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Abstract

This paper analyzes the relationship between aggregate wages and individual wages when there is time series variation in employment and in the dispersion of wages. A new and easily implementable framework for the empirical analysis of aggregation biases is developed. Aggregate real wages are shown to contain three important bias terms: one associated with the dispersion of individual wages, a second reflecting the distribution of working hours, and a third deriving from compositional changes in the (selected) sample of workers. Noting the importance of these issues for recent experience in Britain, data on real wages and participation for British male workers over the period 1978-1996 are studied. A close correspondence between the estimated biases and the patterns of differences shown by aggregate wages is established. This is shown to have important implications for the interpretation of real wage growth over this period.

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Executive Summary

Aggregate figures for real wage growth are used extensively in policy debate to analyse changes in the well-being of workers over time and to compare different groups of people both within and across countries. However, if participation (employment) rates change across time periods or across the groups used in these comparisons, then aggregate real wages may give a misleading impression of changes in the structure of real wages facing individual workers. For example, if participation drops and the people moving out of the labour market are drawn disproportionately from the lower end of the earnings distribution this can lead to an increase in the measured average wage which is an artefact of sample selection rather than an increase in welfare. This paper develops a simple characterisation of the relationship between participation and aggregate (average) hourly wage measures, showing that aggregate real wage indices contain three important bias terms: one associated with the dispersion of individual wages, a second reflecting the distribution of working hours, and a third deriving from compositional changes in the (selected) sample of workers.

The empirical part of the paper investigates whether these biases offer an accurate characterisation of the behaviour of male wages in Britain from 1978 to 1995, in the light of large secular and cyclical movements in male participation over the period. Using data from the UK Family Expenditure Survey, an aggregate earnings 'index' for men is constructed and then compared with wage predictions from a selectivity-adjusted micro-level wage equation with controls for cohort, education level, region, and a flexible trend. The selection term in the wage equation is identified using exogenous variations in the level of housing benefit available to men in the FES when out of work using simulated budget constraints from the IFS's TAXBEN microsimulation model. By explicitly constructing the bias terms using the micro-model, it is possible to look at the relationship between the aggregate earnings index and the micro-model predictions. The results show a close correspondence between corrected aggregate wages and the mean wages implied by the micro-regressions which is found to be robust to relaxation of the parametric assumptions of the model framework. Correcting for selection due to reductions in the male employment rate over the period reduces our estimate of real aggregate male hourly earnings growth from around 30% to less than 20%. Interesting differences in the wage patterns for different educational groups, cohorts, and regional groups are also found, and the model specification also appears to perform well within these population subgroups. Overall, the estimates seem to offer clear evidence that the biases in log aggregate wages are substantial and can lead to misleading depictions of the progress of wages of individual male workers.

1. Introduction[1]

Aggregate ¯gures for real wage growth appear extensively in policy debate. They are used to re°ect changes in the well being of workers over time and are also used for comparisons across education or cohort groups and for comparisons across countries or regions. However, as pointed out in the original study by Bils (1985), if participation rates change di®erentially across the time periods or across the groups used in these comparisons, then aggregate real wages are likely to provide a misleading picture of changes in the structure of real wages facing individual workers. For example, if the overall distribution of skills in the workforce remains unchanged, aggregate wages will increase when relatively low wage individuals leave employment, but it is hard to argue that `well being' has been improved in any meaningful way. This paper develops a simple characterization of the relationship between employment and aggregate wages and derives the precise form of the bias in inferring the behavior of individual wages from the analysis of aggregate (average) hourly earnings, or aggregate wages.

Our approach has its foundations in a basic model of human capital and skill price as developed in Heckman and Sedlacek (1985) but can be cast in a number of di®erent frameworks. Returns to human capital are allowed to be time varying in response to sectoral and cyclical demand and supply shocks. Bias occurs when trying to assess the cyclicality or trend behavior of wages or returns to education

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using aggregate wage measures. In this paper the bias is shown to decompose into three interpretable terms re°ecting changes in the distribution of individual wages, changes in participation and changes in hours worked. The ¯rst term describes the dispersion of wages and arises from aggregation over the standard log-linear model of individual wages. This term explicitly measures the e®ect of increasing wage dispersion separately from the impact of participation. The second term measures the adjustment for composition changes in hours and depends on the size of the covariance between wages and hours. The ¯nal term highlights the importance of the participation decision, capturing the e®ects of composition changes within the selected sample of workers from which measured wages are recorded. As in the standard selection bias literature, this third factor depends on the covariance between participation and wages. These bias terms are then investigated using data for male wages from the British economy in the 1980s and 1990s. These data analyses point to signi¯cant deviations between aggregate and individual measures that imply important revisions in the interpretation of real wage growth over this period.

We identify three reasons why the British labor market experience during the last two decades is particularly attractive for this analysis. First, there have been strong secular and cyclical movements in male employment over this period. Second, there exists a long and representative time series of individual survey data, collected at the household level, that records detailed information on individual hourly wages as well as many other individual characteristics and income sources. Finally, over this period, there has been a systematic change in the level of real out-of-work income. The household survey data utilized in this study allows an accurate measure of this income variable which, in turn, acts as an informative instrument in controlling for participation in our analysis of wages.

Labor market behavior in Britain over the last twenty years serves to reinforce the importance of these issues. Indeed the relationship between wage growth and employment in Britain has often been the focus of headline news.[2] Figure 1.1 displays the time series of aggregate hourly wages and aggregate employment for men in the UK between 1978 and 1996. In 1978-9, over 90% of men aged between 19 and 59 were employed. The participation rate fell dramatically in the recession of the early 1980s and then recovered somewhat in the late 1980s (although not to its initial level). In the early 1990s there was another recession and another sharp decline. In contrast, log average wages show reasonably steady increase from 1978 through the 1990s, growing more than 30% in real terms over this period and even displaying some growth during the severe recession of the early 1990s.[3]

The analysis presented in this paper shows this picture of the evolution of real wages to be highly misleading. Making our three corrections reveals real wage growth to have been no more than 20% with no evidence of real growth whatsoever in the early 1990s. Moreover, we show this corrected series is precisely estimated and robust to parametric speci¯cation. The large discrepancy in the level and growth between the aggregate and individual wage paths that we ¯nd is shown to be almost completely captured by the aggregation factors we develop, validating our model speci¯cation and providing a detailed interpretation of the aggregation biases involved. The discrepancy is associated with an important upward bias in the aggregate trend of real wages and a reduction in the degree of procyclicality.

The picture of employment °uctuations is even more dramatic between education groups and date-of-birth cohorts. Given the strong interest in the economics literature on returns to education across education and cohort groups (see Card

[2] For example, \Rise in Earnings and Jobless Sparks Concern", Financial Times, front page, June 18th, 1998.

[3] As we show below, over the same period, average weekly hours show very limited variation.

and Lemieux (1999) and Gosling, Machin and Meghir (1998), for example), the impact of these employment °uctuations on estimated returns to education across these groups is important. Figure 1.2 presents the picture of employment by education level for two central cohorts. For the cohort born 1945-54, the steep fall in employment experienced by the lower education group in the early 1980s is not matched in the employment patterns of the higher educated groups. Indeed, the level and growth in dispersion also di®ers substantially across cohort and education groups. The results from this paper show that the selection e®ect is often substantial and suggests a large underestimate in the level and growth in education returns. However, this selection e®ect that adjusts for the di®erential employment pro¯les across cohort and education groups is often more than o®set by adjustments for the di®erent level and growth in dispersion across these education and cohort groups.

To identify these corrections to the aggregate series we need some variable that moves male employment rates but does not e®ect the distribution of wages conditional on education, age and other observed wage determinants. For this we use another feature of recent British experience: the large changes in the real value of transfer income which individuals receive (or would receive) while out of work. Figure 1.3 shows the time series variation of out-of-work income. This income measure is simulated for all households of a particular type using a tax and bene¯t simulation model. This ¯gure shows the time series for a group of married low education men in rented accommodation - a particularly relevant group. The housing bene¯t component of out-of-work income, which is a means tested bene¯t covering a large proportion of rental costs, is a major contributory factor in the rise of out-of-work income for low education families. Although it is unlikely that variation in real value of bene¯t income can explain all of the variation in participation rates, we argue that changes in real bene¯ts serve as an important \instrumental variable" for controlling for endogenous selection in real wages. Moreover, housing bene¯t varies strongly across time, location and cohort group. The cohort variation occurs because individuals in lower educated older cohorts had a much higher chance of spending their lives in public housing. We take this variation to be exogenous to the individual employment decision conditional on the cohort, education, region, trend and cycle e®ects. Using this \instrument" for selection, the individual level wage equation results show a signi¯cant selection e®ect that varies systematically over the trend and cycle and di®ers across education groups.

The layout of the remainder of this paper is as follows. Section 2 presents the modeling framework that will underlie the empirical work. We derive some new results on aggregating over lognormal distributions, and then we apply the results to spell out the empirical implications of our model to individual and aggregate level wage data. These aggregation biases are likely to be particularly important for the study of wages and returns in Europe where there have been dramatic and systematic changes in the variance of hourly wages, the distribution of hours of work and in participation rates; features that have occurred both secularly and cyclically. Our application to real wages for men in Britain presented in Section 3 shows important impacts of heterogeneity and labor participation. To anticipate, we ¯nd that changes in dispersion of individual wages, attributable to both observable and unobservable factors, lead to a secular increase in the bias from using aggregate wage measures. In contrast we ¯nd that the changes in composition, induced by the pattern of labor market participation, induce a counter cyclical bias in the aggregate measure. Section 4 draws some conclusions.

2. Aggregation and Selection

2.1. A Model for Real Wages

The approach we use for modeling individual wages follows Roy (1951) in basing wages on human capital or skill levels, assuming that any two workers with the same human capital level are paid the same wage. Thus we assume that there is no comparative advantage, and no sectoral di®erences in wages for workers with the same human capital level.[4] We assume that the mapping of skills to human capital is time invariant, and that the price or return to human capital is not a function of human capital endowments. In particular, we begin with a framework consistent with the proportionality hypothesis of Heckman and Sedlacek (1990).

The simplest version of the framework assumes that each worker i possesses a human capital (skill) level of H_i. Human capital is nondi®erentiated, in that it commands a single price r_t in each time period t. In this case the wage paid to worker i at time t is

$$w_{ti} = r_t H_i \tag{2.1}$$

Human capital H_i is assumed log-normally distributed[5], with mean

$$E\,(\ln H_i) = \pm_{js}$$

and variance ¾^2, where $\pm_{js}$ is a level that varies with the cohort j to which i belongs and the education level s of worker i. In other words, the log wage equation has

[4] Heckman and Sedlacek (1985) provide an important generalization of this framework to multiple sectors. We plan on examining a multisectoral model as part of future research. In addition, the importance of normality assumptions in such a generalization is explored further in Heckman and Honore (1993).

[5] Although we utilize lognormality assumptions extensively in this section, their reliability is assessed in the empirical analysis that follows.

the additive form

$$\ln w_{it} = \ln r_t + \delta_{js} + \varepsilon_{it} \tag{2.2}$$

where ε_{it} is $N(0; \sigma^2)$.[6] In this model growth in returns is constant across all individuals. Below we allow education returns to differ over time.

Reservation wages w^*_{it} are also assumed to be lognormal, with

$$\ln w^*_{it} = \alpha \ln b_{it} + \eta_{js} + \zeta_{it} \tag{2.3}$$

where ζ_{it} is $N\left(0; \sigma^2_\zeta\right)$ and where b_{it} can be interpreted as an exogenous benefit level that varies with individual characteristics and time. Participation occurs if $w_{it} \geq w^*_{it}$, or with

$$\ln r_t - \alpha \ln b_{it} + \delta_{js} - \eta_{js} + \varepsilon_{it} - \zeta_{it} > 0 \tag{2.4}$$

and we represent the participation decision by the indicator $I_i = 1[w_{it} \geq w^*_{it}]$.

For examining hours, we will make one of two assumptions in our empirical work. The first is to assume that the distribution of hours is fixed. The other is to assume that desired hours h_{it} are chosen by utility maximization, where reservation wages are defined as $h_{it}(w^*) = h_0$ and h_0 is the minimum number of hours available for full-time work.[7] We assume $h_{it}(w)$ is normal for each w, and approximate desired hours by

$$\begin{aligned} h_{it} &= h_0 + \gamma(\ln w_{it} - \ln w^*_{it}) \\ &= h_0 + \gamma(\ln r_t - \alpha \ln b_{it} + \delta_{js} - \eta_{js} + \varepsilon_{it} - \zeta_{it}). \end{aligned}$$

In our derivations of aggregation formulae below, we retain the second assumption (since we can easily specialize to the first assumption).

[6] Clearly, there is an indeterminacy in the scaling of r_t and H_i. Therefore, to study r_t, we will normalize r_t for some year $t = 0$ (say to $r_0 = 1$). We could equivalently set one of the δ's to zero.

[7] This allows for a simple characterisation of fixed costs, see Cogan (1981).

This is our base level specification that maintains the proportionality hypothesis. There are no trend or cycle interactions with cohort or education level in either equation.

Two extensions of this basic framework are made necessary by our empirical findings. First, suppose that education produces a differentiated type of human capital. That is, a high education worker i has human capital (skill) level of H_i^H and is paid the wage $r_t^H H_i^H$. A low education worker i has human capital (skill) level of $r_t^L H_i^L$ and is paid the wage $r_t^L H_i^L$. As before, similar workers with a particular skill level are paid the same in all sectors. If D_i is the high education dummy, the log wage equation has the form

$$\ln w_{it} = D_i \ln r_t^H + D_i \delta_{js}^H + (1 - D_i) \ln r_t^L + (1 - D_i) \delta_{js}^L + \varepsilon_{it}. \qquad (2.5)$$

Here, education can have a time varying impact on wages.

The second extension is to allow the different stock of labor market experience that is associated with each cohort at any specific calender time to have an impact on returns. This generalizes the basic model to allow log wages to display different trend behavior for each date-of-birth cohort group.

2.2. Aggregate Wages and Micro-Macro Comparisons

Measured wages at the individual level are represented by an entire distribution. Therefore, there are many ways to pose the question of whether aggregate wage movements adequately reflect movements in individual wages. We consider various alternatives here, each of which could be adopted.

The aggregate wage is measured by

$$\overline{w}_t = \frac{\sum_{i \in (I=1)} e_{it}}{\sum_{i \in (I=1)} h_{it}} = \sum_{i \in (I=1)} \mu_{it} w_{it} \qquad (2.6)$$

where $i \in (I = 1)$ denotes a labor market participant and where $e_{it} = h_{it}w_{it}$ is the earnings of individual i in period t, and where ω_{it} are the hours weights

$$\omega_{it} = \frac{h_{it}}{\sum_{i \in (I=1)} h_{it}}.$$

We take the population of participating workers as sufficiently large so that we can ignore sampling variation in average earnings and average hours; modeling the aggregate wage as

$$\overline{w}_t \approx \frac{E\left[h_{it}w_{it} | I_{it} = 1\right]}{E\left[h_{it} | I_{it} = 1\right]}$$

where $E[\cdot]$ refers to the mean across the population.

The basic framework suggests an economically sensible answer to how to compare individual and aggregate wages. From (2.1), the natural question is whether aggregate wage movements accurately reflect movements in the skill price r_t, or the price of human capital. For example, if aggregate production in the economy has total human capital ($\sum_i H_i$) as an input, then the appropriate price for that input is r_t. Therefore, the economic comparison to the relevant (quality adjusted) price of labor is

$$r_t \text{ versus } \overline{w}_t.$$

Other interpretable comparisons arise on statistical grounds. Following the tradition of measuring "returns" from coefficients in log wage equations, one could focus on the behavior of the mean log wage. This refers to the comparison

$$E(\ln w_{it}) \text{ versus } \ln \overline{w}_t.$$

This approach is adopted in the work of Solon, Barsky and Parker (1994), as well as in our empirical work. Note that if the log mean of H_i is constant over time in our basic framework, then the mean log wage comparison matches the original

"r_t versus $\bar{w}_t$" comparison (in log form). We have listed these comparisons separately because one might be interested in the log wage comparison even without a framework tracing wages to human capital. For completeness, note that one could compare aggregate wages with many other individual concepts, such as the mean log wage for participating workers, as in

$$E(\ln w_{it} | I = 1) \text{ versus } \ln \bar{w}_t.$$

2.3. Micro Regressions

The underlying individual model is comprised of the following log-wage equation, an hours equation and an employeemnt selection equation

$$\begin{aligned} \ln w &= \beta_0 + \beta' x + \varepsilon, \\ h &= h_0 + \gamma \cdot \left(\alpha_0 + \alpha' z + \nu \right), \\ I &= 1\left[\alpha_0 + \alpha' z + \nu > 0 \right]. \end{aligned} \tag{2.7}$$

where x refers to predictors in the log-wage equation, such as human capital variables that would represent δ_{js} in (2.2), or the predictors in the extended versions of the model.

Our formulations of aggregate wages are based on results on aggregation of nonlinear relationships. We make use of several standard formulae familiar from the analysis of selection bias collected in Appendix A. To derive the implications of the behavioral model on individual level data (at time t), we require

Micro Assumption: (ε, ν) is a joint normal random variable: namely

$$\begin{pmatrix} \varepsilon \\ \nu \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\nu} \\ \sigma_{\varepsilon\nu} & \sigma_\nu^2 \end{pmatrix} \right)$$

Using the results in Appendix A1, the log mean wage is given by

$$\ln E[w|I;x;z] = \beta_0 + \beta' x + \frac{1}{2}\sigma_2^2 + \ln\frac{\Phi_{\sigma_{2o}}}{\Phi}$$

where $\frac{1}{2}\sigma_2^2$ captures the dispersion in the unobservable determinants of wages and

$$\frac{\Phi_{\sigma_{2o}}}{\Phi} = \left[\frac{\Phi\left[\frac{1}{\sigma_o}\left(\alpha_0 + \alpha' z + \sigma_{2o}\right)\right]}{\Phi\left[\frac{1}{\sigma_o}(\alpha_0 + \alpha' z)\right]}\right]$$

measures the impact of selective participation.

Allowing for hours variation, we can likewise compute average hours and weighted average wages. The micro log-wage regression for participants is

$$E[\ln w|I;x;z] = \beta_0 + \beta' x + \frac{\sigma_{2o}}{\sigma_o}\lambda\left[\frac{\alpha_0 + \alpha' z}{\sigma_o^2}\right];$$

where $\lambda[\cdot] = \phi[\cdot]/\Phi[\cdot]$ is the inverse Mills ratio, and where ϕ and Φ are the standard normal density and c.d.f. respectively.

Combining the dispersion, hours and participation terms we have a complete summary of the adjustments required to relate the mean of the unconditional expected wage with the empirical measure of the average wage from a sample of workers:[8]

$$\ln\left(\frac{E[hw|I;x;z]}{E[h|I;x;z]}\right) = \beta_0 + \beta' x + \frac{1}{2}\sigma_2^2 + \ln\left(\frac{\Lambda_{\sigma_{2o}}}{\Lambda}\right) + \ln\left(\frac{\Phi_{\sigma_{2o}}}{\Phi}\right)$$

where

$$\frac{\Lambda_{\sigma_{2o}}}{\Lambda} = \frac{h_0 + \gamma\alpha_0 + \gamma\alpha' z + \gamma\sigma_{2o} + \gamma\sigma_v\lambda\left[\frac{\alpha_0 + \alpha' z + \sigma_{2o}}{\sigma_o^2}\right]}{h_0 + \gamma\alpha_0 + \gamma\alpha' z + \gamma\sigma_v\lambda\left[\frac{\alpha_0 + \alpha' z}{\sigma_o^2}\right]}$$

[8] Appendix A2 contains some intermediate derivations for this formula.

2.4. Macroeconomic Equations

Because we have extensive individual level data on wages, we can model aggregate wages by "adding up" the respective terms; namely microsimulation. However, it is useful to derive specific representations of the impact of participation and hours heterogeneity, and for this we need an assumption on the distribution of the micro variables x and z in the population for a given time period t. We make the following distributional assumption, which is not only convenient but (as we show) reasonably accurate in our applications.[9]

Distributional Restriction: The indexes determining log wages and participation are joint normally distributed: namely

$$\begin{pmatrix}\beta_0+\beta' x\\ \alpha_0+\alpha' z\end{pmatrix} \sim N\left(\begin{pmatrix}\beta_0+\beta' E(x)\\ \alpha_0+\alpha' E(z)\end{pmatrix};\begin{pmatrix}\beta'\Sigma_{xx}\beta & \alpha'\Sigma'_{xz}\beta\\ \beta'\Sigma_{xz}\alpha & \alpha'\Sigma_{zz}\alpha\end{pmatrix}\right)$$

>From Appendix A1, we derive the macroeconomic participation equation as

$$E[I] = \Phi\left[\frac{\alpha_0+\alpha' E(z)}{\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_0^2}}\right];$$

which is in the same form as the micro participation equation with z replaced by $E(z)$ and the spread parameter σ_0 replaced by the larger value $\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_0^2}$, that reflects the influence of heterogeneity in the predictors in the selection criteria.[10] Because[11]

$$E\left[\beta' x | I=1\right] = \beta' E(x) + \frac{\beta'\Sigma_{xz}\alpha}{\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_0^2}}\,\lambda\left[\frac{\alpha_0+\alpha' E(z)}{\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_0^2}}\right];$$

[9] Since we utilize many discrete regressors in our application (cohort and education indicators), it is important that the normal distribution assumption is on the indexes $\beta_0+\beta' x$; $\alpha_0+\alpha' z$. If this assumption only applies within different population segments, then our equations could be applied segment by segment, and aggregated across segments to form the final specification of aggregate wages.

[10] This formula was first derived by McFadden and Reid (1975)

[11] A formula of this form was originally derived by McCurdy (1987).

we can get an interesting formula

$$E[\ln w|I=1] = \beta_0 + \beta' E(x|I=1) + \frac{\sigma_{\varepsilon\nu}}{\sqrt{\alpha'\Sigma_{zz}\alpha + \sigma_\nu^2}}\,\lambda\left[\frac{\alpha_0 + \alpha' E(z)}{\sqrt{\alpha'\Sigma_{zz}\alpha + \sigma_\nu^2}}\right];$$

which has the same form as the selection adjusted micro equation, with the spread parameter $\sigma_{\varepsilon\nu}$ changed to $\sqrt{\alpha'\Sigma_{zz}\alpha + \sigma_\nu^2}$.

If there were no variation in hours (i.e. if hours weights were equal across individuals),), the appropriate macroeconomic wage equation (by Lemma A1) is

$$E[w|I=1] = e^{\beta_0+\beta' E(x)+\frac{1}{2}\left[\beta'\Sigma_{xx}\beta+\sigma_\varepsilon^2\right]}\left[\frac{\Phi^*_{\sigma_{\varepsilon\nu}}}{\Phi^*}\right]$$

with
$$\left[\frac{\Phi^*_{\sigma_{\varepsilon\nu}}}{\Phi^*}\right] = \left[\frac{\Phi\left[\frac{\alpha_0+\alpha' E(z)+\left(\beta'\Sigma_{xz}\alpha+\sigma_{\varepsilon\nu}\right)}{\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_\nu^2}}\right]}{\Phi\left(\frac{\alpha_0+\alpha' E(z)}{\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_\nu^2}}\right)}\right]$$

For later comparison, we can write the log of mean wage as

$$\ln E[w|I=1] = \beta_0 + \beta' E(x) + \frac{1}{2}\left[\beta'\Sigma_{xx}\beta + \sigma_\varepsilon^2\right] + \ln\left[\frac{\Phi^*_{\sigma_{\varepsilon\nu}}}{\Phi^*}\right] \qquad (2.8)$$

Turning to hours h (in (2.7)), analogous calculations give average hours as

$$E[h|I=1] = h_0 + \gamma\alpha_0 + \gamma\alpha' E(z) + \gamma\sqrt{\alpha'\Sigma_{zz}\alpha + \sigma_\nu^2}\cdot\lambda^*$$

in which

$$\lambda^* = \lambda\left[\frac{\alpha_0 + \alpha' E(z)}{\sqrt{\alpha'\Sigma_{zz}\alpha + \sigma_\nu^2}}\right]:$$

Drawing these results together we have that log aggregate wages are given as[12]

$$\ln\frac{E[hw|I=1]}{E[h|I=1]} = \beta_0 + \beta' E(x) + \frac{1}{2}\left[\beta'\Sigma_{xx}\beta + \sigma_\varepsilon^2\right]$$

[12] As before, intermediate calculations for this result are given in Appendix A2.

$$
+\ln\left[\frac{\Lambda^{a}_{\sigma_{ev}}}{\Lambda^{a}}\right]+\ln\left[\frac{\Phi^{a}_{\sigma_{\varepsilon\nu}}}{\Phi^{a}}\right]. \tag{2.9}
$$

where we have defined the hours adjustment term

$$
\frac{\Lambda^{a}_{\sigma_{ev}}}{\Lambda^{a}} \equiv \frac{h_0+\gamma\alpha_0+\gamma\alpha' E(z)+\gamma\beta'\Sigma_{xz}\alpha+\gamma\sigma_{\varepsilon\nu}+\gamma\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_\nu^2}\cdot\lambda^{a}_{\sigma_{ev}}}{h_0+\gamma\alpha_0+\gamma\alpha' E(z)+\gamma\sqrt{\alpha'\Sigma_{zz}\alpha+\sigma_\nu^2}\cdot\lambda^{a}}.
$$

To summarize, there are three aggregation factors that need to be accounted for in examining the evolution of aggregate wages. The first term, $\frac{1}{2}\left[\beta'\Sigma_{xx}\beta+\sigma_\varepsilon^2\right]$, describes the variance of returns (observable and unobservable). The second term, $\ln\left[\Lambda^{a}_{\sigma_{ev}}/\Lambda^{a}\right]$, measures the adjustment for composition changes in hours and depends on the size of the covariance between wages and hours. The final term, $\ln\left[\Phi^{a}_{\sigma_{\varepsilon\nu}}/\Phi^{a}\right]$, highlights the importance of composition changes within the selected sample of workers from which measured wages are recorded. As in the standard selection bias literature, it too depends on the covariance between participation and wages.

2.5. The Nature of the Aggregation Bias

To anticipate our application, we now illustrate how the aggregation biases can manifest themselves in data on labor participation and wages. Setting $\beta_0+\beta' x_{it}=\ln r_t+\delta_{st}$ in (2.7) generates our baseline formulation (2.2). Participation follows the simple reservation wage rule (2.4), that is

$$
\begin{aligned}
\Pr[I_{it}=1] &= \Phi\left(\frac{\ln r_t-\alpha\ln b_{it}+\delta_{js}-\eta_{js}}{\sigma_v}\right)\\
&\equiv \Phi\left(\frac{\alpha_0+\alpha_1' z_{it}}{\sigma_v}\right).
\end{aligned}\tag{2.10}
$$

The time series evolution of the log aggregate hourly real wage, measured among workers, is characterized by

$$\ln \overline{w}_t = \ln r_t + E(\delta_{st}) + \frac{\sigma^2_{\delta,t} + \sigma^2_{\varepsilon,t}}{2} + \ln\left[\frac{\Lambda^{*}_{\sigma_{ev},t}}{\Lambda^{*}_t}\right] + \ln\left[\frac{\Phi^{*}_{\sigma_{\varepsilon\nu},t}}{\Phi^{*}_t}\right] \tag{2.11}$$

The latter term is the adjustment to the aggregate wage to allow for the selectivity on unobservable attributes ε_{it} in the log wage equation induced by participation.

Focusing on the aggregation factor $\ln\left[\Phi^{*}_{t\sigma_{\varepsilon\nu},t}/\Phi^{*}_t\right]$, for the typical case in which $\sigma_{\varepsilon\nu} > 0$; selection induces an upward bias in the average wage. Consider what happens as the return $\ln r_t$ increases over time with $E(\delta_{st})$ constant. For $\sigma_{\varepsilon\nu} > 0$ this results in a decrease in $\ln[\Phi_{\sigma_{\varepsilon\nu},t}/\Phi_t]$ and the corresponding downward bias in the average wage. Aggregation can therefore offset the procyclicality of wages, because of the entry of individuals with lower values of unobserved attributes ε_{it} during upturns: That is

$$d \ln E[w_t | I_t = 1] = d \ln r_t + d \ln\left[\frac{\Phi_{\sigma_{\varepsilon\nu},t}}{\Phi_t}\right]$$

$$= (1 + \lambda_{\sigma_{\varepsilon\nu},t} - \lambda_t) d \ln r_t$$

The composition bias term

$$\lambda_{\sigma_{\varepsilon\nu},t} - \lambda_t = \left(\frac{\phi_{\sigma_{\varepsilon\nu},t}}{\Phi_{\sigma_{\varepsilon\nu},t}} - \frac{\phi_t}{\Phi_t}\right)$$

is negative for a increase in $\ln r_t$ over time since

$$\left(\frac{\phi_{\sigma_{\varepsilon\nu},t}}{\Phi_{\sigma_{\varepsilon\nu},t}} - \frac{\phi_t}{\Phi_t}\right) = \left(\frac{\phi_t \Phi_{\sigma_{\varepsilon\nu},t} - \phi_{\sigma_{\varepsilon\nu},t}\Phi_t}{\Phi_t \Phi_{\sigma_{\varepsilon\nu},t}}\right) \leq 0 \text{ for } \sigma_{\varepsilon v} \geq 0.$$

This analysis is easily extended to the case of two (or more) education or skill groups. Suppose there is a decrease in returns for the lower skilled workers. That is, suppose $\ln r^L_t$ in (2.5) falls. The decline in r^L reduces participation among lower skilled workers and the conditional wage may rise, since the remaining participants will be a more severely selected sample with higher ϵ_{it} on average. This implies that the average wage could show growth even though $\ln r_t^L$ is declining.

3. British Aggregate Wages and Participation

3.1. The Data

The microeconomic data used for this study are taken from the UK Family Expenditure Survey (FES) for the years 1978 to 1996. The FES is a repeated continuous cross-sectional survey of households which provides consistently defined micro data on wages, hours of work, employment status and education for each year since 1978.[13] Our sample consists of all men aged between 19 and 59 (inclusive).[14] For the purposes of modeling, the participating group consists of employees; the non-participating group includes individuals categorized as searching for work as well as the unoccupied. The hours measure for employees in FES is defined as usual weekly hours including usual overtime hours. The weekly earnings measure includes usual overtime pay. We divide nominal weekly earnings by weekly hours to construct an hourly wage measure, which is deflated by the quarterly UK retail price index to obtain real hourly wages. The measure of education used in our study is the age at which the individual left full-time education. Individuals are classified in three groups; those who left full-time education at age 16 or lower (the base group), those who left aged 17 or 18, and those who left aged 19

[13] Prior to 1978 the FES contains no information on educational attainment.

[14] We exclude individuals classified as self-employed. This could introduce some composition bias, given that a significant number of workers moved into self employment in the 1980s. However, given that we have no data on hours and relatively poor data on earnings for this group, there is little alternative but to exclude them. They are also typically excluded in aggregate figures.

or over.[15] We model cohort e®ects on wage levels by a set of cohort dummies; ¯ve date-of-birth cohorts (b.1919-34, b.1935-44, b.1945-54, b.1955-64 and b.1965-77).

Our measure of out-of-work income (income at zero-hours) is constructed for each individual as follows. This measure is evaluated using the tax and bene¯t simulation model[16], which constructs a simulated budget constraint for each individual given information about his age, location, bene¯t eligibility and partner's income (if married/cohabiting). The measure of out-of-work income is largely comprised of income from state bene¯ts; only small amounts of investment income are recorded. For married men we do not include the spouse's income from employment. We control for the spouse's characteristics, in particular her level of education and full set of interactions between, age, region and calendar time. State bene¯ts include eligible unemployment bene¯ts[17] and housing bene¯t, which gives assistance with housing costs.

Since our measure of out-of-work income will serve to identify the participation structure, it is important that variation in the components of out-of-work income are as exogenous to the decision to work or the level of wages as possible. In the UK, the level of bene¯ts which individuals receive out-of-work varies with age, time, household size and (in the case of the housing bene¯t) by region. As mentioned before, housing bene¯t varies systematically with time, location and cohort. One of the primary features of housing bene¯t is that older cohorts

[15] An alternative to our method for constructing the education dummy would use those who left education at the statutory minimum age as the base group. This method is equivalent to ours from 1973 onwards in the UK; before this date the minimum school leaving age was a year lower, at 15. Nonetheless, interactions between date-of-birth cohort e®ects and the education dummy will capture any e®ects of the change in minimum leaving age on the relative returns to education enjoyed by the 17+ group. See Gosling et. al (1996).

[16] The IFS tax and bene¯t simulation model TAXBEN (see www.ifs.org.uk), designed to utilise the British Family Expenditure Survey data used in this paper.

[17] Unemployment Bene¯t included an earnings-related supplement in the late 1970s, but this was abolished in 1980.

had much higher availability of public housing during their household formation period and would have been likely to stay in public housing. Since 1978 the rents in public housing have risen dramatically. For those out of work, housing benefit would have covered these increases, which may have had the effect of increasing the reservation wage for those in public housing.

After making the sample selections described above, our sample contains 71,902 observations. The number of employees in the data is 52,089, or 72.4% of the total sample. Tables 3.1 and 3.2 provide a description of the cell proportions by marital status and education level over the period of our analysis. As Table 3.1 shows, the proportions of single and married men in the data are relatively constant from 1984 onwards, although there were rather less single men in the late 1970s and early 1980s.

3.2. Results

We consider a number of possible specifications for our individual level participation and wage equations which relate to the various specifications discussed in Section 2.[18] Our model of participation includes out-of-work income interacted with marital status, as well as the variables included in the log wage equation. The results of estimating the participation (probit) equation show a strong significance of this benefit income variable. This is important as it is our primary source of identification.[19] The sheer number of interactions makes it hard to discern the impact of the various regressors, and we conduct joint significance tests for sets of regressors and interactions between them. These are presented in Table 3.3 for the participation probit and the wage equation with the selectivity correction via

[18] A full set of results is available from the authors. It also appears as Appendix B in the Institute for Fiscal Studies (www.ifs.org.uk) working paper version.

[19] The full results are available on request.

the inverse Mills ratio.

In estimation we are unable to use data on housing bene¯t for the year 1983. This is because the system of bene¯t assistance for tenants was reformed in 1983 and the information on rent levels and bene¯t receipts was not collected properly by Family Expenditure Survey interviewers. We do, however, have a consistent series for 1978-82 and 1984-1996. Below we present results for the complete period 1978-1996 omitting 1983 data.

Our chosen speci¯cation, which the results below focus on, models participation and wages as a function of the three education groupings, cohort dummies, a cubic trend, and region, plus interactions between the cubic trend and education, cubic trend and cohort, education and cohort, linear trend by education and cohort, and a quadratic trend times region. This speci¯cation was chosen in comparison to a number of alternatives through a standard speci¯cation search.[20] Further details of the validation of this model are presented in the model validation section below.

The necessity of the inclusion of the interaction terms means that our preferred speci¯cation of the log wage equation departs from the full proportionality hypothesis as set out in Section 2. The additional interactions between cohort and education and trend which we introduce could re°ect many di®erences in minimum educational standards across cohorts such as the systematic raising of the minimum school leaving age over the postwar period in the UK. Meanwhile the prices of di®erent (education level) skills are allowed to evolve in di®erent ways, by including an interaction between the education dummies and the trend terms. The selectivity correction using the inverse Mills ratio from the participation equation is interacted with marital status and by education group, because

[20] It is also in accordance with much of the literature on the evolution of British male wages (see Meghir and Whitehouse (1996), for example).

first, the way out-of-work income is defined implies that it attains different levels for single and married people, and second, it is quite possible that selection may have different effects at different skill levels. As Table 3.3 shows the benefit income terms are strongly significant in the participation equation and the Mills ratio, education, cohort and trend terms are all significant in the wage equation.

3.2.1. Aggregate Wages and Corrections: Overall Sample Measures

We now consider aggregate wages and the corrections due to heterogeneity, the distribution of hours and labor participation.[21] We plot the values over time, to allow a quick assessment of the path of aggregate wages and the relative importance of the corrections, as well as how well the corrected aggregate wage matches up with the mean log wage implied by the micro-level wage equations. We have found this graphical approach much more straightforward than trying to directly analyze the numerous estimated coefficients underlying the graphs.

Overall aggregate wages and the various correction terms are plotted in Figure 3.1. Panel (a) of Figure 3.1 displays the behavior of all the measures of wages we look at over the entire period. First there is the selectivity-adjusted prediction from the micro-level wage equation. Second, there is the aggregate measure of wages calculated as the log of average wages for those in work.[22] The remaining three lines shown on the figure give the (cumulative) application of the correction terms to aggregate wages. First is the correction for the distribution of hours. As we may have expected given the relatively stable pattern of hours worked, this has little impact on the time-series evolution of wages. Second is the selection correction for covariance between wages and participation. This has a more

[21] The disturbance "variance" terms are computed by standard variance estimates from the structure of the estimated truncated regression.

[22] This is also calculated from the FES and corresponds closely to the measure of 'average earnings' which media commentators in the UK have focused on.

dramatic effect, with growing gaps over time associated with large decreases in participation. Finally, we apply the correction for the heterogeneity (dispersion) of individual wages. This gives the impact of the increasing heterogeneity in wages that is separated from participation effects.

In sum, this final series gives the aggregate wage after all corrections. For comparison, we plot the mean log wage implied by the micro regressions (adjusted for participation, or omitting the selection term). Finally, in order to see the relative growth of the various series more clearly, panel (b) of Figure 3.1 shows exactly the same series for the micromodel prediction, the aggregate wage measure and the fully-corrected aggregate series, but rebased to 1978.[23] Plotting each series starting at the 1978 level makes it easier to see what the implementation of the adjustment formula does to the measured aggregate hourly earnings growth.

A key evaluation of our framework is whether the fully corrected aggregate series lines up with the selectivity-adjusted micromodel prediction. Panel (a) of Figure 3.1 shows that there is a very close correspondence between the series. Later on we use bootstrap methods to check whether any difference which does arise between the micromodel and the corrected aggregate series is statistically significant.

Several features of this figure are noteworthy. For instance, the direction of movement of the uncorrected log aggregate wage does not always mirror that of the mean micro log wage. During the recession of the early 1980s, aggregate wages grow rather more than the corrected micromodel wage. Whilst there is a reasonably close correspondence between the trend of the two lines in the latter half of the 1980s, in the 1990s we find that there is a reasonably substantial increase in log aggregate wages but essentially no growth in the corrected measure.

[23] That is, the 1978 values are subtracted from all values in the series.

The lower panel of Figure 3.1, which rebases to 1979, shows these patterns even more vividly. Correcting for selection over the period reduces our estimate of real aggregate wage growth from more than 30% to less than 20%.

3.2.2. Wage Measures by Education Group

Next we break our sample up by the three education groups used in the analysis. We plot the wage series defined just as before but this time we are taking the micromodel prediction, the `aggregate' wage series and the corrections to the aggregate series within education group for each year. Hence we have three plots in Figure 3.2, which present the path of the series for each education group.

For the low education group — those that left full time education at age 16 or younger — the picture is particularly clear. This is presented in the first panel of Figure 3.2. Controlling for the biases induced by shifts in participation rates over the 1980s and 1990s reduces our estimate of average wage growth for this group from over 20% to around 10%. The corrected aggregate series and the selectivity-adjusted micromodel prediction appear to line up very well here.

For those individuals with more schooling, presented in the subsequent two panels of Figure 3.2, the fit between the two series is less good largely because these are smaller subsamples, and so the data on wages for them is more noisy. Nevertheless, there appears to be evidence that selection effects do bias measured wage growth estimates upwards for both of the better-educated groups.

3.2.3. Education Returns by Cohort

Disaggregating wages by education and cohort reveals another important aspect of the impact of participation on aggregate wages. As we noted in the introduction the employment rate fell sharply over this period with strong cohort di®erences. Figure 3.3(a)-(c) graphs the estimated returns with and without the correction factors for three di®erent cohorts: those born between 1935 and 1944 (who were the oldest cohort with representatives in every sample year), those born between 1945-1954 and those born between 1955 and 1964 (who were the youngest). It is very noticeable how strongly the returns increased in the early 1980s but equally interesting how the increase is only maintained into the 1990s for the youngest cohort.

The impact of selection e®ects on returns are clearly important. In Figure 3.4 (a)-(c) the time series variation in the selection bias term is presented for each cohort. This follows the cyclical pattern of employment - as one might expect given the analysis presented so far. But what is rather more interesting is that, although selection e®ects always lead to an underestimate of the return, the impact of increasing dispersion is not so clear-cut. Dispersion is often greater for the higher education group, and also rises more quickly over time for the better educated. Consequently the dispersion correction can actually reduce the over all return. For example, in the case of the older cohort Figure 3.3(a) shows that at the end of the 1980s and through the 1990s the dispersion correction is enough to turn around the selection e®ect.

3.2.4. A Regional Breakdown

There are several further breakdowns of the FES wage data which are interesting to look at in our framework in addition to the split by educational group. Regional di®erences in real wages and labor market participation are characteristic of Britain as they are of many European economies. We examine di®erences in the path of measured average wages and the wages predicted by our micromodel, and corrections to the average measure for two broad regions, the `North' and the

'South' of Britain[24].

As the raw earnings indices plotted in panels (b) and (c) of Figure 3.5 show, the two regions experienced marked differences in male wages over this period. Figure 3.5 (a) shows that participation levels and changes have also been very different. In 1978 participation for the South was only around 3-4 percentage points higher than it was in the North. By 1983 this North-South gap had widened to more than 10% as the North was affected a lot more severely by the decline of traditional manufacturing sectors than was the South (mainly because the old industries were mainly located in the North). Growth in participation in the late 1980s in the North then closed some of the increase in the gap, and in the 1990s recession both regions appear to have been affected a lot more equally. Comparing Figure 3.5(b) and (c) shows that wages grew faster on average in the South than they did in the North over the 1980s; in the 1990s the experience of both regions has been relatively similar.

For the North in Figure 3.5 (b), there is much slower growth in the early eighties than the aggregate figures portray and a reasonably continuous divergence between the uncorrected aggregate wage measure and the micromodel prediction from 1979 until 1995. The corrected aggregate measure tracks the micromodel prediction closely for the most part. In the South in Figure 3.5 (c), the aggregate measure and the micromodel prediction grow at a similar rate between 1979 and 1990, although there are some fluctuations around the trend for the aggregate measure. After 1990, the gap between the two measures opens out as falling participation increases the importance of selection. The corrected index indicates that average wages actually fell back in the South. Again there is a close cor-

[24] More precisely, our definition of the 'North' comprises the FES standard regions Northeast, Northwest, Yorkshire & Humberside, West Midlands, Wales and Scotland. The 'South' comprises London and the Southeast. The Southwest, East Midlands and East Anglia are omitted.

respondence of the corrected aggregate measure and the micromodel prediction although there is some divergence between the two in the mid-80s.

Figure 3.5(d) presents the uncorrected and corrected South-North di®erential. Biases induced by di®erential employment behavior in the North and the South of Britain appear to indicate that the behavior of individual wages was very di®erent from that which would be surmised from the aggregate ¯gures.

3.3. Model Validation

Our model and the econometric assumptions underlying have been tested as far as is possible in order to ascertain their plausibility. The validation procedures undertaken include (a) a check to see whether the corrections to aggregate wages line them up su±ciently well with the predictions from the selectivity-adjusted micromodel, (b) relaxing the normality assumption on the unobservables by estimating an analogous model using semiparametric methods, and (c) plots of the predicted indices from the probit and the wage equation to assess whether the distributions of observable attributes conform to normality. We now assess each of these in turn.

3.3.1. Bootstrapping the Accuracy of the Model Fit

To assess the accuracy with which the corrections which we make to the aggregate average male log wage series `line up' against the prediction from our micro-model of wages (with the selectivity correction included), we used bootstrap methods to simulate the di®erence between the two measures[25]. The results are shown in Figure 3.6.[26] They show that the di®erence between the two measures is not signi¯cantly di®erent from zero in most of the years covered by the sample.

[25] The number of repetitions in the bootstrap simulation was 500.
[26] Very similar, broken down by educational group, are available on request.

Occasionally the difference is significantly positive (indicating that the corrected aggregate measure is higher than the micromodel prediction), but in general the corrections to the aggregate measure and the selectivity-adjusted micromodel line up very well. This provides a very positive validation of the model framework.

3.3.2. Semiparametric Estimation

Our model, as set out in Section 2, makes the assumption that the unobservable factors affecting participation and wages are normally distributed. This can of course be called into question. The properties of the estimator rely on the parametric distributional assumptions on the joint distribution of the errors. However, given our exclusion assumption on the continuous out-of-work income variable, semiparametric estimation can proceed in a fairly straightforward manner. To estimate the slope parameters we follow the suggestion of Robinson (1988) which is developed in Ahn and Powell (1993). These techniques are explored in a useful application to labor supply by Newey, Powell and Walker (1990). In Figure 3.7 we graph a comparison between the predicted wages estimated using semiparametric techniques and the wage predictions from the selectivity-adjusted micromodel which we use. Bootstrap confidence bands (95%) refer to the parametric selectivity model. There is a very close correspondence between the predictions from the parametric micromodel and the semiparametric version. We conclude that the assumption of normality of the unobservables in the model is not unduly restrictive.

3.3.3. Normality of the Wage and Participation Indexes

In addition to checking the validity of the normality assumption on the unobservables, we are also interested in the normality of the probit index and of the fitted wage distribution from the selectivity-adjusted wage equation. Taking the participation probit first of all, Figure 3.8 plots the distribution of the standardized probit index $\gamma' z$ over all years of the sample (plots for individual years are all quite similar). The index is distributed roughly normally although with a slight negative skew.[27]

We also checked the validity of the normality assumption on log wages by plotting the standardized wage predictions from the model overlaid with a standard normal curve. This is shown in Figure 3.9. The distribution is not obviously skewed left or right, and there appears to be a higher density of observations around the mean than is the case with a standard normal. In any case, while these plots do not show exact concordance with the normal distribution assumptions, we feel that the proximity of the empirical distributions to normal helps explain the close correspondence between corrected aggregate wages and the mean wages implied by the micro regressions.[28]

4. Conclusion

This aim of this paper has been to provide a systematic assessment of the way changes in labor market participation affect our interpretation of aggregate real wages. We have developed and implemented an empirical framework for understanding this relationship which reduces to the calculation of three aggregation factors. These can be interpreted as correction terms reflecting changes in selection due to participation, changes in the distribution of returns and changes in

[27] For further validation, kernel regressions of participation on $\gamma' z$ show a normal shape, details of which are available from the authors on request.

[28] While there are some visible departures from normality, the entire impact of those departures on the analysis is summarized in the difference between the plots from the corrected aggregate measure and the micro model. As we have noted above these plots are extremely close.

hours of work, respectively. We have shown that they do a remarkably good job of explaining the di®erences between individual and aggregate wages in the British context.

British data was used for three reasons. First, there have been signi¯cant changes in labor market participation over the last two decades. Participation rates for men have seen a secular decline and have displayed strong cyclical variation. The secular decline is largely re°ected in increasing decline in participation among older men across cohorts while the cyclical variation shows strong regional variation. This phenomena is common to many other developed economies. Second, in Britain, there are strong changes in real wages and the distribution of real wages over this sample period. Third, there is important exogenous variation in certain components of out of work incomes across time and across individuals that allows the identi¯cation of the correction terms.

The empirical analysis of aggregate wages is shown to provide a coherent picture of the relationship between individual male wages and aggregated wages over this period. Moreover, the statistical model adopted appears to accord well with the empirical facts. The correction terms explain the di®erences between log aggregate wages and the average of log wages implied by our analysis. The di®erences are interesting and have valuable implications. They show an important role for wage dispersion and for selection in charaterising the distortion in the measurement of wage growth from aggregate data. Most noteworthy is how mean individual log-wages are largely °at throughout the early 1990's, whereas measured aggregate wages are rising. As such, we see our estimates as giving clear evidence that the biases in log aggregate real wages are substantial and can lead to misleading depictions of the progress of wages of individual male workers.

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A. Appendix A: Aggregation Results

Appendix A1: Lemma A1

Our formulations of aggregate wages are based on results on aggregation of nonlinear relationships over normal and lognormal distributions. We make use of several standard formulae familiar from the analysis of selection bias, as well as some further results presented in Lemma A1. While these further results are rather basic, we could not find specific references to them in the literature, and so we have included a proof below. Finally, we close with the correspondences used to derive the specific results of the main text.

Begin by assuming that $(U; V)$ are jointly normal random variables: namely

$$\begin{pmatrix} U \\ V \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_U \\ \mu_V \end{pmatrix}; \begin{pmatrix} \sigma_U^2 & \sigma_{UV} \\ \sigma_{UV} & \sigma_V^2 \end{pmatrix} \right):$$

and denote $I = 1[V < 0]$. The event $V < 0$ is equivalent to the event $(V - \mu_V)/\sigma_V < -\mu_V/\sigma_V$, so that

$$E[I] = \Phi\left(\frac{-\mu_V}{\sigma_V}\right)$$

follows by definition, where $\Phi[\cdot]$ is the standard normal c.d.f.

Note that

$$\frac{\partial}{\partial\eta}\left(e^{-\frac{\eta^2}{2\sigma^2}}\right) = -\frac{\eta}{\sigma^2}e^{-\frac{\eta^2}{2\sigma^2}}:$$

Therefore, with

$$\begin{aligned} u &\equiv U - \mu_U \\ v &\equiv V - \mu_V \end{aligned} \tag{A.1}$$

normality implies that

$$u = \frac{\sigma_{UV}}{\sigma_V^2}v + s \tag{A.2}$$

where s is independent of v: Therefore,

$$\begin{aligned} E(uI) &= \frac{\sigma_{UV}}{\sigma_V^2}\int_{-\infty}^{-\mu_V}\frac{v}{\sqrt{2\pi}\sigma_V}e^{-\frac{v^2}{2\sigma_V^2}}dv \\ &= -\frac{\sigma_{UV}}{\sigma_V}\frac{1}{\sqrt{2\pi}}e^{-\frac{(-\mu_V)^2}{2\sigma_V^2}} \\ &= -\frac{\sigma_{UV}}{\sigma_V}\phi\left(\frac{-\mu_V}{\sigma_V}\right): \end{aligned} \tag{A.3}$$

Noting that $E(UI) = \mu_U E(I) + E(uI)$ and $E(U|I) = E(UI)/E(I)$, we have that

$$E[UI] = \mu_U\Phi\left(\frac{-\mu_V}{\sigma_V}\right) - \frac{\sigma_{UV}}{\sigma_V}\phi\left(\frac{-\mu_V}{\sigma_V}\right) \tag{A.4}$$

where $\phi[\cdot]$ is the standard normal density function. Consequently, we have

$$E[U|I=1] = \frac{E[UI]}{E[I]} = \mu_U - \frac{\sigma_{UV}}{\sigma_V}\lambda\left(\frac{-\mu_V}{\sigma_V}\right) \tag{A.5}$$

where $\lambda[\cdot] = \phi[\cdot]/\Phi[\cdot]$ is the inverse Mill's ratio.[29]

[29] Recall that our notational convention is that $E(\cdot|I)$ denotes expectation conditional on $I = 1$.

Applying (A.4) to the case with $U = a + bV$ gives

$$E[(a+bV)I] = (a+b\mu_V)\Phi\left(\frac{-\mu_V}{\sigma_V}\right) - b\sigma_V\phi\left(\frac{-\mu_V}{\sigma_V}\right)$$

and

$$E[(a+bV)|I=1] = (a+b\mu_V) - b\sigma_V\lambda\left(\frac{-\mu_V}{\sigma_V}\right).$$

This concludes the basic selection formulae that we use. To study log-normal variables (wages in our applicaition), we require:

Lemma A.1. Suppose that $(U;V)$ are jointly normal random variables with

$$\begin{pmatrix} U \\ V \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_U \\ \mu_V \end{pmatrix};\begin{pmatrix} \sigma_U^2 & \sigma_{UV} \\ \sigma_{UV} & \sigma_V^2 \end{pmatrix}\right).$$

and denote

$$\ln W = U \text{ and } I = 1[V<0].$$

Then:

A.

$$E[W|I=1] = e^{\mu_U+\frac{1}{2}\sigma_U^2}\cdot\frac{\Phi\left[\frac{-\mu_V-\sigma_{UV}}{\sigma_V}\right]}{\Phi\left[\frac{-\mu_V}{\sigma_V}\right]}. \tag{A.6}$$

B.

$$E[VW|I=1] = e^{\mu_U+\frac{1}{2}\sigma_U^2}\cdot\left\{\mu_V+\sigma_{UV}-\sigma_V\lambda\left(\frac{-\mu_V-\sigma_{UV}}{\sigma_V}\right)\right\}\cdot\frac{\Phi\left[\frac{-\mu_V-\sigma_{UV}}{\sigma_V}\right]}{\Phi\left[\frac{-\mu_V}{\sigma_V}\right]}. \tag{A.7}$$

Proof of Lemma A1:
For A, first note that

$$E[WI] = e^{\mu_U}E(e^S)E\left(e^{\frac{\sigma_{UV}}{\sigma_V^2}V}I\right) \tag{A.8}$$

since s (of (A.2)) is independent of v. Now

$$
\begin{aligned}
E\left(e^{s}\right) &= e^{E(s)+\frac{1}{2}\sigma_s^2} &\quad (A.9)\\
&= e^{\frac{1}{2}\sigma_u^2\left(1-\rho_{uv}^2\right)}
\end{aligned}
$$

where $\rho_{uv} = \sigma_{uv}/\sigma_u\sigma_v$.

The final term of (A.6) is developed as

$$
\begin{aligned}
E\left(e^{\frac{\sigma_{uv}}{\sigma_v^2}v} I\right) &= \int_{v<-\mu_v} e^{\frac{\sigma_{uv}}{\sigma_v^2}v}\left[\frac{1}{\sqrt{2\pi}\sigma_v} e^{-\frac{v^2}{2\sigma_v^2}}\right] dv\\
&= \int_{v<-\mu_v} \frac{1}{\sqrt{2\pi}\sigma_v} e^{\left[-\frac{v^2}{2\sigma_v^2}+\frac{\sigma_{uv}}{\sigma_v^2}v\right]} dv
\end{aligned}
$$

This term is simplified by completing the square in the exponent of the latter integral. The exponent is

$$
\begin{aligned}
-\frac{v^2}{2\sigma_v^2}+\frac{\sigma_{uv}}{\sigma_v^2}v &= -\frac{1}{2\sigma_v^2}\left[v^2-2\sigma_{uv}v\right]\\
&= -\frac{1}{2\sigma_v^2}\left[v-\sigma_{uv}\right]^2+\frac{\sigma_{uv}^2}{2\sigma_v^2}
\end{aligned}
$$

This implies that

$$
\begin{aligned}
E\left(e^{\frac{\sigma_{uv}}{\sigma_v^2}v} I\right) &= e^{\frac{\sigma_{uv}^2}{2\sigma_v^2}} \int_{v<-\mu_v}\left[\frac{1}{\sqrt{2\pi}\sigma_v} e^{-\frac{1}{2\sigma_v^2}\left[v-\sigma_{uv}\right]^2}\right] dv\\
&= e^{\frac{\sigma_{uv}^2}{2\sigma_v^2}} \int_{v^*<-\mu_v-\sigma_{uv}}\left[\frac{1}{\sqrt{2\pi}\sigma_v} e^{-\frac{1}{2\sigma_v^2}\left(v^*\right)^2}\right] dv^*\\
&= e^{\frac{\sigma_{uv}^2}{2\sigma_v^2}}\,\Phi\left(\frac{-\mu_v-\sigma_{uv}}{\sigma_v}\right)
\end{aligned}
$$

Collecting all of the terms gives

$$
\begin{aligned}
E[WI] &= e^{\mu_u}E\left(e^{s}\right)E\left(e^{\frac{\sigma_{uv}}{\sigma_v^2}v} I\right)\\
&= e^{\mu_u}e^{\frac{1}{2}\sigma_u^2\left(1-\rho_{uv}^2\right)}e^{\frac{\sigma_{uv}^2}{2\sigma_v^2}}\,\Phi\left(\frac{-\mu_v-\sigma_{uv}}{\sigma_v}\right)\\
&= e^{\mu_u+\frac{1}{2}\sigma_u^2}\,\Phi\left(\frac{-\mu_v-\sigma_{uv}}{\sigma_v}\right)
\end{aligned}
$$

Dividing by the formula for $E[WI]$ by $E[I]$ gives the result for $E[W|I]$, or (A.6).

For part B, using (A.2), we have that

$$VW = \mu_V W + e^{\mu_U} e^s \left(v \cdot e^{\frac{\sigma_{UV}}{\sigma_V^2} v} \right)$$

so that

$$E[VWI] = \mu_V E[WI] + e^{\mu_U} E(e^s)\, E\left(v \cdot e^{\frac{\sigma_{UV}}{\sigma_V^2} v} I \right)$$

The first term can be solved for from part A, so we focus on the second term. We have

$$\begin{aligned}
E\left(v \cdot e^{\frac{\sigma_{UV}}{\sigma_V^2} v} I \right) &= \int_{v<-\mu_V} v \cdot e^{\frac{\sigma_{UV}}{\sigma_V^2} v} \left[\frac{1}{\sqrt{2\pi\sigma_V}} e^{-\frac{v^2}{2\sigma_V^2}} \right] dv \\
&= \int_{v<-\mu_V} \frac{v}{\sqrt{2\pi\sigma_V}} e^{-\frac{v^2}{2\sigma_V^2} + \frac{\sigma_{UV}}{\sigma_V^2} v} dv \\
&= e^{\frac{\sigma_{UV}^2}{2\sigma_V^2}} \int_{v^*<-\mu_V-\sigma_{UV}} (v^* + \sigma_{UV}) \left[\frac{1}{\sqrt{2\pi\sigma_V}} e^{-\frac{1}{2\sigma_V^2}(v^*)^2} \right] dv^* \\
&= e^{\frac{\sigma_{UV}^2}{2\sigma_V^2}} \left\{ \int_{v^*<-\mu_V-\sigma_{UV}} v^* \left[\frac{1}{\sqrt{2\pi\sigma_V}} e^{-\frac{1}{2\sigma_V^2}(v^*)^2} \right] dv^* + \sigma_{UV} \Phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) \right\} \\
&= e^{\frac{\sigma_{UV}^2}{2\sigma_V^2}} \left\{ -\sigma_V \phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) + \sigma_{UV} \Phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) \right\}
\end{aligned}$$

where the third equality follows from completing the square as in part A, and the last equality follows from direct integration as in (A.3) above. Now, collecting terms gives

$$\begin{aligned}
E[VWI] &= \mu_V E[WI] + e^{\mu_U} E(e^s)\, E\left(v \cdot e^{\frac{\sigma_{UV}}{\sigma_V^2} v} I \right) \\
&= \mu_V e^{\mu_U + \frac{1}{2}\sigma_U^2} \Phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) \\
&\quad + e^{\mu_U + \frac{1}{2}\sigma_U^2} \left\{ -\sigma_V \phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) + \sigma_{UV} \Phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) \right\}
\end{aligned}$$

$$= e^{\mu_U + \frac{1}{2}\sigma_U^2} \left\{ (\mu_V + \sigma_{UV}) \Phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) - \sigma_V \phi\left(\frac{-\mu_V - \sigma_{UV}}{\sigma_V} \right) \right\}$$

Equation (A.7) follows from dividing by $E[I]$. This completes the proof of the Lemma A1.

The formulations (A.6)-(A.7) can be rewritten in terms of the unconditional mean of W, since

$$E(W) = e^{\mu_U + \frac{1}{2}\sigma_U^2}.$$

For instance, (A.6) can be rewritten as an adjustment to the unconditional mean as

$$E[W|I = 1] = E(W) \cdot \frac{\Phi\left[\frac{-\mu_V - \sigma_{UV}}{\sigma_V}\right]}{\Phi\left[\frac{-\mu_V}{\sigma_V}\right]}$$

and the other equations can be similarly recast.

To derive the results in the text we apply the following correspondence

$$\begin{aligned} U &= \beta_0 + \beta' x + \varepsilon; \\ V &= -\alpha_0 - \alpha' z - \nu. \end{aligned} \tag{A.10}$$

For the individual formulations of Section 2.3, we apply the formulae to the population distributions conditional on the values of x and z. This gives

$$\begin{aligned} \mu_U &= \beta_0 + \beta' x \\ \mu_V &= -\alpha_0 - \alpha' z \\ \sigma_U^2 &= \sigma_\varepsilon^2 \\ \sigma_{UV} &= -\sigma_{\varepsilon\nu} \\ \sigma_V^2 &= \sigma_\nu^2 \end{aligned} \tag{A.11}$$

For the macroeconomic equations of Section 2.4, we apply the same correspondence, slightly rewritten as

$$\begin{aligned} U &= \beta_0 + \beta' E(x) + \beta' (x - E(x)) + \varepsilon \\ V &= -\alpha_0 - \alpha' E(z) - \alpha' (z - E(z)) - \nu. \end{aligned} \tag{A.12}$$

and apply the formulae to the (unconditional) expectations over the joint distribution of x and z and the disturbances ε and ν: This gives

$$\begin{aligned}
\mu_U &= \beta_0 + \beta' E(x) \\
\mu_V &= -\alpha_0 - \alpha' E(z) \\
\sigma_U^2 &= \beta' \Sigma_{xx} \beta + \sigma_\varepsilon^2 \\
\sigma_{UV} &= -\beta' \Sigma_{xz} \alpha - \sigma_{\varepsilon\nu} \\
\sigma_V^2 &= \alpha' \Sigma_{zz} \alpha + \sigma_\nu^2
\end{aligned} \tag{A.13}$$

that are substituted into the general aggregation results.

Appendix: A2: Some Further Derivations

The following formulae are needed as intermediate steps in the derivation of our main aggregation bias terms. First, noting that $h = h_0 - \gamma V$, we have

$$E[h|I; x; z] = h_0 + \gamma\alpha_0 + \gamma\alpha' z + \gamma\sigma_V \lambda\left[\frac{\alpha_0 + \alpha' z}{\sigma_\nu}\right]:$$

Applying (A.7) of Lemma A1 in Appendix A gives

$$\begin{aligned}
E[hw|I; x; z] = {} & e^{\beta_0 + \beta' x + \frac{1}{2}\sigma_\varepsilon^2} \cdot \\
& \left(h_0 + \gamma\alpha_0 + \gamma\alpha' z + \gamma\sigma_{\varepsilon\nu} + \gamma\sigma_V \lambda\frac{\alpha_0 + \alpha' z + \sigma_{\varepsilon\nu}}{\sigma_\nu}\right)\left[\frac{\Phi_{\sigma_{\varepsilon\nu}}}{\Phi}\right]
\end{aligned}$$

Carrying out a similar calculation on the unconditional (overall) distribution gives

$$\begin{aligned}
E[hw|I = 1] = {} & e^{\beta_0 + \beta' E(x) + \frac{1}{2}\left[\beta' \Sigma_{xx}\beta + \sigma_\varepsilon^2\right]} \\
& \cdot \left\{h_0 + \gamma\alpha_0 + \gamma\alpha' E(z) + \gamma\beta' \Sigma_{xz}\alpha + \gamma\sigma_{\varepsilon\nu} + \gamma\sqrt{\alpha' \Sigma_{zz}\alpha + \sigma_\nu^2}\,\lambda^a_{\sigma_{\varepsilon\nu}}\right\}\left[\frac{\Phi^a_{\sigma_{\varepsilon\nu}}}{\Phi^a}\right]
\end{aligned}$$

in which

$$\lambda^a_{\sigma_{\varepsilon\nu}} = \lambda\left[\frac{\alpha_0 + \alpha' E(z) + \beta' \Sigma_{xz}\alpha + \sigma_{\varepsilon\nu}}{\sqrt{\alpha' \Sigma_{zz}\alpha + \sigma_\nu^2}}\right]:$$

Appendix B: Full Regression Results

KEY

Variable name	Description
s_zero	log of simulated TAXBEN out-of-work income, single men
m_zero	log of simulated TAXBEN out-of-work income, married men (asssuming *both* partners not working)
no_zero	simulated TAXBEN out-of-work income zero or missing
spoused	spouse's education dummy (=1 if left school after 16)
married	marital status dummy (=1 if married)
ed17	education dummy (=1 if left FT education aged 17-18)
ed19	education dummy (=1 if left FT education aged 19 or over)
trend	trend (=year-77)
trend_2	$trend^2$
trend_3	$trend^3$
c1919_34	cohort dummy: born 1919-34
c1935_44	cohort dummy: born 1935-44
c1955_64	cohort dummy: born 1955-64
c1965_77	cohort dummy: born 1965-77
c19_ed17	interaction: c1919_34*ed17
c35_ed17	interaction: c1935_44*ed17
c55_ed17	interaction: c1955_64*ed17
c65_ed17	interaction: c1965_77*ed17
c19_ed19	interaction: c1919_34*ed19
c35_ed19	interaction: c1935_44*ed19
c55_ed19	interaction: c1955_64*ed19
c65_ed19	interaction: c1965_77*ed19
c19_tr, c19_tr2, c19_tr3	interactions: c1919_34*trend, $*trend^2$, $*trend^3$
c35_tr, c35_tr2, c35_tr3	interactions: c1935_44*trend, $*trend^2$, $*trend^3$
c55_tr, c55_tr2, c55_tr3	interactions: c1955_64*trend, $*trend^2$, $*trend^3$
c65_tr, c65_tr2, c65_tr3	interactions: c1965_77*trend, $*trend^2$, $*trend^3$
ed17_tr, ed17_tr2, ed17_tr3	interactions: ed17*trend, $*trend^2$, $*trend^3$
ed19_tr, ed19_tr2, ed19_tr3	interactions: ed17*trend, $*trend^2$, $*trend^3$
c19_17_t, c35_17_t, c55_17_t, c65_17_t	interactions: c1919_34*ed17*trend, c1935_44*ed17*trend, c1955_64*ed17*trend, c1965_77*ed17*trend
c19_19_t, c35_19_t, c55_19_t, c65_19_t	interactions: c1919_34*ed19*trend, c1935_44*ed19*trend, c1955_64*ed19*trend, c1965_77*ed19*trend
reg_d1	region: Northern
reg_d2	region: Yorkshire & Humberside
reg_d3	region: North Western
reg_d4	region: East Midlands
reg_d5	region: West Midlands
reg_d6	region: East Anglia
reg_d7	region: Greater London
reg_d8	region: South East (except Greater London)
reg_d9	region: South Western
reg_d10	region: Wales
reg1_t, reg2_t, … reg10_t	interactions: regional dummies*trend
reg1_t2, reg2_t2,… reg10_t2	interactions: regional dummies$*trend^2$
millsi	Inverse Mills' ratio * single
millma	Inverse Mills' ratio * married

Table B.1: Participation Probit

dependent variable = working dummy

Probit estimates — Number of obs = 71901

LR chi2(78) =9862.99

Prob > chi2 = 0.0000

Log likelihood = -28335.311 — Pseudo R2 = 0.1482

work	dF/dx	Std. Err.	z	P>|z|	x-bar	[95%	C.I.]
sdbz	-.0685447	.002333	-29.07	0.000	.90383	-.073117	-.063972
mdbz	-.1377394	.0036845	-36.33	0.000	3.5209	-.144961	-.130518
no_dbz*	.1142545	.0058884	8.82	0.000	.025938	.102713	.125796
spoused*	.0521162	.0034607	13.59	0.000	.200748	.045333	.058899
married*	.7129586	.0245823	25.14	0.000	.724441	.664778	.761139
ed17*	.0636748	.0222094	2.44	0.014	.138997	.020145	.107204
ed19*	.0454274	.0239729	1.70	0.088	.134532	-.001559	.092413
trend	-.0310929	.0065642	-4.74	0.000	9.82081	-.043959	-.018227
trend_2	.0342862	.00684	5.01	0.000	12.6716	.02088	.047692
trend_3	-.0118253	.0021916	-5.39	0.000	18.3757	-.016121	-.00753
c1919_34*	.010342	.0199493	0.51	0.611	.14762	-.028758	.049442
c1935_44*	.0265571	.01921	1.32	0.186	.207744	-.011094	.064208
c1955_64*	-.1775103	.0291358	-7.00	0.000	.254948	-.234615	-.120405
c1965_77*	-.9903533	.0033246	-9.55	0.000	.119525	-.996869	-.983837
c19_ed17*	-.1167392	.0490357	-2.83	0.005	.010348	-.212847	-.020631
c35_ed17*	-.0401304	.0361052	-1.21	0.228	.020973	-.110895	.030634
c55_ed17*	-.0094561	.0277547	-0.35	0.728	.045368	-.063854	.044942
c65_ed17*	-.1190364	.0759068	-1.86	0.063	.023769	-.267811	.029738
c19_ed19*	.0358679	.0318798	1.00	0.316	.008206	-.026615	.098351
c35_ed19*	.0109473	.0300164	0.35	0.723	.020904	-.047884	.069778
c55_ed19*	.0410211	.0212199	1.71	0.088	.042572	-.000569	.082611
c65_ed19*	-.1250612	.0989909	-1.51	0.132	.01751	-.31908	.068957
c19_tr	-.0180338	.0101164	-1.78	0.075	.831574	-.037861	.001794
c35_tr	.003205	.0085802	0.37	0.709	1.94195	-.013612	.020022
c55_tr	.0098374	.0083916	1.17	0.241	2.72756	-.00661	.026285
c65_tr	.4601365	.0538138	8.55	0.000	1.75589	.354663	.56561
ed17_tr	.0115365	.0101206	1.14	0.254	1.4791	-.0083	.031373
ed17_tr2	-.0087879	.0109401	-0.80	0.422	1.98007	-.03023	.012654
ed17_tr3	.0018958	.0034845	0.54	0.586	2.92933	-.004934	.008725
ed19_tr	.00986	.010686	0.92	0.356	1.48225	-.011084	.030804
ed19_tr2	-.0002327	.0116365	-0.02	0.984	2.02982	-.02304	.022575
ed19_tr3	-.0018782	.0036944	-0.51	0.611	3.05034	-.009119	.005363
c19_17_t	.0032464	.0037791	0.86	0.390	.063393	-.00416	.010653
c35_17_t	-.0016828	.0025082	-0.67	0.502	.198718	-.006599	.003233
c55_17_t	-.0006529	.0022063	-0.30	0.767	.499659	-.004977	.003671
c65_17_t	.0064879	.0035833	1.81	0.070	.348173	-.000535	.013511
c19_19_t	-.0039854	.0044121	-0.90	0.366	.050347	-.012633	.004662
c35_19_t	-.0026946	.0025551	-1.05	0.292	.206826	-.007702	.002313
c55_19_t	-.0032974	.0021823	-1.51	0.131	.507768	-.007575	.00098
c65_19_t	.0068479	.0043329	1.58	0.114	.275226	-.001644	.01534
c19_tr2	.0026269	.0138457	0.19	0.850	.693711	-.02451	.029764
c19_tr3	.000708	.005572	0.13	0.899	.704376	-.010213	.011629
c35_tr2	-.0149225	.0096857	-1.54	0.123	2.42231	-.033906	.004061
c35_tr3	.0050972	.0031588	1.61	0.107	3.42328	-.001094	.011288
c55_tr2	.0030662	.0093429	0.33	0.743	3.6035	-.015246	.021378
c55_tr3	-.0014964	.0030189	-0.50	0.620	5.26727	-.007413	.004421

c65_tr2	-.3258694	.0407671	-7.99	0.000	2.70399	-.405771	-.245967
c65_tr3	.076083	.0100139	7.60	0.000	4.3189	.056456	.09571
reg_d1*	-.0352825	.0239148	-1.58	0.114	.064784	-.082155	.01159
reg_d2*	.0039765	.0194331	0.20	0.839	.093351	-.034112	.042065
reg_d3*	.0101134	.0179885	0.55	0.582	.114324	-.025143	.04537
reg_d4*	.0713913	.0148853	3.78	0.000	.076341	.042217	.100566
reg_d5*	.0445241	.016201	2.45	0.014	.097314	.012771	.076278
reg_d6*	.0043725	.0276139	0.16	0.876	.037232	-.04975	.058495
reg_d7*	.0306896	.0169073	1.69	0.092	.104783	-.002448	.063827
reg_d8*	.0635671	.0142713	3.91	0.000	.187257	.035596	.091538
reg_d9*	.048895	.0171858	2.47	0.013	.07808	.015211	.082579
reg_d10*	-.0039396	.0231322	-0.17	0.864	.052433	-.049278	.041399
reg1_t	.0048434	.0046909	1.03	0.302	.625805	-.004351	.014037
reg2_t	.0033078	.0044334	0.75	0.456	.920307	-.005382	.011997
reg3_t	.0007642	.0041897	0.18	0.855	1.11781	-.007447	.008976
reg4_t	-.0038878	.0050102	-0.78	0.438	.763369	-.013708	.005932
reg5_t	-.0050552	.0044739	-1.13	0.259	.940015	-.013824	.003713
reg6_t	.0149104	.0062843	2.37	0.018	.373861	.002593	.027227
reg7_t	.0076762	.0043746	1.75	0.079	1.00405	-.000898	.01625
reg8_t	.0069887	.0040575	1.72	0.085	1.85591	-.000964	.014941
reg9_t	.0043744	.0049013	0.89	0.372	.803104	-.005232	.013981
reg10_t	-.0024889	.0051066	-0.49	0.626	.499798	-.012498	.00752
reg1_t2	-.0028384	.0022722	-1.25	0.212	.800445	-.007292	.001615
reg2_t2	-.0012655	.0021394	-0.59	0.554	1.19083	-.005459	.002928
reg3_t2	-.0003293	.0020187	-0.16	0.870	1.43816	-.004286	.003627
reg4_t2	.0008202	.0023751	0.35	0.730	.991075	-.003835	.005475
reg5_t2	.0023763	.0021487	1.11	0.269	1.196	-.001835	.006588
reg6_t2	-.0066026	.0030037	-2.20	0.028	.488365	-.01249	-.000716
reg7_t2	-.0057894	.0021137	-2.74	0.006	1.28218	-.009932	-.001647
reg8_t2	-.0040872	.0019426	-2.10	0.035	2.4032	-.007895	-.00028
reg9_t2	-.0023909	.0023291	-1.03	0.305	1.06661	-.006956	.002174
reg10_t2	.0012647	.0024688	0.51	0.608	.634458	-.003574	.006104
obs. P	.825677						
pred. P	.8676316	(at x-bar)					

(*) dF/dx is for discrete change of dummy variable from 0 to 1
z and P>|z| are the test of the underlying coefficient being 0

Table B.2: Wage equation (including selectivity adjustment)

dependent variable = log real wage

Source	SS	df	MS
Model	4019.50634	76	52.8882414
Residual	9820.73938	59290	.165639052
Total	13840.2457	59366	.233134214

Number of obs =	59367
F(76, 59290) =	319.30
Prob > F =	0.0000
R-squared =	0.2904
Adj R-squared =	0.2895
Root MSE =	.40699

logrw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
millsi	.2008087	.0146226	13.733	0.000	.1721483	.2294691
millma	.1413254	.0191778	7.369	0.000	.1037368	.178914
married	.2323243	.0081163	28.624	0.000	.2164162	.2482323
ed17	.1745378	.0286755	6.087	0.000	.1183337	.2307418
ed19	.2493489	.0281713	8.851	0.000	.194133	.3045648
trend	.0093508	.0079933	1.170	0.242	-.0063161	.0250177
trend_2	.0139255	.0084488	1.648	0.099	-.0026343	.0304853
trend_3	-.0063356	.0027523	-2.302	0.021	-.0117301	-.0009411
c1919_34	.0172652	.0232878	0.741	0.458	-.0283789	.0629093
c1935_44	.038349	.0224502	1.708	0.088	-.0056535	.0823515
c1955_64	-.0739112	.0249322	-2.964	0.003	-.1227784	-.0250439
c1965_77	-2.130157	.3590534	-5.933	0.000	-2.833903	-1.426411
c19_ed17	.1411372	.0354563	3.981	0.000	.0716428	.2106316
c35_ed17	.1132332	.0292551	3.871	0.000	.0558931	.1705733
c55_ed17	-.1517167	.0270713	-5.604	0.000	-.2047765	-.098657
c65_ed17	-.2455389	.0667992	-3.676	0.000	-.3764656	-.1146122
c19_ed19	.3856498	.0367668	10.489	0.000	.3135868	.4577128
c35_ed19	.1574245	.0293621	5.361	0.000	.0998747	.2149744
c55_ed19	-.2308073	.0289465	-7.974	0.000	-.2875427	-.174072
c65_ed19	-.3278073	.0912167	-3.594	0.000	-.5065924	-.1490223
c19_tr	.0017094	.0125377	0.136	0.892	-.0228646	.0262834
c35_tr	.0073628	.0099587	0.739	0.460	-.0121563	.026882
c55_tr	-.032532	.0100916	-3.224	0.001	-.0523116	-.0127524
c65_tr	.408846	.0842272	4.854	0.000	.2437603	.5739317
ed17_tr	.0018844	.0107116	0.176	0.860	-.0191103	.0228791
ed17_tr2	.015739	.012081	1.303	0.193	-.0079397	.0394178
ed17_tr3	-.0065763	.0039533	-1.664	0.096	-.0143247	.0011721
ed19_tr	.0211364	.0108976	1.940	0.052	-.0002229	.0424958
ed19_tr2	.0089118	.0123286	0.723	0.470	-.0152523	.0330759
ed19_tr3	-.0063701	.0040296	-1.581	0.114	-.0142682	.0015279
c19_17_t	-.0063433	.0047188	-1.344	0.179	-.0155921	.0029056
c35_17_t	-.0038804	.002766	-1.403	0.161	-.0093019	.0015411
c55_17_t	.0041489	.0023564	1.761	0.078	-.0004697	.0087674
c65_17_t	.0028379	.0046284	0.613	0.540	-.0062337	.0119095
c19_19_t	-.0247369	.0049201	-5.028	0.000	-.0343804	-.0150935
c35_19_t	-.0086038	.0027035	-3.182	0.001	-.0139027	-.0033048
c55_19_t	.0091267	.0024078	3.790	0.000	.0044074	.0138461
c65_19_t	.0059935	.0059335	1.010	0.312	-.0056361	.0176231
c19_tr2	-.0117648	.0185694	-0.634	0.526	-.048161	.0246314
c19_tr3	.0004788	.007996	0.060	0.952	-.0151934	.0161509
c35_tr2	-.0146516	.0118279	-1.239	0.215	-.0378344	.0085311

c35_tr3	.0034335	.0039949	0.859	0.390	-.0043965	.0112634
c55_tr2	.0369395	.011481	3.217	0.001	.0144368	.0594423
c55_tr3	-.0101353	.0037594	-2.696	0.007	-.0175037	-.0027669
c65_tr2	-.3020248	.0637196	-4.740	0.000	-.4269155	-.1771342
c65_tr3	.0732498	.0155956	4.697	0.000	.0426823	.1038173
reg_d1	.0136009	.0265299	0.513	0.608	-.0383979	.0655996
reg_d2	.0216178	.0238727	0.906	0.365	-.0251728	.0684084
reg_d3	.0245066	.0228085	1.074	0.283	-.0201982	.0692114
reg_d4	.0097633	.0252544	0.387	0.699	-.0397354	.059262
reg_d5	.0297409	.0233063	1.276	0.202	-.0159394	.0754213
reg_d6	-.0156145	.0316444	-0.493	0.622	-.0776376	.0464086
reg_d7	.0712609	.0228072	3.124	0.002	.0265587	.1159631
reg_d8	.0776007	.0204878	3.788	0.000	.0374446	.1177568
reg_d9	-.0692193	.0250961	-2.758	0.006	-.1184078	-.0200308
reg_d10	.033723	.0282949	1.192	0.233	-.0217351	.0891811
reg1_t	-.0039414	.0064961	-0.607	0.544	-.0166737	.0087909
reg2_t	-.0032615	.0057809	-0.564	0.573	-.0145921	.008069
reg3_t	-.0002022	.0055335	-0.037	0.971	-.0110479	.0106435
reg4_t	.0009392	.0060478	0.155	0.877	-.0109145	.012793
reg5_t	-.0053226	.005658	-0.941	0.347	-.0164123	.0057672
reg6_t	.0039001	.0075573	0.516	0.606	-.0109122	.0187124
reg7_t	.0237002	.0055971	4.234	0.000	.0127299	.0346704
reg8_t	.0141669	.0049477	2.863	0.004	.0044693	.0238645
reg9_t	.0191713	.0059616	3.216	0.001	.0074864	.0308561
reg10_t	-.014574	.0069052	-2.111	0.035	-.0281082	-.0010398
reg1_t2	.0010914	.0032927	0.331	0.740	-.0053622	.0075451
reg2_t2	.0010626	.0029054	0.366	0.715	-.0046321	.0067573
reg3_t2	.0002216	.0027815	0.080	0.937	-.0052302	.0056734
reg4_t2	-.001229	.0030249	-0.406	0.685	-.0071579	.0046999
reg5_t2	.0018275	.0028563	0.640	0.522	-.003771	.0074259
reg6_t2	-.0009432	.0037756	-0.250	0.803	-.0083434	.0064569
reg7_t2	-.0101735	.0028392	-3.583	0.000	-.0157384	-.0046087
reg8_t2	-.0047758	.0024865	-1.921	0.055	-.0096494	.0000978
reg9_t2	-.00826	.0029638	-2.787	0.005	-.0140691	-.002451
reg10_t2	.005746	.0034721	1.655	0.098	-.0010593	.0125513
constant	1.480557	.0232106	63.788	0.000	1.435064	1.526049

Table B.3: Wage equation (without selectivity adjustment)

dependent variable = log real wage

Source	SS	df	MS
Model	3984.60015	74	53.845948
Residual	9855.64557	59292	.166222181
Total	13840.2457	59366	.233134214

Number of obs	= 59367
F(74, 59292)	= 323.94
Prob > F	= 0.0000
R-squared	= 0.2879
Adj R-squared	= 0.2870
Root MSE	= .4077

logrw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
married	.1816041	.004433	40.966	0.000	.1729153	.1902929
ed17	.1641939	.028713	5.718	0.000	.1079164	.2204715
ed19	.2411035	.0282147	8.545	0.000	.1858027	.2964044
trend	.0171608	.0079644	2.155	0.031	.0015506	.032771
trend_2	.0076859	.0084309	0.912	0.362	-.0088387	.0242105
trend_3	-.0045346	.0027478	-1.650	0.099	-.0099202	.000851
c1919_34	.0177044	.0233215	0.759	0.448	-.0280059	.0634146
c1935_44	.0414158	.0224858	1.842	0.066	-.0026565	.085488
c1955_64	-.0830804	.0248699	-3.341	0.001	-.1318254	-.0343353
c1965_76	-2.024938	.3595664	-5.632	0.000	-2.729689	-1.320186
c19_ed17	.1555518	.0354903	4.383	0.000	.0859907	.2251128
c35_ed17	.1212828	.0293009	4.139	0.000	.0638529	.1787128
c55_ed17	-.1579711	.0271033	-5.828	0.000	-.2110938	-.1048485
c65_ed17	-.2435678	.0667881	-3.647	0.000	-.3744728	-.1126628
c19_ed19	.3818706	.0368296	10.369	0.000	.3096843	.4540569
c35_ed19	.1585953	.0294135	5.392	0.000	.1009447	.2162459
c55_ed19	-.2293752	.0289964	-7.910	0.000	-.2862083	-.1725421
c65_ed19	-.3025943	.0912816	-3.315	0.001	-.4815066	-.1236821
c19_tr	.0032707	.0125587	0.260	0.795	-.0213444	.0278858
c35_tr	.0048689	.0099739	0.488	0.625	-.0146801	.0244178
c55_tr	-.0331251	.0101088	-3.277	0.001	-.0529384	-.0133118
c65_tr	.3721684	.0843284	4.413	0.000	.2068844	.5374524
ed17_tr	-.0008072	.0107223	-0.075	0.940	-.021823	.0202087
ed17_tr2	.017821	.0120971	1.473	0.141	-.0058894	.0415314
ed17_tr3	-.0071567	.003959	-1.808	0.071	-.0149163	.0006029
ed19_tr	.0195526	.0109047	1.793	0.073	-.0018208	.0409259
ed19_tr2	.0082498	.0123423	0.668	0.504	-.0159412	.0324408
ed19_tr3	-.0057802	.0040344	-1.433	0.152	-.0136877	.0021273
c19_17_t	-.0070538	.0047267	-1.492	0.136	-.0163181	.0022104
c35_17_t	-.0036529	.0027702	-1.319	0.187	-.0090824	.0017767
c55_17_t	.0046529	.00236	1.972	0.049	.0000272	.0092786
c65_17_t	.001682	.0046319	0.363	0.717	-.0073966	.0107606
c19_19_t	-.0248123	.0049288	-5.034	0.000	-.0344727	-.0151519
c35_19_t	-.0084459	.0027082	-3.119	0.002	-.0137539	-.0031379
c55_19_t	.0088351	.002412	3.663	0.000	.0041076	.0135625
c65_19_t	.0034379	.0059391	0.579	0.563	-.0082028	.0150786
c19_tr2	-.0107356	.0186018	-0.577	0.564	-.0471953	.025724
c19_tr3	.0004268	.00801	0.053	0.958	-.0152729	.0161265
c35_tr2	-.0115291	.0118448	-0.973	0.330	-.0347449	.0116867
c35_tr3	.0028208	.0040014	0.705	0.481	-.0050219	.0106636
c55_tr2	.0395802	.0114992	3.442	0.001	.0170417	.0621187
c55_tr3	-.0113121	.0037648	-3.005	0.003	-.0186912	-.003933
c65_tr2	-.2659035	.063777	-4.169	0.000	-.3909066	-.1409004
c65_tr3	.0630552	.0156058	4.040	0.000	.0324677	.0936427

reg_d1	.0223311	.0265622	0.841	0.401	-.0297308	.0743931
reg_d2	.0224189	.0239145	0.937	0.349	-.0244537	.0692914
reg_d3	.024818	.0228485	1.086	0.277	-.0199651	.069601
reg_d4	-.0018827	.0252621	-0.075	0.941	-.0513964	.0476311
reg_d5	.0210079	.0233296	0.900	0.368	-.0247181	.066734
reg_d6	-.0143533	.0316997	-0.453	0.651	-.0764849	.0477783
reg_d7	.0686842	.0228437	3.007	0.003	.0239105	.113458
reg_d8	.0695135	.0204957	3.392	0.001	.0293418	.1096852
reg_d9	-.0741253	.0251248	-2.950	0.003	-.1233701	-.0248805
reg_d10	.0323453	.0283444	1.141	0.254	-.0232099	.0879005
reg1_t	-.0052846	.0065063	-0.812	0.417	-.018037	.0074677
reg2_t	-.0044291	.00579	-0.765	0.444	-.0157775	.0069193
reg3_t	-.0007927	.005543	-0.143	0.886	-.011657	.0100716
reg4_t	.0004672	.0060583	0.077	0.939	-.0114071	.0123416
reg5_t	-.0044784	.0056674	-0.790	0.429	-.0155865	.0066297
reg6_t	.0001902	.0075627	0.025	0.980	-.0146326	.0150131
reg7_t	.021533	.0056039	3.842	0.000	.0105493	.0325168
reg8_t	.0117477	.0049526	2.372	0.018	.0020406	.0214548
reg9_t	.0169295	.0059699	2.836	0.005	.0052286	.0286305
reg10_t	-.0135639	.0069163	-1.961	0.050	-.0271199	-7.89e-06
reg1_t2	.0019533	.0032974	0.592	0.554	-.0045096	.0084163
reg2_t2	.0014963	.0029103	0.514	0.607	-.004208	.0072005
reg3_t2	.0004716	.0027864	0.169	0.866	-.0049897	.0059329
reg4_t2	-.0009867	.0030302	-0.326	0.745	-.0069259	.0049525
reg5_t2	.0013214	.002861	0.462	0.644	-.0042861	.006929
reg6_t2	.0005953	.0037794	0.158	0.875	-.0068123	.0080029
reg7_t2	-.0086072	.0028411	-3.030	0.002	-.0141758	-.0030387
reg8_t2	-.0036405	.002489	-1.463	0.144	-.008519	.0012379
reg9_t2	-.0073205	.0029682	-2.466	0.014	-.0131381	-.0015028
reg10_t2	.0053272	.0034777	1.532	0.126	-.0014891	.0121436
constant	1.54265	.0226178	68.205	0.000	1.498319	1.586981

Table B.4: Results from Semiparametric estimation

Semiparametric estimation of wage equation

dependent variable =log wage

variable	coeff.	standard error	T-statistic
married	0.2325	0.0054	42.7527
ed16	0.1618	0.0275	5.8866
ed18	0.2372	0.0268	8.8618
trend	0.0057	0.0073	0.7796
trend_2	0.0171	0.0081	2.1169
trend_3	-0.0074	0.0027	-2.7205
c1925_34	0.0128	0.0208	0.6167
c1935_44	0.0370	0.0197	1.8746
c1955_64	-0.0986	0.0208	-4.7316
c1965_76	-2.1077	0.3424	-6.1561
c25_ed16	0.1439	0.0401	3.5876
c35_ed16	0.1130	0.0306	3.6914
c55_ed16	-0.1233	0.0255	-4.8317
c65_ed16	-0.2344	0.0612	-3.8282
c25_ed18	0.3805	0.0429	8.8758
c35_ed18	0.1484	0.0307	4.8315
c55_ed18	-0.1958	0.0271	-7.2139
c65_ed18	-0.2987	0.0972	-3.0727
c25_tr	0.0029	0.0122	0.2348
c35_tr	0.0072	0.0096	0.7564
c55_tr	-0.0331	0.0091	-3.6131
c65_tr	0.3999	0.0807	4.9537
ed16_tr	0.0044	0.0108	0.4039
ed16_tr2	0.0133	0.0124	1.0721
ed16_tr3	-0.0057	0.0041	-1.3789
ed18_tr	0.0226	0.0113	2.0048
ed18_tr2	0.0075	0.0133	0.5610
ed18_tr3	-0.0058	0.0045	-1.2867
c25_16_t	-0.0055	0.0057	-0.9512
c35_16_t	-0.0036	0.0033	-1.0957
c55_16_t	0.0024	0.0024	1.0256
c65_16_t	0.0032	0.0045	0.7114
c25_18_t	-0.0227	0.0064	-3.5675
c35_18_t	-0.0076	0.0032	-2.3747
c55_18_t	0.0070	0.0025	2.7873
c65_18_t	0.0054	0.0065	0.8398
c25_tr2	-0.0156	0.0190	-0.8192
c25_tr3	0.0019	0.0085	0.2197
c35_tr2	-0.0142	0.0119	-1.1878
c35_tr3	0.0029	0.0042	0.6978
c55_tr2	0.0403	0.0109	3.6901
c55_tr3	-0.0113	0.0037	-3.0586
c65_tr2	-0.2947	0.0615	-4.7886
c65_tr3	0.0714	0.0152	4.7023
reg_d1	0.0119	0.0219	0.5418
reg_d2	0.0177	0.0203	0.8714
reg_d3	0.0210	0.0198	1.0613
reg_d4	0.0037	0.0214	0.1706
reg_d5	0.0241	0.0194	1.2396
reg_d6	-0.0220	0.0261	-0.8416
reg_d7	0.0656	0.0207	3.1671
reg_d8	0.0695	0.0184	3.7756
reg_d9	-0.0752	0.0221	-3.4085
reg_d10	0.0306	0.0259	1.1844
reg1_t	-0.0036	0.0059	-0.6135
reg2_t	-0.0019	0.0053	-0.3578
reg3_t	0.0009	0.0052	0.1695
reg4_t	0.0035	0.0056	0.6262

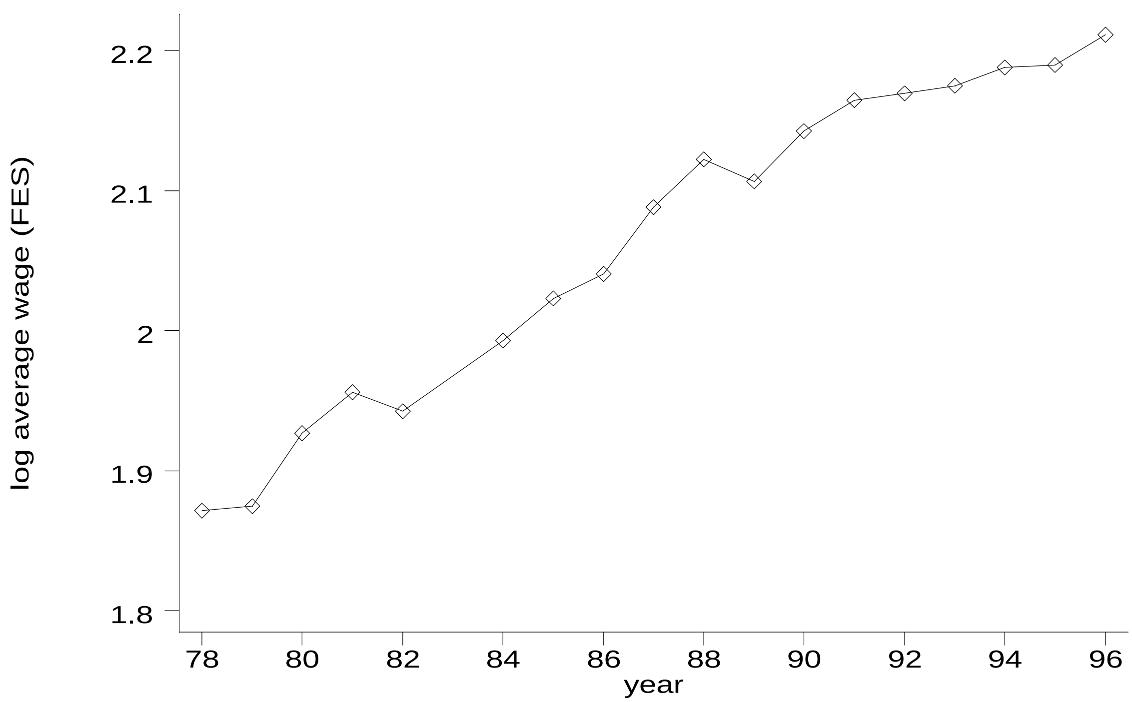
reg5_t	-0.0039	0.0052	-0.7436
reg6_t	0.0063	0.0069	0.9136
reg7_t	0.0264	0.0056	4.7559
reg8_t	0.0167	0.0048	3.5026
reg9_t	0.0215	0.0056	3.8165
reg10_t	-0.0149	0.0066	-2.2648
reg1_t2	0.0007	0.0031	0.2173
reg2_t2	0.0005	0.0027	0.1976
reg3_t2	-0.0002	0.0027	-0.0859
reg4_t2	-0.0023	0.0029	-0.7820
reg5_t2	0.0014	0.0027	0.4974
reg6_t2	-0.0019	0.0036	-0.5145
reg7_t2	-0.0117	0.0029	-3.9875
reg8_t2	-0.0057	0.0025	-2.3277
reg9_t2	-0.0092	0.0029	-3.1637
reg10_t2	0.0059	0.0034	1.7684

$R^2 = 0.2723$
N = 59367

TABLES AND FIGURES

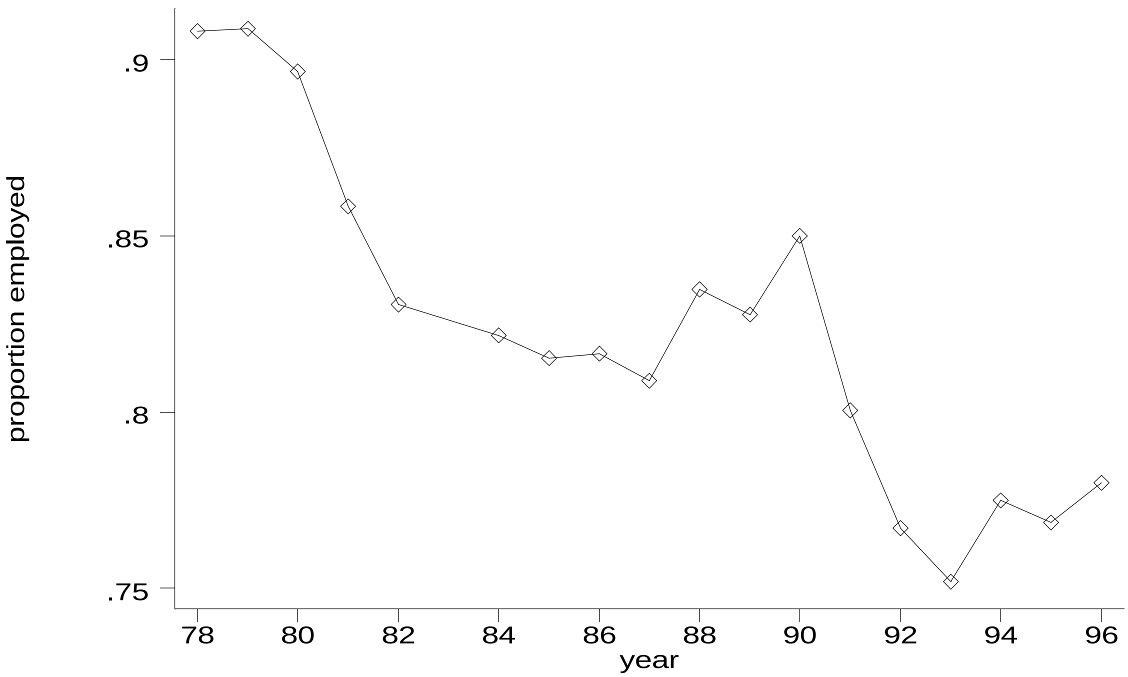
Figure 1.1. British males – wages and labour market participation

(a)



Overall log average wages, 1978-96

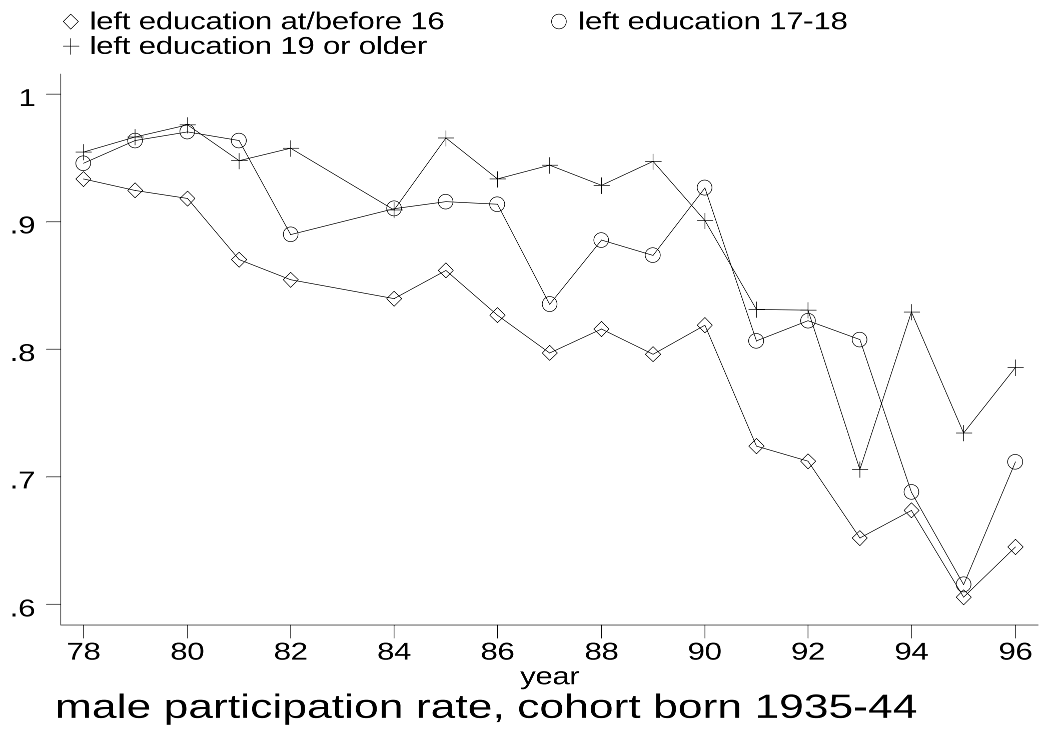
(b)



Overall male participation rate, 1978-96

Figure 1.2. Employment rates for two male cohorts

(a) date of birth 1935-44



(b) date of birth 1945-54

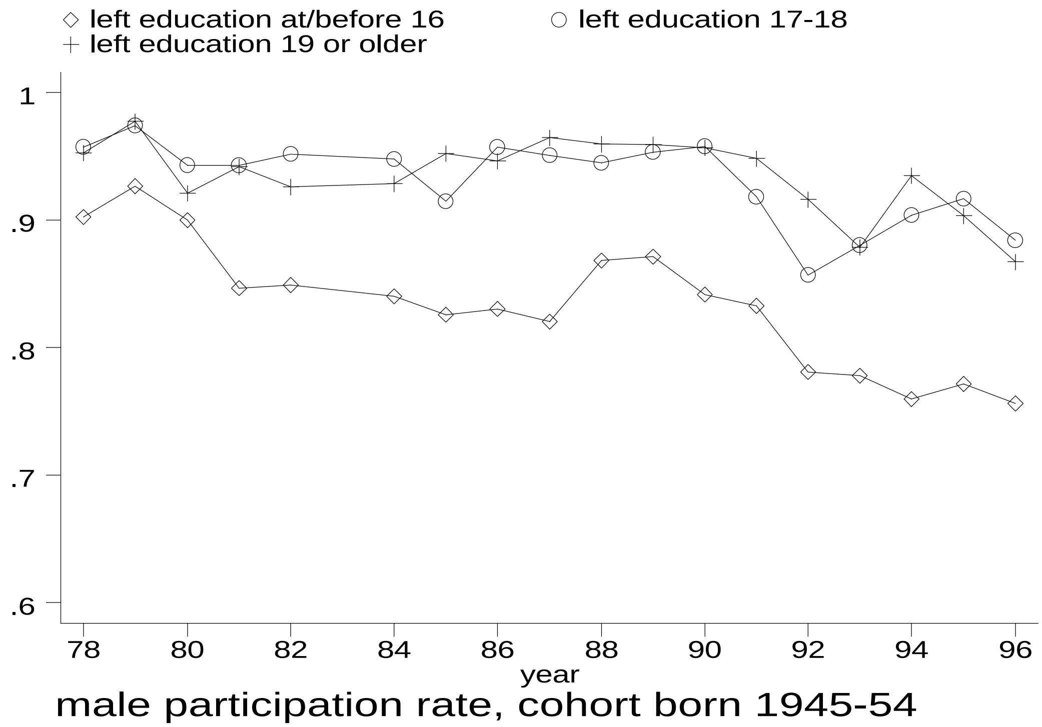


Figure 1.3. Simulated average income when out of work

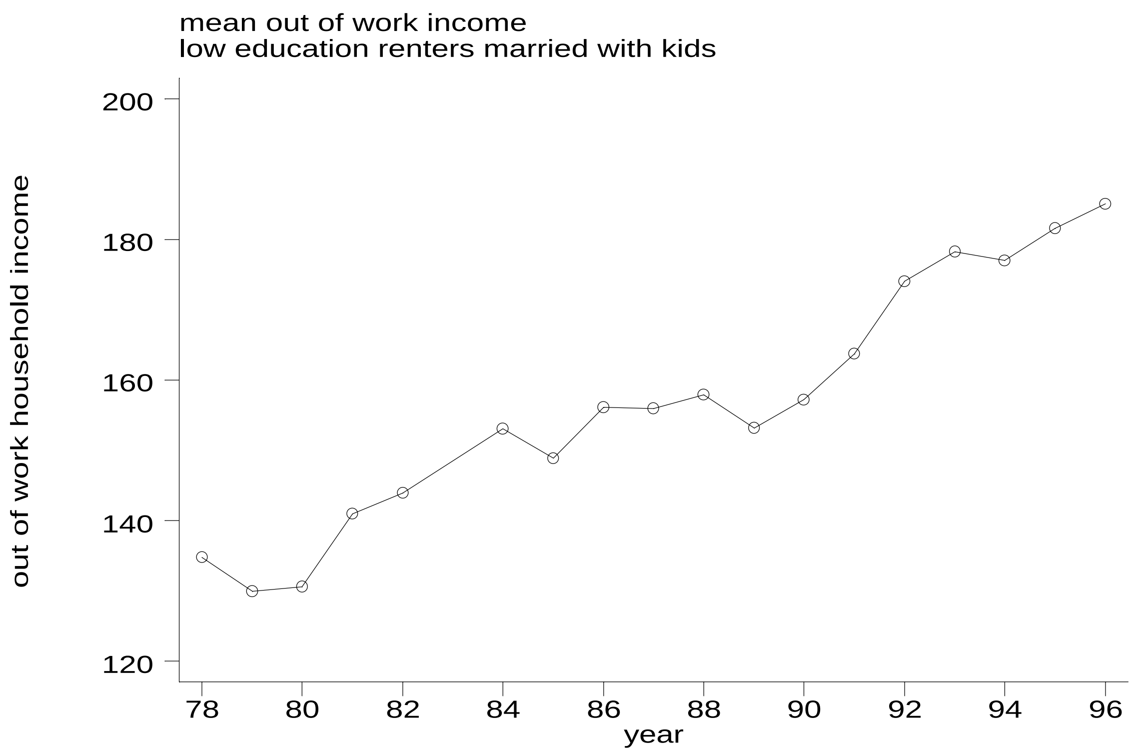


Table 3.1: Proportions of single and married in FES data by year, whole sample

Year	single		married		Total
	Number	**%**	**Number**	**%**	
1978	991	22.98	3322	77.02	4313
1979	978	23.60	3166	76.40	4144
1980	964	22.75	3274	77.25	4258
1981	1124	24.55	3454	75.45	4578
1982	1189	25.90	3401	74.10	4590
1984	1110	27.18	2974	72.82	4084
1985	1138	27.81	2954	72.19	4092
1986	1279	30.96	2852	69.04	4131
1987	1210	29.28	2922	70.72	4132
1988	1232	30.82	2765	69.18	3997
1989	1247	30.81	2801	69.19	4048
1990	994	27.35	2640	72.65	3634
1991	1080	28.73	2679	71.27	3759
1992	1181	29.78	2785	70.22	3956
1993	1136	30.41	2599	69.59	3735
1994	1040	29.12	2532	70.88	3572
1995	1012	28.66	2519	71.34	3531
1996	908	27.04	2450	72.96	3358
Total	**19813**	**27.56**	**52089**	**72.44**	**71902**

Table 2. Educational attainment by marital status

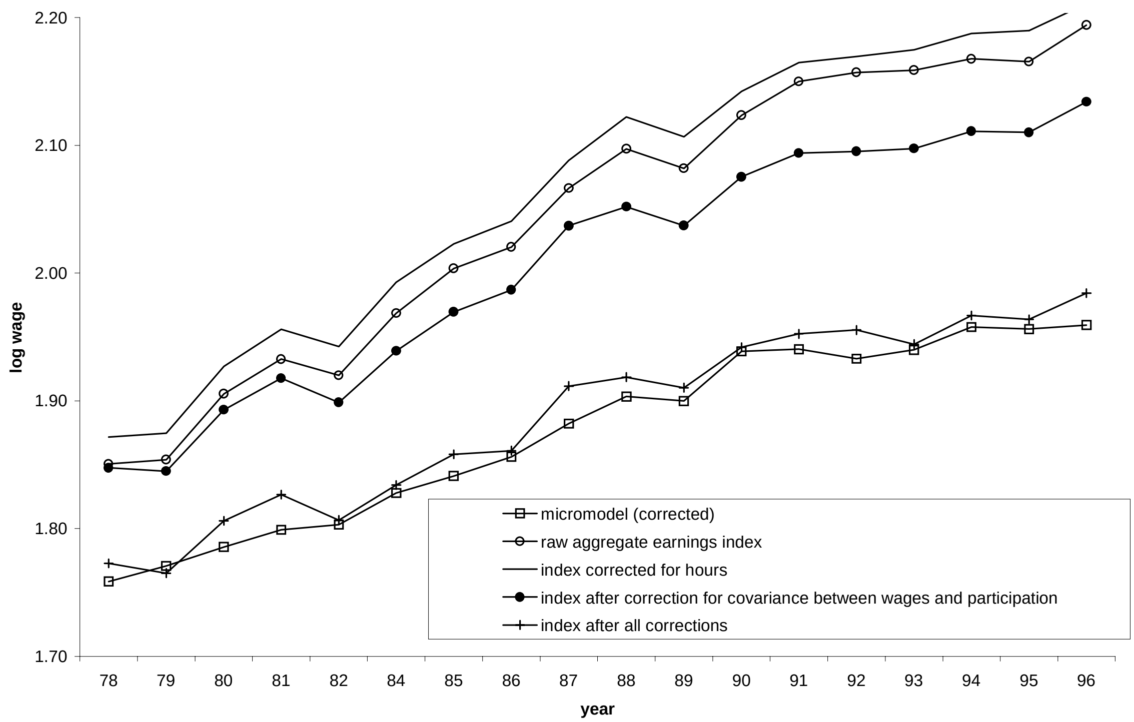
	Education group			TOTAL
	(i) left school <=16	(ii) left 17-18	(iii) left 19+	
Single	13607	3232	2974	19813
(%)	68.68	16.31	15.01	100.00
Married	38627	6763	6699	52089
(%)	74.16	12.98	12.86	100.00
TOTAL	52234	9995	9673	71902
(%)	72.65	13.90	13.45	100.00

Table 3.3. Significance tests for regression specification

Coefficients	Participation equation		Wage equation	
	χ^2 (d.o.f).	P-value	F-test (k) n=	P-value
Instruments				
(out of work income *marital status)	2556.65(3)	.000	N/A	
education (left 17-18, left 19+)	8.05(2)	.018	50.05(2)	.000
Trend (3^{rd} order polynomial)	53.47(3)	.000	57.12(3)	.000
cohort (b.1919-34, b. 1935-44, b. 1955-64, b. 1965-77)	164.47(4)	.000	13.58(4)	.000
education * trend	15.34(6)	.018	28.65(6)	.000
education * cohort	18.46(8)	.018	41.62(8)	.000
trend * cohort	833.46(12)	.000	25.74(12)	.000
education * trend (1^{st} order) * cohort	12.70(8)	.123	8.47(8)	.000
region (11 standard regions)	55.24(10)	.000	5.92(10)	.000
region * trend, region * $trend^2$	61.29(20)	.000	6.52(20)	.000
mills ratio * marital status	N/A		105.37(2)	.000
married (single coefficient)	631.87(1)	.000	819.35(1)	.000
spouse's education (single coefficient)	184.77(1)	.000	N/A	

Figure 3.1. Wage predictions from micromodel, aggregate wage and corrections

a) in levels



b) rebased to 1978

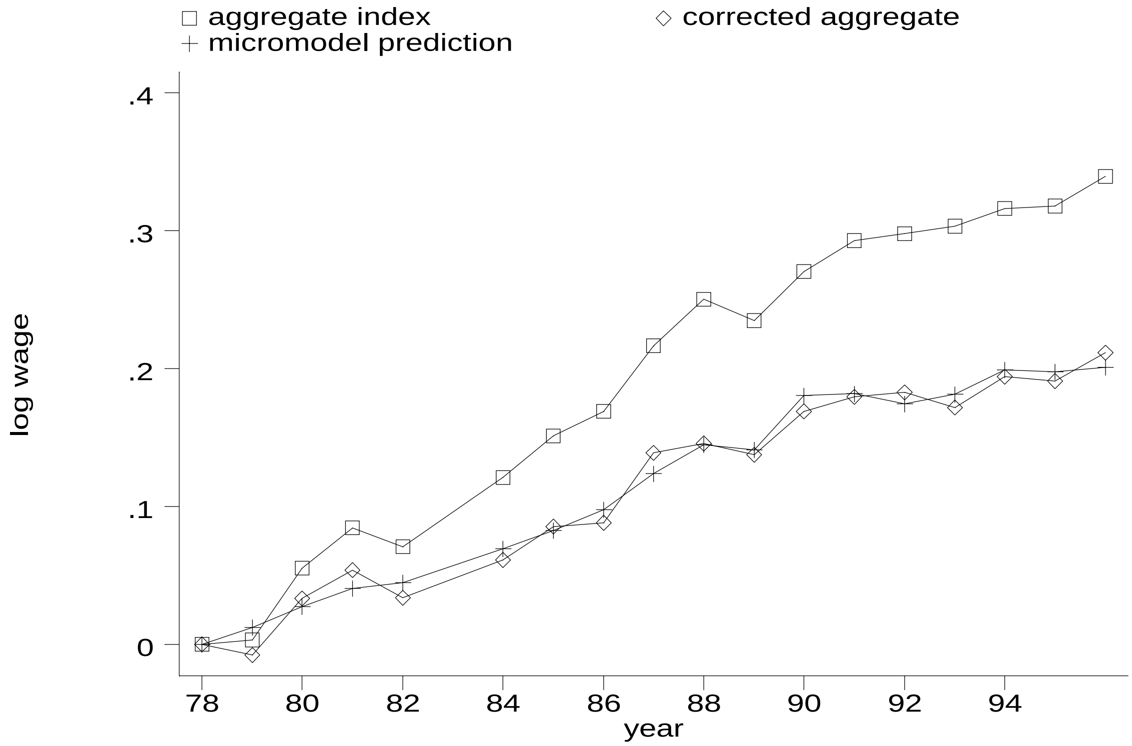
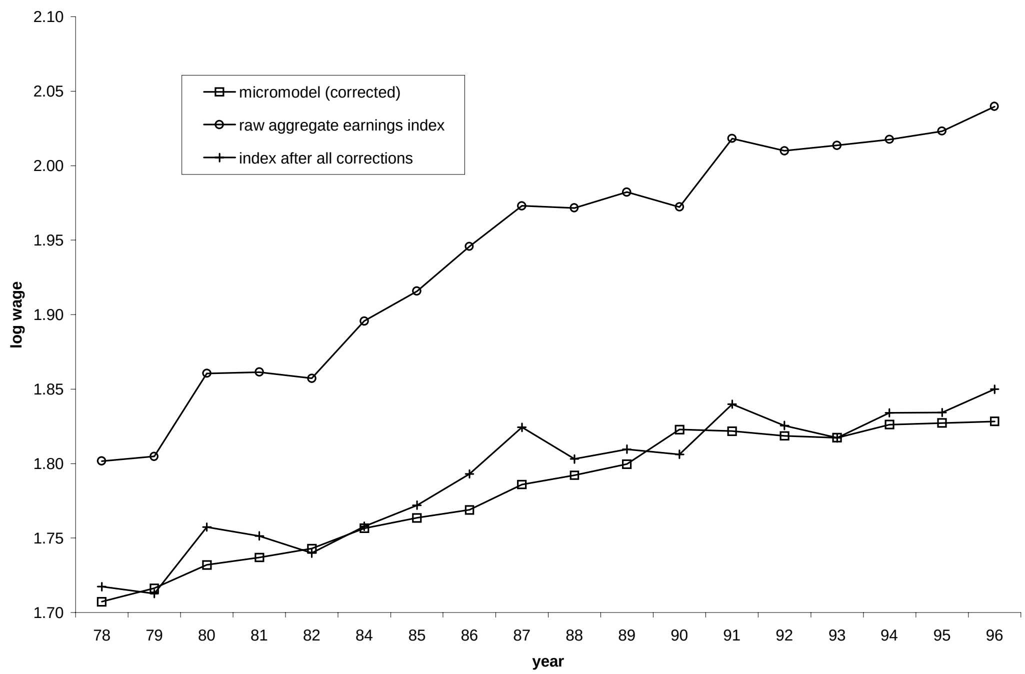
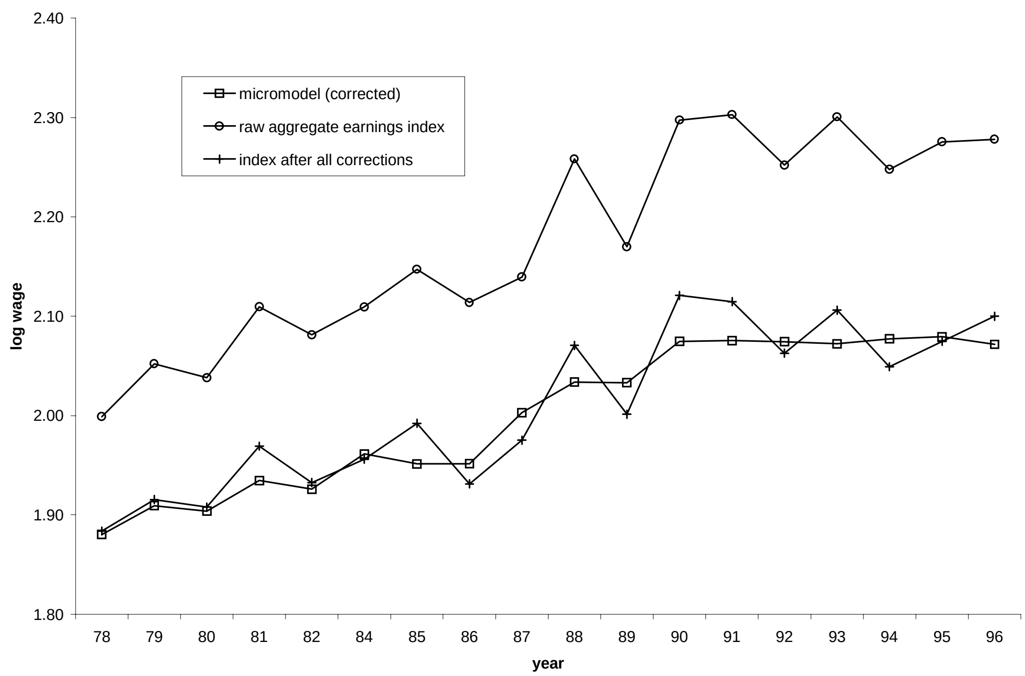


Figure 3.2. Wage predictions by education group

a) left education at or before 16



b) left education aged 17-18



c) left education aged 19 or older

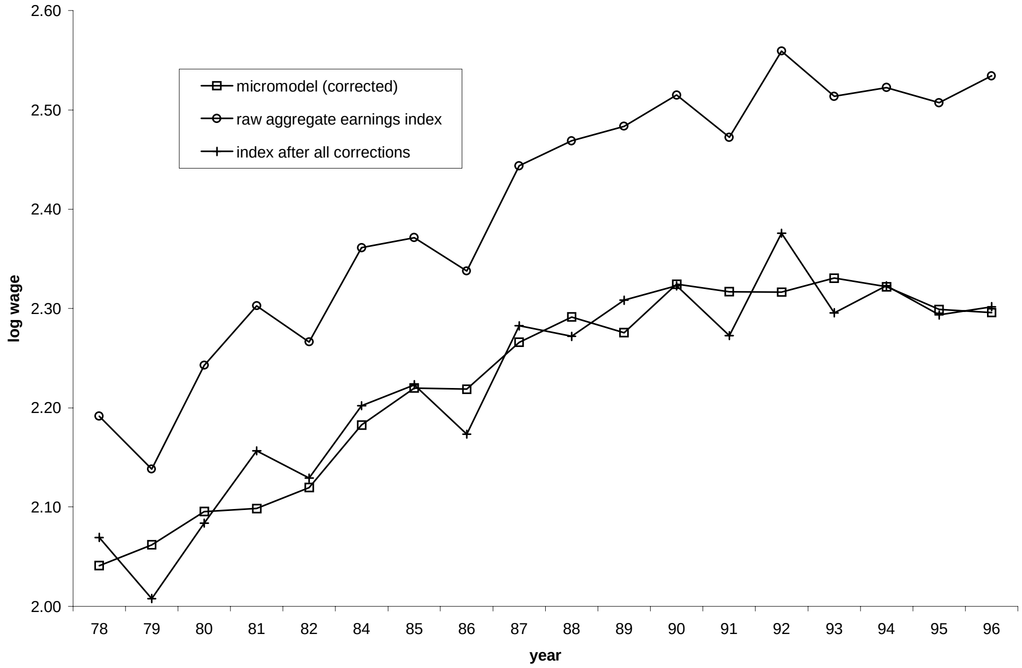
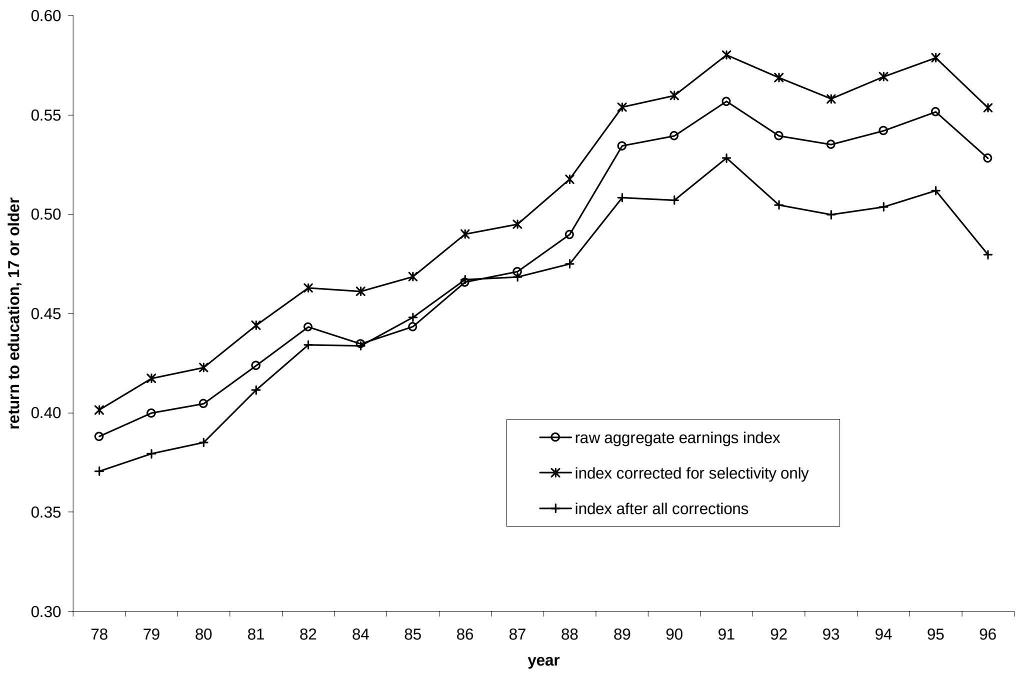


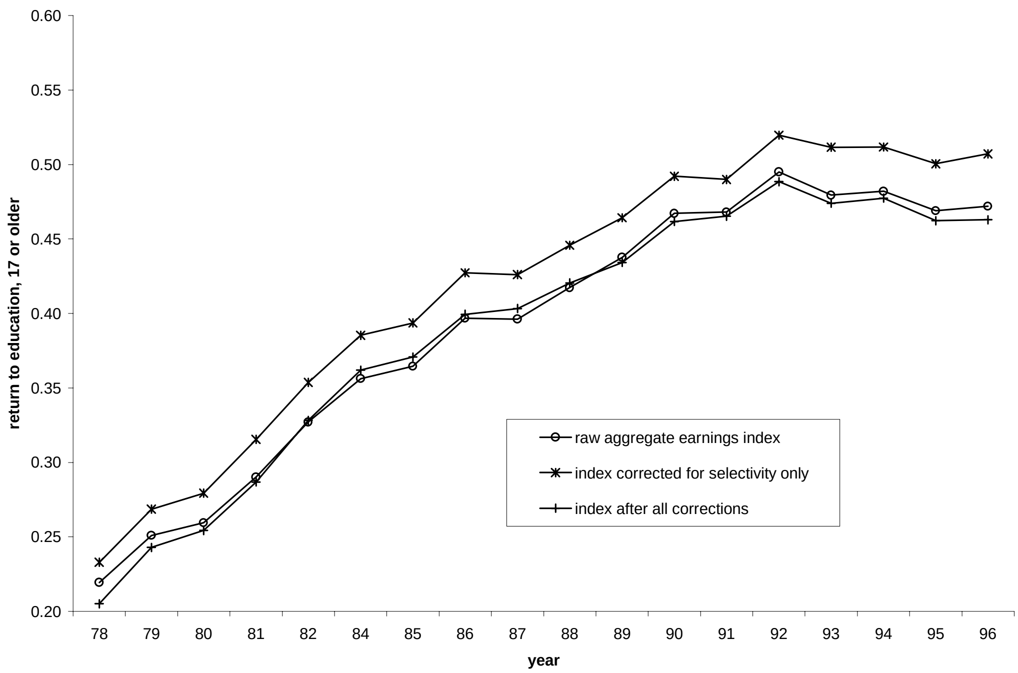
Figure 3.3. Education Returns by Cohort

Graphs below show average wages for those who left education aged 17 or older relative to those who left education at or before the age of 16.

a) born 1935-44



b) born 1945-54



c) born 1955-64

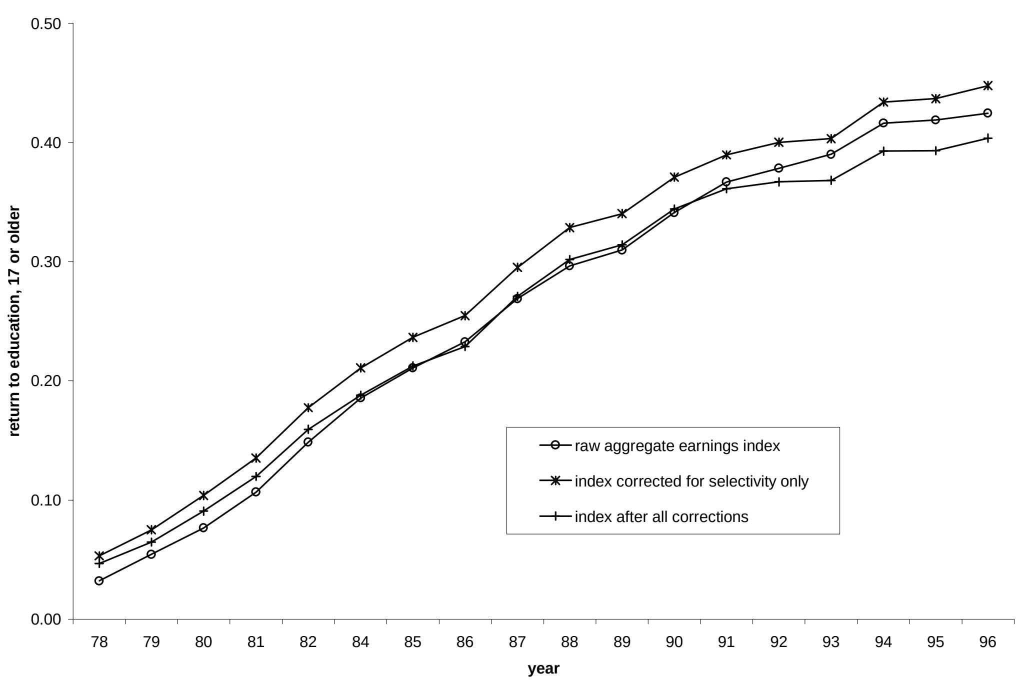
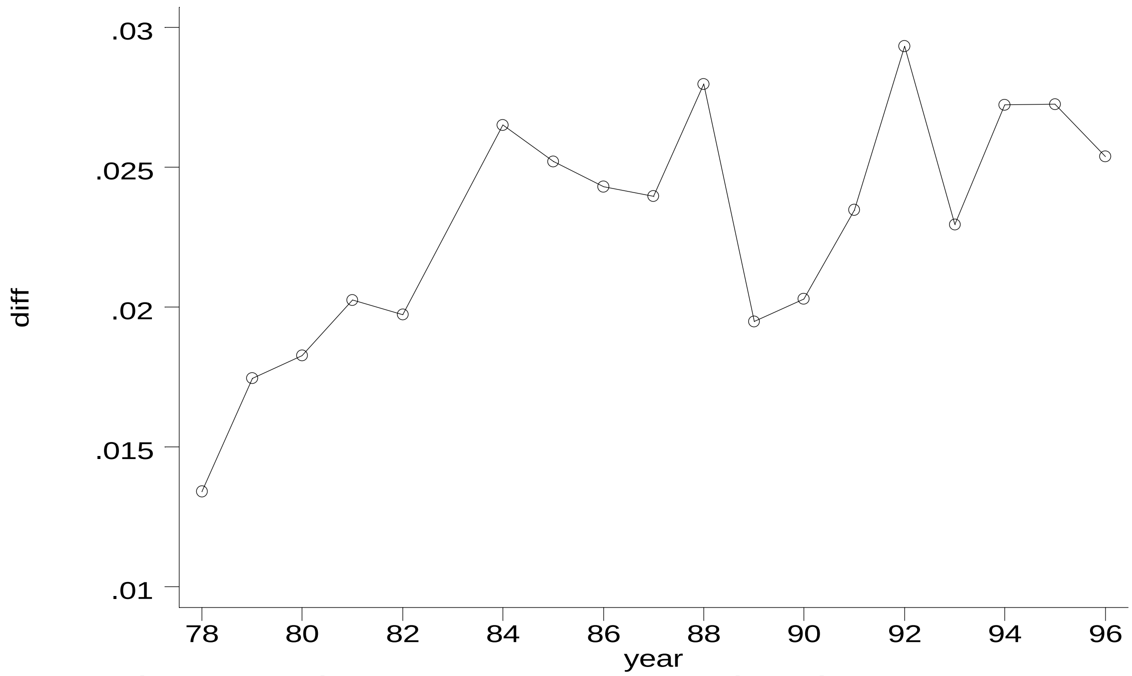


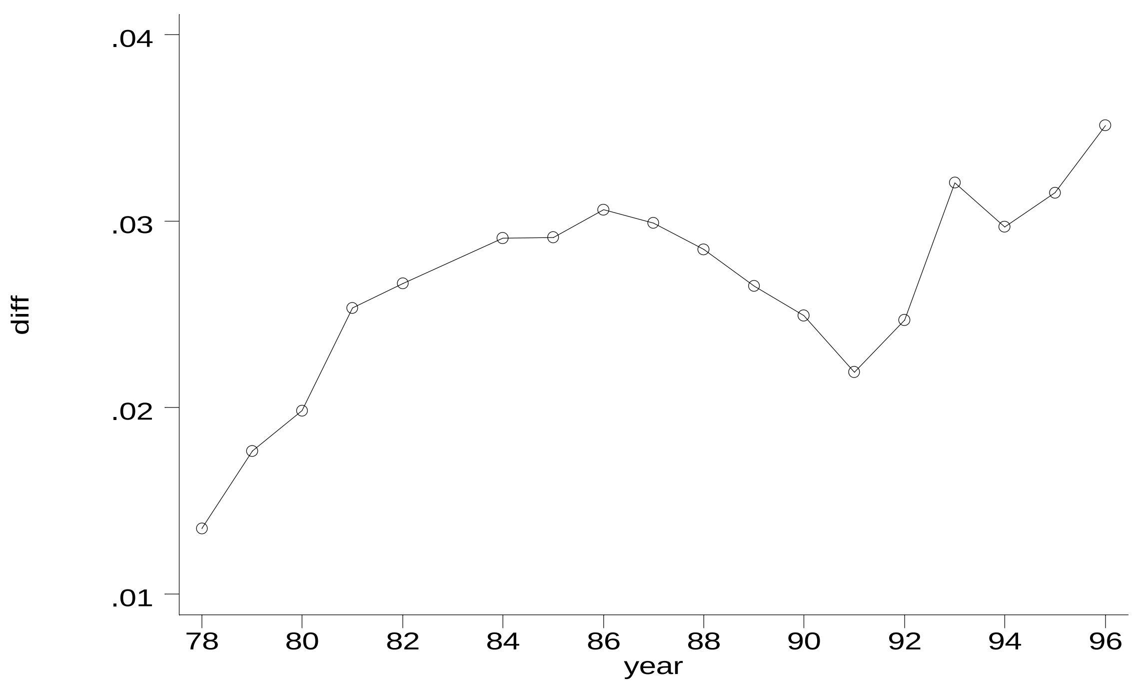
Figure 3.4. Selection bias by cohort

a) born 1935-44



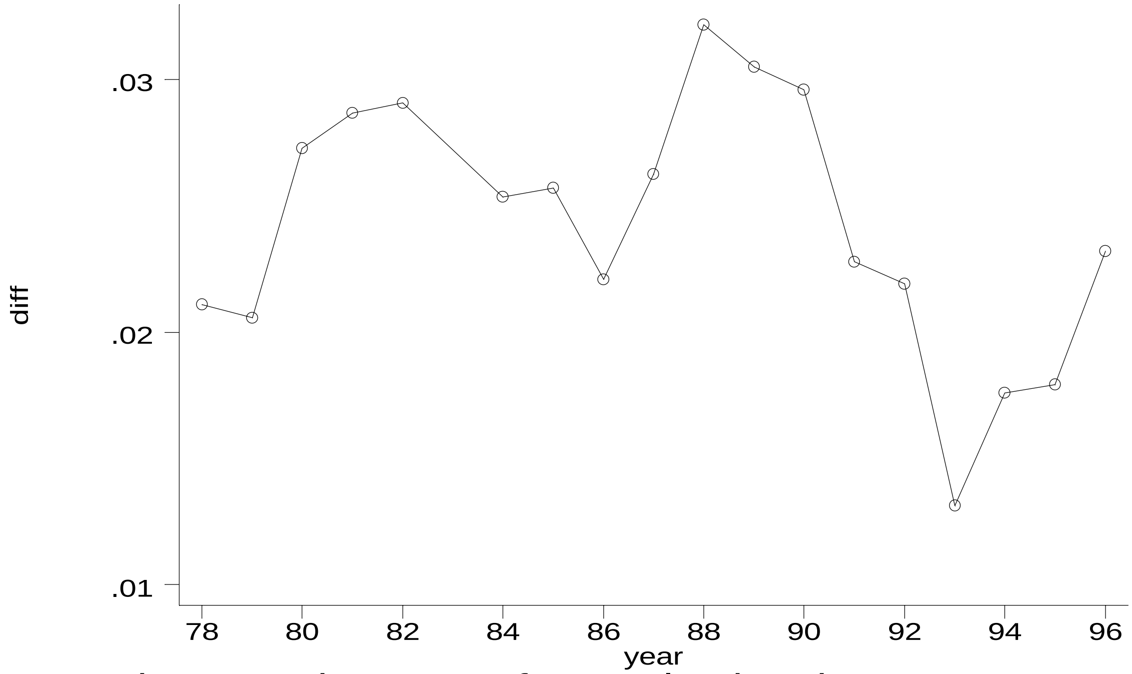
increase in returns from selection: b 1935-44

b) born 1945-54



increase in returns from selection: b 1945-54

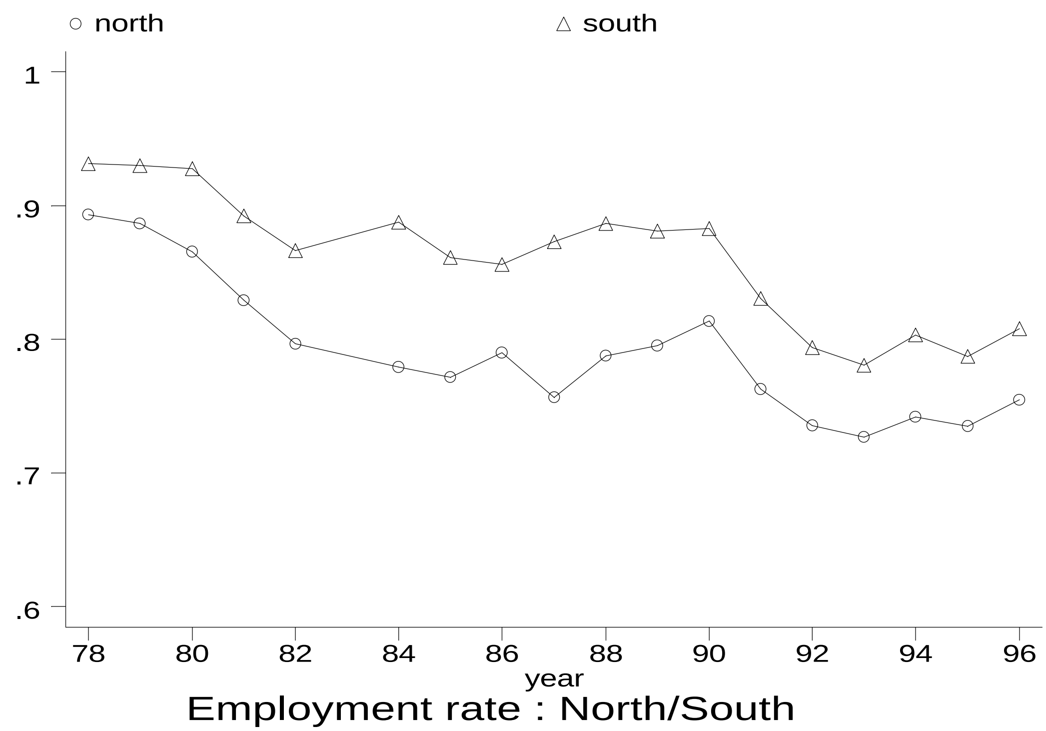
c) born 1955-64



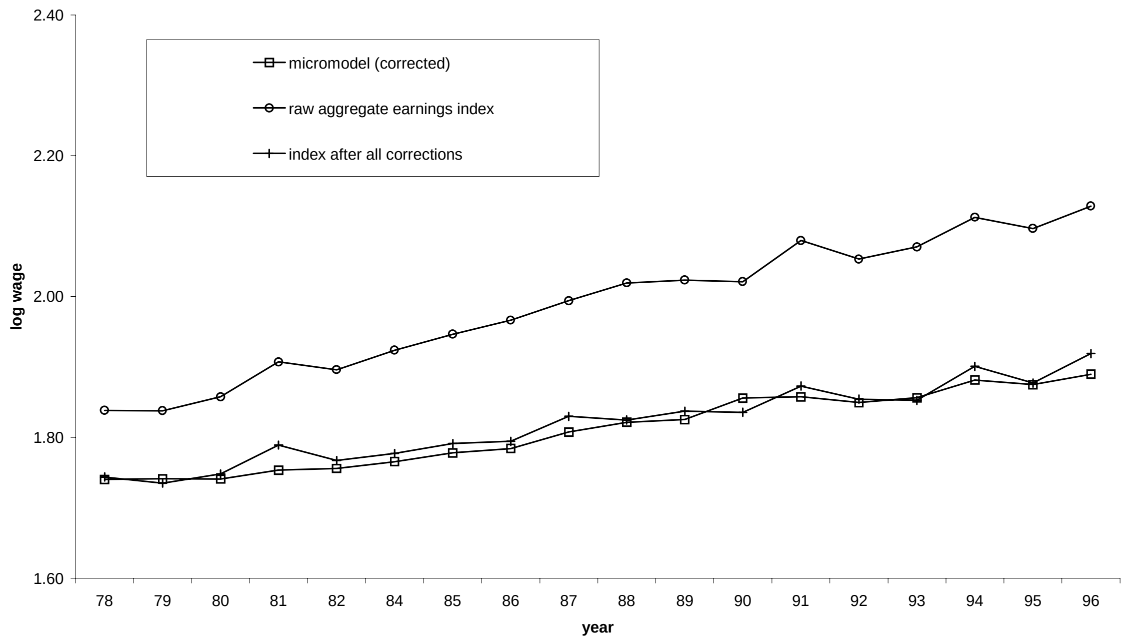
increase in returns from selection: b 1955-64

Figure 3.5: Regional trends in wages and participation

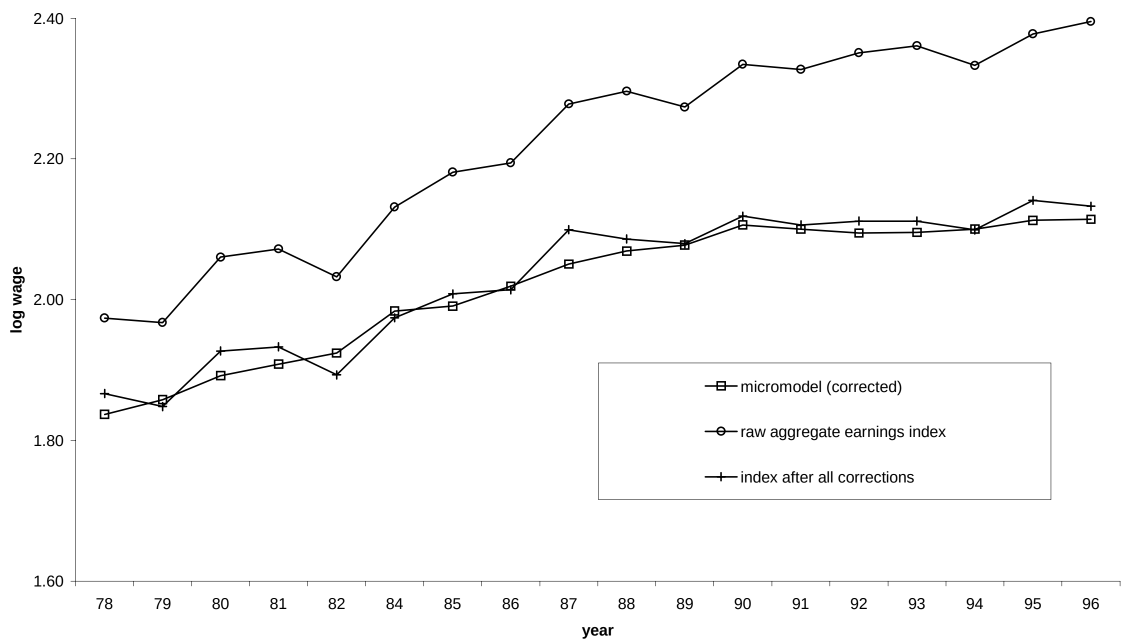
(a) participation by region



(b) wage predictions: 'North' region



(c) wage predictions: 'South' region



(d) South-North differential

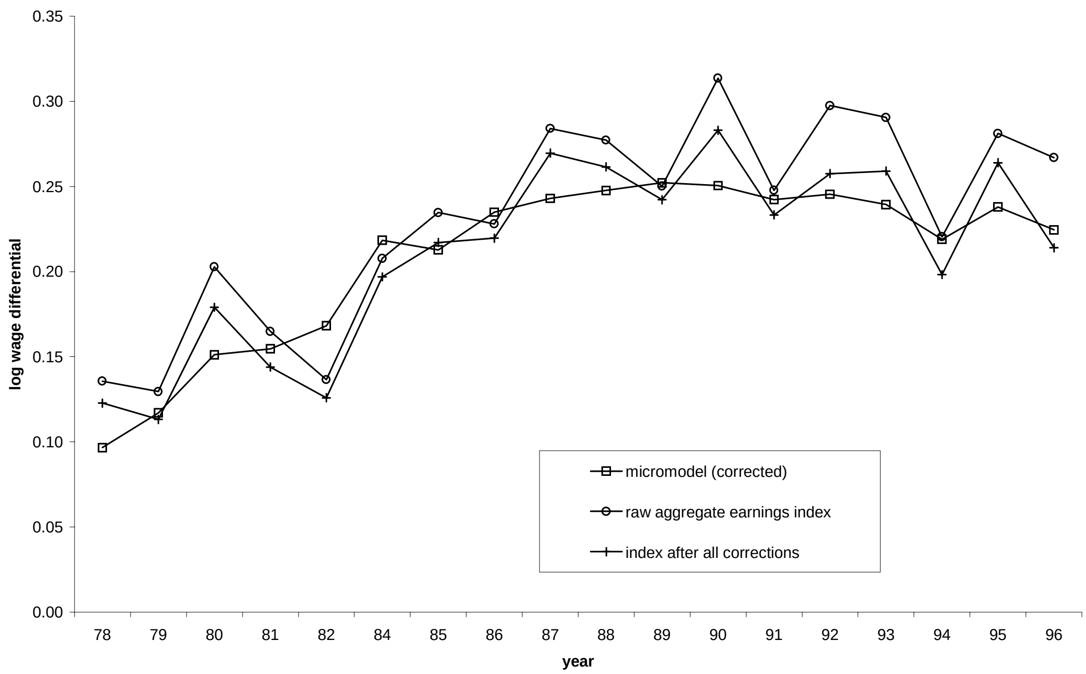


Figure 3.6: Bootstrapped standard errors on micromodel predictions (95% confidence intervals)

overall sample

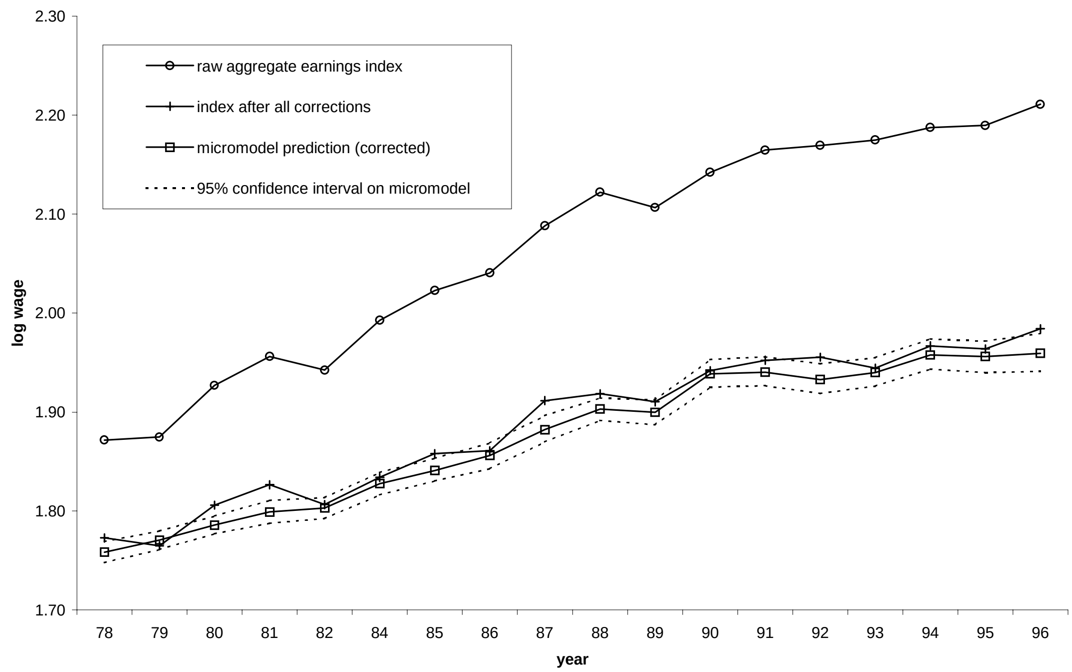


Figure 3.7. Results of semiparametric estimation

overall sample

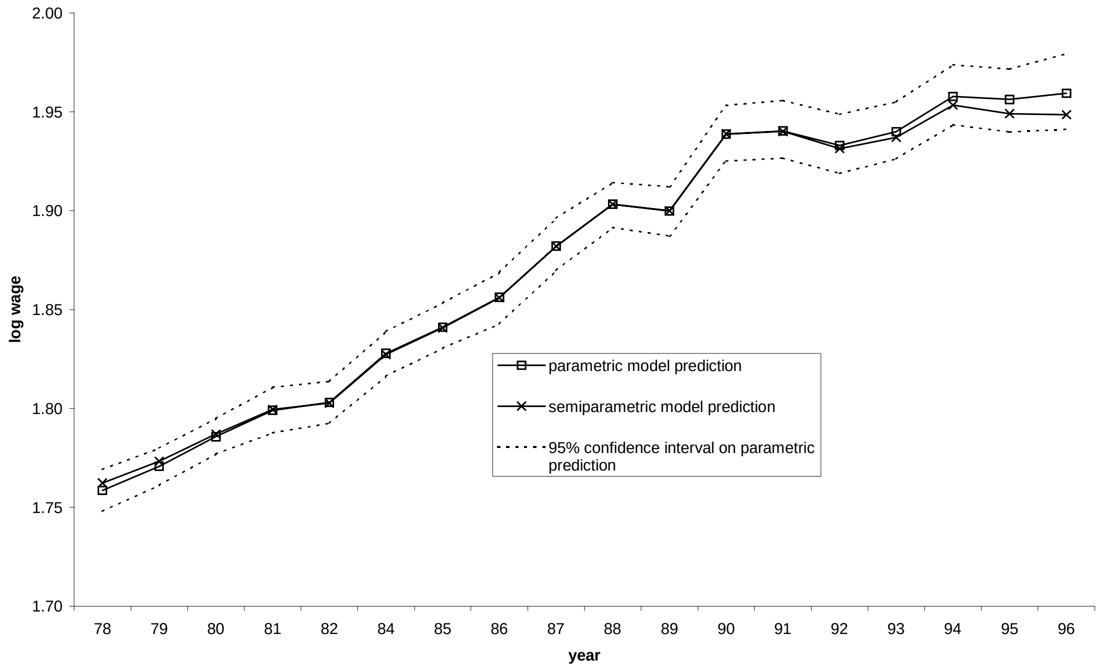


Figure 3.8. Plot of z'α index from probit equation

overall sample

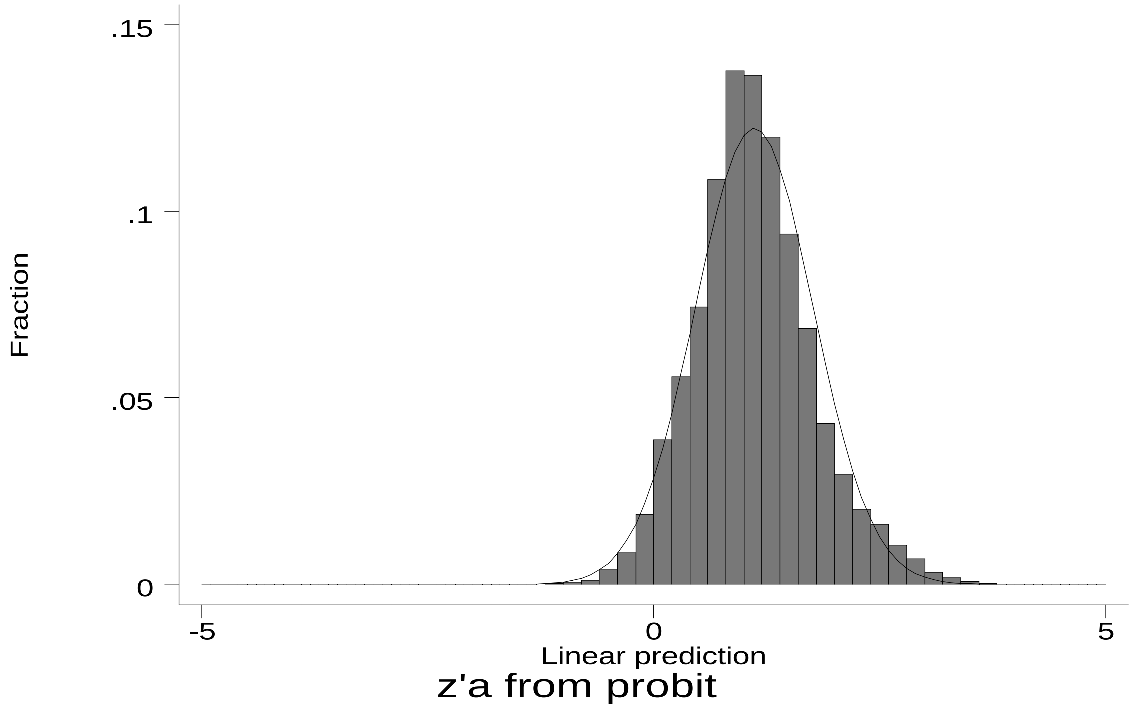
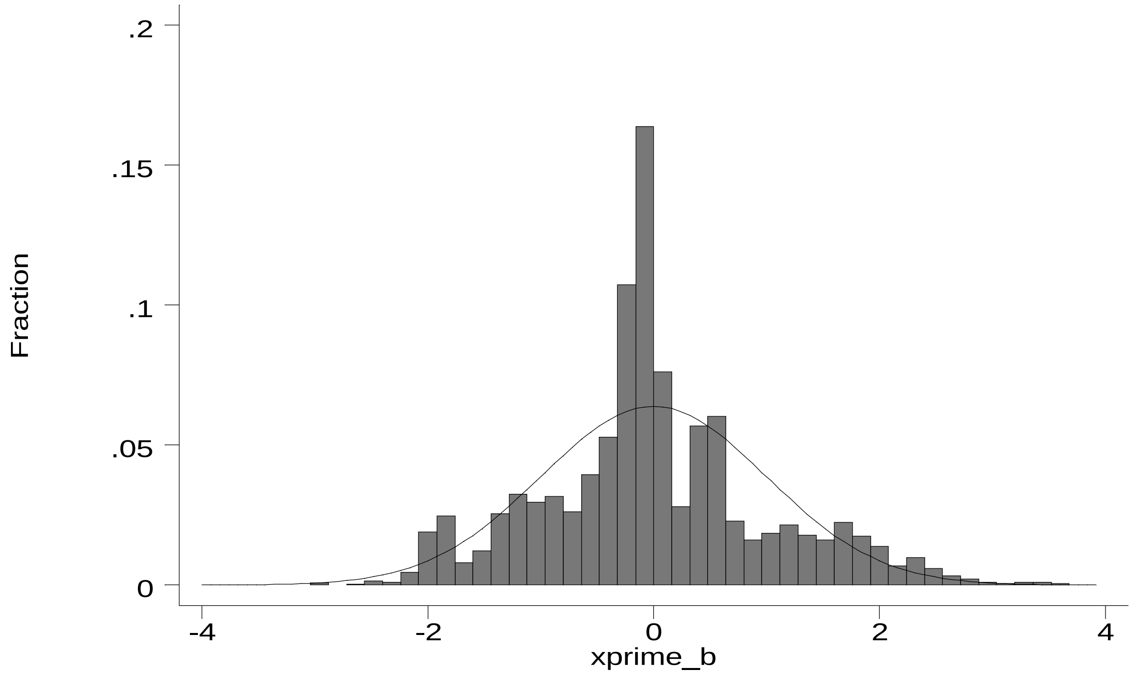


Figure 3.9: plot of standardised predictions from wage equation

overall sample



index measures from wage equations, 50