Specific Human Capital Accumulation and Job Match Quality –

Implications for Measuring Returns to Tenure

TIM BARMBY[1] and BARBARA EBERTH[2] (University of Aberdeen)

February 2006

Preliminary (Please do not quote without authors' consent)

Abstract

This paper makes use of a simplified form of the theoretical argument presented by Stevens (2003) that suggests a clear and unambiguous negative bias in the returns to tenure if observed wage functions are interpreted as wage offer functions. We show that the simplified version of Stevens theory offers a possible explanation for the apparent puzzle presented by Medoff and Abraham (1980, 1981) who found that the estimated coefficient on tenure did not fall when direct measures of productivity were introduced into their wage equation. The paper makes use of methodology as outlined by DiNardo, Fortin and Lemieux (1996) of constructing counterfactual wage densities to illustrate this empirically.

[1] Address for correspondence:- Department of Economics, University of Aberdeen, Old Aberdeen, Scotland AB24 3SQ tim.barmby@abdn.ac.uk
[2] Health Economics Research Unit, University of Aberdeen, Aberdeen, Scotland AB25 2ZD b.eberth@abdn.ac.uk

Studying the way earnings distributions evolve within internal labour markets (ILM's) can reveal a number of things about the way organisations seek to reward and give incentives to their workers. Reflected in these distributions will also be aspects of worker's behaviour in terms of their decisions to stay with or leave the organisation. This paper seeks to disentangle these two things.

To illustrate the basic idea of this paper, consider the following distributions in figure 1: -

[Figure 1]

Figure 1 plots the distribution of real average log hourly wages for employees of an internal labour market (ILM) entering the firm for the first time in the year 1989 at three points in their employment history with the firm: in the year of entry (1989), five years after entry (1994), and ten years after entry (1999). We would expect the observed earnings growth in figure 1 to be based on the idea that workers accumulate specific human capital, Becker (1993), and that firms will pay for this increased productivity. Secondly, firm's may also choose to construct seniority wage profiles that are steeper than the growth in productivity, Lazear (1979), which will have implications for the observed distributions in figure 1, but the underlying link will be from the flow of productivity of the worker. Thirdly, workers are in a market for their services and may receive or indeed seek out alternative offers from other firms in the market. If these offers will dominate existing remuneration, then workers will move. As a consequence of this, workers who leave the firm will not be accounted for in subsequent earnings distributions. Therefore, if workers systematically leave the firm, one cannot infer from earnings distributions subsequent to entry how the productivity and consequently the remuneration of the initial cohort of workers evolves over time. If on the other hand, workers leave the firm randomly, earnings distributions subsequent to that on entry for that cohort will be in fact informative about the evolution of productivity and hence remuneration of workers of that cohort.

Traditionally, the implications of Becker's human capital on-the-job training hypothesis have been tested empirically by estimation of least squares regressions as proposed by Mincer (1974) and Mincer and Jovanovic (1981) indexing general human capital by labour market experience and specific human capital by tenure. In particular one of the main theoretical predictions of Becker's specific human capital on-the-job training hypothesis is that wages increase as tenure on the job increases. The acquisition of firm specific human-capital can also give incentives to workers and firms to establish long-term employment relationships, and reduce the incidence of turnover. This last prediction implies that the probability of a job change declines with tenure[3]. On the other hand, workers who are characterised by high tenure are predicted to experience earnings losses if their employment were to end[4].

The above two studies have become a benchmark case for other studies in the literature such as Abraham and Farber (1987), Topel (1991) and Altonji and Williams (2005) that identify several problems regarding the observed positive correlation between tenure and wages that may not be sufficient enough to support the view that earnings increase with seniority due to increases in productivity because of either omitted variables accounting for worker/job or worker/employer match quality, or the endogeneity of tenure in an earnings equation. The attention that the returns to tenure has received in the literature concerns itself with the question of how to modify earnings equations to arrive at the "true returns" to tenure. Topel (1991 p.146) summarizes that the empirical evidence to that date "ignores the job-changing

[3] See for example Parsons (1972), Blau and Kahn (1981a, 1981b) , Mincer and Jovanovic (1981) and Abraham and Farber (1987) for empirical evidence.
[4] See for example Bartel and Borjas (1978), Jacobson (1993), et al. and Topel (1990).

decisions that have brought workers to the combination of wages, job tenure, and market experience that are observed in survey data". One reason for a job change is finding a better job match elsewhere increasing productivity but also job attachment in that job. The implication for the relationship between tenure and wages as postulated by job matching is that a good match will produce a high wage and that over time high wage/good matches persist while low wage/bad job matches dissolve implying that workers with long employment spells earn relatively more. It can also be interpreted as highly productive workers having a lower probability of leaving a job compared to relatively less productive workers. Since tenure is endogenous to wages, tenure can simply be written as a function of wages and thus, the inverse of an earnings function presents a function of quit behaviour. If those workers with high unobserved match quality consistently receive high wage offers from their current employers and accept these wage offers, a positive bias between wages and tenure will be generated in an empirical earnings equation. At the same time, those employees who are characterised by low tenure will move jobs since their outside offers are higher than offers from the current employer which will generate a negative bias in the returns to tenure in a cross-section of data. The empirical literature on the bias in the returns to tenure at present holds this to be ambiguous, see Altonji and Williams (2005) p374.

Stevens (2003) focuses on this self-selection problem generated by job matching arguing that it does not account for specific human capital and derives a theoretical model of earnings functions that incorporates both, specific human capital and matching. Contrary to the empirical studies in the literature on the returns to tenure, Stevens (2003) models wage offer functions endogenously rather than exogenously in order to pinpoint exactly how tenure and match quality affect wages. The implication of Stevens' model is that sample selection does exist but that the bias on tenure is unambiguously negative. The reason for this is that workers with high levels of firm specific human capital have a higher probability of staying with the firm even if their match quality is low.

Therefore, in order to fully understand observed wages in firms and how they change over time (figure 1), one needs to understand the process by which external offers are made, internal counter offers might be forthcoming and which of these are accepted by the worker. This was discussed by Lazear (1986) and more recently by Stevens (2003)[5]. In what follows, a simplified version of the Stevens (2003) model is presented and applied empirically to firm level data with the use of counterfactual kernel density wage estimation as outlined by DiNardo, Fortin and Lemineux (1996) to illustrate the empirical negative bias in the returns to tenure as implicated by Stevens (2003). It will also be shown how the model can explain the puzzle presented by Medoff and Abraham (1980, 1981) who observe that wages grow with seniority even though productivity does not.

Model

We propose a model of observed earnings within an organisation of the form

$$w = g + k + \varepsilon_0 \tag{1}$$

where w is the (natural) logarithm of earnings so that the above equation can be thought of as a standard Mincer earnings equation with g representing general human capital, k specific human capital and ε_0 match quality.

This formulation is very close to Stevens (2003) who considers these relationships explicitly within an auction framework. Lazear (1986) deals with very similar issues, though he concentrates on the asymmetry of information concerning the productivity of the worker

[5] See also Burdett and Coles (2003) and Stevens (2004), for related discussions on matching models.

between the present employer and a single prospective employer. Our formulation essentially assumes that the labour market here is relatively “transparent” and the possibility that both the present and prospective employer are well informed about any given workers productivity. Contrary to Stevens (2003), Lazear (1986) however views the specific (human) capital component within the earnings equation as being the value of the employment match. We follow Stevens (2003) in maintaining a distinction between the specific human capital component in the earnings equation and match quality.

We think of this distinction in the following way – a worker can acquire specific knowledge of the way an organisation works that can enhance his productivity and consequently his earnings. Thus specific human capital can be thought of as acquiring the correct skill-mix to operate effectively within the organisation as in Lazear (2003). However, we argue in line with Stevens (2003) that there will be effectively an “unobserved” component to an individual’s efficiency within the organisation. This can be thought of as how well, maybe, an individual gets on with certain co-workers or his/her perception of the degree of managerialism that the firm employs. These things are not firm specific as co-workers may leave and people may perceive procedures in different ways.

To simplify the structure we assume that when in an organisation individuals accumulate specific human capital, k, at the rate of one unit per time period so that the amount of specific human capital can be measured by tenure. Firms are defined as a collection of workers engaged on one common productive enterprise. Firms have some optimal size (which we don’t define here); all we assume is that firms start at some point of time zero, are only able to recruit some proportion of their final size initially and by recruitment grow to their optimal size.

Assume, for just a moment, that once a worker joins a firm, he/she stays there indefinitely. Also assume for simplicity, that a firm whose optimal size is 25 is able to recruit 1/5 of its optimal workforce each period so that optimal firm size is achieved after 5 periods. Workers will accept jobs if $\varepsilon_0 > 0$ (i.e. an offer that at least equals the observable productive worth of their general human capital). After 5 periods the plot of *k* (specific human capital) against ε_0 (match quality) might look something like this

[Figure 2]

Now the distribution of ε_0 conditional on *k* will be invariant and the mean and variance not a function of *k*. Therefore we can assert that $\operatorname{cov}(k, \varepsilon_0) = 0$.

In Stevens' (2003) model the main attribute of the external market is that it is one of matching where the quality of the match is the private information of the employer. General and specific human capital endowments of an employee are generally known. In this market, current and alternative firms simultaneously produce wage offers with the highest offer being accepted by the employee.

Following the Stevens' notation, consider a worker whose productivity (v_0) with his/her current employer is given by:

$$v_0 = g + k + \varepsilon_0 \tag{2}$$

Where ε_0 denotes the match quality of the employee with his current employer.

The external market offers a number of potential employers i = 1,…, n where the productivity of an employee, were he to move employer, is given by:

$$v_i = g + \varepsilon_i \qquad (3)$$

Match quality ε_i in (3) is only known by the alternative employer and is distributed as:

$$\varepsilon \sim f(\varepsilon);\ \varepsilon \in (\underline{\varepsilon}, \overline{\varepsilon}) \qquad (4)$$

One can immediately see that the model in equation (2) and (3) is an extension of Lazear's (1986) model of raids and offer matching. Lazear's (1986) model focuses specifically on earnings functions within an internal labour market describing individual firm wage offer processes. It has the same form as equation (2) and (3) with the crucial difference that Stevens *explicitly* adds the error term to account for match quality. Unlike Lazear (1986), Stevens is not considering the incumbent firm's decision to match or not to match an offer. In Lazear's model this will depend on the information the raiding firm has about a worker's match quality. Stevens' interest rests on the direction the bias on tenure in earnings functions will take once job- matching effects are specifically accounted for.

In Stevens' model, each period employees working for a given employer have a probability of a wage offer arriving from an alternative firm in the external market. Assuming that the current and alternative employers know their specific match quality, workers, if receiving an offer, will only stay with their current employer if productivity with the current employer is greater than productivity with external employers.

The important point here is that it will be the operation of the external market that will generate a negative covariance between k and ε both in any single firm and by extension in the market overall.

A worker's earnings in the incumbent firm will be

$$w_0 = g + k + \varepsilon_0 \tag{5}$$

The value of the worker to a potential employer will be

$$w_i = g + \varepsilon_i \tag{6}$$

We assume that the worker will leave if $w_i > w_0$ or $\varepsilon_i > k + \varepsilon_0$ assuming that $g_0 = g_i$. This process describes a non-random selection from the distribution of match quality. Diagrammatically this can be represented as

[Figure 3]

Figure 3 gives the joint distribution of specific capital, k and match quality with the current employer, ε_0, with $\text{cov}(k, \varepsilon_0) = 0$. That is, the initial distribution of k and ε_0 are independent. Assume all employees receive an alternative offer with match quality ε_i, depicted by the solid black line in figure 3, with probability 1. Workers for whom the sum of the value of specific capital (k) and match quality with the current employer (ε_0) exceeds the outside offer (ε_i) will stay. These are workers in the area above and to the right of the outside offer line. On the other hand workers will leave if the sum of the value of specific capital (k) and match quality with the current employer (ε_0) is below the outside offer (ε_i). Clearly this process will induce a negative correlation between k and ε_0 relative to the internal distribution. In other words, it demonstrates that within the group of *stayers*, the effect of non-random exits generates a negative correlation between k and ε_0. Secondly, this negative correlation will generate a negative bias in the coefficient on tenure from a regression of earnings on tenure[6]. Thirdly, figure 3 visualises Stevens (2003) assertion that employees with high specific capital (k) tend

[6] This is a standard result in the econometric literature where OLS is biased and inconsistent. See for example Johnston and DiNardo (1997) page 155 on attenuation bias.

to stay with their current employer even though their match quality (ε_0) is relatively low precisely because the error term in a sample of accepted wage offers accounting for unobserved match quality is negatively correlated with specific human capital. Note the direction of the effect on the correlation between k and ε_0 would not be affected if we assumed that workers only received an outside offer with some probability.

One of the predominant theoretical ideas is due to Topel (1986, 1991) where "high" quality workers tend to move as these are the ones who receive outside offers. Consequently, one would observe movers (low tenure employees) with high earnings. The framework above would indeed predict this since movers will have $\varepsilon_i > k + \varepsilon_0$ with g being common. This will imply $w_i > w_0$ which is not surprising, but what the operation of the external labour market induces is a correlation between k and ε_0 and not k and ε_i. Therefore, estimating and earnings equation for a given firm of the form

$$w = g + k + \varepsilon_0 \tag{7}$$

with a negative correlation between k and ε_0 will unambiguously bias downward the least squares coefficient on k (tenure).

The Stevens conjecture provides a direct link in explaining the apparent puzzle presented by Medoff and Abraham (1980, 1981) who empirically test the human capital on-the-job training hypothesis that increasing experience earnings profiles can be explained by increasing productivity profiles using single firm data. At the heart of their empirical test lies the assumption that performance indicators are an appropriate instrument to estimate relative within grade employee productivity. Therefore, if the human capital on-the-job training hypothesis was true, adding controls for performance indicators into a human capital type log earnings equation should drive the effect of tenure on wages to zero. Amongst others Medoff and Abraham find that wages increase with tenure but that the introduction of performance indicators into an OLS earnings equation results in the coefficient on tenure to either increase or remain unchanged. Hence, they conclude that the effect of tenure on wages is unaffected by controls for performance indicators. Medoff and Abraham find this result particularly troubling because their interpretation rests on the assumption that there exists a positive correlation between seniority and performance. Given this assumption, their finding suggests that although higher seniority moves an employee up the distribution of earnings within a grade, it does not necessarily improve an employees position in the within grade performance distribution. Consequently Medoff and Abraham infer that the human capital on-the-job training hypothesis must be questioned as a candidate to explain why wages increase with seniority since it argues that they do so because of productivity increases. The puzzle Medoff and Abraham are presented with given their assumption of a positive correlation between seniority and performance is that productivity has nothing to offer in terms of an explanation of why wages are observed to grow with tenure on the job.

To explain the link with the Stevens argument outlined above, consider the following earnings function:

$$\ln w = \beta_0 + \beta_1 k + u \qquad (8)$$

Here, k is specific human capital as conventionally measured by tenure and u is the error term of the equation. One can estimate the true returns to specific human capital if $\operatorname{cov}(k,u) = 0$. If it is the case that $\operatorname{cov}(k,u) \neq 0$, the model outlined above implies that the estimated $\hat{\beta}_1$ will be negatively biased because unobserved match quality accounted for by the error term in (8) is negatively correlated with specific capital (tenure). Medoff and Abraham argue that by introducing performance ratings into the earnings equation as in equation (9) below, the returns to tenure should move towards zero because performance ratings are a direct measure of productivity.

$$\ln w = \beta_0 + \beta_1 k + \beta_2 performance + v \tag{9}$$

What they find instead is that $\hat{\beta}_1$ either increases or remains the same. The Stevens framework can offer an explanation of this apparent puzzle:- if performance dummies are a proxy for match quality. Hence, the error term in (8) is equal to $u = \beta_2 perf + v$. Removing unobserved match quality from the error term *u* in equation (9) will result in the remaining error *v* in (9) to be uncorrelated with specific human capital *k.* Therefore, the inclusion of performance ratings into the earnings equation will reduce the existing negative bias on tenure. What Medoff and Abraham are in fact observing when including performance ratings into their earnings equations is the extent of the negative bias in tenure induced by the outside offer story developed by Stevens.

Empirical Methodology

In order to empirically illustrate the theoretical prediction of the above model of a negative bias in the returns to tenure one needs to ask whether it is possible in analogy to figure 1 to draw the distribution of earnings of cohorts that would have existed if exits from the cohort had not been systematic (i.e. had been random). In this case, the movement of the distribution of earnings will reveal the way in which productivity, and we are assuming correspondingly, the reward of the worker in the initial cohort of workers would have evolved over time. We seek to do this by constructing the distribution of earnings that would have prevailed at subsequent time periods if the distribution of characteristics of workers had remained as it was on entry to the firm. Since if exits are random, the distribution of characteristics will, in expectation, remain the same. The empirical illustration will be based on data for three cohorts, cohort 89, 90, and 91, of an internal labour market (ILM) of a large financial sector firm with operations in the UK. The constructed distributions will also reflect other wage setting devices such as back loading payments to give workers incentives not to shirk early on in their careers (Lazear's (1979, 1981) delayed payment hypothesis) as well as specific human capital accumulation. But we do not attempt to disentangle these two things here.

The empirical test is based on the estimation of semi-parametric counterfactual wage densities using methodology as outline by DiNardo, Fortin and Lemieux (1996). This method allows for a visual presentation of wage densities of the three cohorts that would have prevailed at time periods subsequent to entry to the firm if characteristics of workers had prevailed at their entry level[7]. The goal of such decomposition is to fix a set of employee characteristics when they enter the firm and then look at the distribution of wages at a later point in time having controlled for these baseline characteristics. In this context, assuming that exits of workers are random, the distribution of expected characteristics in years after entry to the firm will stay the same as on entry. This approach allows for a graphical comparison of the actual and counterfactual wage distributions of a cohort at a given point in time. The counterfactual distribution being the distribution showing the extent to which the observed growth in earnings of a cohort in years after entry under- or overstates earnings growth that would have been observed if those workers who left the firm over time did so in a random fashion. For example, imagine that workers of a cohort whose qualification on entry is a university degree as opposed to no university degree have a higher propensity to leave the firm between time t and t+5. The intuition behind the DiNardo et al (1996) methodology is to reweight the observations in the wage distribution at t+5 by the relative weight of degree versus non-degree holders as of time t. This will give non-degree holders in the wage distribution in t+5 a lower weight than degree holders. This re-weighting mechanism

[7] Of course this is similar to the Oaxaca (1973) decomposition. Since the Oaxaca decomposition focuses entirely on the mean, constructing counterfactual wage densities allows for making inferences about how wages evolve across the distribution of wages over time.

therefore allows simulating randomness so that every worker in the cohort has a similar probability of leaving the firm.

Considering a cohort of employees that was recruited by the firm in 1989. We would like to reweight this cohort's wage distribution in 1994 by the distribution of employee characteristics as of entry to the firm. DiNardo et al. (1996) derive the following reweighting function ψ(z)[8] to achieve this

$$\psi(z) = \frac{dF(z \mid t = 1989)}{dF(z \mid t = 1994)} \tag{10}$$

where z refers to individual characteristics and t to the time period. Given this, the counterfactual wage density that would have prevailed in 1994 if the characteristics of workers who entered the firm in 1989 had remained as on entry is the density of wages in 1994 reweighted as stated by the function in (10).

Reweighting the 1994 density allows for the simulation of randomness and thus provides a mechanism to model non-random attrition. To see this, consider equation (11):

$$\psi(z) = \frac{dF(z \mid t = 1989)}{dF(z \mid t = 1994)} = \frac{\dfrac{dF(t = 1989 \mid z)dF(z)}{dF(t = 1989)}}{\dfrac{dF(t = 1994 \mid z)dF(z)}{dF(t = 1994)}} = \frac{\Pr(t = 1989 \mid z)\Pr(t = 1994)}{\Pr(t = 1994 \mid z)\Pr(t = 1989)} \tag{11}$$

In the above, $\Pr(t = k \mid z)\ k = 1989{,}1994$ is the attrition probability that can be estimated using a conventional logit or probit model. These probabilities are not probabilities of individuals remaining in the firm in year t=1989, 1990,… since the sample space would be the number of individuals on entry. Here the sample space is the individual/date points given by the probability observing date t = 1989, 1990,… given particular characteristics. If there

[8] See appendix 1 for the full derivation of the reweighting function ψ(z).

was no systematic transition out of the firm, $\Pr(t=k \mid z) = \Pr(t=k)\ \forall\ k$ and $\psi(z) = 1$. Once $\hat{\psi}(z)$ is estimated the counterfactual density can be computed by weighted kernel density estimation.

Empirical illustration of a negative bias between tenure and match quality

Applying the above outlined methodology to workers of cohort 89, 90, and 91 of an ILM five and ten years after entry to the firm yields actual and counterfactual real log hourly wage densities as shown in figure 4a-c. The counterfactual wage densities are the adjusted densities that would have prevailed five and ten years after the respective workers in each cohort joined the firm if the characteristics of cohort individuals had stayed as on entry, or as was argued earlier if exits from the firm had been random[9].

[Figure 4a]

[Figure 4b]

[Figure 4c]

The empirical evidence embodied in figure 4a-c suggests for all three cohorts that the actual ln wage distributions consistently understate the growth in wages that would have occurred if cohort individuals had left the firm randomly. In other words, figure 4a-c shows direct empirical evidence of the theoretical assertion presented by Stevens that there is an apparent negative bias in the returns to tenure.

[9] The probit estimates used in constructing the weights ψ(z) as given by equation 16 are reported in Appendix 2. A further point to note is that exits are random once baseline characteristics are controlled for in the vector z. This approach is similar to the propensity score method used in the treatment evaluation literature. See for example Rosenbaum and Rubin (1983) where the selection into a programme is based on observables as in the case above. Propensity score methods do not work if selection is on unobservables. The analysis presented here using the DiNardo et al. (1996) methodology may also run into problem if systematic exits were based on unobservables such as job satisfaction or employee motivation in that the estimators can be seriously biased. See Heckman (1990) for a discussion on sample selection bias and DiNardo (2002) for a discussion on the use of propensity scores as weights as an alternative to regression techniques.

In order to get a numerical understanding of the observed empirical negative biases, consider table 1a-c. Approximations of the expected hourly wages in pound sterling for the actual and counterfactual hourly wage distributions are computed at the mean, the 25th and the 75th percentile corresponding to figure 4a-c. For all three cohorts, actual wages after 5 and 10 years of entry fall short of counterfactual wages at the mean, the 25th and the 75th percentile, the exception being cohort 90 in 1995 where the approximated counterfactual wage at the 25th percentile is the same as the actual wage, and cohort 91 for which the approximated counterfactual wage in 1996 and 2001 falls marginally short of the actual wage at the 25th percentile. Table 1a-c also computes the implied annual wage growth for the respective cohort individuals over time. Actual average annual wage growth over ten yeas for cohort 89 is approximated to be 4.3%. If characteristics of cohort 89 employees had remained as they were on entry, implied average annual wage growth would have been 5.6% suggesting a downward bias in average annual wage growth of 1.3 percentage points. Similarly for cohort 90, the approximated negative bias in average annual wage growth over ten yeas is 0.6 percentage points and for cohort 91 it is a whopping 2.9 percentage points.

[Table 1a]

[Table 1b]

[Table 1c]

The graphical and numerical presentation of the bias in tenure suggests that there is an existing negative bias in tenure for all three cohorts. Going back to figure 3, it was argued that the points are drawings from the joint distribution of specific capital (k) and match quality (ε_0) with the current employer. One can think of these points as the joint distribution of specific capital and match quality of individuals belonging to different cohorts in a given firm. The question thus arises whether the empirical result for the specific cases of three different cohorts as presented above also holds for the general case.

To make this more clear, the argument implies that if there exists a negative bias on the return to tenure for a given cohort as above due to the selection effect of outside offers being received by incumbents as illustrated by figure 3, and since any cross section is made up of different cohorts, the negative bias in the returns to tenure should be observed more generally. The magnitude of the bias will differ depending on the "age" of the cohorts but the direction of the bias will be the same.

To test this hypothesis, a cross-sectional panel of cohort 89, cohort 90 and cohort 91 has been utilised to estimate the actual wage distribution for the sum of all three cohort individuals remaining in the firm in year 1996 and the sum of the counterfactuals to derive the counterfactual wage distribution for this cross section in year 1996. The result is depicted in figure 5.

[Figure 5]

One can clearly see that the Stevens hypothesis also holds true for the general case. Again, there exists an inherent negative bias in the returns to tenure when comparing the counterfactual real average log hourly wage distribution in 1996 (solid line) with the actual distribution of real average log hourly wages (dashed line) in 1996. Note that the negative bias in this case is not as pronounced as in figures 4a-c. This is clearly not surprising and certainly anticipated. The counterfactuals for figures 4a-c were drawn for three different cohorts five years and ten years after entry to the firm. In the case of figure 5, the counterfactual density embodies three different weighting functions, one for cohort 89 seven years after entry, one for cohort 90 six years after entry and one for cohort 91 five years after entry. Figure 5 shows the combined effect of the three different weightings. Figures 4a-c have already shown the biases for cohort 89, 90, and 91 five and ten years after entry. The counterfactual for cohort 91 five years after entry clearly embodies a negative bias that is much more pronounced at the upper end of the log hourly wage distribution whereas the biases lie more to the right of that for cohort 89 and 90 five years after entry. For the negative bias observed in the combined effect seven years after entry (figure 5) this means that the weightings for the counterfactual density of cohorts 89 and 90 will push the counterfactual more to the right when at the same time the weighting for cohort 91 will push it to the left with the former outweighing the latter, thereby generating a negative bias that is less pronounced than for the three cohorts in separation.

Conclusion

The paper makes a valuable contribution to the ongoing debate in the literature surrounding the question of the bias in the returns to tenure by testing empirically the theoretical prediction of Stevens (2003) that the returns to tenure are unambiguously negatively biased. Her contribution rests on modelling wage offer functions endogenously rather than exogenously. Modelling wage offer functions endogenously allows for the incorporation of both job matching and human capital. The model shows that employees accumulating higher levels of specific human capital have a higher propensity of staying with the firm even if their match quality is low resulting in a negative correlation between seniority and match quality for a sample of accepted wages.

Constructing counterfactual wage densities in the spirit of DiNardo et al. (1996) allowed for testing the Stevens assertion in a first instance for three cohorts in the British bank. Here the question was asked how the distribution of wages would have looked like five and ten years after entry of the three cohorts to the firm if characteristics had remained as they were on entry. For all three cohorts the empirical evidence supports the Stevens hypothesis that the returns to tenure are unambiguously negatively biased. Secondly, the DiNardo et al. (1996) methodology has been applied to the general case whereby the three cohorts have been pooled into a cross section panel dataset to establish whether the sum of the three cohort's counterfactual wage densities also suggest an inherent negative bias in the returns to tenure. Again, the results clearly suggest a negative bias in the returns to tenure.

Thirdly, a reinterpretation on the basis of the theoretical work by Stevens and the empirical support offered by the counterfactual density estimations of Stevens' hypothesis that the returns to tenure are unambiguously negatively biased can now be offered to shed new light on the apparent puzzle in Medoff and Abraham's (1980, 1981) work. They find that the introduction of performance indicators into an OLS earnings equation appear to either increase or leave the estimated coefficient on tenure unchanged. This presents the researcher with a puzzle if it is assumed that tenure and performance are in fact positively correlated. Under this assumption, exclusion of performance ratings results in tenure acting as a proxy for performance thereby inflating the estimated coefficient on tenure. Including performance ratings thus should reduce the estimated coefficient on tenure. However, in the framework of Stevens and the counterfactual analysis, it is shown that there is an existing negative bias on tenure. Adding performance ratings to an OLS equation has been argued to serve as a proxy for match quality and therefore reduces some of the inherent negative bias on tenure. According to the Stevens' story Medoff and Abraham's results are therefore consistent with the existence of a negative bias induced by unobservable match quality.

Appendix 1: Derivation of the reweighting function ψ(z)

DiNardo et al (1996) start off their methodological analysis by proposing to think about each observation as a realisation of a random vector (w,z,t) that belongs to a joint distribution *F*(w,z,t) of wages w, individual characteristics z, and a date t. To start with, lets consider the marginal distribution of wages of cohort 89 on entry, t=1989,

$$f(w \mid t=1989)=\int_z f(w,z \mid t=1989)dz \tag{1A}$$

Since $f(w \mid z,t=1989)=\dfrac{f(w,z \mid t=1989)}{f(z \mid t=1989)}$ and $\dfrac{dF(z)}{dz}=f(z)$ equation (1A) can be written as,

$$\begin{aligned} f(w \mid t=1989) &= \int_z f(w \mid z,t=1989) f(z \mid t=1989)dz \\ &= \int_z f(w \mid z,t=1989)dF(z \mid t=1989) \end{aligned} \tag{2A}$$

Equation (2A) clearly refers to time period 1989. However, if we meant the right hand side of equation (2A) as

$$\int_z f(w \mid z,t=1994)dF(z \mid t=1989) \tag{3A}$$

we would be constructing a counterfactual density of wages that would have prevailed in 1994 (five years after the cohort entered the firm) if the distribution of characteristics (z) would have remained as of 1989. Following DiNardo et al. (1996) this can be indicated by

$$\int_z f(w \mid z,t=1994)dF(z \mid t=1989)=f(w \mid t_w=1994,t_z=1989) \tag{4A}$$

The density in (4A) is what we would like to estimate. The question is simply how to estimate it. Note that (4A) can be written as

$$\begin{aligned} f(w \mid t_w=1994,t_z=1989) &= \int_z f(w \mid z,t=1994)\frac{dF(z \mid t=1989)}{dF(z \mid t=1994)}dF(z \mid t=1994) \\ &= \int_z f(w \mid z,t=1994)\psi(z)dF(z \mid t=1994) \end{aligned} \tag{5A}$$

From this, the counterfactual density that would have prevailed in 1994 if the characteristics of workers who entered the firm in 1989 had remained as on entry is the density of wages in 1994 reweighted as stated by the function

$$\psi(z) = \frac{dF(z \mid t = 1989)}{dF(z \mid t = 1994)} \tag{6A}$$

Reweighting the 1994 density allows for the simulation of randomness and thus provides a mechanism to model non-random attrition. Equation 7A below corresponds to equation (11) in the text.

$$\psi(z) = \frac{dF(z \mid t = 1989)}{dF(z \mid t = 1994)} = \frac{\dfrac{dF(t = 1989 \mid z) dF(z)}{dF(t = 1989)}}{\dfrac{dF(t = 1994 \mid z) dF(z)}{dF(t = 1994)}} = \frac{\Pr(t = 1989 \mid z) \Pr(t = 1994)}{\Pr(t = 1994 \mid z) \Pr(t = 1989)} \tag{7A}$$

Appendix 2: Probit estimations for the reweighting function $\psi(z)$

Probit estimations for the reweighting function $\psi(z)$ for cohort 89			
	Coefficient (Standard error)[b] t=1989	Coefficient (Standard error) t=1994	Coefficient (Standard error) t=1999
Gender	-0.091	0.027	-0.231
	(0.060)	(0.075)	(0.119)*
Age	-0.079	0.006	0.049
	(0.002)***	(0.001)***	(0.002)***
Grade on entry[a]	-0.665	0.060	0.514
	(0.040)***	(0.043)	(0.052)***
Higher Education	-0.549	0.145	0.405
	(0.100)***	(0.097)	(0.111)***
A-level	-0.362	0.060	0.283
	(0.043)***	(0.049)	(0.058)***
O-level	-0.623	0.141	0.387
	(0.040)***	(0.042)***	(0.051)***
Children aged 0 to 4	-0.302	0.074	0.210
	(0.057)***	(0.051)	(0.056)***
Asian/Ashian British	-5.724	0.285	0.247
	(0.367)***	(0.136)**	(0.150)*
Black/Black British	0.103	-0.033	-0.194
	(0.150)	(0.171)	(0.218)
Chinese/Ethnic		0.258	0.417
		(0.213)	(0.218)*
Gender*Grade on entry	0.415	-0.038	-0.080
	(0.068)***	(0.081)	(0.122)
Gender*Further Education	-0.293	0.019	0.179
	(0.132)**	(0.127)	(0.148)
Gender*A-level	-0.321	0.051	0.256
	(0.056)***	(0.065)	(0.080)***
Gender*O-level	-0.295	0.035	0.167
	(0.049)***	(0.054)	(0.066)**
Gender*Children aged 0-4	-0.223	-0.106	0.282
	(0.087)**	(0.072)	(0.075)***
Gender*Asian/Asian British	4.266	0.101	-0.061
	(0.000)	(0.162)	(0.183)
Gender*Black/Black British	-0.339	0.047	0.299
	(0.175)*	(0.193)	(0.242)
Gender*Chinese/Ethnic		0.168	-0.140
		(0.286)	(0.321)
Constant	1.844	-1.737	-3.770
	(0.067)***	(0.066)***	(0.082)***
Observations	30656	30778	30778
χ^2	3179.64	77.88	1068.74
Log-likelihood	-11152.74	-8385.67	-5126.23

a) If staff on entry, grade on entry = 1, 0 otherwise.
b) * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.
c) The omitted category for the qualification groups is degree holders. The omitted category for ethnic background is whites.

Probit estimations for the reweighting function $\psi(z)$ for cohort 90			
	Coefficient (Standard error)[b] t=1990	Coefficient (Standard error) t=1995	Coefficient (Standard error) t=2000
Gender	-0.130	-0.013	0.006
	(0.079)*	(0.093)	(0.127)
Age	-0.080	0.011	0.053
	(0.002)***	(0.002)***	(0.002)***
Grade on entry[a]	-0.701	0.108	0.569
	(0.052)***	(0.057)*	(0.070)***
Higher Education[c]	-0.480	0.124	0.434
	(0.105)***	(0.102)	(0.116)***
A-level	-0.363	0.078	0.325
	(0.052)***	(0.059)	(0.073)***
O-level	-0.659	0.165	0.512
	(0.047)***	(0.050)***	(0.062)***
Children aged 0 to 4	-0.275	0.021	0.362
	(0.068)***	(0.063)	(0.066)***
Asian/Ashian British[c]		0.299	0.274
		(0.123)**	(0.142)*
Black/Black British		0.096	-0.038
		(0.171)	(0.236)
Chinese/Ethnic	0.029	0.389	0.289
	(0.154)	(0.265)	(0.319)
Gender*Grade on entry	0.465	-0.041	-0.254
	(0.085)***	(0.097)	(0.128)**
Gender*Further Education	-0.336	0.126	-0.007
	(0.151)**	(0.146)	(0.183)
Gender*A-level	-0.384	0.105	0.238
	(0.064)***	(0.074)	(0.094)**
Gender*O-level	-0.287	0.082	0.108
	(0.055)***	(0.061)	(0.076)
Gender*Children aged 0-4	-0.061	-0.042	-0.003
	(0.092)	(0.083)	(0.087)
Gender*Asian/Asian British		0.034	-0.092
		(0.150)	(0.178)
Gender*Black/Black British		-0.071	0.048
		(0.194)	(0.263)
Gender*Chinese/Ethnic	-0.004	-0.178	0.112
	(0.178)	(0.333)	(0.393)
Constant	1.947	-1.898	-4.037
	(0.081)***	(0.081)***	(0.107)***
Observations	22279	22886	22886
χ^2	2278.60	95.85	883.57
Log-likelihood	-8487.52	-6528.19	-3840.79

a) If staff on entry, grade on entry = 1, 0 otherwise.
b) * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.
c) The omitted category for the qualification groups is degree holders. The omitted category for ethnic background is whites.

Probit estimations for the reweighting function ψ(z) for cohort 91			
	Coefficient (Standard error)[b] t=1991	Coefficient (Standard error) t=1996	Coefficient (Standard error) t=2001
Gender	-0.059	0.067	-0.191
	(0.101)	(0.127)	(0.179)
Age	-0.069	0.015	0.057
	(0.004)***	(0.004)***	(0.004)***
Grade on entry[a]	-0.569	0.233	0.550
	(0.077)***	(0.088)***	(0.106)***
Higher Education	-0.205	0.052	0.170
	(0.154)	(0.149)	(0.163)
A-level	-0.264	0.119	0.235
	(0.098)***	(0.107)	(0.128)*
O-level	-0.276	0.105	-0.042
	(0.111)**	(0.117)	(0.153)
Children aged 0 to 4	-0.308	0.178	0.251
	(0.112)***	(0.108)*	(0.122)**
Asian/Ashian British	-0.487	0.008	0.318
	(0.364)	(0.317)	(0.314)
Black/Black British	-0.144		
	(0.535)		
Chinese/Ethnic		-4.560	
		(0.538)***	
Gender*Grade on entry	0.262	-0.162	-0.141
	(0.118)**	(0.139)	(0.186)
Gender*Further Education	-0.173	0.034	-0.163
	(0.254)	(0.266)	(0.347)
Gender*A-level	-0.073	0.020	0.067
	(0.137)	(0.153)	(0.190)
Gender*O-level	-0.106	0.074	0.312
	(0.135)	(0.144)	(0.188)*
Gender*Children aged 0-4	-0.155	0.031	0.246
	(0.181)	(0.162)	(0.184)
Gender*Asian/Asian British		0.103	0.033
		(0.646)	(0.664)
Gender*Black/Black British	1.149		
	(1.098)		
Gender*Chinese/Ethnic		4.794	
		(0.000)	
Constant	1.449	-2.087	-3.906
	(0.146)***	(0.147)***	(0.187)***
Observations	4644	4653	4640
χ^2	416.46	31.87	212.57
Log-likelihood	-1845.10	-1285.47	-785.15

a) If staff on entry, grade on entry = 1, 0 otherwise.
b) * significant at the 10% level, ** significant at the 5% level, *** significant at the 1% level.
c) The omitted category for the qualification groups is degree holders. The omitted category for ethnic background is whites.

References

Abraham, Katherine G., and Henry S. Farber. (1987) "Job Duration, Seniority, and Earnings." *American Economic Review*, Vol. 77, no. 3: pp. 278-97.

Altonji, Joseph G., and Nicolas Williams. (2005) "Do Wages Rise with Seniority: A Reassessment." *Industrial and Labor Relations Review*, Vol. 58, no. 3: pp. 370-97.

Bartel, Ann P., and George J. Borjas. (1978) "Wage Growth and Job Turnover: An Empirical Analysis." In *NBER Working Paper no.285*: National Bureau of Economic Research. Cambridge, MA.

Becker, Gary S. (1993) *Human Capital*. 3rd ed: University of Chicago Press.

Blau, Francine D., and Lawrence Kahn. (1981a) "Causes and Consequences of Layoffs." *Economic Inquiry*, Vol. 19, no. 2: pp. 270-96.

Blau, Francine, and Lawrence Kahn. (1981b) "Race and Sex Differences in Quits by Young Workers." *Industrial and Labor Relations Review*, Vol. 34, no. 4: pp. 563-77.

Burdett Ken, and Coles Melvyn. (2003) "Equilibrium Wage-Tenure Contracts." *Econometrica*, Vol. 71, no. 5: pp. 1377-404.

DiNardo, John. (2002) "Propensity Score Reweighting and Changes in Wage Distributions", University of Michigan

DiNardo John, Nicole Fortin, and Thomas Lemieux. (1996) "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica*, Vol. 64, no. 5: pp. 1001-44.

Heckman, James. (1990) "Varieties of Selection Bias." *American Economic Review*, Vol. 80, no. 2: pp. 313-18.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan. (1993) "Earnings Losses of Displaced Workers." *American Economic Review*, Vol. 83, no. 4: pp. 685-709.

Johnston, Jack, and John DiNardo (1997) *Econometric Methods*. 4th ed. Singapore: McGraw-Hill.

Lazear Edward, P. (1979) "Why Is There Mandatory Retirement." *Journal of Political Economy*, Vol. 87, no. 6: pp. 1261-64.

Lazear, Edward P. (1981) "Agency, Earnings Profiles, Productivity, and Hours Restrictions." *American Economic Review*, Vol. 71, no. 4: pp. 606-20.

Lazear Edward, P. (1986) "Raids and Offer Matching." In *Research in Labor Economics*, 141-65.

Lazear, Edward P. (2003) "Firm-Specific Human Capital: A Skill-Weights Approach." In *NBER Working Paper no.9679*: National Bureau of Economic Research. Cambridge, MA.

Medoff, James, and Katherine Abraham. (1980) "Experience, Performance and Earnings." *Quarterly Journal of Economics*, Vol. 95, no. 4: pp. 703-36.

Medoff, James, L., and Katherine Abraham. (1981) "Are Those Paid More Really More Productive? The Case of Experience." *Journal of Human Resources*, Vol. 16, no. 2: pp. 186-216.

Mincer, Jacob (1974) *Schooling, Experience, and Earnings*. New York: Columbia University Press.

Mincer, Jacob, and Boyan Jovanovic. (1981) "Labor Mobility and Wages." In *Studies in Labor Markets*, edited by Sherwin Rosen, 21-63. Chicago, IL: University of Chicago Press.

Oaxaca, Ronald. (1973) "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review*, Vol. 14, no. 3: pp. 693-709.

Parsons, Donald O. (1972) "Specific Human Capital: An Application to Quit Rates and Layoff Rates." *Journal of Political Economy*, Vol. 80, no. 6: pp. 1120-43.

Rosenbaum, Paul R., and Donald B. Rubin. (1983) "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika*, Vol. 70, no. 1: pp. 41-55.

Stevens, Margaret. (2003) "Earnings Functions, Specific Human Capital, and Job Matching: Tenure Bias Is Negative." *Journal of Labor Economics*, Vol. 21, no. 4: pp. 783-805.

———. (2004) "Wage-Tenure Contracts in a Frictional Labour Market: Firm's Strategies for Recruitment and Retention." *Review of Economic Studies*, Vol. 71, no. 4: pp. 535-51.

Topel, Robert. (1986) "Job Mobility, Search and Earnings Growth: A Reinterpretation of Human Capital Earnings Functions." In *Research in Labor Economics*, 199-233.

———. (1990) "Specific Capital and Unemployment: Measuring the Costs and Consequences of Job Loss." *Carnegie-Rochester Conference Series on Public Policy*, Vol. 33 181-214.

———. (1991) "Specific Capital, Mobility and Wages: Wages Rise with Job Seniority." *Journal of Political Economy*, Vol. 99, no. 1: pp. 145-76.

Figure1
Distribution of real average log hourly wages
in 1989, 1994 and 1999

Figure 2
Cov(e,k)=0 before the arrival of outside offers

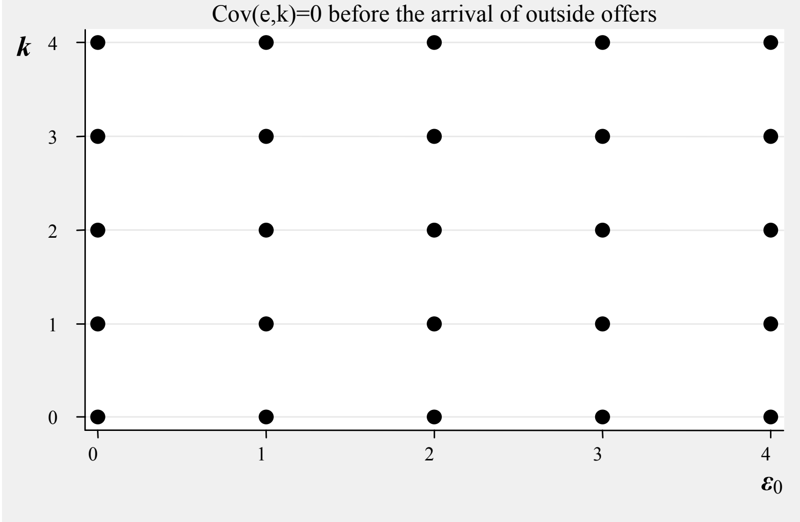

Figure 3
Cov(e,k)unequal 0 after the arrival of outside offers

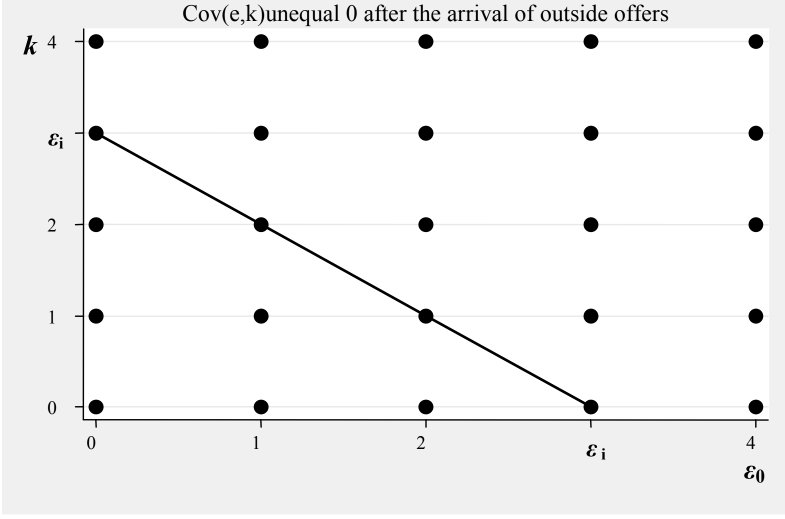

Figure 4a

Actual and counterfactual average real log hourly wage distributions in 1989, 1994 and 1999

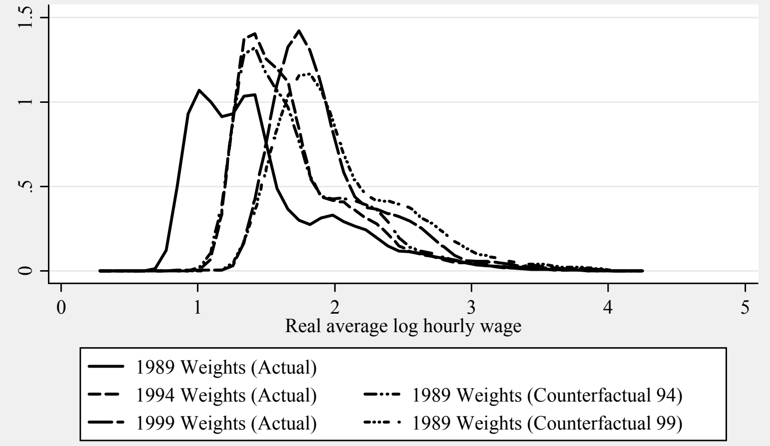

Figure 4b

Actual and counterfactual average real log hourly wage distributions for cohort 1990 in 1990, 1995 and 2000

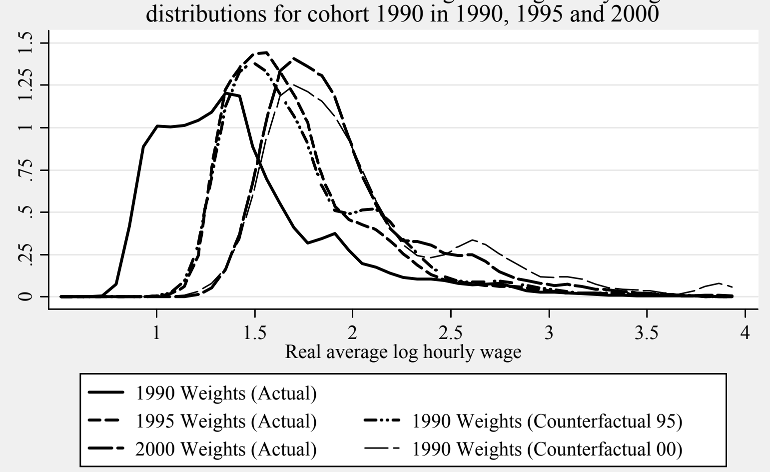

Figure 4c

Actual and counterfactual average real log hourly wage distributions for cohort 1991 in 1990, 1996 and 2001

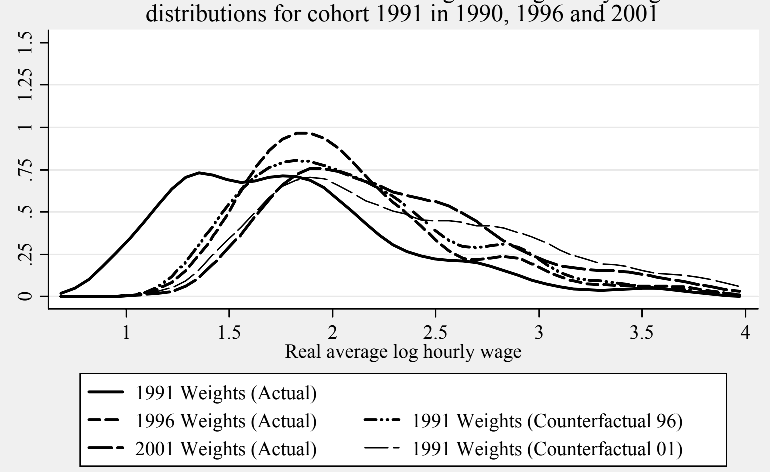

Figure 5
Actual and sum of counterfactual average real log hourly wage distributions for cohort 1989, 1990, and 1991 in 1996

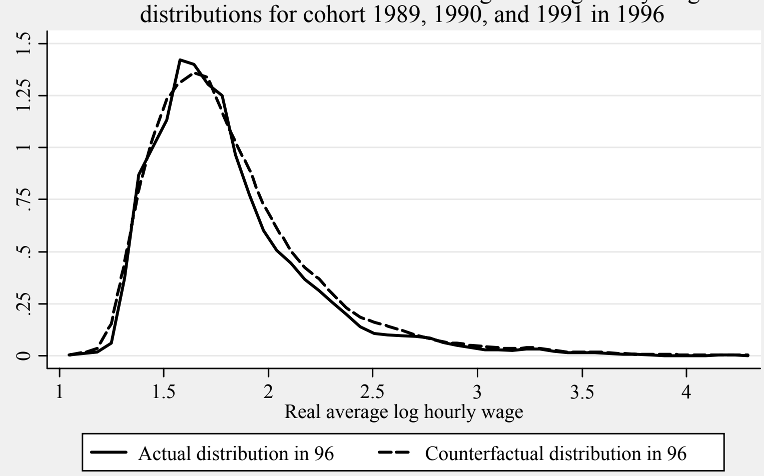

Table 1a

Approximated hourly wages (£) and percentage annual hourly wage growth from actual and counterfactual kernel wage densities for cohort 89 in 1989, 1994 and 1995					
	Actual 89	Actual 94	Counterfactual 94	Actual 99	Counterfactual 99
Average	5.12	6.32	6.56	7.80	8.80
25th percentile	2.785	3.912	3.989	5.195	5.461
75th percentile	5.534	6.277	7.220	8.632	10.149
			Implied annual wage growth		
Average		4.3%	5.1%	4.3%	5.6%
25th percentile		7.0%	7.5%	6.4%	7.0%
75th percentile		2.6%	5.5%	4.5%	6.3%

Table 1b

Approximated hourly wages (£) and percentage annual hourly wage growth from actual and counterfactual kernel wage densities for cohort 90 in 1990, 1995 and 2000					
	Actual 90	Actual 95	Counterfactual 95	Actual 00	Counterfactual 00
Average	4.73	5.98	7.77	6.34	8.94
25th percentile	2.93	4.26	4.26	5.25	5.35
75th percentile	5.15	6.79	7.15	8.23	9.15
			Implied annual wage growth		
Average		4.8%	5.1%	6.0%	6.6%
25th percentile		7.8%	7.8%	6.0%	6.2%
75th percentile		5.7%	6.8%	4.8%	5.9%

Table 1c

Approximated hourly wages (£) and percentage annual hourly wage growth from actual and counterfactual kernel wage densities for cohort 91 in 1991, 1996 and 2001

	Actual 91	Actual 96	Counterfactual 96	Actual 01	Counterfactual 01
Average	7.28	9.38	11.59	9.69	12.78
25th percentile	3.98	5.64	5.62	6.61	6.54
75th percentile	8.38	10.52	11.51	14.35	16.75
			Implied annual wage growth		
Average		5.2%	9.7%	2.9%	5.8%
25th percentile		7.2%	7.1%	5.2%	5.1%
75th percentile		4.7%	6.6%	5.5%	7.2%