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WAGE ASPIRATIONS AND UNEMPLOYMENT PERSISTENCE.

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Wage Aspirations and Unemployment Persistence[*]

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Abstract

The reservation wage is an integral part of most theories of involuntary unemployment. We use panel data to examine the empirical determinants of the reservation wage – in particular the influence of previous wages – and consider what this implies for the evolution of the natural rate of unemployment. We find that previous wages have a significant but relatively small effect on reservation wages (an elasticity between 0.15 and 0.47). We also find considerable differences across genders with previous wages being more important for men and market wages being more important for women. Overall our results suggest that unemployment will adjust relatively quickly to shocks.

JEL Classification: J64, E24

Keywords: Unemployment Duration; Wages.

1   Introduction

In most models of the labour market, the reservation wage – the wage that makes workers indifferent between taking a job or remaining unemployed – is a central determinant of the actual wage, and in turn, of the unemployment rate. The purpose of this paper is to increase our understanding of the dynamic behaviour of aggregate unemployment by exploring empirically how individuals form their reservation wages. In particular, we ask do the unemployed set reservation wages irrationally close to previous wages even if previous wages are no longer a good guide to the current market value of their labour? This question is important because reservation wage formation rooted in the past will inhibit the timely adjustment of aggregate unemployment to shocks.

In the short run, following a negative shock (increase in payroll taxes, decrease in terms of trade etc.), workers might seek to maintain living standards, reservation wages remain unchanged and unemployment results. In the long run, however, workers' aspirations would tend to adjust to reality and unemployment would return to its previous level. Precisely how long this adjustment takes, depends on the extent to which reservation wages are determined by reality (current unemployment levels, current market wage levels, unemployment benefits etc.) or by workers aspirations that may be influenced by out of date variables (e.g. pre-shock wage levels). Unemployment will persist for as long as it takes aspirations to adjust to the new reality. Furthermore, if we embed this process in a structural search model such as Mortensen and Pissarides (1997), any exogenous decline in workers' reservation wages would induce employers to post more vacancies, further reducing both the level of unemployment and spell length.

We use the British Household Panel Survey over ten years (1991-2001) to provide direct evidence of the link between reservation wages and previous wages at the micro level. We examine explicitly to whether an individual's reservation wage is determined more by his own "lagged" wage (i.e. the wage received in a previous job) or by the prevailing market wage. If the former is important, then we will have micro level evidence of slow adjustment to shocks, supporting the macro-empirical evidence of persistent unemployment. The main econometric challenge is to disentangle whether the effect of the previous wage reflects causality, or the fact that the previous wage contains information about the unobservable characteristics of workers and is probably subject to measurement error. We control for measurement errors and unobservables using an instrument (previous observations of the same wage) and the panel dimension of our data.

Our empirical conclusions are clear, and appear robust to a number of alternative specifications and econometric treatments. We find a significant, but relatively small effect of the previous wage on the reservation wage. An increase in the previous wage of 10% increases the reservation wage by between 1.5% and 4.7%. We find a large and significant effect of the mean of the distribution of wages on the reservation wage (an elasticity of around 0.3). The effect of local unemployment rates

on the reservation wage, is small (elasticity of around -0.1), and in some regressions, statistically insignificant. One other surprising result is that we find no significant effect of unemployment benefits.

Our results suggest that the reservation wage (and therefore unemployment) will adjust to any shock relatively quickly. The coefficient on the previous wage is much less than unity but significantly greater than zero. This suggests that the presence of persistence in wage formation and unemployment but less than is suggested by aggregate data. Our results also highlight considerable variation across genders with previous wages being more important for men and market wages being more important for women. This is consistent with the view that women have more flexible labour market behaviour than men.

This paper complements a number of papers in macro and labour economics. Ball and Moffitt (2001) investigate similar questions using aggregate U.S. data. They construct an index of workers' wage aspirations and show that the decline is U.S. unemployment during late 1990s can be explained by the fact that their aspirations variable was slow to adjust to rapid improvements in productivity. Blanchard and Katz (1997,1999) suggest that differences in the estimated Phillips curves between the E.U. and U.S. may possibly be explained by differences in the link between reservation wages and previous wages.

Christensen (2001) shows that previous wages have an important effect on reservation wage formation in Germany. Fledstein and Poterba (1984) and Jones (1989) get similar results for the U.S. and U.K. respectively. However these three studies interpret their results as reflecting the impact of current wage offers rather than backward looking behaviour of workers. We clearly distinguish between the effect of current offers and the effect of previous wages on reservation wage formation as well as account for possible measurement error.

The paper is organised as follows. Section two discusses the data. Section three presents the econometric results using OLS, IV and Fixed Effects estimators. Section four presents some refinements and tests the robustness of our basic results. Section five concludes.

2   A First Look at the Data

In order to conduct the analysis we need three basic variables: the reservation wage, the wage in a previous job, and the person specific market wage rate. We use the British Household Panel Survey (BHPS), a representative survey of randomly selected households over the 10 years from 1991-2001.[1] Table 1 contains the definitions and summary statistics (for the pooled cross sections) of the variables used in the analysis. All the monetary variables are in 1991 pounds sterling per week.

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[1]For full details see Taylor et. al. (2002). The dataset excludes individuals living in the north of Scotland.

The BHPS contains observations of the first two crucial variables (reservation wage and previous wages) and allows construction of the third (expected market wage). In particular it contains an after tax reservation wage variable, W_{it}^{R}, that the result of direct observation. Individuals who reported that they were not working were asked the following question:

"What is the lowest weekly take home pay you would consider accepting for a job?"

We take the answer to this question to be a measure of wage aspirations and leave to section 4.1 consideration of its accuracy. The other crucial variable for our analysis is the wage in the previous job[2], W_{it}^{L}. This is calculated as the net weekly wage received in the most recent spell of employment. Note that it is not the case that the previous wage variable is simply the wage reported at the last survey date (although it could be). An advantage of the BHPS is that it contains detailed information on respondents labour market behaviour between waves. In principle, every time period is accounted for.[3]

Table 2 show summary statistics for some key variables and ratios for both active searchers and non-searchers.[4] We are particularly interested in the relationship between the reservation wage (W_{it}^{R}) and the wage in the previous job (W_{it}^{L}). We might expect that the ratio of these two variables (Reservation Wage Ratio - RWR) would be approximately one on average. But as can be seen from the table, while the median is less than one, on average the reservation wage is higher than the previous wage for both searchers and non-searchers.[5] One would expect that unemployed individuals would set a reservation wage less than their previous wage. The fact that so many values of the reservation wage appear to be set so high suggests that there would be a degree of persistence in unemployment. At the very least, the unemployed – whether actively searching or not – do not appear to be particularly eager to price themselves into a job.

It is also clear from table 2 that the ratio is more skewed than either the reservation wage or the previous wage. This can be seen more clearly in table 3 which shows the cumulative distribution for the ratio for the sample as a whole and nine interesting sub groups. For all groups, about sixty percent of individuals set their reservation wage less than the wage in their previous job. However, the tails of the distribution are quite thick implying that there are a substantial number of individuals who appear to set the reservation wages completely out of line with their previous

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[2]We use the superscript "L" to denote lagged wage and use the terms "lagged wage" and "previous wage" interchangeably.

[3]See Halpin (1997) for a detailed discussion of this aspect of the BHPS.

[4]Table 1 shows that 54% of those providing a reservation wage satisfied the OECD's definition of involuntary unemployment i.e. actively searched for a job last month. The fact that individuals said that they would "like" a job, and could suggest what sort of job it might be, was sufficient for them to be asked their reservation wage.

[5]Jones (1989) reports the mean and standard deviation of RWR to be 1.05 and 0.5 respectively. Feldstein and Poterba (1984) report a mean of 1.07. Christensen (2001) reports a mean of 1.2 and a median of 1.04.

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wages.[6]

An interesting aspect of table 3 is that there appears to be little difference between the various groups, at all but the lowest RWR. Jones (1989) found a similar result. Women do not appear to have RWR much different from men, although the left tail is more massive for women. This may be evidence that women have slightly more flexible labour market behaviour than men. More of them seem prepared to set a reservation wage substantially less than their previous wage.

Table 3 and table 2 suggest some difference between searchers and non-searchers. Searchers have higher reservation wages than non-searchers (by about 45%), longer duration of unemployment and also higher wages upon re-employment (W_{it}^{A} - "Accepted Wage"). Interestingly the ratio of the reservation wage to the re-employment wage (W^{R}/W^{A}) is similar for both. Table 3 shows that the distribution of the RWR is shifted to the left for the non-searchers i.e. more mass in the lower tail. This suggests that as search intensity increases, fewer individuals are prepared to set a reservation wage lower than the previous wage.

This raises the issue of whether to include self-reported non-searchers in the analysis at all. The normal procedure in the literature dealing with reservation wages seems to be to restrict the sample to searchers only (for example, see Bloemen and Stancanelli, 2001). However, fully 28% of those who said they had *not* searched during the previous 4 weeks, were in paid employment by the next wave of the data. The comparable figure for the searchers is only 47%. This could indicate that there are frequent changes in the level of search intensity by the same individuals throughout a period of unemployment or, more likely, it may just reflect the ambiguity in the question. Clearly, the two groups are different — but not that different. So in what follows, we include both groups in the estimation sample and in section 4.3 we look at the implications for our results of any differences between them.

It is apparent from this preliminary analysis that the unemployed (whether searching or not) are doing something wrong if they truly want to work. A degree of persistence in unemployment seems likely because so many individuals fail set their reservation wages lower than the wage in previous job, pricing themselves out of the market. However, we must admit the possibility of an alternative explanation: that the reservation wages data is measured with a high degree of error because individuals have no real idea how to set reservation wages or how to respond to the reservation wage question – making W^{R} only a weak reflection of the unemployed's desire to work. We discuss this "errors in variables" argument in section 4.1.

In any case, a crucial variable is missing from the analysis. We have made no attempt to take into account the market wage an individual can expect to get if employed. The reservation wage is only really of interest when set against this market wage. A high reservation wage may be perfectly

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[6]Thick tails have been found in other studies. For example, Jones (1989) reported that 44% of his sample had a RWR of more than 1.0. Feldstein and Poterba (1984) report that 24% of their sample had a RWR of less than 0.9.

reasonable for a highly trained individual who can expect to secure a high paying job with relative ease. Implicitly, we have used the previous wage as a proxy for the mean of the current wage offer distribution. Feldstein and Poterba (1984) and Jones (1989) adopted this procedure explicitly. However, we want to examine the possibility that the wage in a previous job may have influence on reservation wage formation independently of the current wage offer distribution. Once we have controlled correctly for the current distribution of wage offers, previous wages should be irrelevant. If previous wages still matter, then that in itself represents a real rigidity in the labour market and can generate persistent unemployment. In order to examine this possibility we need to control for the previous and market wage rates separately. To do this we turn to a regression framework.

3   An Econometric Framework

In essence we want to run a regression with the reservation wage as the dependent variable and various potential influences on reservation wages as regressors. Of particular interest is the possibility that the reservation wage could be a function of the wage received during a previous period of employment and that this effect is independent of the effect of the distribution of current wage offers. We will estimate equation (1) where, W_{it}^R is the reservation wage of person i at time t, W_{it}^L is the individual's wage when last employed, $\bar{W}_{it}$ is the mean of the distribution of wage offers, u_{rt} is the regional unemployment rate[7], and X_{it} is a vector of control variables (such as age, sex, number of dependent children, asset income and the level of unemployment benefits).

$$\ln W_{it}^R = \beta_0 + \beta_1 \ln W_{it}^L + \beta_2 \ln \bar{W}_{it} + \beta_3 \ln u_{rt} + \beta_4 X_{it} + \varepsilon_{it} \tag{1}$$

It is important to note also that the previous wage is indexed by time t, not $t-1$. This conveys the idea that reservation wage formation is backward looking from time t, to the period when last employed – which need not be the previous wave of the panel. Also note that the value of the previous wage variable does not change with the passage of time unless the individual gets a new job.

We include the mean of the current, person specific, distribution of wage offers, $\bar{W}_{it}$ and a measure of the probability of receiving an offer, u_{rt} to counter-balance the lagged wage variable. Whereas W_{it}^L represents history, now possibly economically irrelevant, $\bar{W}_{it}$ and u_{rt} represent current economic reality. In principle, once $\bar{W}_{it}$ and u_{rt} are included in the regression, W_{it}^L should have no effect, unless reservation wage formation is influenced by subjective processes such as pride. Thus (1) is a regression of reservation wage on (our best measure of) objective reality and an individuals subjective perception of that reality. We want to see which is the more important determinant of reservation wages.

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[7]Regional unemployment is from UK Labour Force Survey.

We do not observe $\bar{W}_{it}$, so we construct $\hat{W}_{it}$, a measure of the mean of the distribution of offered wages.[8] We first estimate a standard wage equation on a sample consisting of all the *newly employed* i.e. all those whose are in their current job for less than a year.[9] The exogenous variables are human capital variables (age, experience, education); household composition variables (marital status, the number of dependent children of various ages, gender); local unemployment rates; and region-time fixed effects and their interactions. Heckman's two step procedure was used to correct for sample selection problem.[10] We interpret these fitted values, $\hat{W}_{it}$, as being the mean of the distribution of wage offers that an individual faces, conditional on his/her (observable) characteristics and the characteristics of the local labour market.

3.1 OLS

We report the OLS estimates of equation (1) in Table 4. At this point, no attempt is made to account for the panel nature of the data, all waves are pooled together. The regressions in column 1 uses a sample of both men and women and columns 2 and 3 perform the analysis on both gender groups separately.[11] We proxy the probability of receiving offers by regional unemployment rates. The benefits variable is the level of state benefits the respondent reported receiving at time of interview. It is worth noting that, in the UK, the size of unemployment benefits are not linked to the wage received when last employed.[12]

For the moment we ignore the effect of spell duration on reservation wages and confine the regressions in Table 4 to a sub-sample consisting of only one observation per spell. In the case of

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[8]There is an expected wage variable in the dataset. But it seems to refer to $E[W|W > W^R]$, and not $E[W]$ as it is less than W^R in only 30% of cases. In any case, we want is an objective measure of the potential wage offers that the individual actually faces. In our framework the subjectivity is captured by the lagged wage variable.

[9]Restricting this first stage regression to new hires as opposed to all the employed seems reasonable as we are trying to capture the market opportunities faced by the currently unemployed. Using a sample of all employed, did not change the results much. The magnitude and significance of the coefficient on W_{it}^L was unaffected while the coefficient on $\hat{W}_{it}$ was found to be higher in magnitude in some regressions - the difference being significant at the 5% level. Details of these results are available from the author.

[10]The dependent variable is log of usual weekly take home pay. The sample size at this first stage is $9,535$. The coefficient on the inverse Mill's ratio is -0.59 with a standard error of 0.05. The $\bar{R}^2$ of the wage equation is 0.28 and the standard error of the residual is 0.81. We follow Bloemen and Stancanelli (2001) and identify the mills ratio by including total household non-labour income and investment income in the selection equation but not in the wage equation.

[11]All regressions also include a cubic polynomial in age of respondent and the number of dependent children. These variables are of no particular interest and so are omitted from the tables for clarity. We also experimented with the inclusion of variance of the wage offer distribution, but in all cases this was found to be insignificant and so was excluded from the estimation.

[12]About 26% of the observations in the sample are of zero benefits. We treat these individuals as having £0.25 in benefits per week in order to avoid taking logs of zero. We also applied this adjustment to the asset income variable. About 35% of individuals did not report any asset income.

a spell that spans multiple survey points (so that we have multiple observations of W_{it}^R but only one observation of W_{it}^L) we take the observation closest to the start of the spell.

For our purposes, the most important coefficient is the coefficients on the "wage in the previous job" variable, W_{it}^L. It is significantly different both from zero and unity and is much lower than what we might have anticipated from the evidence of aggregate data (see Blanchard and Katz, 1997). This suggests the presence of persistence in wage setting, but to a much lesser extent than suggested by aggregate data.

The coefficient on the benefits variable, b_{it}, is correctly signed but statistically insignificant. The results are similar to Jones (1989) who found a significant coefficient of 0.24 on the previous wage and a statistically insignificant coefficient on benefits. His regression was crucially different from ours, however, in so far as he interpreted W_{it}^L as the mean of the distribution of wage offers.

The effect of the regional unemployment rate is significant. Reservation wages are lower in regions with higher unemployment - but the size of the effect is small. Unemployment appears to be less of an influence on reservation wages than either market wages or own previous wages.[13]

The coefficient on asset income in all of Table 4 seems to be incorrectly signed but significant. The negative coefficient could be explained by a spurious correlation caused by the intertemporal nature of savings. Those who have relatively high savings would tend to be those with less experience of unemployment through time. And those with relatively low reservation wages would, ceteris paribus, tend to experience less unemployment. Thus the regression could pick up the effect of previous unemployment on asset accumulation rather than the effect of assets on labour market behaviour.

It is useful to see if the effect of previous employment is different for men and for women. In columns 2 and 3 of Table 4 we report the estimates of the model where the full sample is split into two gender specific sub-samples. It seems that the pooled estimates conceal substantial differences between the behaviour of men and women. The market wage matters very little for men – in fact it is statistically insignificant. In contrast, for women, the coefficient on the market wage is both significant and much larger numerically, while the coefficient on the lagged wage is smaller than for men. It appears that the current "objective" variable matters for women, whereas male reservation wage formation is more heavily influenced by the "subjective" historical variable. This result is consistent with the view that labour market behaviour of women is more flexible.

3.2 Measurement Error and IV Estimates

If we take the results of the last section at face value, then they suggest that there is some persistence in reservation wages (and therefore unemployment) but that it is less than suggested by aggregate

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[13]This high standard error on unemployment may be due the fact, noted by Card (1995), that there are relatively few independent observations of the regional level data (only 120 here).

data and that it varies substantially by gender. Unfortunately, however, the OLS estimates are likely biased downwards because of the presence of measurement error in the lagged wage variable. Such error could arise as a result of recall/reporting error and the effects of unobserved compensating differentials.

Bound et. al. (1994) suggest that recall error has a significant impact on wage history data. However, in a detailed examination of this issue, Halpin (1997) suggests that recall error in BHPS is low with data relating to 90% of employment spells was internally consistent through time. Furthermore, the median length of time from the end of employment to initial survey was 4 months and 90% of spells were recorded within 11 months, limiting the opportunity for recall error.

Unobserved compensating differentials are a more problematic source of error. We could control for to the extent that we knew the characteristics of the previous job and the characteristics of the job to which the reservation wage relates. Unfortunately, the only characteristics recorded for previous jobs in the BHPS are occupation and industry choice – which are probably endogenous.[14] Similarly hours worked, are not recorded in the BHPS job history data so we cannot control for hours in the regression.[15]

One way of dealing with errors is to duplicate the procedure of Bound and Krueger (1991) and Bound et. al. (1994) who conducted validation studies of the CPS and PSID by comparing the wages reported in the two surveys with administrative data. They found that there were appreciable measurement errors in reported wages and that the errors were negatively correlated with the true value of the variables. This reduces the bias, relative to that of classical measurement error, when earnings is an independent variable.

There is no similar study for the BHPS, but we can get an idea of how measurement error might affect our results by assuming that the structure of errors is the same as that observed by Bound et. al. (1994) for the PSID and CPS and use their formula to adjust our OLS estimates. To be specific, for the moment assume that only W^L is measured with error and that the error is negatively correlated with the true value. We assume that a regression of the error on the observed value would produces a coefficient of 0.2, a value that is at the upper end of the range of results reported by them. Applying their formula[16], we get a corrected estimate for β^L of 0.45.

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[14]Nevertheless, controlling for occupation and industry related compensating differentials did not change the results significantly.

[15]As an alternative, I tried to predict the hours worked in the last job on the basis of a regression of the hours worked of currently employed individuals on job and worker characteristics. When lagged wages were adjusted by these predicted hours, the overall results were similar. This procedure does not inspire great confidence, however, especially as the first stage hours regression produced an R^2 of only 0.2 suggesting a large errors in variables problem with the hourly wage.

[16]$\beta = \frac{\hat{\beta}_{OLS}}{1-b_{uX}}$ where $\hat{\beta}_{OLS}$ is the uncorrected OLS estimate and b_{uX} is the coefficient from the regression of the error on the observed value of W^L. We also assume that the error is uncorrelated with any other variable.

A more rigorous way of dealing with measurement error is to use IV. We can make use of the dynamic nature of the BHPS. For a spell of employment that spans two survey dates, we will have two observations of the wage in that job. One will be the lagged wage variable from the employment history question in the current wave. The other will be the wage of the then employed worker as reported in a previous wave of the survey. If we are prepared to assume that any measurement error is uncorrelated through time, we can use the earlier observation to instrument for the current one.[17]

Table 5 shows the results. As expected, the coefficient on the lagged wage variable has risen by about third – a statistically significant difference at the 5% level. The coefficient on the market wage variable $(\hat{W})$ has fallen slightly, although the change is not significant. Overall, the other coefficients are relatively unchanged when compared to their values under OLS: benefits and regional unemployment have numerically small elasticities, with benefits being statistically insignificant. Thus the only effect of IV is to increase the importance of lagged wage relative to the market wage. This is sufficient for a Hausman test to reject the null hypothesis that there is no difference between OLS and IV.

As in the case of OLS, the regression on the full sample hides significant differences between the sexes. The null hypothesis of parameter stability across gender groups can easily be rejected (p-value 0.005). Basically the wage in the previous job is more important to men whereas the market wage has almost no impact on reservation wage formation. In contrast, for women, the market wage is as important as the wage in previous job. This suggests that women would be more realistic in the formation of reservation wages adjusting more quickly to current reality and being less influenced by the past than are men – again consistent with the view that women are more flexible participants in the labour market.

There is a problem with the IV estimates in table 5, however. They are probably not consistent because of a form of measurement error in $\hat{W}_{it}$. When we replace $\bar{W}_{it}$ with $\hat{W}_{it}$, we introduce the term $\bar{W}_{it} - \hat{W}_{it}$ into the residual of the estimated equation. This will typically have an individual specific component (μ_i) i.e. the component of the expected wage that is specific to the individual and is not correlated with the observed characteristics that were used to construct $\hat{W}_{it}$. It is almost certainly the case that W_{it}^L will be positively correlated with μ_i, because wages received in the past, will probably have been affected by the same individual specific unobservable. Our IV won't control for this and will yield upward biased estimates of the effect of the previous wage on the reservation wage.

It was for this reason that Feldstein and Poterba (1984) and Jones (1989) rejected the use of

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[17]I am grateful to an anonymous referee for this suggestion. An F-test on the exclusion of the instrument from the first stage regression produces a test statistic of 295 well above the value of 5 that Staiger and Stock (1997) recommend to avoid the problem of weak instruments.

a fitted value as an estimate of the mean of the wage offer distribution, using instead W_{it}^L as a proxy for $\bar{W}_{it}$. As noted already, this is not an option for us as we are interested precisely in the possibility that W_{it}^L has an independent influence on the reservation wage.[18]

Nevertheless it is worth noting that even if the IV estimates of the effect of W_{it}^L are biased upwards, we can treat them as upper bounds on the true values. A striking implication of this observation is that the true coefficient must be very low – certainly much lower than unity – implying a degree of persistence lower than suggested by aggregate data. Furthermore there is no reason to suspect that any bias would differ by gender, so the reservation wage formation of women still seems more firmly rooted in current economic reality than is men's.

3.3   Fixed Effects

We can use of the panel aspect of the data to combat the potential inconsistency caused by the correlation between W_{it}^L and the residual when $\hat{W}_{it}$ is a regressor. Providing we are prepared to assume that the individual unobservable effect is constant over time, we should be able to difference it out using the fixed effects or "within groups" estimator.

However, we can apply the fixed effects estimator only to those individuals who experienced two or more periods of unemployment during the sample period (so that we can have two independent observations of W_{it}^L).[19] Obviously there are relatively few individuals who match this criteria. More importantly there is an issue of sample selection. We might expect those who have experienced several periods of unemployment to have systematically different labour market behaviour than those who experienced only one spell of unemployment over a period of several years. One would suspect that it is the latter group which would rely on the lagged wage the most. If so, the fixed effects procedure, by excluding them, will tend to underestimate the significance of the lagged wage for the population as a whole. The results must be interpreted with this caveat in mind.

We present the fixed effects results in the first column of Table 6. These are quite different from the OLS and IV estimates. As was to be expected, the estimate of the coefficient on W_{it}^L is substantially lower than OLS or IV – measurement error is exacerbated by taking differences. The coefficient on the expected future wage is also smaller than the OLS estimate but is significant at the 10% level. The coefficient on the benefits variable is correctly signed, but is insignificant. The coefficient on the local unemployment rate is also insignificant (p-value of 0.11) but correctly signed. Finally, note that the coefficient on asset income is now positive but insignificant, suggesting that

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[18]Alternatively, we run a reduced form version of the model where $\hat{W}$ is replaced by the covariates used to generate it and we instrument for W_{it}^L using previous observations as before. This procedure generates an elasticity of previous wage of 0.45 with a standard error of 0.05, suggesting that the size of any bias is small.

[19]In particular it is not the case that these individuals experienced one long spell of unemployment during which we took two (or more) observations of W_{it}^R at different survey points during the same spell. We examine multiple observations of the same spell in the next section.

the fixed effects estimator correctly accounts for the dynamic relationship between savings and employment.

As before the estimates for the overall sample conceal substantial differences between the behaviour of men and women (columns two and three of Table 6). The point estimate for the lagged wage is very close for both gender groups. But, as before, the market wage matters very little for men – in fact it is statistically insignificant. While, for women, the market wage is both significant and much larger numerically. Again it appears that women's reservation wages are more influenced by market forces than are men's.

In an attempt to assess whether the fixed effects estimator induces a sample selection bias, we estimated OLS on the same sub-sample i.e. those who experienced two or more periods of unemployment. These estimates (available on request) were not significantly different from OLS for the whole sample (table 4) suggesting that the sample selection induced by the fixed effects estimator is not a problem.[20]

In any case, even if the fixed effects estimate itself is biased downwards (whether because of sample selection or errors in variables) we can view it as being a lower bound for the true value. Combining this with IV upper bound we have a range for the true value of the coefficient of $(0.15, 0.47)$ – a region bounded away from both zero and one.

4   Robustness

The analysis so far produces a range around the true effect of previous wages on current reservation wage formation. In this section we see how robust this relationship is when we allow for errors in the reservation wage variable, search intensity and the effects of duration of unemployment spell.

4.1   Errors in the Reservation Wage Variable

Dominitz (1998) conducted a detailed study of various subjective measures of earnings found that they were quite accurate on average. Although his study his study did not explicitly include the reservation wage, the conclusion that subjective measures of future earnings are relatively accurate lends credibility to our reservation wage measure.

Nevethesless the reservation wage variable could still be measured with error. If that error is classical i.e. uncorrelated with the true value of any regressors it will not affect the consistency our estimates so far, only their efficiency. We have to consider the possibility, however, of non-classical measurement error in the dependent variable, which may bias our results.

Some aspects of the data could be interpreted as evidence of error in W^R. For example we noted in section 2 that on average the re-employment earnings of those unemployed who subsequently got

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[20]An appendix detailing these and other auxiliary results referred to in the text is available from the author.

jobs were 43% lower than their previously reported reservation wages (but note that the median is close to unity). This may indicate that the reservation wage is measured with error i.e. that individuals actually accept wages substantially less than they said they would. Alternatively, it may just be the effect of duration. As individuals find themselves spending more time in unemployment they may moderate their reservation wage until it is low enough for them to secure employment.

We examine the issue of duration dependence in the next subsection. For the moment we will proceed on the assumption that W^R is measured with error. We use the re-employment wage to perform a analysis of measurement error along the lines of Bound et. al. (1994). We first interpret the re-employment wage (W^A) as being the true value of the reservation wage (i.e. we ignore the possibility for duration effects) and the treat the variable W^R as being the reservation wage observed with error. We regress the implied measurement error on all the independent variables used in the model. It turns out that the "error" is uncorrelated with any of the variables (including W^L and $\hat{W}$) and the adjusted R^2 for the regression is only 0.03. This suggests that any measurement error W^R is classical in nature and therefore does not affect the consistency of any regression where W^R is the dependent variable.

As a further check of the robustness of our results. We run our four main regressions with the (log) reservation wage ($\ln W^R$) replaced with the (log) re-employment wage ($\ln W^A$). The results are not shown for brevity but are virtually the same as using the reservation wage. Bassically the lagged wage and the market wage can explain both the reservation wage and the re-employment wage in the same manner.

4.2 Duration

In the analysis so far we have ignored the issue of duration except to say that it was a possible explanation of the difference between re-employment earnings and previously reported reservation wages. We have also excluded multiple observations of the same unemployment spell from the estimation sample. The two issues are related. If we have multiple observations of the same spell then the only reason that the relationship between the reservation wage and the previous wage would be different at the two points is due to the effect of duration. This could be the result of a deliberate strategy to reduce reservation wages and/or their link to previous wages in response to the failure to secure employment. Alternatively, it could just be recall error. Over time individuals may simply remember the last wage with less accuracy leading to a lower coefficient. Either way we would observe the effect of previous wages on reservation wages weakening over time. We now examine this issue explicitly.

In Table 7 we estimate the model controlling for duration using both the IV and Fixed Effects estimators. The estimation sample includes all those who experience more than two separate periods of unemployment (i.e. as in table 6) and, in addition, all those for whom we have multiple

observations of the same unemployment spell. The addition of this latter group increases the sample size dramatically.

We estimate the same specification as before with the addition of variables representing the spell length (for clarity scaled in units of 120 months) and its interaction with the lagged wage and the market wage. For clarity we report only the variables of primary interest. The first thing to note is that there is no direct effect of spell length on reservation wages. Spell length matters only via its interaction with the previous and market wage variables.[21]

The IV and FE estimators give similar results. For the sample as a whole, the effect of the lagged wage diminishes with increasing spell duration.[22] Conversely reservation wage formation becomes progressively more influenced by market wages as the length of unemployment increases. For example, after one year of unemployment, the IV estimates imply that the elasticity of the reservation wage with respect to lagged wage would be 0.38 and the market wage elasticity would have increased to 0.17.

These results allow us to say something about the prevalence of genuine duration dependence as opposed to recall error. We would expect to find the negative interaction of duration with the lagged wage in the case when individuals deliberately reduce their reliance on past wages in order to secure employment. We would also expect to find a negative interaction when individuals simply remember their previous wage with increasing vagueness over time. However, in this case, we would not expect to see the increasing influence of the market wage (except in the unlikely event that the recall error in W_{it}^L is positively correlated with $\hat{W}_{it}$).

As before it is instructive to split the sample by gender. For men, both of the interaction terms are insignificant whereas for women the interaction with the previous wage is highly significant. At the onset of unemployment the lagged wage has a slightly bigger impact on women's than on men's reservation wage formation (0.49 vs. 0.41). This is the opposite result to what we had earlier (see Table 5 and Table 6). But the effect of W_{it}^L declines about nine times faster for women than for men. Similarly, at the onset of unemployment the market wage has much more impact on women than men.

The results are pretty striking. They suggest that women adjust more completely and more quickly to market reality than do men. Furthermore for both groups the wage received in the previous job has a significant affect on reservation wages. But the coefficient is much less than unity – even at the start of the spell.

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[21]Higher orders of interaction and interactions with other variables also proved insignificant.

[22]A caveat: we have ignored the possibility of simultaneous relationship beween duration and unemployment.

4.3　Search Intensity

Recall from section 2 that searchers and non-searchers seemed to have different – but not completely different reservation wage formation. Specifically searchers have both higher reservation wages and higher wages upon re-employment. We can now analyse this more formally. In table 8 we show the results of our IV procedure and our FE estimator applied to the sample as a whole and separately to searchers and non-searchers. For clarity we focus on the two coefficients of interest i.e. the coefficients on $\ln W^L$ and $\ln \hat{W}$. The first column summarizes the results from tables 5 and 6. From columns two and three we see that lagged wages matter more to searchers than to non-searchers whereas the market wage matters more to non-searchers. Although for men, the effect of lagged wage is approximately the same for both searchers and non-searchers. The pattern is the same for both the IV and FE estimates. (The sample size is so small as to render the fixed effects estimates for the separate gender groups insignificant). In all cases F-tests of parameter stability across search status are rejected at 1% significance level.

These results are capable of several interpretations. The first point to note is that search intensity – which is proxied by our dichotomous search vs. non-searching classification – is probably chosen jointly with reservation wages. Secondly, even allowing for any endogeneity, we might expect that those who searched more intensively would also have a more realistic approach to the labour market and place less weight on previous wages. But this is not what the results suggest. They show that the reservation wage formation of searchers is more firmly rooted in the past than is the reservation wages of the non-searchers insofar as the lagged wage matters more (and the market wages matters less) for the searchers than for the non-searchers. This is a curious result. What seems to be behind it, is the effect of duration. Searchers have shorter duration than non-searchers. As we showed above, increased duration leads to more realistic reservation wage formation. Therefore the results could be picking up a discouraged worker effect i.e. as duration of unemployment increases, workers adopt more realistic wage demands but also search less intensely.

5　Conclusions

This paper set out to find the determinants of the reservation wage and to indicate what the structure of reservation wages implies for the evolution of the natural rate of unemployment. We find that the wage in a previous job and the expected future wage are both important determinants of the reservation wage.

Our results are clear, and appear robust to a number of alternative specifications. The central result of the paper is the effect of the wage in the previous job on reservation wages. Allowing for measurement error and individual specific unobservables, we show that this elasticity lies in the range $(0.15, 0.47)$.

As this range is significantly greater than zero, we have found evidence of wage inertia at the micro level. Nevertheless this entire range is surprisingly low – lower than we might have expected from looking at the aggregate data. The implication of this result is that the reservation wages of the unemployed will adjust to any shock relatively quickly. This in turn implies that the natural rate of unemployment will adjust relatively quickly to shocks. This result is at odds with Ball and Moffit (2001) who find evidence in aggregate data that U.S. workers adjust their (aggregate) wage aspirations slowly to productivity shocks. Further work is needed to reconcile these results.

Our results also show that there is considerable variation across genders, suggesting that women react more completely and more quickly to market reality than do men. The wage in the previous job is more important to men whereas the market wage has almost no impact on their reservation wage formation. In contrast, for women, the market wage is at least as important as the wage in previous job. This suggests that women would be more realistic in the formation of reservation wages adjusting more quickly to current reality and being less influenced by the past than are men. This is consistent with the view that labour market behaviour of women is more flexible than men's.

We also find evidence for a duration effect. As duration of unemployment grows reservation wage formation becomes more realistic with lagged wages exerting progressively less influence, while market wages exerts a greater influence, on reservation wage formation. Similarly we find that the reservation wages of searchers (non-searchers) are more (less) heavily influenced by previous wages than market wages. We interpret this as evidence of a discouraged worker effect: as duration increases individuals reduce the linkage between previous wages and reservation wages, but they also search less intensely.

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Table 1: The BHPS Data

Variable	Definition	Mean	Stn. Dev
age	age at interview	35.79	13.3
b_{it}	benefits received (per week)	45.86	55.01
W_{it}^R	reservation wage (per week)	126.25	84.32
a_{it}	investment income (per week)	3.94	17.46
$\hat{W}_{it}$	constructed mean wage (per week)	171.41	73.87
W_{it}^L	net wage in previous job (per week)	152.72	124.9
U_{rt}	Regional unemployment rate[2]	6.72	2.44
W_{it}^A	Wage accepted on re-employment	127.30	86.61
length	time since last job (in months)	17.45	21.3
search	=1 if "actively searched" for a job during past month	0.57	0.49
white	ethnic background (=1 if white)	0.94	0.22
sex	sex (=1 if male)	0.48	0.49

1. Statistics are calculated for the pooled cross section

2. From UK Office of National Statistics

Table 2: Some Key Variables

Variable			Mean	Stn. Dev	Median	Percentiles 5th	95th
Spell Length (months)[1]		Searchers	12.89	17.52	7	0	50
		Non Searchers	23.58	24.22	13	1	77
Reservation Wage	(W_{it}^R)	Searchers	145.95	86.04	136.59	42.51	285.44
		Non Searchers	99.76	74.14	78.53	21.81	236.97
Previous Wage[1]	(W_{it}^L)	Searchers	164.81	137.43	142.86	34.22	374.56
		Non Searchers	136.49	103.69	118.88	22.78	344.31
Re-employment Wage	(W_{it}^A)	Searchers	143.04	85.64	134.02	25.48	290.72
		Non Searchers	96.15	79.89	73.85	15.35	219.03
Reservation/Previous	(W_{it}^R/W_{it}^L)	Searchers	1.28	1.94	0.94	0.36	2.84
		Non Searchers	1.12	1.43	0.79	0.16	3.26
Reservation/Re-emp.	(W_{it}^R/W_{it}^A)	Searchers	1.39	1.64	0.99	0.42	3.64
		Non Searchers	1.47	1.84	0.93	0.19	4.21

1. Includes multiple observations of the same spells at different points in time

Table 3: The Distribution of Reservation Wage Ratio

	Proportion of (W^R/W^L) less than						
Sample	0.5	0.8	1.0	1.2	1.5	2.0	3.0
All	0.20	0.43	0.61	0.73	0.83	0.90	0.95
Male	0.16	0.40	0.61	0.74	0.86	0.92	0.96
Female	0.25	0.46	0.62	0.71	0.80	0.87	0.93
Searchers	0.12	0.37	0.58	0.71	0.82	0.90	0.95
Non-Searchers	0.31	0.51	0.66	0.75	0.84	0.90	0.94
Male Searchers	0.09	0.35	0.59	0.73	0.85	0.92	0.96
Male Non-Searchers	0.31	0.51	0.66	0.77	0.88	0.93	0.96
Female Searchers	0.15	0.40	0.57	0.67	0.77	0.87	0.94
Female Non-Searchers	0.32	0.50	0.66	0.74	0.82	0.88	0.93

Table 4: OLS Estimation

Dependent Variable: $\ln W_{it}^R$

	(1)	(2)[2]	(3)[2]
Sample	All	Male	Female
$\ln W_{it}^L$	0.35	0.42	0.28
	(0.03)	(0.03)	(0.04)
$(\ln b_{it})/100$	1.06	0.93	2.30
	(0.74)	(0.71)	(1.42)
$\ln \hat{W}_{it}$	0.29	0.06	0.40
	(0.07)	(0.06)	(0.09)
$(\ln U_{rt})/100$	-8.59	-9.51	-9.34
	(4.02)	(4.35)	(6.59)
$(\ln a_{it})/100$	-0.97	-2.63	0.84
	(1.22)	(1.28)	(2.07)
N	1,248	614	634
$\bar{R}^2$	0.40	0.35	0.22

1. Standard errors (in parentheses) are adjusted for estimation of $\hat{W}_{it}$

2. $\hat{W}_{it}$ calculated separately for each sub-sample.

3. All regressions also include a constant, cubic in age and number of dependent children.

4. $\ln a$, $\ln U$ and $\ln b$ are all divided by 100

Table 5: IV Estimation

Dependent Variable: $\ln W_{it}^R$

Sample	(1) All	(2)[2] Male	(3)[2] Female
$\ln W_{it}^L$	0.47	0.57	0.38
	(0.04)	(0.06)	(0.06)
$(\ln b_{it})/100$	1.13	1.21	2.09
	(0.73)	(0.73)	(1.39)
$\ln \hat{W}_{it}$	0.25	0.06	0.36
	(0.07)	(0.06)	(0.09)
$(\ln U_{rt})/100$	-8.52	-10.0	-8.76
	(3.94)	(4.43)	(6.44)
$(\ln a_{it})/100$	-2.01	-3.88	-0.08
	(1.24)	(1.38)	(2.08)
N	1,248	614	634
$\bar{R}^2$	0.40	0.33	0.21
Hausman test χ^2	25.37	34.66	12.04
(p-value)	(0.00)	(0.00)	(0.15)

1. Standard errors (in parentheses) are adjusted for
   estimation of $\hat{W}_{it}$

2. $\hat{W}_{it}$ calculated separately for each sub-sample.

3. All regressions also include a constant, cubic
   in age and number of dependent children.

4. W^L is instrumented by alternative observations of the previous wage

Table 6: Fixed Effects

Dependent Variable: $\ln W_{it}^R$

	(1) All	(2) Male[2]	(3) Female[2]
$\ln W_{it}^L$	0.15	0.16	0.14
	(0.04)	(0.04)	(0.07)
$(\ln b_{it})/100$	0.84	1.15	-1.19
	(0.96)	(0.88)	(2.39)
$\ln \hat{W}_{it}$	0.18	0.01	0.23
	(0.11)	(0.08)	(0.16)
$(\ln U_{rt})/100$	-0.20	-0.12	-0.29
	(0.13)	(0.13)	(0.23)
$(\ln a_{it})/100$	3.14	-3.18	9.04
	(2.49)	(2.66)	(4.45)
N	320	189	131
$\bar{T}$	2.3	2.3	2.2
R^2	0.11	0.20	0.11

1. Standard errors (parentheses) adjusted for estimation of $\hat{W}_{it}$

2. $\hat{W}_{it}$ calculated separately for each sample

3. All regressions also include a constant, cubic in age and number of dependent children.

4. N = number of persons, $\bar{T}$ = avg. number of obs. per person

Table 7: Duration Dependence

Dependent Variable: $\ln W_{it}^R$

	(1)		(2)		(3)	
	All		Men		Women	
IV	$\ln W_{it}^L$	$\ln \hat{W}_{it}$	$\ln W_{it}^L$	$\ln \hat{W}_{it}$	$\ln W_{it}^L$	$\ln \hat{W}_{it}$
Level	0.45	0.13	0.49	0.02	0.41	0.38
	(0.04)	(0.07)	(0.07)	(0.08)	(0.06)	(0.11)
Interaction	-0.72	0.41	0.13	0.17	-1.19	-0.32
with length/120	(0.24)	(0.23)	(0.37)	(0.34)	(0.32)	(0.43)
N	2,204		1,026		1,178	
Fixed Effects						
Level	0.21	0.04	0.16	0.00	0.23	0.32
	(0.04)	(0.07)	(0.04)	(0.09)	(0.06)	(0.13)
Interaction	-0.44	0.46	-0.19	0.04	-0.76	-0.24
with length/120	(0.10)	(0.18)	(0.16)	(0.26)	(0.16)	(0.36)
NT	2,493		1,297		1,196	

1. Standard errors are in parentheses

2. $\hat{W}_{it}$ calculated separately for each sample

3. All regressions also include a constant, cubic in age

and number of dependent children

Table 8: Control for Search Intensity

Dependent Variable: $\ln W_{it}^R$

	(1) All		(2) Search		(3) Non-Search	
	$\ln W_{it}^L$	$\ln \hat{W}_{it}$	$\ln W_{it}^L$	$\ln \hat{W}_{it}$	$\ln W_{it}^L$	$\ln \hat{W}_{it}$
IV: All	0.47	0.25	0.58	0.12	0.29	0.52
	(0.04)	(0.07)	(0.05)	(0.07)	(0.08)	(0.14)
N	1,248		782		466	
IV: Men	0.57	0.07	0.54	0.07	0.61	0.11
	(0.06)	(0.07)	(0.07)	(0.07)	(0.13)	(0.18)
N	614		465		149	
IV: Women	0.39	0.43	0.59	0.16	0.22	0.67
	(0.07)	(0.12)	(0.09)	(0.14)	(0.10)	(0.19)
N	634		317		317	
FE: All	0.16	0.18	0.20	-0.00	0.02	-0.29
	(0.04)	(0.10)	(0.04)	(0.11)	(0.12)	(0.35)
N	320		181		139	

1. Standard errors are in parentheses

2. $\hat{W}_{it}$ calculated separately for each sample

3. All regressions also include a constant, cubic in age
and number of dependent children