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The UK Minimum Wage at Age 22: A Regression Discontinuity Approach[♦]

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Abstract: A regression discontinuity approach is used to analyse the effect of the legislated increase in the UK National Minimum Wage (NMW) that occurs at age 22 on various labour market outcomes. Using data from the Labour Force Survey we find a 2-4% point increase in the employment rate of low skilled individuals. Unemployment declines among men and inactivity among women. We find no such effect before the NMW was introduced and no robust impacts at age 21 or 23 years. Our results are robust to a range of specification tests.

JEL Classification: J31, J38

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1. Introduction

Estimating the impact of the minimum wage in the UK has proved somewhat difficult. Like minimum wages in many countries, the UK minimum is set at the National level so there are no sizeable groups who are excluded from coverage. Consequently, finding a suitable control group with which to compare employment outcomes is not easy. Since the introduction of the UK National Minimum Wage (NMW) in April 1999 a substantial literature has emerged looking at its impact on the labour market. The main focus of this research has been the impact on jobs from which a consensus has emerged that there is no evidence of significant employment effects (Metcalf, 2008).

The studies that exist tend to compare groups that are more or less affected by the minimum wage; i.e. by looking at employment retention among those directly affected by increases in the minimum with those slightly higher up the wage distribution (Linnerman, 1982, Stewart, 2004), or by comparing employment rates in regions that are affected by the NMW to a greater or lesser extent (Stewart, 2002). This general method, termed the "differential impact" approach (Dolado et al, 1995), is often reliant on somewhat questionable identification assumptions. For example, the Linnerman (1982) approach can be biased by measurement error in wages or spillover effects from the minimum wage further up the pay distribution. Similarly, using regional variation in minimum wage impacts is dependent on the assumption that the initial distribution of wages is uncorrelated with employment outcomes. This may be violated if, for example, low wage regions are growing more slowly.

Many countries with minimum rates set at the National level face this identification problem. This is in contrast to the situation in the US where a large literature has exploited significant variation in minimum rates at the State level (Card and Krueger, 1995, and Neumark and Wascher, 2008). In this paper we use a novel approach to estimate the impact of a nationally set minimum wage on labour market outcomes. We exploit the fact that the National Minimum Wage in the UK is set differently for different age groups so that individuals experience a legislated hourly wage increase at age 22 of about 16-20%. Our focus is on what happens to employment at age 22 when individuals qualify for the adult minimum rate. Specifically, we use a regression discontinuity approach that compares employment outcomes for individuals around this age threshold. In this framework, changes in employment for individuals who are a few months younger and older than 22 years provide an estimate of the employment effect of the legislated wage increase.

Our approach contrasts with the "differential impact" approach in that identification of the employment impact arises from the existence of different minimum rates for very similar individuals, those just a few months older or younger than 22 years. Identification in the "differential impact" approach tends to arise from there being different actual wages for individuals or regions, with the same minimum rate. We believe that our approach provides a relatively clean quasi-experiment where similar individuals are either subjected to the higher adult rate or the lower youth rate. The allocation of individuals into these groups is essentially random as it is determined by age which is not something that individuals can influence.[1]

Our focus here is on the effect of this legislated wage increase on the probability of being in paid work for those turning 22. We use data from the UK Labour Force Survey (LFS) and pool together all observations from July 1999 to March 2009 in order to maximise the sample. We concentrate on low skilled individuals since they are the group most likely to be affected by the NMW.[2] We report a large number of specification and falsification tests to assess the robustness of our results. A concern with this type of analysis is that there is some other coincident change that may impact on labour market outcomes (e.g. benefit increases at age 22). We can find no important changes that occur at age 22 either in policy or in the survey methodology of the LFS that should impact on individuals' labour market outcomes. The main changes in the benefit system happen to individuals at age 18 and then at 25.

We find a positive and significant discontinuity parameter on the employment rate of low skilled workers at age 22 of about 2-4% points. This is robust to a range of different functional forms. When we disaggregate the results by men and women they become less robust, but the impact for men is strongest. We can find no significant discontinuity parameter in the years preceding the introduction of the NMW, nor a robust impact at ages 21 or 23. This employment increase at age 22 appears to some extent to be accounted for by reductions in unemployment for men and reductions in inactivity for women. We also report non-parametric results which impose fewer constraints on the evolution of employment over the age range under consideration. Again we find a positive and significant discontinuity parameter in most specifications. It is plausible that these results are reflective of an increase in effective labour supply at age 22 among these low skilled individuals in response to a 20% increase in the wage on offer.

The paper is organized as follows. In the next section we present the empirical methodology we use, section 3 then describes the data and presents some descriptive statistics and examines wage changes, section 4 our main results on labour market outcomes and section 5 summarises.

2. The Regression discontinuity methodology

[1] A number of papers using regression discontinuity where age is the forcing variable exist in the literature.For example, Card, Dobkin and Mestas (2009) examine the impact on health outcomes of Medicare coverage at age 65 and Lemieux and Milligan (2008) examine the impact of welfare benefit increases at age 30.

[2] These are defined as individuals with no educational qualifications or with educational qualifications no higher than exams taken at minimum school leaving age (O-levels/GCSEs) or the lowest level of National Vocational Qualifications (Level 1).

The use of regression discontinuity (RD) in economics has grown in recent years. Two guides, by Imbens and Lemieux (2008) and Lee and Lemieux (2010), have assisted in bringing the RD methodology into mainstream applied econometrics. We utilise a regression discontinuity approach to examine the impact of qualifying for the adult NMW when an individual becomes 22 years old. Typically the youth rate is some 18-20% below the adult rate (see Table 1) so when an individual turns 22 they experience a legislated pay rise of this order. We examine the impact that this increase in the NMW has on a number of labour market outcomes; probability of employment, unemployment, inactivity.

Define a dummy variable that is an indicator for whether someone has passed their 22 birthday:

$$Dum_i = \begin{cases} 1 \ if \ age_i \geq 22 \\ 0 \ if \ age_i < 22 \end{cases}$$

Where age_i is the individual's age measured in weeks.[3] We then estimate the following reduced form regression:

$$y_i = f(age_i, a) + \beta Dum_i + \delta X_i + u_i \quad (1)$$

y_i is an employment related measure for individual i (i.e. a dummy indicating employment status), $f(age_i, a)$ is a flexible polynomial with parameters a , X_i is a set of covariates for individual *i* and u_i is an error term. We interpret β as the causal effect on employment of the increase in the NMW from the youth to the adult rate. The assumption underlying this estimation procedure is that assignment to either side of the discontinuity at the 22nd birthday is random. The approach then essentially treats those above the threshold as the treatment group and those just below as the control group; where the treatment is exposure to the adult NMW.

Since our threshold is defined by age then everyone will receive treatment at some point (Lee and Lemieux, 2010). This means one cannot interpret treatment as random as one might in the context of a random experiment. More importantly, it also means that the group of individuals to the left of the threshold may change their behaviour since they know ultimately they will also receive the treatment. Those just a few weeks short of 22 may turn down job offers that they would have taken in the absence of the NMW if they know they will receive a higher wage offer once they turn 22. Ultimately there is little we can do to test this but it does seem rather implausible that, in a high turnover, unskilled labour market, individuals will reject job offers when they can easily change jobs again once they turn 22.

The estimate of the discontinuity parameter β is likely to be sensitive to the functional form of the polynomial. In practice we report a range of specifications for the age function $f(age_i, a)$, including spline specifications where we allow for this function to have different parameters either side of the threshold. We then estimate the following regression:

$$y_i = f(age_i - c, a) + Dum_i * f(age_i - c, a^*) + \beta Dum_i + \delta X_i + u_i \quad (2)$$

Where, as is common practice, we also define age (in weeks) as the age minus the cut-off point c (where c is 1144, the age in weeks at 22 years). We present results of a test for goodness of fit proposed by Lee and Lemieux (2010). Here one compares the estimated (restricted) model with a (unrestricted) model that has a separate dummy variable for each discrete value of age. This is essentially a test of whether the discontinuity in the restricted model might result from an overly restrictive functional form for the age polynomial. Since age is measured in discrete

[3] The LFS data allows us to measure age in days but we group the age measure into weeks in order to increase the sample of observations at each age.

units (measured in weeks) we also cluster our standard errors on age in weeks to avoid biased standard errors (Moulton, 1986; Lee and Card, 2008).

3. The Data and Descriptive Statistics

We estimate this model using LFS data on individuals' labour market status around their 22nd birthday. The LFS includes just over a thousand 21 year olds each quarter, and a similar number of 22 year olds. Because the identification strategy relies on comparing individuals very close to their 22nd birthday, and because we focus on the subset of individuals that are most likely to be affected by low pay, we pool together all LFS records over the period since the introduction of the NMW; July 1999 – March 2009.[4]

The LFS includes information on the year, month and day an individual was born, and on the year, month and last day of the survey response week. From this information we can calculate an individual's age measured in days at the time the survey was recorded.[5] If we measure age in days we have very small sample numbers in each age category and the data become very erratic. Consequently, we use age in weeks as our age measure for our main results. Individuals who are 1144 weeks old are exactly 22 years old. This is the point at which individuals qualify for the adult rate. Age is measured in weeks distance from this cut-off; $age_i - 1144$.[6]

It is important that there is no coincident discontinuity in any of the potential covariates at age 22 that may explain any change in the outcome variable. When age is the forcing variable it is unlikely that any of the baseline covariates will change with age as manipulation of the forcing variable is not possible. Table 2 shows the distribution of the covariates across age measured in months distance from the 22nd birthday. We grouped age into months here to facilitate the exposition of these descriptive statistics. These statistics are for the low skilled, defined as those whose highest educational qualifications are equivalent to GCSEs (those school exams obtained at minimum school leaving age of 16). This group also includes those without educational qualifications. The focus on this group is because they are more likely to be exposed to low pay and because they are less likely to be in full-time education. There do not appear to be any significant changes in these covariates across the discontinuity as one would expect when age is the forcing variable.

The LFS has a series of questions about income and earnings from employment. There are two main measures of hourly wages. One is derived from information on pay and hours in the reference week. This has been shown to contain a significant amount of measurement error (see Dickens and Manning, 2002). In April 1999, the LFS introduced a question on hourly rates of pay. Individuals in employment are first asked whether they are paid by the hour and if they respond positively they are then asked their hourly rate. There is evidence that this variable contains much less error. However, the drawback of this measure is that we only have

[4] Note in our estimation results we treat the discontinuity to be the same in each year. While the difference between the adult and youth rates do vary from year to year, Table 1 shows that the difference is always in a fairly narrow range in most years. We have also estimated the discontinuity allowing for different impacts depending on the size of the increase at age 22 and the results are largely unchanged.

[5] We exclude individuals who are both 21 and 22 during the week to which the survey response refers.

[6] We have also estimated results using age measured in months. The results are very similar to those reported here.

information on those paid by the hour. About half of all jobs are hourly paid but this increases to around 65% among 21 and 22 year olds.

What happens to an individual's hourly wages when they turn 22 is of interest since it is the driving mechanism by which we expect any potential employment changes. Unfortunately the earnings data we have from the LFS is poor. Earnings data are collected from approximately 40% of LFS respondents as income questions are only asked in waves 1 and 5, and response is typically such that we have hourly rate information for less than 20% of the LFS sample. Response rates are particularly low for younger groups; we have hourly rate information for 13% of employees age 21 or 22. Thus the data we have on wages is estimated on a severely restricted sample.

Given this restricted sample, any examination of wages by week or even month of birth is subject to lots of noise. Consequently, we focus our analysis on wage changes by age in years. Table 3 shows the proportion of employees at ages 18 to 23 years who are paid less than the adult NMW. About 30% of 18 years olds are paid below the adult minimum rate. This proportion declines with age so that approximately 10% of low skilled employees age 21 are paid less than the adult NMW. When the adult rate kicks in at age 22 the proportion below drops to 6%. There may be several reasons why the share paid less than the adult NMW does not drop to zero at age 22. There may be non-compliance by employers. There is also likely to be some measurement error in the wage data which means that wages recorded below the NMW are actually above it (Dickens and Manning, 2002). It is also the case that those aged 22 on a recognised apprenticeship programme are exempt from the NMW for the first 12 months of their employment, although we excluded these from the data as best we can.[7] Note that even at age 23, a significant proportion (5%) of employees are paid below the legislated minimum rate. This suggests a significant degree of measurement error in the LFS wage data.

We also examine wage changes using the Annual Survey of Hours and Earnings (ASHE). This has the advantage of larger samples sizes and also greater accuracy in the wage data, since wages are reported by the employer from payroll records. The disadvantage with the ASHE is that we cannot identify the low skilled so have to focus on all workers. Furthermore, we only have age in years so cannot examine potential changes close to age 22. Table 4 again reports the proportion at different ages who are paid below the adult minimum rate. The pattern of change across years is similar to the LFS data reported above. The key difference is that we see a larger fall in the proportion below the adult NMW at age 22; from 9% to 3% of workers. This falls again to 1% at age 23.

These numbers of affected workers may seem relatively small but they should be compared with the overall impact of the NMW on employees. Estimates from the Low Pay Commission suggest that approximately 5% of employees had their pay raised by the NMW on introduction, compared to about 9-10% of low skilled young workers.

[7] Note that there are a number of potential reasons why individuals can legally be paid below the NMW. For example, those living in employer provided accommodation can be paid with an accommodation offset.

The figures reported here are indicative of significant shifts in the distribution of wages for young workers as they become 22. Note however that in terms of the impact on employment, the key driver is likely to be the wage on offer to individuals. We do not observe offer wages but the actual wage when an individual enters work. If there is selection into work at different wages then we may not observe a sharp discontinuity in wages at age 22; firms may be reluctant to hire those over 22 on the adult rate or those aged 21 may not enter at the lower offer wage.

4. Estimation results

4.1 Parametric results

We begin by looking at the impact of the minimum wage change on employment. We restrict our analysis to low skilled individuals since these are the group most likely to be affected by the increase to the adult NMW. Analysis of the whole population suggests no overall impact on employment. We focus on those aged twelve months either side of the age 22 threshold.[8]

Table 5 presents our results from estimating equation (2) above. We estimate a probit regression where the dependent variable is a dummy indicating whether the individual is in employment or not. The reported coefficients are marginal effects. Results are very similar if we estimate a linear probability model. Results may be sensitive to the choice of functional form for the polynomial. Consequently, we report estimates for a wide range of different polynomial functions in age; a quadratic and cubic (where we constrain the parameters of the age polynomial to be the same either side of the discontinuity), and also a piecewise quadratic and cubic that allows for different parameters either side of the discontinuity (as in equation (2) above). Different specifications are reported with and without control variables.

The first column reports the results for all unskilled workers with no controls. The results are rather striking. We find a positive discontinuity coefficient β that is statistically significant. The size and significance of this parameter varies somewhat with the different polynomial functions but the estimates in column (1) are mostly significant at the 5% level. Even in the richest specification, the cubic spline specification we find these results hold up. The estimated coefficient implies that on turning 22 the probability of employment increases by about 2-4% points on average for this group of workers.[9]

The choice of the polynomial in age $f(age_i, a)$ is crucial for robust estimation using a regression discontinuity approach. We follow Lee and Lemieux (2010) and test our specification. The final row for each functional form reports a chi squared test of each specification against a specification with a full set of dummy variables for age measured in weeks. We cannot reject any of the reported specifications against this much more general specification that allows for a different employment rate at each week from age 21 to 23.

[8] We also estimated the employment effect using alternative age bands. For example, the results for 9 months either side of age 22 are very similar to those for 12 months.
[9] See notes to Table 5 for a list of control variables.

These goodness of fit tests suggest that even the relatively simple quadratic and quadratic spline models fit the data well.

One can perhaps get a better idea of how well these models fit the data by looking at the results graphically, since one would like to be able to observe any discontinuity in the data. Figure 1 presents the employment rate for each week 52 weeks above and below age 22. These are the average employment rates for each discrete value of age measured in weeks. Also presented on the figure is the predicted employment rate from equation (2) above using the results from column 2 of Table 5. These solid lines represent the piecewise quadratic (quadratic spline) with the jump at age 22 being the estimated discontinuity parameter. We see considerable variation from week to week in the employment rate due to relatively small sample sizes. However, there does appear to be an increase in employment rates around the discontinuity. The estimated jump at the threshold is approximately 3% points, taking the estimated employment rate from just over 56% to 59%.

Table 5 also presents results separately for men and women. The results are less robust when we disaggregate by men and women. The robustness of regression discontinuity is impacted by the sample size close to the discontinuity. Overall we have about 300 individuals at each age in weeks. This is approximately halved when we split the sample by men and women, and so is likely to result in an increase in sampling variability. The estimated discontinuity coefficient for men and women is now much less robust across the different specifications. For women we find evidence of a positive impact on employment of about 4% points which is significant in the cubic and quadratic spline models. The results for men are a little less robust still, with a positive employment effect only in the quadratic model.

Our results suggest that when a low skilled individual turns 22 years of age and they become eligible for the adult NMW their employment rate increases. The estimated impact is non-trivial. With an approximate wage rise of 18-20% we find that the employment rate increases by about 2-4% points. These results are robust to the definition of the forcing variable. If we measure age in months we find very similar results. They are also robust to estimating on different age bands around age 22.

4.2 Robustness and falsification tests

Our results on the full sample above suggest a statistically significant employment effect across the different polynomial specifications. However, it is important to test further whether we have found what seems likely to be a minimum wage effect or just an artefact of the data. If the National Minimum Wage is the driving force behind the results above, then one would expect to find no employment discontinuity at age 22 in those years when there was no National wage floor. Since the British National Minimum Wage was introduced in 1999 we can estimate the above models on the period prior to introduction. As such, we take the Labour Force Survey data for the period January 1994 - December 1998 and estimate our discontinuity model once again.

The results are presented in the Table 6. Again we report results across a wide range of specifications as in Table 5, both with and without control variables. The results clearly indicate no statistically significant employment discontinuity at age 22 prior to the introduction of the National Minimum Wage. For the pooled sample of men and women we estimate a positive discontinuity parameter of about 0.02 but across all the polynomial specifications this is not significant. Of the 24 discontinuity parameters we estimate in Table 6, we find one that is significant at the 10% level for females with the quadratic specification. However, this model fails the goodness of fit test when tested against the fully saturated dummy variable model.

Another potential concern with our results is that we have just picked up a spurious employment effect that happens to exist at age 22. The goodness of fit tests above partially test for this, since they allow for discontinuities at each week from age 21 to 23. We could not reject our polynomial models in favour of the dummy variable model. Nevertheless, it is sensible to check for discontinuities at other ages. We estimate the same parametric discontinuity model taking data 52 weeks either side of age 21 and then 52 weeks either side of age 23 to test the robustness of our results.

The results for 21 year olds are reported in Table 7. Again we present results for the four different polynomial models, with and without controls. The results are once again reassuring. The estimated discontinuity parameters are close to zero and statistically insignificant. Only in the cubic spline model do we find a positive and significant impact. Note that the more parsimonious models all pass the goodness of fit tests so we may well be over-fitting the data here.

Table 8 presents the same results for the discontinuity model at age 23. Again the overall story is one of no employment discontinuity. We do find a negative effect in the cubic spline model but this is only significant at the 10% level. At both ages 21 and 23 we can find no robust evidence of a significant discontinuity in employment among any of our estimated specifications for all individuals, men and women. These results confirm that the discontinuity only exists at age 22, but there is very little evidence that employment changes at other age thresholds in the early 20s.

4.3 Other labour market outcomes

The results above appear to show that the employment rate increases at age 22 as young workers become eligible for the adult minimum wage. These results hold up pretty well to a number of robustness and falsification tests. However, if employment is rising then one or both of the other labour market states must also be changing. Here we examine what happens to unemployment and inactivity at the age 22 threshold. Here we define the unemployed according to the ILO definition to capture those who say they are searching for work. Table 9 presents the results from the discontinuity regression in equation (2) where the dependent variable is unemployment. We report results across the range of different specifications. The results indicate that the employment gains reported above are to some extent a result of falls in unemployment. Negative discontinuities are found that suggest a 1.7-1.9% point fall in the unemployment probability. These are precisely estimated in the cubic and the quadratic spine models. Focussing on males, we find stronger results for unemployment. The unemployment probability falls by roughly 2.5-3% points for males. This is significant in all but the cubic spline model.

If the increase in the minimum wage at age 22 is encouraging individuals into the labour market then we may expect to see changes in inactivity at this age threshold. Table 10 reports the full set of specifications where the dependent variable is a dummy indicating whether the individual is inactive or not. While we find a negative discontinuity parameter these are mostly not precisely estimated. For women, we find somewhat stronger results in some of the specifications, suggesting a 4% point fall in the probability of inactivity. But this is only significant at the 10% level.

Overall these results tie in quite nicely with our results on employment presented above. There we found an employment increase of approximately 2-3% points among the low skilled. The results here suggest that some of that fall is coming about from reductions in unemployment, particularly among men. There is some weak evidence that falls in inactivity are important for women.

4.4 Non-parametric estimates

The results presented so far are conditional on a specific functional form for the employment rate either side of the discontinuity. We have experimented with a range of functional forms; a quadratic and cubic and a piecewise quadratic and cubic specification. These may be unduly restrictive, even though our model specification tests against the saturated dummy model suggest not. In this section we utilise non-parametric regression discontinuity techniques to check the robustness of our results.

We adopt the methodology of Hahn, Todd and van der Klaauw (2001) and Porter (2003) and estimate local linear regressions in intervals either side of the discontinuity. We now measure age in days to allow more flexibility in the smoothing process. The size of the bandwidth can be crucial to the estimates so we experiment with a number of different bandwidths (as suggested by Lee and Lemeiux, 2009). We employ the Imbens-Kalyanaraman algorithm to estimate the optimal bandwidth (Imbens and Kalyanaraman, 2010) but this presents us with very small bandwidths which appear to be under-smoothing the data**.** The trade off here is between precision and bias. Ideally, one would compare mean outcomes of a relatively small group either side of the threshold. But without large samples one has to increase the bandwidth in order to estimate the discontinuity more precisely. This, however, can introduce a bias if those individuals further away from the threshold are systematically different (Lee and Lemeiux, 2009). We present a range of results allowing for different bandwidths of 15, 20, 30, 40 and 60 days. We also experimented with different kernel density functions but the results were not particularly sensitive to the chosen kernel.[10]

The results are presented in Table 11 for the discontinuity at age 22. Here we report the estimated discontinuity parameter for low skilled individuals and men and women separately. The results are somewhat sensitive to the chosen bandwidth. However, for all low skilled individuals we find a positive and statistically significant discontinuity parameter for all bandwidths other than 15 days. The implied employment increase at age 22 ranges from about 6.8% points to 14.4% points, somewhat larger than the parametric findings. The estimated parameter increases as the bandwidth is reduced. But, the precision of the estimates declines with smaller bandwidths as fewer data points are present within the smaller bandwidths. Splitting the sample into the sexes results in a further loss of precision. The results for men suggest positive employment effects that are significant at the 10% level in all but the 15 day bandwidth. Again the point estimates are inflated compared to the parametric results, suggesting a 7.8-15.7% point increase in employment. For women, we find large positive discontinuity parameters but they are all statistically insignificant.

The second and third panels of Table 11 report the non-parametric results where the outcome variables are unemployment and inactivity respectively. The estimated discontinuity parameter for unemployment is negative but is not estimated with any precision in most specifications. For men we do find a large negative impact that is significant at the 10% level with the 15 day bandwidth. As with the parametric results we do find a negative discontinuity in inactivity that is significant in a number of specifications. This result is stronger for women.

We also use the non-parametric estimation approach to check the same falsification tests we conducted above. Table 12 reports results on the employment outcome for those aged 22 in the period before the UK National Minimum Wage was introduced, and those aged 21 and 23 years in the period following introduction. We find no significant estimates for 22 year olds prior to the minimum wage, which is consistent with our parametric findings. Nor can we find any effects for 21 year olds, or among all 23 year olds. For 23 year old women we do find a negative discontinuity parameter that is precisely estimated for a number of the bandwidths.

[10] This is consistent with much of the literature which suggests estimates are not particularly sensitive to the choice of kernel (Fan and Gijbels, 1996).

These non-parametric results are broadly supportive of our parametric findings. It doesn't appear to be the case that the statistically significant positive effects found in the parametric results above are being driven by an overly restrictive functional form. The non-parametric results themselves imply somewhat larger impacts on employment rates. But it may be that we just don't have enough data to precisely estimate the impacts on labour market outcomes.

5. Conclusions

In this paper we utilise the legislated increase in the UK National Minimum Wage at age 22 to identify employment effects of the minimum wage on the youth labour market. We use a regression discontinuity approach that compares changes in employment outcomes around this age threshold. We find a significant positive effect on employment. Our results suggest that on turning 22, the employment rate among low skilled individuals increases by about 2-4% points. We have estimated these effects across a wide range of different parametric and non-parametric specifications. This finding is robust to a large number of these specifications. Furthermore, we have conducted a range of falsification tests; testing for effects prior to the introduction of the minimum wage and testing for effects at other ages. In addition, we find evidence that reductions in unemployment and inactivity account for some of this change.

While we should be cautious about generalising these results to the wider labour market they do offer some insight into the mechanisms impacting upon employment among these young workers. A natural question to ask is what might be driving these results. While the standard model predicts an unambiguous reduction in employment from increases in the minimum wage, a number of notable studies have found positive employment effects (See Card and Krueger, 1995 for the US, and Dickens, Machin and Manning, 1999, for the UK). These positive effects are often explained by appealing to monopsony.

The analysis here of young workers can be set in the context of a simple model of intertemporal labour supply. When an individual turns age 22 they receive a legislated pay rise of about 18-20%. This is an anticipated permanent increase in the wage. The simple model would predict only a substitution effect from this wage increase and no income effect, since estimated lifetime wealth has not changed. We would therefore expect a positive labour market participation impact at age 22. Consequently, the results here are consistent with the predictions of the simple model of intertemporal labour supply. On turning 22, young workers now find work more attractive compared to when they were 21 years old. This may induce them to increase participation in the labour market, or to increase their job search intensity.

The general consensus from research into the NMW in the UK is that there is little evidence that it has harmed employment. However, one controversy that has remained is the appropriate age at which to implement the main adult rate. This study provides some important results on the impact of the UK minimum wage on the youth labour market that suggests that when the adult rate is payable at age 22 years employment rises. Our paper also offers a way to examine minimum wage effects where the minimum is set at the national level and identification across different groups in the labour market is problematic.

References:

Card, D., C. Dobkin and N. Mestas. 2009. "Does Medicare Save Lives?" NBER Working Paper 13668.

Card, D. and A. Krueger. 1995 *Myth and Measurement: The New Economics of the Minimum Wage*. Princeton: Princeton University Press.

Dickens, R, S. Machin and A. Manning 1999 "The Effects of Minimum Wages on Employment: Theory and Evidence from Britain", *Journal of Labor Economics*, 17(1), 1-23.

Dickens, R and A. Manning. 2002 "Has The National Minimum Wage Reduced UK Wage Inequality?" CEP Discussion Paper 0533.

Dolado, J., F. Kramarz, S. Machin, A. Manning, D. Margolis and C. Teulings. 1995. "The

economic impact of minimum wages in Europe", *Economic Policy*, Vol.23, 317–372.

Fan, J. and I. Gijbels. 1996 *Local Polynomial Modelling and Its Applications*. London; New York and Melbourne: Chapman and Hall.

Imbens, G. and T. Lemieux. 2008 "Regression Discontinuity Designs: A Guide to Practice", *Journal of Econometrics*, 142, 615-635.

Imbens, G. and K. Kalyanaraman. 2009 ."Optimal Bandwidth Choice for the Regression Discontinuity Estimator", NBER Working Paper No. 14726.

Hahn, J., P. Todd, and W. van der Klaauw. 2001 "Identification and Estimation of Treatment Effects with a Regression Discontinuity Design", *Econometrica* 69 (1), 201-209.

Lee, D. and D. Card. 2008 "Regression Discontinuity Inference with Specification Error," *Journal of Econometrics*, *142* (2), 655–674.

Lee, D. S. and T. Lemieux. 2010 “Regression discontinuity designs in economics”, *Journal of Economic Literature* 48, 281–355

Lemieux, T. and K. Milligan. 2008 “Incentive Effects of Social Assistance: A Regression Discontinuity Approach,” *Journal of Econometrics*, *142* (2), 807–828.

Linnerman, P. 1982. “The economic impacts of minimum wage laws: a new look at an old question”, *Journal of Political Economy*, 90, 443–469.

Metcalf, D. 2008. “Why has the British National Minimum Wage had Little or No Impact on Employment?”, *British Journal of Industrial Relations* 50: 489-512.

Moulton, B., R. 1986. “Random group effects and the precision of regression estimates” *Journal of Econometrics*, Vol. 32, 385-397.

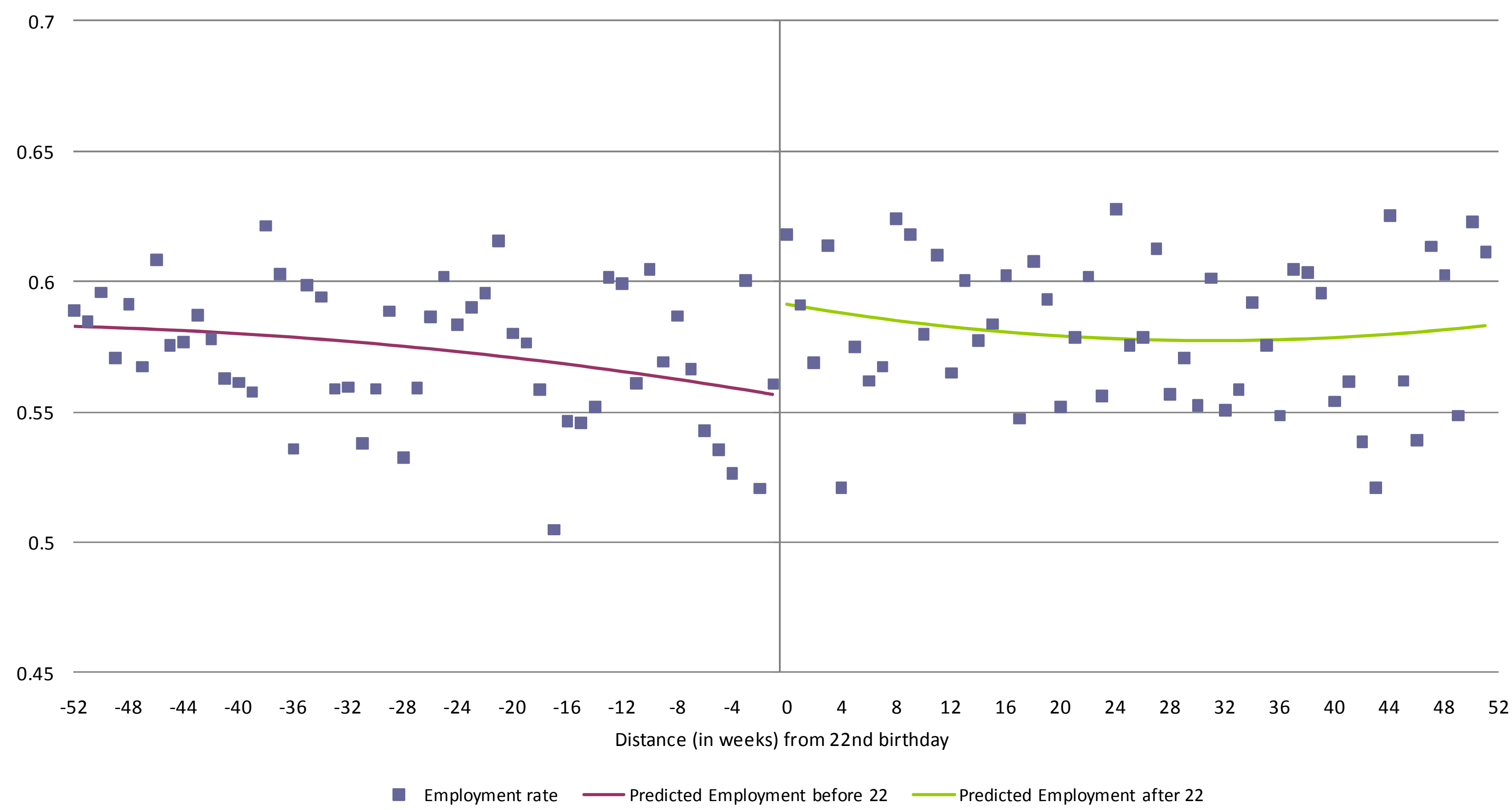
Neumark, D and W. Wascher. 2008. *Minimum Wages*. Cambridge, MA: MIT Press.

Porter, J 2003. “Estimation in the Regression Discontinuity Model.” Unpublished.

Stewart, M. 2002. “Estimating the Impact of the Minimum Wage Using Geographical Wage Variation” *Oxford Bulletin of Economics and Statistics*, 64, Supplement 0305-9049.

Stewart, M. 2004 "The Impact of the Introduction of the UK Minimum Wage on the Employment Probabilities of Low Wage Workers", *Journal of the European Economic Association*, 2004, 2(1), 67-97.

Figure 1: Employment Rate by Age in Weeks for All Low Skilled Individuals



Source: Labour Force Survey

Table 1: NMW adult and development rates

	Adult rate £	Development rate £	NMW increase at age 22 %
Apr-99	3.60	3.00	20.0
Oct-00	3.70	3.20	15.6
Oct-01	4.10	3.50	17.1
Oct-02	4.20	3.60	16.7
Oct-03	4.50	3.80	18.4
Oct-04	4.85	4.10	18.3
Oct-05	5.05	4.25	18.8
Oct-06	5.35	4.45	20.2
Oct-07	5.52	4.60	20.0
Oct-08	5.73	4.77	20.1

Notes: Adult rate applies to employees age 22 and above; Development rate applies to 18-21 year old employees.

Table 2: Descriptive statistics (low skilled)

	Months from 22nd birthday																							
	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11
Male	0.51	0.50	0.52	0.52	0.50	0.52	0.51	0.48	0.50	0.50	0.47	0.50	0.48	0.48	0.48	0.46	0.48	0.48	0.46	0.47	0.49	0.46	0.46	0.48
Full-time education	0.07	0.06	0.06	0.07	0.05	0.05	0.05	0.05	0.06	0.05	0.06	0.05	0.05	0.06	0.04	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.04	0.04
White	0.88	0.87	0.88	0.88	0.87	0.88	0.88	0.87	0.88	0.88	0.86	0.89	0.88	0.86	0.89	0.87	0.86	0.89	0.86	0.86	0.89	0.88	0.86	0.89
Head of household	0.33	0.32	0.31	0.33	0.33	0.35	0.32	0.34	0.36	0.34	0.36	0.38	0.34	0.37	0.38	0.37	0.38	0.39	0.40	0.40	0.41	0.40	0.40	0.42
Children under 5	0.25	0.27	0.25	0.24	0.27	0.26	0.25	0.27	0.28	0.27	0.28	0.29	0.27	0.29	0.30	0.29	0.30	0.29	0.30	0.31	0.31	0.30	0.33	0.30
Married	0.06	0.05	0.06	0.06	0.07	0.06	0.08	0.08	0.07	0.08	0.09	0.08	0.08	0.09	0.09	0.09	0.10	0.09	0.10	0.12	0.09	0.12	0.12	0.10
No qualifications	0.22	0.23	0.23	0.22	0.25	0.23	0.24	0.25	0.23	0.23	0.24	0.23	0.24	0.25	0.24	0.24	0.24	0.23	0.23	0.26	0.23	0.24	0.25	0.22
Respondents	1346	1401	1311	1332	1344	1352	1360	1366	1323	1384	1380	1189	1271	1374	1318	1322	1373	1282	1311	1339	1232	1334	1366	1326

Source: Labour Force Survey

Notes: Calculations take into account survey weights; Low skilled are individuals with highest educational qualification equivalent to GCSE (minimum school leaving age exams); Average July 1999-March 2009.

Table 3: Share of employees paid less than the adult NMW from age 18-23

	All	Male	Female
Age 18	29%	27%	30%
Age 19	19%	16%	22%
Age 20	15%	13%	17%
Age 21	10%	9%	12%
Age 22	6%	4%	7%
Age 23	5%	5%	5%

Source: Labour Force Survey

Notes: Low skilled are individuals with highest educational qualification equivalent to GCSE (minimum school leaving age exams); Average July 1999-March 2009.

Table 4: Share of employees paid less than the adult NMW from age 18-23

	All	Male	Female
Age 18	30%	30%	29%
Age 19	20%	20%	20%
Age 20	13%	13%	14%
Age 21	9%	7%	11%
Age 22	3%	2%	3%
Age 23	1%	1%	1%

Source: Annual Survey of Hours and Earnings
Notes: All employees

Table 5: Employment outcomes for the low skilled at age 22

		All		Females		Males	
Quadratic	Discontinuity	0.025**	0.027**	0.015	0.017	0.041**	0.042**
		(0.011)	(0.011)	(0.015)	(0.017)	(0.018)	(0.019)
	Chisq(100)	91.8	95.1	93.5	93.4	94.1	105.8
	Pr>Chisq(100)	(0.709)	(0.621)	(0.664)	(0.667)	(0.647)	(0.325)
Cubic	Discontinuity	0.034**	0.030**	0.042**	0.028	0.029	0.030
		(0.015)	(0.015)	(0.020)	(0.023)	(0.023)	(0.025)
	Chisq(99)	91.1	95.0	90.1	92.8	93.3	105.2
	Pr>Chisq(99)	(0.703)	(0.595)	(0.728)	(0.656)	(0.643)	(0.316)
Quadratic spline	Discontinuity	0.036**	0.032*	0.047**	0.031	0.027	0.029
		(0.017)	(0.017)	(0.022)	(0.026)	(0.025)	(0.027)
	Chisq(98)	91.1	95.0	90.1	92.5	93.2	105.1
	Pr>Chisq(98)	(0.676)	(0.568)	(0.703)	(0.637)	(0.619)	(0.295)
Cubic spline	Discontinuity	0.037	0.042**	0.038	0.037	0.042	0.046
		(0.024)	(0.021)	(0.029)	(0.032)	(0.029)	(0.030)
	Chisq(96)	88.0	91.0	87.9	90.7	91.4	102.9
	Pr>Chisq(96)	(0.708)	(0.624)	(0.710)	(0.633)	(0.613)	(0.297)
Observations		32274	31917	16546	16374	15728	15543
Controls		N	Y	N	Y	N	Y

Notes: Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Robust standard errors in parentheses corrected for clustering on age measured in weeks; Sample of low skilled individuals 12 months either side of 22nd birthday July 1999-March 2009; Apprentices excluded; Controls include: gender, qualification level, white, head of household, marital status, region of residence; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to minimum school leaving age exams); Chi-squared test statistic from likelihood ratio test of the estimated model against a model with dummy variables for age measured in weeks.

Source: Labour Force Survey

Table 6: Employment outcomes before the National Minimum Wage

		All		Females		Males	
Quadratic	Discontinuity	0.019	0.015	0.039*	0.037	-0.003	-0.003
		(0.013)	(0.014)	(0.021)	(0.023)	(0.020)	(0.021)
	Chisq(100)	119.6	119.7	145.5	148.8	106.1	109.5
	Pr>Chisq(100)	(0.088)	(0.088)	(0.002)	(0.001)	(0.320)	(0.243)
Cubic	Discontinuity	0.028	0.023	0.043	0.041	0.010	0.004
		(0.017)	(0.017)	(0.029)	(0.030)	(0.026)	(0.026)
	Chisq(99)	119.1	119.3	145.4	148.7	105.6	109.3
	Pr>Chisq(99)	(0.082)	(0.081)	(0.002)	(0.001)	(0.307)	(0.225)
Quadratic spline	Discontinuity	0.026	0.020	0.036	0.033	0.013	0.005
		(0.019)	(0.019)	(0.031)	(0.033)	(0.029)	(0.029)
	Chisq(98)	118.6	118.2	144.7	147.8	105.3	108.9
	Pr>Chisq(98)	(0.077)	(0.081)	(0.002)	(0.001)	(0.288)	(0.212)
Cubic spline	Discontinuity	0.002	-0.005	-0.014	-0.020	0.016	0.007
		(0.023)	(0.023)	(0.036)	(0.040)	(0.038)	(0.039)
	Chisq(96)	117.2	116.7	141.2	144.7	104.9	108.8
	Pr>Chisq(96)	(0.070)	(0.074)	(0.002)	(0.001)	(0.251)	(0.176)
Observations		21506	21484	11457	11446	10049	10038
Controls		N	Y	N	Y	N	Y

Notes: Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Robust standard errors in parentheses corrected for clustering on age measured in weeks; Sample of low skilled individuals 12 months either side of 22nd birthday January 1994-December 1998; Apprentices excluded; Controls include: gender, qualification level, white, head of household, marital status, region of residence; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to lower grade minimum school leaving age exams); Chi-squared test statistic from likelihood ratio test of the estimated model against a model with dummy variables for age measured in weeks.

Source: Labour Force Survey

Table 7: Employment outcomes around age 21 years

		All		Females		Males	
Quadratic	Discontinuity	0.000	-0.003	-0.011	-0.025*	0.007	0.012
		(0.008)	(0.009)	(0.015)	(0.015)	(0.014)	(0.015)
	Chisq(100)	69.0	82.6	109.8	99.8	85.4	86.5
	Pr>Chisq(100)	(0.992)	(0.896)	(0.236)	(0.487)	(0.851)	(0.831)
Cubic	Discontinuity	-0.001	-0.001	-0.011	-0.026	0.007	0.015
		(0.011)	(0.011)	(0.021)	(0.019)	(0.020)	(0.020)
	Chisq(99)	69.0	82.6	109.8	99.8	85.4	86.4
	Pr>Chisq(99)	(0.991)	(0.883)	(0.215)	(0.459)	(0.834)	(0.812)
Quadratic spline	Discontinuity	0.002	0.004	-0.006	-0.020	0.010	0.019
		(0.012)	(0.012)	(0.024)	(0.022)	(0.024)	(0.024)
	Chisq(98)	68.9	82.4	109.0	99.6	84.8	85.9
	Pr>Chisq(98)	(0.989)	(0.871)	(0.210)	(0.435)	(0.826)	(0.803)
Cubic spline	Discontinuity	0.033**	0.036**	0.026	0.020	0.042	0.046
		(0.013)	(0.015)	(0.035)	(0.033)	(0.033)	(0.033)
	Chisq(96)	65.3	78.4	107.1	97.1	82.5	83.8
	Pr>Chisq(96)	(0.993)	(0.904)	(0.206)	(0.450)	(0.835)	(0.808)
Observations		32516	32178	16203	16042	16313	16136
Controls		N	Y	N	Y	N	Y

Notes: Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Robust standard errors in parentheses corrected for clustering on age measured in weeks; Sample of low skilled individuals 12 months either side of 21st birthday July 1999-March 2009; Apprentices excluded; Controls include: gender, qualification level, white, head of household, marital status, region of residence; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to minimum school leaving age exams); Chi-squared test statistic from likelihood ratio test of the estimated model against a model with dummy variables for age measured in weeks.

Source: Labour Force Survey

Table 8: Employment outcomes around age 23 years

		All		Females		Males	
Quadratic	Discontinuity	0.007	0.007	0.009	0.010	0.002	0.002
		(0.010)	(0.010)	(0.017)	(0.015)	(0.013)	(0.013)
	Chisq(100)	73.0	70.0	81.1	79.1	74.7	80.9
	Pr>Chisq(100)	(0.981)	(0.990)	(0.917)	(0.939)	(0.973)	(0.920)
Cubic	Discontinuity	0.004	0.008	-0.006	0.005	0.017	0.014
		(0.014)	(0.014)	(0.025)	(0.023)	(0.016)	(0.017)
	Chisq(99)	72.9	70.0	79.9	79.0	73.5	80.3
	Pr>Chisq(99)	(0.977)	(0.988)	(0.920)	(0.931)	(0.974)	(0.916)
Quadratic spline	Discontinuity	-0.001	0.004	-0.019	-0.003	0.021	0.016
		(0.016)	(0.016)	(0.030)	(0.028)	(0.018)	(0.018)
	Chisq(98)	72.5	69.9	78.3	78.4	72.9	79.5
	Pr>Chisq(98)	(0.975)	(0.986)	(0.928)	(0.928)	(0.973)	(0.914)
Cubic spline	Discontinuity	-0.036*	-0.027	-0.067	-0.045	0.006	0.002
		(0.021)	(0.023)	(0.044)	(0.043)	(0.025)	(0.025)
	Chisq(96)	67.7	66.1	73.3	74.7	72.5	79.1
	Pr>Chisq(96)	(0.987)	(0.992)	(0.959)	(0.947)	(0.965)	(0.895)
Observations		31794	31433	16705	16535	15089	14898
Controls		N	Y	N	Y	N	Y

Notes: Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Robust standard errors in parentheses corrected for clustering on age measured in weeks; Sample of low skilled individuals 12 months either side of 23rd birthday July 1999-March 2009; Apprentices excluded; Controls include: gender, qualification level, white, head of household, marital status, region of residence; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to minimum school leaving age exams); Chi-squared test statistic from likelihood ratio test of the estimated model against a model with dummy variables for age measured in weeks.

Source: Labour Force Survey

Table 9: Unemployment outcomes for the low skilled at age 22

		All		Females		Males	
Quadratic	Discontinuity	-0.011	-0.010	0.004	0.004	-0.024**	-0.025**
		(0.007)	(0.006)	(0.009)	(0.009)	(0.010)	(0.011)
	Chisq(100)	85.7	84.6	97.3	100.5	87.4	88.7
	Pr>Chisq(100)	(0.846)	(0.865)	(0.558)	(0.467)	(0.811)	(0.783)
Cubic	Discontinuity	-0.018**	-0.017**	-0.008	-0.006	-0.028**	-0.029**
		(0.009)	(0.008)	(0.012)	(0.012)	(0.013)	(0.013)
	Chisq(99)	84.5	83.5	95.0	99.0	87.3	88.5
	Pr>Chisq(99)	(0.851)	(0.868)	(0.595)	(0.482)	(0.793)	(0.765)
Quadratic spline	Discontinuity	-0.019**	-0.018*	-0.011	-0.008	-0.029*	-0.030**
		(0.010)	(0.009)	(0.014)	(0.014)	(0.015)	(0.015)
	Chisq(98)	84.0	83.0	95.1	99.0	86.7	87.8
	Pr>Chisq(98)	(0.843)	(0.861)	(0.565)	(0.453)	(0.785)	(0.759)
Cubic spline	Discontinuity	-0.018	-0.018	-0.007	-0.005	-0.026	-0.031
		(0.015)	(0.014)	(0.021)	(0.021)	(0.021)	(0.021)
	Chisq(96)	83.4	82.6	95.0	98.9	85.7	86.7
	Pr>Chisq(96)	(0.817)	(0.833)	(0.511)	(0.400)	(0.766)	(0.740)
Observations		32274	31917	16546	16374	15728	15543
Controls		N	Y	N	Y	N	Y

Notes: Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Robust standard errors in parentheses corrected for clustering on age measured in weeks; Sample of low skilled individuals 12 months either side of 22nd birthday July 1999-March 2009; Apprentices excluded; Controls include: gender, qualification level, white, head of household, marital status, region of residence; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to minimum school leaving age exams); Chi-squared test statistic from likelihood ratio test of the estimated model against a model with dummy variables for age measured in weeks.

Source: Labour Force Survey

Table 10: Inactivity outcomes for the low skilled at age 22

		All		Females		Males	
Quadratic	Discontinuity	-0.014	-0.018*	-0.022	-0.023	-0.015	-0.014
		(0.011)	(0.010)	(0.016)	(0.016)	(0.012)	(0.012)
	Chisq(100)	108.7	103.5	100.6	90.8	86.7	97.2
	Pr>Chisq(100)	(0.258)	(0.385)	(0.464)	(0.733)	(0.827)	(0.561)
Cubic	Discontinuity	-0.018	-0.013	-0.039*	-0.028	0.001	0.002
		(0.015)	(0.014)	(0.021)	(0.021)	(0.016)	(0.016)
	Chisq(99)	108.6	103.3	99.1	90.7	84.2	94.6
	Pr>Chisq(99)	(0.239)	(0.363)	(0.478)	(0.711)	(0.857)	(0.605)
Quadratic spline	Discontinuity	-0.018	-0.014	-0.043*	-0.029	0.005	0.004
		(0.018)	(0.016)	(0.025)	(0.024)	(0.017)	(0.017)
	Chisq(98)	108.6	103.4	98.8	90.4	83.0	93.2
	Pr>Chisq(98)	(0.218)	(0.336)	(0.457)	(0.696)	(0.860)	(0.618)
Cubic spline	Discontinuity	-0.019	-0.027	-0.045	-0.047	-0.004	-0.005
		(0.026)	(0.020)	(0.033)	(0.029)	(0.023)	(0.022)
	Chisq(96)	107.0	100.6	96.6	87.7	82.6	92.7
	Pr>Chisq(96)	(0.209)	(0.353)	(0.463)	(0.714)	(0.833)	(0.576)
Observations		32274	31917	16546	16374	15728	15543
Controls		N	Y	N	Y	N	Y

Notes: Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Robust standard errors in parentheses corrected for clustering on age measured in months; Sample of low skilled individuals 12 months either side of 22nd birthday July 1999-March 2009; Apprentices excluded; Controls include: gender, qualification level, white, head of household, marital status, region of residence; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to minimum school leaving age exams); Chi-squared test statistic from likelihood ratio test of the estimated model against a model with dummy variables for age measured in months.

Source: Labour Force Survey

Table 11: Non-parametric estimates of the discontinuity at age 22

	Bandwidth	All	Females	Males
Employment	15 days	0.129	0.127	0.142
		(0.083)	(0.128)	(0.114)
	20 days	0.144**	0.137	0.157*
		(0.061)	(0.100)	(0.090)
	30 days	0.096**	0.093	0.108*
		(0.045)	(0.075)	(0.066)
	40 days	0.075**	0.061	0.102*
		(0.038)	(0.062)	(0.057)
	60 days	0.068**	0.070	0.078*
		(0.030)	(0.049)	(0.046)
Unemployment	15 days	-0.076	0.016	-0.155*
		(0.054)	(0.047)	(0.093)
	20 days	-0.033	0.029	-0.088
		(0.043)	(0.042)	(0.072)
	30 days	-0.010	0.015	-0.031
		(0.029)	(0.030)	(0.056)
	40 days	-0.009	0.020	-0.033
		(0.023)	(0.027)	(0.044)
	60 days	-0.017	0.003	-0.031
		(0.017)	(0.022)	(0.034)
Inactivity	15 days	-0.095	-0.167	-0.051
		(0.086)	(0.136)	(0.092)
	20 days	-0.125**	-0.190*	-0.075
		(0.064)	(0.104)	(0.068)
	30 days	-0.089*	-0.129*	-0.066
		(0.046)	(0.070)	(0.049)
	40 days	-0.064*	-0.102*	-0.048
		(0.036)	(0.057)	(0.039)
	60 days	-0.046*	-0.089**	-0.025
		(0.028)	(0.044)	(0.032)
	Observations	32274	16546	15728

Notes: Age measured in days; Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Bootstrapped standard errors in parentheses; Sample of those 12 months either side of 22nd birthday July 1999-March 2009; Apprentices excluded; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to minimum school leaving age exams).

Table 12: Non-parametric estimates of the discontinuity at ages 21 and 23 and age 22 before the NMW

	Bandwidth	All	Females	Males
Prior to NMW	15 days	-0.046	-0.074	-0.005
		(0.108)	(0.140)	(0.191)
	20 days	0.016	-0.024	0.039
		(0.086)	(0.109)	(0.142)
	30 days	0.069	0.031	0.091
		(0.066)	(0.085)	(0.101)
	40 days	0.062	-0.001	0.115
		(0.052)	(0.070)	(0.078)
	60 days	0.035	-0.003	0.061
		(0.040)	(0.056)	(0.055)
	Observations	21506	11457	10049
21st birthday	15 days	0.077	0.106	0.065
		(0.093)	(0.134)	(0.126)
	20 days	0.057	0.013	0.102
		(0.072)	(0.104)	(0.106)
	30 days	0.056	0.007	0.111
		(0.055)	(0.075)	(0.078)
	40 days	0.057	0.029	0.092
		(0.045)	(0.061)	(0.061)
	60 days	0.052	0.031	0.079
		(0.035)	(0.045)	(0.045)
	Observations	32516	16203	16313
23rd birthday	15 days	0.056	0.045	0.075
		(0.096)	(0.141)	(0.161)
	20 days	-0.012	-0.088	0.085
		(0.070)	(0.105)	(0.128)
	30 days	-0.063	-0.153**	0.058
		(0.048)	(0.076)	(0.093)
	40 days	-0.049	-0.123*	0.052
		(0.038)	(0.064)	(0.071)
	60 days	-0.035	-0.100**	0.053
		(0.028)	(0.045)	(0.051)
	Observations	31794	16705	15089

Notes: Age measured in days; Statistical significance of the discontinuity indicated: * 10, ** 5, and *** 1 per cent level; Bootstrapped standard errors in parentheses; Sample of those 12 months either side of 21st and 23rd birthdays July 1999-March 2009 and around 22 birthday from Jan 1994-Dec 1998; Apprentices excluded; Low skilled includes individuals in the bottom third of the skill distribution (individuals with highest educational qualification equivalent to minimum school leaving age exams).

Source: Labour Force Survey