UK National Minimum Wage and Labor Market Outcomes of Young Workers*

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Abstract

The UK national minimum wage (NMW) is age-specific with the most important threshold at the age of 22 (lowered to 21 from 2010 onwards) when workers become eligible for the adult rate. We estimate the impact of this threshold on employment by means of a regression discontinuity analysis. Because this threshold is known in advance, we investigate the presence of discontinuities in both the level and the slope of employment probabilities at different ages around the threshold. Our results indicate that turning 22 does not significantly change the employment probability. However, we find a significant change in the slope of the probability of being employed around one year before, suggesting a smooth deterioration of employment probability before turning 22 rather than a sudden change at a particular age. This finding is confirmed by a difference-in-difference analysis. However, no such effect can be found during the period preceding the introduction of the NMW.

Keywords: minimum wage; employment; young workers; regression discontinuity design.

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1 Introduction

The imposition of a mandatory minimum wage, whether at national, regional or industry level, is a common instrument of economic policy. Most OECD countries impose some form of a minimum wage (Dolton and Rosazza-Bondibene, 2012). Germany introduced a new national minimum wage in 2015, replacing the previous system of sector-wide collective bargaining, while the UK has recently introduced a new national living wage, which is set to rise at a rates substantially exceeding the recent increases in the national minimum wage. Many less developed countries have embraced the minimum wage, even Hong Kong, traditionally a bastion of the laissez-faire approach, introduced a minimum wage in 2010. Nevertheless, the minimum wage is a contentious measure, potentially raising workers' earnings at the expense of worse employment prospects for those out of work. Indeed, standard neoclassical economic theory predicts that, under competitive markets, a wage floor should either have no effect on employment (if set at a sufficiently low rate) or should lower employment by preventing the least productive workers from finding work at market-clearing wages.[1]

To date, the empirical evidence on employment effect of minimum wage rules is inconclusive. Neumark and Wascher (2004, 2007 and 2008) argue that the bulk of the evidence from the US as well as from other countries points to a negative employment effect of introducing (or increasing) the minimum wage. The range of estimated elasticities, however, is very broad: from significantly negative to significantly positive. This resonates with the findings of Dolado et al. (1996) who consider the employment effect of minimum wage rules in France, the Netherlands, Spain and the UK, and also present estimates ranging from negative (especially for young workers) to positive. The meta-studies by Card and Krueger (1995b) and Doucouliagos and Stanley (2009), in contrast, conclude that there is little evidence that the minimum wage lowers employment.[2]

[1] Once we relax the assumption of competitive markets, however, the theoretical predictions can change dramatically. Assuming monopsony in the labor market, in particular, can result in a positive employment effect of the minimum wage (Dolado et al., 1996): monopsony employer can push wages below the marginal product of labor, thereby maximizing profits while depressing employment. Imposing a wage floor, correspondingly, reduces the employer's profits and increases employment.

[2] The unsettled state of the debate is typified by the recent polemic concerning the sign of employment effects of state minimum wages in the US. On the one hand, Dube, Lester and Reich (2010) and Allegretto, Dube and Reich (2011) argue that the previous research, summarized, inter alia, in Neumark and Wascher (2008), produces spurious results because it fails to account for state-level heterogeneity. They conclude that when the analysis controls for this heterogeneity, increases in state minimum wages have no disemployment effects. Neumark, Salas and Wascher (2014), in turn argue that the research of Dube et al. (2010) and Allegretto et al. (2011) is

In all of the aforementioned studies, workers who are most likely to be affected by the minimum wage, such as the young and the low-skilled, are found to experience especially large disemployment effects. The negative effect is mitigated when young workers are subject to a lower minimum-wage rate (see also Croucher and White, 2011; Dolton and Rosazza-Bondibene, 2012; and Clemens, 2015). Abolishing the lower minimum-wage rates for young workers, likewise, tends to have a potentially large adverse effect on their employment and to lead to substitution of older workers for young workers (Hyslop and Stilman, 2007).

The UK introduced the current national minimum wage (NMW) framework relatively late, in April 1999.[3] Since then, the NMW has been subject to regular annual revisions, coming into effect every October from 2000 onwards. After its introduction, the effect of the NMW on employment has been analyzed by a number of studies. Stewart (2004) and Dickens and Draca (2005) consider the effect of the NMW's introduction and the annual increases, respectively. Dolton, Rosazza-Bondibene and Wadsworth (2009) utilize the fact that, unlike the NMW rates, average earnings vary considerably across the regions of the UK. They use the resulting variation in the 'bite' of the NMW at the regional level to assess its impact on employment. These studies find little evidence that the UK NMW has had an adverse effect on employment. The main (and probably only) exception is a recent study by Dickens, Riley and Wilkinson (2012) who present evidence that the introduction, and annual NMW increases, reduce the employment of part-time women, a segment of the labor market that is especially exposed to the minimum wage.

In this paper, we focus on the effect of the lower rates for young workers on their employment when they are no longer eligible for the reduced rate. At its introduction in 1999, the NMW was formulated with two distinct rates: the adult rate for workers aged 22 and over, and the so-called development rate for those between 18 and 21 years of age.[4] In 2004, an additional rate was introduced for those aged 16 and 17 who were not subject to the NMW until then. The ratio between the adult rate and the development rate has remained in the close neighborhood of 1.2 while the ratio between the development rate and the 16/17 rate has been

flawed and present results confirming the previous findings of disemployment effects of minimum wage increases.

[3] Until 1993, the Wages Councils had the power to set minimum wages for specific industries (not all industries had a Wages Council). No minimum wage was in place in the period between 1993 and 1999.

[4] From 2010, the upper age limit for the development rate has been lowered to 20. In 2016, an additional rate, the National Living Wage, applying to workers aged 25 and older, was introduced as well. The data used in our analysis, however, pertain to the period before these changes.

approximately 1.35. This implies that young workers earning the NMW rate relevant for their age are subjected to a sharp wage increase upon turning 18 and then again at 22.[5]

The previous literature has studied the impact of 'age-specific' NMW changes by means of a regression discontinuity design (henceforth RDD; see Imbens and Lee, 2008; van der Klaauw, 2008; and Lee and Lemieux, 2010). This intuition behind this is that the fact that workers on either side of the cutoff ages are eligible for substantially different NMW rates creates a quasi-experimental setting. Arguably, the characteristics of workers on either side of the cutoff age are very similar and therefore the main difference between them is the applicable NMW rate.[6] The forcing variable, age, can be influenced neither by the workers nor by their employers (or anyone else, for that matter). Therefore, when comparing the workers who are just above the cutoff age and those just below this age, the difference between them is as good as random. The 'treatment' category then consists of workers older than the cutoff age while the rest constitute the 'control' group.

However, the fact that aging is a deterministic rather than a random process[7] suggests that employers could adjust their employment decisions well in advance of the workers reaching the age threshold. Moreover, this reaction can be gradual rather than abrupt at a specific age. Therefore, we investigate the presence of level and slope discontinuities at not only at 22 years of age, but also one year earlier and later. We do this by following the recent literature, initiated by Card et al. (2012) and Nielsen et al. (2010), who propose the estimation of regression discontinuities affecting not only the level but also the slope of the outcome. Card et al. (2012) define this estimator for both fuzzy and sharp designs.

In our analysis, we start by extending the earlier work by Dickens, Riley and Wilkinson (2014, henceforth DRW) who consider the effect of age-related increases in the NMW on the employment of low-skilled young workers in the UK and also use the regression discontinuity

[5] Note that this increase only applies to those young workers who earn less than the adult minimum wage: nothing prevents employers from paying young workers the full adult rate. It is a difficult task to compute the proportion of workers who are affected by the adult minimum wage as only a small proportion of them reports their salaries. Based on the available information it is possible, at least, to compute the lower bound for the proportion of affected workers. This share is relatively low: across our data set, we find that 3.3% of workers within four months of turning 22 earn less than the adult rate. For comparison, 4.3% of workers who are similar distance from turning 21 earn less than the adult rate.

[6] In most of our analysis, we focus on comparing those subject to the 18-21 rate with workers earning the adult rate. The workers aged 16-17 differ from their older counterparts in several important ways: they are more likely to be in full-time education, their employability is lowered by restrictions such as not being allowed to sell alcoholic beverages, and their eligibility to benefits is more limited. Therefore, it is difficult to discern whether any employment effects that may occur upon turning 18 are due to becoming eligible to the higher NMW rate or whether they are entirely attributable to the age effect.

[7] See section 6.3.1 in Lee and Lemieux (2010).

design. They find, somewhat surprisingly, that low-skilled young workers are significantly more likely to be employed and significantly less likely to be either unemployed or out of the labor force as they turn 22. They attribute this to an increase in their labor supply: if the 18-21 rate is below the reservation wage of some workers, such workers postpone their labor market entry until they can be certain of earning at least the adult NMW rate. However, the result disappears when they consider all workers rather than only the low-skilled ones.[8] In most of our analysis, we consider all workers rather only low-skilled ones (although we also report separately regression results for low-skilled workers).[9]

We also find no significant NMW impact when we look for discontinuities in the levels of employment probabilities at different ages. However, the results are different when looking at slope changes. In particular, we find a significant and negative impact in the slope of employment probabilities for males aged around 21. This suggests a gradual change in employability before reaching the threshold age. A plausible explanation is that this happens in anticipation of the workers reaching the age threshold: savvy cost-conscious employers may gradually start to avoid employing workers who approach the 22 years of age. Interestingly, this effect is not found when we use a pre-NMW sample, suggesting that it is indeed attributable to the presence of age-related NMW rates.

Two recent papers, Kabatek (2015) and Kreiner, Reck and Skov (2017), consider the employment effects of age-related minimum-wage increases in the Netherlands and Denmark, respectively. In the Netherlands, the minimum wage changes in small increments with every year of age between the ages of 15 and 23. In Denmark, the minimum wage increases substantially when young workers turn 18. Both studies utilize the regression discontinuity design to find compelling evidence of negative age-related employment effects. Both studies find evidence of negative employment effects at/around the age discontinuity. However, in a context where economic agents adjust gradually rather than abruptly to the expected increase in wage, the minimum wage could have an effect on employment by altering the relationship between age and the employment probability rather than by having a one-off effect on the

[8] Low skilled workers are defined as those whose qualifications are no higher than the GCSE exams (i.e. incomplete high school).

[9] Young workers are often subject to the minimum wage more or less independently of their skill level. DRW (Table 3) indeed report that the shares of low and high skilled workers paid the minimum wage are only marginally different from one another: 10% of high skilled vs 11% of low skilled workers earn less than the adult rate at the age of 21. Furthermore, we also extend the data by three quarters. This does not have a material effect, as we are able to replicate DRW's results in our extended data set when we follow their methodology.

probability level. In our analysis, we employ a methodology that allows for the identification of a gradual adjustment of employment to age-specific NMW.

The next Section presents the data used in our analysis and outlines our methodological strategy. The results of the discontinuity analysis are in Section 3. Section 4 presents some complementary results that explore the effect of age-specific NMW rates on labor-market outcomes further. Finally, Section 5 concludes the paper by summarizing the results and suggesting some tentative avenues for further work.

2 Data and Methodology

We investigate the issue at hand using the UK Labour Force Survey (LFS), a quarterly nationally-representative survey of UK households. Each quarter, it reports on approximately 60 thousand households and over 100 thousand individuals aged 16 and above. Each household is retained in the survey for five consecutive quarters, with one-fifth of households replaced in each wave. The survey contains detailed demographic and socio-economic information on the respondents, including their labor-market outcomes. As the NMW was introduced in April 1999 and the age threshold for the adult rate was lowered in October 2010, we restrict our analysis to the period from the NMW introduction (i.e. starting with the April-June 1999 LFS) until the end of 2009 (so that the last quarterly LFS data set that we use is the October-December 2009 one).

The LFS contains information on the exact date of birth of every respondent.[10] We use this information to compute the age of each individual in months. Using the exact date the survey was carried out, we can determine the precise age of each respondents in months on the day of the survey was carried out (even when their birthday falls within the month in which they were interviewed). The discontinuity occurs at the workers' 22nd birthday. As is common in the RDD literature, we redefine age so that it equals 0 in the month during which the individual reaches the cutoff age. That is, instead of age we use *age–264*, where *age* is expressed in months and 264 corresponds to 22 years. Although each LFS quarterly data set contains information on around 100 thousand individuals, only a relatively small fraction of them are close to the cutoff age. Therefore, we consider the widest possible observation window: workers whose ages are between 15 months below and 15 months above the cutoff

[10] This information is not available in the publicly released LFS datasets. We are grateful to the Low Pay Commission and the Office for National Statistics for giving us access to the restricted release of the LFS.

age (recall that each worker appears in the LFS for five quarters, or 15 months). As a robustness checks, we replicate the analysis also for windows of 12 and 6 months.

To provide an initial illustration of the pattern at hand, Figure 1 shows the proportion of employed and economically active people by age in months between the ages 18 and 23, with zero corresponding to the threshold age of 22) and gender. Clearly, there is no pronounced jump in the probability of being employed when reaching the age of 22. Rather, the graph plotting the employment probability seems to become steeper around the threshold age, especially for men, suggesting a change in slope (i.e. increasing probability of being employed with growing age), rather than a jump in that probability at the age of 22. There seems to be a similar increase in the slope of the graph plotting the activity rate, around two years before the 22nd birthday. However, a more formal analysis is necessary to control for the individual characteristics and to test whether the level and/or slope effects are significantly different from zero.

The regression discontinuity design is concerned with determining how the outcome of interest (labor-market status in this case) changes when individuals pass the relevant cutoff point (18 or 22 years of age). The RDD method, however, assumes that the forcing variable, age, is continuous. If this assumption is met, we can compare outcomes observed in an arbitrarily small neighborhood around the cutoff, with *age* approaching 0 (recall that the forcing variable, *age* is defined as age less the cutoff age). Age, however, is as a discrete rather than continuous variable. Lee and Card (2008) argue that this introduces uncertainty in the choice of functional forms in regression discontinuity designs. In this setting, it is no longer possible to estimate the impact of a covariate on the dependent variable by simply computing averages within arbitrarily small neighborhoods of the cutoff point, even with an infinite amount of data. Instead, it is necessary to choose a particular functional form for the model relating the outcomes of interest to the forcing variable. Of course, it has to be tested whether the specification error of the proposed functional form is not significantly different from a fully flexible functional form that allows for different impacts of the discrete values of the covariate for each different age.

In a standard RDD specification, we would estimate $E[Y_1 - Y_0|X_i = 0]$, where Y_0 and Y_1 are the pre-treatment and post-treatment outcomes of interest, respectively, evaluated at the cutoff of the forcing variable, $X_i = 0$. Note that Y_0 and Y_1 can be described by the following functions

$$E[Y_1|X_i = 0] = \theta + \alpha^* * X_i + \beta * d + \varepsilon_1 \quad (1)$$

$$E[Y_0|X_i = 0] = \theta + \alpha * X_i + \varepsilon_0 \quad (2)$$

where θ includes the constant and any other covariates and d is a dummy taking value 0 before and 1 after the cutoff. Note also that

$$Y = d * Y_1 + (1 - d) * Y_0.$$

The standard approach therefore is concerned with identifying the change in the mean outcome associated with a discrete change in the threshold variable, i.e. $E[Y_1 - Y_0|X_i = 0]$. This can be estimated using the following functional form (see Lee and Card, 2008):

$$E[Y|X_i = 0] = \theta + \alpha * X_i * (1 - d) + \alpha^* * X_i * d + \beta * d + \varepsilon \quad (3)$$

where Y is the variable of interest, X_i is the forcing variable less the cutoff, and $\varepsilon = d * \varepsilon_1 + (1 - d) * \varepsilon_0$. When evaluated at $X_i = 0$, the discontinuity effect is captured by the coefficient estimate of β.

Nevertheless, recent literature points out that the discontinuity effect may not be limited to the estimate of β. In particular, the discontinuity may be associated with a slope change (kink) in addition to, or instead of, a jump in the intercept of the response function at the cutoff point. This possibility is discussed in detail in Dong (2014) who demonstrates the two possibilities and presents evidence of kink effects with respect to the take-up of early retirement in the US. Other studies offer analogous findings. Jacob and Lefgren (2004) find evidence of a slope change instead of a level effect at the cutoff with respect to the impact of remedial education programs on academic performance. Card et al. (2008) show that the change in the probability of retirement at 65 (the age of Medicare eligibility) is again more consistent with a change in the slope than with a level effect. Card et al. (2009) label this approach 'Regression Kink Design (RKD)'. Theorem 2 in Dong (2014) generalizes these arguments by showing that the treatment effect is equal to the ratio between the combination of the RD and RKD in the numerator and a similar combination of their associated probabilities of treatment in the denominator. If there is no jump (level effect) the treatment effect reduces to the RDK. As explained by Dong (2014), the sharp design RD model is just a special case in which everybody is a complier.

We therefore consider both types of discontinuity effects: the level (jump) effect and the slope (kink) effect. More specifically, the outcome of interest is the probability of being employed, unemployed or inactive at the cutoff age. We estimate the following equation:

$$E[y|age, d] = \mathrm{F}(\theta + \alpha_0 * age_i * (1-d) + \alpha_1 * age_i^2 * (1-d) + \alpha_0^* * age_i * d + \alpha_1^* * age_i^2 * d + \beta * d) = \mathrm{F}(\mathrm{u}) \qquad (4)$$

where y_i is equal to one if the individual is employed (unemployed, inactive), F is the standard normal cumulative distribution function, age_i is the age in months less the cutoff, d is a dummy variable equal to one when the individual's is at the cutoff age or older and θ again includes any remaining terms such as the constant and the covariates (qualifications, ethnic origin, apprenticeship, region of usual residence and being a full time student). We allow for the effect of age to be different before and after the young workers attain the threshold age. This is standard in the regression discontinuity approach, reflecting the fact that the effect of the forcing variables may change after the cutoff. If we did not allow different slope coefficients, the pre-cutoff and post-cutoff relationships would be estimated using information contained in the both parts of the sample: those pertaining to the pre-treatment sub-sample would be estimated using information affected by the treatment and vice versa (see Lee and Lemieux, 2010). Age takes the form of a quadratic polynomial which we test against an alternatives fully-flexible specification with each age in months captured by a separate dummy.

In expression (4), the jump in the probability of a particular employment status at the cutoff point (level effect) is measured as the marginal effect associated with the discontinuity dummy, d. We also estimate the change in the slope of F with respect to age at the discontinuity point. Note that because F is a non-linear (probit) function in which slope parameters are is associated with different interaction terms, neither the differences in the coefficients of the age polynomial before and after the cutoff (α_0 and α_1 vs α_0^* and α_1^*) nor the marginal effects of changing just the interaction terms have any relevant interpretation (see Norton *et al.*, 2004). Instead, following Norton *et al.* (2004), the interaction effect between age and d corresponds to the discrete double difference, which for expression (4) takes the following form:

$$\frac{\Delta \frac{\Delta F(.)}{\Delta age}}{\Delta d} = F(\theta + \beta) - F(\theta - \alpha_0^* + \alpha_1^* + \beta) - F(\theta) + F(\theta - \alpha_0 + \alpha_1) \qquad (5)$$

Note that expression above is nowadays implemented in the Stata margins command to compute marginal effects. We evaluate this expression by double-differencing the functional form at age equal 0 and -1 and at d equal 1 and 0. For robustness we also treat age as a continuous variable and compute the slope change as the difference of the derivative of the response function at d equal 1 and 0 but it does not change our findings (these results are available under request).

3 NMW and Young Workers: Regression Discontinuity Analysis

To assess the impact of age-related MNW increases, we start by looking at individuals whose age is on either side of 22 years (264 months). Table 1 reports regression results for the probability of being employed. We present estimates for males and females separately as well as for both genders together, with and without additional covariates. We consider all individuals regardless of their skill level (in contrast to DRW, 2014), since skilled and unskilled young workers have very similar propensities to be paid the NMW. Specification (4) is tested against a fully flexible functional form. For men, we cannot reject that both specifications are significantly different at the conventional levels while for women the quadratic specification is rejected, we also consider the cubic specification with no material change in the results. The row denoted *discontinuity* reports the slope (kink) marginal effect at the discontinuity, as given by equation (5). *Dummy*, in contrast, stands for the marginal effect of d (jump).

Neither the slope effect, nor the discontinuity dummy on its own, is significant when workers turn 22. This is in line with the previous findings of DRW who also report an insignificant result when they include all individuals rather than only the low-skilled ones. For the sake of comparability, we replicate DRW's analysis of low-skilled workers: these are those who left school at the age of 16 after completing their GCSEs as well as those who report having no qualifications. DRW find a significant positive effect of turning 22 for low-skilled workers, suggesting that becoming eligible for the adult NMW rate increases rather than reduces their employment. These results are in Table 2. They are broadly in line with DRW's but appear somewhat weaker.[11] In particular, while the discontinuity dummy is always positive, it is never significant for females, and it is significant only in the 5-10% range for males and for both genders together. More importantly, the combined level and slope effect is never even close to being significant. We are therefore unable to confirm the finding of a positive employment effect of becoming eligible for the adult NMW rate at the age of 22.

[11] Note that while we attempt to replicate DRW's results, there are some potentially important differences between their analysis and ours. In particular, we consider a 15-month window before/after the individual's 22nd birthday while they only consider 12 months, we compute the age in months slightly differently as discussed above, our data include three additional quarters in 2009, and, finally, although we sought to include the same covariates as them, it is possible that some of the covariates may be coded or formatted differently.

Next, Tables 3 and 4 present the regression results for unemployment and inactivity, respectively, considering again all workers regardless of their skill level. As before, the slope effect is never significant. Note however that the dummy alone is significant and negative in the regressions for unemployment with all individuals, which mirrors the similar finding of DRW. As we argue above, accepting this as the effect of the discontinuity would be wrong as it ignores the fact that the effect of age may also change upon surpassing the age threshold.

In summary, we find no evidence that the approximately 20% increase in the rate of the NMW at the age of 22 has any effect – whether positive or negative – on young workers' employment, unemployment or inactivity. This conclusion does not depend on whether we consider all young workers or only the unskilled ones.

To probe the NMW effect on young workers further, we undertake a number of extensions. In Table 5, we consider the effect of turning 22 on employment conditional on labor-market status (employed, unemployed or inactive) in the previous quarter. It may well be that the increase in the NMW rate that applies to workers from their 22nd birthday affects employed and unemployed workers differently. For instance, some of those who were employed at 21 may lose their jobs, while others enter the labor market or intensify their job search because of the higher NMW rate. If this is the case, the result presented in Table 1 could be insignificant because these two kinds of effects cancel out. The analysis is again presented separately for males and females (to save on space, we omit the results for both genders together). In the first two columns of Table 5, we present the estimates for the probability of remaining employed, conditional on being previously employed. The estimated effect of turning 22 is negative, especially for men, but it is not even close to being significant at conventionally accepted levels. Hence, young workers who were employed at the age of 21 are no more or less likely to be employed after their 22nd birthday. The next two columns present the estimates of the probability of being employed at 22, conditional on being unemployed before. The last two columns, in turn, present the corresponding estimates for those who were inactive before the quarter in which they turned 22. Again, none of these coefficients are significant, suggesting that controlling for the labor market status of young workers just before they turn 22 makes little difference to our findings.

Next, in Table 6, we consider only those young workers who earn less than the adult rate when they are 21. Such workers are bound to be affected by the age-mandated increase in the NMW upon turning 22. The previous analysis, in contrast, included all workers, regardless of whether their wages had to be raised or not. As before, we are unable to find any significant discontinuity effect (level or slope) on the employment probability. One drawback of this analysis, however, is the rather small sample size, which may be responsible for the lack of significant results.

Finally, we also test the possibility that the employment effect occurs at an age different from 22. As discussed before, since the timing of becoming eligible for the adult rate is deterministic, employers can reflect it in their decisions at any time either before or after the workers reach the threshold age. Therefore, we repeat the discontinuity analysis for workers turning 21 and 23 years of age (Table 7). The result at the age of 21 is striking: the slope effect suggests that male workers are significantly less likely to remain employed after turning 21. In contrast, reaching their 23rd birthday has no significant impact on employment of males or females.

The fall in the slope of the employment probability at 21 for men may be driven by an anticipation effect: employers are aware of the age-related NMW increase that young workers are entitled to after their 22nd birthday and gradually start to dismiss them well in advance of the relevant date and/or they refrain from hiring workers aged around 21. Note that the effect on employment occurs because the effect of age on the employment probability changes when workers are around 21 years old (slope/kink effect), rather than because of a level change in the employment probability.[12] This may be also due to the low share of workers earning less than the adult rate of the minimum wage[13]: given the relatively small number of young workers affected, the impact occurs gradually through a change in the relationship between employment probability and age rather than taking the shape of a discrete jump in that probability.

Finally, we also consider the NMW threshold at 18 years of age. Recall that those turning 18 become eligible for the 18-21 rate which historically has been some 35% above the 16-17 rate. As before, we consider all workers, irrespective of skills (although the differences in skill levels at this age are not particularly large). Table 8 reports the results. Turning 18 is associated with a significantly negative slope effect for both genders (as is already apparent in Figures 2-4): becoming eligible for the higher NMW rate is associated with lower

[12] We replicate the discontinuity analysis at 21st, 22nd and 23rd birthday with 6 and 12 month estimation windows instead of 15 months (see the Appendix). The results obtained with the 6 month window are never significant. This may be due to the lower number of observations when using the shorter estimation window. Moreover, the discontinuity effect may take time to become sufficiently pronounced. The regressions with the 12 month window generally paint the same picture as those discussed above. In particular, the discontinuity effect is negative both at the age of 21 and 22 for males: the former is significant at 10% while the latter is not significant.

[13] Recall that only 3.3% of workers within four months of turning 22, and 4.3% of those approaching their 21st birthday, earn less than the adult rate.

employment probability. Note that again this negative effect is observed only when we consider the slope effect: the dummy itself is not significantly different from zero (except for females). The insignificant coefficient for the discontinuity dummy is in line with the finding of DRW. The differences in the conclusions reached when considering the discontinuity dummy only and when looking also at the changed effects of the age polynomial again underscores the importance of assessing the full effect of the discontinuity.

As we argued before, turning 18 is associated with a host of other important changes besides becoming eligible for a higher NMW rate. For example, UK law requires anyone selling or serving alcohol to be 18 or older, which makes those under 18 ineligible to work in bars, restaurants and many shops. This makes the negative effect that we found all the more remarkable. An alternative explanation would link the effect that we observe to the end of full-time secondary education. In the UK, education was compulsory until the age of 16 during the time covered by our analysis but many students would stay enrolled for another two years to complete their secondary education. Those who do so without enrolling in higher education upon graduating then generally enter the job market when aged 18. This may explain why the employment probability first dips around the 18th birthday and then rises, both for males and females.

Finally, we return to the possibility that the age-related effects we observe are caused by factor other than the NMW: such as features of the UK education system or welfare state. We therefore re-estimate the discontinuity effects for the period before the NMW introduction. Throughout much of its post-WWII history, the UK had a number of sector-specific wage floors maintained by the so-called Wages Councils. The Wages Councils were abolished in 1993 while the NMW was introduced only in 1999. We therefore replicate our discontinuity analysis for 1994-98, a period during which no minimum wage or similar rules were in effect. We are not aware of any significant changes to the UK education or welfare systems that would coincide with the introduction of the NMW in 1999. Therefore, if the effect of age is different during the 1994-98 period, it is highly probable that this difference can be attributed to the effect of age-specific NMW rates.

Table 9 presents the results for young workers turning 18, 21, 22 and 23 during 1994-98. None of the age-discontinuity effects is even remotely significant (and the discontinuity dummy is not significant either). These results increase our confidence that the observed age-related effects discussed above are indeed attributable to the MNW rules.

4 Robustness

One implication of the results presented so far is that the regression discontinuity design should not be used when the forcing variable is deterministic rather than random. In other words, the RDD methodology is applicable when the agents (workers and employers in this setting) have no incentive to act before the discontinuity actually occurs. That is not the case here: employers who do not wish employ workers older than 22 can dismiss workers who are close but below this age, and/or hire only workers substantially younger than 22. This may explain why in our analysis the negative employment effect occurs well before the workers actually turn 22.

Therefore, we employ an alternative method to verify our results. A standard difference-in-difference analysis is not possible in this case because all workers are treated: there is no control group composed of workers who reach the cutoff age but do not become eligible to the higher NMW rate. Therefore, we estimate the following modified difference-in-difference model:

$$p(e_{it} = 1 | e_{it-1} = 0) = F(\alpha + \beta I(age_{it} > \delta) + \gamma X_t) \quad (1)$$

where e_{it} is a dummy variable that takes value of one if the individual is employed and zero if unemployed; p is the probability of transition from being unemployed to employed, X_t is the usual vector of covariates that includes also age and age squared, and $I(.)$ is an indicator function that takes the value of 1 when the age is higher or equal to a given threshold δ and zero otherwise. We define analogous probabilities for the other transitions between the various labor-market states. The sample contains all individuals aged between 18 and 40. The marginal effect associated with $I(.)$ reflects the structural change in the probability of changing employment status in the neighborhood of δ, the age where there new national minimum wage applies. Therefore, the difference-in-difference aspect is entailed in the fact that we compare the change in the probability of being employed between two consecutive quarters for workers not attaining the threshold age (control group) with the corresponding change in the employment probability for those workers attaining the threshold age (treatment group). Hence, while it is not a standard difference-in-difference approach, it is very similar in spirit. Consistently with our previous analysis, we also explore the possibility that the effect associated with reaching this age applies before workers turn 22.

The results are presented in Tables 10 to 13. First, in Tables 10-11, we consider the probability of staying employed and the transition from unemployment to employment, respectively. However, this leaves out the flows to and from inactivity. Therefore, in Tables 12-13, we consider the probability of staying active and the transition from inactivity to being active, respectively. We estimate the marginal effect associated with $I(.)$ for the age of 22 and for ages up to one year below and above this age, in quarterly increments.

The findings from this analysis are generally in line with those presented in the preceding section. In Table 10, males aged 21-22 have a negative probability of staying employed: this effect is not significant at conventional levels but is close to being significant at 10% at the ages of 21 and 21 and one-quarter. We see similar negative effect on the probability of becoming employed if previously unemployed for males and females aged 21-22; these are significant for females aged 21 to 21 and half. In contrast, attaining ages between 22 and a quarter and 23 has either insignificant or significantly positive effect on the probability of staying employed and on the transition from unemployment to employment.

These effects are even stronger when we consider transitions to/from inactivity. In Table 12, males aged 21-22 have a negative probability of staying active. The effects of turning 21 and a quarter, 21 and half and 22 are significantly negative, the remaining two ages are close to being significant. Both males and females aged 21-22 face a negative probability of transition from inactivity to being active (Table 13), with these effects being significant for males aged between 21 and 21 and half (and close to being significant at the remaining two ages) and for all ages for females. Again, being older than 22 has either an insignificant or significantly positive effect on the transition probabilities we consider.

As a further robustness check, we replicate the above analysis with only individuals aged between 18 and 26, so as to only consider workers who are relatively close to the threshold age. The results, while weaker because of the lower number of observations, are generally consistent with those reported above. For the sake of brevity, we are not reporting these results here but they are available upon request.

In summary, these results obtained with standard regression analysis confirm our findings based on the RDD analysis: young workers aged between 21 and 22 are in an unfavorable labor market position, relative to workers older than 22. A plausible explanation is that the age-specific NMW rates affect the employment of young workers: being close to the age threshold makes workers between 21 and 22 years of age less employable.

5 Conclusions

The received wisdom in the UK concerning the national minimum wage is that it has had little adverse impact on employment. In this paper, we revisit this result. We consider young workers and investigate whether their labor-market outcomes are affected by the age-specific minimum-wage rates. Specifically, during the period covered by our analysis, the NMW featured different rates for those who aged 16-17, 18-21 and more than 22 years old. Using the regression-discontinuity approach, we find that although the effect of turning 22 is negative, it is not statistically significant. In contrast, we do find evidence of a negative employment effect for males aged 21. While in the period we have studied the NMW does not change at this age, we believe this result may be driven by the anticipation of the minimum wage increase at 22. Importantly, we only observe a change in the relationship between age and employment probability (i.e. slope effect), not a discrete jump in the underlying probability of being employed (level effect). The fact that most regression-discontinuity analysis only consider level effects can be the reason why previous studies failed to observe an effect at this age.

Finding a negative effect for workers aged 21 reflects the specific nature of the case that we consider. While the regression discontinuity approach is usually used to study outcomes that are assigned (approximately) randomly, there is nothing random about the outcome in this case: young workers turn 22 in an entirely deterministic fashion. The employment effect associated with the discontinuity (higher NMW rate applying to those aged 22 and above) therefore can occur anywhere in the neighborhood of the cutoff age, whether before or after. We find a negative effect approximately one year before the cut-off age: this is consistent with employers avoiding hiring or dismissing workers who are 21 and older. This finding is similar to that of Kabátek (2015) who finds that Dutch young workers face lower employment probability around their birthday, in a setting where the minimum wage rate changes with every year of age. In the UK context, where each NMW rate applies to broader age bands, the overlap of the negative employment effects with the workers' birthdays is less close.

Our results are further strengthened by the fact that no such negative effects occur during the pre-NMW period, 1994-98. Furthermore, we obtain similar results with a difference-in-difference analysis of transition probabilities between the various labor-market states: again, being aged between 21 and 22 is associated with generally unfavorable labor-market outcomes: lower probability of staying employed (active) and/or lower probability of moving from unemployment (inactivity) to employment (becoming active) while no unfavorable outcomes are observed for workers aged above 22 and up to 23.

The UK NMW rules concerning young workers were modified in October 2010 in that the threshold age for the adult rate has been lowered from 22 to 21. From April 2016, a new and higher National Living Wage applies to all workers above the age of 25. Our findings (and results reported elsewhere in the literature) suggest that these changes may negatively affect the young workers approaching the respective cutoff ages.

Finally, our work has two important methodological implications. First, it underscores that when applying the regression discontinuity approach to deterministic processes, the effect need not coincide with the discontinuity. Instead, it can occur either before or after the discontinuity is reached. Second, it is important to correctly account for the effect of the regression discontinuity in cases when it can entail both level and slope effects. In particular, the negative employment effects that we find at 18 and 21 are only apparent when we consider the slope effect in addition to the more conventional level effect.

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Table 1 Discontinuity effect on employment: All young workers.

	All		Males		Females	
	with covariates	without covariates	with covariates	without covariates	with covariates	without covariates
Discontinuity[1]	.00122 (.00244)	.00227 (.00236)	-.00228 (.00331)	.00055 (.00328)	.00368 (.00353)	.00356 (.00336)
Dum[2]	.00482 (.00800)	.00480 (.00772)	.00567 (.01097)	.00502 (.0107)	.00589 (.01154)	.00348 (.01103)
No. observations	136,591	136,591	66,582	66,582	70,009	70,009
Chi-statistic for Whole regression	26345.97	638.70	15412.56	480.74	12942.46	218.54
Pr>Chi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1524	0.0037	0.1918	0.0060	0.1411	0.0024
Chi-statistic for quadratic	27.11	29.11	27.55	. 34.08	44.13	53.25
Pr>Chi	0.3503	0.2539	0.3292	0.1063	0.0105	0.0008

Notes: (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 2 Discontinuity effect on employment: Low skilled young workers.

	All		Males		Females	
	with covariates	without covariates	with covariates	without covariates	with covariates	without covariates
Discontinuity(1)	.00211 (.00418)	.00224 (.00415)	.00214 (.00555)	.00270 (.00561)	.00061 (.00595)	.00193 (.00589)
Dum(2)	.02940 (.01402)*	.02241 (01386)	.03380 (.01852)	.02807 (.01859)	.02486 (.02002)	.01822 (.01971)
No. observations	43809	43809	20457	20457	23352	23352
Chi-statistic for Whole regression	2686.26	3.24	1621.56	42.32	1174.80	14.47
Pr>Chi	0.0000	0.6633	0.0000	0.0000	0.0000	0.0129
R2	0.0478	0.0001	0.0705	0.0018	0.0370	0.0005
Chi-statistic for quadratic	45.31	43.99	24.89	30.52	61.38	58.20
Pr>Chi	0.0077	0.0109	0.4683	0.2054	0.0001	0.0002

Notes: (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 3 Discontinuity effect on unemployment.

	All		Males		Females	
	with covariates	without covariates	with covariates	without covariates	with covariates	without covariates
Discontinuity(1)	.00118 (.00126)	.00107 (.00135)	.00190 (.00195)	.00175 (.00212)	.00037 (.00160)	.000200 (.00170)
Dum(2)	-.008830 (.00425)*	-.00919 (.00452)*	-.01013 (.00659)	-.01104 (.0071)	-.00844 (.00535)	-.00819 (.00565)
No. observations	136,591	136,591	66,582	66,582	70,009	70,009
Chi-statistic for Whole regression	3489.80	61.34	2721.18	44.54	1170.22	15.95
Pr>Chi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0070
R2	0.0446	0.0008	0.0621	0.0010	0.0347	0.0005
Chi-statistic for quadratic	19.40	15.69	26.00	23.85	23.16	20.95
Pr>Chi	0.7776	0.9237	0.4078	0.5278	0.5682	0.6955

Notes: (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 4 Discontinuity effect on inactivity.

	All		Males		Females	
	with covariates	without covariates	with covariates	without covariates	with covariates	without covariates
Discontinuity(1)	-.00151	-.00347	.00038	-.00252	-.00451	-.00389
	(.00160)	(.00220)	(.00249)	(.00291)	(.00334)	(.00323)
Dum(2)	.00539	.00444	.00695	.00615	.00287	.00474
	(.00698)	(.00705)	(.00819)	(.00919)	(.01072)	(.01047)
No. observations	136,591	136,591	66,582	66,582	70,009	70,009
Chi-statistic for Whole regression	29973.84	541.74	20380.64	446.08	13752.84	189.13
Pr>Chi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1971	0.0036	0.3135	0.0069	0.1614	0.0022
Chi-statistic for quadratic	21.83	25.18	27.69	24.00	30.59	46.73
Pr>Chi	0.6455	0.4521	0.3225	0.5194	0.2030	0.0053

Notes: (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 5 Probability of employment conditional on being employed in previous quarter.

	Males	Females	Males	Females	Males	Females
	Emp from emp (without covariates)	Emp from emp (without covariates)	Emp from unemp (without covariates)	Emp from unemp (without covariates)	Emp from inact (without covariates)	Emp from inact (without covariates)
Discontinuity[(1)]	-.00184 (.00158)	-.00004 (.00181)	-.01189 (.00936)	.01636 (.01102)	.00030 (.00663)	-.00500 (.00518)
Dum[(2)]	.00483 (.00822)	.00114 (.00843)	-.01864 (.04345)	.01636 (.05514)	.03364 (.02418)	.02886 (.01552)
No. observations	27921	26030	3956	2671	6795	11815
Chi-statistic for Whole regression	42.09	30.76	7.89	11.21	7.48	10.13
Pr>Chi	0.0000	0.0000	0.1625	0.0473	0.1876	0.0716
R2	0.0037	0.0029	0.0017	0.0033	0.0016	0.0014

Notes: (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 6 Probability of employment for workers earning less than adult rate.

	Males	Females
Discontinuity[(1)]	-.0271372	-.0196407
	(.0203325)	(.0188205)
Dum[(2)]	-.0142615	-.0391771
	(.07441)	(.04997)
No. observations	644	1097
Chi-statistic for Whole regression	8.22	6.70
Pr>Chi	0.1444	0.2438
R2	0.0161	0.0088

Notes: None of the estimations include covariates. (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey. The regressions do not contain additional control variables due to low number of observations.

Table 7 Discontinuity effect at 21 and 23.

	21 years		23 years	
	Males	Females	Males	Females
Discontinuity[(1)]	-.00994	-.001039	.00435	-.00179
	(.00326)**	(.00349)	(.00318)	(.00336)
Dum[(2)]	-.00764	-.00186	.01043	-.01325
	(.01150)	(.01184)	(.01023)	(.01138)
No. observations	68324	70647	65206	70622
Chi-statistic for Whole regression	17001.14	12155.02	13443.49	14310.83
Pr>Chi	0.0000	0.0000	0.0000	0.0000
R2	0.1947	0.11285	0.1879	0.1602

Notes: All estimations include covariates. (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 8 Discontinuity effect at 18.

	Males	Females	All
Discontinuity(1)	-0.01018	-.01009	-0.00984
	(0.00361)**	(.00362)**	(0.00255)**
Dum(2)	-0.00238	-.0253495	-.012706
	(0.01253)	(.01263)*	(0.00888)
No. observations	67641	65023	132664
Chi-statistic for Whole regression	16587.27	9896.45	25665.83
Pr>Chi	0.0000	0.0000	0.000
R2	0.1788	0.1110	0.1410

Notes: All estimations include covariates. (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 9 Discontinuity Effect on Employment: All Young Workers, Pre-NMW Period (1994-98).

	18 years			21 years			22 years			23 years		
	All	Males	Females	All	Males	Females	All	Males	Females	All	Males	Females
Discontinuity(1)	0.003 (0.004)	0.006 (0.006)	0.0003 (0.005)	-0.00072 (0.0038)	-0.004 (0.0181)	-0.0056 (0.0183)	0.0004 (0.00368)	0.00528 (0.017)	0.0175 (0.018)	0.0018 (0.0034)	0.0144 (0.0156)	0.0072 (0.005)
Dum(2)	-0.008 (0.013)	-0.009 (0.018)	-0.008 (0.018)	-0.00582 (0.00842)	0.00804 (0.0055)	-0.0097 (0.0053)	0.006 (0.0122)	-0.0008 (0.005)	0.00205 (0.0053)	0.0056 (0.011)	-0.0047 (0.0045)	-0.0036 (0.0166)
No. observations	60,708	30428	30280	60,422	29872	30,550	62,871	30,606	32,265	66,377	31,839	34,538
Chi-statistic for Whole regression	12724.21	8069.34	5136.23	13128.36	7964.52	5768.08	13647.50	7556.75	6809.31	13466.25	6873.88	7512.05
Pr>Chi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1555	0.1993	0.1246	0.1634	0.2052	0.1396	0.1685	0.1994	0.1592	0.1656	0.1877	0.1698
Chi-statistic for quadratic	27.12	25.42	20.72	26.78	26.25	22.92	36.29	39.64	22.88	35.07	37.19	18.56
Pr>Chi	0.35	0.43	0.71	0.37	0.39	0.58	0.07	0.03	0.58	0.09	0.06	0.81

Notes: Marginal effects at mean values and standard deviations between brackets. (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Table 10 Probability of employment if previously employed

	Age								
Both genders	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	13470.60	13470.52	13470.52	13468.17	13467.87	13472.21	13473.56	13484.51	13483.61
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.0761	0.0761	0.0761	0.0761	0.0761	0.0762	0.0762	0.0762	0.0762
Number of obs	684,033	684,033	684,033	684,033	684,033	684,033	684,033	684,033	684,033
Age dummy	.0016209	.001581	.001581	.0002122	.0004836	.0020363	.0023356	.004018	.0038974
	(.00095)	(.00094)	(.00094)	(.00088)	(.00087)	(.00097)*	(.00098)*	(.00103)**	(.00102)**
Males	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	8263.71	8263.76	8264.18	8266.26	8265.38	8263.70	8263.83	8266.98	8267.26
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1020	0.1020	0.1020	0.1020	0.1020	0.1020	0.1020	0.1020	0.1020
Number of obs	351,448	351,448	351,448	351,448	351,448	351,448	351,448	351,448	351,448
Age dummy	-.0000747	-.000252	-.0006966	-.0015604	-.0012496	-.0000396	.0003798	.0020187	.0021046
	(.00105)	(.00103)	(.001)	(.00094)	(.00094)	(.00106)	(.00109)	(.00115)	(.00116)
Females	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	5792.36	5792.96	5790.09	5790.68	5791.39	5794.72	5794.96	5800.54	5799.33
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.0606	0.0606	0.0606	0.0606	0.0607	0.0607	0.0607	0.0607	0.0607
Number of obs	332,585	332,585	332,585	332,585	332,585	332,585	332,585	332,585	332,585
Age dummy	.0030462	.0032544	.0018685	.0021727	.0024771	.0039468	.0040406	.0056201	.0052968
	(.00161)	(.00161)*	(.00154)	(.00152)	(.00151)	(.00166)*	(.00167)*	(.00172)**	(.0017)**

Notes: Coefficients reported are marginal effects at mean values, with standard deviations in parentheses.

Table 11 Probability of employment if previously unemployed

	Age								
Both genders	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	11369.60	11370.79	11371.38	11374.41	11377.23	11369.27	11371.05	11372.83	11374.85
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R2	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745	0.0745
Number of obs	205,763	205,763	205,763	205,763	205,763	205,763	205,763	205,763	205,763
Age dummy	-.0020543	-.0041112	-.0047481	-.007242	-.0088428	.000814	.0045338	.0063867	.0079904
	(.00332)	(.00331)	(.00326)	(.00323)*	(.00318)**	(.00333)	(.00332)	(.00332)	(.00332)*
Males	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	4803.38	4803.76	4804.06	4805.60	4805.40	4803.46	4806.13	4807.74	4811.31
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R2	0.0806	0.0806	0.0806	0.0806	0.0806	0.0806	0.0806	0.0807	0.0807
Number of obs	66,314	66,314	66,314	66,314	66,314	66,314	66,314	66,314	66,314
Age dummy	-.0036223	-.0052805	-.0061938	-.0096835	-.0090775	.0040812	.0114005	.0141526	.0188503
	(.00643)	(.00636)	(.00624)	(.00614)	(.006)	(.00645)	(.00647)	(.0065)*	(.00651)**
Females	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	6888.01	6890.43	6891.96	6891.96	6901.52	6887.54	6886.67	6886.55	6886.60
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R2	0.0754	0.0754	0.0754	0.0754	0.0755	0.0754	0.0753	0.0753	0.0753
Number of obs	139,449	139,449	139,449	139,449	139,449	139449	139,449	139,449	139,449
Age dummy	-.0046483	-.007522	-.0087743	-.011327	-.0143219	-.0038875	-.0014756	.0005819	.0010565
	(.00387)	(.00389)	(.00386)*	(.00386)**	(.00387)**	(.0039)	(.00388)	(.00385)	(.00386)

Notes: Coefficients reported are marginal effects at mean values, with standard deviations in parentheses.

Table 12 Probability of being active if previously active

	Age								
Both genders	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	16699.80	16699.88	16699.64	16699.58	16699.68	16700.34	16701.62	16703.27	16704.95
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1017	0.1017	0.1017	0.1017	0.1017	0.1017	0.1017	0.1017	0.1017
Number of obs	729,603	729,603	729,603	729,603	729,603	729,603	729,603	729,603	729,603
Age dummy	.0003973	.0004493	-.0002401	-.0001433	.0002721	.0007158	.0011729	.0015888	.0019234
	(.00079)	(.00078)	(.00075)	(.00074)	(.00074)	(.00081)	(.00083)	(.00084)	(.00085)*
Males	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	10633.70	10631.93	10633.70	10633.47	10632.12	10631.84	10629.32	10629.28	10630.67
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1728	0.1727	0.1728	0.1728	0.1727	0.1727	0.1727	0.1727	0.1727
Number of obs	376,571	376,571	376,571	376,571	376,571	376,571	376,571	376,571	376,571
Age dummy	-.0014179	-.0010987	-.0013673	-.0013047	-.0010599	-.0011169	-.0002173	.0001574	.0009088
	(.00064)*	(.00064)	(.00061)*	(.0006)*	(.0006)	(.00066)	(.00072)	(.00074)	(.00078)
Females	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	7264.46	7263.42	7261.77	7261.79	7262.20	7265.31	7264.25	7265.38	7264.80
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.0723	0.0723	0.0722	0.0722	0.0722	0.0723	0.0723	0.0723	0.0723
Number of obs	160,193	160,193	160,193	160,193	160,193	160,193	160,193	160,193	160,193
Age dummy	.0025263	.0019857	.0006259	.0006483	.0010871	.0029148	.002468	.0029646	.0027163
	(.00153)	(.0015)	(.00143)	(.00141)	(.0014)	(.00156)	(.00155)	(.00157)	(.00156)

Notes: Coefficients reported are marginal effects at mean values, with standard deviations in parentheses.

Table 13 Probability of being active if previously inactive

	Age								
Both genders	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	8471.42	8480.07	8488.36	8502.44	8518.01	8464.80	8463.44	8465.82	8468.76
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.0688	0.0689	0.0689	0.0691	0.0692	0.0688	0.0688	0.0688	0.0688
Number of obs	160,193	160,193	160,193	160,193	160,193	160,193	160,193	160,193	160,193
Age dummy	-.0114645	-.0164531	-.0198498	-.0245086	-.0285808	-.0047801	.0005206	.0063091	.0094293
	(.00414)**	(.00416)**	(.00413)**	(.00411)**	(.00409)**	(.00411)	(.00408)	(.00404)	(.00402)*
Males	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	3814.32	3815.49	3818.74	3824.39	3823.83	3813.48	3813.49	3815.90	3817.42
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.0993	0.0993	0.0994	0.0996	0.0996	0.0993	0.0993	0.0994	0.0994
Number of obs	41,191	41,191	41,191	41,191	41,191	41,191	41,191	41,191	41,191
Age dummy	-.0095377	-.0129862	-.019417	-.0267907	-.0253449	.0055336	.0057296	.0147712	.0184615
	(.00852)	(.0084)	(.00827)*	(.00814)**	(.0079)**	(.00854)	(.00868)	(.00871)	(.00878)*
Females	**22**	**21.75**	**21.5**	**21.25**	**21**	**22.25**	**22.5**	**22.75**	**23**
LR Chi2 (59)	4994.53	5002.71	5006.75	5015.52	5031.50	4992.16	4987.86	4987.81	4988.55
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.0597	0.0598	0.0598	0.0600	0.0601	0.0597	0.0596	0.0596	0.0596
Number of obs	119,002	119,002	119,002	119,002	119,002	119,002	119,002	119,002	119,002
Age dummy	-.012263	-.0181837	-.0202577	-.0243045	-.0304249	-.0100238	-.0023293	.0020671	.0044669
	(.0048)*	(.00489)**	(.00487)**	(.00489)**	(.00495)**	(.00482)*	(.00468)	(.00462)	(.00458)

Notes: Coefficients reported are marginal effects at mean values, with standard deviations in parentheses.

Figure 1a Proportion of employed people by age (in month, with 22 years indicated as 0)

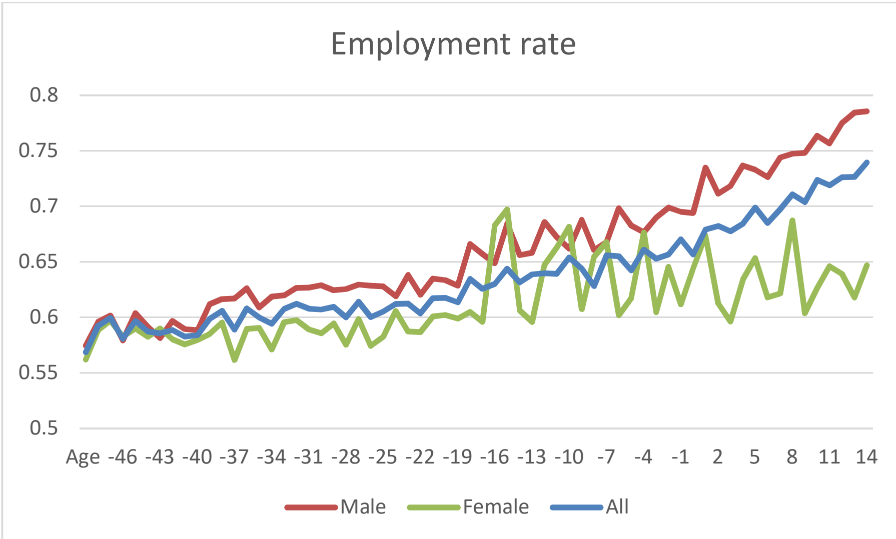
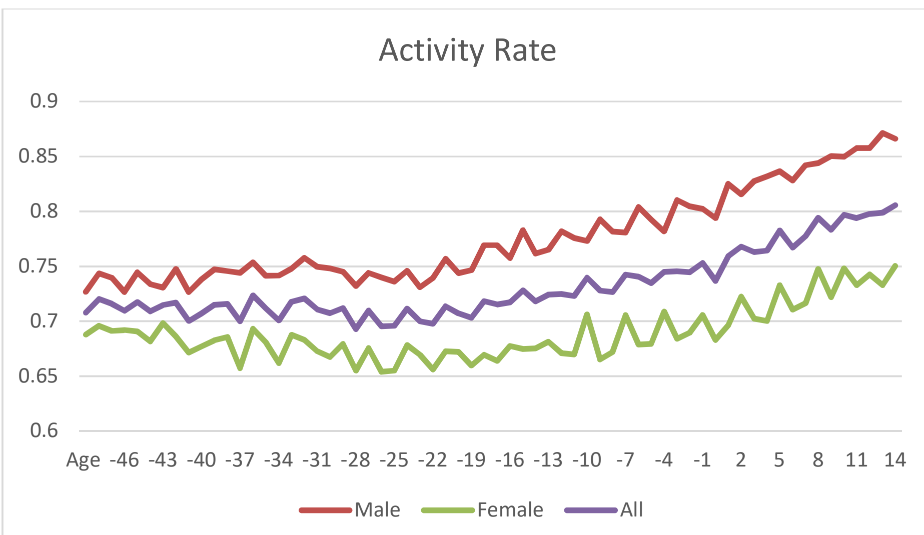


Figure 1b Proportion of economically active people by age (in month, with 22 years indicated as 0)



Appendix (not for publication)

Regression-discontinuity analysis: Alternative time windows

All workers. Discontinuity effect at 21, 22 and 23

	21 years		22 years		23 years	
	6 months	12 months	6 months	12 months	6 months	12 months
Discontinuity(1)	.00092	-.00461	.00116	-.00045	-.00961	.00096
	(.00969)	(.00350)	(.00965)	(.00350)	(.00891)	(.00334)
Dum(2)	.01341	-.00430	.01026	.01483	-.01239	-.00188
	(.01425)	(.00945)	(.01395)	(.02617)	(.01323)	(.00876)
No. observations	57797	109453	57513	108102	56417	107005
Chi-statistic for Whole regression	11048.03	21478.97	11245.37	20836.73	10430.78	19855.19
Pr>Chi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1458	0.1496	0.1536	0.1520	0.1563	0.1562

Notes: All estimations include covariates. (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Male workers. Discontinuity effect at 21, 22 and 23

	21 years		22 years		23 years	
	6 months	12 months	6 months	12 months	6 months	12 months
Discontinuity(1)	.01042	-.00883	-.00024	-.00239	.01077	.00532
	(.01352)	(.00476)	(.00793)	(.00479)	(.01269)	(.00459)
Dum(2)	.02918	-.00307	.00052	-.00303	-.00365	.00668
	(.01976)	(.01316)	(.01919)	(.01260)	(.01750)	(.01159)
No. observations	28583	53899	27978	52724	27086	51396
Chi-statistic for Whole regression	6610.71	13098.40	6656.79	12248.60	5547.02	10567.76
Pr>Chi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1812	0.1900	0.1955	0.1919	0.1885	0.1888

Notes: All estimations include covariates. (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.

Female workers. Discontinuity effect at 21, 22 and 23

	21 years		22 years		23 years	
	6 months	12 months	6 months	12 months	6 months	12 months
Discontinuity[(1)]	-.00925	-.00136	-.00665	.01457	-.01932	-.00362
	(.01389)	(.00508)	(.01375)	(.01321)	(.01955)	(.00484)
Dum[(2)]	-.00170	-.00589	.02335	.00031	-.02845	-.01020
	(.02049)	(.01353)	(.02011)	(.00506)	(.01264807)	(.01295)
No. observations	29214	55554	29535	55378	29331	55609
Chi-statistic for Whole regression	5040.66	9529.44	5505.22	10287.81	5987.72	11228.77
Pr>Chi	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R2	0.1290	0.1282	0.1417	0.1417	0.1628	0.1602

Notes: All estimations include covariates. (1) estimated discontinuity effect taking into account the impact of age and the threshold dummy variable; (2) estimated impact of the threshold dummy variable. Coefficients reported are marginal effects at mean values, with standard deviations in parentheses. Significance levels denoted as * 5% and ** 1%. Source: Labour Force Survey.