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ABSTRACT

A number of measures of intertemporal poverty have recently been proposed in the theoretical literature. In this paper, we apply two of these measures to analyse intertemporal poverty in Great Britain during the period 1991-2005, using data from the British Household Panel Survey. Previous studies on poverty using this data-set have employed static measures of poverty. We illustrate how the use of intertemporal poverty measures makes it possible to analyse aspects of poverty which cannot be captured by static, annual, measures of poverty. We then model the determinants of intertemporal poverty, conditional upon being poor, using a Heckman two-step selection model.

Keywords: Intertemporal poverty measurement, BHPS, Great Britain
JEL Classifications: D31, I32.

1 Introduction

In the recent literature on poverty measurement, there has been a significant emphasis on developing indices designed to capture dynamic aspects of poverty, where income data is available for a number of time periods.[1] This new approach has enabled the construction of poverty indices which are sensitive to a number of important aspects of poverty that cannot be captured by static measures. These aspects include, for example, the particularly damaging impact of poverty early in life (Hoy and Zheng (2011)), the detrimental impact of spending a high proportion of one's time in poverty (Foster (2009)), the debilitating impact of prolonged periods spent in poverty (Bossert, Chakravarty and D'Ambrosio, 2012) and the mitigating impact that affluent

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[1] This paper is an extract from a doctoral thesis by Roope (2013).

spells might have on subsequent periods of poverty (Dutta, Roope and Zank (2012), Zheng (2011)). The various measures that have been proposed differ in the underlying assumptions that are made regarding how the time dimension should be dealt with and, in some cases, these assumptions have been made explicit through the provision of axiomatic characterizations.[2]

In this paper, the measures introduced by Dutta et al. (2012) and, as a special case of these, those of Foster (2009), are applied to analyse intertemporal poverty and its determinants in Great Britain during the period 1991-2005, using data from the British Household Panel Survey (BHPS).[3] A number of empirical studies on poverty dynamics have been undertaken using this data-set and are discussed below. However, most of these studies pre-date the recent advances that have been made in measuring intertemporal poverty and have typically been conducted using static poverty measures for each time period. As such, they are able to consider movements into and out of poverty and the determinants of such movements, where poverty is measured over a relatively short term. Evaluating overall levels of poverty, and its determinants, across a longer time-frame requires a new set of tools.

As discussed by Jenkins and Rigg (2001), previous research on poverty dynamics using the BHPS has to date focused broadly on three main aspects. Firstly, a number of papers have studied the extent of movement into and out of poverty from one year to the next. These papers have generally found a significant amount of such movement. For example, Jarvis and Jenkins (1995, 1997) found that roughly half of those who are poor in any given year are non-poor in the following year. Nevertheless, significant numbers of individuals have been found to be stuck in poverty for a number of consecutive years - see Department of Social Security (2000) and Jarvis and Jenkins (1997). A second strand of literature studies the determinants of movements into and out of poverty, from one year to the next. Jenkins (2000), for example, found that while changes in income were the primary route to escaping poverty, falling into poverty was often a result of changes in household demographics. Jenkins and Rigg (2001) also emphasised the importance of the labour market for providing a route to escape poverty for individuals of working age.[4] A third area of research has been on attempting to model the lengths of poor spells and non-poor spells. Antolín et al (1999), Devicienti (2001, 2002) and Jenkins and Rigg (2001) have found that after controlling for differences in personal characteristics, the longer an individual has been poor for, the less likely is a subsequent escape from poverty. Antolín et al (1999) and Devicienti (2001, 2002) found that certain demographics, notably individuals who live in households with single parents or pensioners, are particularly likely to spend long

[2]Axiomatic characterizations have been provided for the measures of Bossert et al. (2012), Dutta et al. (2012), Hoy and Zheng (2011) and Zheng (2011). Measures have also been proposed by Jalan and Ravallion (2000), Cruces (2005), Calvo and Dercon (2009), Grab and Grimm (2007), Carter and Ikegami (2007), Foster (2009), Porter and Quinn (2008), Foster and Santos (2012), Gradín, del Río and Cantó (2012) and Duclos, Araar and Giles (2010).

[3]Throughout this paper, we are referring to Foster (2009)'s total intertemporal poverty measure, not his chronic poverty measure.

[4]See also Antonín et al. (1999).

periods in poverty. Jenkins and Rigg (2001)'s analysis found that shorter spells of poverty were associated with having more working individuals in the household, while longer spells (and shorter recovery times) were associated with the presence of children in the household. More recently, and using a longer panel of the BHPS (Waves 1-16, which corresponds to 1991-2006), Devicienti (2011) has found a number of correlates of long spells in poverty. Living in a household with relatively many children and few adults, living in a household headed by a female with a low level of education and travelling to work in areas with high local unemployment rates are all associated with prolonged spells in poverty. Devicienti (2011) also found that young and elderly individuals face a relatively high risk of remaining poor for long periods, as do those from an ethnic minority group.

All of the literature above is concerned with dynamic aspects of poverty and has provided valuable insights into the patterns and determinants of movements into and out of poverty in Great Britain. However, to the best of our knowledge, none of the literature to date has explicitly accounted for the dynamic nature of poverty in its actual measurement using BHPS data. This paper seeks to begin to fill this gap. Using the measures proposed by Dutta et al. (2012), we aim to provide a richer ordering of poverty profiles in Great Britain, explicitly taking account of the time dimension.

Having estimated the level of intertemporal poverty in Great Britain, the focus of the paper then shifts to attempting to model the determinants of intertemporal poverty. Various econometric approaches have been used in the literature to model determinants of poverty. Most research has been in a static framework, where the dependent variable has typically been a standard 'snapshot' poverty measure defined on the [0,1] interval, such as a member of the popular 'FGT' class of measures introduced by Foster et al. (1984). A common approach has been to perform a Tobit regression, where the poverty measure is treated as a variable which is left-censored at zero, observed only if an individual's income is below the poverty line. This methodology has been adopted, for example, by Bhaumik, Gang and Yun (2006) and Walker et al. (2006). Appleton (2001), in a study using household survey data from Uganda, also performed Tobit regressions to model the determinants of poverty but took a rather different approach. In that paper, the dependent variable in the poverty regressions was the logarithm of real consumption, the variable being right censored at the median income.[5]

As Jalan and Ravallion (2000) have discussed, in a study on chronic and transient poverty in rural China, applying Tobit models in the context of poverty regressions can be problematic. Citing Arabmazar and Schmidt (1982), they pointed out that Tobit estimates are not robust to misspecifications of the error distribution. In particular, if there is heteroskedasticity or non-normality in the errors, the estimates will be both inconsistent and inefficient. Jalan and

[5] This approach is possible in a static poverty setting, where poverty can be defined as a simple function of income. With intertemporal measures, this is usually not the case. As will become clear, such measures typically depend on incomes in a number of periods and on the sequencing of those incomes.

Ravallion (2000) preferred instead to use a semi-parametric method, employing the Censored Quantile Regression model (Powell (1984, 1986)). In a study on chronic and transient seasonal poverty in Rwanda, Muller (2003) considered a Tobit specification but found the error terms to be both heteroskedastic and non-normal. As a consequence, Muller (2003) also rejected the Tobit model in favour of Censored Quantile Regressions and noted that non-normality and heteroskedasticity in the errors is usually to be expected in the context of poverty regressions.

Both Jalan and Ravallion (2000) and Muller (2003) are concerned with whether chronic poverty and transient poverty have fundamentally different determinants. Rather than focusing on decomposing intertemporal poverty into chronic and transient components, most of the recent contributions to the theoretical literature on poverty measurement have concentrated on capturing the overall severity of intertemporal poverty. This was the focus in Bossert et al. (2012), Dutta et al. (2012), Hoy and Zheng (2011) and Zheng (2011), among others.[6] Consistent with this recent approach to measurement, we attempt to analyse the determinants of the overall severity of an individual's intertemporal poverty. Nevertheless, we take seriously the possibility that the phenomenon of having a non-zero level of intertemporal poverty might be determined by factors which differ somewhat from those which determine the overall degree of intertemporal poverty. This suggests that the determinants of intertemporal poverty should be obtained by modelling the level of intertemporal poverty conditional on being intertemporally poor.[7] Ignoring this possibility would run the risk that there might be a type of 'selection bias.' Our approach is to use a Heckman two-step selection model (Heckman (1979)). Heckman selection models have been used in a number of studies on the determinants of poverty but, to the best of our knowledge, not in quite the manner employed here, where the severity of individuals' poverty is modelled conditional on their being poor.

Our approach bears some resemblance to that used by Coulombe and McKay (1996) in a study on the determinants of poverty in Mauritania. They modelled the socioeconomic group to which individuals belonged and, conditional on that choice, the determinants of living standards (and hence poverty) within that group. A multinomial logit selection model was used in the first stage to capture the determinants of choosing a particular socioeconomic group. The determinants of living standards were then modelled, conditional on this choice, by including a Heckman-like selection term in an OLS regression of living standards for that group. Related approaches to that employed in this paper are also sometimes used to evaluate the impact of various programmes on poverty, if it is suspected that there may be a sample selection bias

[6] Foster (2009) is a notable exception.

[7] Note that throughout this paper, an individual is regarded as being 'intertemporally poor' if they have a non-zero level of intertemporal poverty. Moreover, being 'poor' during some given time spell, and being 'intertemporally poor' during that same time spell are taken to mean the same thing. This reflects the fact that the intertemporal poverty measures used are weighted averages of the per-period static poverty measures. Therefore, an individual has a non-zero level of intertemporal poverty in a given spell if and only if he has a non-zero level of static poverty in at least one of the time periods of which the spell is composed. To put it another way, an individual is poor, or intertemporally poor, if he is poor during any time period.

associated with access to the programme. For example, in a recent paper, Imai, Arun and Annim (2010) studied the impact of microfinance in India and used a Heckman sample selection model to account for possible sample selection bias or endogeneity associated with household access to microfinance institutions.

The rest of the paper is organised as follows. In Section 2, we describe the data and apply a class of measures introduced by Dutta et al. (2012) to evaluate the overall levels of intertemporal poverty in Great Britain, using data from the BHPS. As a special case of the measures of Dutta et al. (2012), we also employ the measures of Foster (2009). In Section 3, econometric techniques are used to model the determinants of intertemporal poverty. Concluding remarks are offered in Section 4.

2 Intertemporal Poverty in Great Britain during 1991-2005

2.1 Intertemporal poverty measures

We begin this section by providing a brief recap of one of the classes of measures proposed by Dutta et al. (2012) and specifying the particular parameters which are used in this empirical application. Dutta et al. (2012) proposed a class of measures which take into account both the poverty mitigation arising from the presence of affluent periods and the intensification of poverty due to consecutive poor periods. Their *constant-relative affluence-dependent intertemporal poverty measure* P_R is defined as

$$P_R(\mathbf{p}) = \frac{1}{T}\sum_{t=1}^{T}\frac{k_t^{\alpha}}{(1+n_t)^{\beta}}p_t^{\theta}, \text{ where } \alpha, \beta, \theta \geq 0. \tag{1}$$

In general, p_t can be any static poverty measure from the literature, but for the purposes of this study we will use the popular normalized poverty gap. If $x_t \geq z_t$, the individual is non-poor and $p_t = 0$. This static measure of an individual's poverty has some appealing properties. It is decreasing in x_t and is scale invariant since for any $\lambda \neq 0, (\lambda z_t - \lambda x_t)/\lambda z_t = (z_t - x_t)/z_t$. It also has a money-metric interpretation. When denormalized it can be interpreted as the minimum cost to society of removing the individual from poverty.

The number of consecutive non-poor periods immediately prior to period t is given by n_t.

The parameter θ captures the degree of sensitivity of the poverty experienced in each time period to the income shortfall. The detrimental impact of consecutive periods of poverty, which serve to intensify the overall impact of poverty, is captured by k_t. The parameter α determines the extent of this intensification of poverty. If $\alpha = 0$, there is no intensification. Similarly, β can be interpreted as an index representing how much one chooses to discount the impact of an individual's poor episodes because of preceding uninterrupted spells of non-poverty. When $\beta = 0$, there is no mitigation. As noted by Dutta et al. (2012), if both $\alpha = 0$ and $\beta = 0$, the measure reduces to the simple average of static poverty measures advocated by Foster (2009) and defined as

$$P_F(\mathbf{p}) = \frac{1}{T}\sum_{t=1}^{T} p_t^{\theta}, \text{ where } \theta \geq 0. \tag{2}$$

For the remainder of this study, we will set the parameters for P_R to be $\alpha = \beta = \theta = 1$. From here on, we will refer to P_R, with these particular parameters, as being P_{DRZ}. By way of comparison, we will also provide results using the P_R measures with $\alpha = \beta = 0$ and $\theta = 1$, or, equivalently, the measures of Foster (2009) with $\theta = 1$. From here on, we will refer to the latter measures as P_{FOS}. We might very readily have also used a number of other measures from the literature to provide further comparisons with P_{DRZ}, such as, for example, those of Bossert et al. (2012) or Hoy and Zheng (2011). However, an exhaustive study, using all the attractive measures from the literature, is beyond the scope of this paper. Rather, our intention is to demonstrate the kind of analysis that can be performed using intertemporal poverty measures generally. We illustrate this using a class of measures proposed by Dutta et al. (2012) which has some attractive properties. The P_{FOS} measure represents an interesting special case of these measures, and is useful for comparative purposes with P_{DRZ}, since it embodies very different normative judgements. In contrast to P_{DRZ}, no specific importance is attached to the precise ordering of poor periods or non-poor periods; all that matters is the level of static poverty in each time period and the proportion of periods which are poor.

The main focus in Dutta et al. (2012) was on evaluating intertemporal poverty at an individual level. Subsequently measures of societal intertemporal poverty can be constructed by aggregating across individuals. In this paper, the focus is also mainly on intertemporal poverty at an individual-level. We do, however, make reference to aggregate intertemporal poverty at a regional level. In this case, the aggregate level of intertemporal poverty is evaluated as a simple average of individual-level intertemporal poverty.

2.2 Data and Measures

The data are derived from the BHPS, Waves 1 to 15, which cover the period 1991 to 2005.[8] The BHPS was designed as an annual survey of each adult member (aged 16 years and over) of a nationally representative sample of over 5,000 households. The Wave 1 panel consists of 5,500 households and 10,300 individuals drawn from throughout Great Britain. The same individuals were re-interviewed in successive waves. If and when an individual left their original household, all adult members of their new households were also interviewed. Individuals were re-interviewed at approximately annual intervals. In 1999, for Wave 9 onwards, the main sample was supplemented with additional samples of 1,500 households in each of Scotland and Wales. Few panels have individual-level income data at such regular time intervals and over such a long

[8] The period studied in each wave started on 1st September and finished on 31st August. So, for example, Wave 1 covers the period from 1st September 1990 to 31st August 1991.

time-frame. This makes the BHPS a particularly suitable data-set for an intertemporal poverty study, the data requirements of which are quite demanding.[9]

An individual's income is taken to be their equivalised household net income. The household net income variable used was provided by Bardasi et al. (2008) as an unofficial supplement to the set of derived income variables in the official BHPS release (which provide gross income rather than net income). The variable (referred to in the data-set as 'whhnetde2') was obtained by summing across all household members, cash income from all sources (except for any earnings from a second job) and deducting direct taxes (except for local taxes such as the community charge and council tax) and occupational pension contributions. The variable uses the Modified OECD equivalence scale to adjust for differences in household size and composition, and a monthly 'before housing costs' price index to express incomes in January 2008 prices.[10][11]

As highlighted in the introduction, the purpose of this study is two-fold. Firstly, by using measures designed to evaluate poverty over a longer time-frame than static measures, we aim to provide a more nuanced view of poverty in Great Britain than previous studies have been able to do. Secondly, having evaluated intertemporal poverty at an individual-level, we seek to analyse its determinants. This two-fold task presents considerable challenges from a practical point of view. For example, suppose we begin with the premise that the starting point must be to obtain a definitive measure of intertemporal poverty, across the full fifteen years of analysis. An immediate drawback is that this necessarily dramatically reduces the size of the sample, since, as discussed above, income observations in every time period are required for computation of the intertemporal poverty measures employed. Another serious difficulty is the following. Many likely determinants of poverty, such as an individual's age, employment status, number of children in household and in many cases even their level of education, can change dramatically over such long periods of time. Moreover, while it may be appropriate to treat such possible determinants of poverty over a relatively short time-frame as being exogenous factors, it may be increasingly difficult to maintain this assumption as the time-frame increases.[12] The approach taken in this paper is something of a compromise between our desire to measure poverty over a long time-frame and being able to successfully evaluate its possible determinants. We use the measures P_{DRZ} and P_{FOS} to provide an indication of intertemporal poverty over 5-year

[9] It is clear from the definitions of the intertemporal poverty measures referred to in the previous subsection that it is highly desirable to have income observations in each time period. If an individual's income data is missing for some time periods, P_{FOS} can still be estimated because each time period receives an equal weight. However, missing values for most of the other measures in the literature, including P_{DRZ}, are more problematic because the weights assigned to certain time periods will be dependent on the missing information.

[10] The variable was constructed using the same definition of net income as that used in Britain's official income distribution statistics, as published annually in the Households Below Average Income from the Department for Work and Pensions (formerly the Department of Social Security). See for example Department for Work and Pensions (2008).

[11] For further information on the data-set and the construction of the 'whhnetde2' variable, see Bardasi, Jenkins and Rigg (1999) and Levy and Jenkins (2008). For more detailed information on the main BHPS data-set, see Taylor et al. (2010). Details on how to order the data, and an order form, can be obtained at http://www.data-archive.ac.uk.

[12] See Rodgers (1989) for a discussion of such issues.

stretches, which we loosely refer to as 'eras.'

Our study is therefore divided into three sections or eras, corresponding to Waves 1-5, Waves 6-10 and Waves 11-15 and we evaluate both intertemporal poverty and its determinants separately for these three eras.

After losing individuals due to attrition and non-response, we are left with panels of the following sizes in the three eras. In Waves 1-5, there are 5,968 individuals of which 2,904 are male and 3,064 are female. In Waves 6-10, there are 6,386 individuals of which 3,134 are male and 3,252 are female. In Waves 11-15, there are 8,341 individuals of which 4,075 are male and 4,266 are female.[13]

We recognise that the loss of individuals due to attrition and other types of non-response is likely to bias our results in ways that are difficult to predict. This is a common problem in studies using panel data and there is a large literature on the subject but not, unfortunately, a comprehensive solution. In a study on the nature and causes of attrition in the BHPS, Uhrig (2008) found that there was no impact of being at the low end of the income distribution on non-response generally, but a slightly increased chance of being unable to contact individuals and a slightly decreased chance of refusal. Uhrig (2008, p. 39) concluded from this that "...low income respondents in Britain are happy to participate in an ongoing survey in which income and financial well-being are central themes but can be somewhat difficult to maintain in the sample." If this is the case, the poverty estimates in this study might be expected to have a slight downward bias.

The measures P_{DRZ} and P_{FOS} allow for the poverty line to change in each time period. The measures are computed by estimating the official poverty line, of 60% of the median household income, in each time period. The poverty lines used in each year, expressed as annual equivalised household net incomes (defined as above) are displayed in Table 1. As this table indicates, apart from a slight dip in the late 1990s, the official poverty line has increased steadily over time.

[13] The large increase in the sample size in the third era is due to the additional samples introduced in Scotland and Wales in Wave 9, as mentioned above. These individuals are not represented in the second era, since we only consider those individuals for whom we have income data for all five of an era's constituent years. This requirement has some further impact on the variation in sample sizes between eras. For example, despite losing individuals due to attrition and non-response, the total sample in the second era is 418 higher than in the first era. This is because there are some individuals for whom there is no information on income during at least one of the first five waves but no missing data during Waves 6-10. In fact, there are only 2,734 individuals for whom we have income data during all 15 waves and who are, therefore, represented in the analysis for all three eras. The numbers of individuals who are represented in both the first and second eras and in the second and third eras are 4,256 and 4,067, respectively.

Table 1: Poverty Lines in Each Year

Year	Poverty Line (£)
1991	7,002
1992	7,217
1993	7,409
1994	7,435
1995	7,575
1996	7,676
1997	7,437
1998	7,480
1999	7,401
2000	7,796
2001	7,890
2002	8,551
2003	8,605
2004	8,787
2005	8,908

Note: Poverty lines are in terms of the household net income variable 'whhnetde2,' as described in the text.

Estimates of intertemporal poverty in Great Britain, using both P_{DRZ} and P_{FOS}, are displayed in Tables 2, 3 and 4. Estimates are provided both on a regional basis and for Great Britain as a whole. The three tables correspond to the three eras.

Table 2: Regional Sample Sizes and Poverty Estimates During 1991-1995

Region	Sample	% poor	P_{DRZ}	P_{FOS}
Inner London	144	46.5	0.118	0.072
Outer London	313	31.3	0.086	0.046
Rest of South-East	1,074	30.0	0.074	0.039
South-West	506	32.6	0.102	0.047
East Anglia	272	38.2	0.161	0.070
East Midlands	527	42.9	0.132	0.060
West Midlands Conurb	225	42.7	0.251	0.096
Rest of West Midlands	376	39.6	0.118	0.057
Greater Manchester	206	25.7	0.069	0.035
Merseyside	120	34.2	0.122	0.052
Rest of North-West	243	27.2	0.086	0.036
South Yorkshire	171	38.0	0.213	0.087
West Yorkshire	201	40.3	0.166	0.069
Rest of Yorks & Hum	180	32.8	0.140	0.061
Tyne & Wear	134	46.3	0.134	0.064
Rest of North	240	26.7	0.092	0.040
Wales	312	44.6	0.109	0.056
Scotland	475	34.9	0.129	0.058
Total Sample	5,968	35.2	0.117	0.054
Males	2,904	34.0	0.109	0.051
Females	3,064	36.4	0.125	0.058

Note: Individuals were defined as living in a given region if they lived in that region during both Wave 1 and Wave 5. The sum of the regional sample sizes add up to 5,719, which is 249 less than the total sample of 5,968. The remaining 249 individuals lived in different regions during Waves 1 and 5 and so were excluded from the regional analysis.

Table 3: Regional Sample Sizes and Poverty Estimates During 1996-2000

Region	Sample	% poor	P_{DRZ}	P_{FOS}
Inner London	121	29.8	0.069	0.042
Outer London	338	25.1	0.083	0.037
Rest of South-East	1,151	23.0	0.042	0.024
South-West	577	25.8	0.062	0.031
East Anglia	263	35.4	0.149	0.067
East Midlands	553	36.9	0.096	0.050
West Midlands Conurb	221	35.3	0.181	0.077
Rest of West Midlands	374	31.6	0.070	0.035
Greater Manchester	202	20.8	0.064	0.036
Merseyside	146	34.9	0.098	0.045
Rest of North-West	283	29.7	0.076	0.038
South Yorkshire	182	37.9	0.113	0.056
West Yorkshire	211	35.1	0.102	0.054
Rest of Yorks & Hum	216	31.0	0.114	0.048
Tyne & Wear	138	41.3	0.155	0.064
Rest of North	253	25.3	0.056	0.030
Wales	336	34.2	0.095	0.047
Scotland	502	35.3	0.089	0.048
Total Sample	6,386	30.2	0.083	0.041
Males	3,134	28.8	0.075	0.038
Females	3,252	31.4	0.090	0.045

Note: Individuals were defined as living in a given region if they lived in that region during both Wave 6 and Wave 10. The sum of the regional sample sizes add up to 6067, which is 319 less than the total sample of 6,386. The remaining 319 individuals lived in different regions during Waves 6 and 10 and so were excluded from the regional analysis.

Table 4: Regional Sample Sizes and Poverty Estimates During 2001-2005

Region	Sample	% poor	P_{DRZ}	P_{FOS}
Inner London	85	18.8	0.050	0.038
Outer London	265	26.0	0.073	0.038
Rest of South-East	1,063	18.2	0.015	0.013
South-West	557	28.5	0.042	0.027
East Anglia	255	27.8	0.102	0.046
East Midlands	523	33.5	0.056	0.033
West Midlands Conurb	190	32.6	0.074	0.037
Rest of West Midlands	298	20.8	0.051	0.025
Greater Manchester	214	31.8	0.056	0.034
Merseyside	137	39.4	0.050	0.037
Rest of North-West	286	26.9	0.042	0.026
South Yorkshire	160	23.8	0.084	0.036
West Yorkshire	144	36.1	0.104	0.050
Rest of Yorks & Hum	215	26.5	0.036	0.027
Tyne & Wear	107	35.5	0.064	0.036
Rest of North	213	30.0	0.056	0.034
Wales	1,608	35.5	0.084	0.045
Scotland	1,692	33.9	0.066	0.038
Total Sample	8,341	29.7	0.060	0.034
Males	4,075	28.1	0.052	0.030
Females	4,266	31.2	0.068	0.038

Note: Individuals were defined as living in a given region if they lived in that region during both Wave 11 and Wave 15. The sum of the regional sample sizes add up to 8,012, which is 329 less than the total sample of 8,341. The remaining 329 individuals lived in different regions during Waves 11 and 15 and so were excluded from the regional analysis.

Tables 2 through to 4 indicate that the percentage of poor individuals declined from each era to the next, for both males and females. There is a substantial decline in the percentage of poor from the first era to the second and a relatively modest decline from the second to the third. Only in Scotland, Merseyside and the Rest of the North-West was there an increase in the percentage of individuals who were poor from the first era to the second. From the second era to the third era, the percentage of poor individuals increased in a number of regions, namely Wales, Outer London, the South-West, West Yorkshire, Merseyside, Greater Manchester and the Rest of the North.

There is a striking change in the regional ranking of Inner London over the three eras, with respect to its percentage of poor individuals. However, this result should be treated with a good deal of caution as the sample sizes for Inner London are very small.

Some regions, such as Tyne & Wear, remained consistently among the poorest regions throughout the three eras. Merseyside and West Yorkshire became relatively poorer regions over time. The Rest of the West Midlands saw a steady improvement in its regional ranking over the three eras. The Rest of the South-East is ranked consistently over the three eras as an area with a relatively low proportion of poor individuals. The ranking of South Yorkshire fluctuated somewhat, worsening from the first to the second era but later improving. The rankings of Greater Manchester, the Rest of the North, the Rest of the North-West and Scotland all deteriorated somewhat over the three eras.

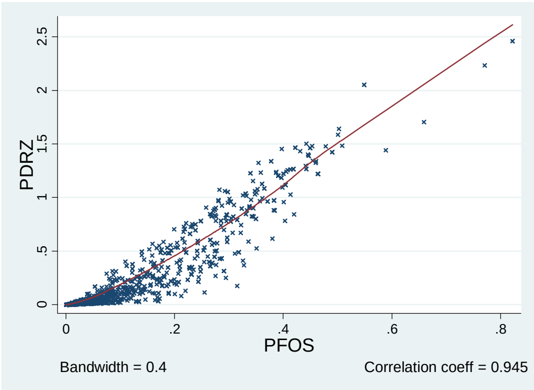
Intertemporal poverty levels also declined from each era to the next, for both males and females and according to both measures. Focusing firstly on the P_{DRZ} measure, intertemporal poverty was found to decrease between the first and second era in all regions apart from Tyne and Wear. The simple percentages of poor individuals portrayed a very mixed picture with regard to the changes in poverty from the second era to the third. The percentage of poor decreased only very slightly overall and with significant numbers of regions in which poverty increased. In marked contrast, the P_{DRZ} measures indicate that poverty fell in all regions apart from the Rest of the North, where it remained unchanged and in West Yorkshire, where it rose very slightly. This indicates that although the overall percentages of poor individuals changed little from the second to the third era, when both the extent of individual-level per-period poverty and the sequencing of those poor episodes is accounted for in the manner advocated by Dutta et al. (2012), the overall level of intertemporal poverty decreased nearly everywhere. The relative ranking of the different regions according to P_{DRZ} also displays some notable differences to those indicated simply by the percentages of poor individuals. West Midlands Conurbations, which had the fifth highest percentage of poor individuals in each of the first two eras, is ranked as the intertemporally poorest region by P_{DRZ} in these eras. Whilst the percentage of poor in Merseyside increased by 4.5 percentage points from the second era to the third to become the region with the highest proportion of poor people, both the extent of intertemporal poverty and the regional ranking substantially improved over this time-frame according to P_{DRZ}. The P_{DRZ} measures paint a relatively bleaker picture of poverty in East Anglia than the simple percentages of poor people indicate. Although the level of intertemporal poverty decreased in successive waves, the regional ranking according to P_{DRZ} is worse than the percentages suggest and, moreover, deteriorated from each era to the next. South Yorkshire's ranking improved dramatically between the second and third era in terms of the percentage of poor individuals but, according to P_{DRZ}, its ranking actually deteriorated. Tyne and Wear's relative ranking fares better with P_{DRZ} than is indicated by the simple percentages of poor individuals. Inner London's ranking fluctuated less under P_{DRZ} than indicated by the simple percentages of poor, moving from the tenth ranked region in the first era to the fourteenth in the second and third eras.

The measures of P_{FOS} paint a broadly similar picture to those of P_{DRZ} but with a few notable differences. There is a greater fluctuation in Inner London's regional ranking between eras than indicated by P_{DRZ} (though less fluctuation than is indicated simply by focusing on the percentage of poor people). Conversely, there is less fluctuation in Merseyside's regional ranking between eras, it ranging from twelfth in the first era to eighth in the third era. In the third era, South Yorkshire, the East Midlands and the Rest of the West Midlands are all ranked more favourably by P_{FOS} than by P_{DRZ}. Since the extent of each individual's static poverty in each wave is the same for P_{FOS} and P_{DRZ}, the fact that P_{DRZ} ranks these regions as relatively poor ones compared to P_{FOS} suggests that when individuals are poor in these regions, their poor spells tend to be relatively more bunched together and with relatively fewer preceding periods of non-poverty than is the case in some of the other regions. Such differences in the P_{FOS} and P_{DRZ} rankings reflect the different normative judgements embodied by the respective measures; in particular, whether or not the precise ordering of poor episodes is important.

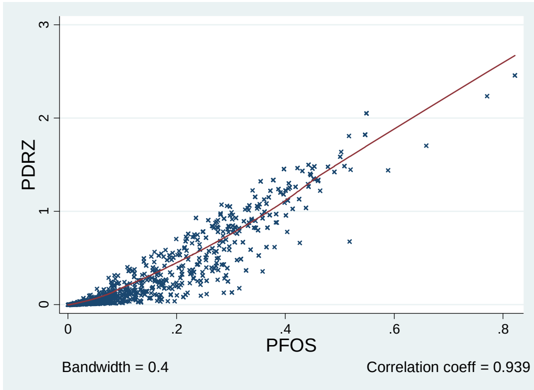
As an overall comparison between the estimates of poverty of P_{FOS} and of P_{DRZ} at an individual level, the plots in Figure 1 chart the relationship between the two variables over the three eras. Separate plots are displayed for Males and Females. It is clear from these plots that the two measures are very highly correlated and this is confirmed by the correlation coefficients. Simple OLS regressions of P_{DRZ} on P_{FOS} were also performed and are displayed in Tables 5 and 6. The high R^2 values serve as further confirmation of the high degree of correlation between the two measures. In each of these regressions, the constant has a negative and highly significant sign. This indicates that the P_{DRZ} measures are displaced downwards from the P_{FOS} measures. However, as can be seen from the plots in Figure 1, except at very low levels of poverty, the P_{DRZ} measures tend to have a higher value than the P_{FOS} measures. This is consistent with the relatively high coefficients of P_{FOS} in the regression results. Except at very low values of P_{FOS}, the effect of the comparatively high P_{FOS} coefficient dominates that of the negative regression constant. These results are not surprising and reflect the functional form of the respective measures. For example, at very low levels of poverty, where an individual is poor in perhaps just one of five time periods, the P_{DRZ} measures will typically have a lower value than P_{FOS}, since the poverty in the poor period is discounted by the number of preceding periods of relative affluence. At higher levels of poverty, where an individual is poor in most time periods, the P_{DRZ} measures are typically higher than P_{FOS} due to the effect of the parameter k_t, which is intended to explicitly account for the exacerbating impact of consecutive periods of poverty.

Figure 1: Plots Of PDRZ Against PFOS

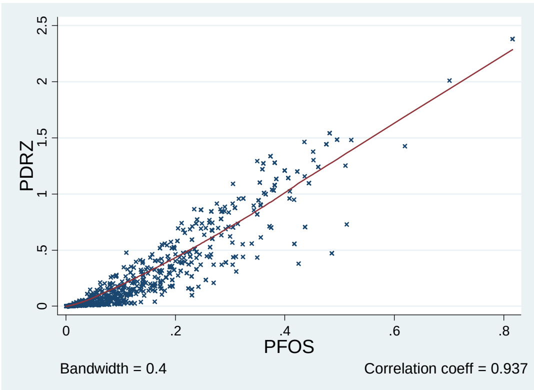
(a) P_{DRZ} v P_{FOS} For Males In 1991-1995



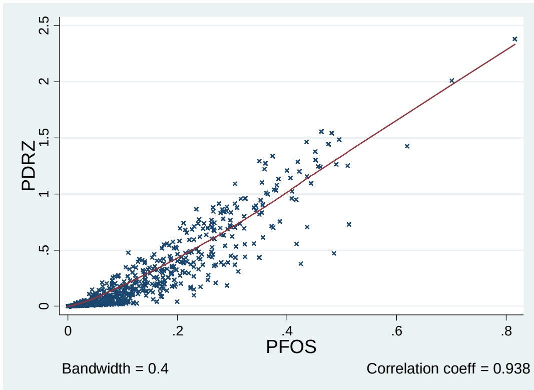
(b) P_{DRZ} v P_{FOS} For Females In 1991-1995



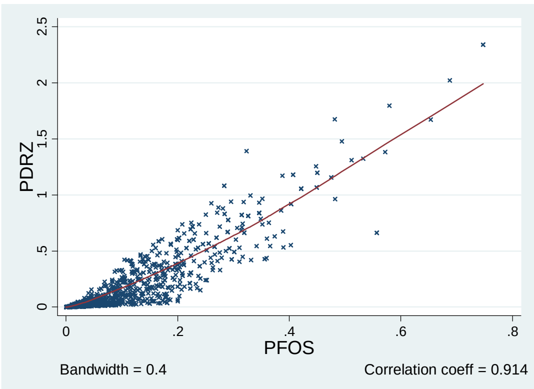
(c) P_{DRZ} v P_{FOS} For Males In 1996-2000



(d) P_{DRZ} v P_{FOS} For Females In 1996-2000



(e) P_{DRZ} v P_{FOS} For Males In 2001-2005



(f) P_{DRZ} v P_{FOS} For Females In 2001-2005

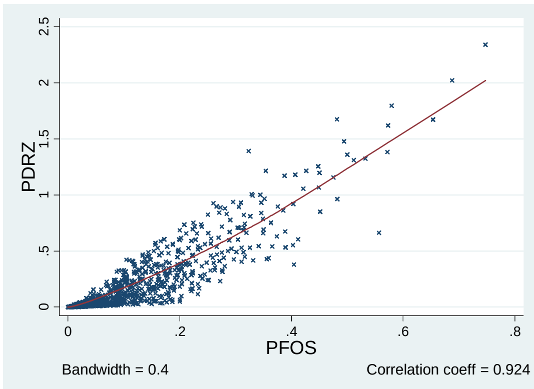


Table 5: OLS Regressions of PDRZ on PFOS for Males During Each Era

	P_{DRZ} (1991-1995)		P_{DRZ} (1996-2000)		P_{DRZ} (2001-2005)	
	Coeff.	t-statistic	Coeff.	t-stat	Coeff.	t-statistic
P_{FOS}	2.567	64.65	2.348	45.85	2.095	34.68
Constant	-0.021	-18.33	-0.014	-12.93	-0.011	-9.59
Observations	2,904		3,134		4,075	
R^2	0.8933		0.8777		0.8345	

Note: The standard errors used to compute the t-statistics are White-corrected for heteroskedasticity.

Table 6: OLS Regressions of PDRZ on PFOS for Females During Each Era

	P_{DRZ} (1991-1995)		P_{DRZ} (1996-2000)		P_{DRZ} (2001-2005)	
	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
P_{FOS}	2.593	65.72	2.356	52.95	2.144	45.03
Constant	-0.025	-19.00	-0.016	-14.14	-0.013	-11.62
Observations	3,064		3,252		4,266	
R^2	0.8825		0.8802		0.8533	

Note: The standard errors used to compute the t-statistics are White-corrected for heteroskedasticity.

3 Determinants of Intertemporal Poverty in Great Britain

3.1 Econometric Models

Thus far we have presented a brief descriptive summary of the patterns of intertemporal poverty in Great Britain. We now turn our attention to the determinants of intertemporal poverty. As discussed in the introduction, our interest is in understanding which factors determine the degree of severity of an individual's intertemporal poverty. We wish to allow for the possibility that the determinants of having a non-zero level of intertemporal poverty may differ somewhat from the factors which shape the overall extent of intertemporal poverty.[14] The approach taken is therefore to model the degree of intertemporal poverty conditional on being intertemporally poor. Ignoring this possibility would run the risk that there might be a type of 'selection bias.' The methodology adopted is the Heckman two-step procedure. In the first stage, we perform a Probit regression, for the probability of being intertemporally poor. This regression is of the form

$$Pr(I = 1|\mathbf{W}) = \Phi(\mathbf{W}\gamma). \tag{3}$$

In this specification, I indicates whether or not an individual is intertemporally poor. If an individual has a non-zero level of intertemporal poverty, $I = 1$; otherwise $I = 0$. $\mathbf{W}$ is a vector of explanatory variables, γ is a vector of unknown parameters, and Φ is the cumulative distribution function of the standard normal distribution. Estimation of (3) yields results which

[14] Note that both the P_{DRZ} and the P_{FOS} measures regard an individual to have a non-zero level of intertemporal poverty if he is poor in at least one time period; otherwise he is intertemporally non-poor.

can be used to predict the probability that any given individual is intertemporally poor. In the second stage, we correct for possible selection bias by including a transformation of the predicted individual probabilities as an extra explanatory variable. The intertemporal poverty equation can be specified as

$$P^* = \mathbf{X}\beta + u \tag{4}$$

where P^* denotes the individual's level of intertemporal poverty, which may or may not take a non-zero value. However, it is only included in the second stage of the regression if it is non-zero, that is if $I = 1$. The conditional expectation of the level of intertemporal poverty given that the person is intertemporally poor is then

$$E(P|\mathbf{X}, I = 1) = \mathbf{X}\beta + E(u|\mathbf{X}, I = 1). \tag{5}$$

Assuming that the error terms are jointly normal, we then have that

$$E(P|\mathbf{X}, I = 1) = \mathbf{X}\beta + \rho\sigma_u\lambda(\mathbf{W}\boldsymbol{\gamma}) \tag{6}$$

where ρ is the correlation between unobserved determinants of an individual having a non-zero level of intertemporal poverty, and unobserved determinants of the overall level of intertemporal poverty P^* (i.e. u), σ_u is the standard deviation of u, and λ is the inverse Mills ratio evaluated at $\mathbf{W}\boldsymbol{\gamma}$.[15]

Here the interpretation of 'selection' is rather different from more common usages of this methodology, such as propensity to work in the labour market context. Individuals do not, of course, self-select whether or not to be poor. Nevertheless, sample 'selection' of including only non-zero intertemporally poor observations in (6) can, as in the more familiar labour market context, be viewed as a form of omitted-variables bias.

Unbiased estimates of the determinants of the severity of intertemporal poverty, conditional on being intertemporally poor, can then be obtained simply by including the inverse Mills ratio λ as an additional explanatory variable in OLS estimation of (4). It is clear that the coefficient of λ can only be zero if the correlation $\rho = 0$. We can therefore test the null hypothesis that there is no selection bias by the equivalent null hypothesis that the coefficient of λ equals zero.

The methodology described in this subsection was applied to all three eras, running separate regressions for males and females and using both poverty measures P_{DRZ} and P_{FOS}.

[15] This follows in a similar way to that described in Greene (2000), pp. 928-929.

3.2 Misspecification tests

Two related types of misspecification tests were performed on the output of all the Heckman regressions described in the previous subsection. Each test was a type of reset test. The first one was a link test, of the form suggested by Pregibon (1979), which in turn was based on an earlier idea by Tukey (1949). A link error is a common form of specification error which occurs when the dependent variable requires a transformation in order to appropriately relate or 'link' to the independent variables. Consider again equation (4). Let $\widehat{\beta}$ be the parameter estimates. A standard link test is performed by regressing P^* on $\mathbf{X}\widehat{\beta}$ and $\left(\mathbf{X}\widehat{\beta}\right)^2$. The idea behind the test is that the $\left(\mathbf{X}\widehat{\beta}\right)^2$ term is likely to be significant if there is a link error, whereas under the null hypothesis of no misspecification it should not be.

To apply this test in the context of the Heckman regressions above we regressed P^* on $\left(\mathbf{X}\widehat{\beta} + \lambda\widehat{\alpha}\right)$ and $\left(\mathbf{X}\widehat{\beta} + \lambda\widehat{\alpha}\right)^2$, where $\alpha = \rho\sigma_u$, and tested whether the second term was significant. However, Pregibon (1979)'s link test was designed to apply to single equation systems and incorporating the inverse Mills ratio λ to the test in this manner may not be valid. Because of these doubts, we also performed a modified version of the test, regressing P^* on $\left(\mathbf{X}\widehat{\beta} + \lambda\widehat{\alpha}\right)$ and $\left(\mathbf{X}\widehat{\beta}\right)^2$ and testing whether the latter term was significantly different from zero.

3.3 Variables used in study

The possible explanatory variables considered in the study are displayed in Table 7.

Table 7: Variables Considered For Inclusion In Probit/Selection and Heckman/OLS Models

Variable	Description	Probit	Heckman
age	Individual's age	Y	Y
agesq	Square of individual's age	Y	Y
retire	Retired	Y	Y
mortgage	Have a mortgage	Y	Y
degree	Highest educ qual: Degree	Y	Y
hndcteach	Highest educ qual: HNC, HND or teaching	Y	Y
alevel	Highest educ qual: A-Levels	Y	Y
nkids	Number of children in household	Y	Y
inactive	Economically inactive	Y	Y
evermarryliv	Have ever married or lived with partner	Y	Y
hidegree	Have a higher degree	Y	Y
unemploy	Unemployed	Y	Y
laha	Live in a local authority / housing authority	Y	Y
student	Student	Y	Y
ownedout	Home owned outright	Y	Y
immigrant	Immigrant	N	Y
r1	Live in Inner London	Y	Y
r2	Live in Outer London	Y	Y
r3	Live in rest of South-East	Y	Y
r4	Live in South-West	Y	Y
r5	Live in East Anglia	Y	Y
r6	Live in East Midlands	N	Y
r7	Live in West Midland Cities	N	Y
r9	Live in Greater Manchester	Y	N
r10	Live in Merseyside	N	Y
r11	Live in rest of North-West	Y	Y
r12	Live in South Yorkshire	Y	Y
r13	Live in West Yorkshire	Y	N
r14	Live in rest of Yorkshire and Humberside	N	Y
r15	Live in Tyne & Wear	Y	Y
r16	Live in rest of North	Y	Y

In our choice of variables, we closely followed the approach of Clark and Peters (2005). The variables employed are also broadly in line with those used in other studies on the determinants of poverty using BHPS data. In fact the variables in Table 7 were chosen from a slightly larger set of variables by stepwise regressing, at the 10% level of significance, (3) and (4) using Probit and OLS regressions respectively. The stepwise regressions were performed for each of the three eras. Variables were omitted from the subsequent analysis only if they were dropped in the stepwise regressions for all three eras. It follows that the variables listed in Table 7 in the Probit/Selection column were all found to be significant at the 10% level or lower in the Probit regression of at least one of the three eras. Similarly, the variables listed in the Heckman/OLS column of Table 7 were all found to be significant at the 10% level or lower in the OLS regression of at least one of the three eras. One additional variable, a dummy for Wales, survived the stepwise regression analysis but was subsequently dropped as it was found to be insignificant in all of the subsequent analysis. The dummy variable for being an immigrant was dropped in the second era as the sample size for the number of immigrants who were also poor was extremely small during this period.

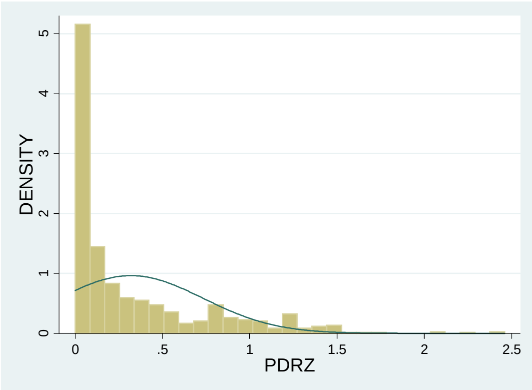
Descriptions of the variables are contained in Table 7. Apart from 'age,' 'agesq' and 'nkids,' which refer, respectively, to the age of the individual, the square of the age of the individual and the number of children in the individual's household, all the remaining variables are dummies.

It is clear that most of the variables in Table 7 can change over time. The approach taken in our analysis was to use each variable's value in the first wave of each of the three eras. For example, in the first era studied, the variable 'degree' has a value of 1 if the individual held a degree in Wave 1; in the second era, the variable has a value of 1 if the individual held a degree in Wave 6.

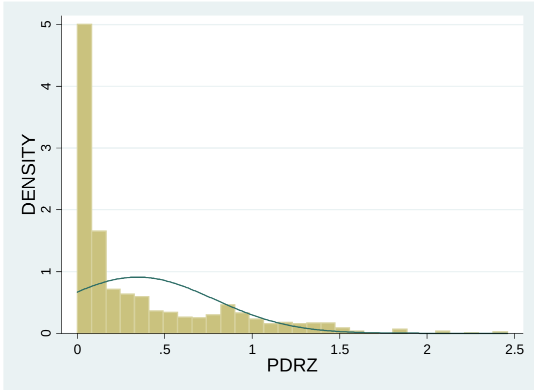
We now turn our attention to the dependent variable. An important assumption in Heckman regressions is that the dependent variable is normally distributed. Histograms were plotted for both poverty measures in each of the three eras, for males and females separately, and the charts overlaid with appropriately scaled normal density functions. These results are displayed in Figure 2 and Figure 3 for the P_{DRZ} and P_{FOS} measures respectively. It is clear from these histograms that the densities are heavily skewed towards lower levels of poverty and that a normality assumption cannot be maintained. Natural logarithms of each of the poverty measures were then taken and the corresponding histograms plotted for the logged poverty measures. These are displayed, for P_{DRZ} and P_{FOS}, in Figure 4 and Figure 5 respectively. Compared to the overlaid normal density functions, these histograms are slightly skewed to the right and there is some evidence of a possible bi-modality. Nevertheless, a normal approximation does not appear to be a bad one. Overall, the results in Figure 2, Figure 3, Figure 4 and Figure 5 strongly suggest that the ensuing analysis be conducted with the dependent variables in their logarithmic form and this is the approach taken.

Figure 2: Histograms For PDRZ Measures

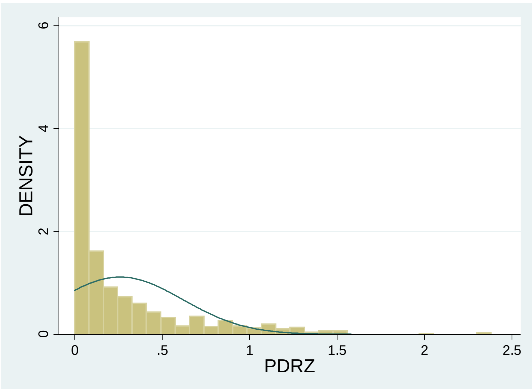
(a) P_{DRZ} Histogram For Males During 1991-1995



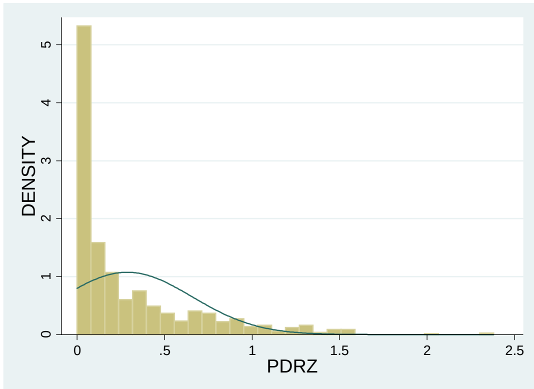
(b) P_{DRZ} Histogram For Females During 1991-1995



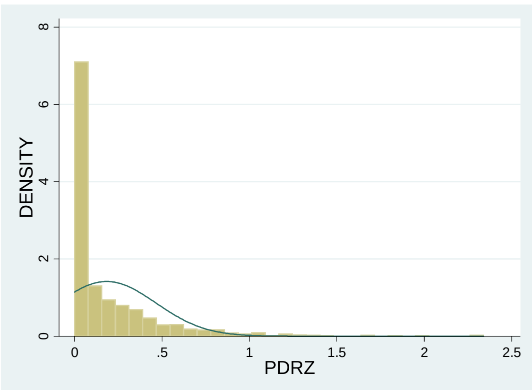
(c) P_{DRZ} Histogram For Males During 1996-2000



(d) P_{DRZ} Histogram For Females During 1996-2000



(e) P_{DRZ} Histogram For Males During 2001-2005



(f) P_{DRZ} Histogram For Females During 2001-2005

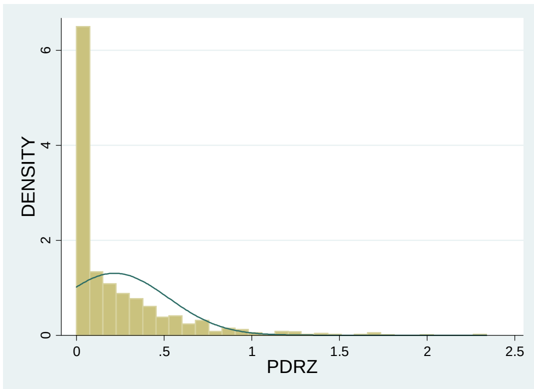
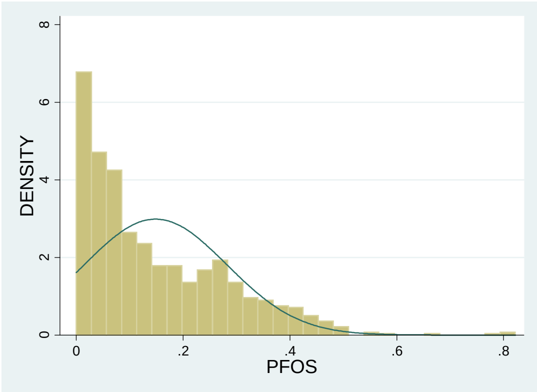
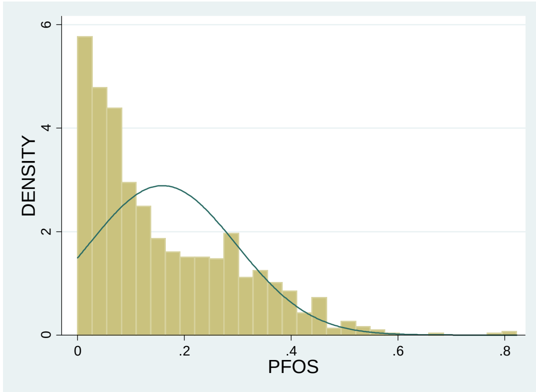


Figure 3: Histograms For PFOS Measures

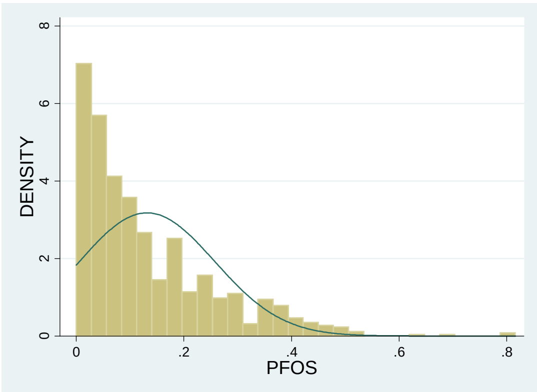
(a) P_{FOS} Histogram For Males During 1991-1995



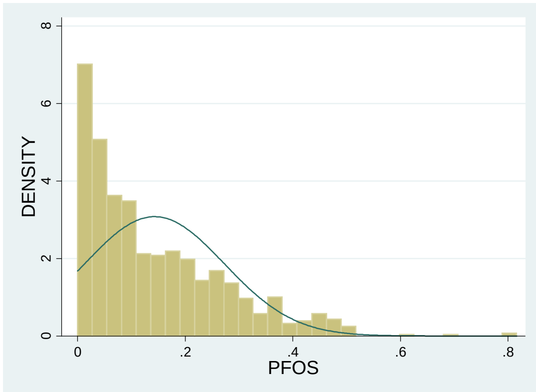
(b) P_{FOS} Histogram For Females During 1991-1995



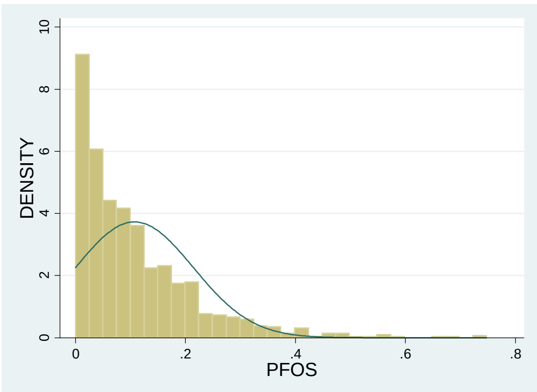
(c) P_{FOS} Histogram For Males During 1996-2000



(d) P_{FOS} Histogram For Females During 1996-2000



(e) P_{FOS} Histogram For Males During 2001-2005



(f) P_{FOS} Histogram For Females During 2001-2005

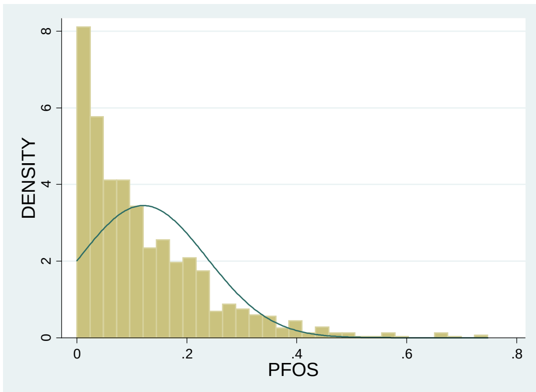
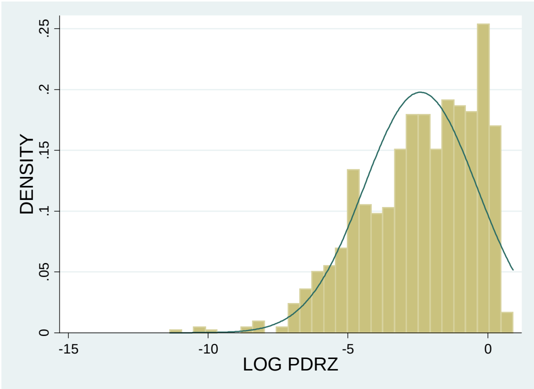
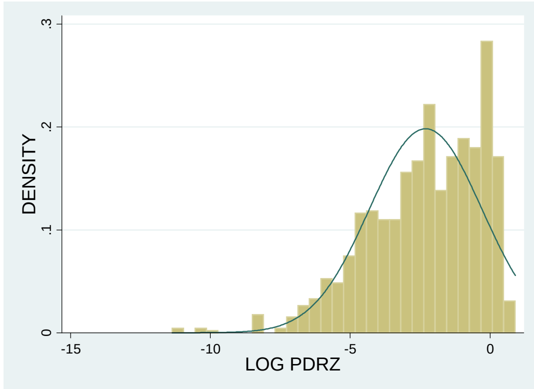


Figure 4: Histograms For Logged PDRZ Measures

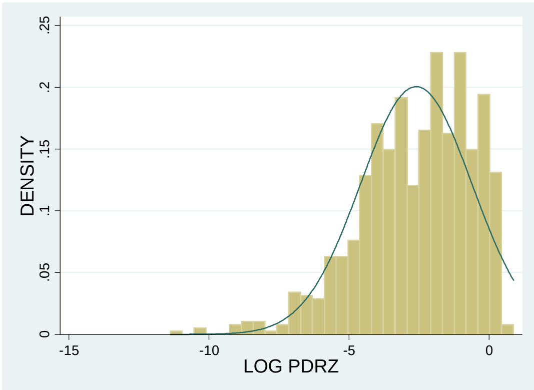
(a) Log P_{DRZ} Histogram For Males During 1991-1995



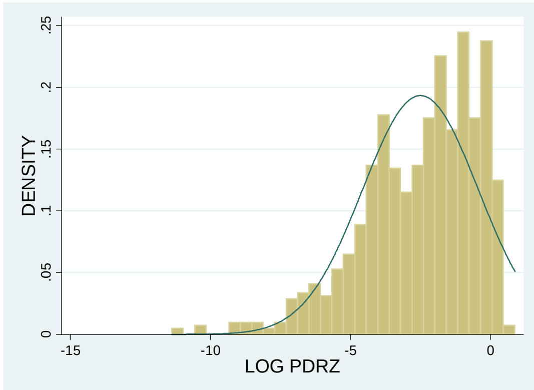
(b) Log P_{DRZ} Histogram For Females During 1991-1995



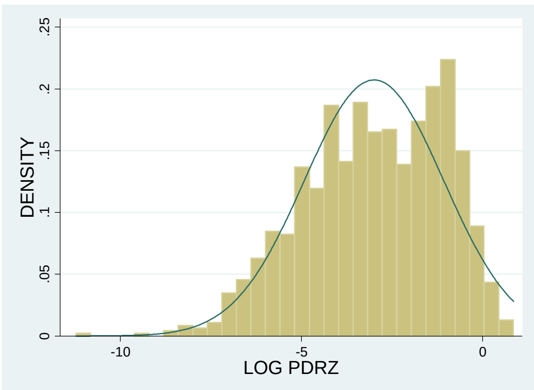
(c) Log P_{DRZ} Histogram For Males During 1996-2000



(d) Log P_{DRZ} Histogram For Females During 1996-2000



(e) Log P_{DRZ} Histogram For Males During 2001-2005



(f) Log P_{DRZ} Histogram For Females During 2001-2005

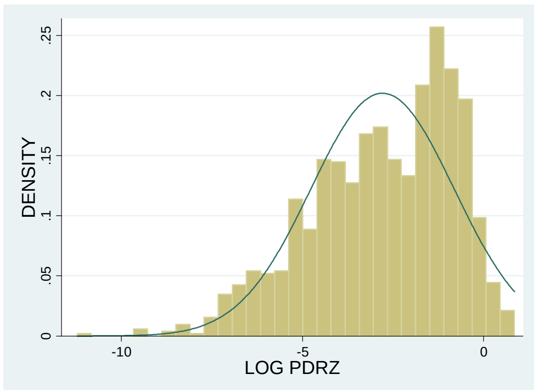
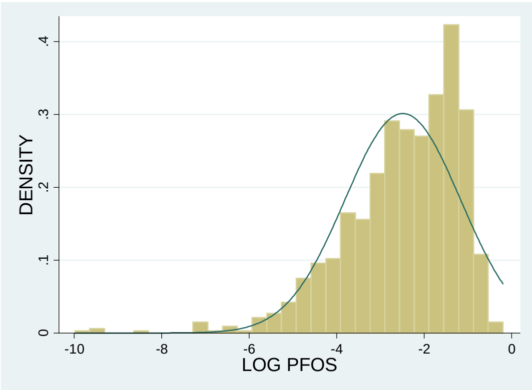
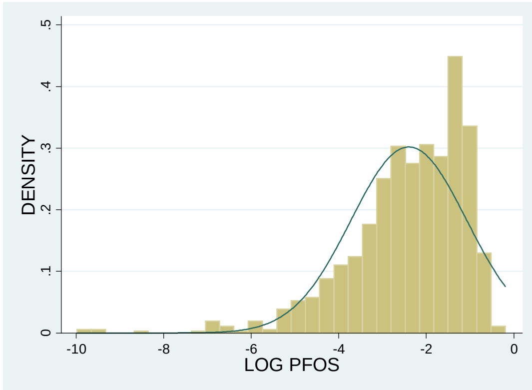


Figure 5: Histograms For Logged PFOS Measures

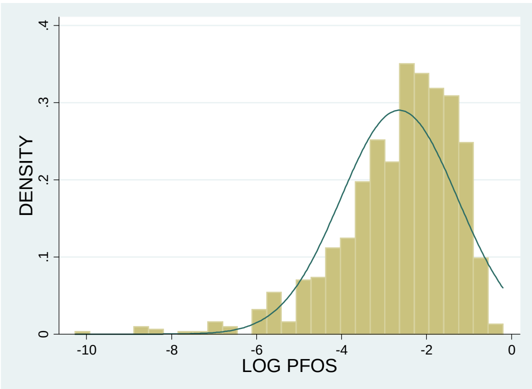
(a) Log P_{FOS} Histogram For Males During 1991-1995



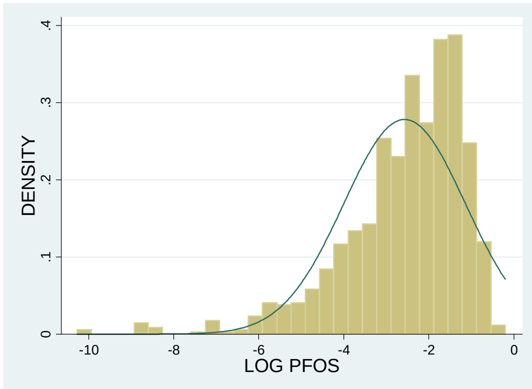
(b) Log P_{FOS} Histogram For Females During 1991-1995



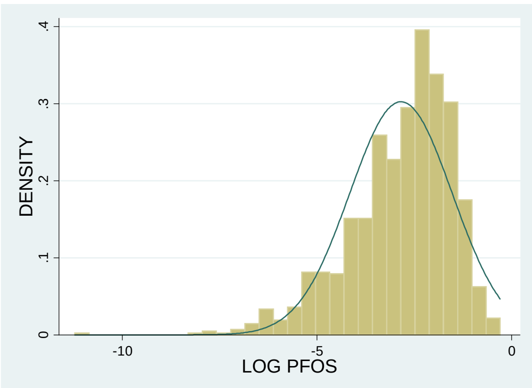
(c) Log P_{FOS} Histogram For Males During 1996-2000



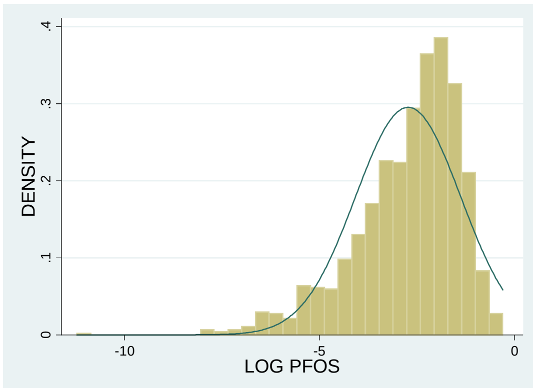
(d) Log P_{FOS} Histogram For Females During 1996-2000



(e) Log P_{FOS} Histogram For Males During 2001-2005



(f) Log P_{FOS} Histogram For Females During 2001-2005



The results of the regressions for each of the three eras are presented in the next subsection. By way of comparison, results are also presented in Appendix A.2 for simple OLS estimation of (4).

3.4 Empirical Results

The results for all the regressions are displayed in Tables 8 through to 13.[16] Scotland was the omitted region in all the regressions. The omitted category with respect to housing tenure was 'any other tenure,' such as, for example, living in privately rented accommodation. The omitted category with respect to highest educational qualification was having O-Levels, CSEs or below as the highest qualification attained.

Both the standard link test and the amended version described in Section 3.2 were performed on all the Heckman regressions displayed in Tables 8 through to 13. In all cases, the tests failed to reject the null hypothesis of no misspecification.[17]

[16] In these tables, and throughout the rest of the paper, statistical significance at the 5% and 1% levels is denoted by * and ** respectively.

[17] The p-values for these misspecification tests are displayed in Appendix A.3. The lowest p-value was 0.175.

Table 8: Heckman Regressions For Logged PDRZ Measures By Gender For 1991-1995

Variables	Probit Male	Heckman Male	Probit Female	Heckman Female
age	-0.026	-0.098*	-0.031*	-0.138**
agesq	0.0003*	0.001	0.0003*	0.001**
retire	0.312*	1.367**	0.625**	1.590*
mortgage	-0.574**	-1.312*	-0.648**	-1.706**
degree	-0.659**	-1.279	-0.802**	-2.447**
hndcteach	-0.496**	-0.305	-0.952**	-1.727
alevel	-0.300**	-0.902**	-0.265**	-0.800*
nkids	0.360**	0.582*	0.280**	0.699**
inactive	0.594**	1.465**	0.647**	2.129**
evermarryliv	0.123	1.535**	0.278*	0.574
hidegree	-1.156**	-0.694	-0.670	-2.053
unemploy	1.054**	2.339**	0.816**	2.742**
laha	0.192	0.582	0.281*	0.784
student	0.545**	1.906**	0.537**	1.377
ownedout	-0.183	-0.349	-0.335*	-0.992
immigrant		0.154		0.004
r1	0.029	0.257	-0.089	-0.405
r2	0.078	0.250	-0.102	-0.756
r3	-0.072	-0.135	-0.087	-0.414
r4	-0.037	0.150	-0.142	-0.539
r5	0.093	0.328	-0.029	-0.202
r6		-0.033		-0.375
r7		0.103		-0.336
r9	-0.180		-0.090	
r10		-1.022		-0.033
r11	-0.182	-0.759	-0.219	-1.037
r12	-0.047	1.164*	-0.022	0.883
r13	0.196		0.220	
r14		0.451		0.260
r15	0.226	1.091*	0.414*	1.009
r16	-0.294	-1.010	-0.188	-0.386
constant	-0.272	-4.384**	-0.032	-3.827**
No. individuals	2,047	577	2,228	723
Mills Ratio λ		2.000		3.158*
R-squared		0.2178		0.1855

Table 9: Heckman Regressions For Logged PDRZ Measures By Gender For 1996-2000

Variables	Probit Male	Heckman Male	Probit Female	Heckman Female
age	-0.049**	-0.065	-0.030*	-0.032
agesq	0.0006**	0.001	0.0003*	0.000
retire	0.214	0.583	0.413**	1.140**
mortgage	-0.754**	-0.701	-0.922**	-1.238*
degree	-0.566**	0.240	-0.680**	-0.604
hndcteach	-0.746**	-0.714	-0.447**	-0.149
alevel	-0.151	0.104	-0.316**	-0.062
nkids	0.378**	0.429	0.376**	0.513**
inactive	0.915**	0.724	0.642**	1.357**
evermarryliv	0.450**	0.703	-0.226	-0.317
hidegree	-0.497*	0.074	-0.298	-1.149
unemploy	1.202**	1.493*	1.053**	1.848**
laha	0.051	-0.115	0.092	0.136
student	0.757**	0.802	0.198	-0.214
ownedout	-0.174	0.095	-0.346*	-0.354
r1	-0.037	-0.557	-0.383	-0.448
r2	-0.253	-0.524	-0.336*	-0.615
r3	-0.157	-0.143	-0.300**	-0.296
r4	-0.077	-0.319	-0.232*	-0.519
r5	0.271	0.534	-0.039	0.397
r6		0.143		-0.077
r7		0.142		0.077
r9	-0.023		-0.307	
r10		-0.151		-0.360
r11	-0.121	-0.479	-0.270	-0.400
r12	0.040	0.871	0.152	0.559
r13	-0.036		-0.102	
r14		0.975*		0.540
r15	0.044	0.644	0.015	-0.011
r16	-0.016	-0.715	0.051	-0.309
constant	-0.122	-3.296**	0.428	-3.305**
No. individuals	2,238	495	2,403	660
Mills Ratio λ		0.301		0.892
R-squared		0.1548		0.1814

Table 10: Heckman Regressions For Logged PDRZ Measures By Gender For 2001-2005

Variables	Probit Male	Heckman Male	Probit Female	Heckman Female
age	-0.027*	0.008	-0.002	0.037
agesq	0.0004**	0.000	0.000	-0.000
retire	0.172	0.686*	0.429**	1.490**
mortgage	-0.670**	-1.009	-0.680**	-1.546**
degree	-0.570**	-0.908	-0.725**	-1.652**
hndcteach	-0.514**	-0.340	-0.354**	-0.489
alevel	-0.188*	-0.063	-0.219**	-0.432
nkids	0.317**	0.417	0.297**	0.606**
inactive	0.817**	1.282	0.711**	1.583**
evermarryliv	0.124	0.291	-0.360**	-0.754*
hidegree	-0.676**	-1.268	-0.757**	0.582
unemploy	0.891**	1.466	0.803**	2.108**
laha	0.233	-0.075	0.359**	-0.024
student	0.477*	1.640*	0.737**	1.861**
ownedout	-0.290*	-0.208	-0.334**	-0.649
immigrant		1.574		0.265
r1	-0.394	0.284	-0.522	-1.140
r2	-0.002	0.781	-0.126	0.500
r3	-0.323**	-0.772	-0.336**	-1.353**
r4	-0.086	-0.177	-0.091	-0.249
r5	-0.095	0.371	-0.119	0.018
r6		-0.314		-0.295
r7		-0.811		-0.475
r9	0.127		0.260	
r10		-0.174		-0.451
r11	-0.153	-0.573	-0.102	-0.484
r12	-0.584*	0.906	-0.373	-0.152
r13	-0.031		-0.021	
r14		-0.045		0.047
r15	-0.217	-0.104	-0.225	-1.085
r16	-0.114	-0.018	0.096	0.168
constant	-0.268	-5.357**	-0.344	-5.854**
No. individuals	2,903	682	3,135	882
Mills Ratio λ		1.215		2.029*
R-squared		0.0812		0.1081

Table 11: Heckman Regressions For Logged PFOS Measures By Gender For 1991-1995

Variables	Probit Male	Heckman Male	Probit Female	Heckman Female
age	-0.026	-0.062*	-0.031*	-0.094*
agesq	0.0003*	0.001	0.0003*	0.001*
retire	0.312*	0.670*	0.625**	1.272*
mortgage	-0.574**	-0.817*	-0.648**	-1.259*
degree	-0.659**	-1.024*	-0.802**	-1.881**
hndcteach	-0.496**	-0.197	-0.952**	-1.388
alevel	-0.300**	-0.576*	-0.265**	-0.563
nkids	0.360**	0.367*	0.280**	0.473*
inactive	0.594**	0.970*	0.647**	1.599**
evermarryliv	0.123	1.050**	0.278*	0.483
hidegree	-1.156**	-0.809	-0.670	-1.594
unemploy	1.054**	1.607**	0.816**	2.034**
laha	0.192	0.429	0.281*	0.542
student	0.545**	1.384**	0.537**	1.197
ownedout	-0.183	-0.222	-0.335*	-0.784
immigrant		0.161		0.185
r1	0.029	0.266	-0.089	-0.128
r2	0.078	0.325	-0.102	-0.447
r3	-0.072	0.054	-0.087	-0.218
r4	-0.037	0.213	-0.142	-0.373
r5	0.093	0.230	-0.029	-0.110
r6		-0.031		-0.278
r7		0.038		-0.412
r9	-0.180		-0.090	
r10		-0.606		0.014
r11	-0.182	-0.407	-0.219	-0.740
r12	-0.047	0.762*	-0.022	0.560
r13	0.196		0.220	
r14		0.304		0.210
r15	0.226	0.741*	0.414*	0.810
r16	-0.294	-0.555	-0.188	-0.276
constant	-0.272	-4.138**	-0.032	-3.827**
No. individuals	2,047	577	2,228	723
Mills Ratio λ		1.482*		2.572*
R-squared		0.1838		0.1678

Table 12: Heckman Regressions For Logged PFOS Measures By Gender For 1996-2000

Variables	Probit Male	Heckman Male	Probit Female	Heckman Female
age	-0.049**	-0.035	-0.030*	-0.025
agesq	0.001**	0.000	0.0003*	0.000
retire	0.214	0.210	0.413**	0.738**
mortgage	-0.754**	-0.730	-0.922**	-0.988**
degree	-0.566**	0.414	-0.680**	-0.344
hndcteach	-0.746**	-0.657	-0.447**	0.013
alevel	-0.151	0.040	-0.316**	-0.139
nkids	0.378**	0.250	0.376**	0.342**
inactive	0.915**	0.572	0.642**	0.953**
evermarryliv	0.450**	0.394	-0.226	-0.316
hidegree	-0.497*	0.078	-0.298	-0.302
unemploy	1.202**	1.148*	1.053**	1.299**
laha	0.051	-0.292	0.092	-0.028
student	0.757**	0.408	0.198	-0.125
ownedout	-0.174	-0.080	-0.346*	-0.354
r1	-0.037	-0.338	-0.383	-0.234
r2	-0.253	-0.328	-0.336*	-0.357
r3	-0.157	-0.063	-0.300**	-0.200
r4	-0.077	-0.316	-0.232*	-0.438*
r5	0.271	0.525	-0.039	0.305
r6		0.140		-0.023
r7		0.218		0.135
r9	-0.023		-0.307	
r10		-0.018		-0.131
r11	-0.121	-0.395	-0.270	-0.288
r12	0.040	0.727*	0.152	0.390
r13	-0.036		-0.102	
r14		0.807*		0.496
r15	0.044	0.473	0.015	-0.045
r16	-0.016	-0.424	0.051	-0.103
constant	-0.122	-3.155**	0.428	-2.981**
No. individuals	2,238	495	2,403	660
Mills Ratio λ		0.343		0.831
R-squared		0.1398		0.1446

Table 13: Heckman Regressions For Logged PFOS Measures By Gender For 2001-2005

Variables	Probit Male	Heckman Male	Probit Female	Heckman Female
age	-0.027*	0.012	-0.002	0.020
agesq	0.0004**	-0.000	0.000	-0.000
retire	0.172	0.271	0.429**	0.742*
mortgage	-0.670**	-0.910	-0.680**	-1.176**
degree	-0.570**	-0.440	-0.725**	-0.909*
hndcteach	-0.514**	-0.443	-0.354**	-0.291
alevel	-0.188*	0.035	-0.219**	-0.277
nkids	0.317**	0.229	0.297**	0.360**
inactive	0.817**	0.658	0.711**	0.927**
evermarryliv	0.124	0.312	-0.360**	-0.291
hidegree	-0.676**	-1.021	-0.757**	0.573
unemploy	0.891**	1.188*	0.803**	1.346**
laha	0.233	-0.263	0.359**	-0.194
student	0.477*	1.328**	0.737**	1.143**
ownedout	-0.290*	-0.310	-0.334**	-0.519
immigrant		1.132		0.263
r1	-0.394	-0.083	-0.522	-0.859
r2	-0.002	0.578*	-0.126	0.389
r3	-0.323**	-0.550	-0.336**	-0.840**
r4	-0.086	-0.137	-0.091	-0.183
r5	-0.095	0.146	-0.119	-0.069
r6		-0.232		-0.199
r7		-0.488		-0.232
r9	0.127		0.260	
r10		-0.059		-0.275
r11	-0.153	-0.279	-0.102	-0.175
r12	-0.584*	0.419	-0.373	-0.176
r13	-0.031		-0.021	
r14		0.126		0.173
r15	-0.217	-0.322	-0.225	-0.790
r16	-0.114	0.002	0.096	0.102
constant	-0.268	-4.489**	-0.344	-4.544**
No. individuals	2,903	682	3,135	882
Mills Ratio λ		0.951		1.391*
R-squared		0.0653		0.0748

Before analysing the results in detail, it is perhaps worth drawing attention to the fact that the respective Probit/Selection regressions for both males and females in each of the three eras are exactly the same for both P_{DRZ} and P_{FOS}. This is necessarily the case since both measures are equal to zero for a given individual if and only if they have incomes above the poverty line during each of the five years.

There are a number of notable trends in the results. Firstly, it is interesting to note that the R-squared values of the Heckman regressions display a marked and steady decline from each era to the next. This is true for both males and females and using both the P_{DRZ} and the P_{FOS} measures. It is not clear why this should be so but there are a number of possibilities. It might simply be that some of the missing variables which impact upon poverty became more important predictors of poverty in the later eras. Another possibility, as alluded to in Section 2.2, is that in later waves the poverty estimates may be biased downwards due to a higher probability of non-response from less well-off individuals. This could affect the predicted values and so too the R-squared values. In any case, there appears to be some evidence that the model specification is not exactly the same during each of the three different eras. This is corroborated by the fact there is also a fair degree of variation between eras in both the magnitudes of coefficients and of their statistical significance.

The R-squared values are higher in all the regressions for P_{DRZ} than for the corresponding regressions for P_{FOS}. This suggests that P_{DRZ} is a more precise estimator of intertemporal poverty than P_{FOS} - at least in so far as intertemporal poverty is satisfactorily explained by the variables in our models. Dutta et al. (2012) provided a justification, on purely axiomatic grounds, for the manner in which measures from the P_R class, such as P_{DRZ}, account for the sequencing of poor and non-poor periods. The results in this study lend some empirical support to their approach. Relative to taking a neutral stance on the impact of the sequencing of poor spells on overall intertemporal poverty, as in Foster (2009), penalising consecutive periods of poverty and allowing affluent spells to have a mitigating impact on subsequent poverty results in a measure more closely correlated with a number of plausible correlates of poverty.

The coefficient of the inverse Mills ratio is statistically significant at the 5% level in five of the twelve Heckman regressions. It can be inferred from this that, at least in these five regressions, performing a simple OLS regression on the dependent variable would have resulted in sample selection bias. As noted above, by way of comparison, results for OLS regressions corresponding to all twelve specifications are displayed in Appendix A.2.

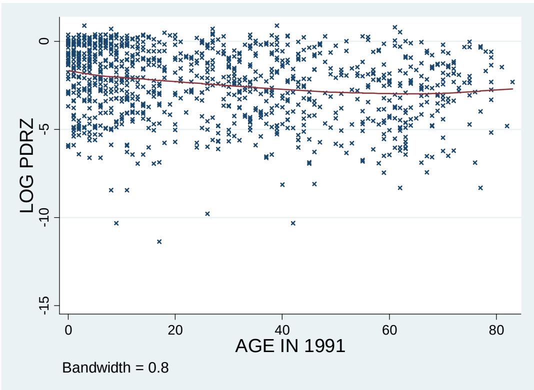
Leaving aside the regional dummy variables, with a few notable exceptions, the other explanatory variables have the expected signs in most specifications. The coefficient of 'age' is negative in all of the Probit/Selection regressions, suggesting that being older decreases the probability of being poor. Moreover, this variable is found to be significant at the 5% level or lower in eight of the twelve selection regressions. However, the coefficient of 'agesq' is positive in all the selection regressions, indicating that the impact of age is non-linear. This coefficient is significant at the 5% level or lower in ten of the twelve selection regressions. Our results suggest that even after age has been accounted for in the 'selection' of poverty, there is still some effect of age on the extent of intertemporal poverty. However, these results are less emphatic. The coefficient of 'age' is negative in eight of the twelve Heckman regressions and significant at the 5% level or lower in just four of these. There is again some evidence of a non-linear impact of age but the evidence is rather weak. The coefficient of 'agesq' is positive in nine of the twelve Heckman regressions but significant at the 5% level or lower in just two of these.

To further study the relationship between the level of intertemporal poverty and age, the logs of P_{DRZ} and P_{FOS} were plotted against 'age' and Lowess smoothers fitted. This was done for each of the three eras, separately for males and females. The plots for P_{DRZ} and P_{FOS}

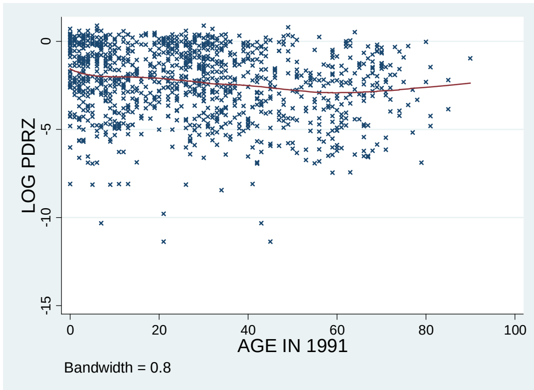
respectively against age are displayed in Figure 6 and Figure 7.

Figure 6: Plots Of Log PDRZ Against Age

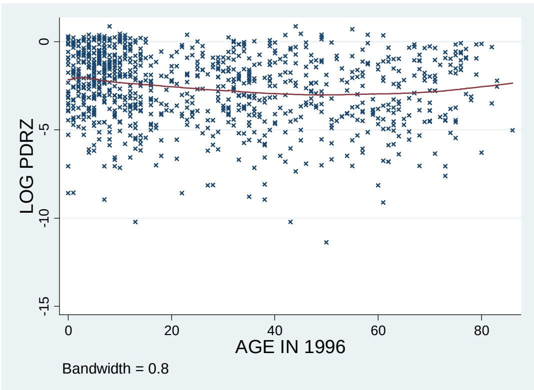
(a) Log P_{DRZ} v Age for Males During 1991-1995



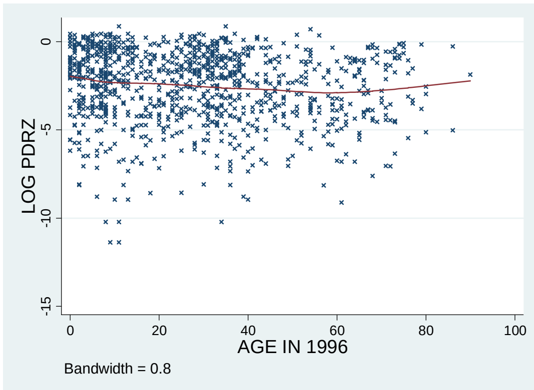
(b) Log P_{DRZ} v Age for Females During 1991-1995



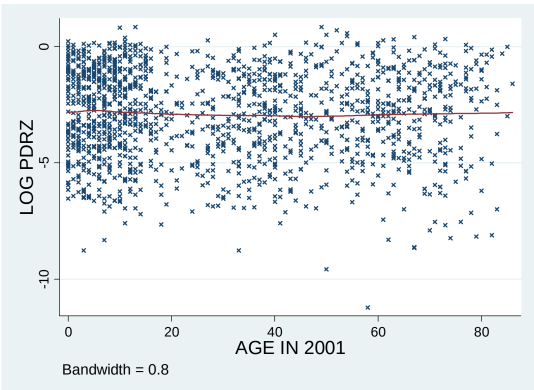
(c) Log P_{DRZ} v Age for Males During 1996-2000



(d) Log P_{DRZ} v Age for Females During 1996-2000



(e) Log P_{DRZ} v Age for Males During 2001-2005



(f) Log P_{DRZ} v Age for Females During 2001-2005

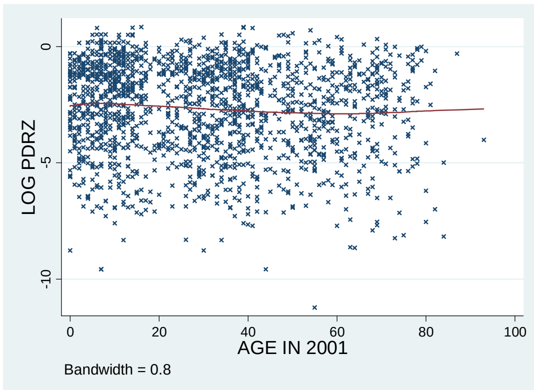
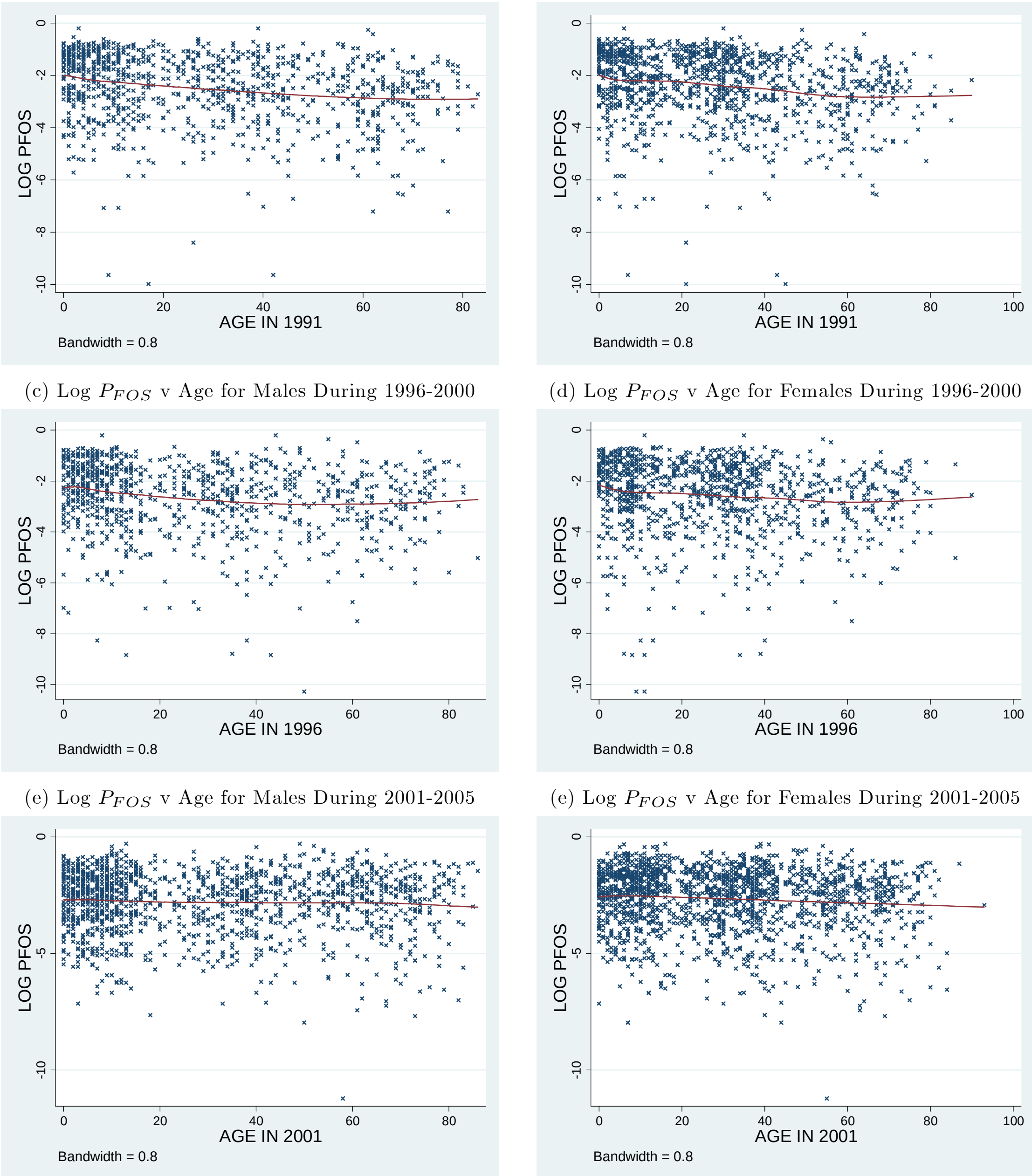


Figure 7: Plots Of Log PFOS Against Age



(a) Log P_{FOS} v Age for Males During 1991-1995

(b) Log P_{FOS} v Age for Females During 1991-1995

(c) Log P_{FOS} v Age for Males During 1996-2000

(d) Log P_{FOS} v Age for Females During 1996-2000

(e) Log P_{FOS} v Age for Males During 2001-2005

(e) Log P_{FOS} v Age for Females During 2001-2005

Even in these simple plots, there appears to be some evidence of a possible non-linear relationship between poverty and age, which is decreasing at lower levels of age and increasing at higher levels. Interestingly, in a number of the plots, notably 6(a), 6(b), 6(d), 6(f), 7(b), 7(c) and 7(d), there appear to be turning points (minima) that might correspond roughly to ages close to the official retirement age in Great Britain, which was 65 for men and 60 for women throughout the period of analysis. To investigate this possibility further, the dependent variable in each of the twelve Heckman regression models displayed in Tables 8 through to 13 was differentiated with respect to the age variable and set equal to zero, in order to determine whether, *ceteris paribus*, there are 'optimal' ages for minimising poverty. In other words, after controlling for a number of other possible causal factors of poverty, is there a particular age at which poverty is likely to be lowest. The results are displayed in Table 14.

Table 14: Estimates Of Optimal Ages For Minimising Poverty

Era	Sex	'Optimal' Age for P_{DRZ} Measure	'Optimal' Age for P_{FOS} Measure
1	Male	60	58
1	Female	53	56
2	Male	46	46
2	Female	54	63
3	Male	No optimum	95
3	Female	64	57

Although the numbers in Table 14 do not correspond exactly to the apparent turning points in the respective plots in Figure 6 and Figure 7, it is interesting to note that in two thirds of the twelve regressions, an apparent turning point emerges at ages between 53 and 63, in and around the ages at which many people retire. It would be naive to read too much into these results, especially given the relatively large confidence intervals of some of the parameter estimates of both the 'age' and (especially) the 'agesq' variables. Nevertheless, comparing the results for each of the three eras as a whole in Table 14, it is interesting to note that the most plausible sounding results emerge for Era 1, and it is in Era 1 that almost all the coefficients for 'age' and 'agesq' are statistically significant in the Heckman regressions.

The coefficients of 'retire' are positive in all twelve of the Probit/Selection regressions, suggesting that being retired increases the probability of being poor. This variable is significant at the 5% level or lower in eight of the twelve selection regressions. The coefficients of 'retire' are also positive in all twelve of the Heckman regressions, and are significant at the 5% level or lower in all but three. This suggests that being retired tends to increase the extent of intertemporal poverty, conditional on being intertemporally poor. It is interesting to note that in all cases, the magnitude of the coefficient is larger in the Heckman regressions for females than in the corresponding regressions for males. This is likely to be largely due to differences between the sexes in entitlement to a full basic state pension. The state pension in Great Britain is a contributory system. In order to be entitled to a full basic state pension, individuals need to have made contributions for at least 90% of their working lives. Credits are given not only for participation in the labour market, but also for being registered as unemployed or as long-term ill or disabled. Prior to 1978, no credits were given to individuals who were out of the labour market in order to look after children.[18] This disproportionately affected women and resulted in women having lower state pensions than men. Given the long-term nature of contributory pension schemes, inequality between male and female state pension eligibility persisted for many years after the introduction of the HRP system. According to Blundell and Johnson (1998), at the time of their writing, whilst almost all men aged 65 and over received a full basic pension, there were "...low rates of entitlement among married women [reflecting] long periods spent out

[18] In 1978, this changed through the introduction of the Home Responsibilities Protection (HRP) system.

of the labor market by older cohorts." (p. 169). Blundell and Johnson (1998) expected this inequality to disappear in the early years of the twenty-first century.

Unsurprisingly, being unemployed is found to have a highly significant impact both on the probability of being intertemporally poor, and conditional on being poor, on the extent of intertemporal poverty. In fact our results suggest that this is the single most important explanatory variable for intertemporal poverty. The variable 'unemploy' is significant at the 1% level in all of the Probit/Selection regressions and in all cases has a bigger coefficient than any of the other variables which tend to increase the probability of being poor. The variable also has a significantly positive coefficient in all but one of the Heckman regressions and in eight of the twelve regressions it is significant at the 1% level. With just one exception, the magnitudes of the coefficients of 'unemploy' in the Heckman regressions are higher than for any of the other variables which tend to increase poverty. It is also interesting to note that the magnitudes of the coefficients are somewhat higher in the Heckman regressions for females than in the respective regressions for males.

Another unsurprising implication of our results is that being economically inactive increases the probability of being poor. According to our results, this variable is second only to being unemployed in its importance for increasing the probability of being intertemporally poor. The variable 'inactive' is significantly positive at the 1% level in all of the Probit/Selection regressions. It is also significantly positive, at the 5% level or lower, in two thirds of the Heckman regressions, suggesting that, conditional on being poor, being economically inactive also tends to increase the extent of intertemporal poverty. As was the case with both retirement and unemployment, the coefficient of the dummy variable for being economically inactive has a greater magnitude in the Heckman regressions for females than in the corresponding regressions for males.

Being a student also significantly increases the probability of being poor according to our results. The variable student is significantly positive at the 5% level in ten of our twelve Probit/Selection regressions, and significant at the 1% level in eight of these. Being a student also tends to increase the extent of intertemporal poverty, conditional upon being poor, according to our results; the variable 'student' has a positive coefficient in all but two of the Heckman regressions and is significant at the 5% level or lower in six of them.

We now turn attention to housing tenure. The coefficients of 'mortgage' are negative, and significant at the 1% level, in all twelve of the Probit/Selection regressions. This suggests that having a mortgage is an important predictor of being intertemporally non-poor. The coefficients of 'mortgage' are also negative in each of the Heckman regressions, and significantly so, at the 5% level or lower, in two thirds of them. This suggests that having a mortgage tends to reduce the extent of intertemporal poverty, conditional on being intertemporally poor. It is also worth noting that the magnitudes of the coefficients of this variable are relatively large, and larger in the regressions for females than in those for males.

Owning a home outright is also found to significantly decrease the probability of being poor. The coefficient of 'ownedout' is negative in all of the Probit/Selection regressions. It is significant at the 5% level or lower in two thirds of these regressions. The coefficient of 'ownedout' is also negative in all but one of the Heckman regressions, but it is not significantly so in any, so providing only tentative evidence to suggest that owning one's own home decreases the extent of intertemporal poverty, conditional on being poor.

Our results also provide some evidence to suggest that living in a local authority / housing authority dwelling increases the probability of being poor. The coefficient of the variable 'laha' is positive in each of the Probit/Selection regressions. It is significantly positive at the 5% level in one third of these regressions. However the results provide no evidence to suggest that living in a local authority / housing authority dwelling increases the extent of intertemporal poverty, conditional on being poor.

Overall, the results with respect to housing tenure seem broadly in line with what one might expect.

We now consider the impact of educational qualifications. Note that all of the educational dummy variables are for the highest level of qualification attained. These results are also generally in keeping with what one might expect. Having a degree is found to be an important determinant of being intertemporally non-poor. The coefficient of 'degree' has a negative coefficient, significant at the 1% level, in all twelve of the Probit/Selection regressions. The coefficients of 'degree' are also negative in all but two of the Heckman regressions, and significantly so, at the 5% level or lower, in nearly half of them. This suggests that having a degree also tends to reduce the extent of intertemporal poverty, conditional on being intertemporally poor. It is interesting to note that the magnitudes of the coefficients of this variable too are higher in the Heckman regressions for females than in the corresponding regressions for males.

Having a higher degree also appears to reduce the probability of being intertemporally poor. The coefficient of 'hidegree' is negative in all twelve of the Probit/Selection regressions and is significant at the 5% level or lower in two thirds of them. Conditional on being intertemporally poor, our results do not provide any firm evidence that having a higher degree tends to reduce the level of intertemporal poverty. The variable is not significant in any of the twelve Heckman regressions and has a positive coefficient in one third of them. However, this result should not be considered robust as there are very small numbers of individuals in the sample who have a higher degree and are intertemporally poor. For example, in Waves 1-5 only 4 of the 55 individuals with a higher degree are poor.

Our results suggest that having an HNC, HND or teaching qualification significantly reduces the probability of being poor. The coefficient of the variable 'hndcteach' is significantly negative at the 1% level in all the Probit/Selection regressions. The variable also has a negative coefficient in all but one of the Heckman regressions, suggesting that conditional upon being poor, it tends to reduce the extent of intertemporal poverty. However this evidence is extremely weak as the variable is not significant in any of these regressions.

The coefficients of ‘alevel’ are negative in all the Probit/Selection regressions. The coefficients are significant at the 5% level or lower in all but two regressions, and at the 1% level in two thirds of them. This suggests that having A-Levels tends to reduce the probability of being intertemporally poor. In three quarters of the Heckman regressions, ‘alevel’ has a negative coefficient, suggesting that conditional upon being poor, having A-Levels also tends to reduce the extent of intertemporal poverty. However, the coefficient is only statistically significant in three of these regressions so the evidence is relatively weak.

Our results imply that the number of children in the household has a significant impact both on the probability of being intertemporally poor and, conditional on being poor, on the extent of intertemporal poverty. The coefficient of the variable ‘nkids’ is significantly positive, at the 1% level, in all twelve of the Probit/Selection regressions. The coefficients are also positive in all the Heckman regressions, and are significant at the 5% level or lower in two thirds of them. Also of interest is that the magnitudes of the coefficients are higher in all the Heckman regressions for females than in the corresponding regressions for males.

The results on the impact on poverty of ever having been married or having lived with a partner are rather mixed and it is difficult to draw firm conclusions here. This may well be due to the nature of the variable, which arguably covers too wide a range of possible domestic situations. Nevertheless, it is interesting to note that the results do provide tentative evidence for a differing impact among the sexes. In all six of the Probit regressions for males, the coefficient of the variable ‘evermarryliv’ is positive, indicating that ever having married or lived together increases the probability of being intertemporally poor. However, the coefficient is only statistically significant in two of the six regressions, so the evidence is not overwhelming. Conversely, in four of the six Probit regressions for females, the coefficient is negative, suggesting that ever having married or lived together decreases the probability of being intertemporally poor. Again, the evidence is not overwhelming as the coefficient is only statistically significant in one of these regressions. A similar story emerges with regard to the impact of ever having been married or having lived with a partner on the extent of intertemporal poverty, conditional on being intertemporally poor. The coefficient of ‘evermarryliv’ is positive for all six of the Heckman regressions for males and statistically significant at the 5% level or lower in two of them. This provides some evidence that ever having been married or having lived with a partner also tends to increase the extent of intertemporal poverty for males, conditional on being intertemporally poor. The coefficient of ‘evermarryliv’ is negative in four of the six Heckman regressions for females but is statistically significant in just one of these. This provides some very tentative evidence to suggest that that ever having been married or having lived with a partner tends to reduce the extent of intertemporal poverty for females, conditional on being intertemporally poor.

As can be inferred from the absence of the variable 'immigrant' in the Probit/Selection column of Table 7, we found no evidence to suggest that being an immigrant either increases or decreases the probability of being poor. There is very tentative evidence to suggest that conditional upon being poor, being an immigrant tends to increase the extent of intertemporal poverty. In the two eras for which the variable was included, it was found to have a positive coefficient in all eight of the regressions. However, none of these coefficients were statistically significant.

Finally, we turn our attention to the regional dummy variables. In most cases, our results provide only tentative evidence at most to suggest that living in a given region has a significant impact either on the probability of an individual being poor or, conditional on being poor, on the extent of poverty. Living in the rest of the South-East (i.e. the South-East excluding London) is a notable exception. The variable 'r3' has a negative coefficient in all of the Probit/Selection regressions and is significant (at the 1% level) in half of them. This suggests that living in this part of England tends to reduce the probability of being poor. The variable 'r3' also has a negative coefficient in eleven of the twelve Heckman regressions but is statistically significant (at the 1% level) in just two of them. This provides some evidence to suggest that conditional on being poor, living in this region also tends to reduce the extent of intertemporal poverty. Much of this region lies within London's commuter belt and is home to a relatively high proportion of professional people so these results are perhaps not surprising.

Our results also provide some evidence that living in the South-West of the country reduces the probability of being poor, however these results are less strong. Although the coefficient for the variable 'r4' is negative in all the Probit/Selection regressions, it is only statistically significant in two of them. The variable is also negative in ten of the twelve Heckman regressions, but is only statistically significant at the 5% level in one of them. This provides tentative evidence to suggest that conditional upon being poor, living in the South-West may also tend to reduce the extent of intertemporal poverty.

In two thirds of the Probit/Selection regressions, the dummy variable for living in South Yorkshire ('r12') is found to have a negative coefficient. The negative coefficient is statistically significant negative at the 5% level in two of these regressions. This provides tentative evidence to suggest that living in this region reduces the probability of being intertemporally poor. Interestingly, the same variable has a positive coefficient in all but two of the Heckman regressions. The positive coefficient is statistically significant at the 5% level in three of these regressions. This suggests that whilst living in South Yorkshire tends to reduce the probability of being intertemporally poor, conditional on being poor, it tends to increase the extent of intertemporal poverty.

In ten out of the twelve Probit/Selection regressions, the dummy variable for living in Outer London has a negative coefficient, indicating that living there tends to reduce the probability of being intertemporally poor. However, the coefficient is only significant at the 5% level for the two female regressions in the second era. There is no clear picture with regard to the impact of living in this region on intertemporal poverty, conditional on being poor. The coefficient is negative in half of the Heckman regressions and positive in the other half.

There is very tentative evidence to suggest that living in the rest of the North-West reduces both the probability of being poor and also, conditional on being poor, the extent of intertemporal poverty. The coefficients of the variable 'r11' are negative in all the Probit/Selection regressions and in all the Heckman regressions. However, none of these coefficients are statistically significant at conventional levels.

The dummy variable for living in the rest of Yorkshire and Humberside ('r14') was omitted from our Probit/Selection regressions but included in our Heckman models. There is some evidence to suggest that, conditional upon being poor, living in this region tends to increase the extent of poverty. The variable has a positive coefficient in all but one of the Heckman regressions. However, it is only statistically significant at the 5% level in the two regressions for males in the second era.

Our results provide tentative evidence to suggest that living in Tyne & Wear increased the probability of being poor during the first two eras - but not during the third. The coefficients of the variable 'r15' are positive in all the Probit/Selection regressions for the first two eras and significantly so at the 5% level in a quarter of these. In the third era the coefficients are negative (but not significantly so) for all the Probit/Selection regressions. Overall, there is no compelling evidence regarding the impact of living in Tyne & Wear on the extent of intertemporal poverty, conditional upon being poor. However, the variable's coefficients are positive and statistically significant for the two male Heckman regressions for the first era, indicating a possible detrimental impact of living in this region for males during that period of time.

There is no real evidence to suggest that living in East Anglia has any significant impact on either the probability of being intertemporally poor or, conditional on being poor, on its extent. The coefficient of 'r5' is negative in two thirds of the Probit/Selection regressions but is not statistically significant in any of them. It is positive in three quarters of the Heckman regressions but again, not statistically significant in any.

The dummy variable for living in conurbations in the West Midlands only came into our Heckman regressions. However, there is no real evidence to suggest that, conditional upon being poor, living in this region tends to either increase or decrease the extent of intertemporal poverty.

No compelling results emerge either regarding the impact of living in the Rest of the North on poverty. The 'r16' variable coefficients are negative for all the male Probit/Selection regressions but positive for all the female Probit regressions in the second and third eras. This might be interpreted as suggesting that the impact on the probability of being poor in this region is different for the two sexes, but none of the results are statistically significant so such an inference would be rather tenuous. The variable has a negative coefficient in three quarters of the corresponding Heckman regressions, but none of the coefficients are significant so there is no clear impact of living in this region on the extent of intertemporal poverty, conditional upon being poor.

4 Conclusions

It has long been recognised that poverty is a dynamic phenomenon. In the last few years there have been significant developments in the theoretical literature on attempting to measure it as such. The poverty analyst now has at his disposal a number of tools specifically designed to evaluate poverty over a relatively long time-frame, in a more nuanced way than is possible with conventional static indicators of poverty.

In this paper, two of the indices proposed in this recent literature were applied to measure intertemporal poverty in Great Britain, using data from the BHPS. As far as we are aware, this is the first study to apply any of the new intertemporal poverty measures to this data-set. Using measures introduced by Dutta et al. (2012) and, as a special case of these, those of Foster (2009), we analysed regional patterns of poverty in Great Britain during three separate eras - 1991 to 1995, 1996 to 2000 and 2001 to 2005. The new measures provide a richer picture of poverty than can be captured simply by using static, annual, measures of poverty.

Having estimated the overall levels of intertemporal poverty in Great Britain, we then analysed the determinants of an individual's level of intertemporal poverty. In order to account for possible sample selection bias, where the determinants of being intertemporally poor or non-poor might differ from the determinants of the overall severity of intertemporal poverty, we adopted the Heckman two-step selection model. This well-known technique, and related approaches, have been used in a number of studies on the determinants of poverty and living standards. However, to the best of our knowledge, this is the first study which uses it to model the determinants of the severity of poverty, conditional upon being poor.

There is some evidence to support the suitability of our methodology. Firstly, in almost half of our Heckman regressions, the inverse Mills ratio was found to be statistically significant, which suggests that a simple OLS approach would have suffered from sample selection bias and yielded biased and inconsistent estimates. Secondly, we subjected all our regressions to two different kinds of link tests to test for misspecification. In all cases, the null hypothesis of no misspecification was strongly rejected. Thirdly, in most cases, the signs of the explanatory variables in our regressions were broadly in line with what one might expect. All this gives us a degree of confidence in our methodology and in our results.

We found that being unemployed, retired, economically inactive or a student all increase one's probability of being intertemporally poor and further, conditional on being intertemporally poor, tend to increase its severity. The type of housing tenure (especially home ownership) and the level of educational attainment were also found to be broadly important determinants of the probability of being intertemporally poor and, conditional on this, of the extent of intertemporal poverty.

It can also be observed from our results that, again broadly speaking, the magnitudes of the coefficients of the explanatory variables tend to be larger for females than for males. This is true both for variables which tend to increase poverty, such as unemployment and being retired, and for those variables which tend to reduce poverty, such as home ownership and educational attainment. In the case of retirement, we have discussed a plausible explanation for why the magnitude of the coefficient might be expected to be higher for females. It is not, however, immediately apparent why this feature should hold across such a range of variables. Further analysis of this phenomenon could form the basis for future research.

Our results and analysis provide some evidence to suggest that age has a non-linear impact on the extent of intertemporal poverty. Intertemporal poverty tends to decrease with age initially but later increase, with possible turning points in and around the age at which people typically retire.

Another interesting observation emerged from comparing the fit of each model for P_{DRZ} with the corresponding one for P_{FOS}. Since the explanatory variables and the data are exactly the same for both measures, the fact that the R-squared values were higher in every regression for P_{DRZ} suggests that it is a more precise estimator of intertemporal poverty than P_{FOS} - at least in so far as intertemporal poverty is satisfactorily explained by the variables in our models. It would be interesting to see whether a similar result emerges when these measures are applied to other data-sets. It would also be interesting to explore whether, in general, measures which penalise the chronicity, or 'bunching,' of poor spells, typically provide more precise (in the same sense as above) estimates of intertemporal poverty than those, such as P_{FOS}, which do not.

This study differs from earlier works that have used the BHPS data-set by measuring poverty over a longer term, in a more nuanced way. As such, the results in this paper are not directly comparable with those of other studies. Nevertheless, we conclude by noting that a number of our findings do seem broadly consistent with those of earlier papers. For example, our results on the detrimental impact of retirement echo those of Antolín et al. (1999) and Devicienti (2001, 2002), who found that individuals who live in households with pensioners are particularly likely to spend long periods in poverty. Unemployment was found to be the single most important explanatory variable for intertemporal poverty in this study. This is at least broadly consistent with Jenkins and Rigg (2001)'s findings on shorter poverty spells being associated with having more working individuals in the household. Finally, our results on an apparent non-linear impact of age on intertemporal poverty is consistent with the results of Devicienti (2011), who found that young and elderly individuals face a relatively high risk of remaining poor for long periods.

References

Antolín, P., Dang, T.-T. and Oxley, H. (1999), "Poverty dynamics in four OECD countries," Economics Department Working Paper 212 (ECO/WKP(99)4), Paris: OECD, Paris. Shortened version published as: OECD (1998), "Low-income dynamics in four OECD countries," OECD Economic Outlook, 171–185

Appleton, S. (2001), " 'The Rich Are Just Like Us, Only Richer': Poverty Functions or Consumption Functions?" Journal of African Economies 10 (4), 433-469

Arabmazar, A. and Schmidt, P. (1982), "An Investigation of the Robustness of the Tobit Estimator to Non-Normality," Econometrica, 50, 1053-63

Bardasi, E., Jenkins, S.P., and Rigg, J.A. (1999), "Documentation for derived current and annual net household income variables, BHPS Waves 1-7," Working Paper 99-25, Institute for Social and Economic Research, University of Essex. http://content.imamu.edu.sa/Scholars/it/net/1999-25.pdf

Bardasi, E. et al. (2008), British Household Panel Survey Derived Current and Annual Net Household Income Variables, Waves 1-16, 1991-2007 [computer file]. 8th Edition. University of Essex. Institute for Social and Economic Research, [original data producer(s)]. Colchester, Essex: UK Data Archive [distributor], November 2008. SN: 3909.

Bhaumik, S., Gang, I. and Yun, M. (2006), "Field Report: A Note on Poverty in Kosovo," J. Int. Dev. 18, 1177–1187 (2006)

Blundell, R. and Johnson, P. (1998), "Pensions and Labor-Market Participation in the United Kingdom," The American Economic Review, Vol. 88, No. 2, Papers and Proceedings of the Hundred and Tenth Annual Meeting of the American Economic Association, pp.168-172

Bossert, W. Chakravarty, S. and D'Ambrosio, C. (2012), "Poverty and Time," Journal of Economic Inequality 10: 145–162.

Calvo, C. and Dercon, S. (2009), "Chronic Poverty and All That: The Measurement of Poverty Over Time," in T. Addison, D. Hulme, and R. Kanbur (eds), Poverty Dynamics: Interdisciplinary Perspectives, Oxford University Press, Oxford, 29–58.

Carter, M. and Ikegami, M. (2007), "Looking Forward: Theory-based Measures of Chronic Poverty and Vulnerability," CPRC Working Paper No. 94. Manchester, UK: Chronic Poverty Research Centre (CPRC)

Clark, K. and Peters, S. (2005), "Area-Level Welfare Measures for Ethnic Minorities in Britain: An Initial Investigation" mimeo, University of Manchester

Coulombe, H. and McKay, A. (1996), "Modeling Determinants of Poverty in Mauritania," World Development, Vol. 24, No. 6, pp. 1015-1031

Cruces, G. (2005), "Income Fluctuations, Poverty and Well-Being Over Time: Theory and Application to Argentina," London School of Economics, Discussion paper No. DARP 76

Department of Social Security (2000), "Opportunity for All. Tackling Poverty and Social Exclusion," Second Annual Report, Cm 4865, London: The Stationery Office

Department for Work and Pensions (2008), Households Below Average Income 1994/5–2006/07. Corporate Document Services, Leeds. http://www.dwp.gov.uk/asd/hbai/hbai2007/contents.asp

Deininger, K. and Okidi, J. (2003), "Growth and Poverty Reduction in Uganda, 1999-2000: Panel Data Evidence," Development Policy Review, 2003, 21 (4): 481-509

Devicienti, F. (2001), "Poverty persistence in Britain," unpublished paper, LABORatorio, Turin. Presented at the BHPS-2001 Conference, Colchester, 4–6 July 2001

Devicienti, F. (2002), "Poverty persistence in Britain: a multivariate analysis using the BHPS, 1991–1997." J Econ Suppl 9:1–34

Devicienti, F. (2011), "Estimating poverty persistence in Britain," Empirical Economics 40:657–686 DOI 10.1007/s00181-010-0350-2

Duclos, J.-Y., Araar, A. and Giles, J. (2010), "Chronic and Transient Poverty: Measurement and Estimation, with Evidence from China," Journal of Development Economics 91 266-277

Dutta, I., Roope, L. and Zank, H. (2012), "On Intertemporal Poverty Measures: The Role of Affluence and Want," forthcoming, Social Choice and Welfare

Foster, J. (2009), "A Class of Chronic Poverty Measures," in T. Addison, D. Hulme, and R. Kanbur (eds), Poverty Dynamics: Interdisciplinary Perspectives, Oxford University Press, Oxford, 59–76, 2009

Foster, J. and Santos, M. E. (2012), "Measuring Chronic Poverty," Oxford Poverty & Human Development Initiative (OPHI) Working Paper No. 52

Foster, J., Greer, J. and Thorbecke, E. (1984), "A Class of Decomposable Poverty Measures," Econometrica 52, 761-766

Grab, J. and Grimm, M. (2007), "Robust Multiperiod Poverty Comparisons," Ibero-America Institute for Economic Research Working Paper No. 160

Gradín, C., del Río, C. and Cantó, O. (2012), "Measuring Poverty Accounting For Time," Review of Income and Wealth, 58, 330-354

Greene, W. (2000), "Econometric Analysis," (4th. ed.) Upper Saddle River, NJ: Prentice-Hall

Heckman, J. (1979), "Sample selection bias as a specification error," Econometrica, 47, 153–161

Hoy, M. and Zheng, B. (2011), "Measuring Lifetime Poverty," Journal of Economic Theory 146 (6), 2544-2562

Imai, K., Arun, T. and Annim, S. (2010), "Microfinance and Household Poverty Reduction: New Evidence from India," World Development Vol. 38, No. 12, pp. 1760–1774

Jalan, J. and M. Ravallion (2000), "Is Transient Poverty Different? Evidence for Rural China," Journal of Development Studies, 36(6), 82–99, 2000

Jarvis, S. and Jenkins, S.P. (1995), "Do the poor stay poor? New evidence about income dynamics from the British Household Panel Survey," Occasional Paper 95–2, Colchester: ESRC Research Centre on Micro-Social Change, University of Essex

Jarvis, S. and Jenkins, S.P. (1997), "Low income dynamics in 1990s Britain," Fiscal Studies, 18: 1–20

Jenkins, S.P. (2000), "Modelling household income dynamics," Journal of Population Economics, 13: 529–67

Jenkins, S. and Rigg, J. (2001), "The Dynamics of Poverty in Britain," Department for Work and Pensions Research Report No 157

Levy, H. and Jenkins, S. (2008), "Documentation for Derived Current and Annual Net Household Income Variables, BHPS waves 1–16," UK Data Archive Study Number 3909, available at http://www.esds.ac.uk/doc/3909%5Cmrdoc%5Cpdf%5C3909userguide.pdf

Muller, C. (2003), "Censored Quantile Regressions of Chronic and Transient Seasonal Poverty in Rwanda," Journal of African Economies 11 (4) 503-541

Porter, C. and Quinn, N. (2008), "Intertemporal Poverty Measurement: Tradeoffs and Policy Options," CSAE WPS/2008-21

Powell, J.L. (1984), "Least Absolute Deviations Estimation For the Censored Regression Model," Journal of Econometrics, Vol.25, pp.303-25.

Powell, J.L. (1986), "Censored Regression Quantiles," Journal of Econometrics, Vol.32, pp. 143-55.

Pregibon, D. (1979), "Data analytic methods for generalized linear models," PhD diss., University of Toronto.

Rodgers, G. (Ed.) (1989), "Population Growth and Poverty in Rural South Asia," (New Delhi: Sage Publications for the International Labour Organisation)

Roope, L. S. J. (2013), "Essays on the measurement of poverty," Doctoral dissertation, University of Manchester.

Taylor, Marcia Freed (ed). with John Brice, Nick Buck and Elaine Prentice-Lane (2010), "British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices," Colchester: University of Essex

Tukey, J. W. (1949), "One degree of freedom for non-additivity," Biometrics 5: 232–242

Uhrig, Noah (2008), "The Nature and Causes of Attrition in the British Household Panel Survey," ISER Working Paper 5/2008

Walker, T., Boughton, D., Tschirley, D., Pitoro, R., and Tomo, A. (2006), "Using Rural

Household Income Survey Data to Inform Poverty Analysis: An Example from Mozambique," Contributed paper prepared for presentation at the International Association of Agricultural Economists Conference, Gold Coast, Australia, August 12-18, 2006

Zheng, B. (2011), "Measuring Chronic Poverty: A Gravitational Approach," Mimeo, University of Colorado, Denver

A Appendix

A.1 Dummy Variable Sample Sizes

Table 15: Dummy Variable Sample Sizes For Poor And Non-Poor Males

Variable	Era 1		Era 2		Era 3	
	Poor	Non-Poor	Poor	Non-Poor	Poor	Non-Poor
retire	111	164	100	229	218	393
mortgage	401	1,343	321	1,547	490	2,268
degree	19	151	17	185	36	336
hndcteach	18	116	11	159	34	246
alevel	72	302	82	379	117	552
inactive	42	41	61	53	89	79
evermarryliv	500	1,273	437	1,510	738	2,250
hidegree	2	34	6	52	9	107
unemploy	91	47	70	41	49	35
laha	337	158	336	170	496	232
student	26	38	28	56	29	70
ownedout	169	323	163	404	302	711
immigrant	29	61	0	1	5	16
r1	40	52	22	54	9	34
r2	52	117	44	142	40	103
r3	156	365	133	441	95	446
r4	78	176	75	222	79	201
r5	48	84	49	88	37	94
r6	122	158	101	180	82	173
r7	45	66	32	75	28	67
r9	25	88	20	85	34	79
r10	17	40	23	53	31	45
r11	33	86	42	103	29	110
r12	31	56	32	65	16	71
r13	38	61	41	71	25	52
r14	31	66	38	85	26	86
r15	33	40	32	46	22	37
r16	33	92	33	108	28	80

Table 16: Dummy Variable Sample Sizes For Poor And Non-Poor Females

Variable	Era 1		Era 2		Era 3	
	Poor	Non-Poor	Poor	Non-Poor	Poor	Non-Poor
retire	99	133	90	206	209	374
mortgage	426	1,349	368	1,556	568	2,264
degree	15	132	15	162	36	350
hndcteach	9	106	19	126	49	202
alevel	64	201	72	285	141	476
inactive	308	264	270	263	434	360
evermarryliv	643	1,344	557	1,568	927	2,369
hidegree	2	17	5	31	5	84
unemploy	32	28	26	23	46	24
laha	422	169	398	199	659	250
student	24	37	37	72	61	75
ownedout	170	338	159	382	305	708
immigrant	40	73	1	4	16	19
r1	35	57	17	51	7	38
r2	49	117	50	135	42	122
r3	184	410	154	489	110	459
r4	91	181	82	218	80	208
r5	57	92	57	95	39	91
r6	115	156	110	179	95	180
r7	53	67	48	87	34	69
r9	31	75	23	78	37	70
r10	27	41	28	45	23	43
r11	40	93	53	108	50	109
r12	34	54	39	54	22	64
r13	49	62	40	70	31	48
r14	29	62	34	75	32	75
r15	29	34	25	45	16	40
r16	34	88	38	85	39	72

A.2 Regression Results

Table 17: Regressions For Logged PDRZ Measures For Males For 1991-1995

Variables	Probit	Heckman	OLS
age	-0.026	-0.098*	-0.063
agesq	0.0003*	0.001	0.000
retire	0.312*	1.367**	0.956**
mortgage	-0.574**	-1.312*	-0.538
degree	-0.659**	-1.279	-0.356
hndcteach	-0.496**	-0.305	0.500
alevel	-0.300**	-0.902**	-0.473*
nkids	0.360**	0.582*	0.149
inactive	0.594**	1.465**	0.688*
evermarryliv	0.123	1.535**	1.361**
hidegree	-1.156**	-0.694	1.058**
unemploy	1.054**	2.339**	1.138**
laha	0.192	0.582	0.405
student	0.545**	1.906**	1.177**
ownedout	-0.183	-0.349	-0.106
immigrant		0.154	0.197
r1	0.029	0.257	0.284
r2	0.078	0.250	0.166
r3	-0.072	-0.135	-0.012
r4	-0.037	0.150	0.196
r5	0.093	0.328	0.233
r6		-0.033	-0.003
r7		0.103	0.193
r9	-0.180		
r10		-1.022	-1.033
r11	-0.182	-0.759	-0.452
r12	-0.047	1.164*	1.245**
r13	0.196		
r14		0.451	0.482
r15	0.226	1.091*	0.836*
r16	-0.294	-1.010	-0.610
constant	-0.272	-4.384**	-2.466**
No. individuals	2,047	577	577
Mills Ratio λ		2.000	
R-squared		0.2178	0.2114

Table 18: Regressions For Logged PDRZ Measures For Females For 1991-1995

Variables	Probit	Heckman	OLS
age	-0.031*	-0.138**	-0.079**
agesq	0.0003*	0.001**	0.001*
retire	0.625**	1.590*	0.214
mortgage	-0.648**	-1.706**	-0.385
degree	-0.802**	-2.447**	-0.724
hndcteach	-0.952**	-1.727	0.380
alevel	-0.265**	-0.800*	-0.283
nkids	0.280**	0.699**	0.211**
inactive	0.647**	2.129**	0.811**
evermarryliv	0.278*	0.574	0.087
hidegree	-0.670	-2.053	-0.962
unemploy	0.816**	2.742**	1.121**
laha	0.281*	0.784	0.360
student	0.537**	1.377	0.307
ownedout	-0.335*	-0.992	-0.302
immigrant		0.004	0.066
r1	-0.089	-0.405	-0.231
r2	-0.102	-0.756	-0.508
r3	-0.087	-0.414	-0.204
r4	-0.142	-0.539	-0.218
r5	-0.029	-0.202	-0.092
r6		-0.375	-0.335
r7		-0.336	-0.205
r9	-0.090		
r10		-0.033	-0.017
r11	-0.219	-1.037	-0.525
r12	-0.022	0.883	0.951**
r13	0.220		
r14		0.260	0.374
r15	0.414*	1.009	0.232
r16	-0.188	-0.386	0.047
constant	-0.032	-3.827**	-1.237*
No. individuals	2,228	723	723
Mills Ratio λ		3.158*	
R-squared		0.1855	0.1734

Table 19: Regressions For Logged PDRZ Measures For Males For 1996-2000

Variables	Probit	Heckman	OLS
age	-0.049**	-0.065	-0.055
agesq	0.0006**	0.001	0.001
retire	0.214	0.583	0.539
mortgage	-0.754**	-0.701	-0.548
degree	-0.566**	0.240	0.368
hndcteach	-0.746**	-0.714	-0.537
alevel	-0.151	0.104	0.134
nkids	0.378**	0.429	0.362**
inactive	0.915**	0.724	0.553*
evermarryliv	0.450**	0.703	0.608
hidegree	-0.497*	0.074	0.170
unemploy	1.202**	1.493*	1.276**
laha	0.051	-0.115	-0.118
student	0.757**	0.802	0.646
ownedout	-0.174	0.095	0.130
r1	-0.037	-0.557	-0.534
r2	-0.253	-0.524	-0.486
r3	-0.157	-0.143	-0.120
r4	-0.077	-0.319	-0.304
r5	0.271	0.534	0.486
r6		0.143	0.139
r7		0.142	0.134
r9	-0.023		
r10		-0.151	-0.128
r11	-0.121	-0.479	-0.461
r12	0.040	0.871	0.870*
r13	-0.036		
r14		0.975*	0.968*
r15	0.044	0.644	0.626
r16	-0.016	-0.715	-0.715
constant	-0.122	-3.296**	-3.029**
No. individuals	2,238	495	495
Mills Ratio λ		0.301	
R-squared		0.1548	0.1546

Table 20: Regressions For Logged PDRZ Measures For Females For 1996-2000

Variables	Probit	Heckman	OLS
age	-0.030*	-0.032	-0.014
agesq	0.0003*	0.000	0.000
retire	0.413**	1.140**	0.913*
mortgage	-0.922**	-1.238*	-0.703**
degree	-0.680**	-0.604	-0.186
hndcteach	-0.447**	-0.149	0.117
alevel	-0.316**	-0.062	0.103
nkids	0.376**	0.513**	0.325**
inactive	0.642**	1.357**	0.997**
evermarryliv	-0.226	-0.317	-0.201
hidegree	-0.298	-1.149	-0.964
unemploy	1.053**	1.848**	1.265**
laha	0.092	0.136	0.114
student	0.198	-0.214	-0.339
ownedout	-0.346*	-0.354	-0.158
r1	-0.383	-0.448	-0.251
r2	-0.336*	-0.615	-0.475
r3	-0.300**	-0.296	-0.160
r4	-0.232*	-0.519	-0.409
r5	-0.039	0.397	0.403
r6		-0.077	-0.091
r7		0.077	0.073
r9	-0.307		
r10		-0.360	-0.362
r11	-0.270	-0.400	-0.286
r12	0.152	0.559	0.458
r13	-0.102		
r14		0.540	0.552
r15	0.015	-0.011	-0.065
r16	0.051	-0.309	-0.374
constant	0.428	-3.305**	-2.809**
No. individuals	2,403	660	660
Mills Ratio λ		0.892	
R-squared		0.1814	0.1796

Table 21: Regressions For Logged PDRZ Measures For Males For 2001-2005

Variables	Probit Male	Heckman Male	OLS
age	-0.027*	0.008	0.032
agesq	0.0004**	0.000	-0.000
retire	0.172	0.686*	0.534
mortgage	-0.670**	-1.009	-0.437
degree	-0.570**	-0.908	-0.357
hndcteach	-0.514**	-0.340	0.116
alevel	-0.188*	-0.063	0.107
nkids	0.317**	0.417	0.172*
inactive	0.817**	1.282	0.646**
evermarryliv	0.124	0.291	0.170
hidegree	-0.676**	-1.268	-0.629
unemploy	0.891**	1.466	0.833**
laha	0.233	-0.075	-0.226
student	0.477*	1.640*	1.263*
ownedout	-0.290*	-0.208	0.029
immigrant		1.574	1.505**
r1	-0.394	0.284	0.633
r2	-0.002	0.781	0.804*
r3	-0.323**	-0.772	-0.480
r4	-0.086	-0.177	-0.107
r5	-0.095	0.371	0.468
r6		-0.314	-0.284
r7		-0.811	-0.805
r9	0.127		
r10		-0.174	-0.142
r11	-0.153	-0.573	-0.443
r12	-0.584*	0.906	1.405**
r13	-0.031		
r14		-0.045	-0.056
r15	-0.217	-0.104	0.033
r16	-0.114	-0.018	0.069
constant	-0.268	-5.357**	-4.226**
No. individuals	2,903	682	682
Mills Ratio λ		1.215	
R-squared		0.0812	0.0798

Table 22: Regressions For Logged PDRZ Measures For Females For 2001-2005

Variables	Probit Female	Heckman Female	OLS
age	-0.002	0.037	0.045
agesq	0.000	-0.000	-0.000
retire	0.429**	1.490**	0.892**
mortgage	-0.680**	-1.546**	-0.604*
degree	-0.725**	-1.652**	-0.516
hndcteach	-0.354**	-0.489	-0.009
alevel	-0.219**	-0.432	-0.160
nkids	0.297**	0.606**	0.262**
inactive	0.711**	1.583**	0.648**
evermarryliv	-0.360**	-0.754*	-0.386
hidegree	-0.757**	0.582	1.777**
unemploy	0.803**	2.108**	1.160**
laha	0.359**	-0.024	-0.379
student	0.737**	1.861**	0.862*
ownedout	-0.334**	-0.649	-0.188
immigrant		0.265	0.220
r1	-0.522	-1.140	-0.514
r2	-0.126	0.500	0.726*
r3	-0.336**	-1.353**	-0.861**
r4	-0.091	-0.249	-0.107
r5	-0.119	0.018	0.215
r6		-0.295	-0.255
r7		-0.475	-0.427
r9	0.260		
r10		-0.451	-0.412
r11	-0.102	-0.484	-0.303
r12	-0.373	-0.152	0.342
r13	-0.021		
r14		0.047	0.100
r15	-0.225	-1.085	-0.876
r16	0.096	0.168	0.041
constant	-0.344	-5.854**	-3.846**
No. individuals	3,135	882	882
Mills Ratio λ		2.029*	
R-squared		0.1081	0.1017

Table 23: Regressions For Logged PFOS Measures For Males For 1991-1995

Variables	Probit	Heckman	OLS
age	-0.026	-0.062*	-0.036
agesq	0.0003*	0.001	0.000
retire	0.312*	0.670*	0.366
mortgage	-0.574**	-0.817*	-0.243
degree	-0.659**	-1.024*	-0.340
hndcteach	-0.496**	-0.197	0.399
alevel	-0.300**	-0.576*	-0.259
nkids	0.360**	0.367*	0.046
inactive	0.594**	0.970*	0.395*
evermarryliv	0.123	1.050**	0.921**
hidegree	-1.156**	-0.809	0.489*
unemploy	1.054**	1.607**	0.717**
laha	0.192	0.429	0.298
student	0.545**	1.384**	0.844**
ownedout	-0.183	-0.222	-0.042
immigrant		0.161	0.193
r1	0.029	0.266	0.287
r2	0.078	0.325	0.263
r3	-0.072	0.054	0.145
r4	-0.037	0.213	0.247
r5	0.093	0.230	0.159
r6		-0.031	-0.010
r7		0.038	0.104
r9	-0.180		
r10		-0.606	-0.614
r11	-0.182	-0.407	-0.180
r12	-0.047	0.762*	0.822**
r13	0.196		
r14		0.304	0.327
r15	0.226	0.741*	0.552**
r16	-0.294	-0.555	-0.259
constant	-0.272	-4.138**	-2.717**
No. individuals	2,047	577	577
Mills Ratio λ		1.482*	
R-squared		0.1838	0.1758

Table 24: Regressions For Logged PFOS Measures For Females For 1991-1995

Variables	Probit	Heckman	OLS
age	-0.031*	-0.094*	-0.047*
agesq	0.0003*	0.001*	0.0004*
retire	0.625**	1.272*	0.152
mortgage	-0.648**	-1.259*	-0.183
degree	-0.802**	-1.881**	-0.478
hndcteach	-0.952**	-1.388	0.327
alevel	-0.265**	-0.563	-0.142
nkids	0.280**	0.473*	0.076
inactive	0.647**	1.599**	0.527**
evermarryliv	0.278*	0.483	0.086
hidegree	-0.670	-1.594	-0.706
unemploy	0.816**	2.034**	0.715*
laha	0.281*	0.542	0.197
student	0.537**	1.197	0.326
ownedout	-0.335*	-0.784	-0.222
immigrant		0.185	0.236
r1	-0.089	-0.128	0.013
r2	-0.102	-0.447	-0.246
r3	-0.087	-0.218	-0.047
r4	-0.142	-0.373	-0.112
r5	-0.029	-0.110	-0.020
r6		-0.278	-0.245
r7		-0.412	-0.305
r9	-0.090		
r10		0.014	0.027
r11	-0.219	-0.740	-0.323
r12	-0.022	0.560	0.616**
r13	0.220		
r14		0.210	0.303
r15	0.414*	0.810	0.177
r16	-0.188	-0.276	0.076
constant	-0.032	-3.827**	-1.718**
No. individuals	2,228	723	723
Mills Ratio λ		2.572*	
R-squared		0.1678	0.1494

Table 25: Regressions For Logged PFOS Measures For Males For 1996-2000

Variables	Probit	Heckman	OLS
age	-0.049**	-0.035	-0.024
agesq	0.001**	0.000	0.000
retire	0.214	0.210	0.160
mortgage	-0.754**	-0.730	-0.556*
degree	-0.566**	0.414	0.561*
hndcteach	-0.746**	-0.657	-0.455
alevel	-0.151	0.040	0.075
nkids	0.378**	0.250	0.173**
inactive	0.915**	0.572	0.378
evermarryliv	0.450**	0.394	0.285
hidegree	-0.497*	0.078	0.188
unemploy	1.202**	1.148*	0.901**
laha	0.051	-0.292	-0.294
student	0.757**	0.408	0.230
ownedout	-0.174	-0.080	-0.040
r1	-0.037	-0.338	-0.312
r2	-0.253	-0.328	-0.284
r3	-0.157	-0.063	-0.036
r4	-0.077	-0.316	-0.299
r5	0.271	0.525	0.471
r6		0.140	0.136
r7		0.218	0.210
r9	-0.023		
r10		-0.018	0.010
r11	-0.121	-0.395	-0.375
r12	0.040	0.727*	0.726**
r13	-0.036		
r14		0.807*	0.799**
r15	0.044	0.473	0.453
r16	-0.016	-0.424	-0.423
constant	-0.122	-3.155**	-2.851**
No. individuals	2,238	495	495
Mills Ratio λ		0.343	
R-squared		0.1398	0.1393

Table 26: Regressions For Logged PFOS Measures For Females For 1996-2000

Variables	Probit	Heckman	OLS
age	-0.030*	-0.025	-0.008
agesq	0.0003*	0.000	0.000
retire	0.413**	0.738**	0.527*
mortgage	-0.922**	-0.988**	-0.491**
degree	-0.680**	-0.344	0.045
hndcteach	-0.447**	0.013	0.260
alevel	-0.316**	-0.139	0.014
nkids	0.376**	0.342**	0.166**
inactive	0.642**	0.953**	0.618**
evermarryliv	-0.226	-0.316	-0.209
hidegree	-0.298	-0.302	-0.129
unemploy	1.053**	1.299**	0.758**
laha	0.092	-0.028	-0.048
student	0.198	-0.125	-0.242
ownedout	-0.346*	-0.354	-0.172
r1	-0.383	-0.234	-0.051
r2	-0.336*	-0.357	-0.227
r3	-0.300**	-0.200	-0.073
r4	-0.232*	-0.438*	-0.335
r5	-0.039	0.305	0.311
r6		-0.023	-0.036
r7		0.135	0.131
r9	-0.307		
r10		-0.131	-0.134
r11	-0.270	-0.288	-0.182
r12	0.152	0.390	0.296
r13	-0.102		
r14		0.496	0.507*
r15	0.015	-0.045	-0.096
r16	0.051	-0.103	-0.164
constant	0.428	-2.981**	-2.520**
No. individuals	2,403	660	660
Mills Ratio λ		0.831	
R-squared		0.1446	0.1413

Table 27: Regressions For Logged PFOS Measures For Males For 2001-2005

Variables	Probit	Heckman	OLS
age	-0.027*	0.012	0.032
agesq	0.0004**	-0.000	-0.000
retire	0.172	0.271	0.153
mortgage	-0.670**	-0.910	-0.463*
degree	-0.570**	-0.440	-0.009
hndcteach	-0.514**	-0.443	-0.086
alevel	-0.188*	0.035	0.168
nkids	0.317**	0.229	0.037
inactive	0.817**	0.658	0.160
evermarryliv	0.124	0.312	0.217
hidegree	-0.676**	-1.021	-0.521
unemploy	0.891**	1.188*	0.693**
laha	0.233	-0.263	-0.381*
student	0.477*	1.328**	1.033**
ownedout	-0.290*	-0.310	-0.124
immigrant		1.132	1.078**
r1	-0.394	-0.083	0.190
r2	-0.002	0.578*	0.596**
r3	-0.323**	-0.550	-0.321
r4	-0.086	-0.137	-0.082
r5	-0.095	0.146	0.222
r6		-0.232	-0.209
r7		-0.488	-0.483
r9	0.127		
r10		-0.059	-0.033
r11	-0.153	-0.279	-0.177
r12	-0.584*	0.419	0.809**
r13	-0.031		
r14		0.126	0.117
r15	-0.217	-0.322	-0.215
r16	-0.114	0.002	0.070
constant	-0.268	-4.489**	-3.604**
No. individuals	2,903	682	682
Mills Ratio λ		0.951	
R-squared		0.0653	0.0635

Table 28: Regressions For Logged PFOS Measures For Females For 2001-2005

Variables	Probit	Heckman	OLS
age	-0.002	0.020	0.026
agesq	0.000	-0.000	-0.000
retire	0.429**	0.742*	0.332
mortgage	-0.680**	-1.176**	-0.530**
degree	-0.725**	-0.909*	-0.130
hndcteach	-0.354**	-0.291	0.038
alevel	-0.219**	-0.277	-0.091
nkids	0.297**	0.360**	0.124**
inactive	0.711**	0.927**	0.286*
evermarryliv	-0.360**	-0.291	-0.039
hidegree	-0.757**	0.573	1.392**
unemploy	0.803**	1.346**	0.697**
laha	0.359**	-0.194	-0.437**
student	0.737**	1.143**	0.458
ownedout	-0.334**	-0.519	-0.204
immigrant		0.263	0.232
r1	-0.522	-0.859	-0.429
r2	-0.126	0.389	0.544**
r3	-0.336**	-0.840**	-0.503*
r4	-0.091	-0.183	-0.086
r5	-0.119	-0.069	0.065
r6		-0.199	-0.172
r7		-0.232	-0.199
r9	0.260		
r10		-0.275	-0.248
r11	-0.102	-0.175	-0.051
r12	-0.373	-0.176	0.162
r13	-0.021		
r14		0.173	0.209
r15	-0.225	-0.790	-0.646
r16	0.096	0.102	0.015
constant	-0.344	-4.544**	-3.168**
No. individuals	3,135	882	882
Mills Ratio λ		1.391*	
R-squared		0.0748	0.0685

A.3 Misspecification Test Results

Table 29: Results of Misspecification Tests For Heckman Regressions of Logged PDRZ Measures

	p-Values from Standard Link Test	p-Values from Amended Link Test
Males in Era 1	0.266	0.857
Females in Era 1	0.333	0.857
Males in Era 2	0.688	0.784
Females in Era 2	0.532	0.908
Males in Era 3	0.680	0.885
Females in Era 3	0.222	0.967

Table 30: Results of Misspecification Tests For Heckman Regressions of Logged PFOS Measures

	p-Values from Standard Link Test	p-Values from Amended Link Test
Males in Era 1	0.175	0.806
Females in Era 1	0.369	0.892
Males in Era 2	0.278	0.606
Females in Era 2	0.668	0.970
Males in Era 3	0.757	0.938
Females in Era 3	0.209	0.993