mao was 'exceptionally egalitarian' (Parish, 1984, p. 99), and China as a whole 'was at least as equal as the most egalitarian states of socialist Europe' (Parish, 1984, p. 89). The post-Mao market reform, at its initial stage, did not bring a high level of inequality either. From the late 1970s through to the mid-1980s, the Gini coefficient of China's income distribution was at the mid-0.20s level (Khan *et al.*, 1992, p. 1056). Thirty years on, it now stands at 0.5 or higher (Khan and Riskin, 1998, 2005; Li and Sicular, 2014; Xie and Zhou, 2014). In other words, income inequality in China has, within a generation, gone from the Scandinavian level to the Latin American level.

In this paper, we contribute to the literature on income inequality in contemporary China in two ways. First, most research in this field is based on repeated cross-sectional data (e.g. Xie and Zhou, 2014). Whilst very informative, they do not speak to questions of intragenerational income mobility. This is an important gap as mobility tends to equalise income as the accounting period is extended (Shorrocks, 1978a; Atkinson *et al.*, 1992). In this paper, we reassess income inequality in China in light of several dimensions of income mobility in that country. We are able to do so because longitudinal data collected in a new, large-scale, and nationally representative household panel survey has recently become available.

Second, although we are primarily concerned with China, we carry out parallel analyses for Germany, the UK, and the US—the three countries that feature in most existing cross-national income mobility research. As it turns out, this comparative framework brings out just how outlying the Chinese case is on both income inequality and income mobility.

In the rest of this paper, we first set out the institutional bases of income inequality in China. We then discuss several ways to define and measure income inequality and income mobility. In particular, we draw attention to the distinction between permanent income and transitory income which proves to be useful in our analysis. Afterwards, we introduce the panel data sets and report the results. To anticipate some key findings, income mobility is at a much higher level in China than in the three Western countries. Income mobility should ameliorate inequality. But even after income mobility has been taken into account, permanent income is still more unequally distributed in China than in the West. Moreover, the lion's share of the overall income inequality is *between* individuals in the West, but *within* individual in China. This means that Chinese can be much less certain of their income over time. Put differently, not only is permanent income more unequally distributed in China, inequality in transitory income is greater there too. Finally, the most important determinants of income inequality in China are those long-standing institutions that predate the market reform.

1.1 The institutional bases of inequality in China

There was, under Mao, 'a determined and pervasive effort to ... reduce the income and other status disparities between elites and ordinary people, managers and subordinates, and so forth' (Whyte, 2005, p. 6). As a result, China was more egalitarian than most developing countries, including those with a socialist government (Walder, 1990). But the compressed income difference between *individuals* co-existed with large inequalities between *categories* of people. As Whyte (2005, p. 10) argues, 'one's location in China's socialist organizational/institutional structure ... was more central to your standard of living and status than were individual status characteristics, such as educational attainment and occupation.'

A prime example of this is the urban–rural divide. Before the market reform, the Chinese state financed industrial growth by squeezing the countryside (Oi, 1989). Through a monopoly of grain procurement, the state was able to set the grain price at an arbitrarily low level. This ensured a cheap food supply to the cities, helping the state gain and consolidate political support from urbanites. Furthermore, 'urban wages could be kept down in relation to industrial prices, and the resultant high profits would be reinvested in industry' (Knight and Song, 1999, p. 7).

Inevitably, this meant a large urban–rural gap in living standards. To prevent peasants from voting with their feet, a system of household registration, or *hukou*, was put in place in the late 1950s which for decades 'effectively bound peasants to the soil' (Whyte, 2005). Although there are now some 221 million internal migrants in China (Liang *et al.*, 2014), *hukou* still exists as a legal status, and it remains a key determinant of life chances (Wu and Treiman, 2004). Migrants with rural *hukou* living in cities do not have the same access to housing, health care, education, or other public services as individuals with urban *hukou*.

Moreover, the large urban–rural income gap has persisted. Based on official statistics, Li and Sicular (2014, p. 10) report that 'the urban–rural income ratio increased from less than 3.0 in the late 1990s to a peak of more than 3.3 in 2007–2009; thereafter it declined slightly but remained above 3.0.' Milanovic (2014) observes that 'the urban–rural gap in China is greater than in any country in the world.'

In addition to the urban–rural divide, China also has very large regional disparities. Khan *et al.* (1992, p. 1,050) report that in 1988 'the per capita income of Shanghai [was] 7.8 times that of Guizhou,' a province in Southwestern China. The market reform in the 1980s and 1990s saw faster economic growth in the already richer coastal provinces, exacerbating regional disparities (Li and Sicular, 2014). The fiscal decentralisation that accompanies the market reform also means that richer provinces can retain a greater share of their revenue, again favouring the coastal provinces (Kanbur and Zhang, 2005; Tsui, 2007). Research consistently shows that region is one of the most important predictors of earnings in urban China (Xie and Hannum, 1996; Hauser and Xie, 2005).

A third institutional source of inequality, relevant to cities only, is the work unit, or *danwei*. All urban workers have a *danwei* which is far more than a workplace. Walder (1986, p. 29) points out that *danwei* 'directly supplies a wide range of public goods, services, and even commodities that in other economies would be supplied through markets and a variety of institutions and government agencies.'[1] Different types of *danwei* offered different terms of employment. Workers of state-owned enterprises, for example, enjoyed much better pensions and other forms of social insurance than workers in the collective sector (Walder, 1986, pp. 44–45). More generally, *danwei*s attached to higher level units in the administrative hierarchy of the state were more resourceful. 'State enterprises run by national ministries, provinces, and by the large cities . . . offer more complete benefits than those run by small cities or by counties far from large metropolitan areas' (Walder, 1986, p. 67). Because of widespread rationing and very low job mobility rates, 'individuals [were] thoroughly dependent upon, and circumscribed by, the particular *danwei* to which they belonged' (Whyte, 2005, p. 8).

With the market reform, state-owned and collective enterprises, which are *danwei par excellence*, are in steep decline. Park and Cai (2011, p. 19) report that in 1978 state-owned and collective enterprises accounted for 78% and 22% of urban employment respectively. By 2005, these figures have dropped to 24% and 3%. The emergence of markets for housing and for other goods and services also means that individuals are less dependent on their *danwei* to meet basic needs. But *danwei* is still an important part of the urban social structure. Many *danwei*s have retained their paternalism towards workers.

[1]Whyte and Parish (1984, p. 25) note that 'work units may run nurseries, clinics, canteens, and recreational facilities; they convene employees to hear government decrees and for political study; they organize campaigns for birth control and to send down youths; they approve marriages and divorces and mediate disputes; they hold meetings to discuss crimes and misbehavior off the job by their members; they distribute rations and carry out cleanliness campaigns; they supervise untrustworthy employees and organize patrols to guard the area; they may employ family members of employees in subsidiary small workshops or vegetable farms.'

Often, they run a side business that is completely unrelated to their main business.[2] The purpose of such 'collective moonlighting' is to generate extra revenue to be shared as bonus among its workers (Xie and Wu, 2008). Thus, *danwei* profitability is a strong predictor of earnings.

The urban–rural divide, the regional disparities, and *danwei* are long-standing institutional bases of inequality in China and, to different degrees, they have persisted. But some aspects of inequality in China are quite clearly changing. Consider, for example, the return to education. Using a Mincer-type earnings determination model, Xie and Hannum (1996, p. 957) show that in 1988 an extra year of schooling was associated with a 3.1% increase in earnings, which was '[b]y international standards ... extremely small.' Similar estimates of low return to education have been reported by other scholars (e.g. Walder, 1990; Peng, 1992). With the market reform, the return to education has been rising steadily. Jansen and Wu (2012, p. 11) report that 'one additional year of schooling translated into a 2 percent ... net increase in income in 1978, 3.5 percent ... in 1985, 4.5 percent in 1990, 5.5 percent in 1995, 6.6 percent in 2000, and 7.7 percent in 2005' (see also Hauser and Xie, 2005; Zhou, 2014).[3] While a higher return to education might be a natural consequence of the market reform, the return to communist party membership has also risen (Hauser and Xie, 2005; Jansen and Wu, 2012).

1.2 Measuring income inequality

There is a very large literature on the definition and measurement of income inequality. It is beyond the scope of this paper to go into this literature in any detail. (See Cowell (2000) and Jenkins and Van Kerm (2011) for reviews.) Suffice it to note that we will use two of the most popular measures, namely the Gini coefficient and the Theil index.

The Gini coefficient can be expressed in a number of equivalent ways, one of which suggests that it is a normalised sum of the absolute difference in income for all pairs of individuals in a population:

$$\text{Gini} = \frac{1}{2n^2\mu} \sum_{i=1}^{n} \sum_{j=1}^{n} \mid y_i - y_j \mid .$$

[2] 'Factories could lease empty offices for rent and could run shops, restaurants and even hotels. The revenues from these sources were often unaccountable to supervising agencies and largely retained at the work units' discretion' (Xie and Wu, 2008, p. 564).

[3] Xie and Hannum (1996, p. 957) suggest 'that the rate of return [to schooling] tends to be higher in less developed countries (with an average of 14.4%) than in more economically advanced countries (with an average of 7.7%).' See also Trostel *et al.* (2002).

In the above expression, y_i and y_j are the income of individuals i and j in a population of n individuals, and μ is the mean income of that population. The Theil index is a member of a family of generalised entropy measures, and can be expressed as follows:

$$\text{Theil} = \frac{1}{n}\sum_i \frac{y_i}{\mu}\log\left(\frac{y_i}{\mu}\right).$$

The Gini coefficient and the Theil index are sensitive to different parts of the income distribution, with 'the Gini being most sensitive to inequalities about the mode of the distribution, ... [while] the Theil index disproportionately weighting inequalities in both the lower and the upper tail of the income distribution' (Gangl, 2005, p. 146). By employing both indices, we can be more certain that our results are not due to the idiosyncracies of any one measure.

1.3 Defining and measuring income mobility

There are several dimensions to income mobility and, correspondingly, different ways to measure it. We follow Jenkins (2011) and consider the following four approaches. (See also Burkhauser and Couch (2011) for discussion of income mobility research). First, income mobility can be defined as positional changes. Individuals would have been mobile if they have moved up or down the income ladder relative to others. Studies based on income decile (or quintile) transition matrices are examples of this genre of research (e.g. Chen, 2009). Under this view of rank mobility, not everyone can achieve upward mobility. For someone to move up, others will have to come down.

A second approach defines income mobility as the income growth of individuals (Fields and Ok, 1996). A mobility index is then a numerical summary of the income changes of all individuals over time. This view of income mobility is, in principle, very different from the first. If everyone's income has increased, then there is upward mobility for all, even if their relative positions have not changed. In practice, however, there are usually winners *and* losers in economic competition, even if the economy as a whole has been growing strongly, as in the case of China.

A third approach is based on the insight that, with income mobility, some individuals with high income initially will have lower income later on, and vice versa. Thus, mobility tends to have an income-equalising effect as the accounting period is extended, and income mobility can be measured as the degree to which it reduces income inequality over time (Shorrocks, 1978a).

The fourth approach is concerned with income instability. Moffitt and Gottschalk (2002) propose a couple of ways to decompose earnings into its permanent and transitory components (see also Gottschalk and Moffitt, 2009).[4] Using data from the Panel Study of Income Dynamics, they show that 'half of the increase in cross-sectional inequality [in male earnings in the US between 1974 and 1990] was a result of an increase in transitory variance' (Gottschalk and Moffitt, 2009, p. 12). Furthermore, they point out that the drivers for the rise in permanent earnings inequality are different from those which explain greater earnings instability, i.e. transitory variance. Specifically, the well-known accounts of skill-biased technological change, globalisation and international trade, and the decline of trade unions, etc. speak to *lasting* divergence in the wages of different groups of workers. But to explain growing earnings instability, we need to refer to other social changes, such as changing employment practice, higher job turnover rates, and so on (Gottschalk and Moffitt, 1994, 2009). The four approaches outlined above address different aspects of income mobility. We will draw on measures related to all four approaches in our analyses.

1.4 Income mobility research

To the best of our knowledge, there are only a couple of papers that examine income mobility in China, mainly due to the paucity of longitudinal data. Khor and Pencavel (2006) analyse data from the China Household Income Project (CHIP) and report that 'China's mobility is substantially greater than that in other countries: the immobility ratio in urban China is about two-thirds of that in the other countries and the correlation coefficient is about three-quarters of the average of the other countries.' But it should be noted the CHIP income data are based on retrospective recall. For example, CHIP respondents interviewed in 1996 were asked to report their income from 1990 to 1995. Clearly, income mobility analysis based on such data is subject to recall bias.

Chen and Cowell (2017) analyse data from the China Health and Nutrition Survey (CHNS) from 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011. Comparing the rate of income mobility before the millennium (i.e. 1989–2000) with that after the millennium (2000–2011), they argue that mobility rates in China have declined. This is an intriguing finding. But again there are data issues. Specifically, CHNS covers only nine provinces: Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning and Shandong;[5] and, crucially, inter-provincial migrants are not followed in

[4]Moffitt and Gottschalk's papers are about earnings inequality. But their methods and arguments apply equally to income inequality.

[5]Not counting Hong Kong and Macau, there are 22 provinces, five autonomous regions and four province-level municipalities in China.

the CHNS. This makes it difficult to interpret the main finding: to what extent is the fall in mobility rates due to the changing levels of interprovincial migration?

As regards income mobility in Western countries, Burkhauser and Poupore (1997) compare data from the Panel Study of Income Dynamics (PSID) and the German Socioeconomic Panel (GSOEP) and report that in the 1980s 'both single-period inequality and the share of that inequality that persists over time are greater in the United States than in Germany' (Burkhauser and Poupore, 1997, p. 10). Covering a later period, Gangl (2005) analyse data from the US (PSID) and eleven countries that took part in the European Community Household Panel (ECHP). He shows that '[e]ven discounting the impact of income mobility ... the United States continues to exhibit the highest level of permanent income inequality' (Gangl, 2005, p. 140). Comparing income panel data from Canada, Germany, the UK, and the US, Chen (2009) argues that, in the 1990s and the early 2000s, Britain is by far the most mobile country, Canada the least mobile, with Germany and the US in-between the two.

Summarising the literature on income mobility in Western countries, Jäntti and Jenkins (2015) make two observations. First, there is considerable income mobility in all countries, though 'most income changes are relatively small so that, even after many years, relative positions are quite highly correlated and substantial inequalities in longer-term incomes remain' (Jäntti and Jenkins, 2015, p. 887). Second, on the comparative question of which country has higher or lower income mobility rates, they note that the evidence is mixed, and 'it remains an open question ... whether there is a systematic cross-national relationship between levels of income mobility and cross-sectional income inequality' (Jäntti and Jenkins, 2015, p. 888). The last point is echoed by Burkhauser and Couch (2011, p. 535) who report that '[m]ost studies find no strong relationship between cross-sectional inequality and mobility.'

2 Data

The data that we analyse come from four household panel surveys: the China Family Panel Studies, the German Socioeconomic Panel, Understanding Society (UK), and the Panel Study of Income Dynamics (US). Of these four, the China Family Panel Studies (CFPS) is probably less familiar to scholars.

CFPS is run by a team based at the Institute of Social Science Survey of Peking University. Using a multi-stage sampling procedure, households were selected from 25 provinces or cities of China. Together these provinces and cities account for over 94% of the Chinese population.[6] So the survey can be considered as (nearly) nationally representative. It was launched in 2010, in which 14,960 households and 42,590 individuals were interviewed using computer-assisted personal interviews (CAPI).[7] Since then, CFPS respondents have been re-interviewed every other year. So far, three waves of data are available for analyses.

The Panel Study of Income Dynamics (PSID) began in 1968 with a sample of about 5,000 households and over 18,000 individuals. The German Socioeconomic Panel (GSOEP) began in 1984 with a sample of about 6,000 households and over 12,000 individuals. Understanding Society is the successor to the British Household Panel Survey. It began in 2009, with a sample of about 30,000 households and over 47,000 individuals. GSOEP and Understanding Society are annual panel surveys, but CFPS and PSID are biannual surveys.[8] In order to maintain comparability across the four surveys, we use the German and British data from every other wave. Specifically, for PSID, GSOEP, and Understanding Society, the data are drawn from 2009, 2011, and 2013, whereas for CFPS, the data are from 2010, 2012, and 2014.[9]

The unit of analysis is the individual rather than the household. This is because households are formed and dissolved over time. So they do not have a stable identity which can 'be followed over time in a consistent manner' (Jenkins, 2011, p. 36). We restrict our analysis to individuals aged 31 to 55, i.e. those of prime working age. By leaving out younger people who might be trying out different jobs at the beginning of their working lives as well as older people who are entering or preparing for retirement, we factor out from our analysis much of the life-cycle effects in income inequality and mobility.

The main variable of interest is real equivalised net household income, i.e. the total post-tax, post-transfer household income after adjustments for inflation and household size. We use the relevant consumer price index to adjust for inflation.[10] To adjust for household size, we divide the total net household income by the square root of household size. It is likely that there is

[6]The provinces or regions not included in CFPS are Hainan, Hong Kong, Macau, Ningxia, Qinghai, Tibet, and Xinjiang.

[7]The response rate and attrition rate of CFPS are very good by international standards. For example, the response rate at wave 1 at the individual level was 84.1% and the attrition rate between waves 1 and 2 was 80.6% (Xie and Hu, 2013, pp. 10–11). For further details, see `http://www.isss.edu.cn/cfps/EN/` and Xie *et al.* (2015).

[8]PSID was an annual panel survey until it turned biannual in 1999.

[9]The fieldwork of each wave of Understanding Society takes two years. Thus, wave 1 data were collected in 2009/10, wave 2 was from 2010/11, and so on. See Appendix A for further discussion of the panel data analysed in this paper.

[10]The consumer price indices that we use are taken from the OECD, see `https://data.oecd.org/price/inflation-cpi.htm`.

some degree of pooling and sharing of income risks within the household. For example, if one household member loses his/her job, another member might compensate by working longer hours. Thus, by focusing on the equivalised household income, some fluctuation in the income of individuals will have been smoothed out (Western *et al.*, 2012). To be clear, we assume that all individuals within a household have the same disposable income. And if individuals move between households, their income is calculated on the basis of the household of which they were currently a member. Finally, following established convention in income mobility research, we drop the top 1% and the bottom 1% of the income distribution from the analysis (Gottschalk and Moffitt, 2009, p. 10). Such data trimming 'inoculate[s] estimates against the adverse effects of outlier income values and changes' (Jenkins, 2011, p. 123).[11]

3 Results

We start with some snapshot measures of income inequality. Figure 1 reports the Gini coefficient and the Theil index of the four countries at each of the three waves. (We also report separate estimates for urban China and rural China throughout this paper.) There are large cross-national differences in the level of income inequality. For example, in wave 1, the Gini coefficient for Germany is 0.25, compared to 0.29 for the UK, 0.35 for the USA, and 0.43 for China. Within China, income inequality is slightly higher in rural areas (0.412) than in urban areas (0.409).[12] This rank order of inequality holds for both the Gini coefficient and the Theil index.[13] Broadly speaking, it also holds for all three waves, although the gap between Germany and the UK becomes smaller in wave 2, and the UK is slightly less unequal than Germany in wave 3. Our results are in line with other studies, which consistently show that the US has a higher level of income inequality than most European countries (e.g. Atkinson *et al.*, 1995; Atkinson, 2008; Gangl, 2005). What is remarkable is that China is, by some distance, even more unequal than the United States (Xie and Zhou, 2014).

[11] It follows that our results do not speak to the question of top income, i.e. the top 1% of the income distribution, for which survey data is not most suited (but see Alvaredo *et al.*, 2017).

[12] Our cross-sectional estimates of the income inequality are lower than those reported in the literature. This is, at least in part, because we have trimmed the top and bottom 1% of the income distribution from the data.

[13] This ranking of inequality also holds for other inequality measures, such as mean log deviation or the coefficient of variation. Details are available from the authors on request. For detailed discussion of various summary indices of inequality, see Cowell (2000) or Jenkins and Van Kerm (2011).

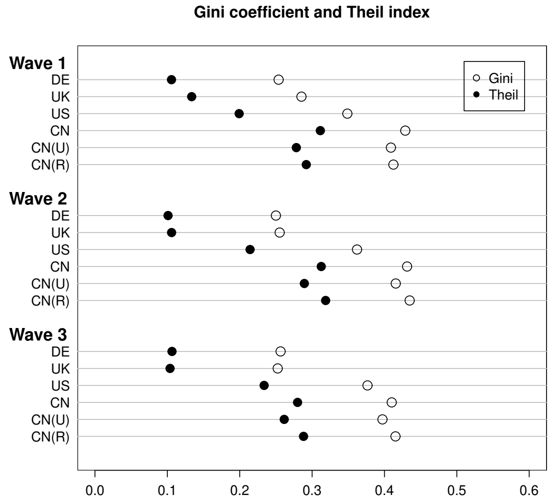

Figure 1: Cross-sectional measures of income inequality by country and wave

With panel data at our disposal, we now turn to examining income mobility. The left panel of Figure 2 reports two indicators of income persistence between waves 1 and 2, namely the Pearson correlation of the logarithm of income, and the proportion of individuals found on the main diagonal of the income quintile transition table.[14] There are, again, large differences between countries. For example, the correlation of log-income is 0.81 for Germany, 0.74 for the US, and 0.62 for the UK. But the correlation for China, at 0.37, is less than half the value for Germany. Within China, the correlation is higher in urban areas (0.39) than in rural areas (0.31). This ranking of income persistence also holds for the second measure, with 59% of Germans found on the main diagonal of the income quintile transition table, compared to 57% of Americans, 48% of Brits, but only 32% of Chinese. Thus, both indicators suggest that income persistence is much lower (or, conversely, income mobility is much higher) in China than in the other three countries. This finding is consistent with the results reported by Khor and Pencavel (2006). In Appendix B, we demonstrate that such large differences cannot be attributed to a higher level of measurement error in the Chinese income data alone.

The right panel of Figure 2 reports a measure of income mobility that is proposed by Shorrocks (1978b). For a square income transition matrix, P,

[14]Figures 2, 3, and 7 report the results for waves 1 and 2 which are, generally speaking, very similar to those for waves 2 and 3 and for waves 1 and 3 (see Appendix D).

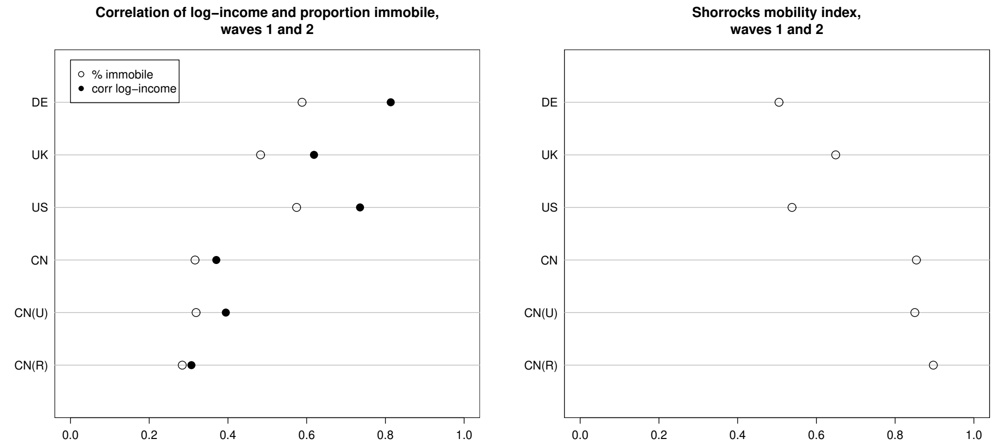

Figure 2: Income persistence and mobility between waves 1 and 2 by country

that distinguishes n income levels, the Shorrocks mobility index is given by the following expression:

$$M(P) = \frac{n - tr(P)}{n - 1},$$

where $tr(P)$ is the trace of the square matrix P, i.e. the sum of the diagonal elements. By design, $0 \leq M(P) \leq 1$; $M(P) = 0$ refers to a state of complete immobility, i.e. all individuals are found on the main diagonal of the transition matrix; while $M(P) = 1$ implies origin independence, i.e. the income level of individuals in wave 2 is independent of their income level in wave 1. According to the Shorrocks index, China is also, by some distance, the most mobile of the four countries with $M(P) = 0.85$, followed by the UK (0.65), the US (0.54), and Germany (0.51). Within China, income mobility is slightly higher in rural areas than in urban areas.

The left panel of Figure 3 reports the Bartholomew's average jump index, which is the mean of the number of quintile boundary crossed by the respondents, whether upwards or downwards (Bartholomew, 1982). The Bartholomew index values are 0.51 for Germany, 0.55 for the US, 0.74 for the UK, and 1.15 for China. The right panel of Figure 3 reports the percentage of respondents who have crossed at least two quintile boundaries.[15] Using this as a rough measure of long-range mobility, about 8% of Germans, 10% of Americans, 16% of Brits, but almost a third of Chinese have experi-

[15]If i and j index the rows and columns in the income transition matrix, the left panel of Figure 3 refers to cells where $|i - j| \geq 2$.

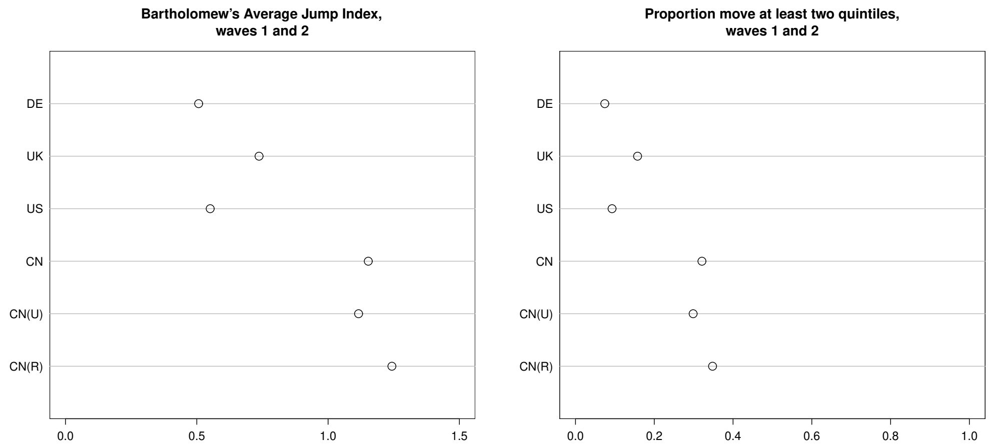

Figure 3: Levels of long-range mobility between waves 1 and 2 by country

enced long-range mobility. Overall, not only is there more income mobility in China, the mobility that takes place in China tends to be of longer range.

To recap our results so far, consistent with previous research, we show that contemporary China is considerably more unequal than the US which, in turn, is more unequal than the UK or Germany (see e.g. Xie and Zhou, 2014; Gottschalk and Smeeding, 1997). Using panel data, we further show that the most unequal country of our sample, namely China, has the highest level of income mobility, while the least unequal country, Germany, has the lowest level of mobility. Of course, one single study does not invalidate the cumulative result of previous research. But our finding is not consistent with Burkhauser and Couch (2011) or Jäntti and Jenkins (2015) who report no systematic relationship between income inequality and income mobility.

The high level of income mobility in China has potentially important implication for its unequal income distribution. This is because, as noted before, with income mobility some individuals with high income initially will have lower income later on, and vice versa. Thus, mobility tends to equalise income as the accounting period is extended. Put differently, snapshot measures such as those shown in Figure 1 tend to overstate the true level of income inequality (Atkinson *et al.*, 1992).

Shorrocks (1978a) has proposed an index, R, to capture this idea. Suppose we observe the income of a sample of individuals over m periods, we can compute the level of inequality for this sample for the entire observation window, $I[Y(t_0, t_m)]$, and also for each period within it, $I[Y(t_{k-1}, t_k)], k = 1, \ldots, m$. Shorrocks' R is a ratio of the overall, multi-period inequality to a

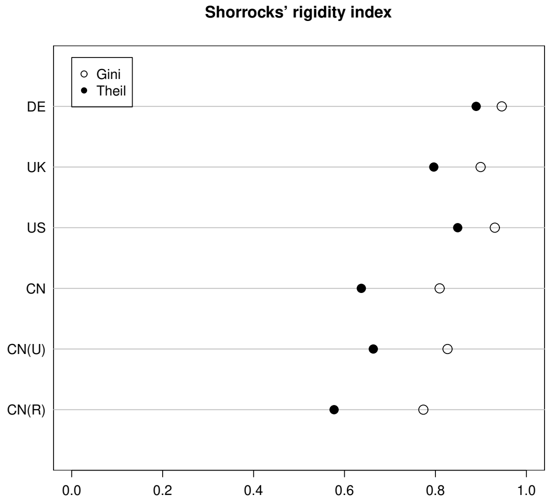

Figure 4: Shorrocks' index of income rigidity over three waves by country

weighted sum of the single-period measures of inequality:

$$R = \frac{I[Y(t_0, t_m)]}{\sum_{k=1}^{m} w_k I[Y(t_{k-1}, t_k)]},$$

where $w_k = \mu(t_{k-1}, t_k)/\mu(t_0, t_m)$, i.e. the weights themselves are ratios of the mean income of the relevant period, $\mu(t_{k-1}, t_k)$, to the overall mean, $\mu(t_0, t_m)$. By design, $0 \leq R \leq 1$. It is a measure of income rigidity, i.e. the extent to which income inequality persists as the accounting period is extended.

Because Shorrocks' R is sensitive to the particular inequality measure used (Schluter and Trede, 2003), it is common to report multiple R scores, using different inequality measures.[16] Figure 4 shows, once again, large cross-national differences. For example, based on the Gini coefficient, about 95% of the income inequality in Germany persists over three waves, as compared to 93% in the USA, 90% in the UK, but only 80% in China. Using the Theil index, R is lower for all countries, but the rank order remains the same. That is to say, income inequality is most persistent over time in Germany, followed by the US, the UK, and then China. This finding is inconsistent with Gangl (2005) who analyses income panel data from the US (PSID) and the fifteen countries that participated in the European Community Household Panel, and concludes that 'low-inequality countries actually also tend to be

[16] R is also sensitive to the length of the observation window.

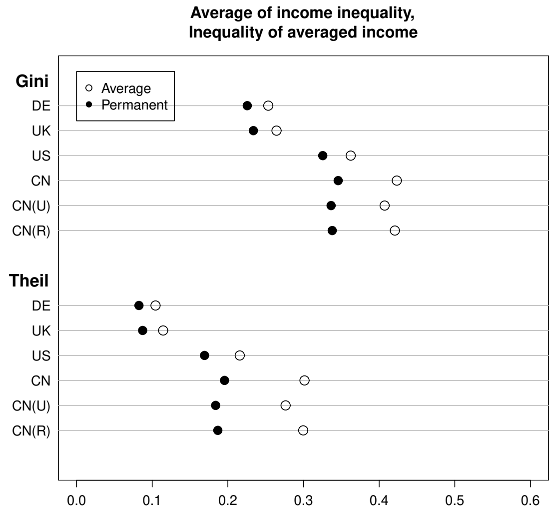

Figure 5: Average level of income inequality and the level of inequality of averaged ('permanent') income by country

the countries exhibiting the lowest degree of persistence in income inequality over time' (Gangl, 2005, p. 151).

As the equalising effect of income mobility is strongest in China, the snapshot measures of Figure 1 overstate the true level of inequality in China to a greater degree than they do for the other three countries. Does this make any difference to the rank order of income inequality between countries? To address this question, we report in Figure 5 two measures of inequality that take into account income data from all three waves. To obtain the first measure, we calculate the Gini coefficient (and the Theil index) of each wave, and then we average them. As for the second measure, we calculate the average income of each individual over three waves before we compute the Gini coefficient (and the Theil index). In other words, the first measure is the average level of income inequality, while the second measure is the level of inequality of averaged income, which we regard as a proxy for the permanent income.

Figure 5 shows that the gap between the average Gini coefficients and the Gini coefficient of averaged (or permanent) income is indeed widest for China. But note that the Gini coefficient of permanent income is 0.22 for Germany, 0.23 for the UK, 0.32 for the US, and 0.34 for China. In other words, even after we have taken into account the equalising effect of income mobility, China is still the most unequal country in the sample. We reach

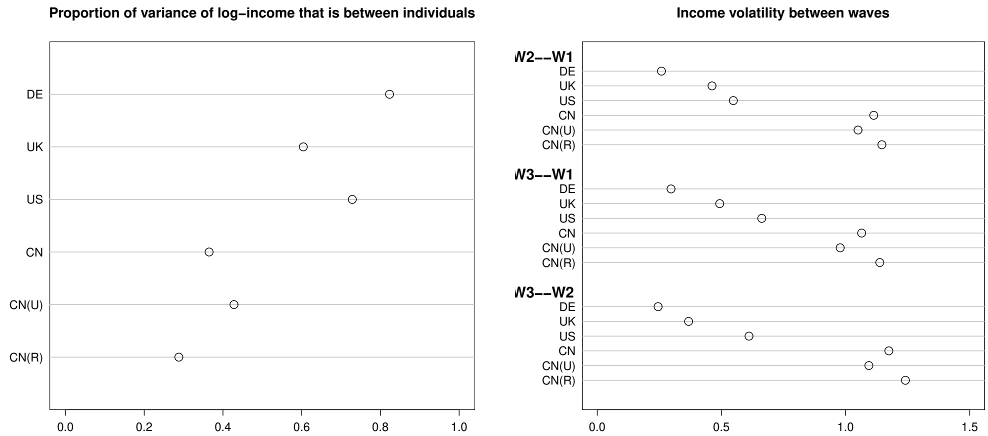

Figure 6: Intra-class correlation and income volatility by country

the same conclusion with the Theil index.

To pursue the permanent income–transitory income distinction further, we employ a very simple random effects model:

$$y_{it} = u_i + v_{it}. \tag{1}$$

Under this model, the log-income of individual i at time t, y_{it}, is expressed as the sum of two components: (i) a permanent income component, u_i, which varies between individuals but is fixed for each individual over time, and (ii) a transitory income component, v_{it}, which represents random income shocks to individual i at time t. As permanent income (u_i) is, by construction, uncorrelated with random shocks (v_{it}), the total variance in log-income is the sum of the variance of permanent income (between individuals) and the variance of transitory income (within individual).[17]

$$\sigma_t^2 = \sigma_u^2 + \sigma_{vt}^2.$$

Given our estimates of σ_u^2 and σ_{vt}^2, we can compute for each country the intraclass correlation, ρ, which is simply the share of the overall variance in log-income that is *between* individuals (i.e. $\rho = \sigma_u^2/(\sigma_u^2 + \sigma_{vt}^2)$). As the left panel of Figure 6 shows, 82% of the overall variance in Germany is between individuals, compared to 73% for the US, 60% for the UK, but only 36% for China (43% for urban China and 29% for rural China). Bearing in mind

[17]Our calculation of permanent and transitory income (and other measures that involve three wave of data, including the Shorrocks' R) are based on a balanced panel, i.e. respondents who are present in all three waves of the surveys.

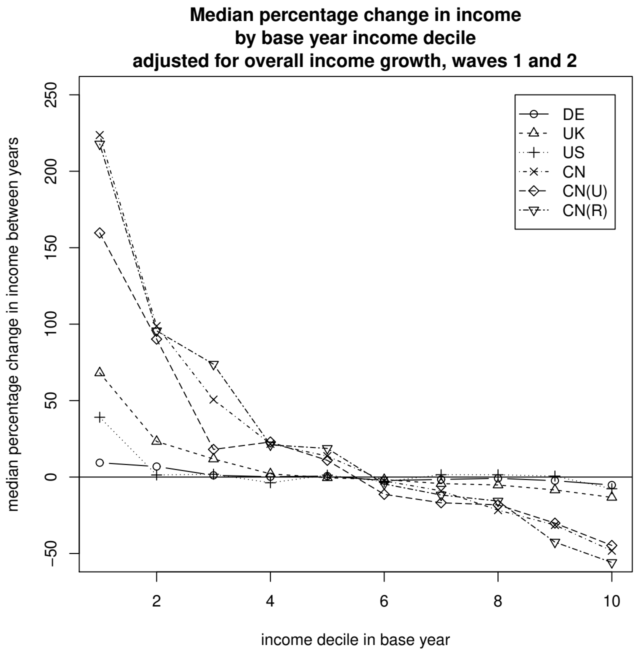

Figure 7: Median percentage change in income between wave 1 and 2 by wave 1 decile and by country

that the variance of log-income is itself a measure of inequality, it is striking that, for Germany, the UK, and the US, the lion's share of the overall income inequality is between individuals. For China, however, the opposite is the case, which implies a much higher degree of income instability. In other words, the average Chinese can be much less certain of his/her income in two or four years' time than the average American, Brit, or German.

The right panel of Figure 6 reports an alternative measure of income volatility (Shin and Solon, 2011). This is the sample standard deviation of the difference in log-income between waves ($sd(y_{i,s} - y_{i,t})$). Between wave 1 and wave 2, income volatility for Germany, the UK, and the US are 0.26, 0.46 and 0.55 respectively, which is a substantial range. But the income volatility for China, at 1.11, is twice as high as the level of the US, and four times the level of Germany. Broadly the same pattern is observed for income volatility between waves 2 and 3, or between waves 1 and 3. Thus, the finding of very high level of income instability and uncertainty in China is *not* dependent on the permanent income–transitory income partition.

Figure 7 reports further evidence on income instability. This shows the median percentage change in income between waves 1 and 2 by income decile in wave 1.[18] The lines in Figure 7 all go from the top-left to the bottom-right. In other words, those who started with lower income tend to have more positive income growth, while those with higher income in wave 1 tend to have lower, or even negative, income growth. So there is regression to the mean in income in all four countries. But what is remarkable is that the magnitude of income change is always larger in China than in the three Western countries, especially at the two ends of the income distribution. Specifically, for those who were in the bottom income decile of their country in wave 1, the median percentage change is 12% for Germany, 42% for the US, 69% for the UK, and 243% for China (175% for urban China ad 243% for rural China). As for those at the top income decile, the median percentage change is -3% for Germany, -5% for the US, -12% for the UK, and -28% for China (-29% for urban China and -30% for rural China). This confirms that not only is permanent income more unequally distributed in China, income instability is also at a much higher level in China than in the West.

It is relevant to note that the four countries faced quite different macroeconomic conditions over the period covered by our panel data. Although China was not immune to the global financial crisis that began in 2008, compared to Germany, the UK, and the US, it has maintained stronger economic growth and lower unemployment.[19] As income instability is counter-cyclical in nature, i.e. we expect greater income instability during economic downturns (Gottschalk and Moffitt, 1994, p. 229), the level of income instability in China would be even higher if the economic slowdown in China was as severe as that in the West.

To explore what might explain the between and within variances of log-income, we include a vector of covariates, $\boldsymbol{x}$, in the random effects model:

$$y_{it} = \boldsymbol{x'\beta} + u_i + v_{it}. \tag{2}$$

Recall that the dependent variable is the logarithm of the equivalised net household income. So, generally speaking, y_{it} might vary because of (i) changes in household members' income (including the respondent's), and/or

[18]To elaborate, we first deflate the equivalised household income by the relevant consumer price index. Then we calculate for each individual the percentage change in income between the two waves, and find the median percentage change for each income decile in the wave 1. To adjust for business cycle, we then subtract from the median value the overall income growth for the country; and plot it against income decile in the base-year.

[19]According to the World Bank, the average annual GDP growth rate for China between 2007 and 2015 is 9.3% (range: 6.9% to 14.2%). The corresponding figures for Germany, the UK, and the US are 1.2% (-5.6% to 4.1%), 1.1% (-4.3% to 3.1%), and 1.3% (-2.8% to 2.6%) respectively. As regards the unemployment rate, the average for China over this period is 4.3%, compared to 6.3% for Germany, 6.8% for the UK, and 7.2% for the US (see `http://data.worldbank.org`).

(ii) changes in household size. The relative importance of these two factors might vary across countries. For example, in countries where the labour market is more flexible, job loss or other employment-related changes might be the main income risk factors. In countries where the divorce rate is high, partnership dissolution might be an equally important income risk.

Given these considerations, apart from age and gender, we include three groups of covariates in our model. Group one are those which influence household income. Specifically, whether or not the respondent was working at the time of interview (either as an employee or a self-employed person), and the ratio of additional-earners-to-household-size.[20] We also include the respondent's highest educational qualifications as education is a key predictor of earnings. The second group refers to a binary indicator of marital status (married or cohabiting versus others) as change in marital status impact on household size and composition. Finally, the third group of covariates are region, the urban–rural contrast and, for China only, *hukou*.[21] As noted in Section 1.1, these covariates relate to institutions which shaped inequality in China in the past, and we would like to assess their contemporary significance in China, relative to the other countries.

We report some descriptive statistics of the covariates in Table 1. Several points are notable here. First, there are large cross-national differences in the distribution of educational attainment. In China, about 2% of individuals aged 31 to 55 have a college degree, compared to 22 to 37% in the three Western countries. Correspondingly, a much higher share of the Chinese respondents have elementary qualifications only. Second, about 95% of the Chinese respondents are married or cohabiting with a partner, compared to 60–78% in the West. Third, significantly fewer Chinese reported to be employed or self-employed in wave 1 (72%) than in waves 2 or 3 (about 84%). This, we believe, is an artefact due to changes in the employment status module of the questionnaire (see Appendix A for details). Fourth, the ratio of the number of additional earners to household size is slightly higher in China (except for wave 1, due to the measurement issue just mentioned). When the number of additional earners and household size are examined separately, we see that Chinese households are larger, and they also have slightly more additional earners.

[20] We count the number of income-earners in the household (i.e. excluding the respondent) and divide it by household size.

[21] Region is defined differently for the four countries. For China, they are the 25 provinces or cities included in CFPS. For Germany, they are the sixteen *Bundesländer*. For the UK, they are the nine regions of England, plus Wales, Scotland and Northern Ireland. For the US, they are the fifty states. The distribution of respondents across these regions is not reported in Table 1, but is available from the authors.

Table 1: Descriptive statistics of covariates

	Germany			UK			US		
	w1	w2	w3	w1	w2	w3	w1	w2	w3
female	52.3	51.5	52.0	51.1	53.5	53.4	52.5	52.3	52.3
elementary	8.5	8.2	9.0	15.4	16.2	16.3	3.1	3.2	3.1
junior high	52.4	52.3	52.3	34.1	34.3	33.9	6.1	5.9	5.9
senior high	7.6	7.7	7.3	9.5	9.2	9.2	32.4	32.4	31.7
vocational	9.6	10.1	9.8	3.3	3.3	3.3	25.5	25.6	25.5
college	22.0	21.7	21.7	37.8	37.0	37.3	33.0	33.0	33.8
working	83.8	87.0	85.8	81.3	80.4	80.9	87.3	83.9	83.7
married	62.0	60.7	61.7	77.5	76.2	75.3	64.6	64.3	63.8
urban	66.9	66.3	66.7	78.6	79.2	78.8	82.2	81.9	81.6
age*	44.0	46.6	48.6	43.2	45.1	47.0	43.4	45.5	47.4
# earners/hh size*	0.21	0.23	0.23	0.22	0.24	0.25	0.23	0.23	0.23
# earners*	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.7
hh size*	2.8	2.5	2.5	3.2	3.2	3.1	3.2	3.2	3.1
	China			China (Urban)			China (Rural)		
	w1	w2	w3	w1	w2	w3	w1	w2	w3
female	49.8	53.6	55.3	50.0	53.3	55.4	49.7	53.9	55.1
elementary	44.9	46.7	46.3	30.0	31.4	32.7	58.6	61.5	62.3
junior high	34.3	32.0	31.9	36.8	34.6	34.3	31.6	29.0	28.6
senior high	14.9	14.8	15.2	21.8	21.9	21.5	8.6	8.3	8.0
vocational	4.0	4.3	4.4	7.5	7.9	7.5	0.9	0.9	0.8
college	2.0	2.2	2.3	3.9	4.3	4.0	0.2	0.3	0.3
working	72.0	85.0	84.0	70.8	78.3	77.8	72.5	91.4	90.6
married	95.8	95.1	94.0	94.9	94.2	93.1	96.4	95.8	95.0
urban	47.1	49.9	56.5						
hukou (urban)	26.0	28.9	30.6	50.4	54.4	53.3	4.4	5.4	5.0
age*	42.7	44.8	46.7	42.4	44.2	46.3	43.2	45.5	47.4
# earners/hh size*	0.21	0.30	0.33	0.22	0.28	0.30	0.21	0.32	0.36
# earners*	0.9	1.3	1.4	0.9	1.1	1.2	0.9	1.4	1.6
hh size*	4.2	4.1	4.1	4.0	3.9	3.8	4.5	4.3	4.3

Note: percentages, except for age and number of additional earners which are mean; regional distribution not shown.

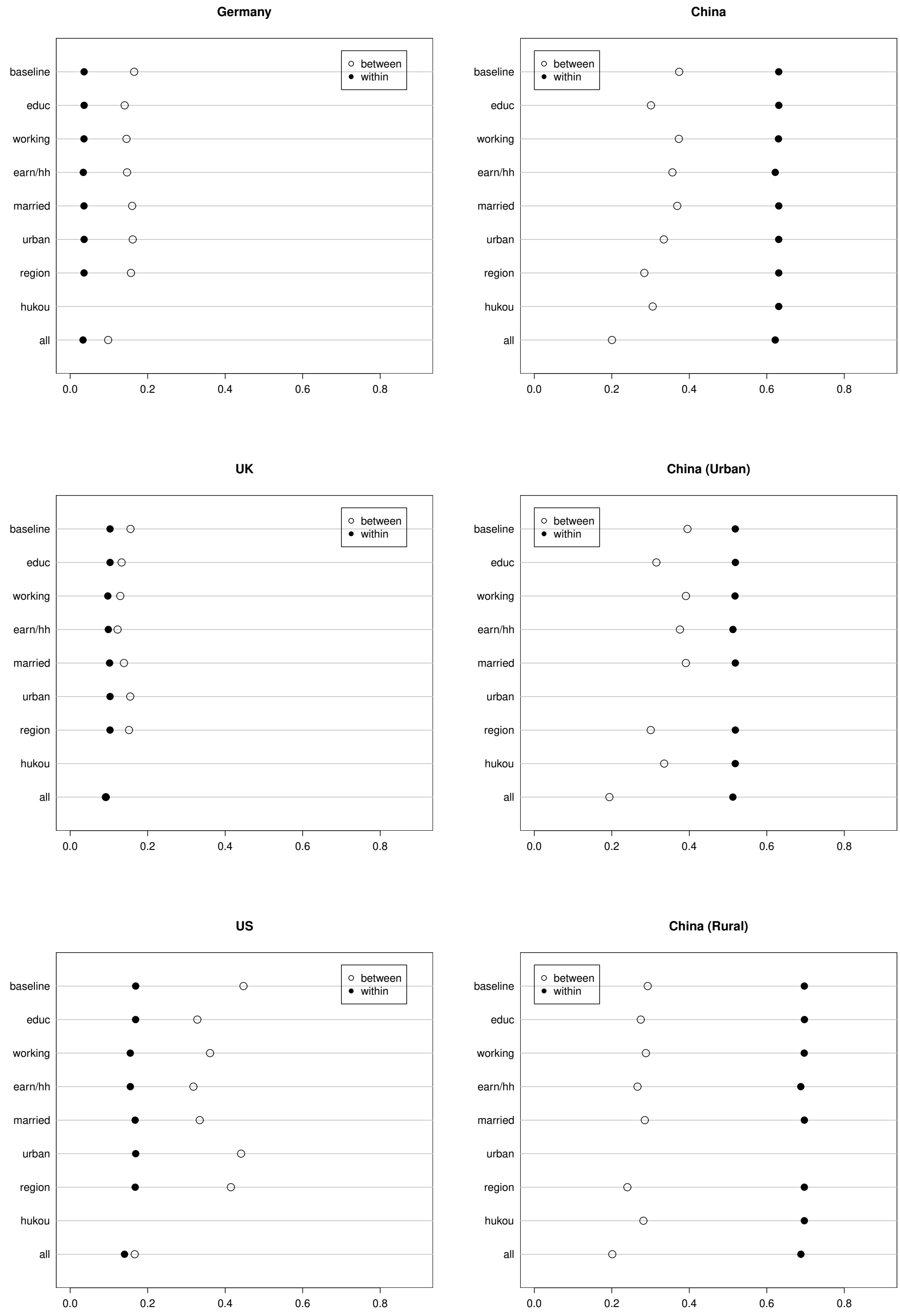

Figure 8: Residual between- and within- variance under different models by country

In the baseline model, $\boldsymbol{x}$ contains the respondents' age and gender only. We then add to the model, one at a time, the covariates listed above. In the full model, we include all covariates. The parameter estimates, $\hat{\boldsymbol{\beta}}$, which are of the expected signs, are reported in Table 3 in Appendix C. Figure 8 reports the residual variance that is between individuals (σ_u^2) and within individuals (σ_{vt}^2). Consistent with the left panel of Figure 6, the residual between-variance is larger than the residual within-variance in Germany, the UK, and the US.[22] But the opposite is true for China. Second, while many of the covariates account for a share, and in some cases a significant share, of the between-variance in the four countries, they barely make a dent on the within-variance. Thus, compared to the baseline model, the covariates of the full model jointly account for 41% of the between-variance in Germany and the UK, 63% in the US, and 46% in China. The corresponding figures for the within-variance are 8% in Germany, 10% in the UK, 17% in the US, and 1% in China.

Third, educational attainment is an important predictor everywhere, explaining about 15% of σ_u^2 in Germany and in the UK, 20% in China, and 27% in the US. As regard the other covariates, their relative importance varies across countries in interesting ways. For example, employment status and the earners-to-household-size ratio are of greater importance in the West than in China. Thus, employment status explains about 12% of the between-variance in Germany, 17% in the UK, 19% in the US; but less than 1% in China. The additional-earners-to-household-size ratio explains 11% of the between-variance in Germany, 21% in the UK, 29% in the US, but just 5% in China. Marital status is important for the UK and the US (the two countries with high divorce rates), explaining 11% and 25% of the between-variance respectively. The corresponding figures for Germany and China are 3% and 1%.

The covariates that matter for China are the urban–rural contrast and region, explaining 11% and 24% of the between-variance. These two covariates are, however, relatively unimportant for the three Western countries. Of course, *hukou* is also important in China, accounting for 18% of the between-variance for China as a whole, and 15% for urban China.[23]

[22] In the full model, between variance and within variance each accounts for about half of the overall residual variance in the UK.

[23] Note that *hukou* explains only 4% of the between-variances in rural China. This is because there are very few people with urban *hukou* living in rural areas (see Table 1).

4 Summary and discussion

Our objective in this paper is to provide a detailed description of the patterns of income mobility in China, and to compare them with the patterns found in Germany, the UK and the US. To this end, we analyse nationally representative household panel data from these four countries. We show that China has a higher level of income inequality than the US which, in turn, is more unequal than the UK or Germany. We then show that income mobility is also at a much higher level in China than in the three Western countries. As mobility has an income-equalising effect, snapshot measures of income inequality overstate the true level of inequality in China to a greater degree. Having said that, even after we have taken into account the impact of income mobility, permanent income is still more unequally distributed in China than in the West. Moreover, in Germany, the UK, and the US the lion's share of income inequality is found between individuals rather than within individuals. But the opposite is true for China, suggesting that the average Chinese face a much higher degree of income instability and uncertainty.

When it comes to predicting who has higher or lower income, education is an important predictor everywhere. But there are interesting cross-national differences too. Employment status, the earners-to-household-size ratio and, to some degree, marital status are important predictors for the between-individual differences in disposable income in the West. What matters for China, however, are the urban–rural contrast, region, and *hukou*, i.e. those long-standing institutions that had structured income inequality in pre-reform China. Despite the massive social change in China over the last thirty years, there is loud echo from the past.

The many differences between China and the three Western countries that we report in this paper call for further systematic investigation that is beyond the scope of this paper. But we finish by offering some comments on the high level of income instability in China. We believe that this is related to broader changes in the Chinese labour market. Under Mao, employment was for life, and job mobility was very rare (Davis, 1992). Moreover, the wages of urban workers were extremely stable, so much so that the respondents of a 1993–94 survey are said to be able to recall accurately their wages as far back as 1955 (Zhou, 2000). But, as noted above, state-owned and collective enterprises are in sharp decline. Taking their place are various forms of non-state enterprises, e.g. foreign-owned firms, joint ventures, private enterprises which, until the passing of the National Labour Law in 1995, were not even nominally required to follow the same labour practice as state-owned and collective enterprises. As state-owned enterprises come under competitive pressure from the less regulated non-state firms, they clamour for greater autonomy to set wages and employment conditions. Similarly, as provinces and cities compete with each other to attract investment, they deregulate and lower labour protection, a process which has aptly been described as 'contagious capitalism' (Gallagher, 2005). Finally, many of the 200 million plus migrant workers are willing to work with less employment protection than urban workers used to have. Park and Cai (2011) estimate that up to 39% of urban workers are informally or casually employed, meaning that they do not have an employment contract. For a very large share of Chinese workers, precarious employment has replaced the 'iron rice bowl' (Kuruvilla *et al.*, 2011).

Given this, it would be useful to examine the changing labour market and employment practices in China. For example, a comparative analysis of the work history of individuals would reveal whether Chinese change jobs more often or face higher unemployment risks than their counterparts in the West. Or do Chinese experience greater income instability even when they have stayed in the same job? These are promising questions to explore in future papers.

References

Alvaredo, F., Garbinti, B., and Piketty, T. (2017). On the share of inheritance in aggregate wealth: Europe and the USA, 1900–2010. *Economica*, **84**, 239–260.

Atkinson, A. B. (2008). *The Changing Distribution of Earnings in OECD countries*. Oxford University Press, Oxford.

Atkinson, A. B., Bourguignon, F., and Morrison, C. (1992). *Empirical Studies of Earnings Mobility*. Harwood Academic Publishers, Reading.

Atkinson, A. B., Rainwater, L., and Smeeding, T. M. (1995). *Income distribution in OECD countries. Evidence from the Luxembourg Income Study*. Organization for Economic Cooperation and Development, Paris.

Bartholomew, D. J. (1982). *Stochastic Models for Social Processes*. Wiley, Chichester, 3rd edition.

Bound, J. and Krueger, A. B. (1991). The extent of measurement error in longitudinal earnings data: do two wrongs make a right? *Journal of Labor Economics*, **9**(1), 1–24.

Bound, J., Brown, C., Duncan, G. J., and Rodgers, W. L. (1994). Evidence on the validity of cross-sectional and longitudinal labor market data. *Journal of Labor Economics*, **12**(3), 345–368.

Burkhauser, R. V. and Couch, K. A. (2011). Intragenerational inequality and intertemporal mobility. In B. Nolan, W. Salverda, and T. M. Sweeding, editors, *Oxford Handbook of Economic Inequality*, chapter 21, pages 522–545. Oxford University Press, Oxford.

Burkhauser, R. V. and Poupore, J. G. (1997). A cross-national comparison of permanent inequality in the United States and Germany. *Review of Economics and Statistics*, **79**(1), 10–17.

Chen, W.-H. (2009). Cross-national differences in income mobility: evidence from Canada, The United States, Great Britain and Germany. *Review of Income and Wealth*, **55**(1), 75–100.

Chen, Y. and Cowell, F. A. (2017). Mobility in China. *Review in Income and Wealth*, **63**(2), 203–218.

Cowell, F. (2000). Measurement of inequality. In A. B. Atkinson and F. Bourguignon, editors, *Handbook of Income Distribution*, volume 1, chapter 2, pages 87–166. Elsevier, Amsterdam.

Davis, D. (1992). Job mobility in post-Mao cities: increases on the margins. *China Quarterly*, **132**, 1062–1085.

Fields, G. S. and Ok, E. A. (1996). The meaning and measurement of income mobility. *Journal of Economic Theory*, **71**, 349–377.

Frick, J. R., Jenkins, S. P., Lillard, D. R., Lipps, O., and Wooden, M. (2007). The cross-national equivalent file (CNEF) and its member country household panel studies. *Schmollers Jahrbuch*, **127**, 627–654.

Gallagher, M. E. (2005). *Contagious Capitalism: Globalization and the Politics of Labor in China*. Princeton University Press, Princeton.

Gangl, M. (2005). Income inequality, permanent incomes, and income dynamics. *Work and Occupations*, **32**(2), 140–162.

Gottschalk, P. and Moffitt, R. (1994). The growth of earnings instability in the U.S. labor market. *Brookings Papers on Economic Activity*, **2**, 217–254.

Gottschalk, P. and Moffitt, R. (2009). The rising instability of U.S. earnings. *Journal of Economic Perspectives*, **23**(4), 3–24.

Gottschalk, P. and Smeeding, T. M. (1997). Cross-national comparisons of earnings and income inequality. *Journal of Economic Literature*, **35**, 633–687.

Hauser, S. M. and Xie, Y. (2005). Temporal and regional variation in earnings in urban China in transition between 1988 and 1995. *Social Science Research*, **34**, 44–79.

Jansen, W. and Wu, X. (2012). Income inequality in urban China, 1978–2005. *Chinese Sociological Review*, **45**(1), 3–27.

Jäntti, M. and Jenkins, S. P. (2015). Income mobility. In A. B. Atkinson and F. Bourguignon, editors, *Handbook of Income Distribution*, volume 2, chapter 10, pages 807–935. Elsevier, Amsterdam.

Jenkins, S. P. (2011). *Changing Fortunes: Income Mobility and Poverty Dynamics in Britain*. Oxford University Press, Oxford.

Jenkins, S. P. and Van Kerm, P. (2011). The measurement of economic inequality. In B. Nolan, W. Salverda, and T. M. Sweeding, editors, *Oxford Handbook of Economic Inequality*, chapter 3, pages 40–67. Oxford University Press, Oxford.

Kanbur, R. and Zhang, X. (2005). Fifty years of regional inequality in China: a journey through central planning, reform, and openness. *Review of Development Economics*, **9**(1), 87–106.

Khan, A. R. and Riskin, C. (1998). Income and inequality in China: composition, distribution and growth of household income, 1988 to 1995. *China Quarterly*, **154**, 221–253.

Khan, A. R. and Riskin, C. (2005). China's household income and its distribution, 1995 and 2002. *China Quarterly*, **182**, 356–384.

Khan, A. R., Griffin, K., Riskin, C., and Zhao, R. (1992). Household income and its distribution in China. *China Quarterly*, **132**, 1029–1061.

Khor, N. and Pencavel, J. (2006). Income mobility of individuals in China and the United States. *Economics of Transition*, **14**(3), 417–458.

Knight, J. and Song, L. (1999). *The Rural–Urban Divide: Economic Disparities and Interactions in China*. Oxford University Press, Oxford.

Kuruvilla, S., Lee, C. K., and Gallagher, M. E., editors (2011). *From Iron Rice Bowl to Informalization: Markets, Workers, and the State in a Changing China*. ILR Press, Ithaca.

Li, S. and Sicular, T. (2014). The distribution of household income in China: inequality, poverty and policies. *China Quarterly*, **217**, 1–41.

Liang, Z., Li, Z., and Ma, Z. (2014). Changing patterns of the floating population in China, 2000–2010. *Population and Development Review*, **40**(4), 695–716.

Milanovic, B. (2014). Inequality in the United States and China. Technical report, Harvard Business Review, Cambridge, MA.

Moffitt, R. A. and Gottschalk, P. (2002). Trends in the transitory variance of earnings in the United States. *Economic Journal*, **112**, C68–C73.

Oi, J. C. (1989). *State and Peasant in Contemporary China: The Political Economy of Village Government*. University of California Press, Berkeley, CA.

Parish, W. L. (1984). Destratification in china. In J. L. Watson, editor, *Class and Social Stratification in Post-Revolution China*, chapter 5, pages 84–120. Cambridge University Press, Cambridge.

Park, A. and Cai, F. (2011). The informalization of the chinese labor market. In S. Kuruvilla, C. K. Lee, and M. E. Gallagher, editors, *From Iron Rice Bowl to Informalization: Markets, Workers, and the State in a Changing China*, chapter 2, pages 17–35. ILR Press, Ithaca, NY.

Peng, Y. (1992). Wage determination in rural and urban China: a comparison of public and private industrial sectors. *American Sociological Review*, **57**(2), 198–213.

Schluter, C. and Trede, M. (2003). Local versus global assessment of mobility. *International Economic Review*, **44**(4), 1313–1335.

Shin, D. and Solon, G. (2011). Trends in men's earnings volatility: what does the Panel Study of Income Dynamics show? *Journal of Public Economics*, **95**, 973–982.

Shorrocks, A. F. (1978a). Income inequality and income mobility. *Journal of Economic Theory*, **19**, 376–393.

Shorrocks, A. F. (1978b). The measurement of mobility. *Econometrica*, **46**(5), 1013–1024.

Trostel, P., Walker, I., and Woolley, P. (2002). Estimates of the economic return to schooling for 28 countries. *Labour Economics*, **9**(1), 1–16.

Tsui, K.-Y. (2007). Forces shaping China's interprovincial inequality. *Review of Income and Wealth*, **53**(1), 60–92.

Walder, A. G. (1986). *Communist Neo-Traditionalism: Work and Authority in Chinese Industry*. University of California Press, Berkeley, CA.

Walder, A. G. (1990). Economic reform and income distribution in Tianjin, 1976–1986. In D. Davis and E. F. Vogel, editors, *Chinese Society on the Eve of Tiananmen: The Impact of Reform*, chapter 6, pages 135–156. Harvard University Press, Cambridge, MA.

Western, B., Bloome, D., Sosnaud, B., and Tach, L. (2012). Economic insecurity and social stratification. *Annual Review of Sociology*, **38**, 341–359.

Whyte, M. K. (2005). Rethinking equality and inequality in the PRC. 50th Anniversary conference for the Fairbank Center for East Asian Research, Harvard University.

Whyte, M. K. and Parish, W. L. (1984). *Urban Life in Contemporary China*. University of Chicago Press, Chicago, IL.

Wu, X. and Treiman, D. J. (2004). The household registration system and social stratification in China. *Demography*, **41**(2), 363–384.

Xie, Y. and Hannum, E. (1996). Regional variation in earnings inequality in reform-era urban China. *American Journal of Sociology*, **101**(4), 950–992.

Xie, Y. and Hu, J. (2013). Introduction. In Y. Xie, X. Zhang, J. Li, X. Yu, and Q. Ren, editors, *China Family Panel Studies 2013*, chapter 1, pages 1–26. Peking University Press, Beijing.

Xie, Y. and Wu, X. (2008). *Danwei* profitability and earnings inequality in urban China. *China Quarterly*, **195**, 558–581.

Xie, Y. and Zhou, X. (2014). Income inequality in today's China. *Proceedings of the National Academy of Scinece*, **111**(19), 6928–6933.

Xie, Y., Zhang, C., Huang, G., Xu, Q., and Xu, H. (2012). China Family Panel Studies: adjustment of rural family income 2010. CFPS Technical Report 14, Institute of Social Science Survey, Peking University, Beijing. In Chinese.

Xie, Y., Zhang, X., Xu, Q., and Zhang, C. (2015). Short-term trends in China's income inequality and poverty: evidence from a longitudinal household survey. *China Economic Journal*, **8**(3), 235–251.

Xu, Q. and Zhang, C. (2014). China Family Panel Studies: adjustment of family income 2012. CFPS Technical Report 27, Institute of Social Science Survey, Peking University, Beijing. In Chinese.

Xu, Q., Zhang, C., Zhou, X., and Xie, Y. (2012). Comparing income in cgss, chip, chfs, and cfps. CFPS Technical Report 16, Institute of Social Science Survey, Peking University, Beijing. In Chinese.

Zhang, X. and Zhang, X. (2016). Income distribution. In Y. Xie, X. Zhang, J. Li, P. Tu, and Q. Ren, editors, *Zhong Guo Min Sheung Fa Zhan Bao Gao 2016*, chapter 2, pages 14–28. Peking University Press, Beijing.

Zhang, X., Zhang, C., and Xie, Y. (2013). Poverty and unemployment. In Y. Xie, X. Zhang, J. Li, X. Yu, and Q. Ren, editors, *Zhong Guo Min Sheung Fa Zhan Bao Gao, 2013*, chapter 3, pages 54–91. Peking University Press, Beijing.

Zhou, X. (2000). Inequality in urban China: evidence from panel data. *American Journal of Sociology*, **105**(4), 1135–1174.

Zhou, X. (2014). Increasing returns to education, changing labor force structure, and the rise of earnings inequality in urban China, 1996–2010. *Social Forces*, **93**(2), 429–455.

A Data sources

For Germany, the UK, and the US, most of the variables that we use come from the Cross-National Equivalent File (CNEF), a project led by Dean Lillard of the Ohio State University. The CNEF contains a set of harmonised variables for household panel surveys from the following eight countries: Australia, Canada, Germany, Korea, Russia, Switzerland, the UK, and the US (Frick *et al.*, 2007). The key CNEF variable that we use is `postgovinc`, which is the total household post-tax, post-transfer income. For more information on the components of this variable and their cross-national comparability, see `https://cnef.ehe.osu.edu/`.

The China Family Panel Studies (CFPS) is not yet included in the CNEF. So we extract the relevant variables from the original CFPS data files. The CFPS collects household income from five sources. The first source is labour income, i.e. the sum of the post-tax wages and salaries of all family members employed in the previous year, including bonuses and the monetary value of in-kind benefits. Second, farming and/or non-farm family business income. As many Chinese farmers consume a substantial share of what they produce, CFPS includes in this income source the monetary value of the produce consumed by the household (Xie *et al.*, 2012, 2015). Third, public transfer income, including pensions, government aids and allowances, and compensation for land appropriation and residential relocation. Fourth, property income which includes rents deriving from land, housing units and other assets. The fifth source is a residual category of 'other income' which includes private transfers and gifts (Xie *et al.*, 2012).

Overall, the CFPS income module is quite comprehensive. But there are some changes over waves in how the income data was collected. Most importantly, in wave 1, the labour income of *all* family members was reported by a single respondent, namely the person who answered the family questionnaire. As the 'family respondent' might not know very accurately the wages of all family members, each family member reported his/her own labour income in wave 2. This, however, led to a considerable amount of missing data on labour income, especially for rural households with members working away from home as migrant workers (and so were not present at the interview). In these cases, the labour income of missing family members was imputed with a regression model (Xu and Zhang, 2014, pp. 3–7). Because of this missing data problem, in wave 3 CFPS reverted to the wave 1 practice (Zhang and Zhang, 2016). In addition, from wave 2 onwards, the CFPS instrument specifies more explicitly certain income components, such as scholarship for students (see Xie *et al.*, 2015, Appendix 1). Given the above consideration, the CFPS variables for 'net household income' that are most comparable to `postgovinc` in CNEF are `faminc_net` (2010), `fincome2_adj` (2012), and `fincome2` (2014).

As regards employment status, in wave 1 of the CFPS, there are only two questions on employment status: whether the respondent is currently working, including farming and self-employment (G3); and whether the respondent is retired or on leave (G301). From wave 2 onwards, the questions on employment status are much more systematic and detailed. Respondents were first asked whether they are currently working (G101) and whether they have worked for at least one hour in the past week (G102). If the answer was 'no', then they would be probed as to whether they are employed, but are on holiday, sick leave, or in training (G103); whether they can return to their job at a specified time or within six months (G105); whether they are self-employed or farmers, and that they are not currently working because of seasonal reasons (G108, G109); whether they have looked for work in the past month (G106); whether they can start work within two weeks if there is a job (G107), and so on (see Zhang *et al.*, 2013, p. 71).

It is quite possible that because the wave 1 module on employment status was much shorter, some Chinese respondents who were in casual employment, or who were self-employed or helping out with the family farm were mistakenly classified as *not* in employment at all. Hence, the low level of employment/self-employment in wave 1 of the CFPS (see Table 1).

B Measurement error

Error in measuring income will lead to biased estimates of income mobility, probably upwards. We outline a simple framework to think about the implications of measurement error on income mobility estimates. We also assess the likely impact of measurement error on our main results.

Let y_{it} be the true value of the log-income of individual i at time t, and let m_{it} be the measurement error. Thus, the observed value of log-income is $y_{it} + m_{it}$, with $\mathrm{E}(m_{it}) = 0$. On the classical measurement error assumption (i.e. y_{it} and m_{it} are uncorrelated), the covariance of two observed income values one period apart is:

$$\mathrm{cov}(y_{it} + m_{it},\ y_{i,t-1} + m_{i,t-1}) = \mathrm{cov}(y_{it},\ y_{i,t-1}) + \mathrm{cov}(m_{it},\ m_{i,t-1}).$$

If m_{it} is mean-reverting, $\mathrm{cov}(m_{it}, m_{i,t-1}) < 0$. This implies that the one-period covariance of observed income understates the covariance of true income:

$$\mathrm{cov}(y_{it} + m_{it},\ y_{i,t-1} + m_{i,t-1}) < \mathrm{cov}(y_{it},\ y_{i,t-1}).$$

The variance of observed income is $\mathrm{var}(y_{it} + m_{it}) = \mathrm{var}(y_{it}) + \mathrm{var}(m_{it})$. Since $\mathrm{var}(m_{it}) > 0$, the variance of observed income overstates the variance of true income.

$$\mathrm{var}(y_{it} + m_{it}) > \mathrm{var}(y_{it}).$$

Furthermore, if, as is plausible, $\mathrm{var}(y_{it}) = \mathrm{var}(y_{i,t-1})$ and $\mathrm{var}(m_{it}) = \mathrm{var}(m_{i,t-1})$, then the one-period correlation is:

$$\frac{\mathrm{cov}(y_{it}, y_{i,t-1}) + \mathrm{cov}(m_{it}, m_{i,t-1})}{\mathrm{var}(y_{it} + m_{it})} < \frac{\mathrm{cov}(y_{it}, y_{i,t-1})}{\mathrm{var}(y_{it})}.$$

Thus, the correlation of observed income underestimates the correlation of true income. Put differently, measurement error leads to overestimation of income mobility. As informal employment and subsistence farming are more common in China than in the West, there is arguably more noise in the CFPS income variables. One of the main results of this paper is that China has higher level of income mobility. Could this result be attributed to measurement error alone?

Consider the following: the correlation of observed income one period apart can be written as follows:

$$\begin{aligned} & \frac{\mathrm{cov}(y_{it}, y_{i,t-1}) + \mathrm{cov}(m_{it}, m_{i,t-1})}{\mathrm{var}(y_{it}) + \mathrm{var}(m_{it})} \\ = \quad & \frac{r(y_{it}, y_{i,t-1})\mathrm{var}(y_{it}) + r(m_{it}, m_{i,t-1})\mathrm{var}(m_{it})}{\mathrm{var}(y_{it}) + \mathrm{var}(m_{it})}. \end{aligned}$$

Table 2: Income correlation with measurement error m_t, given true income correlation 0.9 and true income variance of 1, by variance of m_t and correlation of m_t and m_{t-1}.

	$r(m_t, m_{t-1})$				
var(m_t)	0	-0.1	-0.2	-0.3	-0.4
0	0.90	0.90	0.90	0.90	0.90
0.1	0.82	0.81	0.80	0.79	0.78
0.2	0.75	0.73	0.72	0.70	0.68
0.3	0.69	0.67	0.65	0.62	0.60
0.4	0.64	0.61	0.59	0.56	0.53
0.5	0.60	0.57	0.53	0.50	0.47
0.6	0.56	0.53	0.49	0.45	0.41
0.7	0.53	0.49	0.45	0.41	0.36

Let us assume that the true correlation of log-income one period apart is 0.9, and standardise the variance as unity, then the above expression further simplifies to:

$$\frac{0.9 \times 1 + r(m_{it}, m_{i,t-1})\text{var}(m_{it})}{1 + \text{var}(m_{it})}$$

By plugging in different values of $r(m_{it}, m_{i,t-1})$ and var(m_{it}), we can compute the correlation of the observed log-income. This is summarised in Table 2. (We only consider negative values of $r(m_{it}, m_{i,t-1})$ because we wish to consider 'bad scenarios' for bias; positive ones reduce the bias.)

Recall that the observed correlations are 0.81 for Germany, 0.73 for the US, 0.62 for the UK, and 0.37 for China. If the true correlation of log-income of all four countries is 0.9, the observed correlation of Germany is consistent with var(m_t) $\approx$ 0.1 (second row of Table 2), var(m_t) $\approx$ 0.2 (third row) for the US, and var(m_t) $\approx$ 0.3 (fourth row) for the UK. Such large differences in var(m_t) are implausible, as GSOEP, PSID, and Understanding Society are all established panel studies with well-validated, high-quality data. It seems much more likely that the true correlation of log-income do differ among the three Western countries.

As regards the CFPS, although it is a new panel survey, preliminary validation work, which compares CFPS data with national statistics or other national surveys, suggests that the quality of its income data is quite high (Xie *et al.*, 2012; Xu *et al.*, 2012). Table 2 shows that it would take an implausibly large error variance (var(m_t) $\approx$ 0.7) for us to get an observed correlation of 0.37 if the true correlation for China is 0.9. Conversely put, it is very unlikely that the difference in the level of income mobility between China and the three Western countries is due to measurement error alone.

We can extend the above model by allowing measurement error to correlate with true income. This could arise if, for example, richer people under-report their income, perhaps due to a desire for concealment, and poorer people over-report theirs, say, because of embarrassment. Let $m_{it} = \delta(y_{it} - \mu_t) + \alpha_{it}$, where μ_t is the average true income at t, and α_{it} is white-noise error. We expect $\delta < 0$. In this case, the observed two-period correlation is:

$$\frac{(1 + 2\delta)\,\mathrm{cov}(y_{it}, y_{i,t-1}) + \mathrm{cov}(\alpha_{it}, \alpha_{i,t-1})}{\mathrm{var}(y_{it} + m_{it})},$$

where $\mathrm{var}(y_{it} + m_{it}) = (1 + \delta)^2\,\mathrm{var}(y_{it}) + \mathrm{var}(\alpha_{it})$.

Bound and Krueger (1991) and Bound *et al.* (1994) found with US data (PSID and the Current Population Survey) that δ may be in the region of -0.15 to -0.03. If we assume that $\delta = -0.1$, then the bottom row of Table 2 (which assumes $\delta = 0$) becomes 0.60, 0.56, 0.53, 0.50, and 0.46. But Bound and Krueger (1991) and Bound *et al.* (1994) also find positive correlation in α_{it} in the range of 0.10 to 0.15, and this offsets most of the differences produced by the negative correlation between measurement error and true log-income.

Similar results apply when we consider the impact of measurement error on income mobility over three or more periods. Details are available from the authors on request.

C Regression estimates

Table 3: Parameter estimates of full model

	Germany		UK		US	
age	.006**	.000	.004**	.000	.005**	.000
male	.017*	.009	.015*	.006	.063**	.012
junior high	.105**	.017	.068**	.009	.133**	.044
senior high	.246**	.023	.146**	.013	.398**	.040
vocational	.243**	.021	.207**	.019	.553**	.040
college	.446**	.018	.262**	.009	.863**	.040
working	.150**	.007	.320**	.006	.574**	.012
earners/hh size	.452**	.013	.546**	.012	1.090**	.024
married	.074**	.007	.140**	.007	.274**	.012
urban	.042**	.011	−.029**	.007	.065**	.016
constant	9.268**	.041	8.947**	.028	8.354**	.075
σ_u	.313		.303		.408	
σ_{vt}	.182		.304		.374	
# individuals	5,205		11,980		5,760	
# obs	15,595		35,819		17,250	

	China		China (Urban)		China (Rural)	
age	.007**	.000	.005**	.001	.008**	.001
male	−.034**	.012	−.017	.018	−.038*	.017
junior high	.135**	.014	.141**	.022	.133**	.019
senior high	.268**	.020	.296**	.027	.228**	.032
vocational	.616**	.036	.624**	.040	.432**	.100
college	.904**	.050	.921**	.052	.614**	.212
working	.084**	.013	.083**	.018	.064**	.020
earners/hh size	.832**	.027	.730**	.038	.894**	.038
married	.176**	.026	.155**	.036	.211**	.039
urban	.076**	.015				
hukou (urban)	.258**	.018	.287**	.021	.192**	.041
constant	9.036**	.100	9.168**	.111	8.945**	.149
σ_u	.447		.440		.448	
σ_{vt}	.788		.715		.829	
# individuals	11,379		4,615		6,282	
# obs	31,758		13,026		17,555	

D Further figures

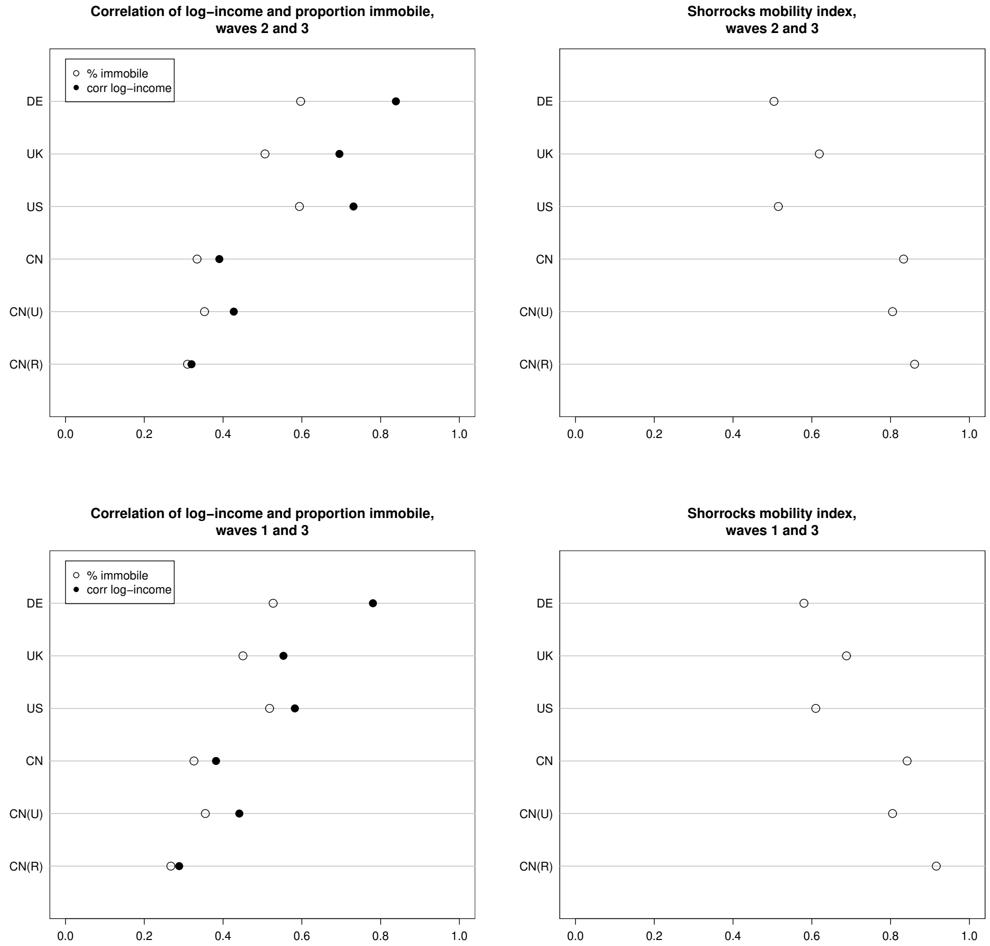

Figure 9: Income persistence and mobility (waves 2–3, waves 1–3) by country

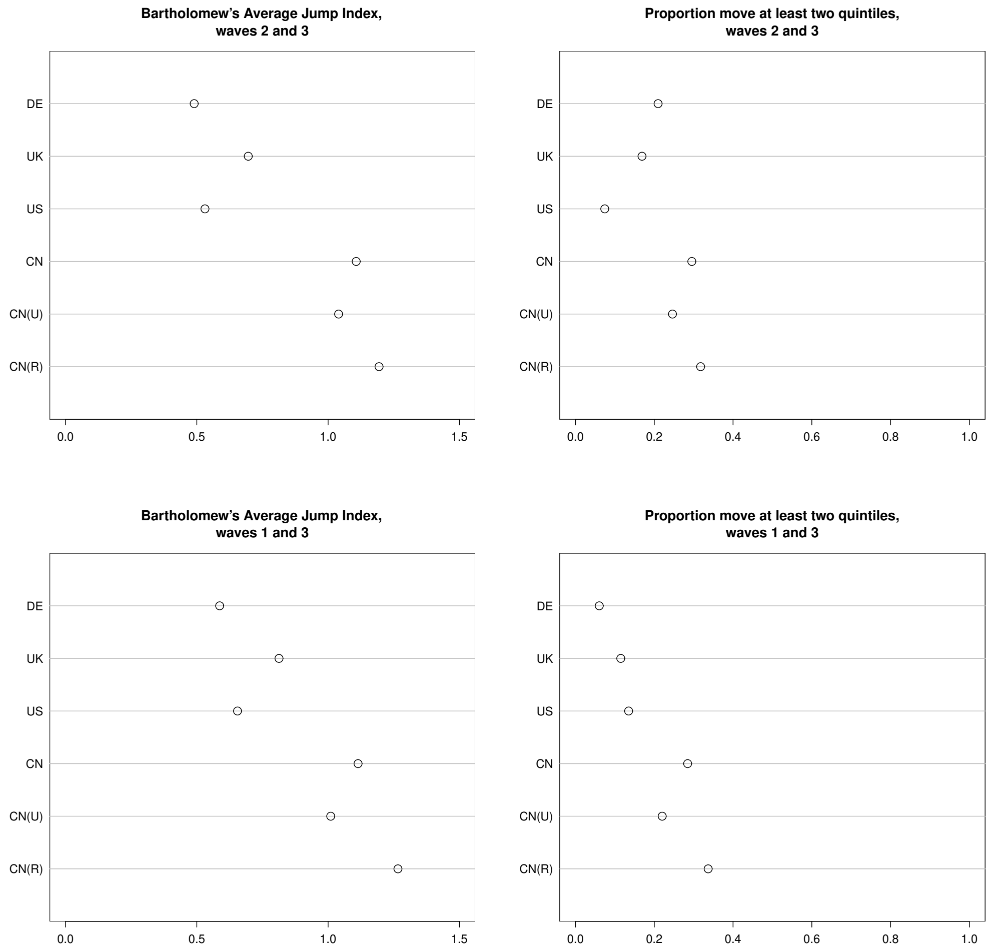

Figure 10: Long-range mobility (waves 2–3, waves 1–3) by country

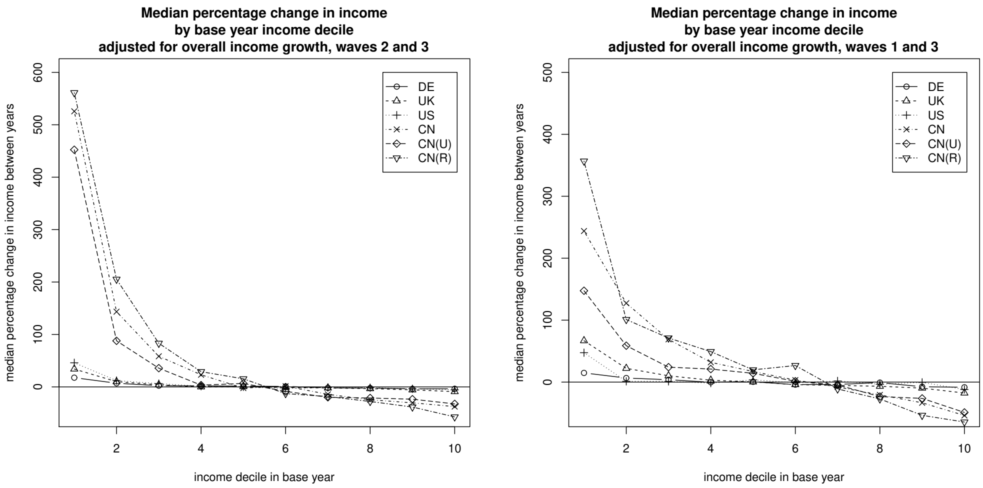

Figure 11: Median percentage change in income between wave 2 and 3 and wave 1 and 3 by base year income decile and by country