Income Mobility and Inequality in the UK

Research in Applied Economics EC331

Abstract

This paper presents an in-depth study of income mobility and its effects on 'permanent' inequality in the UK. The last five available waves of the British household panel survey (waves 9-13), are analysed using several methods in order to develop an understanding of income dynamics. It is shown that a large degree of mobility exists, although it is mainly 'short-range' in nature. Additionally using Shorrocks' immobility index it is shown that whilst the inequality reducing impact of mobility does increase over time, it reaches diminishing returns, suggesting an underlying 'permanent' inequality. Further analysis suggests that not only do females earn less than their male counterparts but they are also less mobile[1]; an important implication for those who point to income mobility as an antidote to an inequality of income.

Acknowledgements:

The author would like to thank Professor Ian Walker, Dr Michael Pitt, Dr Jeremy Smith and Giorgia Maffini for their advice and support throughout the period spent working on this paper.

Word Count: 5848[2]

[1] Mobile is used throughout this paper in the context of mobility through the income distribution.
[2] Not including contents, headers, footers, footnotes, appendix, references, abstract and tables.

Contents

I. Introduction

Using the last five available waves of the British Household Panel Survey (waves 9-13), this paper joins an expanding global literature dedicated to the measuring and understanding of income mobility and its impact on income inequality. The study tracks the same individuals over a five wave period, thus allowing for a longitudinal study to be undertaken. Several empirical and econometric techniques are used to gain an in-depth understanding of income dynamics in the UK today.

Income inequality and mobility and more importantly the interaction between the two, remain one of the key social issues in today's modern economy. The extent to which high levels of income mobility can mitigate the socially undesirable effects of large inequalities in income is much debated by those of a liberal and conservative persuasion. Conservatives argue that if high levels of mobility exist, this would make the extent of inequality during any time period insignificant, because the distribution of income over a longer period would be even. Additionally, if both mobility and inequality are rising, it is argued that, increasing inequality at any point in time can be tolerated, as high mobility suggests that those at the top of the distribution can only fall and those at the bottom of the distribution can only rise.

The argument as outlined above is simplistic in its understanding of the extent to which mobility can eradicate 'permanent' inequality and fails to address the possibility that different sub-groups of society can experience different levels of mobility. With inequality in the UK today remaining 'at historically high levels'[3], a greater understanding of income dynamics is required in order to assess the validity of the conservative argument.

Even if an economy could achieve high mobility simultaneously with high inequality, liberals would still argue that this presents a potentially socially undesirable scenario. For example, a situation could arise where society consistently rotates people in and

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[3] *Brewer, A. Goodman, J. Shaw, A. Shephard* (2005); **Poverty and Inequality in Britain 2005,** The Institute for Fiscal Studies, p28

out of poverty. However this does not mitigate the fact, that at any one time a certain proportion of the population are in poverty.

This paper aims to provide evidence which fuels the debate on UK income dynamics. The methods of analysis include the regression of several auto-regressive AR(1), models, (in some cases separating for quintile groups of origin and individual characteristics), the construction of Markov switching matrices and the computation and analysis of several recognised inequality indices.

The results suggest that a large degree of mobility exists, although it is largely 'short-range' in nature, moreover there appears to be greater mobility at the tails of the distribution. Additionally using Shorrocks' immobility index it is shown that whilst the inequality reducing impact of mobility does increase over time, it reaches diminishing returns, suggesting an underlying 'permanent' inequality. When considering how mobility differs across genders, results suggest that not only do females earn less than their male counterparts but they are also less mobile.

Therefore whilst mobility in income can reduce 'permanent' inequality, the effect is limited and still leaves society with significant 'permanent' inequalities. Moreover women not only have lower incomes but are also less mobile than men, meaning that they in fact receive no 'inequality benefit' as a result of mobility. Similar results were found for non-whites and those without a university education, although these findings failed to provide robust results.

The work undertaken complements an expanding literature on the subject of income mobility and inequality from around the globe. It sits nicely within the UK literature in that it updates previous work from Jarvis and Jenkins (1998), whose work concerned the first four waves of the BHPS[4]. I attempt to incorporate individual characteristics into the otherwise simple AR(1) models, to gain a greater understanding of how mobility differs for different groups in society, a method of analysis not noted elsewhere.

[4] British Household Panel Survey

II. Literature Review

There is a large global literature on the subject of income inequality and mobility. Each study uses a variety of different countries, over different time periods for analysis, each championing their own methods of investigation. The large literature available is symptomatic of the importance attached to the subject[5]. The authority on income inequality and income mobility in the United Kingdom, are Sarah Jarvis and Stephen Jenkins, based at the University of Essex. Their 1998 paper entitled *'How much Income Mobility is There in Britain?[6]'*, will form the bulk of the literature review, as it most closely analyses the relationships I wish to investigate, using the methods of analysis I wish to use. Much of the theory concerning 'permanent' inequality is derived from the work of Shorrocks (1978), in which he develops 'an index of mobility which reflects the variations in income over time'[7]. Other influential papers include Jarvis and Jenkins (1995) and Zurcher (2004), a study of income inequality and mobility in Switzerland[8]. Similar papers to Jarvis and Jenkins (1998) exist for studies in other countries, for example Canto (2000): 7 year mobility in Spain, Hauser and Fabig (1999): 1 year mobility in Germany, Smith (1994): 2 year mobility in the US and Hungerford (1993): 7 year mobility in the US.

Jarvis and Jenkins (1998), use the first four waves of the BHPS, covering the period 1991-4. The BHPS is a longitudinal database tracking individual households through time, thus it is ideal for calculating empirical measurements of income dynamics[9]. Jarvis and Jenkins use several methods to measure mobility. They use the Pearson Correlation between income levels in the different years in tandem with computing a simple regression of log income in wave t +1 against log income in wave t:

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[5] See Atkinson, A.B., Bourguihnon, F., and Morrisson, C. (1992). *'Empirical Studies of Earnings Mobility'*. . Churchill Harwood Academic Publishers, for a survey of the relevance of income mobility in social issues.

[6] S. Jarvis, S.P.Jenkins (1998), *'How Much Income Mobility is There is Britain?'*, The Economic Journal, Vol. 108, No.447,p. 428-443

[7] A.F.Shorrocks (1978).*' Income inequality and income Mobility'*. Journal of Economic Theory, vol 19, p. 383

[8] Many other studies from other countries exist, however the Zurcher paper, is particularly relevant due to the dynamic measure of income mobility used and its use of up to date data.

[9] A.F.Shorrocks (1978).*' Income inequality and income Mobility'*. Journal of Economic Theory, vol 19, p. 377

$$\ln(Y)_{i,t} = \alpha + \phi \ \ln(Y)_{i,t-1} + \upsilon_t \qquad (1)$$

The coefficient on the lagged dependant variable $\ln(Y)_{i,t-1}$ is used as a proxy for mobility[10]. They also calculate a form of Markov Switching Matrix, in order to gain greater understanding of the extent to which individuals move across different income groups. Additionally quintile regressions are performed to see whether there is more or less mobility at different parts of the income scale. They find that a good degree of mobility does exist albeit most changes in income involve only small changes up and down the income distribution, for example 90% of people are found to be in the same or neighbouring quintile group from wave 1-2; additionally a greater degree of mobility can be shown to exist in the tails of the distribution[11].

They extend this ‘simple’ analysis by making a distinction between permanent and transitory incomes. The measure they use was developed by Shorrocks and has been used in many other studies of this type (e.g. Zurcher). Shorrocks motivation was to replace ‘static’ measures of inequality, with ‘dynamic’ measures of changes through time[12]. He correctly predicted that aggregation of incomes over time would result in inequality falling as the accounting period was extended. He states that empirical confirmation of this requires longitudinal data sets[13].

Shorrocks index of income rigidity, R(m), is equal to the inequality of m-period incomes divided by the weighted sum of the inequalities within each of the m periods, where the weights are proportional to mean income in the period[14]. Jarvis and Jenkins used several inequality indices from the Generalised Entropy family, in addition to the Gini coefficient to find estimates of R(m). They found that according to the Gini coefficient, four wave inequality is almost one-tenth smaller than wave 1 inequality, a result of inequality reducing as the accounting period is extended. Their

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[10] Again a coefficient of 1 would imply no mobility.
[11] S. Jarvis, S.P.Jenkins (1998), *‘How Much Income Mobility is There is Britain?’*, The Economic Journal, Vol. 108, No.447,p. 431-432
[12] A.F.Shorrocks (1978).*’ Income inequality and income Mobility’*. Journal of Economic Theory, vol 19, p. 376
[13] Such as the BHPS used by Jarvis and Jenkins.
[14] A.F.Shorrocks (1978).*’ Income inequality and income Mobility’*. Journal of Economic Theory, vol 19, p. 385 and S. Jarvis, S.P.Jenkins (1998), *‘How Much Income Mobility is There is Britain?’*, The Economic Journal, Vol. 108, No.447,p. 435.

results also show that 'permanent inequality' is lower, when more emphasis is given to incomes at either tail of the distribution rather than the middle[15].

Shorrocks goes on to focus upon mobility and social welfare. He comes to the interesting conclusion that mobility is not necessarily desirable; a controversial idea, especially after discussing the inequality reducing effects of mobility. He suggests the uncertainty involved with large fluctuations of incomes around the same average level 'is disliked by individuals who prefer a stable flow'[16], and therefore in this context mobility may not be socially desirable.

Zurcher uses panel data from two periods 1980-2, and 1990-2[17] to investigate two issues; first life-cycle effects (the effect age has on income dynamics) and second the previously explained concept of 'permanent' inequality. He measures changes in both market and disposable income. Zurcher uses similar techniques as those employed by Jarvis and Jenkins (1998), in particular the use of Generalised Entropy measures of inequality coupled with a modified Shorrocks index of income mobility. Zurcher overcomes the life-cycle effects by conditioning inequality on age. He concludes by stating that inequality in market income is more persistent than inequality in disposable income. Furthermore he found that inequality in income opportunities increased between the 80s and 90s. However, the negative social implications associated with this trend have been largely mitigated by the increased mobility in disposable income over the same period. The distinction he makes between market and disposable income is an interesting one which Jarvis and Jenkins fail to explore.

Jarvis and Jenkins' earlier paper (1995) is the first attempt to use the BHPS data to analyse income dynamics. It is very much a cross-over paper, which highlights the differences from using cross-section data sets for example the FES which provide a snap-shot to the longitudinal data set of the BHPS. In the respect that they only had two waves available to them it is very much limited in scope. Nevertheless, it came to a similar conclusion to the 1998 paper: that Britain has a 'substantial amount of

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[15] That is to say the half the coefficient of the variation squared (top sensitive) or the mean log deviation and variance of the logarithms (bottom sensitive) are used.

[16] A.F.Shorrocks (1978).' *Income inequality and income Mobility'*. Journal of Economic Theory, vol 19, p. 392-3

[17] 1980-2 data taken from the Swiss income and Wealth Survey and the 1990-2 is taken from the Swiss national Poverty Survey.

income mobility from one year to the next, on the other hand, much of that mobility is relatively short range'[18].

In summary, Jarvis and Jenkins' (1998) approach seems to be pretty thorough; however it is somewhat limited. First, by design it is highly empirical in nature and fails to address the theoretical arguments surrounding the issues of whether mobility can act as a substitute for inequality or whether inequality is an unnecessary social bad, whatever the degree of mobility[19]. Second, largely due to the data available at the time of investigation the study only looks at 4 income waves; as a result only a limited picture of income dynamics can be developed which makes any conclusions about trends in the data difficult to back up. Third, although an attempt is made to investigate the affect of sex and age on income mobility, the methods used resemble a set of summary statistics rather than a more thorough analysis. A similar extension to this approach could be to analyse the effect of education and race on one's ability to move up and down the income scale.

In contrast to Jarvis and Jenkins, at my disposal are 13 waves of the BHPS covering the period 1991-2004. This paper contains a brief summary of income movements over the duration of that period[20], however for methodological necessity and simplicity not all of that period will be considered in detail. The primary analysis will consist of waves 9-13; the period 1998-2003. I employ many of the methods previously discussed; however, my treatment of quintile regressions differs in both its scope, and detail to that previously researched. I attempt to update and enhance the work already done, using established techniques (i.e Shorrocks), to provide a contemporary understanding of Britain's income dynamics today. When seeking to place this paper in context with the rest of the literature, Jarvis and Jenkins (1998) provides the best benchmark from which comparisons can be made.

[18] S. Jarvis, S.P.Jenkins (1995), *'Do the Poor Stay Poor?'*, New evidence from the BHPS, Occasional paper No.95-2. Colchester:ESRC Research Centre on Micro-Social Change, University of Essex.
[19] For an accessible overview of the topic see Krugman, P (1992), *'The Rich, the Right, and the Facts'*, American Prospect Online.
[20] For example, interquartile ranges of the income distribution for each period were calculated to provide a simple understanding of how the degree of inequality in income has changed.

III. Methodology

The majority of the conclusions drawn in this paper come from running a simple OLS auto-regressive equation and subsequently comparing the coefficients on the lagged dependent variables for each equation to get a proxy for the degree of mobility in that year[21]. To supplement this initial step a series of Pearson Correlations are calculated for adjacent waves[22]. Initially a series of regressions of the form below are run[23]:

$$\ln(Y)_{i,t} = \alpha + \phi \ \ln(Y)_{i,t-1} + \upsilon_t \qquad (1)$$

Where $\ln(Y)_{i,t}$ is log income for each individual in year *t*; which is then regressed against the log of income of the same individual in year *t-1*. α is the intercept and υ_t is the error term. A value of ϕ =1 would imply no mobility in income between the years in question, or rather all of the income in year *t* can be explained by the income in year *t-1*. Conversely a value of ϕ =0 would imply complete mobility. To understand how mobility changes as the time horizon expands other regressions are run with the lagged dependant variable becoming increasing lagged.

A Markov switching matrix is calculated to give a more in-depth look at the shape of mobility that is occurring. It is calculated by cross-tabulating decile group membership in one wave with the individual's decile group membership in subsequent waves. The Markov switching matrix shows the relative mobility of individuals in the sample, it gives no indication of absolute mobility. That is to say it could be possible that everyone's incomes fell during the year but yet an individual's relative position could still exhibit upward mobility.

Quintile regressions are also carried out with the observations restricted by quintile group of origin[24]. Five regressions are then carried out per pairwise wave period and

[21] This type of model may seem primitive because it contains no other variables other than the lagged variable of income itself, however 'it lends itself well to the modelling of the dynamics of the process', which is exactly what I wish to do. Source: *C. Dougherty (2002)* "Introduction to Econometrics", Oxford University Press, New York. p.364
[22] The Pearson Correlation is a common tool of analysis for longitudinal associations.
[23] See Table 3 in results section for summary of results.
[24] See table 4 for a set of summary results.

the coefficient on the lagged dependent variable is analysed in each case. Below are a generic set of equations for one pairwise relationship:

$$\begin{aligned}
\ln(Y)_{i,t} &= \alpha_1 + \phi_1 \ln(Y)^{Q1}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_2 + \phi_2 \ln(Y)^{Q2}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_3 + \phi_3 \ln(Y)^{Q3}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_4 + \phi_4 \ln(Y)^{Q4}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_5 + \phi_5 \ln(Y)^{Q5}_{i,t-1} + \upsilon_t
\end{aligned} \qquad (2)$$

The superscript Q1 identifies the individuals included in the regression are those which were in the lowest quintile in the period *t-1*. This method is preferable to simply comparing for each decile group the proportions of persons remaining in that group, as is the case with the Markov matrix. This suffers from over-estimating the relative immobility at the tails of the distribution, because, those individuals in the bottom decile cannot move down and those in the top decile cannot move up.

As the level of analysis deepens, the nature of the regression equation becomes more complex as qualitative variables are added to the basic regression equations (1) and (2). Regressions continue to be of the AR(1) OLS type, with a dummy variables[25] added controlling for race, gender and education effects[26]:

$$\ln(Y)_{i,t} = \alpha + \beta_1 sex + \phi \ \ln(Y)_{i,t-1} + \lambda_1 sex \ln(Y)_{i,t-1} + \upsilon_t \qquad (3)$$

Above is equation (1) with sex added as a dummy variable. Men are the control dummy (sex=0). The coefficient β_1 gives the difference in the intercept of women over men; and can be considered a proxy for inequality of wages between men and women, whilst the coefficient λ_1 gives a proxy for the difference in mobility of men compared to women. Again equation (3) can be broken down by quintiles to form a similar relationship to equation (2)[27]:

[25] Intercept and interaction.
[26] See table 9 for a set of summary results.
[27] See table 10 for a set of summary results.

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\begin{aligned}
\ln(Y)_{i,t} &= \alpha_1 + \beta_1 sex + \phi_1 \ln(Y)^{Q1}_{i,t-1} + \lambda_1 sex \ln(Y)^{Q1}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_2 + \beta_2 sex + \phi_2 \ln(Y)^{Q2}_{i,t-1} + \lambda_2 sex \ln(Y)^{Q2}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_3 + \beta_3 sex + \phi_3 \ln(Y)^{Q3}_{i,t-1} + \lambda_3 sex \ln(Y)^{Q3}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_4 + \beta_4 sex + \phi_4 \ln(Y)^{Q4}_{i,t-1} + \lambda_4 sex \ln(Y)^{Q4}_{i,t-1} + \upsilon_t \\
\ln(Y)_{i,t} &= \alpha_5 + \beta_5 sex + \phi_5 \ln(Y)^{Q5}_{i,t-1} + \lambda_5 sex \ln(Y)^{Q5}_{i,t-1} + \upsilon_t
\end{aligned}
\tag{4}
$$

The above allows an investigation into how inequality and mobility varies for men over women, at different parts of the income distribution. Initially each qualitative variable is added separately to equation (1) to form the type shown in (3). The next step is to combine together the qualitative variables into one large regression with a full set of interaction dummies for each wave-on-wave pairwise relationship.
The following example is best thought of an extension to equation (3) but with a further two qualitative variables added for race (non_white) and education (uni)[28]. The equation below allows investigation into how mobility changes for each of the different sub-groups in society and allows for direct comparisons among different groups.

$$
\begin{aligned}
\ln(Y)_{i,t} &= \alpha + \beta_1 sex + \beta_2 non\_white + \beta_3 uni + \phi \ \ln(Y)_{i,t-1} + \lambda_1 sex \ln(Y)_{i,t-1} \\
&+ \lambda_2 non\_white \ln(Y)_{i,t-1} + \lambda_3 uni \ln(Y)_{i,t-1} + \lambda_4 sex * non\_white \ln(Y)_{i,t-1} \\
&+ \lambda_5 sex * uni \ln(Y)_{i,t-1} + \lambda_6 non\_white * uni \ln(Y)_{i,t-1} \\
&+ \lambda_7 sex * non\_white * uni \ln(Y)_{i,t-1} + \upsilon_t
\end{aligned}
\tag{5}
$$

An alternative way to measure mobility is by computing a mobility index using one of several inequality indices as an index category. The model followed here is the one as outlined in Shorrocks (1978), and applied in Jarvis and Jenkins (1998) and Buchinsky and Hunt (1999); it is different to the methods already discussed as it does not impose some form of parametric model on the data. Shorrocks proposed that the inequality index for the average income during the accounting period (I) be compared to the average of the individual indexes in the accounting period (i). The Shorrocks' index of immobility can thus be defined as R(m)=I/i.

[28] See appendix, part 2, section J for the regression outputs.

More formally, suppose the population has size *n*, whose income is recorded in *m* consecutive periods. $Y_{i,t}$ is then defined as the income of person *i* in period *t*, and $Y_{i,t} = \sum_t Y_{i,t}$ is *i's* total income over all *m* periods:

Mean period *t* income: $\mu_t = (1/n)\sum_i Y_{i,t}$

Mean *m*-period income: $\mu = (1/n)\sum_i Y_i = \sum_t \mu_t$

If one then lets Y_t denote the vector $(Y_{1,t},......Y_{n,t})$, and $I(Y_t)$ be the inequality of this distribution, where *I* is a convex function of Y_t / μ_t, and in the same vein let *Y* denote the vector $(Y_1,.....,Y_n)$ with inequality $I(Y)$.

One can then define Shorrocks index: $R = I(Y)/\sum_t w_t I(Y_t)$

where weight $w_t = \mu_t / \mu$, the fraction of aggregate *m*-period income received in period *t*. The result being that the index must equal $0 \le R \le 1$[29].

The immobility index will therefore differ depending upon the inequality index originally applied. This paper presents four inequality indices the Mean Log Deviation GE(0), Theil index GE(1), Half the Coefficient of the Variation Squared GE(2) and the Gini Coefficient[30]. The degree of mobility typically varies inversely with R(m), and there is no mobility if R(m)=1. Additionally as the accounting period shortens R(m) typically increases.

Therefore outlined above are the main methods of analysis used in this paper:

- A series of OLS AR(1) type regressions
- The construction of Markov Switching Matrices
- Calculation of the Shorrocks immobility index

[29] Definition taken from: S. Jarvis, S.P.Jenkins (1998), *'How Much Income Mobility is There is Britain?'*, The Economic Journal, Vol. 108, No.447,p. 435

[30]The Half the coefficient of the variation squared; GE(2) (top sensitive),Theil coefficient; GE(1) (middle sensitive), Mean log deviation and variance of the logarithms; GE(0) (bottom sensitive) come from the Generalised Entropy (GE) family of inequality indices. Each one is more or less sensitive to incomes at different parts of the distribution as stated. The Gini coefficient does not come from this family but is commonly used as a measure of inequality it is known to be relatively sensitive to income changes in the middle of the distribution.

IV. Data Description and Preliminary Analysis

Data Source

The empirical section of this paper analyses data obtained from the BHPS, primarily waves 9-13[31]. The BHPS is a longitudinal panel data set which makes it an ideal tool for the investigation of income mobility and inequality[32]. Measurements of income and wealth have always been a fundamental part of the BHPS, making up part of what are termed the 'Core Questions'. In addition several qualitative variables are contained about each individual in the BHPS, enabling investigation into different sub-groups of society.

Process of Manipulation of Dataset: Waves 9-13

The results contained in section V of this paper are obtained by analysis of the final five waves of the BHPS available, waves 9-13. The data has been manipulated into a balanced panel. That is to say non-respondent individuals or those which have dropped out of the survey from waves 9-13 have been removed from the dataset, leaving only those who have provided data for each datapoint over the five years. This left a balanced panel of 8117 observations[33]. This raises certain issues with bias, which are discussed later. Income values for all years were then adjusted for inflation at 2004 prices[34]. The measure of income used is that of annual gross income. Gross income was used in preference to a measure of net income primarily as it distinguishes this work from that of Jarvis and Jenkins (1998), who used a computed figure for net income, thus it would be interesting to see if similar results were found given a different measure of income. Gross income has in its own right some interesting properties which make it a worthy choice. For example, it is a good approximation of social standing and relative valuation by employers. Additionally, by evaluating mobility and inequality solely in terms of income and not taking into account various forms of privately held wealth, measurement error due to short term

[31] The BHPS is conducted by the ESRC UK Longitudinal Studies Centre, together with the Institute for Social and Economic Research (ISER) at the University of Essex. All Data was obtained via the Data archive.
[32] A key benefit being that longitudinal data is able to control for unobserved heterogeneity
[33] For regressions involving qualitative variables the number of observations varies for each wave, the difference being explained by those who recorded an income of 0 for the year dropping out due to the logging process.
[34] All references to income, unless otherwise stated, refer to real income, adjusted for inflation at 2004 prices.

price movements is eliminated. In addition to income over 5 waves of the BHPS, the dataset constructed also contained information on the sex, race and educational attainment of the individuals. Dummy variables are constructed for each qualitative variable. The control individual in a regression containing all three qualitative variables would be a white male who had a university education[35].

Possible Problems with the Dataset: Bias, Measurement Error

The dataset constructed is a balanced panel, a decision born out of the desire to measure income sequences in all five waves. This raises the problem that the panel could in some way be biased. For example, the individuals who dropped out of the panel could predominately display a certain socio-economic trait and thus the dataset would be biased against this group of people. However regressions were carried out with an unbalanced panel and similar results were found, suggesting that no erroneous conclusions were reached as a result of the use of a balanced panel.

Measurement error is always a concern when analysing data. The main concern here is that the BHPS imputes some of the components of income, which could result in measurement error, and in inflating estimates of income mobility. However the BHPS staff are aware of these concerns, and follow strict guidelines which minimise any likelihood of measurement error. There is also concern that at the extremes of the income ranges; very poor and very rich individuals may be disingenuous over their exact income[36]. An outlier problem is worth noting here. If one refers to table 1 below one can see that the range of observations is very large, suggesting the data could suffer from an outlier problem, which could cause a test for the normality for the errors to fail (a necessary assumption for OLS to provide the best linear unbiased estimates). However as income values are logged, this process helps to mitigate the effects of outliers.

[35] See appendix part 1 for variable abbreviations.
[36] This is of particular concern for quintile regressions, where the distribution is split up.

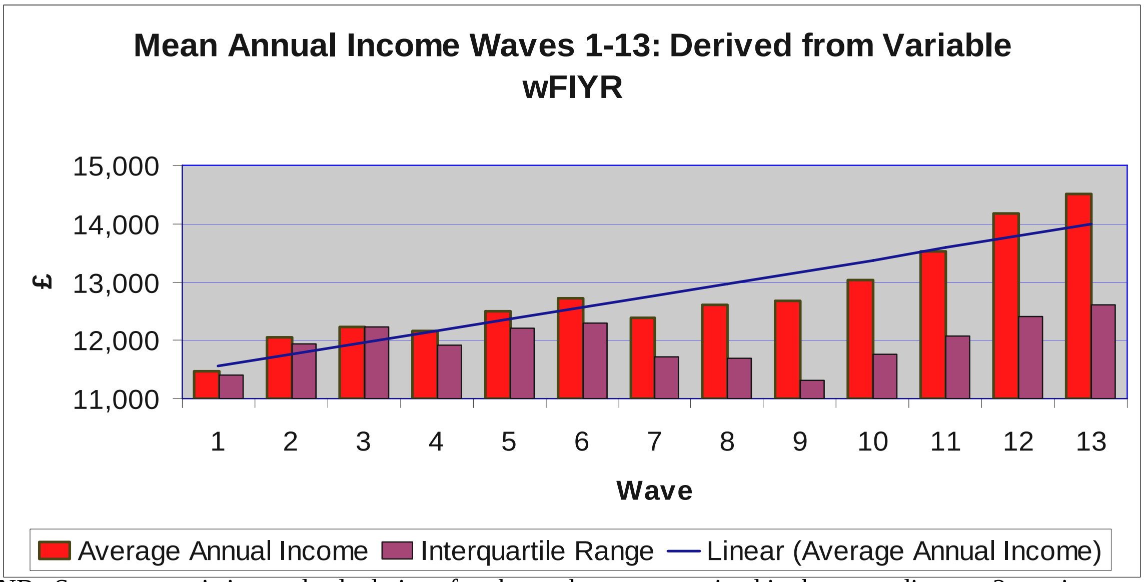
Summary Statistics W9-13 and Overview of Aggregate Income Data

Table 1: Summary Statistics for Income (£) Variable: Waves 9-13							
Wave	Mean	Standard Dev.	Lower Quartile	Upper Quartile	Median	Interquartile Range	Range
9	13,811	15,828	5,789	18,027	10,564	12,238	538,522
10	14,502	13,881	6,337	19,075	11,373	12,738	436,654
11	14,907	14,722	6,498	19,455	11,688	12,957	550,832
12	15,483	13,947	6,753	20,324	12,059	13,571	274,819
13	17,220	16,000	7,680	22,528	13,438	14,848	465,283

Above are the summary statistics for income for waves 9-13, as this is the primary period of analyses. Salient features to point out are that as one would expect both the mean and median income values are rising overtime, symptomatic of a strong and growing economy as was largely the case for the UK during the period 1999-2004. The interquartile range is quite large relative to average income, suggesting that a significant number of individuals earn relatively high and relatively low incomes, suggesting a large degree of inequality[37].

By way of examining longer term movements in income, figure 1 charts average annual income over each wave of the BHPS, with the corresponding interquartile range for that year:

Figure 1



NB. Summary statistics, and calculations for above chart are contained in the appendix, part 2, section A.

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[37] In this sense the interquartile range could be used as a proxy for inequality. However one must bear in mind that if every individual's income rose by the same rate of inflation then the interquartile range would automatically increase, in this way it is best thought of as a measure absolute inequality.

As one would expect the interquartile range to rise when mean income rises, it is interesting to observe what occurred in waves 8 and 9; a period in which annual mean incomes were rising and yet the interquartile range was falling. This could suggest that during this period, the incomes of the poor were rising quicker than the rich. A possible explanation being the introduction of the minimum wage, the effect of which was felt during this period.

Table 2 below gives the summary statistics for the three key qualitative variables used. Salient features include that out of the balanced panel sample of 8117, just over 55% are women, however as there are only two categories concerning gender, one would expect robust results. However the data for race and education is more problematic: over 97% of the sample being white and for education nearly 57% of the sample not answering 'none of the above', these factors might go some way to explaining the problems associated with obtaining robust results when using these qualitative variables.

TABLE 2: Summary Statistics for Qualitative Variables

Gender				Ethnic group membership				Type of further education attended		
	Freq.	**Percent %**			**Freq.**	**Percent %**			**Freq.**	**Percent %**
Male	3,642	44.87		Missing or wild	24	0.3		Missing or wild	34	0.42
Female	4,475	55.13		Inapplicable	14	0.17		Inapplicable	311	3.83
				Refused	4	0.05		Refused	1	0.01
Total	8,117	100		White	7,904	97.38		Don't know	6	0.07
				Black-Carib	19	0.23		Nursing school etc	246	3.03
				Black-African	13	0.16		College of further education	1,451	17.88
				Black-Other	9	0.11		Other training establishment	505	6.22
				Indian	67	0.83		Polytechnic	271	3.34
				Pakistani	24	0.3		University	699	8.61
				Bangladeshi	3	0.04		None of the above	4,593	56.58
				Chinese	4	0.05				
				Other ethnic group	32	0.39		Total	8,117	100
				Total	8,117	100				

V. Results

Year-on-Year Mobility

Table 3 below summarises the findings of the outputs of a series of AR(1) type models, whose outputs are contained in the appendix part 2 section B. Also contained are a set of Pearson correlations for each pairwise comparison. The slope coefficient on the regression of log income varies with the two waves being regressed[38]. Regressions are of the type as outlined in equation (1). All the variables were found to be significant at the 5 % significance level. However it is important to note here that the purpose of this paper is not to find an equation for the determinant of income but to investigate some of the properties of income mobility. As such it is possible that the regression equation maybe misspecified in terms of its predictive qualities of income, however following the standard methodology in this field, I do not consider that to be of concern. The AR(1) models used intuitively can be considered to be a stationary series as income in one year is likely to be related to income the previous year. As there is only one variable which changes through time there will be no issues with cointegration.

TABLE 3: Log Income Mobility Measures Waves 9-13: A Longitudinal Relationship

	Wave on Wave Comparison						
	W9-W10	W10-W11	W11-W12	W12-W13	W9-W11	W9-W12	W9-W13
(i) Slope coefficient on regression of log income	0.683	0.716	0.772	0.700	0.581	0.524	0.489
(ii) Pearson Correlation pairwise comparison	0.722	0.738	0.730	0.738	0.632	0.539	0.530

-Regression outputs and correlation matrix in appendix part 2, section B.

A number of interesting observations can be drawn from the above table. The first four columns of adjacent pairwise relationships suggest that there is a large degree of income fluctuations over just one wave period. If the coefficient on the lagged dependant variable were to equal 1 this would be the zero mobility case. The coefficient value is consistently around 0.7, implying that 70% of income in period *t* can be explained by income in the previous period *t-1*. This is supported by the correlation coefficient which again is significantly less than 1; implying mobility. As the wave interval increases the degree of mobility increases; this is an expected result,

[38] Thus W9-W10 gives the output for the log of income in wave 10 regressed on the log of income in W9.

however the slope coefficient for the longest time interval of five years (W9-W13) is 0.489, and the correlation coefficient is 0.53, suggesting that nearly one half of period *t* income is explained by period *t-5* income. This could suggest permanent underlying differences in income. Moreover as the wave interval increases both the regression coefficient and the correlation coefficient are declining by diminishing amounts, suggesting convergence to some level of permanent level of immobility.

TABLE 4: Log Income Mobility by Quintiles Waves 9-13: A longitudinal Relationship				
Slope Coefficient on regression of log income for each quintile between said waves				
Quintile	W9-W10	W10-W11	W11-W12	W12-W13
1	0.334	0.273	0.457	0.364
2	0.602	0.706	0.747	0.759
3	0.966	0.936	1.17	0.876
4	0.941	0.939	1.006	0.860
5	0.782	0.810	0.828	0.815

-Regression outputs in appendix, part 2, section C

Table 4 above summarises the output for a series of quintile regressions where the slope coefficient varies with the quintile of origin. Quintile 1 contains the 20% of the sample with the lowest income and quintile 5 contains the 20% with the highest income. The results suggest that there appears to be greatest mobility in the tail of the distribution (Quintile 1), meaning the incomes of the poorest in society change the most from one period to the next. This relationship is constant across all pairwise regressions and appears to be robust. Conversely the middle of the income distribution shows high levels of immobility, with the slope coefficients close to 1[39]. An initial conclusion is that significant mobility does exist, and it appears to be greater in the tail of the distribution and much less in the middle.

Controlling for Transitory Income Changes

Up until now no distinction has been made between permanent and transitory (or short term) income variations. To account for transitory changes in income, the log incomes in pairwise waves were averaged together to create a new income variable which will help overcome this problem of transitory income variations, to provide a

[39] One will notice that the coefficients for quintiles 3 and 4 for period W11-W12 are greater than one. However by inspection of the 95% confidence intervals in the regression output one will see that the true value could in fact equal one. See appendix, part 2, section C.

more stable relationship. More formally incomes in waves 10 and 11 and incomes in waves 12 and 13 were averaged together.

The Markov switching matrix below allows us to observe individuals movements within the income distribution. If no individual changed decile group from one period to the next one would expect the matrix to be diagonal. What is obvious is that the matrix is far from diagonal, showing that individuals do move between decile groups. However if one looks more closely at the destination of individuals, given their decile of origin it appears that most movement is short range. For example, for those individuals of origin decile 6, only 7% stay in that decile, however 58% are within one decile above or below. For those originating in the first decile 86% remain in the bottom three quintiles in the following time period. This pattern of short-range mobility is repeated throughout the matrix. Nevertheless some anomalies do exist for example 20% of individuals originating in decile 2 have moved up to the top decile[40]. This appears to be a strange result and maybe an example of measurement error of the type outlined previously. Nevertheless the matrix below does highlight the fact that a limited degree of mobility does exist albeit being mostly short-range.

TABLE 5: Markov Switching Matrix from Averaged Wave 10 and 11 Income to Averaged Wave 12 and 13 Income

Decile Income Group: W10-11	Decile Income group: W12-13										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
1	***63***	*15*	*8*	*2*	*1*	*0*	*1*	*1*	*7*	*2*	*100*
2	*16*	***21***	*16*	*12*	*2*	*1*	*4*	*4*	*4*	*20*	*100*
3	*6*	*18*	***19***	*9*	*8*	*11*	*7*	*17*	*4*	*1*	*100*
4	*5*	*7*	*21*	***22***	*18*	*6*	*1*	*6*	*10*	*4*	*100*
5	*2*	*6*	*8*	*16*	***17***	*14*	*14*	*5*	*9*	*9*	*100*
6	*1*	*5*	*2*	*8*	*29*	***7***	*22*	*7*	*14*	*5*	*100*
7	*0*	*0*	*2*	*2*	*5*	*30*	***36***	*4*	*13*	*8*	*100*
8	*1*	*5*	*6*	*10*	*15*	*15*	*3*	***27***	*12*	*6*	*100*
9	*2*	*9*	*5*	*11*	*9*	*11*	*13*	*17*	***9***	*14*	*100*
10	*4*	*14*	*13*	*6*	*5*	*10*	*1*	*11*	*11*	***25***	*100*

-Derivation of Markov Switching Matrix in appendix, part 2, section D

The results contained in tables 6 and 7 used the same methods as those found in tables 3 and 4. As one would expect when the two averaged income waves are regressed

[40] One might expect some movement from low deciles to high from those individuals leaving education (university) and entering employment for the first time. However it is likely that such movement would not be so great to move an individual from the second to top quintile.

together they show lower levels of income mobility[41]. Nevertheless, even with controlling for transitory changes in income, similar conclusions can be made; that a significant amount of mobility does exist, and as table 7 highlights there appears to be greater mobility for those at the bottom of the distribution.

TABLE 6: Averaged Log Income over wave pairs- Control for Transitory Income Changes	
	W10:11-W12:13
(i) Slope coefficient on regression of log income	0.814
(ii) Pearson Correlation pairwise comparison	0.785

-Regression output, in appendix, part 2, section E.

TABLE 7: Averaged Log Income over wave pairs: Mobility by Quintiles	
Slope Coefficient on regression of log income for each quintile between said waves	
Quintile	W10:11-W12:13
1	0.582
2	0.975
3	0.862
4	1.036
5	0.814

-Regression output, in appendix, part 2, section F.

<u>Mobility and 'Permanent' Inequality</u>

So far the analysis has concentrated solely on longitudinal mobility, mostly over one wave. This section attempts to bridge the gap between mobility and the notion of 'permanent' inequality. Compared to the mobility matrix an immobility index such as the one in shown in table 8 is superior as a method to measure mobility as it is sensitive to movements within deciles and does not depend upon the arbitrary allocation of percentiles. As previously mentioned four inequality indices have been computed[42]. From these Shorrocks immobility (R) index has been calculated.

Part (a) of table 8 is in two parts, first the values of the inequality indices for averaged income over the said number of *m* waves. Second, it details the movement of the

[41] For the averaged W10-11, W12-13 regression, the coefficient was 0.814, roughly 0.1 higher than under the basic pairwise regressions.
[42] Half the coefficient of the variation squared (top sensitive), the gini coefficient and the theil index (middle sensitive) and the mean log deviation and variance of the logarithms (bottom sensitive)

Shorrocks immobility index using the different inequality indices as the accounting period is extended. Part (b) of table 8 gives the value of the inequality indices for each year in isolation and allows the reader to note how inequality has changed over the time period.

The results as expected show that inequality declines as the time period increase, for example using the gini coefficient inequality in W9 was measured at 0.435 this fell to 0.391 for the averaged income over periods 9-13. Values for the immobility index (R) fall as the time period increases; this shows that inequality reducing effect of mobility increases over the accounting period but at a diminishing rate. Moreover it seems to be converging on a fixed position highlighting some position of 'permanent inequality'. The value of the immobility indexes are bigger for those inequality indexes sensitive to the middle part of the distribution, compared to the tails. This supports the earlier findings from the quintile regressions which suggest greater mobility in the tails.

TABLE 8: Inequality and Immobility Indices: Inequality reduction over time

(a)					
	W9	**W9+W10**	**W9+W10+W11**	**W9+W10+W11+W12**	**W9+W10+W11+W12+W13**
M	1	2	3	4	5
Inequality Indices					
Mean Log Deviation GE(0)	0.403	0.331	0.305	0.289	0.277
Theil GE (1)	0.352	0.307	0.288	0.274	0.265
Half the Coefficient of the Variation Squared GE(2)	0.657	0.488	0.426	0.380	0.364
Gini	0.435	0.414	0.404	0.397	0.391
Immobility Indices (R)					
Mean Log Deviation GE(0)	1.000	0.859	0.811	0.775	0.752
Theil GE (1)	1.000	0.923	0.883	0.855	0.837
Half the Coefficient of the Variation Squared GE(2)	1.000	0.876	0.798	0.756	0.746
Gini	1.000	0.967	0.951	0.939	0.929

(b)					
	W9	W10	W11	W12	W13
Inequality Indices					
Mean Log Deviation GE(0)	0.403	0.367	0.357	0.366	0.350
Theil GE (1)	0.352	0.313	0.312	0.305	0.302
Half the Coefficient of the Variation Squared GE(2)	0.657	0.458	0.488	0.406	0.432
Gini	0.435	0.420	0.419	0.419	0.414

Qualitative Effects: Gender

Now we begin to look at how mobility differs for various sub-groups of the population. Below is a summary of the outputs from a series of pairwise regression with a dummy variable added for sex. The summary below suggests that not only do women have lower incomes than men but they are also less mobile. With the exception of the regression for W9-W10, whose coefficients on both the intercept and interaction dummy for sex fail its t-tests, (and thus the coefficients should be treated with scepticism), all the other outputs are found to be significant. A negative value for the coefficient of intercept (row (iii)), suggests women are paid less then men (a proxy for inequality in income), whilst a positive coefficient for the slope dummy (row (ii)), suggests women are less mobile than men. It is surprising that for W9-W10 period this outcome was found, suggesting a spurious regression. As highlighted earlier the nature of the data is not ideal, which raises the question of measurement error.

TABLE 9: Log Income Mobility with Dummy Variables included for Sex: Waves 9-13

	Wave on Wave Comparison			
	W9-W10	W10-W11	W11-W12	W12-W13
(i) Slope coefficient on regression of log income	0.688	0.597	0.694	0.614
(ii)Slope Coefficient on Regression of log income (interaction dummy)	**-0.036**	0.139	0.038	0.105
(iii) Coefficient of Intercept	**0.133**	-1.502	-0.510	-1.500
(iv) Coefficient of Intercept with dummy	3.004	3.886	2.943	3.712

NB. Control Dummy is Male=0

Coefficients in bold indicate insignificant variables. See appendix for details.

-Regression output in appendix, part 2, section G.

Table 10 below gives a summary of the slope coefficients showing the additional mobility for women over men by quintile breakdown over 4 pairwise waves. Several interesting conclusions can be drawn. First, it appears that for the poorest quintile of the sample females seem to become progressively less mobile over this period. More interestingly for the top quintile women are consistently more mobile than men. A possible explanation, remembering that mobility works in both directions is that of career breaks. It is possible to assume that when women give birth and stop working, they immediately transfer from the top to the bottom quintile, resulting in a big negative coefficient.

TABLE 10: Value of Coefficient on interaction dummy variable of Log Income by Quintiles: Waves 9-13				
	Wave on Wave Comparison			
Quintile	W9-10	W10-11	W11-12	W12-13
1	-0.017	0.013	0.024	0.049
2	0.002	0.037	0.042	0.028
3	0.013	0.006	0.005	0.015
4	-0.048	-0.016	-0.054	0.008
5	-0.140	-0.136	-0.245	-0.118

NB. Control Dummy is Male=0

-Regression output in appendix, part 2, section H.

Qualitative Effects: Race and Education

A similar method of analysis was carried out for both race and education, however the results were not found to be stable or robust. No robust conclusions or inferences could be made from analyses undertaken. A possible explanation may lie in the nature of the dataset which was limited in the case of education by, non-respondance[43] , and in the case of race by a very high concentration of whites. Alternatively the regression outputs could be suggestive that no wave on wave relationship holds with any significance although this appears intuitively to be unlikely. Outputs for the regression run for both and race and education variables are included in the appendix part 2, sections I and J respectively.

It therefore follows that when an attempt was made to combine all three qualitative variables into one regression equation with a full set of interaction dummy variables, the outputs were not robust over all pairwise wave periods. Again the outputs for the combined regressions are available in the appendix, part 2, section K. Interestingly the one regression where the coefficients on the variables were found to be stable (W13-12), gave evidence suggesting that the control individual a white, male with a university education not only had a higher income but also had greater mobility. The suggestion is thus that a non-white, female without a university education, were all less mobile than their control counterparts. Reluctantly no comfort could be gained over these results as the findings were not robust over all the time periods.

[43] Shown by the ‘I don’t knows’ option on the survey.

VI. Conclusion

This paper through the use of several empirical and statistical techniques presents an analysis of income dynamics, mobility and inequality in the UK today. Several conclusions can be drawn from the work undertaken, the most salient of which are as follows.

- That a large degree of mobility does exist for the whole distribution, but in particular for those at the bottom of it.
- Most mobility can be described as being relatively short-range.
- That inequality declines as the time period increases.
- Mobility is shown to reduce inequality over time, however this effect decreases over time, converging to a level of ‘permanent inequality’.
- ‘Permanent Inequality’ is lower the more emphasis which is given to incomes in the tails of the distribution. (Effect of Mobility).
- Not only do females have lower incomes, but they also have less mobility.
- Females at the top of the income distribution are consistently more mobile than their male counterparts.

It was unfortunate that robust results could not be established with reference to the effect race and educational attainment has on mobility. Such a relationship must be possible to measure and thus any further work done on this area should strive to find a consistent and robust relationship. Possible reasons why such a relationship could not be determined with certainty may lie with the data used. (See data section).

Looking further afield possible extensions and applications to this paper are manifold. It would be interesting to extend the scope of this paper to incorporate the idea of the life-cycle model into the investigation of mobility. The key notion here is that mobility will occur naturally as one progresses through their working life. It would involve combining the three separate yet interlinked issues of convergence, inequality and mobility[44]. The majority of this study involved only 5 waves of the BHPS; a natural extension is thus to incorporate more waves into an analysis. In such a case

[44] See: *M.Beenstock (2004)* “Rank and Quantity Mobility in the Empirical Dynamics of Inequality”, Review of Income and Wealth, Series 50, Number 4: 519-541

one would have to deal with the problem of people dropping out of the survey. Finally it would be appealing to investigate if mobility was affected by regional variations; in the UK such a project would inevitably address the question of the north-south divide.

In many ways this paper only presents a preliminary discussion of income dynamics in the UK today, nevertheless the models used have allowed several interesting results to be found and it has updated and extended previous work with the most up-to-date data available.

VII. References

-*M.Beenstock (2004)* **“Rank and Quantity Mobility in the Empirical Dynamics of Inequality”**, Review of Income and Wealth, Series 50, Number 4: 519-541

-*J.Blanden, P.Gregg, S.Machin (April 2005),* **Intergenerational Mobility in Europe and North America,** A report supported by the Sutton Trust, Centre for Economic Performance

-*M. Brewer, A. Goodman, J. Shaw, A. Shephard* (2005); **Poverty and Inequality in Britain 2005,** The Institute for fiscal Studies

-M.*Buchinsky and J.Hunt (1999)* **“Wage mobility in the US”,** Review of Economics and Statistics, 81:351-368.

-*O. Canto (2000) “***Income mobility in Spain: how much is there?”** Review of Income and Wealth, 46: 85-102

-*C. Dougherty (2002)* **“Introduction to Econometrics”**, Oxford University Press, New York

-*R.Hauser and Fabig. H (1999)* **“Labour earnings and household income mobility in unified Germany: a comparison of eastern and western states”,** Review of Income and Wealth, 45: 303-324

-*T.L.Hungerford (1993)* **“Income mobility in the 70’s and 80’s”,** Review of Income and Wealth, 39: 403-417

-*S.Jarvis, S.P.Jenkins (1995), “***Do the poor stay poor?”,** *New evidence from the BHPS,* Occasional paper No. 95-2. Colchester: ESRC Research Centre on Micro-Social Change, University of Essex.

-*S. Jarvis, S.P.Jenkins (1998),* **“How Much Income Mobility is There is Britain?”**, The Economic Journal, Vol. 108, No.447,p. 428-443

-*S.P.Jenkins (1997),* **Recent Trends in the U.K income distribution: what happened and why.** Oxford review of Economic policy, vol.12 pp. 29-46.

-*P.Krugman (1992).* **The Rich, the Right, and the Facts,** The American Prospect no.11: 19-31

-*A.F.Shorrocks (1978).* **Income inequality and income Mobility.** Journal of Economic Theory, vol 19 pp, 376-93

-*P.K.Smith (1994)* **“Downward mobility: Is it growing?”** American Journal of Economics and Sociology, 53: 57-72

-*A.Taylor (1994).* **‘Appendix: sample characteristics, attrition and weighting’. *In Changing Households: the BHPS 1990-1992.*** (eds N.Buck, J Gershuny, D.Rose and

J.Scott). pp291-311. Colchester: ESRC Research Centre on Micro-Social Change, University of Essex.

- *M.F.Taylor (ed.) (1996).* **BHPS user manual, Introduction, Technical Reports and Appendices**. Colchester: ESRC Research Centre on Micro-Social Change, University of Essex.

-*B.A.Zurcher (2004).* **Income Mobility and Inequality: A Nonparametric Decomposition by Age for Switzerland in the 80's and 90's.** JEL Vol 140 (2) 265-292

<u>Data Source</u>

- British Household Panel Survey [computer file] principal investigator, ESRC Research Centre on Micro-social Change .-Colchester: The Data Archive [distributor], 199_ .-Data files and associated documentation.

The data used in this paper were made available through the ESRC Data Archive. The data was originally collected by the ESRC Research Centre on Microsocial Change at the University of Essex (now incorporated within the Institute for Social and Economic Research). Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here.

VIII. Appendix

PART 1

Variable Key

Abbreviation	**Variable**
lnincomeW9	Log income in wave 9
lnincome W10	Log income in wave 10
lnincome W11	Log income in wave 11
lnincome W12	Log income in wave 12
lnincome W13	Log income in wave 13
lnaverageincomeW12-13	Averaged log income of waves 12 and 13
lnaverageincomeW10-11	Averaged log income of waves 10 and 11
sex	Gender variable: sex=1, for female, 0 for male
Non_white	Race variable: non_white=1, for non-white, 0 for white
uni	Education variable: uni=1, for didn't go to university, 0 for did attend university

NB. Interaction dummy variables will take the form sex*lnincomeW10, which gives the incremental difference in income mobility in wave 10 for females over the control group males.

PART 2

Section A: Summary Stats for Income (£): Waves 1-13

Wave	Mean	IQ Range	S.D	Obs.	Inflation
1	11,462	11,399	11,287	9,699	1.35
2	12,049	11,949	12,310	9,237	1.328
3	12,218	12,227	11,389	8,794	1.296
4	12,166	11,910	11,598	8,838	1.254
5	12,500	12,211	12,893	8,645	1.219
6	12,710	12,292	12,064	8,907	1.186
7	12,388	11,704	12,376	10,585	1.148
8	12,616	11,690	14,759	10,332	1.121
9	12,674	11,314	15,074	14,637	1.099
10	13,038	11,750	12,538	14,597	1.07
11	13,522	12,074	13,293	17,345	1.057
12	14,168	12,412	14,693	15,150	1.026
13	14,506	12,620	17,651	14,745	1

Section B: Outputs of Regressions for Table 3 and Correlation Matrix

InincomeW10 on InincomeW9

Source	SS	df MS	Number of obs	= 8117	
		F(1, 8115)	= 8828.24		
Model	4195.82499	1 4195.82499	Prob > F	= 0.0000	
Residual	3856.84221	8115 .475273223	R-squared	= 0.5210	
		Adj R-squared	= 0.5210		
Total	8052.6672	8116 .99219655	Root MSE	= .6894	
lnincomeW10	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW9	.683332	.0072727 93.96	0.000	.6690756	.6975883
_cons	2.976441	.0668394 44.53	0.000	2.845419	3.107464

InincomeW11 on InincomeW10

Source	SS	df MS	Number of obs	= 8117	
		F(1, 8115)	F(1, 8115)	= 9678.22	
Model	4130.05657	14130.05657	Prob > F	= 0.0000	
Residual	3462.97124	8115 .42673706	R-squared	= 0.5439	
		Adj R-squared	Adj R-squared	= 0.5439	
Total	7593.02781	8116 .935562816	Root MSE	= .65325	
lnincomeW11	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
LnincomeW10	.7161568	.0072796 98.38	0.000	.7018868	.7304268
_cons	2.652697	.0674748 44.53	0.000	2.520429	2.784965

lnincomeW12 on lnincomeW11

Source	SS	df MS	Number of obs	= 8117	
		F(1, 8115)	= 9238.18		
Model	4528.81958	1 4528.81958	Prob > F	= 0.0000	
Residual	3978.20365	8115 .490228422	R-squared	= 0.5324	
		Adj R-squared	= 0.5323		
Total	8507.02323	8116 1.0481793	Root MSE	= .70016	
lnincomeW12	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW11	.7722982	.0080351 96.12	0.000	.7565473	.7880491
_cons	2.135926	.0747483 28.57	0.000	1.9894	2.282452

lnincomeW13 on lnincomeW12

Source	SS df	MS	Number of obs = 8117
	F(1, 8115) = 9709.94		
Model	4170.96999	1 4170.96999	Prob > F = 0.0000
Residual	3485.85239	8115 .429556671	R-squared = 0.5447
	Adj R-squared = 0.5447		
Total	7656.82238	8116 .943423161	Root MSE = .65541
lnincomeW13	Coef.	Std. Err. t	P>t [95% Conf. Interval]
lnincomeW12	.7002123	.0071059 98.54	0.000 .6862828 .7141417
_cons	2.904952	.0663534 43.78	0.000 2.774882 3.035022

lnincomeW11 on lnincomeW9

Source	SS	df MS	Number of obs	= 8117	
		F(1, 8115)	= 5406.87		
Model	3036.15612	13036.15612	Prob > F	= 0.0000	
Residual	4556.87169	8115 .561536869	R-squared	= 0.3999	
		Adj R-squared	= 0.3998		
Total	7593.02781	8116 .561536869	Root MSE	= .74936	
lnincomeW11	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]

lnincomeW9	.5812796	.0079052 73.53	0.000	.5657834	.5967758
_cons	3.945182	.0726525 54.3	0.000	3.802764	4.087599

InincomeW12 on InincomeW9

Source	SS	df MS	Number of obs	= 8117	
		F(1, 8115)	= 3320.22		
Model	2470.01548	1 2470.01548	Prob > F	= 0.0000	
Residual	6037.00775	8115 .743931947	R-squared	= 0.2904	
		Adj R-squared	= 0.2903		
Total	8507.02323	8116 1.0481793	Root MSE	= .86251	
lnincomeW12	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW9	.5242916	.0090989 57.62	0.000	.5064554	.5421278
_cons	4.494647	.0836234 53.75	0.000	4.330724	4.65857

InincomeW13 on InincomeW9

Source	SS	df MS	Number of obs	= 8117	
		F(1, 8115)	= 3170.10		
Model	2150.87802	1 2150.87802	Prob > F	= 0.0000	
Residual	5505.94436	8115 .678489755	R-squared	= 0.2809	
		Adj R-squared	= 0.2808		
Total	7656.82238	8116 .943423161	Root MSE	= .8237	
lnincomeW13	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW9	.4892501	.0086895 56.30	0.000	.4722165	.5062838
_cons	4.937063	.0798606 61.82	0.000	4.780515	5.09361

Pairwise Correlation Matrix

	ln(income)W9	ln(income)W10	ln(income)W11	ln(income)W12	ln(income)W13
ln(income)W9	1				
ln(income)W10	0.7218	1			
ln(income)W11	0.6323	0.7375	1		
ln(income)W12	0.5388	0.6164	0.7296	1	
ln(income)W13	0.53	0.6038	0.6712	0.7381	1

Section C: Outputs of Regressions for Table 4

InincomeW10 on InincomeW9

Quintile 1:

Source	SS df	MS	Number of obs = 1623
	F(1, 1621) = 202.33		
Model	212.617255	1 212.617255	Prob > F = 0.0000
Residual	1703.4586	1621 1.05086897	R-squared = 0.1110
	Adj R-squared = 0.1104		
Total	1916.07586	1622 1.18130447	Root MSE = 1.0251
lnincomeW10	Coef.	Std. Err. t	P>t [95% Conf. Interval]
lnincomeW9	.3344381	.0235121 14.22	0.000 .2883209 .3805554
_cons	5.579885	.180348 30.94	0.000 5.226146 5.933625

Quintile 2:

Source	SS	df MS	Number of obs	= 1624	
		F(1, 1622)	= 40.54		
Model	14.6727997	1 14.6727997	Prob > F	= 0.0000	
Residual	587.019198	1622 .361910726	R-squared	= 0.0244	
		Adj R-squared	= 0.0238		
Total	601.691998	1623 .37072828	Root MSE	= .60159	
lnincomeW10	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW9	.6024081	.0946096 6.37	0.000	.4168383	.7879779
_cons	3.538734	.8321205 4.25	0.000	1.90659	5.170878

Quintile 3:

Source	SS	df MS	Number of obs	= 1623	
		F(1, 1621)	= 83.50		
Model	24.4339546	1 24.4339546	Prob > F	= 0.0000	
Residual	474.321626	1621 .292610503	R-squared	= 0.0490	
		Adj R-squared	= 0.0484		
Total	498.75558	1622 .307494192	Root MSE	= .54093	
lnincomeW10	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW9	.9662481	.1057394 9.14	0.000	.7588478	1.173648
_cons	.2803472	.9799182 0.29	0.775	-1.641692	2.202387

Quintile 4:

Source	SS	df MS	Number of obs	= 1624	
		F(1, 1622)	= 120.33		
Model	22.1145763	1 22.1145763	Prob > F	= 0.0000	
Residual	298.08964	1622 .183779063	R-squared	= 0.0691	
		Adj R-squared	= 0.0685		
Total	320.204216	1623 .197291569	Root MSE	= .42869	
lnincomeW10	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW9	.9407084	.0857558 10.97	0.000	.7725045	1.108912
_cons	.5417269	.831581 0.65	0.515	-1.089359	2.172813

Quintile 5:

Source	SS	df MS	Number of obs	= 1623	
		F(1, 1621)	= 476.06		
Model	126.5828	1 126.5828	Prob > F	= 0.0000	
Residual	298.08964	1621 .265895849	R-squared	= 0.2270	
		Adj R-squared	= 0.2265		
Total	557.599972	1622 .343773102	Root MSE	= .51565	
lnincomeW10	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW9	.7815728	.035821 21.82.	0.000	.7113125	.8518332
_cons	.3691714	.3691714 5.89	0.000	1.449422	2.897628

InincomeW11 on InincomeW10

Quintile 1:

Source	SS	df MS	Number of obs =	1623
	F(1, 1621)	= 122.55		
Model	120.843351	1 120.843351	Prob > F	= 0.0000
Residual	1598.40863	1621 .986063313	R-squared	= 0.0703
	Adj R-squared	= 0.0697		
Total	1719.25198	1622 1.05995806	Root MSE	= .99301
LnincomeW11	Coef.	Std. Err. t	P>t [95% Conf.	Interval]
Lnincomew10	.2727843	.0246411 11.07	0.000 .2244525	.3211161
_cons	6.017523	.1929466 31.19	0.000 5.639072	6.395974

Quintile 2:

Source	SS	df MS	Number of obs	= 1624	
		F(1, 1622)	= 52.62		
Model	18.9522896	1 18.9522896	Prob > F	= 0.0000	
Residual	584.219899	1622 .360184895	R-squared	= 0.0314	
		Adj R-squared	= 0.0308		
Total	603.172189	1623 .371640289	Root MSE	= .60015	
LnincomeW11	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW10	.7061209	.0973444 7.25	0.000	.5151869	.8970548
_cons	2.595114	.8642562 3.00	0.003	.8999385	4.29029

Quintile 3:

Source	SS	df MS	Number of obs	= 1623	
		F(1, 1621)	= 102.05		
Model	20.0780383	1 20.0780383	Prob > F	= 0.0000	
Residual	318.911666	1621 .19673761	R-squared	= 0.0592	
		Adj R-squared	= 0.0586		
Total	338.989704	1622 .208994885	Root MSE	= .44355	
lnincomeW11	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW10	.9360982	.0926626 10.10	0.000	.7543471	1.117849
_cons	.548291	.8651043 0.63	0.526	-1.148549	2.245131

Quintile 4:

Source	SS	df MS	Number of obs	= 1624	
		F(1, 1622)	= 147.69		
Model	21.7273396	1 21.7273396	Prob > F	= 0.0000	
Residual	238.625964	1622 .14711835	R-squared	= 0.0835	
		Adj R-squared	= 0.0829		
Total	260.353304	1623 .160414851	Root MSE	= .38356	
lnincomeW11	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW10	.9390062	.0772678 12.15	0.000	.787451	1.090561
_cons	.55195	.7534763 0.73	0.464	-.9259392	2.029839

Quintile 5:

Source	SS	df MS	Number of obs	= 1623	
		F(1, 1621)	= 699.09		
Model	118.317403	1 118.317403	Prob > F	= 0.0000	
Residual	274.347684	1621 .169245949	R-squared	= 0.3013	
		Adj R-squared	= 0.3009		
Total	392.665087	1622 .242086983	Root MSE	= .4114	
lnincomeW11	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW10	.8098738	.0306304 26.44	0.000	.7497946	.8699531
_cons	1.887151	.3171034 5.95	0.000	1.265175	2.509127

lnincomeW12 on lnincomeW11

Quintile 1:

Source	SS	df MS	Number of obs	= 1623	
		F(1, 1621)	= 284.11		
Model	299.014764	1 299.014764	Prob > F	= 0.0000	
Residual	1706.04924	1621 1.05246714	R-squared	= 0.1491	
		Adj R-squared	= 0.1486		
Total	2005.064	1622 1.23616769	Root MSE	= 1.0259	
lnincomeW12	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW11	.4570213	.027114 16.86	0.000	.403839	.5102035
_cons	4.574387	.2142849 21.35	0.000	4.154083	4.994692

Quintile 2:

Source	SS	df MS	Number of obs	= 1624	
		F(1, 1622)	= 48.26		
Model	20.8992031	1 20.8992031	Prob > F	= 0.0000	
Residual	702.424973	1622 .433061019	R-squared	= 0.0289	
		Adj R-squared	= 0.0283		
Total	723.324176	1623 .445671088	Root MSE	= .65807	
lnincomeW12	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW11	.7468509	.1075087 6.95	0.000	.5359804	.9577215
_cons	2.273333	.9577142 2.37	0.018	.3948463	4.151821

Quintile 3:

Source	SS	df MS	Number of obs	= 1623
		F(1, 1621)	= 87.18	
Model	34.385557	1 34.385557	Prob > F	= 0.0000
Residual	639.386625	1621 .39443962	R-squared	= 0.0510
		Adj R-squared	= 0.0504	

Total	673.772182	1622 .41539592	Root MSE	= .62804	
lnincomeW12	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW11	1.171675	.12549 9.34	0.000	.9255349	1.417814
_cons	-1.674181	1.175 -1.42	0.154	-3.978859	.630497

Quintile 4:

Source	SS df	MS	Number of obs =	1624
	F(1, 1622)	= 131.70		
Model	23.7236409	1 23.7236409	Prob > F	= 0.0000
Residual	292.18106	1622 .180136289	R-squared	= 0.0751
	Adj R-squared	= 0.0745		
Total	315.904701	1623 .194642453	Root MSE	= .42442
lnincomeW12	Coef.	Std. Err. t	P>t [95% Conf.	Interval]
lnincomeW11	1.006207	.0876793 11.48	0.000 .83423	1.178183
_cons	-.1016442	.8570794 -0.12	0.906 -1.782743	1.579455

Quintile 5:

Source	SS	df MS	Number of obs	= 1623	
		F(1, 1621)	= 481.06		
Model	126.985659	1 126.985659	Prob > F	= 0.0000	
Residual	427.893337	1621 .263968746	R-squared	= 0.2289	
		Adj R-squared	= 0.2284		
Total	554.878996	1622 .342095559	Root MSE	= .51378	
lnincomeW12	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
lnincomeW11	.8274553	.0377262 21.93	0.000	.7534579	.9014526
_cons	1.710952	.3914452 4.37	0.000	.9431598	2.478743

lnincomeW13 on lnincomeW12

Quintile 1:

Source	SS df	MS	Number of obs =	1623
	F(1, 1621)	= 305.38		
Model	280.822889	1 280.822889	Prob > F	= 0.0000
Residual	1490.64217	1621 .919581844	R-squared	= 0.1585
	Adj R-squared	= 0.1580		
Total	1771.46506	1622 1.09214862	Root MSE	= .95895
lnincomeW13	Coef.	Std. Err. t	P>t [95% Conf.	Interval]
lnincomeW12	.3643562	.02085 17.48	0.000 .3234605	.4052519
_cons	5.45476	.1652166 33.02	0.000 5.130699	5.778821

Quintile 2:

Source	SS df	MS	Number of obs =	1624
	F(1, 1622)	= 61.52		
Model	20.318133	1 20.318133	Prob > F	= 0.0000
Residual	535.712695	1622 .330279097	R-squared	= 0.0365
	Adj R-squared	= 0.0359		
Total	556.030828	1623 .342594472	Root MSE	= .5747
lnincomeW13	Coef.	Std. Err. t	P>t [95% Conf.	Interval]
lnincomeW12	.7592387	.0968004 7.84	0.000 .5693718	.9491056
_cons	2.237415	.8655502 2.58	0.010 .5397005	3.935129

Quintile 3:

Source SS	df MS	Number of obs = 1623		
		F(1, 1621) = 80.14		
Model	19.7129286	1 19.7129286	Prob > F = 0.0000	
Residual	398.755694	1621 .245993642	R-squared = 0.0471	
		Adj R-squared = 0.0465		
Total	418.468623	1622 .257995452	Root MSE = .49598	
lnincomeW13	Coef.	Std. Err. t	P>t	[95% Conf. Interval]
lnincomeW12	.8756045	.0978125 8.95	0.000	.6837522 1.067457
_cons	1.21351	.9191716 1.32	0.187	-.5893788 3.0164

Quintile 4:

Source	SS df	MS	Number of obs = 1624
	F(1, 1622) = 107.83		
Model	18.0585966	1 18.0585966	Prob > F = 0.0000
Residual	271.64732	1622 .167476769	R-squared = 0.0623
	Adj R-squared = 0.0618		
Total	289.705917	1623 .178500257	Root MSE = .40924
lnincomeW13	Coef.	Std. Err. t	P>t [95% Conf. Interval]
lnincomeW12	.8602369	.0828425 10.38	0.000 .6977473 1.022727
_cons	1.414065	.8131054 1.74	0.082 -.1807828 3.008912

Quintile 5:

Source	SS df	MS	Number of obs = 1623
	F(1, 1621) = 460.50		
Model	123.016051	1 123.016051	Prob > F = 0.0000
Residual	433.026578	1621 .267135458	R-squared = 0.2212
	Adj R-squared = 0.2208		
Total	556.042629	1622 .342812965	Root MSE = .51685
LnincomeW13	Coef.	Std. Err. t	P>t [95% Conf. Interval]
LnincomeW12	.8152602	.037991 21.46	0.000 .7407435 .8897769
_cons	1.894136	.3958705 4.78	0.000 1.117664 2.670608

<u>Section D: Derivation of inputs for Markov Switching Matrix (Table 5)</u>

Origin: Decile 1

Proportion estimation	Number of obs = 811
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .6263872	.0169977 .5930225 .6597519
2 | .1504316	.0125611 .1257755 .1750876
3 | .0838471	.0097384 .0647317 .1029625
4 | .0246609	.0054493 .0139645 .0353573
5 | .0110974	.0036808 .0038723 .0183225
6 | .001233	.001233 -.0011873 .0036534
7 | .0061652	.0027504 .0007666 .0115639
8 | .0061652	.0027504 .0007666 .0115639
9 | .0715166	.0090542 .0537443 .089289
10 | .0184957	.0047341 .0092031 .0277883

Origin: Decile 2

Proportion estimation	Number of obs = 811
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .1578298	.0128101 .132685 .1829747
2 | .2096178	.0143018 .1815448 .2376907
3 | .1639951	.01301 .1384578 .1895324
4 | .1233046	.0115524 .1006284 .1459807
5 | .0160296	.0044128 .0073678 .0246914
6 | .0061652	.0027504 .0007666 .0115639
7 | .0382244	.006737 .0250004 .0514484
8 | .0369914	.0066317 .0239741 .0500087
9 | .0419236	.0070418 .0281011 .055746
10 | .2059186	.0142082 .1780295 .2338078

Origin: Decile 3

Proportion estimation	Number of obs = 812
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .0615764	.008441 .0450075 .0781452
2 | .1773399	.0134123 .151013 .2036668
3 | .1908867	.0138001 .1637986 .2179748
4 | .0899015	.0100442 .0701857 .1096173
5 | .0788177	.0094618 .0602452 .0973903
6 | .1083744	.0109155 .0869484 .1298004
7 | .0665025	.0087491 .0493288 .0836761
8 | .179803	.0134849 .1533336 .2062723
9 | .0394089	.0068321 .0259981 .0528196
10 | .0073892	.0030073 .0014862 .0132922

Origin: Decile 4

Proportion estimation	Number of obs = 812
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .0480296	.0075085 .0332911 .062768
2 | .070197	.0089711 .0525878 .0878063
3 | .2105911	.0143173 .1824878 .2386944
4 | .2167488	.0144683 .188349 .2451486
5 | .1785714	.0134487 .1521731 .2049698
6 | .0640394	.0085969 .0471646 .0809142
7 | .0073892	.0030073 .0014862 .0132922
8 | .0603448	.0083617 .0439317 .0767579
9 | .1022167	.0106374 .0813366 .1230969
10 | .0418719	.0070334 .0280662 .0556777

Origin: Decile 5

Proportion estimation	Number of obs = 812
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .023399	.0053082 .0129796 .0338184
2 | .0615764	.008441 .0450075 .0781452
3 | .0800493	.0095291 .0613447 .0987538
4 | .1637931	.0129955 .1382842 .189302
5 | .1650246	.0130347 .1394389 .1906103
6 | .137931	.0121085 .1141633 .1616988
7 | .135468	.0120171 .1118798 .1590562
8 | .0529557	.0078638 .0375199 .0683914
9 | .0899015	.0100442 .0701857 .1096173
10 | .0899015	.0100442 .0701857 .1096173

Origin: Decile 6

Proportion estimation	Number of obs = 812
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .0073892	.0030073 .0014862 .0132922
2 | .0480296	.0075085 .0332911 .062768
3 | .0160099	.0044074 .0073587 .024661
4 | .0837438	.0097269 .064651 .1028367
5 | .294335	.0160033 .2629222 .3257478
6 | .0726601	.009115 .0547683 .0905519
7 | .2192118	.0145274 .1906961 .2477276
8 | .067734	.0088239 .0504135 .0850545
9 | .135468	.0120171 .1118798 .1590562
10 | .0554187	.0080341 .0396486 .0711888

Origin: Decile 7

Proportion estimation	Number of obs = 812
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .0036946	.0021304 -.0004872 .0078764
2 | .0024631	.0017406 -.0009535 .0058796
3 | .0160099	.0044074 .0073587 .024661
4 | .0197044	.0048803 .0101248 .029284
5 | .046798	.0074164 .0322403 .0613557
6 | .296798	.0160421 .2653092 .3282869
7 | .3559113	.0168125 .3229101 .3889126
8 | .044335	.007228 .0301473 .0585227
9 | .1317734	.0118774 .1084594 .1550874
10 | .0825123	.0096616 .0635476 .101477

Origin: Decile 8

Proportion estimation	Number of obs = 812
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .0110837	.0036763 .0038675 .0183
2 | .046798	.0074164 .0322403 .0613557
3 | .0554187	.0080341 .0396486 .0711888
4 | .1046798	.01075 .0835786 .125781
5 | .1514778	.0125891 .1267667 .176189
6 | .1453202	.0123753 .1210289 .1696115
7 | .0344828	.0064072 .021906 .0470595
8 | .2697044	.0155841 .2391144 .3002944
9 | .1194581	.0113887 .0971034 .1418128
10 | .0615764	.008441 .0450075 .0781452

Origin: Decile 9

Proportion estimation	Number of obs = 810
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .0209877	.0050397 .0110953 .03088
2 | .0938272	.0102517 .0737041 .1139502
3 | .054321	.0079686 .0386794 .0699625
4 | .1123457	.0111026 .0905523 .134139
5 | .0864198	.0098788 .0670286 .1058109
6 | .1111111	.0110491 .0894228 .1327995
7 | .1333333	.0119515 .1098738 .1567929
8 | .1716049	.0132559 .1455849 .197625
9 | .0765432	.0093473 .0581953 .0948911
10 | .1395062	.0121814 .1155953 .163417

Origin: Decile 10

Proportion estimation	Number of obs = 813
|	Binomial Wald
| Proportion	Std. Err. [95% Conf. Interval]
Decile1312 |	
1 | .0393604	.0068239 .0259659 .0527549
2 | .1389914	.01214 .1151619 .1628209
3 | .1291513	.0117691 .1060499 .1522527
4 | .0615006	.008431 .0449515 .0780497
5 | .0467405	.0074075 .0322003 .0612807
6 | .104551	.0107376 .0834744 .1256277
7 | .00369	.0021278 -.0004866 .0078667
8 | .1107011	.0110109 .089088 .1323142
9 | .1143911	.0111696 .0924664 .1363159
10 | .2509225	.0152144 .2210583 .2807867

Section E: Output of Regression for Table 6

InaverageincomW12-13 on InaverageincomeW10-11

Source	SS	df MS	Number of obs	= 8117	
		F(1, 8115)	=14273.88		
Model	3906.46618	1 3906.46618	Prob > F	= 0.0000	
Residual	2220.9075	8115 .273679297	R-squared	= 0.6375	
		Adj R-squared	= 0.6375		
Total	6127.37368	8116 .754974578	Root MSE	= .52314	
InaverageincomeW12-13	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
InaverageincomeW10-11	.8138412	.0068119 119.47	0.000	.8004881	.8271943
_cons	1.836444	.06348 28.93	0.000	1.712007	1.960881

Section F: Outputs of Regressions for Table 7

InincomeW1011 on InincomeW1213

Quintile 1:

Source	SS df	MS	Number of obs = 1623
	F(1, 1621) = 408.99		
Model	217.913758	1 217.913758	Prob > F = 0.0000
Residual	863.675717	1621 .532804267	R-squared = 0.2015
	Adj R-squared = 0.2010		
Total	1081.58947	1622 .666824584	Root MSE = .72993
Inaverageincome1213	Coef.	Std. Err. t	P>t [95% Conf. Interval]
Lnaverageincome1011	.5822393	.0287901 20.22	0.000 .5257696 .638709
_cons	3.717756	.2317636 16.04	0.000 3.263168 4.172344

Quintile 2:

Source	SS	df MS	Number of obs	= 1624	
		F(1, 1622)	= 123.86		
Model	28.4010751	1 28.4010751	Prob > F	= 0.0000	
Residual	371.926626	1622 .229301249	R-squared	= 0.0709	
		Adj R-squared	= 0.0704		
Total	400.327701	1623 .246659089	Root MSE	= .47885	
InaverageincomeW1213	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
InaverageincomeW1011	.9750387	.0876108 11.13	0.000	.8031965	1.146881
_cons	.3234389	.7811701 0.41	0.679	-1.20877	1.855648

Quintile 3:

Source	SS	df MS	Number of obs	= 1623	
		F(1, 1621)	= 75.98		
Model	17.1672027	1 17.1672027	Prob > F	= 0.0000	
Residual	366.275706	1621 .225956636	R-squared	= 0.0448	
		Adj R-squared	= 0.0442		
Total	383.442909	1622 .2364013	Root MSE	= .47535	
InaverageincomeW1213	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
InaverageincomeW1011	.8622394	.0989215 8.72	0.000	.668212	1.056267
_cons	1.346678	.9252421 1.46	0.146	-.4681184	3.161474

Quintile 4:

Source	SS	df MS	Number of obs	= 1624	
		F(1, 1622)	= 207.74		
Model	26.5454375	1 26.5454375	Prob > F	= 0.0000	
Residual	207.259292	1622 .127780081	R-squared	= 0.1135	
		Adj R-squared	= 0.1130		
Total	233.804729	1623 .144057134	Root MSE	= .35746	
InaverageincomeW1213	Coef.	Std. Err. t	P>t	[95% Conf.	Interval]
InaverageincomeW1011	1.035772	.0718623 14.41	0.000	.8948196	1.176725
_cons	-.3145888	.7012908 -0.45	0.654	-1.69012	1.060942

Quintile 5:

Source	SS df	MS	Number of obs =	1623
	F(1, 1621)	= 535.81		
Model	116.728515	1 116.728515	Prob > F	= 0.0000
Residual	353.142663	1621 .21785482	R-squared	= 0.2484
	Adj R-squared	= 0.2480		
Total	469.871178	1622 .2896863	Root MSE	= .46675
InaverageincomeW1213	Coef.	Std. Err. t	P>t [95% Conf.	Interval]
InaverageincomeW1011	.814297	.0351786 23.15	0.000 .7452968	.8832972
_cons	1.907583	.3642148 5.24	0.000 1.193202	2.621965

Section G: Outputs of Regressions for Table 9

Wave 13-12

Source	|	SS	df	MS	Number of obs	=	8409
		F(3, 8405)	=	3401.29			
Model	|	4760.96761	3	1586.9892	Prob > F	=	0.0000
Residual	|	3921.64395	8405	.466584646	R-squared	=	0.5483
		Adj R-squared	=	0.5482			
Total	|	8682.61156	8408	1.03266075	Root MSE	=	.68307

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.6140216	.0107558	57.09	0.000	.5929376	.6351056
sex	|	-1.150498	.1357411	-8.48	0.000	-1.416584	-.8844119
Sex*lnincome12	|	.1048098	.0145769	7.19	0.000	.0762355	.1333841
_cons	|	3.712395	.103154	35.99	0.000	3.510188	3.914602

Wave12-11

Source	|	SS	df	MS	Number of obs	=	8405
		F(3, 8401)	=	2977.74			
Model	|	4872.92952	3	1624.30984	Prob > F	=	0.0000
Residual	|	4582.6153	8401	.545484501	R-squared	=	0.5154

		Adj R-squared	=	0.5152			
Total	|	9455.54482	8404	1.12512432	Root MSE	=	.73857

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.6940213	.0128958	53.82	0.000	.6687423	.7193002
sex	|	-.5099415	.1564707	-3.26	0.001	-.8166625	-.2032204
Sex*lnincome11	|	.0377142	.0168441	2.24	0.025	.0046957	.0707327
_cons	|	2.942606	.1231012	23.90	0.000	2.701297	3.183915

Wave 11-10

Source	|	SS	df	MS	Number of obs	=	8397
		F(3, 8393)	=	3474.58			
Model	|	4844.09009	3	1614.6967	Prob > F	=	0.0000
Residual	|	3900.36604	8393	.464716554	R-squared	=	0.5540
		Adj R-squared	=	0.5538			
Total	|	8744.45612	8396	1.04150264	Root MSE	=	.6817

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.5965942	.0108357	55.06	0.000	.5753535	.6178349
sex	|	-1.502429	.135123	-11.12	0.000	-1.767304	-1.237555
Sex*lnincome10	|	.1391105	.0146905	9.47	0.000	.1103135	.1679075
_cons	|	3.885638	.1026778	37.84	0.000	3.684364	4.086911

Wave 10-9

Source	|	SS	df	MS	Number of obs	=	8322
		F(3, 8318)	=	3160.52			
Model	|	4864.62188	3	1621.54063	Prob > F	=	0.0000
Residual	|	4267.64026	8318	.513060863	R-squared	=	0.5327
		Adj R-squared	=	0.5325			
Total	|	9132.26213	8321	1.09749575	Root MSE	=	.71628

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.6883096	.0116332	59.17	0.000	.6655056	.7111136
sex	|	.1333627	.1394446	0.96	0.339	-.1399835	.4067089

Sex*lnincome9	|	-.0359884	.0152576	-2.36	0.018	-.065897	-.0060797
_cons	|	3.003536	.10942	27.45	0.000	2.789046	3.218026

Section H: Outputs of Regressions for Table 10

W13-12

Quintile 1

Source	|	SS	df	MS	Number of obs	=	1656
		F(3, 1652)	=	171.69			
Model	|	492.558196	3	164.186065	Prob > F	=	0.0000
Residual	|	1579.79051	1652	.956289655	R-squared	=	0.2377
		Adj R-squared	=	0.2363			
Total	|	2072.34871	1655	1.25217444	Root MSE	=	.9779

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.3967017	.0299772	13.23	0.000	.3379043	.455499
Sex	|	-.0287409	.3218494	-0.09	0.929	-.6600166	.6025348
Sex*lnincome12	|	.0485415	.039037	1.24	0.214	-.0280256	.1251087
_cons	|	4.307675	.2508057	17.18	0.000	3.815745	4.799606

Quintile 2

Source	|	SS	df	MS	Number of obs	=	1719
		F(3, 1715)	=	47.82			
Model	|	3.02690356	3	1.00896785	Prob > F	=	0.0000
Residual	|	36.1825242	1715	.021097682	R-squared	=	0.0772
		Adj R-squared	=	0.0756			
Total	|	39.2094278	1718	.022822717	Root MSE	=	.14525

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.054197	.0094533	5.73	0.000	.0356558	.0727382
Sex	|	-.2562268	.1101134	-2.33	0.020	-.4721976	-.040256
Sex*lnincome12	|	.0278347	.0124051	2.24	0.025	.0035039	.0521655
_cons	|	8.428999	.0844276	99.84	0.000	8.263407	8.594591

Quintile 3

Source	|	SS	df	MS	Number of obs	=	1725
		F(3, 1721)	=	24.32			
Model	|	1.05248427	3	.350828091	Prob > F	=	0.0000
Residual	|	24.8216777	1721	.014422823	R-squared	=	0.0407
		Adj R-squared	=	0.0390			
Total	|	25.874162	1724	.015008215	Root MSE	=	.1201

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.0299142	.006157	4.86	0.000	.0178383	.0419902
Sex	|	-.153043	.0870667	-1.76	0.079	-.3238107	.0177247
Sex*lnincome12	|	.0148205	.0094022	1.58	0.115	-.0036204	.0332615
_cons	|	9.091035	.0572591	158.77	0.000	8.97873	9.20334

Quintile 4

Source	|	SS	df	MS	Number of obs	=	1725
		F(3, 1721)	=	21.93			
Model	|	1.06024668	3	.353415559	Prob > F	=	0.0000
Residual	|	27.729817	1721	.016112619	R-squared	=	0.0368
		Adj R-squared	=	0.0351			
Total	|	28.7900636	1724	.016699573	Root MSE	=	.12694

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.0343513	.0060104	5.72	0.000	.0225629	.0461397
Sex	|	-.097537	.0992365	-0.98	0.326	-.2921739	.0970999
Sex*lnincome12	|	.0087849	.0102818	0.85	0.393	-.0113811	.028951
_cons	|	9.458361	.0583272	162.16	0.000	9.343962	9.572761

Quintile 5

Source	|	SS	df	MS	Number of obs	=	1584
		F(3, 1580)	=	189.61			
Model	|	47.7005657	3	15.9001886	Prob > F	=	0.0000

Residual	|	132.492584	1580	.083856066	R-squared	=	0.2647
		Adj R-squared	=	0.2633			
Total	|	180.19315	1583	.113830164	Root MSE	=	.28958

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.3242009	.0150827	21.49	0.000	.2946167	.353785
Sex	|	1.175689	.2754831	4.27	0.000	.6353382	1.71604
Sex*lnincome12	|	-.1181741	.0270144	-4.37	0.000	-.171162	-.0651862
_cons	|	7.07328	.1555169	45.48	0.000	6.768239	7.378322

W12-11

Quintile 1

Source	|	SS	df	MS	Number of obs	=	1670
		F(3, 1666)	=	95.47			
Model	|	356.646606	3	118.882202	Prob > F	=	0.0000
Residual	|	2074.6421	1666	1.24528338	R-squared	=	0.1467
		Adj R-squared	=	0.1452			
Total	|	2431.28871	1669	1.4567338	Root MSE	=	1.1159

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.3787753	.0445768	8.50	0.000	.2913428	.4662077
Sex	|	.3853547	.4469941	0.86	0.389	-.4913745	1.262084
Sex*lnincome11	|	.0239495	.0539679	0.44	0.657	-.0819025	.1298014
_cons	|	4.191087	.3749599	11.18	0.000	3.455645	4.92653

Quintile 2

Source	|	SS	df	MS	Number of obs	=	1709
		F(3, 1705)	=	35.64			
Model	|	2.3640893	3	.788029766	Prob > F	=	0.0000
Residual	|	37.6950826	1705	.022108553	R-squared	=	0.0590
		Adj R-squared	=	0.0574			
Total	|	40.0591719	1708	.023453848	Root MSE	=	.14869

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]

lnincome11	|	.0326742	.0076968	4.25	0.000	.017578	.0477704
Sex	|	-.3899545	.1004501	-3.88	0.000	-.5869728	-.1929361
Sex*lnincome11	|	.041878	.0114085	3.67	0.000	.0195018	.0642542
_cons	|	8.587149	.0680377	126.21	0.000	8.453703	8.720595

Quintile 3

Source	|	SS	df	MS	Number of obs	=	1717
		F(3, 1713)	=	22.53			
Model	|	1.07859475	3	.359531584	Prob > F	=	0.0000
Residual	|	27.332607	1713	.015955988	R-squared	=	0.0380
		Adj R-squared	=	0.0363			
Total	|	28.4112018	1716	.016556644	Root MSE	=	.12632

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.0353158	.0063264	5.58	0.000	.0229076	.047724
Sex	|	-.0581018	.0873495	-0.67	0.506	-.2294248	.1132212
Sex*lnincome11	|	.0052825	.0094965	0.56	0.578	-.0133434	.0239085
_cons	|	9.008226	.0584128	154.22	0.000	8.893658	9.122794

Quintile 4

Source	|	SS	df	MS	Number of obs	=	1729
		F(3, 1725)	=	62.28			
Model	|	2.82092135	3	.940307115	Prob > F	=	0.0000
Residual	|	26.0457907	1725	.015099009	R-squared	=	0.0977
		Adj R-squared	=	0.0962			
Total	|	28.8667121	1728	.016705273	Root MSE	=	.12288

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.1073926	.0094775	11.33	0.000	.0888041	.1259812
Sex	|	.4961932	.1260792	3.94	0.000	.2489089	.7434774
Sex*lnincome11	|	-.0536996	.0130888	-4.10	0.000	-.0793713	-.028028
_cons	|	8.735674	.0917453	95.22	0.000	8.55573	8.915617

Quintile 5

Source	|	SS	df	MS	Number of obs	=	1580
		F(3, 1576)	=	223.53			
Model	|	53.8296656	3	17.9432219	Prob > F	=	0.0000
Residual	|	126.510075	1576	.08027289	R-squared	=	0.2985

		Adj R-squared	=	0.2972			
Total	|	180.339741	1579	.114211362	Root MSE	=	.28332

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.4098677	.0170376	24.06	0.000	.376449	.4432864
Sex	|	2.434531	.2913212	8.36	0.000	1.863113	3.005949
Sex*lnincome11	|	-.2451884	.0286558	-8.56	0.000	-.3013959	-.1889808
_cons	|	6.206262	.1747012	35.53	0.000	5.863591	6.548933

W11-10

Quintile 1

Source	|	SS	df	MS	Number of obs	=	1666
		F(3, 1662)	=	105.00			
Model	|	297.582871	3	99.1942902	Prob > F	=	0.0000
Residual	|	1570.1155	1662	.944714502	R-squared	=	0.1593
		Adj R-squared	=	0.1578			
Total	|	1867.69837	1665	1.12174076	Root MSE	=	.97196

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.2763008	.0331938	8.32	0.000	.2111947	.3414069
Sex	|	-.8518645	.3407924	-2.50	0.013	-1.520292	-.1834369
Sex*lnincome10	|	.130596	.0423602	3.08	0.002	.0475111	.2136809
_cons	|	5.341114	.2692784	19.83	0.000	4.812953	5.869274

Quintile 2

Source	|	SS	df	MS	Number of obs	=	1716
		F(3, 1712)	=	30.25			
Model	|	2.20005647	3	.733352156	Prob > F	=	0.0000
Residual	|	41.5083692	1712	.024245543	R-squared	=	0.0503
		Adj R-squared	=	0.0487			
Total	|	43.7084257	1715	.025485962	Root MSE	=	.15571

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]

lnincome10	|	.026762	.0071895	3.72	0.000	.0126608	.0408633
Sex	|	-.3448482	.0937088	-3.68	0.000	-.5286439	-.1610524
Sex*lnincome10	|	.0366498	.0107229	3.42	0.001	.0156183	.0576812
_cons	|	8.595364	.0632179	135.96	0.000	8.471372	8.719356

Quintile 3

Source	|	SS	df	MS	Number of obs	=	1718
		F(3, 1714)	=	25.07			
Model	|	1.18823282	3	.396077606	Prob > F	=	0.0000
Residual	|	27.0838829	1714	.015801565	R-squared	=	0.0420
		Adj R-squared	=	0.0404			
Total	|	28.2721157	1717	.016465996	Root MSE	=	.1257

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.0358244	.0061154	5.86	0.000	.02383	.0478187
Sex	|	-.072647	.0877222	-0.83	0.408	-.2447009	.0994069
Sex*lnincome10	|	.0061585	.0095862	0.64	0.521	-.0126435	.0249605
_cons	|	8.965215	.0561424	159.69	0.000	8.8551	9.075329

Quintile 4

Source	|	SS	df	MS	Number of obs	=	1724
		F(3, 1720)	=	47.02			
Model	|	2.10395625	3	.70131875	Prob > F	=	0.0000
Residual	|	25.6518346	1720	.014913857	R-squared	=	0.0758
		Adj R-squared	=	0.0742			
Total	|	27.7557908	1723	.016108991	Root MSE	=	.12212

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.0700212	.0078748	8.89	0.000	.054576	.0854664
Sex	|	.1345483	.1101595	1.22	0.222	-.0815124	.3506089
Sex*lnincome10	|	-.0163941	.0115163	-1.42	0.155	-.0389816	.0061934
_cons	|	9.053016	.0756788	119.62	0.000	8.904584	9.201449

Quintile 5

Source	|	SS	df	MS	Number of obs	=	1573
		F(3, 1569)	=	262.55			

Model	|	59.8200783	3	19.9400261	Prob > F	=	0.0000
Residual	|	119.159719	1569	.075946283	R-squared	=	0.3342
		Adj R-squared	=	0.3330			
Total	|	178.979797	1572	.113854833	Root MSE	=	.27558

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.4300539	.016892	25.46	0.000	.3969206	.4631872
Sex	|	1.336263	.3326177	4.02	0.000	.6838407	1.988685
Sex*lnincome10	|	-.1355448	.0328822	-4.12	0.000	-.2000426	-.0710471
_cons	|	5.955334	.1725081	34.52	0.000	5.616963	6.293704

W10-9

Quintile 1

Source	|	SS	df	MS	Number of obs	=	1605
		F(3, 1601)	=	116.61			
Model	|	366.754633	3	122.251544	Prob > F	=	0.0000
Residual	|	1678.43674	1601	1.04836773	R-squared	=	0.1793
		Adj R-squared	=	0.1778			
Total	|	2045.19137	1604	1.27505697	Root MSE	=	1.0239

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.3873216	.0341326	11.35	0.000	.3203723	.4542709
Sex	|	.4263057	.3403023	1.25	0.210	-.2411792	1.093791
Sex*lnincome9	|	-.0171703	.0429484	-0.40	0.689	-.1014114	.0670708
_cons	|	4.299733	.2720635	15.80	0.000	3.766095	4.833371

Quintile 2

Source	|	SS	df	MS	Number of obs	=	1700
		F(3, 1696)	=	21.56			
Model	|	1.69681778	3	.565605926	Prob > F	=	0.0000
Residual	|	44.5009854	1696	.026238789	R-squared	=	0.0367
		Adj R-squared	=	0.0350			
Total	|	46.1978031	1699	.027191173	Root MSE	=	.16198

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.0333218	.0107583	3.10	0.002	.0122209	.0544227
Sex	|	-.0557069	.1089509	-0.51	0.609	-.2693992	.1579853
Sex*lnincome9	|	.0022304	.0125401	0.18	0.859	-.0223654	.0268261

_cons	|	8.480868	.0938968	90.32	0.000	8.296702	8.665033

Quintile 3

Source	|	SS	df	MS	Number of obs	=	1714
		F(3, 1710)	=	25.28			
Model	|	1.11863004	3	.372876678	Prob > F	=	0.0000
Residual	|	25.2179571	1710	.014747343	R-squared	=	0.0425
		Adj R-squared	=	0.0408			
Total	|	26.3365872	1713	.01537454	Root MSE	=	.12144

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.0309945	.0068368	4.53	0.000	.0175851	.0444039
Sex	|	-.128325	.0844035	-1.52	0.129	-.29387	.0372199
Sex*lnincome9	|	.0127841	.0093266	1.37	0.171	-.0055087	.0310769
_cons	|	8.953437	.0621671	144.02	0.000	8.831506	9.075369

Quintile 4

Source	|	SS	df	MS	Number of obs	=	1722
		F(3, 1718)	=	46.30			
Model	|	2.16424347	3	.721414489	Prob > F	=	0.0000
Residual	|	26.7690102	1718	.015581496	R-squared	=	0.0748
		Adj R-squared	=	0.0732			
Total	|	28.9332537	1721	.016811885	Root MSE	=	.12483

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.0854436	.0087591	9.75	0.000	.0682638	.1026233
Sex	|	.4367149	.1101108	3.97	0.000	.2207497	.6526802
Sex*lnincome9	|	-.0480871	.0115944	-4.15	0.000	-.0708277	-.0253466
_cons	|	8.855422	.0836484	105.86	0.000	8.691359	9.019486

Quintile 5

Source	|	SS	df	MS	Number of obs	=	1581
		F(3, 1577)	=	178.76			
Model	|	44.1287789	3	14.709593	Prob > F	=	0.0000
Residual	|	129.764309	1577	.082285548	R-squared	=	0.2538
		Adj R-squared	=	0.2524			
Total	|	173.893088	1580	.110058916	Root MSE	=	.28685

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.306402	.0146182	20.96	0.000	.2777288	.3350752
Sex	|	1.355298	.2601692	5.21	0.000	.8449839	1.865612
Sex*lnincome9	|	-.1401289	.0260037	-5.39	0.000	-.1911344	-.0891234
_cons	|	7.191155	.1482397	48.51	0.000	6.900387	7.481923

Section I: Outputs of Regressions when race is included as a dummy variable

Wave13-12

Source |	SS df	MS	Number of obs =	8409		
		F(3, 8405)	= 3285.45			
Model	|	4686.3358	3	1562.11193	Prob > F	= 0.0000
Residual	|	3996.27576	8405	.4754641	R-squared	= 0.5397
		Adj R-squared	= 0.5396			
Total	|	8682.61156	8408	1.03266075	Root MSE	= .68954

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.6891103	.0071297	96.65	0.000	.6751343	.7030863
non_white	|	-1.856991	.3709729	-5.01	0.000	-2.58419	-1.129793
non_white*lnincome12	|	.1976872	.039751	4.97	0.000	.1197654	.2756089
_cons	|	2.903567	.0659514	44.03	0.000	2.774286	3.032848

Wave12-11

Source	|	SS	df	MS	Number of obs	=	8405
		F(3, 8401)	=	2914.42			

Model	|	4822.15439	3	1607.3848	Prob > F	=	0.0000
Residual	|	4633.39043	8401	.551528441	R-squared	=	0.5100
		Adj R-squared	=	0.5098			
Total	|	9455.54482	8404	1.12512432	Root MSE	=	.74265

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.7393834	.0081045	91.23	0.000	.7234966	.7552702
non_white	|	-.2294861	.3553186	-0.65	0.518	-.9259981	.4670258
Non_white*lnincome11	|	.0310518	.0384934	0.81	0.420	-.0444048	.1065084
_cons	|	2.429448	.0745814	32.57	0.000	2.283251	2.575646

Wave11-10

Source	|	SS	df	MS	Number of obs	=	8397
		F(3, 8393)	=	3252.94			
Model	|	4701.21069	3	1567.07023	Prob > F	=	0.0000
Residual	|	4043.24543	8393	.481740192	R-squared	=	0.5376
		Adj R-squared	=	0.5375			
Total	|	8744.45612	8396	1.04150264	Root MSE	=	.69408

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.7045314	.0072765	96.82	0.000	.6902676	.7187952
non_white	|	.195062	.3291595	0.59	0.553	-.4501717	.8402958
Non_white*lnincome10	|	-.0159223	.0359182	-0.44	0.658	-.0863309	.0544863
_cons	|	2.751063	.0664964	41.37	0.000	2.620714	2.881413

Wave10-9

Source |	SS df	MS	Number of obs = 8322		
		F(3, 8318) = 3061.23			
Model	|	4791.98879	3	1597.3296	Prob > F = 0.0000
Residual	|	4340.27335	8318	.521792901	R-squared = 0.5247
		Adj R-squared = 0.5246			
Total	|	9132.26213	8321	1.09749575	Root MSE = .72235

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.6943696	.0073726	94.18	0.000	.6799175	.7088217
non_white	|	.1375189	.3546962	0.39	0.698	-.5577742	.8328119

Non_white*lnincome9	|	-.0160007	.0390254	-0.41	0.682	-.0925002	.0604988
_cons	|	2.850141	.0667329	42.71	0.000	2.719328	2.980954

Section J: Outputs of Regressions when university education is included as a dummy variable

Wave13-12

Source	|	SS	df	MS	Number of obs	=	8409
		F(3, 8405)	=	3301.56			
Model	|	4696.88513	3	1565.62838	Prob > F	=	0.0000
Residual	|	3985.72644	8405	.474208975	R-squared	=	0.5410
		Adj R-squared	=	0.5408			
Total	|	8682.61156	8408	1.03266075	Root MSE	=	.68863

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.6807365	.0074098	91.87	0.000	.6662115	.6952615
uni	|	-.7942251	.252904	-3.14	0.002	-1.289979	-.2984709
uni*lnincome12	|	.0979061	.0258889	3.78	0.000	.0471576	.1486547
_cons	|	2.966021	.0681543	43.52	0.000	2.832421	3.09962

Wave12-11

Source	|	SS	df	MS	Number of obs	=	8405
		F(3, 8401)	=	2938.92			
Model	|	4841.93394	3	1613.97798	Prob > F	=	0.0000
Residual	|	4613.61087	8401	.549174012	R-squared	=	0.5121
		Adj R-squared	=	0.5119			
Total	|	9455.54482	8404	1.12512432	Root MSE	=	.74106

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.7330111	.0083934	87.33	0.000	.716558	.7494642
uni	|	.2180287	.2739537	0.80	0.426	-.3189882	.7550455
uni*lnincome11	|	-.0039103	.0282497	-0.14	0.890	-.0592867	.0514661
_cons	|	2.473811	.0768049	32.21	0.000	2.323255	2.624368

Wave11-10

Source |	SS df	MS	Number	of obs = 8397
		F(3, 8393) = 3286.48		
Model	| 4723.50167	3 1574.50056	Prob > F = 0.0000	
Residual	| 4020.95446	8393 .479084291	R-squared = 0.5402	
		Adj R-squared = 0.5400		
Total	| 8744.45612	8396 1.04150264	Root MSE = .69216	

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.6938386	.0075252	92.20	0.000	.6790872	.7085899
uni	|	-.0722339	.2472081	-0.29	0.770	-.5568227	.412355
uni*lnincome10	|	.0271628	.0256662	1.06	0.290	-.0231494	.077475
_cons	|	2.833447	.0683844	41.43	0.000	2.699397	2.967497

Wave10-9

Source	|	SS	df	MS	Number of obs	=	8322
		F(3, 8318)	=	3098.89			
Model	|	4819.82724	3	1606.60908	Prob > F	=	0.0000
Residual	|	4312.43489	8318	.518446128	R-squared	=	0.5278
		Adj R-squared	=	0.5276			
Total	|	9132.26213	8321	1.09749575	Root MSE	=	.72003

lnincome10	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9	|	.689536	.0076646	89.96	0.000	.6745114	.7045606
uni	|	.5013534	.2346453	2.14	0.033	.0413902	.9613166
uni*lnincome9	|	-.0312671	.0247001	-1.27	0.206	-.0796854	.0171513
_cons	|	2.875969	.0690184	41.67	0.000	2.740676	3.011262

Section K: Outputs of Regressions for when sex, race and university education are included with full sets of interaction dummy variables

_Wave 13-12

Source |	SS df	MS	Number of obs = 8409		
		F(11, 8397) = 945.66			
Model	|	4804.38352	11	436.762138	Prob > F = 0.0000
Residual	|	3878.22805	8397	.461858765	R-squared = 0.5533
		Adj R-squared = 0.5527			
Total	|	8682.61156	8408	1.03266075	Root MSE = .6796

lnincome13	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome12	|	.5832518	.011293	51.65	0.000	.5611148	.6053888
Sex	|	-1.269712	.1370008	-9.27	0.000	-1.538268	-1.001157
non_white	|	-2.302795	.385884	-5.97	0.000	-3.059222	-1.546367
uni	|	-.9789803	.258031	-3.79	0.000	-1.484785	-.4731759
Sex*lnincome12	|	.1174561	.014791	7.94	0.000	.088462	.1464502
Non_white*lnincome12	|	.2341857	.0409153	5.72	0.000	.1539816	.3143898
uni*lnincome12	|	.1196684	.0259713	4.61	0.000	.0687584	.1705785
Sex*non_white*lnincome12	|	.0252993	.0110208	2.30	0.022	.0036957	.0469028
Sex*uni*lnincome12	|	-.0050497	.0058081	-0.87	0.385	-.016435	.0063355
Non_white*uni*lnincome12	|	-.0054229	.0184292	-0.29	0.769	-.0415487	.0307029
Sex*non_white*uni*lninco~12	|	-.0393442	.028345	-1.39	0.165	-.0949075	.016219
_cons	|	3.985613	.1076683	37.02	0.000	3.774556	4.196669

Wave 12-11

Source |	SS df	MS	Number of obs =	8405	
		F(11, 8393)	= 819.07		
Model	|	4895.32334 11	445.029395	Prob > F	= 0.0000

Residual	|	4560.22147 8393	.543336289	R-squared	= 0.5177
		Adj R-squared	= 0.5171		
Total	|	9455.54482 8404	1.12512432	Root MSE	= .73711

lnincome12	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome11	|	.6821938	.0135781	50.24	0.000	.6555773	.7088102
Sex	|	-.5333168	.1583509	-3.37	0.001	-.8437236	-.22291
non_white	|	-.3355797	.3705601	-0.91	0.365	-1.061969	.3908096
uni	|	.1145081	.2801883	0.41	0.683	-.43473	.6637463
Sex*lnincome11	|	.040274	.0171345	2.35	0.019	.0066861	.0738619
Non_white*lnincome11	|	.0381041	.0396365	0.96	0.336	-.0395933	.1158014
Uni*lnincome11	|	.0071577	.0284658	0.25	0.801	-.0486424	.0629578
Sex*non_white*lnincome11	|	.0036921	.0120034	0.31	0.758	-.0198376	.0272217
Sex*uni*lnincome11	|	-.0020143	.0063198	-0.32	0.750	-.0144027	.010374
Non_white*uni*lnincome11	|	-.0004296	.0195921	-0.02	0.983	-.0388349	.0379757
Sex*non_white*uni*lninco~11	|	.0256305	.0310029	0.83	0.408	-.0351429	.0864039
_cons	|	3.035066	.1289109	23.54	0.000	2.782368	3.287763

Wave 11-10

Source |	SS	Df	MS	Number of obs =	8397		
		F(11, 8385)	=	957.68			
Model	|	4868.97137	11	442.633761	Prob > F	=	0.0000
Residual	|	3875.48476	8385	.462192577	R-squared	=	0.5568
		Adj R-squared	=	0.5562			
Total	|	8744.45612	8396	1.04150264	Root MSE	=	.67985

lnincome11	|	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome10	|	.5844802	.0112817	51.81	0.000	.5623652	.6065952
Sex	|	-1.53086	.1364307	-11.22	0.000	-1.798298	-1.263422
non_white	|	.3890468	.3370464	1.15	0.248	-.2716473	1.049741
Uni	|	-.3111404	.248928	-1.25	0.211	-.7991007	.1768199
Sex*lnincome10	|	.1427199	.0149206	9.57	0.000	.1134718	.1719681
Non_white*lnincome10	|	-.0322872	.0364157	-0.89	0.375	-.1036709	.0390966
Uni*lnincome10	|	.0517798	.0254687	2.03	0.042	.0018547	.1017048
Sex*non_white*lnincome10	|	-.014031	.0111168	-1.26	0.207	-.0358226	.0077605
Sex*uni*lnincome10	|	-.001151	.0058724	-0.20	0.845	-.0126623	.0103603
Non_white*uni*lnincome10	|	-.0030076	.0181796	-0.17	0.869	-.0386441	.032629
Sex*non_white*uni*lninco~10	|	.0264664	.0290126	0.91	0.362	-.0304054	.0833382
_cons	|	3.977234	.1063224	37.41	0.000	3.768816	4.185652

Wave 10-9

Source			SS	df	MS	Number of obs	=	8322
		F(11, 8310)	=	871.63			
Model			4892.15931	11	444.741755	Prob > F	=	0.0000
Residual			4240.10283	8310	.510241014	R-squared	=	0.5357
		Adj R-squared	=	0.5351			
Total			9132.26213	8321	1.09749575	Root MSE	=	.71431

lnincome10			Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnincome9			.6841792	.0119616	57.20	0.000	.6607314	.7076271
Sex			.1457882	.1403464	1.04	0.299	-.1293258	.4209022
non_white			.0394296	.3729985	0.11	0.916	-.6917404	.7705997
Uni			.3604274	.242697	1.49	0.138	-.1153194	.8361742
Sex*lnincome9			-.0376057	.0154469	-2.43	0.015	-.0678854	-.0073259
Non_white*lnincome9			-.0006051	.0407214	-0.01	0.988	-.0804292	.0792189
Uni*lnincome9			-.0207901	.0251224	-0.83	0.408	-.0700364	.0284561
Sex*non_white*lnincome9			-.0114076	.0118202	-0.97	0.335	-.0345782	.0117631
Sex*uni*lnincome9			.008538	.0062667	1.36	0.173	-.0037463	.0208222
Non_white*uni*lnincome9			-.00454	.019453	-0.23	0.815	-.0426728	.0335928
Sex*non_white*uni*lnincome9			.0054434	.0311306	0.17	0.861	-.0555804	.0664673
_cons			3.025166	.1119487	27.02	0.000	2.805718	3.244613