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Cyrus Farsian

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Composition bias in aggregate wages is often a scapegoat for the apparent unresponsiveness of wages over the cycle. Since Bils (1985) and in particular Solon et al. (1994), who find that that real wages are highly pro-cyclical a general consensus has emerged that the observed 'mild' cyclicality in real wages is due to composition effects which cause counter-cyclical biases because low wage jobs are the first to be destroyed during recessions (Pissarides, 2009). In this paper, it is argued that the results of Solon et al. (1994) and other papers using similar techniques cannot possibly disentangle the true effect of composition bias. This is because the assignment of fixed weights used to keep the composition of the work force constant is arbitrary and imposes a particular direction to the bias. Thus, rather than determining the bias it only serves to show the possible magnitude once having assumed the way the bias works. As in Blundell et al. (2003) we can unravel the bias into three interpretable parts. That is biases due to individual movement in and out of work, changes in the variation of hours worked and changes in the variance of wages over the cycle. The findings show that aggregate real wages become cyclically less responsive over the cycle and no evidence of 'counter-cyclical' composition bias.

JEL: C34, E24, J31.

Keywords: Aggregate Real Wage Index, Endogenous Selection, Composition Bias, Wage Dispersion.

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Introduction

Understanding real wages is essential to many questions when addressing the macro-economy. Wages reflect the price of labour effort; has a direct impact to firms' profits, the level employment and is a key determinant of the distribution of income (Carruth and Oswald, 1989). They are not only important to wage earners; they contain vital information about the wellbeing of the overall economy and are highly influential to conditions in other markets. This was well recognized by Karl Marx who claims in 'Das Kapital', that the tendency for commodity prices to systematically exceed the market value of labour used to produce the commodities would essentially result in the deterioration of real wages and ultimately the collapse of the capitalist system. Such a scenario would require a downward trending real wage statistic, which has yet to be observed. In fact, what we see is quite the opposite, if anything real wages are clearly upward trending in aggregate data. Moreover, once we recognize that real wages constitute a large portion of private income the question that naturally arises is how intimate is the relationship between aggregate output and aggregate real wages. Is it that wages and output are positively related because when real wages rise output demand increases? Or on the other hand, is the relationship negative since a wage rise also implies lower profits. In Keynes (1936), 'The General Theory of Employment, Interest and Money', the explanation stems from the interaction of competition given a short-run capital stock, to which employment adapts. In periods of increased product demand, employment levels will rise reducing the capital to labour ratio and increasing the marginal product of capital and reducing that of labour (hence a wage fall). This view implies a countercyclical nature to wages over the business cycle, which means that the firms' labour demand schedule are fixed and shifts in labour supply decisions govern the negative relationship. On the other hand, more recent macro-economic theories such as Real Business Cycle theory (RBC), (e.g. Kydland and Prescott, 1982; Long and Plosser, 1983; King and Plosser, 1984) describe a pro-cyclical nature to real wages. In periods of increased product demand or increased productivity, firms need to hire more workers. Since the short-run labour supply curve is fixed only a wage rise through a 'rightward shift' in labour demand can achieve higher employment and output levels.

Naturally, many economists turned to the empirics for answers, hoping that statistical evidence would give support to either of the two theories. The outcome however, was less than welcoming. Adding even more confusion to the debate the evidence was often contradictory and fragile. The majority of studies identify 'weak' cyclicality (counter or pro) or even an acyclical relationship between real wages and output. For example, Lucas (1977) and Blanchard and Fischer (1989) both agree that real wage cyclicality is often statistically insignificant or very weak. Another more established and common finding is that while employment varies substantially over the cycle, real wages do not (Mankiw, 1989). Consequently, this has made it incredibly hard to prove either counter or pro-cyclicality consistently. Alternatively, to put it another way, it is relatively easy depending on sample time period and choice of price deflator to show either outcome is in-line with theory (Woitek, 2004). On the whole, evidence from time series studies seems to be indifferent between claiming that real wages are acyclical or mildly both; pro and counter cyclical.

Another interesting line of research is very critical on the 'appropriateness' of statistical methods and the misuse of aggregate data. For example, a recurring theme in most studies is the failure to consider issues such as sample selection and composition bias. The problem arises when we do not consider the whole population in our estimated sample. Observations come from a heterogeneous sub-group of non-randomly selected individuals, because they have in-tact (observed) data on wages and explanatory variables. Thus, typically non-employed and self-employed individuals are not included in the estimation procedure, which biases the wage statistic. One of the most notable examples, Solon et al. (1994) address the problem of biases in estimation due to composition changes over the cycle. Yet, they still fail to provide an accurate treatment of composition bias for two primary reasons: Firstly they base their regression on a sample of workers only and secondly they control for composition effects by giving higher fixed weightings to low wage individuals. In essence they assume *a priori* that low wage individuals are the group with high unemployment probabilities during a recession and hence their set-up forces the wage distribution to be truncated from below. These important considerations may have biased the results and thus their conclusion of clear pro-cyclicality in real wages is to a large extent misleading due to these factors. What we find here is that even when controlling for composition bias aggregate real wages become less cyclically responsive and it would be impossible to conclude that composition bias leads to a clear counter-cyclical bias (as in Solon et al. 1994). While our results are not directly comparable to Solon et al. (1994) or similar studies because our data set are different, the discussion is focused on how to appropriately account for composition bias.

The remainder of this paper follows this recent lead. In particular, we adopt a methodology, which can incorporate both non-employed and self-employed individuals in our regression. We find that estimates improve once we include non- and self-employed individuals. Specifically, the inclusion of self-employed individuals differentiates our analysis from many others, as we have not yet found any paper that accounts for this group of market participants. The conclusions are two fold: Firstly the inclusion of self-employed individuals is as important as non-employed, especially when addressing the issues of real wage cyclicality. They constitute a large portion of the labour market, and as economic agents' they respond to wage changes and cycles as much as waged workers do. Secondly, while accounting for composition changes over the cycle is important to understanding the 'true' value of aggregate wages the evidence shows that compositional movements account for the more erratic component of aggregate real wages and once removing them aggregate wages smooth out over the cycle.

Section 1 presents a literature review, to give the reader a grasp of the empirical confusion when estimating aggregate real wages. Emphasis is given to the puzzling results highlighted above (and in more detail below). In particular, we find that the 'puzzles' can be explained by focusing on the problem of sample selection bias and worker heterogeneity. Section 2 describes the methodology for estimating a bias free real wage index. That is, constructing a micro-model, which consists of a wages equation, hours worked equation and the participation decision rule. Some space is also devoted to show in detail how we construct our bias terms. We also include a description of the data set used to obtain our estimates. Section 3 presents the results and discusses our findings. Specifically, we address the importance of including self-employed individuals when dealing with sample selection and heterogeneity in wage data. As usual this is followed by the conclusion summarizing the paper.

1 Literature

Two strands of literature can be identified in the consideration of aggregate wage movements. The first strand of literature typically addresses this issue of real wage cyclicality by estimating an aggregate time series model of the form

$$\ln w_t = \gamma_1 + \gamma_2 t + \gamma_3 t^2 + \gamma_4 \left(u_t - \delta_1 - \delta_2 t - \delta_3 t^2\right) + \epsilon_t \tag{1.1}$$

Taking the first difference to clear any serial correlation problems with the error term gives

$$\Delta \ln w_t = \gamma_2 t - \gamma_3 t + \gamma_4 (\delta_3 -) + [2(\gamma_3 t - \gamma_4 \delta_3)]\, t + \gamma_4 \Delta u_t \tag{1.2}$$

Log aggregate wages ($\ln w_t$) are regressed on some indicator of the stage of the cycle, usually the unemployment rate (u_t). A time trend $\gamma_2 t$, its quadratic trend $\gamma_3 t^2$ and the unemployment rate as the deviation from its own quadratic trend ($u_t - \delta_1 - \delta_2 t - \delta_3 t^2$) are also entered to capture the cyclical component between wages and unemployment (Solon et al. 1994). Given this specification, one can identify cyclicality as depending on the value of the parameter, γ_4.

While the above approach was common throughout the 1970's, it often conjured confusing results. Neftçi (1978) and Sargent (1978) criticized previous studies for the use of very simple ordinary least square regressions (such as equation (1.2) above). They extended their analysis by including distribution lags into similar models and conclude counter-cyclicality in real wages. However, when their analysis was slightly modified by Geary and Kennan (1982) by using the wholesale price deflator instead of the CPI and extending the sample period, the results were insignificant. More to the point, most of these studies were criticized because of 'downward-inconsistent' estimator of the supply elasticity that arises when either the supply equations error term has a positive variance, uncorrelated with the demand equation error (inverse elasticity is 'upward-inconsistent'), or if price (wage) and quantity (labour supply) variables are positively correlated (Leamer, 1981)[1]. Even more confusing, the implied estimated supply elasticity

[1]When we regress hours worked on real wage growth directly, the labour supply estimate is downward-inconsistent because we are actually picking-up some of the negative wage labour demand relationship (simultaneity bias). In other words, the labour

from many regression results, which ranged between 1.2 and 2.7 (Solon et al. 1994) were hard to explain. Thinking in terms of the intertemporal substitution of leisure (labour hours) or the consumption leisure trade-off, it is not reasonable to expect that at the micro-level people drastically alter their hours of work decision when they experience relatively small changes in their real wage (Able and Bernanke, 1992, Mankiw, 1989). It is also very hard to contemplate such highly elastic labour supply curves because it implies that leisure is an inferior good, which it is certainly not. The issue here is that in order to generate an increase in employment when substitution effects are relatively small, it requires that income effects reinforce the substitution effect (negative income effect). These contradictory findings baffled economists, as they were continuously trying to make sense of the results. Since no theory could really explain what the data was producing, many economists started to formulate elaborate explanations such as efficiency wage, implicit contract and insider-outsider models that help explain the large labour supply elasticity estimates (Solon et al. 1994).

The second strand of literature originates from Stockman's unpublished paper *"Aggregation Bias and the Cyclical Behavior of Real Wages"* (1983). Stockman realized, when analyzing aggregate real wage measures that the measure could potentially be subject to composition bias. This is because the typical aggregate wage statistic is constructed by taking the ratio of a sectors total wage bill,

$$B_t = \sum_{j=1}^{J} H_{jt} W_{jt}$$

Where subscript j= 1, 2, 3, J refers to the groups or sectors across which the working population is divided.

This calculation would accurately reflect the true mean if the fluctuation of hours worked and the distribution of wages is uniform across the board. However, if there is group specific variation in hour shares, the statistic will suffer from composition bias. For example, suppose that there are only two groups in an economy, a low wage and a high wage group. If the low wage groups are more sensitive to hours variation over the cycle, or if low wage people are more likely to move in and out of employment during cycles then the hours weighting μ_{jt}, ($\mu_{jt} = H_{jt}/H_t$) will give less weight to low wage groups during a recession and more during an expansion. Thus, during recessions the bias will be upwards as low wage workers are 'removed' from the mean wage measure. Conversely, during expansion the bias is downwards as comparatively more lower wage groups are now 'included' in the mean wage measure.

Unlike previous studies that concentrated on issues such as simultaneity bias, and common econometric diagnostic tests to explain the puzzling results from estimating time series regression on real wages,

supply curve is not perfectly stable, and our estimated labour supply coefficient would be less than its true value, since shifts in labour supply along a labour demand curve produce a negative correlation.

Stockman (1983) emphasized the problems with aggregation when estimating real wages. This quickly sparked a new perspective to the problem and a wave of estimation techniques which utilize micro data. One early example is Bils (1985) who adopts disaggregate data to examine differences in real wage behavior across individuals and access the impact of aggregation. In brief, Bils (1985) takes a sample of individual wage data to track the wages of every individual between 1966-1980. To eliminate possible aggregation bias, Bils (1985) assigns fixed weights to groups and employs fixed- and random- effects estimation techniques to construct a statistic that is biased 'only through cyclical variation' . He then examines the statistical significance of the coefficient that correlates hours to earnings and concludes that the bias (counter-cyclical) is insignificant compared to the strong pro-cyclicality found in the results. Solon et al. (1994) make a very similar assessment to the aggregation problem, assigning fixed weights and using panel data. One key insight from their analysis is their approach to untangling the biases in wages. They conduct various 'tests' using selected 'balanced' and 'unbalanced' samples of workers only, as well as purposely injecting the weightings implied by composition biased statistics to a bias-free panel of individuals. This enabled them to assess the impact of composition bias directly by comparing biased and unbiased wage statistics to check for any cyclical differences. They conclude that hours shares of low-wage groups tend to be more sensitive to cyclical variation than high-wage groups. The implied average wage statistic then gives considerably more weight to low-wage groups during an expansion and much less weight during recessions. Thus, there exists 'counter-cyclical composition bias' which mitigates the pro-cyclicality of real wages. Hence, when a recession occurs and low-wage individuals leave employment and the aggregate wage statistic will show hardly any movement at all. Indeed, it may possibly increase.

Though a step in the right direction the above results suffer from two potentially important factors that need to be accounted for to produce reliable results. Firstly, selectivity bias considerations must be addressed since their estimates do not include the non-employed and only account for observable heterogeneity in individuals by assigning fixed weights. The problem of censored wage and hours data is not considered. Keane et al. (1988) also shows that employing fixed- and random-effects regressions (as in Bils 1985) without controlling for selectivity bias will worsen the bias making wages appear artificially pro-cyclical. The second point of conflict is the assignment of fixed weights. Bils (1985) openly admits that "how different individuals should be weighted is somewhat arbitrary" and justly proposes that because people who stay in one job are insulated from cycle effects, then those whose employment is observed to change over the cycle should be assigned more weighting. Yet, by the mere fact of assigning high weighting to those who's employment behavior is cyclically sensitive both Bils (1985) and Solon et al.(1994) assume a priori that low wage groups (or typically manufacturing sectors) are more sensitive to cycles (hence the need for higher weighting). Although this is the most common presumption, there is limited literature available to support their arguments since most macro-economic theories assume homogeneous labour markets. It is also difficult to identify whether it is consistently low or high wage individuals that leave employment even within the manufacturing sector (Keane et al., 1988). For example, Carruth and Oswald (1989) show that in some sectors, low wage individuals lose employment during a recession (even when they bargain for considerably lower pay), so that the better skilled (more productive) workers are preserved. Conversely, Keane et al. (1988) argue that it is common in many sectors for individuals with high wages and especially high transitory wages (ceteris paribus) to be more likely to lose employment during recessions. To put simply, in order to determine the bias accurately we need to have information regarding individual heterogeneity and self-selection. Without knowing precisely which individuals move in and out of employment, it would be very hard to determine the exact bias with confidence.

Resolving this issue became the next obstacle to estimating aggregate wages. While the composition bias approach incorporates sample selection problems an accurate treatment had not been developed until Blundell et al. (2003). Blundell et al. (2003) take a rigorous approach to tackle the issue and utilize advancements in econometric micro-modeling techniques to consider the effects of sample selection and non-participation. Their approach is different in that they do not attempt to determine the cyclicality of wages. Instead they concentrate on building a model that can accurately account for non-participation, censored hours worked and other statistical issues. Recognizing that the biases in wage statistics come from different sources, they decompose the biases into its different parts. That is, biases that result from the weighting of hours (ala Stockman), biases that come from sample selection, and those that are due to differences in both observed and unobservable characteristics in individuals (heterogeneity) that distort mean aggregate wages via increased wage inequality. This unique method not only reveals the high degree of up-ward bias in wage statistics but is also informative of the cyclical nature of such biases and aggregate wages.

2 Methodology: Resolving Composition Effects

The aforementioned work suggests that self-selection and labour market heterogeneity in both wages and employment outcomes can cause considerable bias in wage statistics. However, in order to estimate this bias accurately we need information regarding the selection rule and degree of heterogeneity across individuals. For this purpose, we must build a model and assume a reasonable selection criterion to identify our equations. We may then proceed to utilize the rich information of individual characteristics available from cross-sectional data to construct wage statistic that controls for compositional changes over the cycle. Section 2.1 describes the model for individual wages and participation. Section 2.2 describes in detail how we obtain the bias terms. While section 2.3 provides a data description.

2.1 A Model for Real Wages and Participation

The model used for individual wages is constructed following the approach of Roy (1951) with some adaptations. Wages are essentially determined by the productivity of individuals such that human capital or skills largely govern the wage one receives. Evidently, this assumes that identically skilled individuals receive an identical wage.

Some basic alterations improves the performance of the model when confronted with data on market wage distributions (Heckamn and Sedlacek, 1990, see). Firstly, we assume that skills which permit agents to perform sector-specific tasks are exogenously given. Consequently, investment in human capital is some-what ignored, and the aggregate stock of skills is roughly fixed. We also depart from the Roy (1951) model in two additional ways: First, agents decide on their labour and non-market activity based on utility maximization rather than income maximization; second, the sector specific attributes including latent traits are log-normally distributed. This would mean that the mapping of human skill to work is time invariant and that our wage equation implies that log wage functions for individuals have identical parameter coefficients but allows for differences in their intercepts. Agents in the same job face the same wage function and any differences in their wages is due to small differences in characteristics such as age and health which are log-normally distributed. Translated to economic jargon, we maintain the Heckman and Sedlacek (1990) *Proportionality Hypothesis*. The proportionality hypothesis is important here since it implies that sector-specific 'skill units' underlie the wage specification. People have skills for specific sectors of the economy but within these sectors wages follow a log-normal distribution. For example, we may have a sector of chartered accountants which requires a qualification but the process that governs the wage within that sector is somewhat random in both observable and unobservable heterogeneity. We adopt this approach because evidence shows that allowing for non-normal human capital distributions' (opposed to log-normal) to explain wages differentials, performs poorly in models that adjust for selection effects (Heckman and Sedlacek 1990).

Following the above argument, the model assumes that each worker i, possesses a human capital (skill) H_{it}, which is non-differentiated in that it commands its own single price r_t in time period t. Worker i'*s* wage is the value of his human capital, which may differ across cohort groups' j and education groups' s. The main assumption is that human capital H_{it} is log normally distributed with mean $\delta_{js} = E_t(\ln H_i)$ and constant variance σ^2. In every time period t we have a mean human capital level δ_{js} for cohort j and education level s. Systematic growth in wages, which are common across workers, perhaps due to productivity shocks are accounted for through changes in r_t. Essentially r_t is the price per unit of human capital, and δ_{js} gives us the mean level of log human capital for the specific cohort and education group that worker i falls into. Since by assumption H_{it} obeys normality with constant variance, the δ_{js} component, along with r_t is sufficient to construct an un-truncated aggregate log wage statistic. In addition, we introduce different types of human capital; and incorporating trend and cycle effects to allow for different stocks of labour market experience to be associated with different cohorts. For the former, we suppose that there exists a high-education worker who receives a skill price r_t^h and a low-education worker, who has skill price r_t^l. Considering d_i as the high-education dummy, the log wage equation has the form

$$\ln w_{it} = d_i \ln r_t^h + d_i \delta_{js}^h + (1 - d_i) \ln r_t^l + (1 - d_i) \delta_{js}^l + \epsilon_{it} \tag{2.1}$$

Where, ϵ_{it} is $N(0,\sigma^2)$

For the latter, we simply include trend, cohort and interactions with regional and education dummies in both the probit and log wage models (Blundell et al. 2003)[2].

Reservation wages w_{it}^R are also assumed log-normal, with

$$\ln w_{it}^R = a \ln b_{it} + \eta_{js} + \zeta_{it} \tag{2.2}$$

Where, ζ_{it} is $N(0,\sigma^2)$

What is important to recognize here is that reservation wages introduces a form of heterogeneity in participation decisions. Since the reservation wages are built on various characteristics, such as skill, age and various unobservables' (that is, ζ_{it}). We can consider this approach as utility maximization rather than income maximization to add some flexibility to the selection rule. Under the former it is more likely that individuals that are unemployed but seeking employment remain out of work even if there are many low wage jobs available, which incorporates an inter-temporal wage leisure choice and wage offer (budget) constraint imposed by the market. Expressing this mathematically by an indicator function we have that participation occurs if;

$$I_i = 1\left[w_{it} \geq w_{it}^R \right] \tag{2.3}$$

One key aspect to estimating this behavior is separating the wage process from the participation decision, to insure identification of equations. This requires a variable that would affect the decision to work but that would not affect wages (Heckman, 1979). As in Blundell et al. (2003), the exogenous benefit level, b_{it} (out-of-work income) available to worker, i, that varies with individual characteristics and time is utilized for identification. Supplementary to having good data on benefit levels in Britain, large varia-

[2]For example, changes in the minimum schooling laws are expected to produce some cohort effects, as older generations will tend to have much less schooling years than the current generation of young workers. In addition, introduction on nationwide schooling examinations (GCSE/ A-levels) will create heterogeneity in wages, since we can distinguish between high and low-quality workers from different education outcomes.

tions in the real value of benefit income and variation across time, along with location and cohort groups provide a good form of isolating selection effects from the determinants of wages (Blundell et al. 2003).

Completing the model requires that we incorporate a role for hours work in the participation decision as biases may arise through hours variation in the composition of various sectors of the work force. Then we can untangle the bias using a measure of the covariance between wage levels and hours worked. This is achieved by using a labour supply model where hours worked is correlated with incentives to participate. Thus, assuming that desired hours h_{it} are chosen by utility maximizing agents, with reservation wage hour combinations defined as $h_{it}(w^{*}) = h_0$. Where h_0 is the minimum number of available hours for full-time work, defining some of the fixed-costs associated with employment. Assuming that $h_{it}(w)$ is normally distributed for each wage (as the location parameter on the support of hours) we can approximate desired hours by

$$h_{it} = h_0 + \gamma\left(\ln w_{it} - \ln w_{it}^{R}\right) \tag{2.4a}$$

$$= h_0 + \gamma\left(\ln r_t - a \ln b_{it} + \delta_{js} - \eta_{js} + \epsilon_{it} - \zeta_{it}\right) \tag{2.4b}$$

This equation states that an individual will work h_{it} amount of hours, so long as obtained wages outweighs the reservation wages at the minimum level of work hours. If one's commanding wage is above their reservation wage, then depending on parameter γ, one would naturally alter their desired work hours. This is quiet neat, because using the combination of reservation wage with the minimum hours work we can incorporate both fixed-costs associated with full-time work and the notion of backward bending labour supply curves into the model.

All in all, our log wage model consists of three equations which is summarized as;

$$\begin{aligned} \ln w &= \beta_0 + \beta^{'} x + \epsilon \\ h &= h_0 + \gamma(\alpha + \alpha^{\prime} z + v) \\ I &= 1[\alpha_0 + \alpha^{\prime} + v > 0] \end{aligned} \tag{2.5}$$

Were the obvious replacement for predictors in each equation have been made.

2.2 Formulating the Correction Terms and Decomposing the Biases

In the above model, aggregate wages are constructed by a linear prediction on individual wages, which is derived from their characteristics. We essentially calculate a 'potential' wage and reservation wage for all individuals that have wage data missing. Though we rid the problem of incidental truncation using these modeling techniques, we cannot rely on these estimates as an accurate representation of real average wages unless we can relate them to aggregate statistics. This section is devoted to resolving this issue and primarily what we hope to gain is a neat formulations that decompose the biases in average wages and apply corrections to the aggregate wage statistic. The sample selection problem is essentially reduced to a probit model since we want to calculate the probability of participation given characteristics x_{it} and z_{it} we have

$$E_t\left[I \middle| x_{it}, z_{it}\right] = \Phi\left[\frac{a_0 + a^{'} z_{it}}{\sigma_v^2}\right] \tag{2.6}$$

Following the Heckman (1979) procedure, we adjust the wage equation for participation effects by inputting (2.5) in the wage equation and correcting for the correlation between the error term in each equation using the Inverse Mills Ratio[3] as shown below

$$E_t\left[\ln w_{it} \middle| x_{it}, z_{it}\right] = \beta_0 + \beta^{'} x_{it} + \frac{\sigma_{\epsilon v}}{\sigma_v} \lambda \left[\frac{a_0 + a^{'} z_{it}}{\sigma_v^2}\right] \tag{2.7}$$

The aim here is to construct a bias free average hourly wage statistic and compare this with an aggregate wage statistic. Unlike previous studies, which control for this by holding constant the weighting μ_{it} to keep the composition of the workforce constant, we extend the definition to control for both movements in and out of work and hours variation. Thus a typical aggregate wage measure would be better defined as;

$$\overline{w}_t = \frac{\sum_{i \in (I=1)} h_{it} w_{it}}{\sum_{i \in (I=1)} h_{it}} = \sum_{i \in (I=1)} \mu_{it} w_{it} \tag{2.8}$$

where $i \in (I = 1)$ is the condition that individual i is a member of the work force and μ is the hours-weights,

[3] $\lambda[.]$ is the Inverse Mills Ratio = $\phi[.]/\Phi[.]$, where $\phi[.]$ is the normal density function, and $\Phi[.]$ is the cumulative distribution function.

gives the 'uncorrected' aggregate wage statistic.

Thus, the problem is decomposing $\overline{w}_{it}$ to its 'true' value, plus three additional bias terms that can interpret the effect of heterogeneity (log-nonlinearity), participation and hours weighting. To put simply, we know that $\overline{w}_{it} = 'true\ average\ wage' + biases$. Then if we know the 'true average wage', we could easily calculate the sum of the biases, and if we know the bias terms we could easily calculate the 'true average wage'. For purpose of comparison and confidence, we calculate both. The 'true average wage' comes from the regression of the micro-model highlighted in Section 2.1. Taking the difference will obviously yield the associated bias as calculated from the micro-model. Conversely, we can do it the other way round and calculate the biases first and obtain the 'true wage' after controlling for these effects. Below we show the methods of obtaining the bias terms.

Constructing the bias terms requires that we make identifying assumption of normality in the distribution of observable heterogeneity, x_{it} and z_{it} in individuals (Blundell and Stocker, 2005)[4]. In detail that is;

$$\begin{pmatrix} \beta_0 + \beta' x_{it} \\ \alpha_o + \alpha' z_{it} \end{pmatrix} \backsim N \left(\begin{pmatrix} \beta_0 + \beta' E(x_{it}) \\ \alpha_0 + \alpha' E(z_{it}) \end{pmatrix}, \begin{pmatrix} \beta' \sum_{xx} \beta & \alpha' \sum_{xz} \beta \\ \beta' \sum_{xz} \alpha & \alpha' \sum_{zz} \alpha \end{pmatrix} \right) \tag{2.9}$$

The simplest of the bias terms is the dispersion term (DSP) which adjusts for log-nonlinearity because aggregate wages statistics take the log of average wages and do not incorporate individual heterogeneity. The degree of bias due to both observed and unobserved heterogeneity can be calculated by taking the difference between average wages, $E[w|I=1]$, which is equal to $e^{\beta_0 + \beta' E(x_{it}) + \frac{1}{2}[\beta' \sum_{xx} \beta + \sigma_\epsilon^2]}$ (we take logs of this calculation), with the individual wage equation evaluated at mean log wages (or mean attributes), $E[\ln w|I=1] = \beta_0 + \beta' E(x_{it}) + \beta' \sum_{xx} \beta + \sigma_\epsilon^2$, where its variance is associated with proportional variation across individual workers in each period t. This gives the spread; half times the variance of individual log wages at every time period t plus the variance of the error term (Blundell et al. 2003), as shown below;

[4]The assumption of Normality in error terms is considered reasonable here. Distribution plots provided in the appendix-A.1 show that the assumption holds.

$$DSP = \ln E[w|I=1] - E[\ln w|I=1] \tag{2.10a}$$

$$= \beta_0 + \beta^{'} E(x_{it}) + \frac{1}{2}[\beta^{'} \sum\nolimits_{xx} \beta + \sigma_\epsilon^2] - \beta_0 + \beta^{'} E(x_{it}) + \beta^{'} \sum\nolimits_{xx} \beta + \sigma_\epsilon^2 \tag{2.10b}$$

$$= -\frac{1}{2}\left[\beta^{'} \sum\nolimits_{xx} \beta + \sigma_\epsilon^2\right] \tag{2.10c}$$

To see this point more clearly, it may help to remember that the micro-model log wage estimate $E_t(\ln W)$ is equal to the mean of wage influencing attributes $\beta_0 + \beta^{'} E(x_{it})$, with variance $\beta^{'} \sum_{xx}\beta + \sigma_\epsilon^2$. Thus, if one takes the difference between the log of the mean wage (un-weighted) at time t and the mean of log wages (where variance is associated with proportional variation across workers) we get the above result. More accurately, the DSP term is in fact a variance adjustment when taking expectations of log variables. If earnings inequality varies throughout the sample period, DSP will increase and decrease accordingly since it is essentially a measure of the variance in wages, which are both observable and unobservable (Blundell et al. 2003, Blundell and Stoker 2005).

The construction of the other terms is slightly more complex and requires some explanation of two formulae. First, using a formula developed by McFadden and Reid (1975) we can express the aggregate participation rate in the same from as the probit model (equation 2.5):

$$E_t\left[I \middle| x_{it}, z_{it}\right] = \Phi\left[\frac{\alpha_0 + \alpha^{'} E(\zeta_{it})}{\sqrt{\alpha^{'} \sum_{zz} \alpha + \sigma_v^2}}\right] \tag{2.11}$$

with, z_{it}, replaced by, $E(z_{it})$, and with the variance, σ_v^2, replaced with, $\sqrt{\alpha^{'} \sum_{zz} \alpha + \sigma_v^2}$, we can account for heterogeneity in individual characteristics that influence the participation selection criterion. Equally, obtaining a measure for mean log wages of (participating) workers only is necessary to construct our bias adjustment terms. This is because we want to use this measure to separate the effects of participation in aggregate wages. Utilising similar techniques to above, the formulae (formally) devised by MaCurdy (1987) gives

$$E_t\left[\ln w_{it}|I_{it}=1, x_{it}z_{it}\right] =$$

$$\beta_0 + \beta' E(x_{it}|I_{it}=1) + \frac{\sigma_{\epsilon v}}{\sqrt{\alpha' \sum_{zz}\alpha + \sigma_v^2}}\lambda\left[\frac{\alpha_0 + \alpha' E(z_{it})}{\sqrt{\alpha' \sum_{zz}\alpha + \sigma_v^2}}\right] \tag{2.12}$$

Again as above, this formula is equivalent to the micro-model log wage equation (2.6), with the obvious replacements, x_{it} with $E(x_{it}|I_{it}=1)$, z_{it} with $E(z_{it})$ and σ_v with $\sqrt{\alpha' \sum_{zz}\alpha + \sigma_v^2}$.

To complete the set-up, we also need an equation that can convert our micro-model results into an aggregate wage statistics that does not adjust for any biases. We use a similar expression to that of Blundell, Reed and Stocker (2003) for the aggregate wage measure as,

$$\ln \overline{W}_t = \ln \sum_{j=1}^{J} w_{jt} \frac{E[h_{it}|I_{it}=1].Pr(I_{it}=1)}{E[\overline{h}_{it}|I_J=1].Pr(I_J=1)} \tag{2.13}$$

Using the information from (2.11), we can construct the participation adjustment term (labelled SEL) in a similar fashion to DSP. All we really need is to take the calculation of (2.11) minus the log of mean wages, as shown below;

$$\ln E[w_{it}|I_{it}=1] - \ln E_t(w_{it}) = SEL \tag{2.14}$$

One key problem here is converting equation (2.10), which takes the expectation of log variables, into one that takes logs of expected variables. Blundell et al. (2003) show that with the distributional assumptions highlighted above we can derive the following transformation using (2.10), (2.11) and (2.9) to deliver the following result[5];

[5] Details are given in a separate appendix upon request

$$\ln E[w_{it}|I_{it},x_{it},z_{it}] =$$

$$\beta_0+\beta^{'}E(x_{it})+\frac{1}{2}[\beta^{'}\sum_{xx}\beta+\sigma_\epsilon^2].\ln\left[\frac{\Phi\left(\frac{\alpha_0+\alpha^{'}E(z_{it})+(\beta^{'}\sum_{xz}\alpha+\sigma_{\epsilon v})}{\sqrt{\alpha^{'}\sum_{zz}\alpha+\sigma_v^2}}\right)}{\Phi\left(\frac{\alpha_0+\alpha^{'}E(z_{it})}{\sqrt{\alpha^{'}\sum_{zz}\alpha+\sigma_v^2}}\right)}\right] \tag{2.15}$$

Taking the difference from log of mean wages, $\ln E(w_{it}) = \beta_0 + \beta^{'}E(x_{it}) + 1/2[\beta^{'}\sum_{xx}\beta + \sigma_\epsilon^2]$, which does not control for selection effects, give us the expression for the bias due selection effects only (SEL);

$$\ln\left[\frac{\Phi\left(\frac{\alpha_0+\alpha^{'}E(z_{it})+(\beta^{'}\sum_{xz}\alpha+\sigma_{\epsilon v})}{\sqrt{\alpha^{'}\sum_{zz}\alpha+\sigma_v^2}}\right)}{\Phi\left(\frac{\alpha_0+\alpha^{'}E(z_{it})}{\sqrt{\alpha^{'}\sum_{zz}\alpha+\sigma_v^2}}\right)}\right] \equiv SEL \tag{2.16}$$

Which reflects the aggregate wage effects of compositional changes within the sample of workers when measuring aggregate wages;

Finally, using the above information we can also isolate the hours-weighting adjustment and calculate the consequent bias due to hours variation, which we label as the, HR, term. This simply requires us to remove the wage calculation that controls for participation bias only (2.14) from the aggregate wage statistic (2.12). The remainder will indicate the bias from hours-weighting in aggregate wage statistics due to variations in hours worked among different workers. It will be particularly useful in understanding the extent to which distortions in the wage distribution function can be attributed to hours changes only and how individuals hours supply responds to real wage changes. Essential this is a calculation of the co-variance between hours worked and real wages;

$$\ln\overline{W}_t = \ln\sum_{j=1}^{J} w_{jt}\frac{E[h_{it}|I_{it}=1].Pr(I_{it}=1)}{E[\overline{h}_{it}|I_J=1].Pr(I_J=1)}$$

$$= \ln E[w_{it}|I_{it},x_{it},z_{it}] + HR$$

$$= \ln\overline{W}_t - \ln E[w_{it}|I_{it},x_{it},z_{it}] = HR \tag{2.17}$$

$$HR \equiv \ln\left[\frac{h_0+\gamma\alpha_0+\gamma\alpha' E(z_{it})+\gamma\beta^{'}\sum_{xz}\alpha+\gamma\sigma_{\epsilon v}+\gamma\sqrt{\alpha'\sum_{zz}\alpha+\sigma_v^2}.\lambda_{\epsilon v,t}^{\alpha}}{h_0+\gamma\alpha_0+\gamma\alpha' E(z_{it})+\gamma\sqrt{\alpha'\sum_{zz}\alpha+\sigma_v^2}.\lambda_t^{\alpha}}\right]$$

2.3 The Data

The U.K. Family Expenditure Survey (FES), a repeated cross-sectional survey of household, from years 1979-2000 provides detailed information on individual characteristics. We have 84,037 observations all males aged between 23 and 59 (85.44% employment rate) for the participation equation and 64,226 for the wage equation when the self-employed are included as if they were waged workers such that our employment variable includes those self-employed. We take log hourly wage, as the log of weekly wages including over-time pay divided by the weekly hours measure (including over-time hours) as defined by the FES. To obtain a real wage measure, the quarterly U.K. retail price index is used as the deflator. The explanatory variables include; two education attainment dummies, measured as; left full time education at age seventeen to eighteen and the second dummy for completion of full-time education at age greater than eighteen, with the remaining observations (both dummies equal to zero) as left education at sixteen or below. Out-of-work income (simulated income at zero hours) is calculated for all individuals using a tax and benefit simulation model (TAXBEN) designed by the Institute for Fiscal Studies (IFS) using FES data[6]. Other explanatory variables comprise of spouse's education dummy, calculated as, completion of full-time education at age greater than sixteen and a marital status dummy, which is also interacted with our out-of-work income simulation variable to capture differences in received benefit income between singles and married couples[7]. A subtle addition to the model is the inclusion of trend and cohort interaction terms to capture time effects and other factors that would not increase wages proportionally across all groups[8]. Cohort dummies are entered as five date-of-birth cohorts (1919-1934, 1935-1944, 1945-1954. 1955-1964 and 1965-1977) and also as interaction variables. That is eleven regional dummies and both education dummies and trend variable (including trend squared and cubed) are all separately interacted with cohort variables. These capture a portion of unobservable or complex time effects such as changes in laws (e.g. minimum school leaving age)[9], wars, or demographics (baby boomers' drastically increasing the available labour supply) that may influence wages. They also perform better when compared with other specifications as noticed by standard specification search, semi-parametric estimations and bootstrapping (Blundell et al. 2003).

[6]Housing benefit assistance reforms in 1983 resulted in poor data collection methods for TAXBEN figures. As a result, we drop this period from the sample.

[7]see Blundell et al. (2003)

[8]The implication is that the model does not conform to the strict proportionally assumption. This may be viewed as a more flexible and realistic framework (see Blundell et al. 2005).

[9]For a detailed discussion on Cohort interactions capturing wage effects (see Gosling et al., 2000).

3 Analysis of Results:

Here the intention is to compare the evolution of real wages once having corrected the wage index for any biases. First, some specification tests to reassure the modeling devices are valid, most importantly is the significance of our selection term and the appropriateness of our exclusion restriction (Benefit Income) which is essential for the identification of equations in our model. In particular, we would like to see to what extent and in which direction selectivity, heterogeneity in the wage distribution and hours weighting biases our wage statistics and how drastically the wage profile changes once we control for these effects. We find the analyses clearly indicate two crucial results: Firstly, composition effects are important over the cycle, but more so, the degree of wage dispersion. Secondly, the magnitude and behavior is not enough to generate a clear pattern of counter or pro-cyclical wage profile.

Table 1: Significance Test for Regression Specification

	Participation Equation		*Wage Equation*	
	$Chi-Squared(df)$	$Prob > chi^2$	$F-Test(df)$	$P-value$
Variables:				
Benefit-Income (when out of work)* marital status	2233.46(3)	0.0000	N/A	
Education (left at 17-18, after 18)	7.36 (2)	0.0000	53.55 (2,n)	0.0000
Trend (1st 2nd and 3rd-order)	43.64 (3)	0.0000	53.55 (3, n)	0.0000
Cohort (all estimated cohort variables)	21.41 (4)	0.0003	0.93 (4, n)	0.4454
Education * trend	17.72 (6)	0.0070	32.47 (6, n)	0.0000
Education * Cohort	9.7 (8)	0.2852	31.05 (8, n)	0.0000
Trend * Cohort	497.60 (12)	0.0000	24.06 (12, n)	0.0000
Education * trend (1st order) * cohort	5.32 (8)	0.4982	7.48 (8, n)	0.0000
Region (11 standard regions)	70.08 (10)	0.0000	7.48 (10, n)	0.0000
Region * trend (1st and 2nd order)	46.86 (20)	0.0006	6.59 (20, n)	0.0000
Mills ratio * marital status	N/A		91.30 (2, n)	0.0000
Couple	873.82 (1)	0.0000	501.64(1, n)	0.0000
Spouse's education	23.23 (1)	0.0000	N/A	

In Table 1 benefit income is statistically significant in explaining participation probabilities. While this exclusion restriction is not directly testable, we show that the exogeneity of benefit income to the wage equation is satisfied once we control for attributes that are collinear to both wages and benefit income entitlement. These are typically number and age of children in the household and also age of claimant and the region in which they reside. Once these factors are conditioned, the exclusion restriction is indeed satisfied given that it is statistically insignificant when included the wage equation[10]. Additional interaction terms are also tested for joint significance in table 1 above and the important result is the significance of the inverse Mills ratios in the wage equation. This would suggest that wages are correlated to employment probabilities and do in fact cause significant changes to log wage outcomes at the individual level. To what extent this translates into aggregate distortions will be determined below.

Taking means of cross sections over time is enough to construct an aggregate wage index that shows the evolution of different wage profiles over the cycle, as shown below.

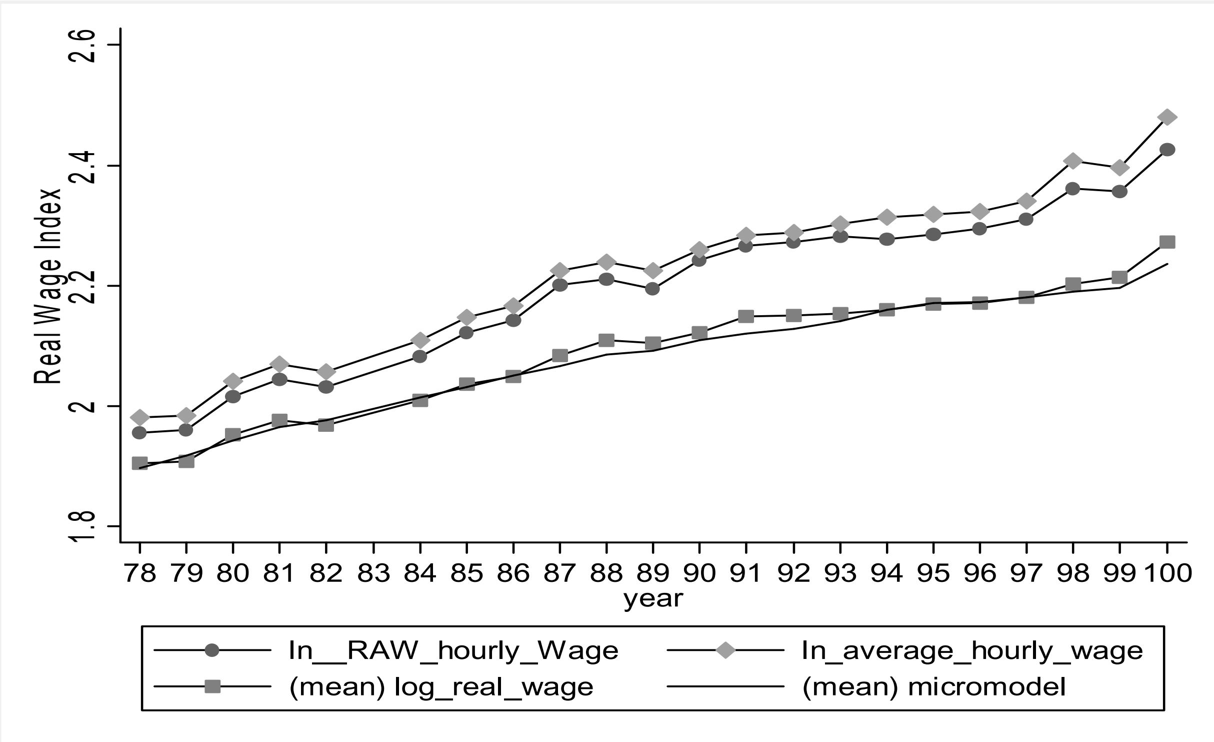

Figure 1: *Plot of Uncorrected Wage Series, Corrected Wages Series for Hours Bias, Dispersion Bias and Selectivity Bias*

Average hourly wages in Britain increased by 34 percent, rather than the 50 percent (for 1978-2000) implied by typical aggregate wage statistics. Most notably, we see that there is a strong element of divergence between both the DSP and SEL bias-adjusted series (labeled (mean) of log_real_wage and micromodel respectively) from the 'raw' aggregate wage index. Another, re-occurring feature is that the uncorrected series consistently exaggerates positive and negative wage fluctuations. Obviously, for there to be a general up-ward bias it must over-exaggerate wage increases more than decreases in wages. However, this does not imply a pro-cyclical bias, particularly so because none of the series displays pro-cyclicality dur-

[10]See appendix for full results on this.

ing cycle periods. Since the direction of wage movements between the series do not always coincide with one another (Blundell et al. 2003 have equivalent findings) the result is much more difficult to explain. In the early 1980's, wage movements do appear to correspond with each other, though the uncorrected series displays more wage growth. By contrast, in the 1990's we see wage growth in the uncorrected series but no growth (or negative growth in 1995-1996) in the dispersion bias corrected and micromodel wage series.

Examining the different bias terms individually can help explain why our results are so different to conventional wisdom. Taking selection effects first, the selectivity corrected series (micromodel) displays a fairly smooth wage profile, which is unresponsive to cycles. While during recessions we find the biases due to selection effects mitigate the observed counter-cyclicality in the 'raw' series, there is still not enough movement in composition required to generate a procyclical wage profile. The main explanation for such mild effects is that the probability of employment or unemployment is roughly equal for members across the full wage distribution (Heckman 1979) and group specific variation seems to be only mildly present during recessions, but more random in all other periods. We also observe in *figure 2* that these effects are not exclusive to cycle periods nor are they more pronounced during recessions. In fact, the effect on aggregate wages due to changing composition is minimal and fluctuates throughout the whole sample period, with the largest of these fluctuations occurring during non-recessionary time frames. The crucial point here is that though selection effects are positively related to wages[11], the ambiguity of composition changes stems from the interaction of demand side effects (distribution of wage offers) with shocks to individuals' willingness to supply labour at a price (such as out-of-work options). Thus the wedge between market wages and reservation wages becomes crucial in determining when labour is willing to participate or not and thus affects the supply curve and market wages.

Turning to hours bias (HR), we can clearly see from the hours-weighting corrected wage index (labeled ln_average_hourly_wage) that the bias is slightly downwards (correction is up-ward) but corresponds very closely to movements in the uncorrected wage statistic. It appears as a shift in the intercept rather than a change in the direction of wage movements and thus 'composition bias' due to variations in working hours does not affect any specific group and the weighting of hours to groups implied by aggregate wage statistics does not cause either counter or pro cyclical composition bias. According to Solon et al. (1994), we would have expected the hours corrected wage index (ln_average_houly_wage) to fall substantially during recession and increase during expansion ('counter-cyclical' composition bias). The fact that this is parallel to uncorrected aggregate series is interesting when considering that the results contradict the widely adopted view that low-wage workers are typically more sensitive to hours variation during business

[11] See appendix for positive correlation coefficient on inverse Mills ratio.

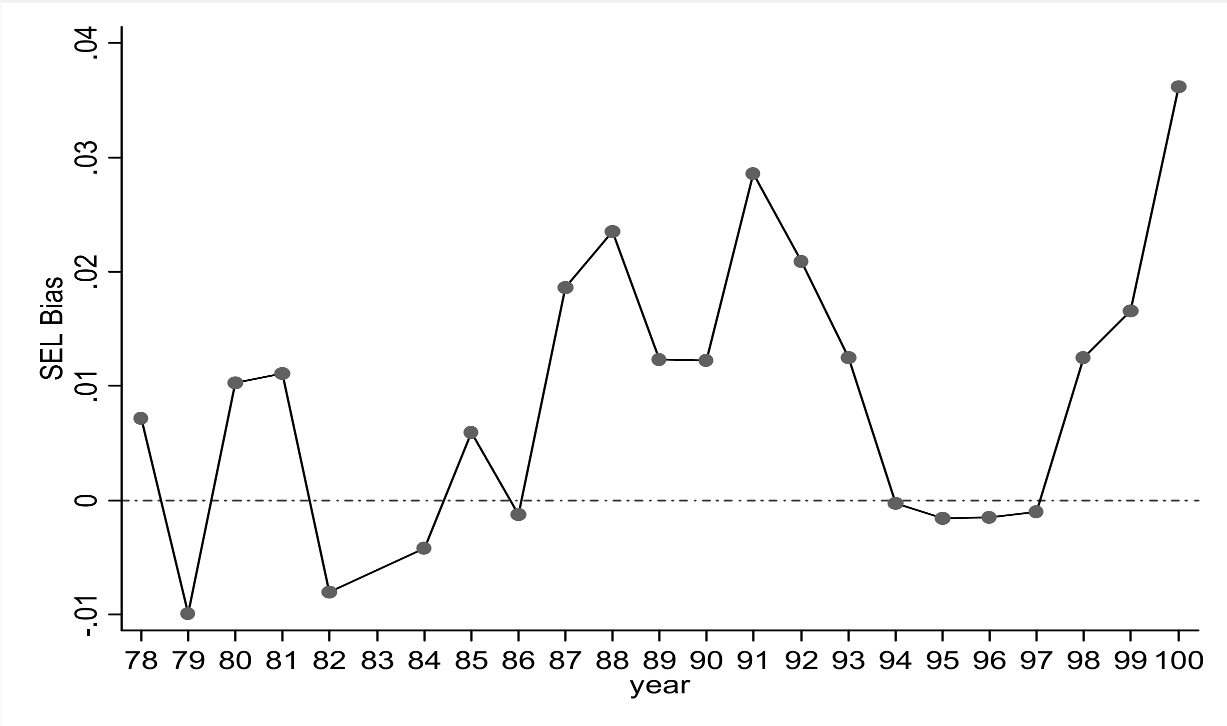

Figure 2: *Plot of Selection Bias Term (SEL)*

cycles. The observed stability and low magnitude of hours bias term in *figure 3* implies that hours variation in the British labour market is limited in explaining cyclical composition bias (see Blundell et al., 2004) for evidence and in-depth discussion). In fact, looking at the systematic time trend in the relationship between hours variation and employment variation (in *figure 4*) it is easy to justify the importance of separating the effect of hours fluctuations and employment fluctuations to resolve composition bias issues. The fact that the HR term is reasonably stable and SEL is far more volatile in conjunction with *Figure 4* can only mean that the largest factor influencing the variation in hours work is due to workers who change employment status (selection bias) rather than worker who adjust hours in their current (on-going) job. This is also provides a strong case for the notion that employees tend to face hours constraints due to employment contracts (see Blundell et al. 2004). While this is nice anecdotal evidence, a more comprehensive study on the variation in hours for job-to-job movers over the cycle would be much more informative about how the degree of hours constraints imposed by wage contracts affects the decisions to move from one job to another or even out-of-employment.

In sum, it is clear from the evidence above that the weighting imposed by variation in hours is irrelevant to the composition bias story. The downward bias suggests that hours worked is censored from the top end of the wage distribution, implying that there is a maximum hours worked (capacity constraint) which restricts the wage hour combination from increasing any further. This would cause a downward

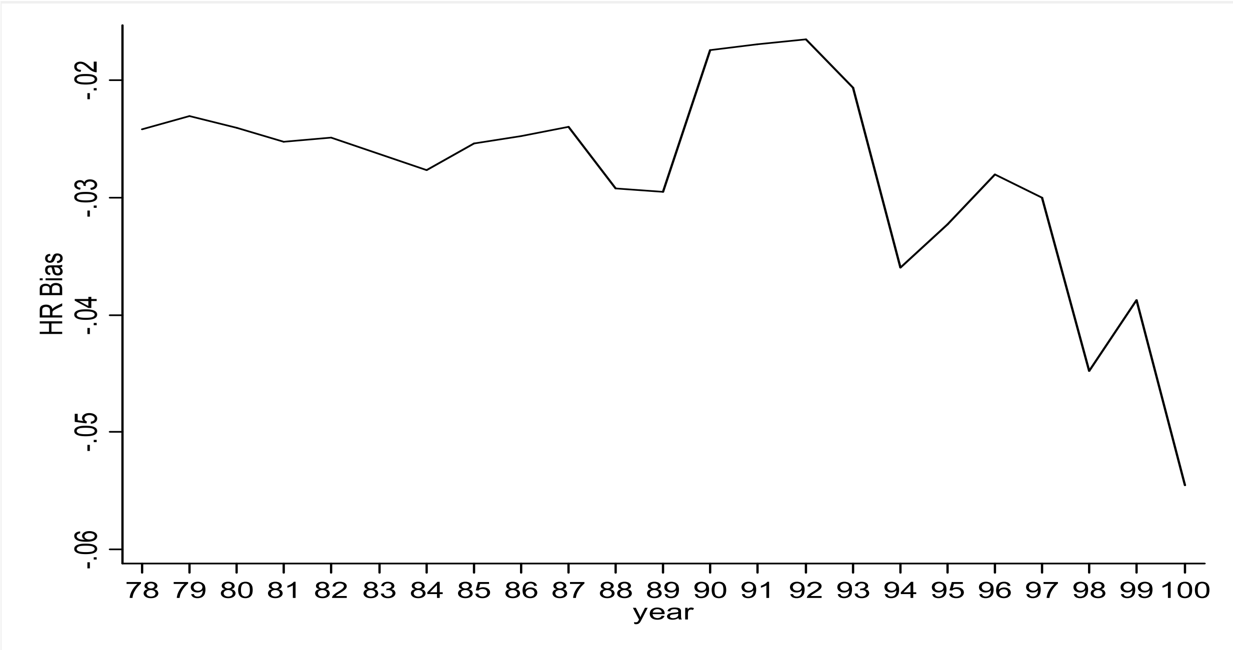

Figure 3: Plot of Hours Weighting Bias (HR)

Figure 4: Plot of Percentage change in Employment (d_work) and Weekly hours (d_weekly_hours)

bias in the mean, as observed above. Our final term is probably the most interesting, as it is evidently the main source of bias in wages, but is rarely ever mentioned in the literature on real wage cyclicality. The correction for heteroskedastic wage distribution reduces the aggregate wage measure by a significant 18.96% for the period 1978-2000. In addition, the adjusted wage index ((mean)log_real_wage) does not always correspond with aggregate uncorrected wage movements, particularly for the 1990s. The differences in both observable and unobservable individual wage characteristics cause a considerable amount of bias in mean wages, but this results does not attach any significance to any particular group of low or high wage individuals, otherwise there would be a clear interpretable pattern (shown by our three bias terms) that would be informative of groups which are sensitive to cycles. The only concrete statement we can make here is that the larger inequality there is in labour markets the larger the biases in mean wage statistics. This would suggest that the majority of bias when measuring wages is due to the selection rule imposed either by the researcher or the process that generates the data (as opposed to self-selection). Thus a constant or random selection criterion due to truncation from the lower end of the wage distribution would cause such a result. Given the large body of literature on the growth of earnings and wealth inequality in Britain throughout the period (Gosling et al., 1994, Brewer et al., 2007), it is easy to see why the DSP term contributes the most to distorting aggregate wage measures. What is even more interesting is that the DSP term behaves more cyclically than all other bias terms though in the 1990s it is far more erratic (*figure 5*).

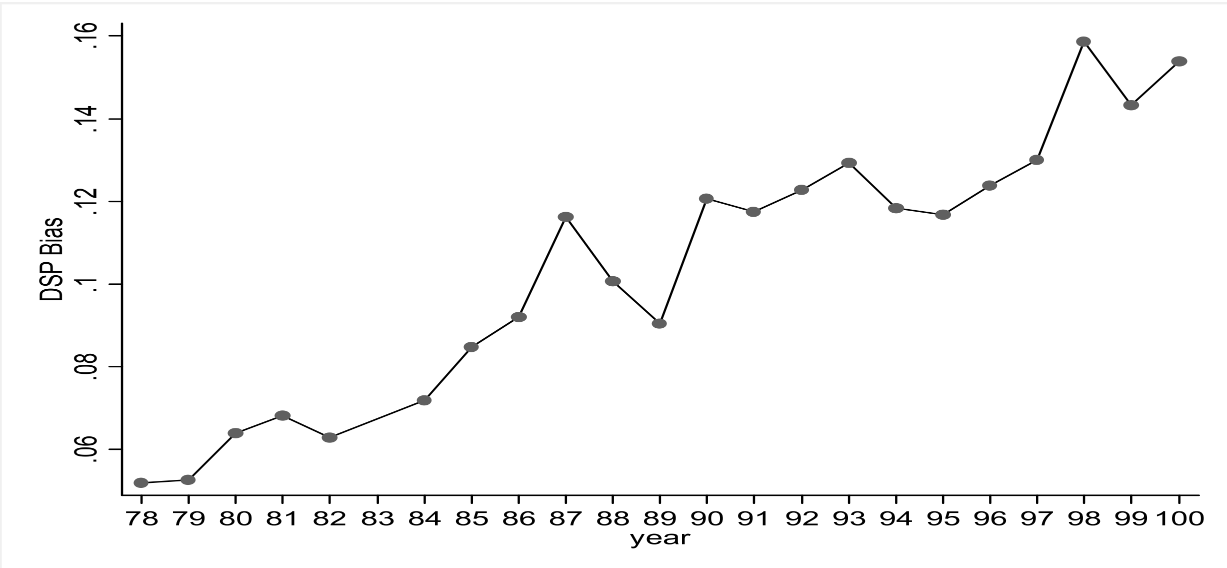

Figure 5: *Plot of Dispersion Bias (DSP)*

4 Conclusion:

The findings here show a clear method that addresses the problems posed in previous studies as well as paving the way for new and informative estimation techniques for addressing the wage problem. In particular, we see that when we do not control for sample selection and heterogeneity there is considerable up-ward bias in real wage statistics because individuals self-select themselves into favorable sectors of the economy whenever they can. Ignoring self-employed and unemployed individuals in the estimation reduces the reliability of results, which is magnified during business cycles as individuals move from waged work to self-employment or register themselves as unemployed since market incentives change during recessions (and in some cases during non-recessionary times). Thus, studies that seek to determine the cyclicality of real wages, must find room to incorporate self-employed and unemployed individuals when estimating aggregate real wage equations. Our main finding is that, selectivity issues cause considerable up-ward bias in aggregate real wages, however these biases do not seem to influence the cyclical profile of wages in a clear cut direction. In fact the initial observations made by Blanchard and Fischer (1989) and Mankiw (1989) correspond to what is observed here and we are essentially back to where we started.

Many papers have address the real wage cyclicality issue but it is incredibly difficult to determine which of the two theoretical stories are true and thus most refer to this as a puzzle. The preceding analysis does suggest that for the given sample of British males during 1978-2000, real wages are generally insensitive to cycles. This is because our results show that selectivity is positively related to wages, such that labour supply shifts during cycle-upswings offsetting the increase in demand by increased competition for jobs. In addition because we have compositional changes and policy changes throughout through time, our results indicate that a large part of the changes in wage movements are due to shifts in the supply and composition of labour. With our corrections to the “raw” data, we are able to understand the “true” cyclicality of real wages, however I doubt that the causes of wage and employment movements will be understood purely through the search of an empirical ‘law’ of real wage cyclicality because demand and supply in labour markets have a complex and intimate relationship that is very hard to capture analytically. Observed patterns of wage behaviour are governed by factors out of the scope of the current paradigm of aggregative macroeconomic models because it is incredible hard to abandon the representative agent framework. Thus a very plausible conclusion and further extension to improve our understanding of the cyclicality of real wages would be to guide research into making attempts to accurately treat heterogeneity in labour supply behavior into macro-models of business cycles. A starting point would be to attempt to build models that match acyclicality in real wages rather that pro or counter cyclicality.

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Appendix

A Full Regression Results

A.1 Participation Equation

Table 2: Probit Regression, Reporting Marginal Effects

Iteration 0: log likelihood = -34394.17	Number of obs	= 84035
Iteration 1: log likelihood = -30370.45	LR $chi^2(78)$	= 8562.52
Iteration 2: log likelihood = -30119.19	Prob>chi^2	= 0.0000
Iteration 3: log likelihood = -30112.93	Pseudo R^2	= 0.1245
Iteration 4: log likelihood = -30112.91	log likelihood	= -30112.91
Iteration 5: log likelihood = -30112.91		

<table>
<tr><th>Dependent variable: Employment Status Dummy |</th><th>dF/dx.</th><th>Std. Err.</th><th>z</th><th>P>|z |</th><th>x-bar</th><th colspan="2">[95% Conf. Interval]</th></tr>
<tr><td>log simulated TAXBEN out-of-work income, single men |</td><td>-0.0458546</td><td>0.0024803</td><td>-18.440</td><td>0.0000</td><td>1.03007</td><td>-0.050716</td><td>-0.040993</td></tr>
<tr><td>log simulated TAXBEN out-of-work income, married men |</td><td>-0.1274595</td><td>0.0028739</td><td>-42.080</td><td>0.0000</td><td>3.66323</td><td>-0.133092</td><td>-0.121827</td></tr>
<tr><td>Simulated out-of-work income zero or missing |</td><td>0.0712091</td><td>0.0112423</td><td>4.080</td><td>0.0000</td><td>0.010389</td><td>0.049174</td><td>0.0932440</td></tr>
<tr><td>sp~educ, Spouse's eductation dummy |</td><td>0.0130416</td><td>0.0026865</td><td>4.820</td><td>0.0000</td><td>0.430737</td><td>0.007776</td><td>0.0183070</td></tr>
<tr><td>Couple, marital status dummy |</td><td>0.8169138</td><td>0.0194596</td><td>29.560</td><td>0.0000</td><td>0.746867</td><td>0.778774</td><td>0.8550540</td></tr>
<tr><td>ed17, education dummy at age 17 |</td><td>0.0560942</td><td>0.0175116</td><td>2.680</td><td>0.0070</td><td>0.138942</td><td>0.021772</td><td>0.0904160</td></tr>
<tr><td>ed18, education dummy at age 18 |</td><td>0.0162486</td><td>0.0212879</td><td>0.730</td><td>0.4630</td><td>0.151877</td><td>-0.025475</td><td>0.0579720</td></tr>
<tr><td>trend1, |</td><td>-0.0122000</td><td>0.0043735</td><td>-2.790</td><td>0.0050</td><td>11.4945</td><td>-0.020772</td><td>-0.003628</td></tr>
<tr><td>trend2, Trend Squared |</td><td>0.0011235</td><td>0.000386</td><td>2.910</td><td>0.0040</td><td>172.873</td><td>0.000367</td><td>0.0018800</td></tr>
<tr><td>trend3, Trend Cubed |</td><td>-0.0000362</td><td>0.0000106</td><td>-3.430</td><td>0.0010</td><td>2923.93</td><td>-0.000057</td><td>-0.000015</td></tr>
<tr><td>c1919_1934, Cohrot dummy: born in 1919-34 |</td><td>0.0177225</td><td>0.0156872</td><td>1.080</td><td>0.3060</td><td>0.13899</td><td>-0.013024</td><td>0.0484690</td></tr>
<tr><td>c1935_1944, Cohrot dummy: born in 1935-44 |</td><td>0.0198561</td><td>0.0147912</td><td>1.290</td><td>0.2140</td><td>0.221741</td><td>-0.009134</td><td>0.0488460</td></tr>
<tr><td>c1955_1964, Cohrot dummy: born in 1955-64 |</td><td>-0.0801869</td><td>0.0289346</td><td>-3.080</td><td>0.0040</td><td>0.244838</td><td>-0.136898</td><td>-0.023476</td></tr>
<tr><td>c1965_1977, Cohrot dummy: born in 1965-77 |</td><td>0.2686747</td><td>0.0894892</td><td>2.260</td><td>0.0440</td><td>0.94294</td><td>0.093279</td><td>0.4440700</td></tr>
<tr><td>c1919~ed17, Cohort 1919 Interaction With ed17 |</td><td>-0.0797786</td><td>0.0403355</td><td>-2.330</td><td>0.0070</td><td>0.010032</td><td>-0.158835</td><td>-0.000723</td></tr>
<tr><td>c1935~ed17, Cohort 1935 Interaction with ed 17 |</td><td>-0.0354454</td><td>0.0286458</td><td>-1.350</td><td>0.1090</td><td>0.023419</td><td>-0.091599</td><td>0.0206900</td></tr>
<tr><td>c1955~ed17, Cohort 1955 Interaction with ed17 |</td><td>-0.0436685</td><td>0.029666</td><td>-1.630</td><td>0.0980</td><td>0.044124</td><td>-0.101813</td><td>0.0144760</td></tr>
<tr><td>c1965~ed17, Cohort 1965 Interaction with ed17 |</td><td>-0.0563042</td><td>0.0810416</td><td>-0.790</td><td>0.3950</td><td>0.01898</td><td>-0.215143</td><td>0.1025340</td></tr>
<tr><td>c1919~ed18, Cohort 1919 Interaction with ed18 |</td><td>0.0301862</td><td>0.0264086</td><td>1.010</td><td>0.4890</td><td>0.008187</td><td>-0.021574</td><td>0.0813460</td></tr>
<tr><td>c1935~ed18, Cohort 1935 Interaction with ed 18 |</td><td>0.0206029</td><td>0.0215897</td><td>0.890</td><td>0.5040</td><td>0.02324</td><td>-0.021712</td><td>0.0629180</td></tr>
<tr><td>c1955~ed18, Cohort 1955 Interaction with ed 18 |</td><td>-0.0019115</td><td>0.0238562</td><td>-0.080</td><td>0.9210</td><td>0.046731</td><td>-0.048669</td><td>0.0448460</td></tr>
<tr><td>c1965~ed18, Cohort 1965 Interaction with ed 18 |</td><td>0.0420859</td><td>0.0440293</td><td>0.800</td><td>0.3570</td><td>0.02224</td><td>-0.044210</td><td>0.1283820</td></tr>
<tr><td>c19~trend1, Cohort 1919 Interaction With Trend 1st order |</td><td>-0.0274894</td><td>0.008099</td><td>-3.390</td><td>0.0020</td><td>0.799572</td><td>-0.043363</td><td>-0.011616</td></tr>
<tr><td>c35~trend1, Cohort 1935 Interaction With Trend 1st order |</td><td>0.0030982</td><td>0.0056036</td><td>0.550</td><td>0.6100</td><td>2.31073</td><td>-0.007885</td><td>0.0140810</td></tr>
<tr><td>c55~trend1, Cohort 1955 Interaction With Trend 1st order |</td><td>0.0066194</td><td>0.0068472</td><td>0.970</td><td>0.4190</td><td>3.3427</td><td>-0.006801</td><td>0.0200400</td></tr>
</table>

c65~trend1, *Cohort 1965 Interaction with Trend 1st order*	-0.2048681	0.0966127	-2.120	0.0610	1.72746	-0.394226	-0.015511
Ed17~trend, *Ed 17 Interaction with Trend 1st order*	0.0075383	0.0072598	1.040	0.3350	1.75128	-0.006691	0.0217670
Ed17~trend2, *Ed 17 Interaction with Trend 2nd order*	-0.0005294	0.0006714	-0.790	0.5090	27.5709	-0.001845	0.0007870
Ed17~trend3, *Ed 17 Interaction with Trend 3rd order*	0.0000089	0.0000182	0.490	0.7670	479.378	-0.000027	0.0000450
Ed18~trend1, *Ed 18 Interaction with Trend 1st order*	0.0261092	0.0072688	3.590	0.0000	1.97815	0.011863	0.0403560
Ed18~trend2, *Ed 18 Interaction with Trend 2nd order*	-0.0021361	0.00068	-3.140	0.0020	31.7567	-0.003469	-0.000803
Ed18~trend3, *Ed 18 Interaction with Trend 3rd order*	0.0000513	0.0000185	2.770	0.0090	559.128	0.000015	0.0000880
c19~ed17~trend1, *Cohort Interaction with 1st order Trend and Ed17*	0.0031944	0.0031411	1.020	0.2500	0.062379	-0.002962	0.0093510
c35~ed17~trend1, *Cohort Interaction with 1st order Trend and Ed17*	0.0003798	0.0017064	0.220	0.9080	0.25324	-0.002965	0.0037240
c55~ed17~trend1, *Cohort Interaction with 1st order Trend and Ed17*	0.0016250	0.001652	0.980	0.2960	0.612566	-0.001613	0.0048630
c65~ed17~trend1, *Cohort Interaction with 1st order Trend and Ed17*	0.0009676	0.0034233	0.280	0.7060	0.350116	-0.005742	0.0076770
c19~ed18~trend1, *Cohort Interaction with 1st order Trend and Ed18*	-0.0014080	0.0036534	-0.390	0.7800	0.051181	-0.008569	0.0057530
c35~ed18~trend1, *Cohort Interaction with 1st order Trend and Ed18*	-0.0024391	0.0017495	-1.390	0.1590	0.257821	-0.005868	0.0009900
c55~ed18~trend1, *Cohort Interaction with 1st order Trend and Ed18*	-0.0007452	0.0016144	-0.490	0.5940	0.663783	-0.003909	0.0024190
c65~ed18~trend1, *Cohort Interaction with 1st order Trend and Ed18*	-0.0043908	0.0034051	-1.290	0.1760	0.414982	-0.011065	0.0022830
c19~trend2, *Cohort Interaction with trend 2nd order*	-0.0017462	0.0011062	1.580	0.1800	6.7619	-0.000422	0.0039140
c19~trend3, *Cohort Interaction with trend 3rd order*	-0.0000438	0.0000449	-0.970	0.4140	69.2541	-0.000132	0.0000440
c35~trend2, *Cohort Interaction with trend 2nd order*	-0.0013969	0.0005469	-2.550	0.0200	32.283	-0.002469	-0.000325
c35~trend3, *Cohort Interaction with trend 3rd order*	0.0000484	0.0000154	3.140	0.0060	514.592	0.000018	0.0000790
c55~trend2, *Cohort Interaction with trend 2nd order*	-0.0001969	0.0006138	-0.320	0.9120	52.6236	-0.001400	0.0010060
c55~trend3, *Cohort Interaction with trend 3rd order*	0.0000086	0.0000165	0.520	0.7790	901.566	-0.000024	0.0000410
c65~trend2, *Cohort Interaction with trend 2nd order*	0.0109256	0.0056726	1.930	0.0910	32.5579	-0.000193	0.0220440
c65~trend3, *Cohort Interaction with trend 3rd order*	-0.0001775	0.0001092	-1.630	0.1630	628.479	-0.000392	0.0000370
reg1, *Region: Northern*	-0.0176156	0.191796	-0.960	0.3410	0.06475	-0.055207	0.0199760
reg2, *Region: Yorkshire Humberside*	0.0067807	0.0159603	0.420	0.7810	0.09045	-0.024501	0.0380620
reg3, *Region: North Western*	0.0030342	0.0153647	0.200	0.7580	0.111323	-0.027080	0.0331490
reg4, *Region: East Midlands*	0.0607447	0.0121278	3.880	0.0000	0.7529	0.369750	0.0845150
reg5, *Region: West Midlands*	0.0373444	0.0132339	2.490	0.0140	0.95448	0.114060	0.0632820
reg6, *Region: East Anglia*	0.0300335	0.0191646	1.400	0.2870	0.38615	-0.007529	0.0675960
reg7, *Region: Greater London*	0.0499535	0.0119285	3.530	0.0000	0.106349	0.026574	0.0733330
reg8, *Region: South East (Greater London excluded)*	0.0664054	0.010983	5.090	0.0000	0.195014	0.044879	0.0879320
reg9, *Region: South Western*	0.0380120	0.0145743	2.290	0.0330	0.083477	0.009447	0.0665770
reg10, *Region: Wales*	0.0022134	0.0185535	0.120	0.9280	0.052811	-0.034151	0.0385780
reg1~trend1, *Regional dummy interaction with 1st order Trend*	0.0004142	0.0033616	0.120	0.7950	0.672851	-0.006174	0.0070030
reg2~trend1, *Regional dummy interaction with 1st order Trend*	0.0025994	0.0031491	0.830	0.3660	1.04403	-0.003573	0.0087720
reg3~trend1, *Regional dummy interaction with 1st order Trend*	0.0023691	0.0029733	0.800	0.6030	1.27191	-0.003458	0.0081970
reg4~trend1, *Regional dummy interaction with 1st order Trend*	-0.0032953	0.0036035	-0.910	0.2450	0.874755	-0.010358	0.0037670
reg5~trend1, *Regional dummy interaction with 1st order Trend*	-0.0036844	0.0031794	-1.160	0.2460	1.07498	-0.009916	0.0025470
reg6~trend1, *Regional dummy interaction with 1st order Trend*	0.0056371	0.0044941	1.250	0.1810	0.449491	-0.003171	0.0144500
reg7~trend1, *Regional dummy interaction with 1st order Trend*	0.0001469	0.003108	0.050	0.7370	1.20669	-0.005945	0.0062390
reg8~trend1, *Regional dummy interaction with 1st order Trend*	0.0034183	0.0028756	1.190	0.4510	2.26604	-0.002218	0.0090540
reg9~trend1, *Regional dummy interaction with 1st order Trend*	0.0069285	0.0034762	1.990	0.1160	1.00825	0.000115	0.0137420
reg10~trend1, *Regional dummy interaction with 1st order Trend*	-0.0005283	0.003579	-0.150	0.7620	0.592777	-0.007543	0.0064860
reg1~trend2, *Regional dummy interaction with 2nd order Trend*	-0.0000593	0.0001401	-0.420	0.5430	9.91726	-0.000334	0.0002150
reg2~trend2, *Regional dummy interaction with 2nd order Trend*	-0.0000858	0.0001298	-0.660	0.4280	15.7243	-0.000340	0.0001690
reg3~trend2, *Regional dummy interaction with 2nd order Trend*	-0.0000911	0.0001229	-0.740	0.6080	19.0652	-0.000332	0.0001500
reg4~trend2, *Regional dummy interaction with 2nd order Trend*	0.0001041	0.0001471	0.710	0.3520	13.142	-0.000184	0.0003920
reg5~trend2, *Regional dummy interaction with 2nd order Trend*	0.0001858	0.0001315	1.410	0.1850	15.9901	-0.000072	0.0004440

reg6~trend2, *Regional dummy interaction with 2nd order Trend* |	-0.0001800	0.000185	-0.970	0.2990	6.79359	-0.000543	0.0001820
reg7~trend2, *Regional dummy interaction with 2nd order Trend* |	-0.0001157	0.0001276	-0.910	0.5700	18.1119	-0.000366	0.0001350
reg8~trend2, *Regional dummy interaction with 2nd order Trend* |	-0.0001495	0.0001181	-1.270	0.3790	34.2305	-0.000381	0.0000820
reg9~trend2, *Regional dummy interaction with 2nd order Trend* |	-0.0003108	0.0001414	-2.200	0.0680	15.5361	-0.000588	-0.000034
reg10~trend2, *Regional dummy interaction with 2nd order Trend* |	-0.0000028	0.0001474	-0.020	0.8960	8.84046	-0.000292	0.0002860

A.2 Wage Equation

Table 3: OLS Wage Regression Results

Source	SS	df	MS		Number of obs	= 61608
Model	3598.83897	76	47.3531443		F(76,61531)	= 258.52
Residual	11270.5417	61531	0.183168512		Prob>F	= 0.000
Total	14869.3807	61607	0.241358623		R-squared	= 0.2420
					Adj R-squared	= 0.2411
Dependent variable: log Real Wage |	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Inverse Mills Ratio for single men |	0.2373891	0.0211775	11.210	0.0000	0.1958812	0.278897
Inverse Mills Ratio for married men |	0.2265723	0.0218929	10.350	0.0000	0.1836622	0.2694824
couple |	0.1961925	0.0087596	22.400	0.0000	0.1790237	0.2133614
ed17 |	0.148942	0.0288533	5.160	0.0000	0.0923894	0.2054946
ed18 |	0.2027708	0.0273791	7.410	0.0000	0.1491076	0.256434
trend |	0.0141395	0.006654	2.120	0.0340	0.0010976	0.0271814
trend2 |	0.0005842	0.0006028	0.970	0.3320	-0.0005972	0.0017657
trend3 |	-0.0000321	0.0000169	-1.900	0.0570	-0.0000652	1.02E-06
c1919_1934 |	0.0347706	0.0237233	1.470	0.1430	-0.0117271	0.0812684
c1935_1944 |	0.0302112	0.0213776	1.410	0.1580	-0.0116889	0.0721113
c1955_1964 |	-0.0089235	0.0328825	-0.270	0.7860	-0.0733732	0.0555262
c1965_1977 |	-0.257635	0.8939805	-0.290	0.7730	-2.009839	1.494569
c1919_ed17 |	0.1273452	0.0370256	3.390	0.0010	0.0547748	0.1999155
c1935_ed17 |	0.1080187	0.0288796	3.740	0.0000	0.0514146	0.1646227
c1955_ed17 |	-0.1266528	0.0316173	-4.010	0.0000	-0.1886227	-0.0646829
c1965_ed17 |	-0.2235333	0.0977064	-2.290	0.0220	-0.4150381	-0.0320285
c1919_ed18 |	0.3855671	0.0384516	10.030	0.0000	0.3102019	0.4609323
c1935_ed18 |	0.1659035	0.0290224	5.720	0.0000	0.1090196	0.2227874
c1955_ed18 |	-0.2254942	0.0306486	-7.360	0.0000	-0.2855655	-0.1654229
c1965_ed18 |	-0.2887085	0.0903772	-3.190	0.0010	-0.4658481	-0.1115689
c19_trend |	-0.007639	0.0124975	-0.610	0.5410	-0.0321341	0.0168562
c35_trend |	0.0144674	0.0082685	1.750	0.0800	-0.0017389	0.0306737
c55_trend |	-0.0322748	0.0100311	-3.220	0.0010	-0.0519359	-0.0126137
c65_trend |	0.0363965	0.160082	0.230	0.8200	-0.2773645	0.3501576
Ed17_trend |	0.021557	0.009485	2.270	0.0230	0.0029664	0.0401476
Ed17_trend2 |	-0.0010233	0.0009203	-1.110	0.2660	-0.0028272	0.0007806
Ed17_trend3 |	0.0000223	0.0000258	0.860	0.3870	-0.0000283	0.0000729
Ed18_trend |	0.0476924	0.0091061	5.240	0.0000	0.0298444	0.0655404
Ed18_trend2 |	-0.0023833	0.0008819	-2.700	0.0070	-0.0041119	-0.0006547
Ed18_trend3 |	0.0000488	0.0000246	1.980	0.0480	4.88E-07	0.0000971
c19_ed17_t d |	-0.0042507	0.004916	-0.860	0.3870	-0.0138862	0.0053847
c35_ed17_t d |	-0.0031985	0.0024385	-1.310	0.1900	-0.0079779	0.0015809
c55_ed17_t d |	0.0034022	0.0022797	1.490	0.1360	-0.0010661	0.0078705
c65_ed17_t d |	0.003808	0.0054031	0.700	0.4810	-0.006782	0.0143981
c19_ed18_t d |	-0.0237026	0.0051276	-4.620	0.0000	-0.0337528	-0.0136525
c35_ed18_t d |	-0.0088918	0.0024139	-3.680	0.0000	-0.0136231	-0.0041605
c55_ed18_t d |	0.0080927	0.0021666	3.740	0.0000	0.0038462	0.0123392

c65_ed18_t d |	0.001531	0.0049728	0.310	0.7580	-0.0082157	0.0112777
c19_trend2 |	-0.0001765	0.0018588	-0.090	0.9240	-0.0038198	0.0034668
c19_trend3 |	-0.0000275	0.000081	-0.340	0.7340	-0.0001862	0.0001312
c35_trend2 |	-0.002467	0.0008611	-2.860	0.0040	-0.0041547	-0.0007792
c35_trend3 |	0.0000687	0.0000253	2.710	0.0070	0.0000191	0.0001184
c55_trend2 |	0.0025862	0.000925	2.800	0.0050	0.0007732	0.0043992
c55_trend3 |	-0.00005	0.0000252	-1.980	0.0470	-0.0000995	-5.56E-07
c65_trend2 |	-0.0037419	0.009383	-0.400	0.6900	-0.0221326	0.0146489
c65_trend3 |	0.000109	0.0001803	0.600	0.5460	-0.0002444	0.0004623
reg1 |	0.0042145	0.0270648	0.160	0.8760	-0.0488325	0.0572615
reg2 |	0.0009004	0.0244921	0.040	0.9710	-0.0471041	0.0489049
reg3 |	0.0131083	0.0233009	0.560	0.5740	-0.0325615	0.058778
reg4 |	0.0134249	0.0257989	0.520	0.6030	-0.037141	0.0639908
reg5 |	0.0302318	0.0237449	1.270	0.2030	-0.0163082	0.0767718
reg6 |	-0.0280472	0.03205	-0.880	0.3820	-0.0908654	0.0347709
reg7 |	0.089654	0.0232696	3.850	0.0000	0.0440455	0.1352624
reg8 |	0.0820614	0.0208726	3.930	0.0000	0.0411511	0.1229717
reg9 |	-0.0723573	0.0257536	-2.810	0.0050	-0.1228345	-0.0218801
reg10 |	0.0122499	0.0287018	0.430	0.6700	-0.0440056	0.0685054
reg1_trend |	-0.0051045	0.0056601	-0.900	0.3670	-0.0161983	0.0059892
reg2_trend |	0.0014987	0.0050003	0.300	0.7640	-0.0083019	0.0112993
reg3_trend |	0.0040249	0.0047863	0.840	0.4000	-0.0053562	0.013406
reg4_trend |	-0.0022799	0.0052345	-0.440	0.6630	-0.0125396	0.0079797
reg5_trend |	-0.0063684	0.0048789	-1.310	0.1920	-0.015931	0.0031942
reg6_trend |	0.005731	0.0064759	0.880	0.3760	-0.0069618	0.0184237
reg7_trend |	0.0166422	0.0048033	3.460	0.0010	0.0072278	0.0260566
reg8_trend |	0.0138713	0.004255	3.260	0.0010	0.0055315	0.0222111
reg9_trend |	0.0187289	0.0051896	3.610	0.0000	0.0085572	0.0289007
reg10_trend |	-0.0084652	0.0059725	-1.420	0.1560	-0.0201713	0.0032409
reg1_trend2 |	0.0002246	0.0002458	0.910	0.3610	-0.0002571	0.0007063
reg2_trend2 |	-0.0000925	0.0002135	-0.430	0.6650	-0.0005109	0.0003259
reg3_trend2 |	-0.0001782	0.0002044	-0.870	0.3830	-0.0005789	0.0002224
reg4_trend2 |	0.000135	0.0002228	0.610	0.5450	-0.0003017	0.0005717
reg5_trend2 |	0.0003124	0.0002088	1.500	0.1350	-0.0000969	0.0007217
reg6_trend2 |	-0.0001084	0.000275	-0.390	0.6930	-0.0006474	0.0004305
reg7_trend2 |	-0.0005362	0.0002059	-2.600	0.0090	-0.0009398	-0.0001325
reg8_trend2 |	-0.0003703	0.0001813	-2.040	0.0410	-0.0007256	-0.000015
reg9_trend2 |	-0.0007022	0.0002195	-3.200	0.0010	-0.0011325	-0.0002719
reg10_trend2 |	0.0002497	0.0002561	0.980	0.3300	-0.0002523	0.0007517
_cons |	1.57453	0.0233165	67.530	0.0000	1.52883	1.62023

B Testing the Normality Assumptions and Validity of Exclusion Restriction

B.1 Predicted Participation Index from Maximum likelihood

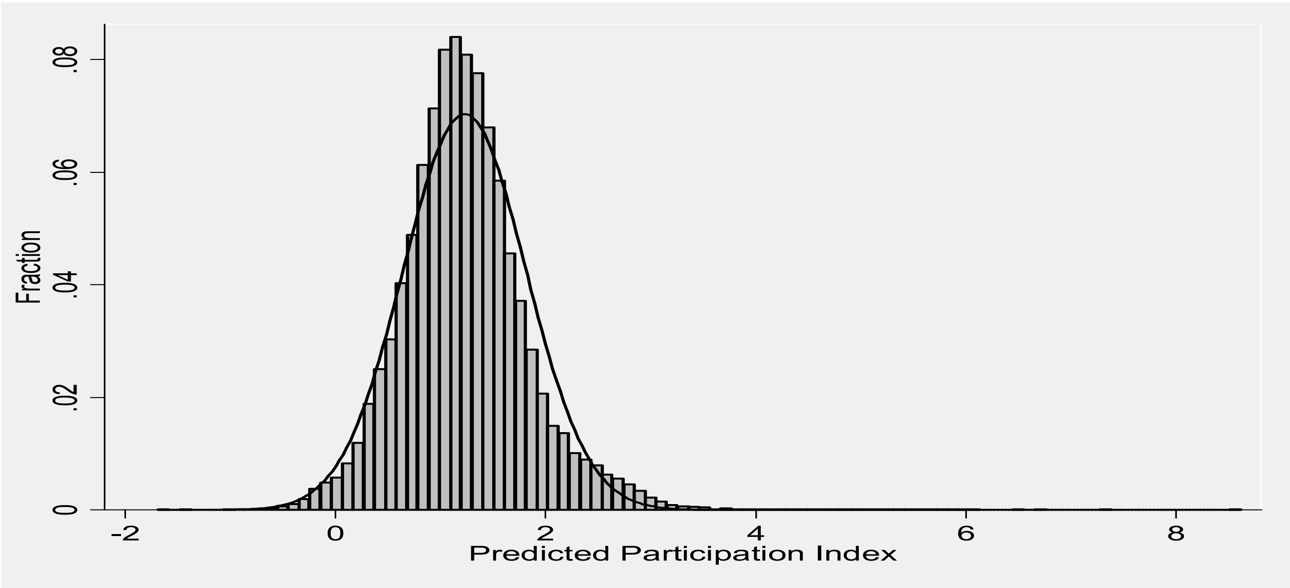

Figure 6: Distribution Plot of Participation Index (Latent Variable over all years) with a Normal Distribution overlay for comparison

B.2 Residual Plot from Wage Equation

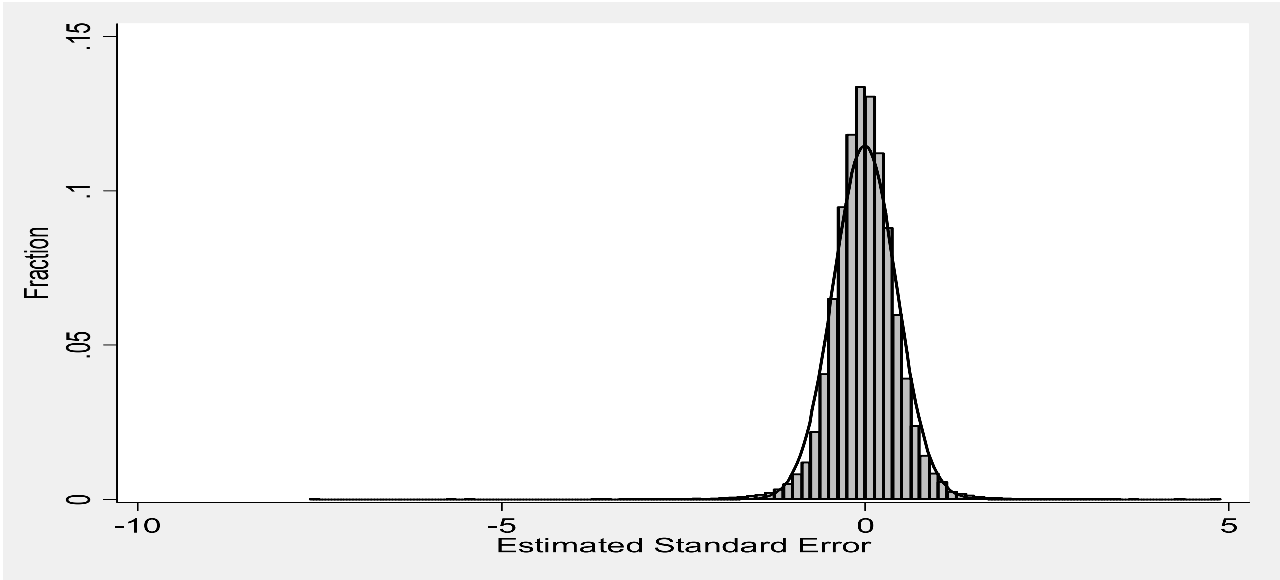

Figure 7: Distribution of Wage Regression Residuals

B.3 OLS Wage Regression on Participation Exclusion Restriction

Source	SS	df	MS		
Model	2914.49852	83	35.114440000	Number of obs	= 50177.0
Residual	9155.56417	50093	0.182771329	F(83,50093)	= 192.12
Total	12070.0627	50176	0.240554502	Prob>F	= 0.000
				R-squared	= 0.24150
				Adj R-squared	= 0.24020

Dependent variable: log Real Wage |	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Spouse Employment Dummy |	-0.0787738	0.0049417	-15.94	0.00000	-0.0884596	-0.0690879
Number of Children aged 3-4 |	0.0165425	0.0058127	2.85	0.00400	0.00514960	0.02793550
Children Aged 5-10 |	0.0092326	0.0031184	2.96	0.00300	0.00312040	0.01534480
Children Aged 11-16 |	0.0141577	0.0032235	4.39	0.00000	0.00783960	0.02047570
Children Aged 17-18 |	0.0703038	0.0102415	6.86	0.00000	0.05023030	0.09037730
Age |	0.0056971	0.0006698	8.51	0.00000	0.00438430	0.00700990
log simulated TAXBEN out-of-work income, single men |	-0.0143257	0.0141635	-1.01	0.31200	-0.0420863	0.01343490
log simulated TAXBEN out-of-work income, married men |	-0.001394	0.0036008	0.39	0.69900	-0.0084516	0.00566370
couple |	0.0311514	0.0720266	0.43	0.66500	-0.1100214	0.17232430
ed17 |	0.1752776	0.0322048	5.44	0.00000	0.11215580	0.23839940
ed18 |	0.2197564	0.0313411	7.01	0.00000	0.15832740	0.28118530
trend |	0.0178501	0.0072504	2.46	0.01400	0.00363930	0.03206100
trend2 |	-0.0002963	0.0006538	-0.45	0.65000	-0.0015778	0.00098520
trend3 |	-5.12E-06	0.0000183	-0.28	0.77900	-0.0000410	0.00003070
c1919_1934 |	-0.0799322	0.0298363	-2.68	0.00700	-0.1384116	-0.0214527
c1935_1944 |	-0.0041607	0.0238516	-0.17	0.86200	-0.0509100	0.04258870
c1955_1964 |	0.0215952	0.0411369	0.52	0.60000	-0.0590335	0.10222390
c1965_1977 |	-2.046683	1.319495	-1.55	0.12100	-4.6329080	0.53954250
c1919_ed17 |	0.1070047	0.0393293	2.72	0.00700	0.02991890	0.18409050
c1935_ed17 |	0.0793425	0.0308018	2.58	0.01000	0.01897060	0.13971440
c1955_ed17 |	-0.1330943	0.0383964	-3.47	0.00100	-0.2083517	-0.0578369
c1965_ed17 |	-0.3957978	0.130758	-3.03	0.00200	-0.6520849	-0.1395107
c1919_ed18 |	0.3653316	0.0418859	8.72	0.00000	0.28323480	0.44742840
c1935_ed18 |	0.1433276	0.0314274	4.56	0.00000	0.08172960	0.20492570
c1955_ed18 |	-0.2348647	0.0389702	-6.03	0.00000	-0.3112468	-0.1584826
c1965_ed18 |	-0.6595391	0.1297736	-5.08	0.00000	-0.9138967	-0.4051814
c19_trend |	-0.0049196	0.0133486	-0.37	0.71200	-0.0310830	0.02124380
c35_trend |	0.0053128	0.0088541	0.60	0.54800	-0.0120414	0.02266700
c55_trend |	-0.0349951	0.0121407	-2.88	0.00400	-0.0587910	-0.0111992
c65_trend |	0.3466425	0.2323225	1.49	0.13600	-0.1087122	0.80199730
Ed17_trend |	0.0095786	0.0105291	0.91	0.36300	-0.0110587	0.03021580
Ed17_trend2 |	-0.0001311	0.001021	-0.13	0.89800	-0.0021324	0.00187010
Ed17_trend3 |	8.38E-07	0.0000287	0.03	0.97700	-0.0000554	0.00005710
Ed18_trend |	0.0322759	0.0102825	3.14	0.00200	0.01212210	0.05242960
Ed18_trend2 |	-0.0012134	0.0009928	-1.22	0.22200	-0.0031592	0.00073240
Ed18_trend3 |	0.0000205	0.0000277	0.74	0.45900	-0.0000338	0.00007490
c19_ed17_t d |	-0.0020113	0.0052493	-0.38	0.70200	-0.0123000	0.00827750
c35_ed17_t d |	-0.0014481	0.0026011	-0.56	0.57800	-0.0065464	0.00365010

c55_ed17_t d	0.0040482	0.0026741	1.51	0.13000	-0.0011930	0.00928940
c65_ed17_t d	0.0127691	0.007069	1.81	0.07100	-0.0010863	0.02662440
c19_ed18_t d	-0.0229028	0.0054974	-4.17	0.00000	-0.0336777	-0.0121279
c35_ed18_t d	-0.007673	0.002608	-2.94	0.00300	-0.0127846	-0.0025613
c55_ed18_t d	0.0085453	0.0026241	3.26	0.00100	0.00340200	0.01368870
c65_ed18_t d	0.0207853	0.0069086	3.01	0.00300	0.00724440	0.03432620
c19_trend2	0.0004755	0.0019827	0.24	0.81000	-0.0034107	0.00436170
c19_trend3	-0.0000613	0.0000863	-0.71	0.47800	-0.0002305	0.00010790
c35_trend2	-0.0013703	0.0009205	-1.49	0.13700	-0.0031745	0.00043390
c35_trend3	0.000041	0.0000271	1.51	0.13000	-0.0000121	0.00009410
c55_trend2	0.0033237	0.0010896	3.05	0.00200	0.00118790	0.00545940
c55_trend3	-0.000078	0.0000292	-2.67	0.00800	-0.0001353	-0.0000208
c65_trend2	-0.0201747	0.0134111	-1.50	0.13300	-0.0464606	0.00611110
c65_trend3	0.0003893	0.0002542	1.53	0.12600	-0.0001089	0.00088750
reg1	-0.0016031	0.029385	-0.05	0.95600	-0.0591980	0.05599180
reg2	-0.0152601	0.0265291	-0.58	0.56500	-0.0672574	0.03673720
reg3	0.0015061	0.025197	0.06	0.95200	-0.0478802	0.05089250
reg4	-0.0225732	0.0278776	-0.81	0.41800	-0.0772136	0.03206730
reg5	0.0076221	0.0256268	0.30	0.76600	-0.0426068	0.05785090
reg6	-0.059017	0.0344018	-1.72	0.08600	-0.1264450	0.00841090
reg7	0.0383358	0.0257776	1.49	0.13700	-0.0121886	0.08886020
reg8	0.0571	0.0225295	2.53	0.01100	0.01294200	0.10125800
reg9	-0.0999057	0.0278148	-3.59	0.00000	-0.1544229	-0.0453885
reg10	-0.0053399	0.0309712	-0.17	0.86300	-0.0660437	0.05536390
reg1_trend	-0.0011924	0.0061974	-0.19	0.84700	-0.0133394	0.01095460
reg2_trend	0.0055941	0.0054876	1.02	0.30800	-0.0051617	0.01634980
reg3_trend	0.0062487	0.0052609	1.19	0.23500	-0.0040627	0.01656010
reg4_trend	0.0027658	0.0057329	0.48	0.62900	-0.0084707	0.01400240
reg5_trend	0.0028589	0.0053532	-0.53	0.59300	-0.0133511	0.00763340
reg6_trend	0.0098008	0.0070774	1.38	0.16600	-0.0040711	0.02367270
reg7_trend	0.019147	0.0054276	3.53	0.00000	0.00850880	0.02978510
reg8_trend	0.0146638	0.0046692	3.14	0.00200	0.00551220	0.02381540
reg9_trend	0.0221946	0.0056826	3.91	0.00000	0.01105650	0.03333260
reg10_trend	-0.0039207	0.0065387	-0.60	0.54900	-0.0167367	0.00889520
reg1_trend2	0.0000967	0.0002705	0.36	0.72100	-0.0004334	0.00062690
reg2_trend2	-0.0003288	0.000236	-1.39	0.16400	-0.0007914	0.00013370
reg3_trend2	-0.000312	0.0002267	-1.38	0.16900	-0.0007563	0.00013220
reg4_trend2	-0.000123	0.0002456	-0.50	0.61700	-0.0006043	0.00035840
reg5_trend2	0.0001266	0.000231	0.55	0.58400	-0.0003261	0.00057920
reg6_trend2	-0.0003692	0.000303	-1.22	0.22300	-0.0009631	0.00022460
reg7_trend2	-0.0006177	0.0002349	-2.63	0.00900	-0.0010781	-0.0001573
reg8_trend2	-0.0004391	0.0002005	-2.19	0.02900	-0.0008321	-0.0000460
reg9_trend2	-0.0008847	0.0002422	-3.65	0.00000	-0.0013595	-0.0004100
reg10_trend2	0.0000845	0.0002828	0.30	0.76500	-0.0004697	0.00063870
_cons	1.622557	0.0766056	21.18	0.00000	1.47240900	1.77270500