Interpreting Aggregate Wage Growth: The Role of Labor Market Participation

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A new and easily implementable framework for the empirical analysis of the relationship between aggregate and individual wages is developed. Aggregate real wages are shown to contain three important bias terms: one associated with the dispersion of individual wages, a second deriving from compositional changes in the (selected) sample of workers, and a third reflecting the distribution of working hours. Their importance for interpreting the path of aggregate wages and of the returns to education for recent experience in Britain is highlighted. A close correspondence between the estimated biases and the patterns of differences shown by aggregate wages is established. (*JEL* C34, E24, J31)

Aggregate figures for real wage growth appear extensively in policy debate. They are used to reflect 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 Mark J. Bils (1985), if participation rates change differentially 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 James J. Heckman and Guilherme Sedlacek (1985) but can be cast in a number of different 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 using aggregate wage measures.

Here we show that the bias decomposes into three interpretable terms reflecting changes in the distribution of individual wages, changes in participation, and changes in hours worked. The first term describes the dispersion of wages and arises because dispersion in percentage wage differences affects the average level of wages.[1] This term explicitly measures the effect of increasing wage dispersion separately from the impact of participation. The second term highlights the importance of the participation decision, capturing the effects of composition

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[1] This term arises as the familiar variance correction from taking expectation of the logarithm of a variable. The standard empirical model of wages applies to log wages and our focus is on the average wage level, so a dispersion correction arises naturally.

changes within the (selected) sample of workers from which measured wages are recorded. As in the selection bias literature,[2] this second factor depends on the covariance between participation and wages. The final term measures the adjustment for composition changes in hours and depends on the size of the covariance between wages and hours. These bias terms are then investigated using data for male wages from the British economy in the 1980's and 1990's. These data analyses point to significant deviations between aggregate measures and individual measures, that give a substantively different picture of actual real wage growth over this period.

There are at least 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 recent past 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.[3] Figure 1 displays the time series of aggregate hourly wages and aggregate employment for men in the United Kingdom over two business cycles between 1978 and 1996. In 1978–1979, over 90 percent of men aged between 19 and 59 were employed. The participation rate fell dramatically in the recession of the early 1980's and then recovered somewhat in the late 1980's (although not to its initial level). In the early 1990's there was a further

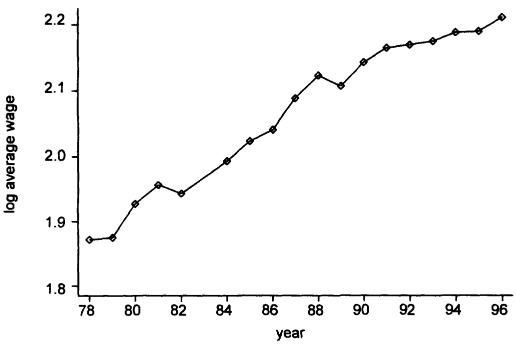

FIGURE 1. BRITISH MALES: LOG AVERAGE REAL WAGES, 1978–1996

recession and another sharp decline in participation. In contrast, log average wages show reasonably steady increase from 1978 through the 1990's, growing more than 30 percent in real terms over this period and even displaying growth during the severe recession of the early 1990's.

The analysis presented in this paper shows this picture of the evolution of real wages to be highly misleading. Making our three corrections reveals no evidence of real growth whatsoever in the early 1990's, and that over the whole period, real wage growth was no more than 20 percent. We show this corrected series is precisely estimated and robust to parametric specification. With our micro-level data, we can directly measure the large discrepancy in the level and growth between the aggregate and individual wage paths, and we find that it is almost completely captured by the aggregation factors we develop. This validates our model specification and supports our interpretation of the overall aggregation biases involved. The large discrepancy is clearly 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 fluctuations 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 Amanda Gosling et al., 2000 and David Card and Thomas Lemieux, 2001, for example), it is important to study how these employment fluctuations impact estimated returns to education

[2] See Heckman (1979).

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

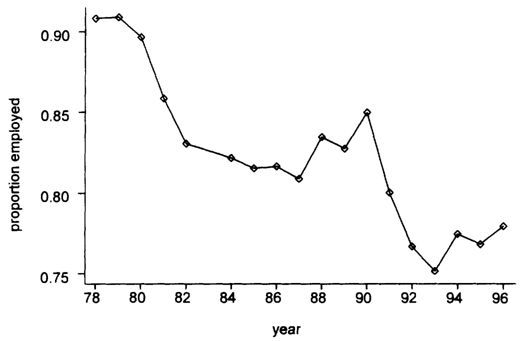

FIGURE 2. BRITISH MALES: LABOR MARKET PARTICIPATION RATE, 1978–1996

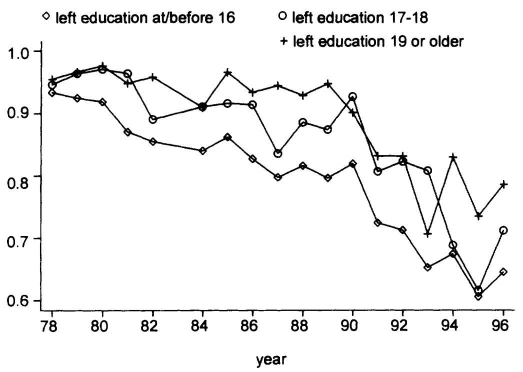

FIGURE 3. MALE COHORT, BORN 1935–1944: LABOR MARKET PARTICIPATION RATE

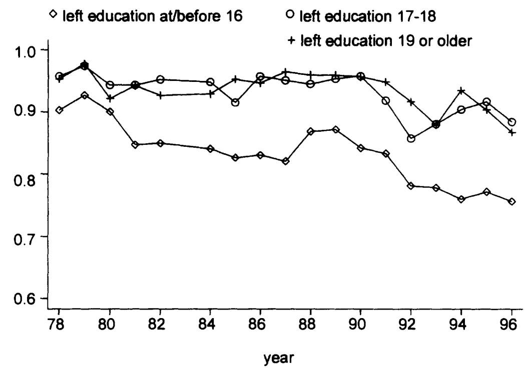

FIGURE 4. MALE COHORT, BORN 1945–1954: LABOR MARKET PARTICIPATION RATE

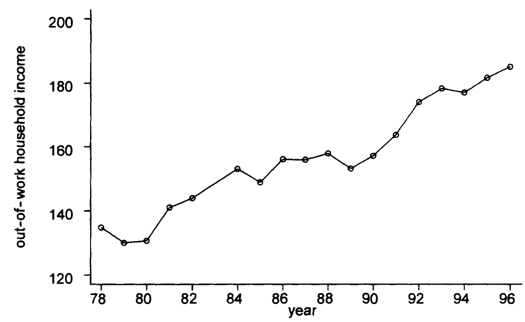

FIGURE 5. SIMULATED AVERAGE INCOME WHEN OUT OF WORK

across these groups. Figures 2–4 present the picture of employment by education level for two central cohorts. For the cohort born between 1945–1954, the steep fall in employment experienced by the lower-education group in the early 1980's is not matched in the employment patterns of the higher-educated groups. Indeed, the level and growth in dispersion also differs substantially across cohort and education groups. Our results show that the selection effect is often substantial and suggests a large underestimate in the level and growth in education returns. However, when aggregated across groups, this selection effect can be offset by differences in wage dispersion across education and cohort groups.

To identify these corrections to the aggregate series we need some variable that affects male employment decisions but does not affect 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 benefit (transfer) income which individuals receive (or would receive) when out of work.[4] Figure 5 shows the time-series variation of out-of-work benefit income for a particularly relevant group—married low-education men in rented housing. The housing component of benefit income[5] increased sharply in real terms over the period 1978 to 1996, an increase which was largely driven by a policy shift from subsidized public sector rents and rent controls in the private rented sector toward a system where rent levels more closely reflected the market value of

[4] The out-of-work income measure is constructed for each household using a tax and benefit simulation model.

[5] This is a means-tested benefit covering a large proportion of rental costs.

housing. This increase in this housing component is a major contributory factor in the rise in benefit income for the "low-education" families depicted in Figure 3.

Although it is unlikely that variation in real value of benefit income can explain all of the variation in participation rates, we argue that changes in real benefits serve as an important instrument in the participation decision, which therefore affect the endogenous selection in real wages. Moreover, we can isolate the selection effects in part because the housing benefit varies strongly across time, location, and cohort group. This variation occurs because individuals with low levels of education in the older cohorts had a much higher chance of spending their lives in public housing. We take this variation to be exogenous to the individual decision to work (conditional on cohort, education, region, trend, and cycle effects), and find evidence of substantial selection effects that vary over the economic cycle and across education groups.

The layout of the remainder of this paper is as follows. Section I gives the modeling framework that underlies the empirical work, and presents the aggregation bias terms.[6] As discussed above, these terms are particularly informative when there have been dramatic and systematic changes in the distributions of hourly wages, hours of work, and in participation rates—features that have occurred both secularly and cyclically in Britain as well as Europe as a whole. Our application to real wages of men in Britain, presented in Section II, well illustrates this value. We find important impacts of wage heterogeneity and labor participation on the interpretation of observed aggregate wages—impacts that differ in magnitude and direction. For example, changes in the dispersion of individual wages lead to a secular increase in the bias of aggregate wages; in contrast, compositional changes induced by labor market participation lead to a countercyclical bias in the aggregate measure. Section III draws some conclusions.

[6] The bias terms are derived from new results on aggregation with lognormal distributions, as spelled out in the Appendix.

I. Aggregation and Selection

A. *A Model for Real Wages*

The approach we use for modeling individual wages follows Andrew 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 differences in wages for workers with the same human capital level. 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 H_{it}, which is nondifferentiated in that it commands a single price r_t in time period t. Worker i's wage is the value of his human capital, which may differ across cohorts j and education groups s. Suppose we assume human capital H_{it} is lognormally distributed[7] with mean δ_{js} and variance σ^2, then log wages are given by the additive equation

$$(1) \qquad \ln w_{it} = \ln r_t + \delta_{js} + \varepsilon_{it}$$

where ε_{it} is $\mathcal{N}(0, \sigma^2)$.[8] In this model the systematic growth in wages is common across workers (through r_t); below we allow growth to differ across groups (e.g., by education) over time.

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

$$(2) \qquad \ln w^*_{it} = \alpha \ln b_{it} + \eta_{js} + \zeta_{it}$$

where ζ_{it} is $\mathcal{N}(0, \sigma^2_\zeta)$. Here b_{it} is the exogenous benefit level (out-of-work income) available to worker i, that varies with individual characteristics and time. Participation occurs if $w_{it} \geq w^*_{it}$, and we represent the participation decision by the

[7] We utilize lognormality assumptions extensively in our derivations and their validity is assessed in the empirical analysis that follows.

[8] Clearly, there is an indeterminacy in the scaling of r_t. In our empirical work we normalize the value of r_t for some year $t = 0$ (say, to $r_0 = 1$).

indicator $I_i = 1[w_{it} \geq w_{it}^*]$. 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.

We are interested in how aggregate wages depend on the distribution of hours of work. One approach is to assume that the distribution of hours worked (when working) is uncorrelated with the participation decision. Alternatively, we can use a labor supply model where hours worked correlate with the incentives to participate. To see how aggregation bias is structured in that case, we consider the following simple model. 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.[9] Assume that $h_{it}(w)$ is normally distributed for each w, and approximate desired hours by

$$(3) \quad \begin{aligned} h_{it} &= h_0 + \gamma(\ln w_{it} - \ln w_{it}^*) \\ &= h_0 + \gamma(\ln r_t - \alpha \ln b_{it} + \delta_{js} \\ &\qquad - \eta_{js} + \varepsilon_{it} - \zeta_{it}). \end{aligned}$$

This model is used in our bias formulation.[10]

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 a skill price r_t^H and a low-education worker i skill price r_t^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

$$(4) \quad \begin{aligned} \ln w_{it} &= d_i \ln r_t^H + d_i \delta_{js}^H \\ &\quad + (1 - d_i)\ln r_t^L + (1 - d_i)\delta_{js}^L + \varepsilon_{it}. \end{aligned}$$

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.

To summarize our discussion, the underlying individual model is comprised of the following log wage equation, an hours equation, and an employment selection equation. We express these equations in compact form as

$$(5) \quad \begin{aligned} \ln w &= \beta_0 + \boldsymbol{\beta}'\mathbf{x} + \varepsilon, \\ h &= h_0 + \gamma \cdot (\alpha_0 + \boldsymbol{\alpha}'\mathbf{z} + \nu), \\ I &= 1[\alpha_0 + \boldsymbol{\alpha}'\mathbf{z} + \nu > 0], \end{aligned}$$

where $\mathbf{x}$ refers to predictors in the log wage equation, such as the variables that represent δ_{js} in (1) or the predictors in the extended versions of the model such as (4), and where $\mathbf{z}$ refers to predictors in the participation equation, including log benefit income. The disturbances ε and ν are normally distributed, each with mean 0.

B. *Bias in Aggregate Wages*

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. The aggregate wage is measured by

$$(6) \quad \bar{w}_t = \frac{\sum_{i \in (I=1)} e_{it}}{\sum_{i \in (I=1)} h_{it}} = \sum_{i \in (I=1)} \mu_{it} w_{it}$$

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 μ_{it} are the hours weights

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

We take the population of participating workers as sufficiently large so that we can ignore

[9] This allows for a simple characterization of fixed costs; see John F. Cogan (1981).

[10] We could easily nest this labor supply model with the situation of hours uncorrelated with participation, by adding another error term u_{it} to (3), which is uncorrelated with participation error but possibly correlated with the log wage error. This adds a further term to the hours adjustment given in the Appendix.

sampling variation in average earnings and average hours; modeling the aggregate wage as

$$\bar{w}_t \cong \frac{E[h_{it} w_{it} | I_{it} = 1]}{E[h_{it} | I_{it} = 1]} \tag{7}$$

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

The basic framework suggests one natural comparison for interpreting $\bar{w}_t$. From (1), we could ask whether movements in the aggregate wage $\bar{w}_t$ accurately reflect movements in the skill price r_t. For instance, if aggregate production in the economy has total human capital ($\Sigma_i H_{it}$) as an input, then the appropriate price for that input is r_t, and so this comparison would ask whether $\bar{w}_t$ accurately reflects the relevant (quality-adjusted) price of labor. With differentiated skills, we could ask whether the aggregate wage $\bar{w}_t$ reflects an average of the various skill prices—for instance, if (4) applies, then we could compare $\bar{w}_t$ to a weighted average of r_t^H and r_t^L. Such comparisons of aggregate wages to skill prices are very natural, but require a human capital framework as the foundation of labor value.

Other interpretable comparisons arise on purely statistical grounds, such as comparing the aggregate wage $\bar{w}_t$ to the unweighted mean wage $E(w_{it})$. Following the tradition of measuring "returns" from coefficients in estimated log wage equations, we focus on the "log" version of this comparison, namely to compare

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

This approach is adopted by Gary Solon et al. (1994), as well as in our empirical work below.[11] We note that our choice of $\ln w_{it}$ follows one of the longest established traditions in empirical economics, where log wage is the primary object of analysis in studying individual earnings data [see Barry R. Chiswick (1970), Jacob Mincer (1972), and Heckman (1974), among many others].

We have extensive individual-level data on wages, and so we could examine aspects of how aggregate wage compares to average log wage empirically. Part of the contribution of this work is to give explicit representations of the biases in interpreting aggregate wages, using the individual model (5). To start, note that the mean log wage is simply

$$E(\ln w_{it}) = \beta_0 + \boldsymbol{\beta}' E(\mathbf{x}_{it}). \tag{8}$$

This equation reflects the key parameters of interest: the mean log wage and the $\boldsymbol{\beta}$ coefficients. It also captures how the $\boldsymbol{\beta}$ coefficients are relevant to aggregates; changes in the mean predictor variables $E(\mathbf{x}_{it})$ are multiplied by the $\boldsymbol{\beta}$'s for associated changes in mean log wage $E(\ln w_{it})$.

To analyze the observed aggregate wage, we characterize the large sample approximation (7) by applying some new results on aggregation with nonlinear models. For that purpose, we assume that the indexes $\beta_0 + \boldsymbol{\beta}'\mathbf{x}$ and $\alpha_0 + \boldsymbol{\alpha}'\mathbf{z}$ are (bivariate) normally distributed in each time period t.[12] We can clearly apply our results to any population segment where this normality assumption is valid.

Our main result is summarized as follows. For each time period t, we have

$$\ln \bar{w}_t \cong \ln \frac{E[h_{it} w_{it} | I_{it} = 1]}{E[h_{it} | I_{it} = 1]} \tag{9}$$

$$= E(\ln w_{it}) + DSP_t + SEL_t + HR_t.$$

These are the three bias terms; DSP_t for bias from wage dispersion, SEL_t for bias deriving from compositional changes in the (selected) sample of workers, and HR_t for bias from heterogeneity in hours worked.

The simplest term is DSP_t, for wage dispersion, and it is equal to ½ times the variance of log wages at time t. This arises because the standard micro model is for log wages (with variance associated with proportional variation across workers), but for observed aggregate

[11] This statistical comparison captures the simplest skill price interpretation as well—if our basic framework applies, and if the log mean of H_{it} is constant over time in our basic framework, then the mean log wage comparison matches the "$\bar{w}_t$ versus r_t" comparison (in log form). We have raised these comparisons separately because one might be interested in the log wage comparison even without a framework tracing wages to human capital.

[12] This assumption as well as all derivations are spelled out in the Appendix.

wage we need to analyze the average wage level. Specifically, we have that the log of mean wage (unweighted, over all possible workers) is

$$(10) \qquad \ln E(w_{it}) = E(\ln w_{it}) + DSP_t,$$

where DSP_t is the variance adjustment from taking expectation of log variables. This term is likely to be very informative during times of increasing or decreasing earnings inequality.

The terms SEL_t and HR_t are given by rather complicated expressions listed in the Appendix, but we can easily interpret their role. The term SEL_t, for selection, arises because observed aggregate wages are computed only using wages of those workers who choose to participate. Specifically, we have that the log mean wage of participating workers is

$$(11) \quad \ln E(w_{it}|I_{it} = 1) = \ln E(w_{it}) + SEL_t.$$

The term SEL_t captures the impact of composition changes within the selected sample of workers from which measured wages are recorded. SEL_t will clearly depend on the covariance between wage levels and participation incentives—such as the covariance between ε and ν in (5).

Finally, the term HR_t, for hours adjustment, measures the impact of heterogeneity in hours worked among participating workers. Specifically, we have that

(12)

$$\ln \frac{E[h_{it} w_{it}|I_{it} = 1]}{E[h_{it}|I_{it} = 1]} = \ln E(w_{it}|I_{it} = 1) + HR_t.$$

This term captures adjustment for composition changes in hours, and will clearly depend on the covariance between wage levels and hours worked.

In sum, we characterize aggregation bias via the three terms in (9). Those terms reflect the successive adjustments that arise in moving from means of log wages to wage levels, from the entire population to only participating workers, and from unweighted wage averaging to hours weights. To see the impact of participation, we can focus on the term SEL_t, and likewise for the other bias sources.

C. *The Nature of the Aggregation Bias*

To anticipate our application, it is useful to discuss some of the features of the bias terms; particularly, the impact of participation SEL_t.[13] Setting $\beta_0 + \boldsymbol{\beta}'\mathbf{x}_{it} = \ln r_t + \delta_{st}$ in (5) generates our baseline formulation (1), with observed aggregate wage (9) given as

(13)

$$\ln \bar{w}_t \cong \ln r_t + E(\delta_{st}) + DSP_t + SEL_t + HR_t.$$

The term SEL_t will induce an upward bias in the average wage in the typical case where participation incentives are positively correlated with wages, namely with primarily low-wage individuals opting not to participate. It is interesting to note what happens when $\ln r_t$ increases. There is a direct effect of raising $\ln \bar{w}_t$ from the first time, but also the indirect effect of lowering SEL_t. This indirect effect arises because greater r_t will draw some low-wage workers back into participation. In other words, aggregation will naturally offset the procyclicality of wages, because of the entry of low-wage individuals during upturns.

This logic easily extends to the case of many (two or more) education or skill groups. Suppose there is a decrease in returns for the lower-skilled workers; suppose $\ln r_t^L$ in (4) falls, and that this decline strongly reduces participation among lower skilled workers. The overall average wage may rise, since the remaining participants will be a more severely selected sample with higher skills and wages on average. This implies that the average wage could show growth *even though* $\ln r_t^L$ *is declining.*

II. Aggregate Wages and Participation in Britain

A. *The Data*

The microeconomic data used for this study are taken from the U.K. Family Expenditure Survey (FES) for the years 1978 to 1996. The FES is a repeated continuous cross-sectional survey of households which provides consis-

[13] Our discussion is rigorously verified in the Appendix.

tently defined micro data on wages, hours of work, employment status, and education for each year since 1978.[14] Our sample consists of all men aged between 19 and 59 (inclusive).[15] 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 U.K. 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 or over.[16] We model cohort effects on wage levels by a set of cohort dummies: five date-of-birth cohorts (b.1919–1934, b.1935–1944, b.1945–1954, b.1955–1964 and b. 1965–1977).

The measure of out-of-work income (income at zero hours) is constructed for each individual as follows. This measure is evaluated using a tax and benefit simulation model,[17] which constructs a simulated budget constraint for each individual given information about his age, location, and benefit eligibility. The measure of out-of-work income is largely comprised of income from state benefits; only small amounts of investment income are recorded. It is important to stress that benefits are not related to available wages of previous wage history.[18] 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 benefits include eligible unemployment benefits and housing benefit, 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 United Kingdom, the level of benefits which individuals receive out of work varies with age, time, household size, and (in the case of the housing benefit) by region. As mentioned before, housing benefit varies systematically with time, location, and cohort. One of the primary features of housing benefit is that older cohorts 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, thereby 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 percent of the total sample. Tables 1 and 2 provide a description of the cell proportions by marital status and education level over the period of our analysis. As Table 1 shows, the proportions of single and married men in the data are relatively constant from 1984 onwards, although there were rather fewer single men in the late 1970's and early 1980's.

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

[15] 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 1980's. 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.

[16] 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 United Kingdom; before this date the minimum school-leaving age was a year lower, at 15. Nonetheless, interactions between date-of-birth cohort effects and the education dummy will capture any effects of the change in minimum leaving age on the relative returns to education enjoyed by the 17+ group. See Gosling et al. (2000).

[17] The IFS tax and benefit simulation model TAXBEN (see www.ifs.org.uk), designed to utilize the British Family Expenditure Survey data used in this paper.

[18] Unemployment benefit included an earnings-related supplement in the late 1970's, but this was abolished in 1980.

TABLE 1—PROPORTIONS OF SINGLE AND MARRIED IN FES DATA BY YEAR, WHOLE SAMPLE

	Single		Married		
Year	Number	Percent	Number	Percent	Total
1978	991	22.98	3,322	77.02	4,313
1979	978	23.60	3,166	76.40	4,144
1980	964	22.75	3,274	77.25	4,258
1981	1,124	24.55	3,454	75.45	4,578
1982	1,189	25.90	3,401	74.10	4,590
1984	1,110	27.18	2,974	72.82	4,084
1985	1,138	27.81	2,954	72.19	4,092
1986	1,279	30.96	2,852	69.04	4,131
1987	1,210	29.28	2,922	70.72	4,132
1988	1,232	30.82	2,765	69.18	3,997
1989	1,247	30.81	2,801	69.19	4,048
1990	994	27.35	2,640	72.65	3,634
1991	1,080	28.73	2,679	71.27	3,759
1992	1,181	29.78	2,785	70.22	3,956
1993	1,136	30.41	2,599	69.59	3,735
1994	1,040	29.12	2,532	70.88	3,572
1995	1,012	28.66	2,519	71.34	3,531
1996	908	27.04	2,450	72.96	3,358
Total	19,813	27.56	52,089	72.44	71,902

TABLE 2—EDUCATIONAL ATTAINMENT BY MARITAL STATUS

	Education group			
	(i) Left school ≤ 16	(ii) Left 17–18	(iii) Left 19+	Total
Single	13,607	3,232	2,974	19,813
(percent)	68.68	16.31	15.01	100.00
Married	38,627	6,763	6,699	52,089
(percent)	74.16	12.98	12.86	100.00
TOTAL	52,234	9,995	9,673	71,902
(percent)	72.65	13.90	13.45	100.00

B. *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 I. Our model of participation includes the out-of-work income (the simulated benefit income variable) interacted with marital status, as well as the variables included in the log wage equation. The χ^2 test reported in the first row of Table 3 shows that the benefit income variable is strongly significant in the participation (probit) equation. This is important as it is our key source of identifying participation separately from the wage.[19] We have argued that this variable is exogenous for wages, conditional on the other included variables (age, region, etc.). This is an identifying restriction which is not directly testable. We do carry out specification testing by conducting joint significance tests for sets of regressors and interactions between them. These are presented in the remaining rows of Table 3 for the participation probit and the wage equation with the selectivity correction via the inverse Mills ratio.

In estimation we are unable to use data on housing benefit for the year 1983. This is because the system of benefit assistance for tenants was reformed in 1983 and the information on rent levels and benefit receipts was not collected properly by Family Expenditure Survey interviewers. We do, however, have a consistent series for 1978–1982 and 1984–1996. Below we present results for the complete period 1978–1996 omitting 1983 data.

The chosen specification, which the results below focus on, models participation and wages

[19] The full results are available on the AER web site (http://www.aeaweb.org/aer/contents/) as Supplement B to the paper.

TABLE 3—SIGNIFICANCE TESTS FOR REGRESSION SPECIFICATION

	Participation equation		Wage equation	
Coefficients	χ^2 (d.o.f.)	p-value	F-test (k, n)	p-value
Instruments:				
Out-of-work income × marital status	2,556.65(3)	0.000	N/A	
Education (left 17–18, left 19+)	8.05(2)	0.018	50.05(2)	0.000
Trend (3rd-order polynomial)	53.47(3)	0.000	57.12(3)	0.000
Cohort (b.1919–1934, b.1935–1944, b.1955–1964, b.1965–1977)	164.47(4)	0.000	13.58(4)	0.000
Education × trend	15.34(6)	0.018	28.65(6)	0.000
Education × cohort	18.46(8)	0.018	41.62(8)	0.000
Trend × cohort	833.46(12)	0.000	25.74(12)	0.000
Education × trend (1st order) × cohort	12.70(8)	0.123	8.47(8)	0.000
Region (11 standard regions)	55.24(10)	0.000	5.92(10)	0.000
Region × trend, region × trend^2	61.29(20)	0.000	6.52(20)	0.000
Mills ratio × marital status	N/A		105.37(2)	0.000
Married (single coefficient)	631.87(1)	0.000	819.35(1)	0.000
Spouse's education (single coefficient)	184.77(1)	0.000	N/A	

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 specification was chosen in comparison to a number of alternatives through a standard specification search. 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 specification of the log wage equation departs from the full proportionality hypothesis as set out in Section I. The additional interactions between cohort and education and trend which we introduce could reflect many differences in minimum educational standards across cohorts such as the systematic raising of the minimum school-leaving age over the postwar period in the United Kingdom. Meanwhile the prices of different (education-level) skills are allowed to evolve in different 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 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. For example, an increase in the level of out-of-work income which families can expect to receive when unemployed might have a larger impact among lower-educated groups, where the financial net returns to working are lower, than among graduates or other highly educated groups, where the ratio of out-of-work income to in-work income may still be very low. As Table 3 shows, the benefit income terms are strongly significant in the participation equation and the selectivity correction, education, cohort, and trend terms are all significant in the wage equation.

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.[20] These correction terms are constructed separately for each year as described in Section I. 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

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

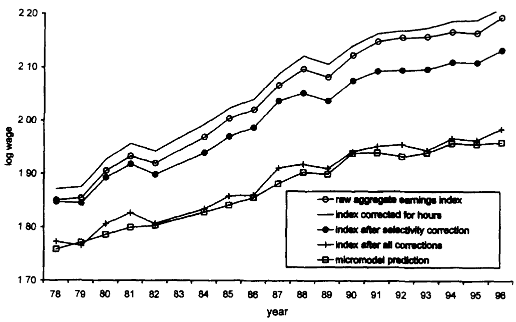

FIGURE 6. WAGE PREDICTIONS FROM MICROMODEL, AGGREGATE WAGE AND CORRECTIONS: LEVELS

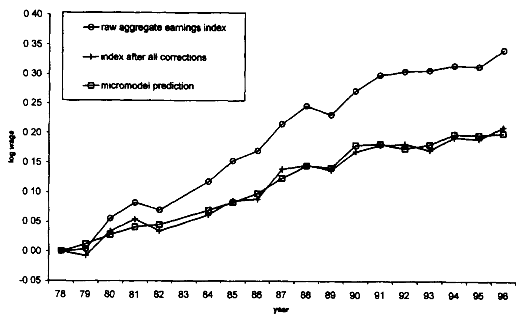

FIGURE 7. WAGE PREDICTIONS FROM MICROMODEL, AGGREGATE WAGE AND CORRECTIONS: REBASED TO 1978

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 6. This displays the behavior of all the measures of wages we look at over the entire period. The raw aggregate earnings index is the aggregate measure of wages calculated as the log of average wages for those in work; this shows an increase of 34 percent over the period 1978–1997.[21] 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 [HR_t in (9)]. 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 [SEL_t in (9)]. This has a more dramatic effect, with growing gaps over time associated with large decreases in participation—it reduces the estimated increase in wages over the period to around 28 percent. Finally, we apply the correction for the heterogeneity (dispersion) of individual wages [DSP_t in (9)]. This gives the impact of the increasing heterogeneity in wages that is separated from participation effects. This final series gives the aggregate wage after all corrections, and shows a growth over the period of only 20 percent.

In order to see the relative growth of the various series more clearly, Figure 7 shows exactly the same aggregate wage measure and the fully corrected aggregate series, but rebased to 1978.[22] 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. For comparison, we also plot the mean log wage (8) implied by the bias-corrected micro regressions (adjusted for participation, or omitting the selection term). A key evaluation of our framework is whether the fully corrected aggregate series lines up with this selectivity-adjusted micromodel prediction. The figure 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 1980's, aggregate wages grow rather more than the corrected micromodel wage. While there is a reasonably close correspondence between the trend of the two lines in the latter half of the 1980's, in the 1990's we find that there is a reasonably substantial increase in log aggregate wages but essentially no growth in the corrected measure.

[21] This is also calculated from the FES and corresponds closely to the measure of "average earnings," which media commentators in the United Kingdom have focused on.

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

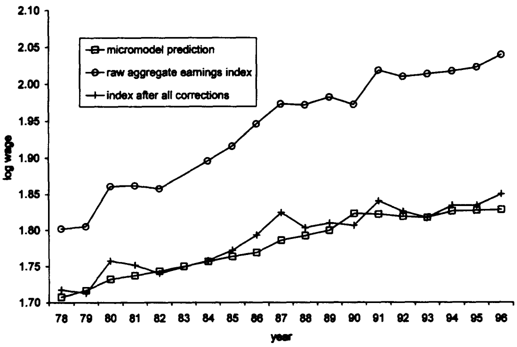

FIGURE 8. WAGE PREDICTIONS BY EDUCATION GROUP: LEFT EDUCATION AT OR BEFORE 16

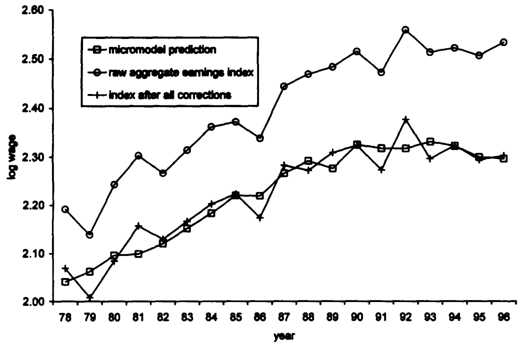

FIGURE 10. WAGE PREDICTIONS BY EDUCATION GROUP: LEFT EDUCATION AGED 19 OR OLDER

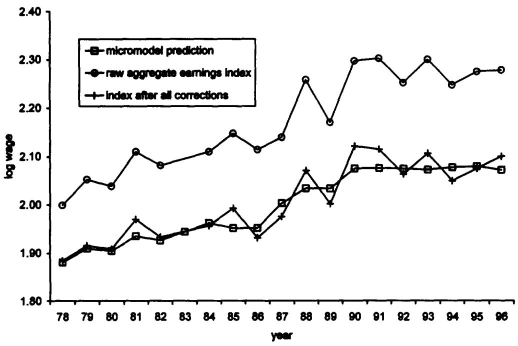

FIGURE 9. WAGE PREDICTIONS BY EDUCATION GROUP: LEFT EDUCATION AGED 17–18

Figure 7, which rebases to 1978, shows these patterns even more vividly. Correcting for selection over the period reduces our estimate of real aggregate wage growth from over 30 percent to around 20 percent.

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 Figures 8–10, 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 Figure 8. Controlling for the biases induced by shifts in participation rates over the 1980's and 1990's reduces our estimate of average wage growth for this group from over 20 percent to around 10 percent. 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 Figures 9 and 10, 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.

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 differences. Figures 11–13 graph the estimated returns with and without the correction factors for three different cohorts: those born between 1935 and 1944 (who were the oldest cohort with representatives in every sample year), those born between 1945 and 1954, and those born between 1955 and 1964 (who were the youngest). It is very noticeable how strongly the returns increased in the early 1980's but equally interesting how the increase is only maintained into the 1990's for the youngest cohort.

The impact of selection effects on returns is clearly important. In Figures 14–16 the time-series variation in the selection bias term is presented for each cohort. This follows the cyclical pattern of employment—as one might

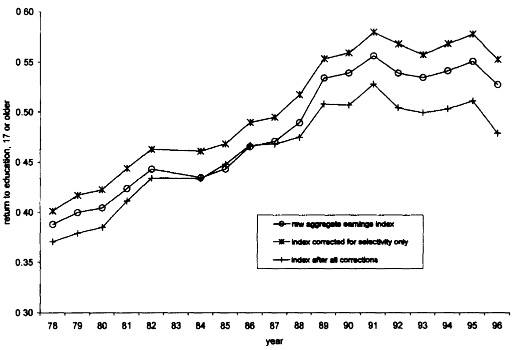

FIGURE 11. RETURN TO EDUCATION: COHORT BORN 1935–1944

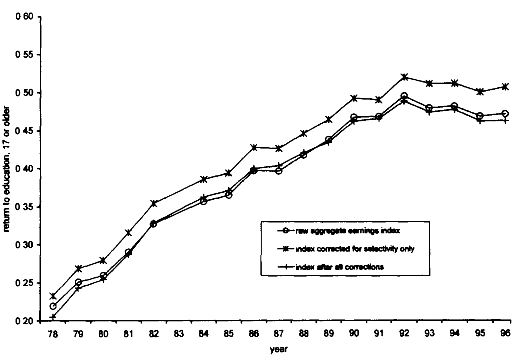

FIGURE 12. RETURN TO EDUCATION: COHORT BORN 1945–1954

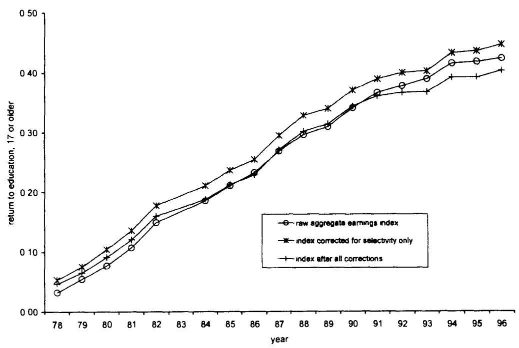

FIGURE 13. RETURN TO EDUCATION: COHORT BORN 1955–1964

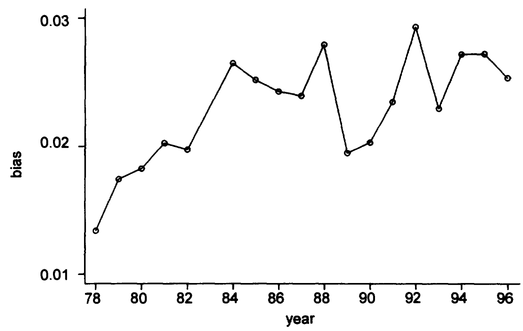

FIGURE 14. SELECTION BIAS IN RETURNS TO EDUCATION, COHORT BORN 1935–1944

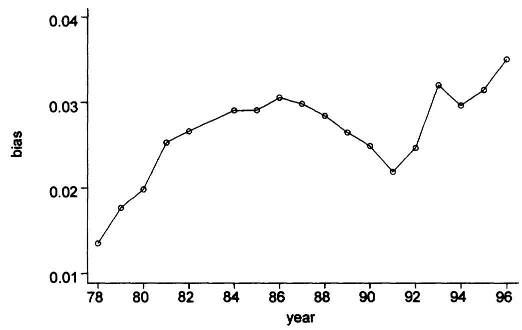

FIGURE 15. SELECTION BIAS IN RETURNS TO EDUCATION, COHORT BORN 1945–1954

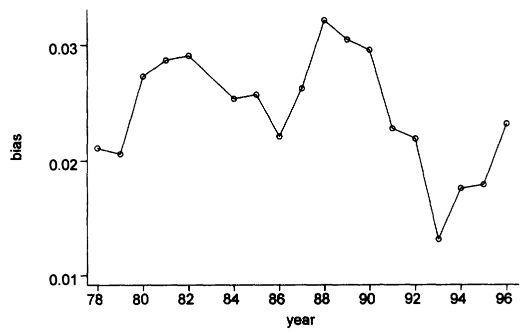

FIGURE 16. SELECTION BIAS IN RETURNS TO EDUCATION, COHORT BORN 1955–1964

expect given the analysis presented so far. But what is rather more interesting is how dispersion effects often operate in the opposite direction to selection effects. Increasing dispersion biases the aggregate wage upward, whereas selection biases the aggregate wage downward. For groups with greater dispersion, such as the higher educated, those effects can be substantial. For instance, in the case of the older cohort illustrated in Figure 14, those two impacts

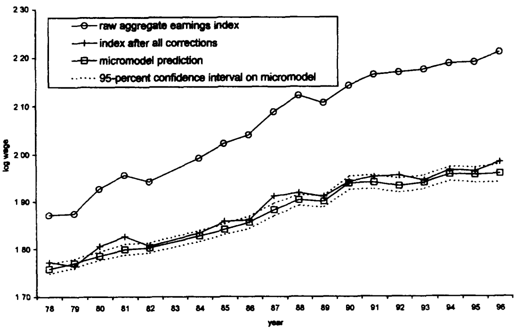

FIGURE 17. BOOTSTRAPPED 95-PERCENT CONFIDENCE INTERVALS ON MICROMODEL PREDICTIONS

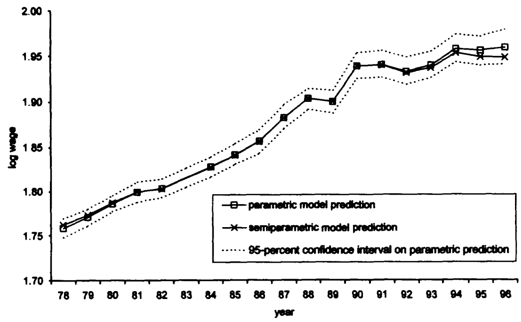

FIGURE 18. RESULTS OF SEMIPARAMETRIC ESTIMATION

roughly cancel each other from the late 1980's through the 1990's.

C. *Model Validation*

Our model and its underlying econometric assumptions 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 sufficiently 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.

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 micromodel of wages (with the selectivity correction included), we used bootstrap methods to simulate the difference between the two measures. This involved sampling with replacement from the Family Expenditure Survey data and reestimating the micromodel a total of 500 times. The 95-percent confidence intervals on the bootstrapped micromodel prediction are shown in Figure 17 together with the corrected aggregate wage series.[23] The figure shows that the two measures are not significantly different over the period covered by the sample. Occasionally the corrected aggregate measure is higher than the 95 percent upper bound on the micromodel prediction, but in general the two series line up very well. This provides a very positive validation of the model framework.

Semiparametric Estimation.—Our model, as set out in Section I, 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 Peter M. Robinson (1988) which is developed in Hyungtaik Ahn and James L. Powell (1993). These techniques are explored in a useful application to labor supply by Whitney K. Newey et al. (1990). In Figure 18 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 percent) 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

[23] Very similar results, broken down by educational group, are available from the authors on request.

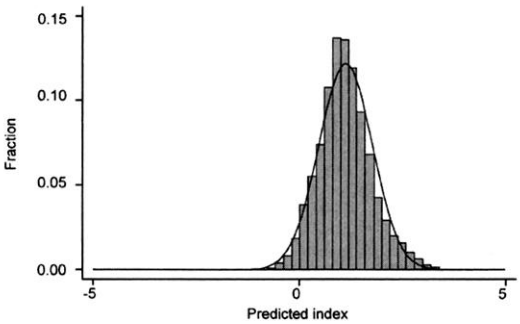

FIGURE 19. PLOT OF $\hat{\alpha}'\mathbf{z}$ INDEX FROM EMPLOYMENT PROBIT EQUATION

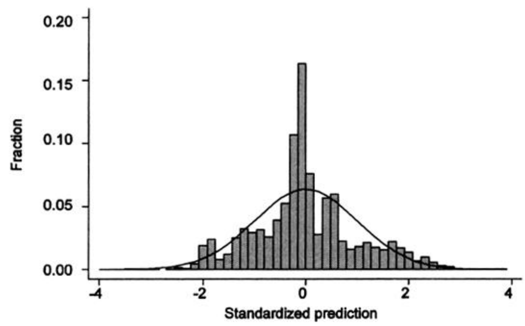

FIGURE 20. PLOT OF STANDARDIZED PREDICTIONS FROM WAGE EQUATION

of normality of the unobservables in the model is not unduly restrictive.

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 19 plots the distribution of the standardized probit index $\hat{\alpha}'\mathbf{z}$ 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.[24]

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 20. 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.[25]

III. 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 the distribution of returns, changes in selection due to participation, and changes in hours of work, respectively. We have shown that they do a remarkably good job of explaining the differences between individual and aggregate wages in the British context.

British data was used for three reasons. First, there have been significant 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 reflected in increasing decline in participation among older men across cohorts while the cyclical variation shows strong regional variation. This phenomenon 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 identification of the correction terms.

[24] For further validation, kernel regressions of participation on $\hat{\alpha}'\mathbf{z}$ show a normal shape, details of which are available from the authors on request.

[25] 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 micromodel. As we have noted above these plots are extremely close.

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 differences between log aggregate wages and the average of log wages implied by our analysis. The differences are interesting and have valuable implications. They show an important role for wage dispersion and for selection in characterizing the distortion in the measurement of wage growth from aggregate data. Most noteworthy is how mean individual log wages are largely flat 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.

APPENDIX

This Appendix presents the explicit formulations of biases in aggregate wages, as well as the aggregation results on which they are based. The mathematical details are provided on the AER web site as Supplement A (see http://www.aeaweb.org/aer/contents/) and draw on the work of Daniel McFadden and Fred Reid (1975) and Thomas E. MaCurdy (1987).

The aggregation results apply to aggregate of nonlinear relationships over normal and lognormal distributions. We make use of standard formulae familiar from the analysis of selection bias, as well as some further results that we present in Lemma A1. A proof of Lemma A1 is given in Supplement A.

Assume that $(\mathcal{U}, \mathcal{V})$ are jointly normal random variables: namely

$$\begin{pmatrix} \mathcal{U} \\ \mathcal{V} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_{\mathcal{U}} \\ \mu_{\mathcal{V}} \end{pmatrix}, \begin{pmatrix} \sigma_{\mathcal{U}}^2 & \sigma_{\mathcal{U}\mathcal{V}} \\ \sigma_{\mathcal{U}\mathcal{V}} & \sigma_{\mathcal{V}}^2 \end{pmatrix} \right) \tag{A1}$$

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

The formulations of aggregate participation utilize the "probit" formula

$$E[I] = \Phi\left[\frac{-\mu_{\mathcal{V}}}{\sigma_{\mathcal{V}}}\right]$$

where $\Phi[\cdot]$ is the standard normal cumulative distribution function (c.d.f.). The impact of participation on mean log wage makes use of the "selection" formula

$$E[\mathcal{U}|I = 1] = \frac{E[\mathcal{U}I]}{E[I]} = \mu_{\mathcal{U}} - \frac{\sigma_{\mathcal{U}\mathcal{V}}}{\sigma_{\mathcal{V}}}\lambda\left[\frac{-\mu_{\mathcal{V}}}{\sigma_{\mathcal{V}}}\right]$$

where $\lambda[\cdot] = \phi[\cdot]/\Phi[\cdot]$ is the inverse Mill's ratio, with $\phi[\cdot]$ the standard normal density function. In addition to these expressions, for analyzing the wage level we use the following results for the lognormal variable $\mathcal{W} = \exp \mathcal{U}$.

LEMMA A1: *We have that:*

A.

$$E[\mathcal{W}|I = 1] = e^{\mu_{\mathcal{U}} + (1/2)\sigma_{\mathcal{U}}^2} \cdot \frac{\Phi\left[\dfrac{-\mu_{\mathcal{V}} - \sigma_{\mathcal{U}\mathcal{V}}}{\sigma_{\mathcal{V}}}\right]}{\Phi\left[\dfrac{-\mu_{\mathcal{V}}}{\sigma_{\mathcal{V}}}\right]}.$$

B.

$$E[\mathcal{V}\mathcal{W}|I=1] = e^{\mu_{\mathcal{U}}+(1/2)\sigma^2_{\mathcal{U}}} \cdot \left\{\mu_{\mathcal{V}} + \sigma_{\mathcal{U}\mathcal{V}} - \sigma_{\mathcal{V}}\lambda\left[\frac{-\mu_{\mathcal{V}} - \sigma_{\mathcal{U}\mathcal{V}}}{\sigma_{\mathcal{V}}}\right]\right\} \cdot \frac{\Phi\left[\frac{-\mu_{\mathcal{V}} - \sigma_{\mathcal{U}\mathcal{V}}}{\sigma_{\mathcal{V}}}\right]}{\Phi\left[\frac{-\mu_{\mathcal{V}}}{\sigma_{\mathcal{V}}}\right]}.$$

To apply the above relationships to the model (5), we require the following assumption:

DISTRIBUTIONAL ASSUMPTION: *The indices determining log wages and participation are joint normally distributed: namely*

$$\begin{pmatrix}\beta_0 + \boldsymbol{\beta}'\mathbf{x} + \varepsilon \\ \alpha_0 + \boldsymbol{\alpha}'\mathbf{z} + \nu\end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix}\beta_0 + \boldsymbol{\beta}'E(\mathbf{x}) \\ \alpha_0 + \boldsymbol{\alpha}'E(\mathbf{z})\end{pmatrix}, \begin{pmatrix}\boldsymbol{\beta}'\boldsymbol{\Sigma}_{xx}\boldsymbol{\beta} + \sigma^2_\varepsilon & \boldsymbol{\alpha}'\boldsymbol{\Sigma}'_{xz}\boldsymbol{\beta} + \sigma_{\varepsilon\nu} \\ \boldsymbol{\beta}'\boldsymbol{\Sigma}_{xz}\boldsymbol{\alpha} + \sigma_{\varepsilon\nu} & \boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma^2_\nu\end{pmatrix}\right).$$

The following correspondence allows application of the results:

$$\text{(A2)} \qquad \mathcal{U} = \beta_0 + \boldsymbol{\beta}'\mathbf{x} + \varepsilon = \beta_0 + \boldsymbol{\beta}'E(\mathbf{x}) + \boldsymbol{\beta}'(\mathbf{x} - E(\mathbf{x})) + \varepsilon$$

$$\mathcal{V} = -\alpha_0 - \boldsymbol{\alpha}'\mathbf{z} - \nu = -\alpha_0 - \boldsymbol{\alpha}'E(\mathbf{z}) - \boldsymbol{\alpha}'(\mathbf{z} - E(\mathbf{z})) - \nu$$

where $\mathcal{U}$ is the log wage and $\mathcal{W}$ is the wage (level). The assumption establishes normality as in (A1), with parameters given as

$$\mu_{\mathcal{U}} = \beta_0 + \boldsymbol{\beta}'E(\mathbf{x})$$

$$\mu_{\mathcal{V}} = -\alpha_0 - \boldsymbol{\alpha}'E(\mathbf{z})$$

$$\sigma^2_{\mathcal{U}} = \boldsymbol{\beta}'\boldsymbol{\Sigma}_{xx}\boldsymbol{\beta} + \sigma^2_\varepsilon$$

$$\sigma_{\mathcal{U}\mathcal{V}} = -\boldsymbol{\beta}'\boldsymbol{\Sigma}_{xz}\boldsymbol{\alpha} - \sigma_{\varepsilon\nu}$$

$$\sigma^2_{\mathcal{V}} = \boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma^2_\nu$$

The bias results follow from working out (10), (11), and (12) using the aggregation results with this correspondence. The results are as follows:

For (10), we have

$$\text{(A3)} \qquad DSP \equiv \frac{1}{2}[\boldsymbol{\beta}'\boldsymbol{\Sigma}_{xx}\boldsymbol{\beta} + \sigma^2_\varepsilon],$$

for (11), we have

$$\text{(A4)} \qquad SEL \equiv \ln\left[\Phi\left(\frac{\alpha_0 + \boldsymbol{\alpha}'E(\mathbf{z}) + (\boldsymbol{\beta}'\boldsymbol{\Sigma}_{xz}\boldsymbol{\alpha} + \sigma_{\varepsilon\nu})}{\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma^2_\nu}}\right)\right] - \ln\left[\Phi\left(\frac{\alpha_0 + \boldsymbol{\alpha}'E(\mathbf{z})}{\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma^2_\nu}}\right)\right]$$

and for (12), we have

(A5)

$$HR \equiv \ln \left[\frac{h_0 + \gamma\alpha_0 + \gamma\boldsymbol{\alpha}'E(\mathbf{z}) + \gamma\boldsymbol{\beta}'\boldsymbol{\Sigma}_{xz}\boldsymbol{\alpha} + \gamma\sigma_{\varepsilon\nu} + \gamma\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma_\nu^2}\cdot\lambda\left(\frac{\alpha_0 + \boldsymbol{\alpha}'E(\mathbf{z}) + \sigma_{\varepsilon\nu}}{\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma_\nu^2}}\right)}{h_0 + \gamma\alpha_0 + \gamma\boldsymbol{\alpha}'E(\mathbf{z}) + \gamma\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma_\nu^2}\cdot\lambda\left(\frac{\alpha_0 + \boldsymbol{\alpha}'E(\mathbf{z})}{\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma_\nu^2}}\right)} \right].$$

Finally, our remarks in Section I, subsection C, are substantiated by noting that an increase in skill price r_t reduces the selection bias term; we have

$$dSEL_t = \left[\lambda\left(\frac{\alpha_0 + \boldsymbol{\alpha}'E_t(\mathbf{z}) + (\boldsymbol{\beta}'\boldsymbol{\Sigma}_{xz}\boldsymbol{\alpha} + \sigma_{\varepsilon\nu})}{\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma_\nu^2}}\right) - \lambda\left(\frac{\alpha_0 + \boldsymbol{\alpha}'E_t(\mathbf{z})}{\sqrt{\boldsymbol{\alpha}'\boldsymbol{\Sigma}_{zz}\boldsymbol{\alpha} + \sigma_\nu^2}}\right) \right] \cdot d \ln r_t$$

with the term in brackets negative when $\boldsymbol{\beta}'\boldsymbol{\Sigma}_{xz}\boldsymbol{\alpha} + \sigma_{\varepsilon\nu} > 0$.

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