How the national minimum wage affects flows in and out of employment: An investigation using worker-level data

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Executive summary

This study explores how the national minimum wage has altered the rate at which people move in and out of jobs. Recent research from North America has found that although minimum wages have little effect on employment, they tend to reduce job turnover rates. However, different explanations have been put forward to account for this relationship. One view is that it is due to employers holding on to probationary workers because the costs of hiring replacements are higher when the minimum wage is raised. Another is that it is due to workers reducing their proclivity to quit when the minimum wage raises their pay.

Individual-level data from the Annual Survey of Hours and Earnings (ASHE), the Labour Force Survey (LFS) and the British Household Panel Survey (BHPS) are analysed. For employed workers, a 'wage gap' variable is defined, equal to the amount the following period's minimum wage is above each worker's wage or zero if the new minimum wage is less than the worker's wage. This is found to be negatively related to the probability of a worker leaving his/her job between periods, but to have no effect on the probability of the worker leaving employment altogether. These findings are consistent with a situation in which the minimum wage reduces quit rates. The largest turnover effects are found among men and among workers aged 24-29.

For unemployed workers, an estimated wage gap is calculated, using data on similar employed workers or on workers' reservation wages. The estimated wage gap is found to reduce the probability of a worker entering employment.

More detailed analysis indicates that the reduction in turnover resulting from the minimum wage is driven by annual changes in the national minimum wage rates, rather than by workers becoming eligible for the youth or adult minimum wages (at ages 18 or 21) or by the reduction in age of eligibility for the adult rate (from 22) in 2010.

Finally, a 'pseudo-panel' is constructed from the ASHE by calculating average employment rates over time for different combinations of industry and region. Industry and region groups that experience large increases in costs because of the minimum wage are found to experience reductions in rates of job turnover. Although weak, some evidence is found of spillovers across workers' age categories and, specifically, that the

employment of 16-17 year olds is positively affected by extent to which the minimum wage raises the cost of hiring older workers.

How the national minimum wage affects flows in and out of employment: An investigation using worker-level data

Matt Dickson and Kerry L. Papps [*]

1. Introduction

Although it remains the subject of much research, a growing body of evidence in developed countries suggests that minimum wages have little effect on overall employment levels (see Stewart 2004 and Dickens *et al*. 2012 for the U.K.). A few recent studies have focused instead on the effects that minimum wages have on the rate of job turnover in the labour market. These have uncovered evidence that minimum wages tend to reduce the level of turnover, although there is no consensus regarding the reason behind this relationship.

This study examines the effect the minimum wage has on flows between jobs and into and out of employment using U.K. data. Individual-level panel data from the Annual Survey of Hours and Earnings (ASHE), Labour Force Survey (LFS) and British Household Panel Survey (BHPS) are used to compare the response of low-wage workers to changes in the national minimum wage. For each employed worker, a wage gap is constructed, measuring the extent to which the minimum wage raises the worker's hourly wage. For unemployed workers, an equivalent wage gap is estimated using data on employed workers with similar characteristics.

In addition, pseudo-panel data from the ASHE are used to provide evidence of whether employers substitute between workers of different ages in response to changes in the minimum wage that affect the cost of hiring one age group relative to another. For each industry/region combination, the annual change in employment of workers in a specific age group is related to the change in labour costs for *each* age group brought about by changes in the various age-specific minimum wage rates.

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By providing evidence of how the minimum wage has changed the level of flows into and out of employment, the study will examine whether the findings of studies in other countries can be replicated in the UK. In addition, the study contributes to the international literature by measuring how much the minimum wage is likely to affect each individual, rather than measuring the effect of the minimum wage on all workers in an age group or state/province.

2. Background

Three recent studies have examined how changes in minimum wages affect the rate of labour market transitions, by examining the likelihood of workers moving into and out of employment in the presence of a minimum wage, relative to some control group of workers.

Portugal and Cardoso (2006) use matched employer-employee data to examine how job turnover among Portuguese teenagers changes relative to adults in response to an increase in the minimum wage in 1987 that affected teenagers only. They find that the teenagers' share of separations fell by 15% in response to a 50% increase in the minimum wage. As Dube *et al*. noted, one drawback with Portugal and Cardoso's approach is that their identification strategy assumes that there are no age-specific trends in turnover during the period studied.

Brochu and Green (2013) use Canadian labour force survey data for 1979-2008 to compare rates of labour market transitions in provinces with different minimum wages. They find that both job separations and accessions decline in the six months after a minimum wage increase. The reduced separation rates are due mainly to reductions in layoffs rather than quits. The reduction in hiring is larger among teenagers than among older workers and it outweighs the reduction in separations among teenagers, leading to an overall reduction in employment for this age group. However, for older workers the hiring and separation effects almost exactly offset each other. Brochu and Green suggest that their findings could be explained by a match quality search model in which employers are less willing to lay off existing workers when the minimum wage rises because this raises the cost of hiring a replacement worker and the match quality of this worker is initially unknown.

Dube *et al*. (2014) analyse U.S. Quarterly Workforce Indicators (QWI) data for 2000-2009. To control for unobserved state-specific factors that might be correlated with the level of the minimum wage, they compare turnover in counties on either side of a state border. Like Brochu and Green, they find that a higher minimum wage leads to a reduction in the rate of employment transitions but not on the overall level of employment. Specifically, they find that a 10% increase in the minimum wage reduces turnover rates by 2.0% among teenagers and 2.1% among restaurant workers. The QWI data do not distinguish between job-to-job moves and flows out of employment. However, the authors find no evidence that the duration of non-employment changes among unemployed workers, suggesting that most of the adjustment in the separation rate takes the form of quits rather than layoffs – in contrast to Brochu and Green's conclusion. Instead, Dube *et al*. note that their evidence is consistent with a search model with endogenous separations, in which the minimum wage reduces the rate at which workers receive better-paying job offers.

No studies have examined whether the national minimum wage has affected the level of job turnover in the U.K., although some studies have separately focused on the effects the minimum wage has on the rate of exit from employment (Dickens *et al*. 2012; Papps and Gregg 2014) or entry to employment (Bryan *et al*. 2014). These studies have largely found insignificant results.

The approach taken in this study is similar to that used by Brochu and Green, in that it uses individual data on job flows. However, rather than assuming that all workers are affected by a change in the minimum wage, it allows workers who are further down the wage distribution to have a larger treatment effect. Similarly, whereas Dube *et al*. looked at aggregate turnover data for entire counties, the benefit of this approach is that it can determine whether any change in job turnover is concentrated among those workers who have actually been affected by changes in the minimum wage.

3. Data

The analysis draws on individual-level longitudinal data from the Annual Survey of Hours and Earnings (ASHE), the Labour Force Survey (LFS) and the British Household Panel Survey (BHPS). Each dataset has strengths and weaknesses, as outlined below.

Annual Survey of Hours and Earnings

The ASHE is an annual survey that collects data on the wages, work hours and other employment arrangements of around 1% of the U.K. working population (Office for National Statistics 2013). Basic additional information, such as age and sex, is also included. The ASHE was introduced in 2004 and replaced the New Earnings Survey (NES). However, by applying ASHE methodologies to NES data for the 1997-2003 period, the Office for National Statistics has produced ASHE datasets for 1997 onwards. The analysis in this study uses data for 1997-2013.

The ASHE sample is drawn from HM Revenue and Customs' Pay As You Earn register, based on the last two digits of a worker's National Insurance Number. Survey forms are sent to all employers of the selected workers to complete. The questions in the ASHE refer to a reference week, which is in early April of each year. Since the responses are provided by employers rather than by employees, the ASHE wage and hours data are considered to be highly accurate.

If a person does not work in a given year, they will not appear in the dataset. Therefore, the only way to determine whether someone has moved out of employment is by their absence from the data in a given year. Obviously, this will also include people who have moved abroad or died. However, as long as the fraction of people making these transitions is constant across the wage distribution, this will not bias the results from the empirical strategy outlined in the next section. Workers might also be absent from the ASHE if an employer fails to respond to the questionnaire or if they are not included in the PAYE register because their earnings fall below the National Insurance Lower Earnings Limit.

Although it has a limited range of personal characteristics compared to the Labour Force Survey, the major benefits of the ASHE are its larger sample size and the fact that its wage and hours data are more accurate, since the responses are provided by employers rather than by employees. In addition, the ASHE tracks respondents year after year, which allows the analyst to separate the effects of the minimum wage from any inherent differences in labour market outcomes across workers.

Labour Force Survey

The LFS is a household survey, which collects information on a wide range of labour force measures and other topics. Since 1992 it has been conducted on a quarterly basis, with each sample household retained for five consecutive quarters and a fifth of the sample replaced each quarter. Although the survey was designed to produce cross-sectional data, by linking together data on individuals across quarters a short-term longitudinal dataset can be produced. The analysis in Section 6 will use pooled data for all cohorts who entered the LFS between the first quarter of 1997 and the final quarter of 2013.

The major benefit of the LFS for the purposes of this study is that it contains considerably more information than the ASHE on these aspects of respondents' jobs. A drawback of the LFS is that workers are only observed for five quarters, which means it is not possible to control for a person's inherent employment stability as accurately as in the ASHE data. In addition, the LFS wage data are known to be less accurate than those in the ASHE. The LFS contains two measures of hourly pay: usual hourly pay, calculated by dividing usual weekly earnings by usual weekly hours, and basic hourly pay rate for those workers who reported having a basic rate. Previous research (Dickens *et al*. 2012; Papps and Gregg 2014) has shown that the latter of these is more accurate, although it is only available for a subset of respondents.

British Household Panel Survey-Understanding Society

The British Household Panel Survey (BHPS) is a panel dataset covering the years 1991 to 2008. The first wave of the BHPS consisted of 10,300 individuals living in 5,500 households, drawn from 250 areas across Great Britain. It was designed to be a nationally representative sample of the population of Great Britain living in private households in the autumn of 1991. The original sample members were re-interviewed each successive year and if they left to form new households they continued to be followed and all adult members of their new households were interviewed. Children in the original sample households were interviewed when they reach 16 years of age. As such, the panel remained broadly representative of the British population over time. This analysis uses information from the waves covering 1997 to 2008.

The greatest drawback of the BHPS is the sample size. As it is a multi-purpose household panel survey, there is not the same focus on individuals of working age as there is in the LFS and more obviously in the ASHE. Nor are there quite as detailed questions regarding employment and wages as are found in the other surveys. Nevertheless, pay information is recorded each year for those in employment both in terms of usual gross monthly pay (and usual hours) and hourly pay rate for those who record being paid at an hourly rate.

A unique advantage of the BHPS is the information recorded on the lowest weekly net pay individuals would be willing to accept to enter employment and the weekly hours they would expect to have to work for that pay. This is asked of all those who are not employed but express that they would like to have a job. By dividing the former by the latter, a reservation wage can be constructed for each unemployed worker. In addition, these individuals are asked the weekly net pay that they would expect to get when they next enter employment and the weekly hours they would expect to work for that pay.

4. Individual-level analysis

The first part of the analysis uses data on individual from the ASHE, LFS and BHPS to examine the effects of the minimum wage on the likelihood of workers moving into or out of employment or of changing jobs.

ASHE sample

To begin with, the ASHE data are used to examine how the minimum wage affects the likelihood of individual workers exiting employment. The sample is restricted to those who are aged between 16 and 64 and are currently employed. In addition, observations with wages less than 95% of the prevailing minimum wage are dropped from the sample.[1]

[1] Using a 90% threshold was found to make little difference to the results.

Following previous studies of the employment effects of the minimum wage using individual-level data (Currie and Fallick 1996; Kramarz and Philippon 2001), a 'wage gap' is defined for each worker, measuring how much extra an employer must pay to retain a current employee after a minimum wage increase. In any period, the minimum wage that applies to a given worker is determined by that worker's age, the rates in force and the age cut-offs used to determine which minimum wage bracket (under 18, youth or adult) the worker is in. Hence, the wage gap for worker *i* in period *t* can be written:

$$WAGEGAP_{it} = \max\{0, \overline{w}(AGE_{i(t+1)}, RATE_{i(t+1)}, BRACKET_{i(t+1)}) - w_{it}\}, \tag{1}$$

where w_{it} is person *i*'s current hourly wage (in 2012 pounds, adjusted using the RPI) and the minimum wage in year t+1, $\overline{w}_{i(t+1)}$, is expressed as a function of the person's age in t+1, $AGE_{i(t+1)}$, the prevailing minimum wage rates, $RATE_{i(t+1)}$, and the age brackets used to determine eligibility for the minimum wage in that period, $BRACKET_{i(t+1)}$:

Workers who initially earn slightly more than the following year's minimum wage will be included in the sample in order to form a control group, as they will be unaffected by the minimum wage change. Hence, this group will provide an estimate of what *would* have happened in the absence of a change in the minimum wage between year *t* and year *t*+1 to the earnings of workers who are 'bound' by the minimum wage. Specifically, all workers who were ever observed to earn a real wage less than £7 (in 2012 pounds) between 1997 and 2013 are included in the sample. Workers whose hourly wage is always higher than this cut-off are excluded from the sample, as they are unlikely to provide a good comparison with minimum wage workers. Means for the sample used in the regressions for job exit are given in Table 1.

To examine the effects the minimum wage has on the probability of leaving a job, a dummy variable for whether the person is employed at the same firm in the following year (*t*+1) is regressed on *WAGEGAP*:

$$E_{i(t+1)} = \alpha WAGEGAP_{it} + \beta CTFLWAGEGAP_{it} + \delta AGE_{it} + \gamma_i + \lambda_t + \varepsilon_{it}, \tag{2}$$

where γ is a person fixed effect (capturing the effects of all person-specific factors, whether observed, such as education, or unobserved, such as a person's inherent level of earnings instability), λ is a year fixed effect (capturing general trends that affect all workers' earnings from year to year) and ε is a stochastic error term.

Because *WAGEGAP* might simply reflect the effect of a person's position in the wage distribution, a counterfactual wage gap is added as a regressor, capturing how much less than £7 (in 2012 pounds) a worker earns, as follows:

$$CTFLWAGEGAP_{it} = \max\{0, 7 - w_{it}\}. \quad (3)$$

By including *CTFLWAGEGAP* in the regressions, the coefficient on *WAGEGAP* is identified *solely* by variation in the wage gap in the specific period the minimum wage was raised and the differences in turnover that always occur at different wage rates are controlled for. This approach has been termed a 'horizontal' difference-in-difference design, and has been used by numerous previous authors (Stewart 2004; Dickens *et al*. 2012).[2] £7 was chosen as a round number larger than the largest value of the incoming minimum wage in the sample (£6.50); however, the results are generally robust to the choice of other cut-offs between £6.50 and £7.50.

The results (reported in the first column of Table 2) indicate that the wage gap has a significant positive effect on the probability of remaining in a job in the following year. The coefficient implies that a 10p increase in the wage gap increases the likelihood of an employed worker remaining in his/her job by 0.10 percentage points and that a 1% increase in the wage gap raises the probability of remaining in the same job by 0.006% at the mean. The counterfactual wage gap has a strong negative effect on the probability of remaining in employment, consistent with a situation of higher turnover among low-wage jobs.

In the second column of the table, the dependent variable is whether a person is still employed – at any firm – in the following year.[3] The coefficient on *WAGEGAP* is insignificant, indicating that although the minimum wage decreases the likelihood of a worker leaving his/her job, it has no effect on the overall level of flows out of employment. The fact that there is a reduction in job turnover but no increase in the rate of flows from employment to unemployment is consistent with Dube *et al*.'s endogenous separations search model, but not Brochu and Green's match quality search model.

[2] The only difference in approaches is that Dickens *et al*. only used years before the introduction of the national minimum wage in their control group. The advantage of using more recent years is that they will provide a better counterfactual, given changes in the wage distribution that have occurred over the past 18 years.

[3] Firm are defined according to their PAYE identifier.

In the third column of Table 2, the change in hours worked between *t* and *t*+1 among those who are still employed on the same job in *t*+1 is used as a dependent variable. The results suggest that there is a significant reduction in work hours among those who remain in the same job, consistent with the findings of previous studies (Papps and Gregg 2014).

As a robustness check, in Table 3 the same dependent variables are used, but the control group is expanded to include all workers earning more than the incoming minimum wage. The results are very similar.

To examine whether the results in Table 2 vary by demographic group, the regressions were repeated for different age brackets and genders (using the original restricted sample of workers). The coefficients on *WAGEGAP* for each subgroup are reported in Table 4. The age brackets used are: 16-19 (workers who will still be bound by the under 18 or 18-21 rates in the following year), 20-23 (workers who are bound by the adult minimum wage but would not be eligible for the forthcoming 'living wage'), 24-29 (workers who would be bound by the living wage but who are still relatively young), 30-64 (older workers). The results indicate that the minimum wage has the largest effect on job turnover among workers aged 24-29 and among men. Significant positive employment effects are found for all groups except workers aged under 20. However, the coefficients are much smaller than those in the first column, indicating that most of the adjustment takes place in the form of changes in jobs, not exit from employment. The work hours effects appear to be exclusively driven by women.

In the preceding regressions, the variation in the wage gap is driven by three factors: people becoming eligible for higher minimum wage rates as they age, annual changes in the four minimum wage rates and the lowering of the adult rate eligibility age to 21 in 2010. To examine the separate effects of each of these, *WAGEGAP* can be decomposed into three additive components, as follows:

$$
\begin{aligned}
WAGEGAP_{it} &= \max\{0, \overline{w}(AGE_{i(t+1)}, RATE_{i(t+1)}, BRACKET_{i(t+1)}) - w_{it}\} \\
&= \max\{0, \overline{w}(AGE_{i(t+1)}, RATE_{it}, BRACKET_{it}) - w_{it}\} \\
&+ \max\{0, \overline{w}(AGE_{i(t+1)}, RATE_{i(t+1)}, BRACKET_{it}) - \overline{w}(AGE_{i(t+1)}, RATE_{it}, BRACKET_{it})\} \\
&+ \max\{0, \overline{w}(AGE_{i(t+1)}, RATE_{i(t+1)}, BRACKET_{i(t+1)}) - \overline{w}(AGE_{i(t+1)}, RATE_{i(t+1)}, BRACKET_{it})\}
\end{aligned}
$$

$$= AGEWAGEGAP_{it} + RATEWAGEGAP_{it} + BRACKETWAGEGAP_{it} \,. \qquad (4)$$

The three components represent the portion of the wage gap that is due to workers moving up a minimum wage bracket on their 18th and 22nd birthdays (*AGEWAGEGAP*); the portion that is due to changing rates from year to year (*RATEWAGEGAP*); and the portion that is due to the reduction in the adult minimum wage age of eligibility to 21 (*BRACKETWAGEGAP*). All three changes could occur simultaneously.

If all three wage gap measures are entered as separate regressors in equation 2, it is possible to determine the separate employment effect of each type of policy change. The results, which are reported in Table 5, indicate that year-to-year variation in minimum wage rates has a significant negative effect on the probability of job exit but not on the probability of employment exit. In contrast, variation in workers' ages has no effect on either probability. Hence, the results are supportive of Dube *et al*.'s endogenous separations model when examining the effects of changes in minimum wage rates and this drives the overall results reported in Table 2. The fact that variation in ages has no effect makes sense because a worker's age is perfectly predictable by firms and workers, so there is unlikely to be any sudden adjustment in employment when workers turn 18 or 21.

Lowering the adult minimum wage eligibility age is found to result in an *increase* in the probability of a worker leaving his/her job, contrary to the predictions of either of the two theoretical models. This result possibly indicates that the one-off change in 2010 led to significant disemployment of 21-year-olds (although there may have been an offsetting increase in hiring rates of 21-year-olds – something that cannot be examined using the ASHE).

LFS sample

Although wage data in the ASHE are known to be much more accurate than those in the LFS, the regression estimates from the latter provide a useful robustness check for the results. As with the ASHE sample, wage observations less than 95% of the prevailing minimum wage or greater than £7 (in 2012 pounds) are dropped. Means for estimation samples used are given in Table 6. Table 7 reports job-exit and employment-exit regressions over both a one-quarter and one-year interval. Since only one job or employment transition is observed for each person, individual fixed effects cannot be added. Instead, a vector **X** of controls for sex, education (the categories are: degree or higher; higher education, below degree; A level or equivalent; GCSE A-C or equivalent; CSE below grade 1 or equivalent; no/other qualification), region, job tenure in months and whether a person is married is included:

$$E_{i(t+1)} = \alpha WAGEGAP_{it} + \beta CTFLWAGEGAP_{it} + \delta AGE_{it} + \mathbf{X}_{it}\boldsymbol{\theta} + \lambda_t + \varepsilon_{it} \,, \tag{5}$$

The results indicate no significant change in either job or employment exit in the quarter immediately following a change in wage gap. As with the ASHE sample, the wage gap has a significantly positive effect on the probability of staying with the same firm in the following year, but no effect on the probability of staying in employment in the following year.

Unlike the ASHE, the LFS includes information on the reason unemployed workers left their last job during the preceding three months. Therefore it is possible to examine whether the minimum wage has a different effect on voluntary job separations ('quits') or involuntary separations ('lay-offs') between quarters. Workers were assumed to have experienced a lay-off if they left their job because they were dismissed, were made redundant, took voluntary redundancy, or had a temporary job which came to an end, and to have quit if they left for any other reason. As revealed in Table 8, no significant evidence is found that the minimum wage affects either type of job exit, although this is not surprising, given that the overall employment separation coefficients in the first and third columns of Table 7 are insignificant.

Table 9 reports the results when the basic hourly pay rate variable is used to construct the wage gap measures. The coefficients on *WAGEGAP* are insignificant in all specifications, perhaps because of the reduced sample size.

Unlike the ASHE, the LFS contains data on people who are not employed. Hence, we can observe how likely workers are to move *into* employment between periods. These workers do not have values for *WAGEGAP*, hence it is necessary to estimate one. This should reflect how much the minimum wage raises the wage a given worker is *likely* to receive in the labour market. Two alternative approaches are used. The first involves estimating the wage a person is likely to be paid by drawing on data on employed workers with similar demographic characteristics. The regressors used are a person's age and dummies for sex, whether married, education (6 categories), region (20 categories) and quarter. Tobit estimation is used to account for the fact that wages are bounded below by the minimum wage and separate regressions were estimated for each period the minimum wage was held constant (1997 quarter 1-1999 quarter 1, 1999 quarter 2-2000 quarter 3 and each year thereafter).[4] Using the estimated wage, each unemployed worker's estimated *WAGEGAP* over a one-year interval is calculated according to equation 1. This is equivalent to the approach taken by Bryan *et al*. (2012) in their study of flows into employment.

In the second approach, a worker's *WAGEGAP* is estimated directly, by regressing each employed worker's value of *WAGEGAP* over a one-year interval on the same regressors as for the first approach. Again, tobit estimation is used to account for the fact that *WAGEGAP* is bounded below by zero and the regressions are repeated same periods as for the first approach.

In Table 10, the results of regressions for whether an unemployed worker is employed either one quarter or one year in the future are reported.[5] The sample is restricted to workers who are currently unemployed and have looked for work in the past four weeks. The same regressors are used as in equation 5, except that months on the job is replaced by months unemployed. The counterfactual wage gap is estimated in a similar manner to *WAGEGAP*, using the predicted values from a series of tobit regressions of *CTFLWAGEGAP* for each quarter. When the first approach to estimating *WAGEGAP* is used, the coefficient on *WAGEGAP* is insignificant. This is consistent with the findings of Bryan *et al*. (2012). However, when the second approach is used, a significant negative coefficient is found, suggesting that unemployed workers are less likely to find work the quarter – or year – after the minimum wage is raised.

By comparing the coefficients on *WAGEGAP* in Tables 7 and 10, we can estimate how the minimum wage changes the overall levels of job turnover in the labour market. The coefficients imply that at the mean a 1% increase in the wage gap will lower the probability of a worker leaving employment by 0.012%, will lower the probability of a

[4] To allow for measurement error, all wages between 95% and 105% of the prevailing minimum wage were recoded to be equal to the minimum wage for the purposes of this step only.

[5] Because data on the person's current wage is not needed, data from the first four waves a person is in the LFS can be used in the one-quarter-ahead specification, unlike in Tables 7 and 8.

worker moving to another job by 0.019% and will lower the probability of an unemployed worker entering employment by between 0.049% and 0.230% (depending on which method of estimating the wage gap is used). Taking into account the average value of the minimum wage among bound workers, these results imply a job separation elasticity with respect to the minimum wage of -0.20, which is very close to the range of values found by Portugal and Cardoso (-0.3), Brochu and Green (between -0.27 and -0.35) and Dube *et al*. (-0.23).

The models are estimated separately by age bracket and gender and the coefficients on *WAGEGAP* are reported in Table 11. The first two columns report the likelihood of an employed worker staying in employment and the last two columns report the likelihood of an unemployed worker entering employment, using the second approach to estimate *WAGEGAP*. The coefficients on *WAGEGAP* are insignificant for most age brackets and no significant variation is seen between the subgroups in the effects of *WAGEGAP*, possibly because of the sample size.

BHPS sample

The LFS employment inflow and outflow regressions are repeated using the BHPS. Means for estimation samples used are given in Table 12.[6] Since the BHPS is a long panel, person fixed effects can be added to the regressions, thereby controlling for any person-specific factors that affect job mobility. As seen in Tables 13 and 14, no evidence is found that *WAGEGAP* has an effect on flows out of employment; however, some weak evidence is found that it has a negative effect on flows into employment, but only using the first approach to estimating the wage gap and only when person fixed effects are included.

As noted in the previous section, the BHPS includes information on the lowest wage a person would accept. Unlike the two approaches used to estimate a wage gap so far, this can be used to construct a wage gap that varies across each unemployed worker by using it in place of *w* in equation 1. Since the reservation wage variable is expressed as net pay, it is first converted into a gross hourly wage by multiplying it by the average ratio of

[6] Table 12 uses the samples in the third and fourth columns of Table 13 (for employed workers) and the third and fourth columns of Table 14 (for unemployed workers).

gross to net hourly pay among (employed) minimum wage workers. The wage gap variable is found to have a significant negative effect on the likelihood of an unemployed worker entering employment, as reported in the first column of Table 15. When a worker's expected pay is used to construct a wage gap in the same way as lowest pay, it is found to have a negative although insignificant effect (as reported in the second column of Table 15).

5. Pseudo-panel analysis

The second part of the project examines whether changes in the minimum wage lead to changes in the overall job turnover rate using the ASHE. A 'pseudo-panel' approach is taken (Blundell *et al*. 1990; Morrison *et al*. 2006; Papps 2012), whereby the data are aggregated within relatively homogenous cells of workers from the perspective of labour demand.

Aggregate flows

To begin with, the individual-level sample is aggregated into industry-region cells. Industry is defined as the SIC03 (or equivalent SIC07) section of the person's employer. Region is defined as the NUTS1 statistical region of the employer. For each cell in each year, the average *WAGEGAP* and the number of people employed are calculated, using survey weights. The average value of *WAGEGAP* within a cell represents the extent to which the minimum wage has raised overall wage costs in that industry and region. Variable means for the pseudo panel are given in Table 16.

In the first column of Table 17, the percentage change in employment in a cell is regressed on the average wage gap within the industry and region in the previous year, a set of year dummies and a set of industry/region cell dummies, as follows:

$$(E_{c(t+1)} - E_{ct}) / E_{ct} = \delta WAGEGAP_{ct} + \mathbf{X}_{it}\boldsymbol{\beta} + \gamma_c + \lambda_t + \varepsilon_{ct}\,. \qquad (6)$$

Weighted least squares is used, whereby each observation is weighted by the number of workers in the industry/region cell. In the second column of Table 17, the change in average hours is used as the dependent variable. The coefficient on *WAGEGAP* is insignificant in both cases. In the final two columns of the table, these two regressions are repeated, restricting the sample to only those workers with a real wage less than £7. This produces significant negative coefficients on *WAGEGAP*. Hence, there is evidence that firms reduce both employment and work hours in response to the minimum wage. The discrepancy in the results between the full sample and the low-wage sample may indicate that firms substitute high-wage workers for low-wage workers when the latter become more expensive because of the minimum wage.

In Table 18, two additional dependent variables are used: the number of workers in a cell leaving their jobs between t and t+1, expressed as a fraction of total employment in t, and the number of workers beginning jobs between t and t+1, expressed as a fraction of total employment in t. The results for the full sample indicate no significant change in either hiring or quits and layoffs when *WAGEGAP* increases. However, in the low-wage sample there is evidence that *WAGEGAP* leads to a significant reduction in job entry rates and has an effect on job exit rates that is just outside the 10% significance level. Again, this is consistent with employers switching from low-wage to high-wage workers in response to a minimum wage increase.

Age-specific flows

Using the pseudo-panel it is possible to examine whether employers substitute between workers of different ages in response to changes in the relative cost of each, brought about by changes in the different minimum wage rates. This reflects the fact that it is not just a worker's *own* wage that determines whether he/she is hired or retained from period to period, but the wage of close substitute workers. Although this has been examined using aggregate data, this possibility has not been studied using worker-level data previously. This benefit of using such disaggregated data is that we can control for individual worker characteristics, as well as the extent to which the minimum wage directly affects the worker's own wage.

The individual-level sample is collapsed by industry, region *and* age bracket (ages 16-17, 18-20, 21-24, 25-30, 31-64).[7] In Table 19, the annual rate of change in employment of workers in each age bracket in industry/region cell c (across the columns)

[7] As in Table 10, the ages correspond to the various minimum wage brackets with the adult bracket split into 21-24, 25-30 and 31 and over. Unlike Table 10, the age in year t is used, not the age in t+1.

is regressed on the average values of *WAGEGAP* among workers in each age bracket in the industry and region (down the rows), as follows:

$$(E_{c(t+1)}^{1617} - E_{ct}^{1617}) / E_{ct}^{1617} = \delta_{11} WAGEGAP_{ct}^{1617} + \delta_{12} WAGEGAP_{ct}^{1820} + \delta_{13} WAGEGAP_{ct}^{2124}$$

$$+ \delta_{14} WAGEGAP_{ct}^{2530} + \delta_{15} WAGEGAP_{ct}^{3164} + \gamma_c + \lambda_t + \varepsilon_{ct} ,$$

$$(E_{c(t+1)}^{1820} - E_{ct}^{1820}) / E_{ct}^{1820} = \delta_{21} WAGEGAP_{ct}^{1617} + \delta_{22} WAGEGAP_{ct}^{1820} + \delta_{23} WAGEGAP_{ct}^{2124}$$

$$+ \delta_{24} WAGEGAP_{ct}^{2530} + \delta_{25} WAGEGAP_{ct}^{3164} + \gamma_c + \lambda_t + \varepsilon_{ct} ,$$

$$(E_{c(t+1)}^{2124} - E_{ct}^{2124}) / E_{ct}^{2124} = \delta_{31} WAGEGAP_{ct}^{1617} + \delta_{32} WAGEGAP_{ct}^{1820} + \delta_{33} WAGEGAP_{ct}^{2124}$$

$$+ \delta_{34} WAGEGAP_{ct}^{2530} + \delta_{35} WAGEGAP_{ct}^{3164} + \gamma_c + \lambda_t + \varepsilon_{ct} ,$$

$$(E_{c(t+1)}^{2530} - E_{ct}^{2530}) / E_{ct}^{2530} = \delta_{41} WAGEGAP_{ct}^{1617} + \delta_{42} WAGEGAP_{ct}^{1820} + \delta_{43} WAGEGAP_{ct}^{2124}$$

$$+ \delta_{44} WAGEGAP_{ct}^{2530} + \delta_{45} WAGEGAP_{ct}^{3164} + \gamma_c + \lambda_t + \varepsilon_{ct} ,$$

$$(E_{c(t+1)}^{3164} - E_{ct}^{3164}) / E_{ct}^{3164} = \delta_{51} WAGEGAP_{ct}^{1617} + \delta_{52} WAGEGAP_{ct}^{1820} + \delta_{53} WAGEGAP_{ct}^{2124}$$

$$+ \delta_{54} WAGEGAP_{ct}^{2530} + \delta_{55} WAGEGAP_{ct}^{3164} + \gamma_c + \lambda_t + \varepsilon_{ct} . \qquad (7)$$

The estimated values of δ_{11}, δ_{22}, δ_{33}, δ_{44} and δ_{55} indicate the direct effect of the minimum wage on a particular group of workers. This should be negative if employers cut back on employing a particular age group when the cost of that group goes up. The other coefficients measure the extent of spillovers between age categories. This will depend on the degree of substitutability or complementarity between workers in different age brackets; however, if substitution occurs across age categories, the coefficients should be positive. The relative magnitudes of these coefficients will provide an indication of which age categories firms are most likely to substitute between.

The full sample is used to estimate the age-specific employment equations (7) in Table 19. The equations are estimated jointly using seemingly unrelated regression. For three out of the five age categories, significant negative direct effects of the minimum wage are found. The results provide an insight into the finding of London Economics (2015) that employment of 16-20 year olds rose relative to that of 21-22 year olds when the minimum wage facing the former fell relative to that facing the latter between 2011 and 2013. The first column of Table 19 indicates that employment of 16-17 year olds rises in response to either a fall in the real cost of 16-17 year olds or a rise in the real cost of 21-24 year olds. Hence, both the absolute and relative cost of low-wage workers is important. However, the results also indicate that the cost of 18-20 year olds has a negative effect on employment of 16-17 year olds, perhaps because employers know these workers will soon be eligible for the 18-20 minimum wage. Unlike London Economics, no significant evidence is found of either direct or spillover effects for 18-20 year olds.[8]

In Tables 20 and 21, the number of workers exiting or entering employment between periods are used as dependent variables, measured as a fraction of employment in year *t*. The results found for overall employment in Table 19 appear to be driven mostly by changes in hires. There is evidence of a significant direct effect of the minimum age on the hire rate of workers aged 31-64 and there is some evidence of spillovers between age categories for both hires and separations.

Tables 22, 23 and 24 repeat Tables 19, 20 and 21, using as a sample only those workers who earned less than £7 per hour (in 2012 pounds). There is less evidence of spillovers here, although there is evidence of a significant direct effect of the minimum wage on hires and separations of workers aged 31-64.

6. Conclusion

This study has examined the effects that the minimum wage has on the rate of job turnover in the labour market. Using ASHE data, evidence is found that workers who are affected by an increase in the minimum wage have a reduced likelihood of changing jobs or exiting employment. The source of a change in the minimum wage facing a given worker is found to be important, with annual increases in the minimum wage rates having the largest negative effect on turnover and the 2010 reduction in the adult rate eligibility age having a positive effect on turnover. As well as reducing the job separation rate, data from the LFS and BHPS reveal that increases in the minimum wage also reduce the likelihood of an unemployed worker finding job.

By analysing aggregated data from the ASHE, evidence is found that an increase in the minimum wage affecting a particular age group reduces employment of workers in

[8] London Economics' results for 18-20 year olds were weaker in significance and magnitude than their results for 16-17 year olds.

that age group. In addition, evidence of spillovers between age groups is found for teenagers.

Overall, the results provide support for a search model with endogenous separations, as put forward by Dube *et al*. (2014). However, some support for Brochu and Green's (2013) match quality explanation is found when analysing the effect of workers becoming eligible for higher rates of the minimum wage on their 18th or 21st birthdays.

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Table 1
Means for the ASHE sample

Variable	Bound	Unbound
Employed at same firm	0.498	0.629
Employed	0.653	0.774
Change in hours	-0.561	-0.155
Wage gap	0.313	0
Counterfactual wage gap	1.243	0.187
Age	36.302	36.953
Male	0.338	0.392
Number of observations	101,494	794,593

Table 2
Individual-level regressions with restricted sample

Variable	Employed at same firm	Employed	Change in hours
Wage gap	0.010***	-0.004	-0.646***
	(0.004)	(0.004)	(0.123)
Counterfactual wage gap	-0.032***	-0.012***	-0.396***
	(0.002)	(0.001)	(0.044)
Age	0.014***	0.017***	-0.072**
	(0.001)	(0.001)	(0.029)
Age squared	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)
R-squared	0.294	0.305	0.211
Number of observations	896,087	914,698	550,059

Notes: All models also include person, year and workplace region dummies.
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 3
Individual-level regressions with all observations

Variable	Employed at same firm	Employed	Change in hours
Wage gap	0.008**	0.000	-0.853***
	(0.004)	(0.003)	(0.104)
Counterfactual wage gap	-0.031***	-0.016***	-0.187***
	(0.001)	(0.001)	(0.035)
Age	0.021***	0.024***	0.018
	(0.001)	(0.000)	(0.018)
Age squared	-0.000***	-0.002***	-0.000
	(0.000)	(0.000)	(0.000)
R-squared	0.276	0.293	0.189
Number of observations	2,278,278	2,322,127	1,480,734

Notes: All models also include person and year dummies.
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 4
Wage gap coefficients for different subgroups

Subgroup	Employed at same firm	Employed	Change in hours
Aged 16-19	0.034***	0.003	0.226
	(0.013)	(0.011)	(0.483)
Aged 20-23	0.059***	0.030**	-0.097
	(0.016)	(0.013)	(0.556)
Aged 24-29	0.132***	0.067***	0.326
	(0.017)	(0.014)	(0.587)
Aged 30-64	0.040***	0.016***	-0.156
	(0.006)	(0.005)	(0.164)
Women	0.001	-0.007*	-1.132***
	(0.005)	(0.004)	(0.148)
Men	0.025***	0.003	0.237
	(0.007)	(0.006)	(0.217)

Notes: All models include the same regressors as in Table 3.
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 5
Regressions with decomposed wage gap

Group	Employed at same firm	Employed	Change in hours
Age wage gap	0.004	0.005	-0.510***
	(0.005)	(0.004)	(0.137)
Rate wage gap	0.010**	-0.001	-0.572***
	(0.004)	(0.004)	(0.125)
Bracket wage gap	-0.037***	-0.033***	-1.381***
	(0.012)	(0.010)	(0.331)
Counterfactual wage gap	-0.033***	-0.011***	-0.392***
	(0.002)	(0.001)	(0.045)
Age	0.013***	0.017***	-0.071**
	(0.001)	(0.001)	(0.029)
Age squared	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)
R-squared	0.294	0.305	0.211
Number of observations	896,087	914,698	550,059

Notes: All models also include person, year and workplace region dummies. Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 6
Means for the LFS sample

Variable	Unemployed observations		Employed observations	
	Unbound	Bound	Unbound	Bound
Employed at same firm next year	–	–	0.692	0.730
Employed next year	0.400	0.411	0.888	0.884
Wage gap	0	0.026	0	0.271
Counterfactual wage gap	0.564	0.183	4.111	3.345
Age	38.018	39.816	33.964	38.641
Male	0.577	0.565	0.337	0.286
Months unemployed/on job	20.258	16.865	24.193	28.418
Number of observations	3,106	10,557	27,345	4,561

Table 7
Regressions for employed workers using LFS

Variable	Employed at same firm		Employed in any job	
	Quarter ahead	Year ahead	Quarter ahead	Year ahead
Wage gap	0.007	0.013*	0.001	0.003
	(0.010)	(0.008)	(0.008)	(0.005)
Counterfactual wage gap	-0.010***	-0.021***	-0.010***	-0.013***
	(0.002)	(0.003)	(0.001)	(0.002)
Age	0.007***	0.014***	0.005***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.000	-0.002	0.002	0.005
	(0.004)	(0.005)	(0.003)	(0.004)
Months on job	0.001***	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.037	0.078	0.022	0.020
Number of observations	31,906	31,906	31,906	31,906

Notes: All models also include dummies for education level (6 categories), region (20 categories) and quarter (68 categories).
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 8
Regressions for lay-offs and quits among employed workers using LFS

Variable	Exit firm within quarter		Exit employment within quarter	
	Lay-off	Quit	Lay-off	Quit
Wage gap	0.001	0.001	0.000	0.002
	(0.005)	(0.008)	(0.004)	(0.006)
Counterfactual wage gap	0.000	0.004***	0.002**	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
Age	0.000	-0.003***	0.001**	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
Age squared	-0.000	0.000***	-0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.016	-0.018***	0.013	-0.015
	(0.002)	(0.003)	(0.002)	(0.002)
Months on job	-0.000***	0.001***	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.014	0.017	0.012	0.009
Number of observations	31,906	31,906	31,906	31,906

Notes: All models also include dummies for education level (6 categories), region (20 categories) and quarter (68 categories).
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 9
Regressions for employed workers using LFS hourly wage rate

Variable	Employed at same firm	Employed in any job

	Quarter ahead	Year ahead	Quarter ahead	Year ahead
Wage gap	-0.040	-0.022	-0.039**	-0.015
	(0.025)	(0.020)	(0.020)	(0.015)
Counterfactual wage gap	-0.013***	-0.032***	-0.008**	-0.007
	(0.004)	(0.007)	(0.003)	(0.005)
Age	0.007***	0.014***	0.006***	0.008***
	(0.001)	(0.002)	(0.001)	(0.001)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.004	-0.002	0.001	0.002
	(0.005)	(0.007)	(0.004)	(0.005)
Months on job	0.001***	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.039	0.084	0.023	0.021
Number of observations	19,998	19,998	19,998	19,998

Notes: All models also include dummies for education level (6 categories), region (20 categories) and quarter (68 categories).
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 10
Regressions for unemployed workers using LFS

Variable	First approach		Second approach	
	Quarter ahead	Year ahead	Quarter ahead	Year ahead

Estimated wage gap	-0.119	-0.151	-0.945***	-0.604***
	(0.083)	(0.093)	(0.239)	(0.159)
Estimated counterfactual	0.002	0.005	-0.001	0.013
wage gap	(0.002)	(0.004)	(0.009)	(0.014)
Age	-0.003***	0.007***	-0.004***	0.004
	(0.000)	(0.000)	(0.001)	(0.003)
Age squared	-0.000***	-0.000***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.054***	-0.061***	-0.060***	-0.067***
	(0.000)	(0.000)	(0.005)	(0.010)
Months unemployed	-0.004***	-0.005***	-0.004***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.077	0.096	0.078	0.097
Number of observations	54,308	13,663	54,308	13,663

Notes: All models also include dummies for education level (6 categories), region (20 categories) and quarter (68 categories).
Standard errors are clustered by estimated wage gap and are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 11
Wage gap coefficients for different subgroups

Subgroup	Currently employed		Currently unemployed	
	Quarter ahead	Year ahead	Quarter ahead	Year ahead

Aged 16-19	-0.012	0.017	0.638	-0.204
	(0.016)	(0.011)	(0.673)	(0507)
Aged 20-23	0.026	0.028	-0.606	-0.565
	(0.030)	(0.019)	(0.680)	(0.485)
Aged 24-29	-0.053	-0.028	-0.941	-0.147
	(0.033)	(0.019)	(0.816)	(0.564)
Aged 30-64	0.008	0.010	-1.091**	-0.303
	(0.010)	(0.007)	(0.433)	(0.435)
Women	-0.008	-0.001	-1.539*	-0.566***
	(0.010)	(0.007)	(0.319)	(0.227)
Men	0.017	0.009	-1.651***	-0.556*
	(0.013)	(0.008)	(0.424)	(0.307)

Notes: The first and second columns use the specifications from the third and fourth columns of Table 7, respectively. The third and fourth columns use the specifications from the third and fourth columns of Table 10, respectively.
Standard errors are clustered by (estimated) wage gap and are shown in brackets.
*, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 12
Means for the BHPS sample

Variable	Unemployed observations		Employed observations	
	Unbound	Bound	Unbound	Bound
Employed at same firm next	–	–	0.691	0.732

year				
Employed next year	0.455	0.325	0.871	0.851
Wage gap	0.000	0.085	0.000	0.299
Counterfactual wage gap	-0.697	0.279	0.639	1.109
Age	35.959	27.582	34.472	38.127
Male	0.860	0.470	0.304	0.220
Months unemployed/on job	29.901	31.316	41.115	44.885
Number of observations	121	668	4,364	2,860

Table 13
Regressions for employed workers using BHPS

Variable	Employed at same firm		Employed in any job	
Wage gap	-0.051	-0.066	-0.018	-0.032
	(0.036)	(0.050)	(0.026)	(0.030)
Counterfactual wage gap	-0.005	-0.032	-0.017*	0.015
	(0.015)	(0.026)	(0.010)	(0.016)
Age	0.017***	0.011	0.018***	0.031
	(0.003)	(0.028)	(0.000)	(0.019)
Age squared	-0.0001***	0.000	-0.0002***	-0.0002**
	(0.0000)	(0.000)	(0.0000)	(0.0001)
Male	-0.016	–	0.028***	–
	(0.0145		(0.010)	
Months on job	0.001***	-0.002***	0.0003***	-0.0003**
	(0.000)	(0.000)	(0.0000)	(0.0001)
Person fixed effects	No	Yes	No	Yes
R-squared	0.112	0.0004	0.042	0.001
Number of observations	6,044	6,044	7,224	7,224

Notes: All models also include dummies for education level (6 categories), region (11 categories) and quarter (68 categories).
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 14
Regressions for unemployed workers using BHPS

Variable	First approach		Second approach	
Wage gap	-0.128	-1.587***	0.285	-1.969
	(0.231)	(0.471)	(0.247)	(1.243)

Counterfactual wage gap	-0.024	-0.742**	-0.079	1.370**
	(0.057)	(0.375)	(0.114)	(0.596)
Age	0.031***	-0.0233	0.015	0.212
	(0.011)	(0.376)	(0.025)	(0.372)
Age squared	-0.0004***	-0.003***	-0.000	-0.006***
	(0.0002)	(0.001)	(0.000)	(0.002)
Male	-0.020	–	-0.031	–
	(0.052)		(0.084)	
Months unemployed	-0.001***	0.000	-0.001***	-0.000
	(0.000)	(0.002)	(0.000)	(0.002)
Person fixed effects	No	Yes	No	Yes
R-squared	0.126	0.014	0.144	0.018
Number of observations	661	661	789	789

Notes: All models also include dummies for education level (6 categories), region (11 categories) and quarter (50 categories).
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 15
Regressions for unemployed workers using BHPS reservation wage

Variable	Lowest wage considered	Expected wage
Wage gap	-0.309***	-0.238
	(0.102)	(0.187)

Counterfactual wage gap	0.033	-0.011
	(0.052)	(0.059)
Age	0.041**	0.035**
	(0.017)	(0.017)
Age squared	-0.001**	-0.001**
	(0.000)	(0.000)
Male	-0.097	-0.091
	(0.067)	(0.072)
Months unemployed	-0.002	-0.002
	(0.002)	(0.002)
R-squared	0.218	0.176
Number of observations	308	304

Notes: All models also include dummies for education level (6 categories), region (11 categories) and quarter (50 categories).
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 16
Means for pseudo-panel regressions

Variable	All jobs sample	Low wage sample
Change in employment	0.005	-0.009
Change in average hours	0.000	-0.002
Percentage exiting job	0.346	0.454
Percentage entering job	0.356	0.498
Wage gap	0.015	0.095
Counterfactual wage gap	0.133	0.862
Cell size	960.750	161.319
Number of observations	2,488	2,199

Notes: All means are weighted by cell size.

Table 17
Pseudo-panel regressions

Variable	All jobs sample		Low wage sample	
	Employment	Average hours	Employment	Average hours

Wage gap	0.022	0.029	-0.400***	-0.079*
	(0.200)	(0.042)	(0.119)	(0.043)
Counterfactual wage gap	-0.045	0.007	0.074	0.027
	(0.040)	(0.008)	(0.058)	(0.021)
R-squared	0.080	0.151	0.404	0.103
Number of observations	2,488	2,488	2,199	2,199

Notes: All models also include cell and year dummies.
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 18
Pseudo-panel regressions

Variable	All jobs sample		Low wage sample	
	Job exit	Job entry	Job exit	Job entry
Wage gap	-0.050	0.152	-0.081	-0.226**
	(0.169)	(0.197)	(0.057)	(0.090)
Counterfactual wage gap	-0.119***	-0.159***	-0.047*	-0.071
	(0.034)	(0.039)	(0.028)	(0.044)
R-squared	0.728	0.545	0.785	0.451
Number of observations	2,502	2,488	2,260	2,199

Notes: All models also include cell and year dummies.
Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 19
Pseudo-panel regressions by age group – employment change

Variable	Age group of dependent variable				
	16-17	18-20	21-24	25-30	31-64
Wage gap for 16-17	-0.187*	-0.013	-0.018	0.031	0.015
	(0.112)	(0.048)	(0.031)	(0.021)	(0.009)

Wage gap for 18-20	-0.714*	0.100	0.151	-0.042	0.049
	(0.430)	(0.223)	(0.146)	(0.103)	(0.094)
Wage gap for 21-24	1.273*	0.065	-0.587**	0.059	0.188
	(0.684)	(0.378)	(0.295)	(0.221)	(0.099)
Wage gap for 25-30	-1.857	0.357	-0.169	0.400	0.352
	(1.425)	(0.809)	(0.626)	(0.473)	(0.219)
Wage gap for 31-64	0.570	-0.436	0.877	-0.399	-0.694***
	(1.464)	(0.859)	(0.683)	(0.538)	(0.257)
R-squared			0.115		
Number of observations			8,741		

Notes: All models also include the counterfactual wage gap, cell and year dummies. Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 20

Pseudo-panel regressions by age group – job exit change

Variable	Age group of dependent variable				
	16-17	18-20	21-24	25-30	31-64
Wage gap for 16-17	-0.038	-0.009	-0.021*	0.006	0.010
	(0.080)	(0.036)	(0.023)	(0.015)	(0.007)
Wage gap for 18-20	-0.198	-0.066	-0.006	-0.140*	-0.110***
	(0.310)	(0.165)	(0.108)	(0.076)	(0.033)
Wage gap for 21-24	0.270	0.088	0.182	0.340***	0.309***
	(0.483)	(0.280)	(0.219)	(0.164)	(0.074)
Wage gap for 25-30	0.609	0.355	0.205	0.184	-0.025
	(1.032)	(0.600)	(0.464)	(0.351)	(0.162)
Wage gap for 31-64	-0.787	-0.160	-0.032	-0.565	-0.473**
	(1.063)	(0.637)	(0.507)	(0.399)	(0.191)
R-squared			0.754		
Number of observations			8,870		

Notes: All models also include the counterfactual wage gap, cell and year dummies. Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 21

Pseudo-panel regressions by age group – job entry change

Variable	Age group of dependent variable				
	16-17	18-20	21-24	25-30	31-64
Wage gap for 16-17	-0.010	-0.002	-0.023	0.027	0.027***
	(0.110)	(0.047)	(0.030)	(0.020)	(0.009)

Wage gap for 18-20	-0.651	0.172	0.083	-0.158	-0.084*
	(0.422)	(0.219)	(0.144)	(0.101)	(0.043)
Wage gap for 21-24	1.211*	0.017	-0.159	0.279	0.392***
	(0.671)	(0.371)	(0.290)	(0.217)	(0.098)
Wage gap for 25-30	-1.231	0.820	0.269	0.513	0.171
	(1.399)	(0.794)	(0.615)	(0.464)	(0.215)
Wage gap for 31-64	0.423	-0.577	0.426	-0.732	-0.852***
	(1.437)	(0.843)	(0.671)	(0.528)	(0.252)
R-squared			0.626		
Number of observations			8,741		

Notes: All models also include the counterfactual wage gap, cell and year dummies. Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 22
Pseudo-panel regressions by age group with low-wage sample – employment change

Variable	Age group of dependent variable				
	16-17	18-20	21-24	25-30	31-64
Wage gap for 16-17	-0.298***	0.016	-0.064	-0.061	-0.055**
	(0.113)	(0.057)	(0.057)	(0.055)	(0.023)
Wage gap for 18-20	-0.759**	-0.029	0.153	-0.085	0.044
	(0.355)	(0.205)	(0.196)	(0.191)	(0.079)
Wage gap for 21-24	0.560*	-0.073	-0.603***	-0.116	-0.098
	(0.328)	(0.201)	(0.230)	(0.219)	(0.093)
Wage gap for 25-30	-0.005	-0.410*	-0.228	-0.230	0.032
	(0.359)	(0.226)	(0.244)	(0.245)	(0.100)
Wage gap for 31-64	0.450	-0.114	0.364	0.038	-0.196
	(0.531)	(0.331)	(0.345)	(0.359)	(0.157)
R-squared			0.311		
Number of observations			7,354		

Notes: All models also include the counterfactual wage gap, cell and year dummies. Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 23
Pseudo-panel regressions by age group with low-wage sample – job exit change

Variable	Age group of dependent variable				
	16-17	18-20	21-24	25-30	31-64
Wage gap for 16-17	-0.037	-0.014	-0.014	-0.014	-0.000
	(0.043)	(0.023)	(0.023)	(0.023)	(0.009)

Wage gap for 18-20	-0.029	-0.064	-0.021	-0.003	-0.058
	(0.138)	(0.083)	(0.080)	(0.078)	(0.032)
Wage gap for 21-24	0.114	0.070	0.016	0.105	0.103***
	(0.126)	(0.082)	(0.092)	(0.088)	(0.038)
Wage gap for 25-30	0.171	0.021	0.098	0.066	0.012
	(0.139)	(0.092)	(0.098)	(0.099)	(0.041)
Wage gap for 31-64	-0.162	-0.144	-0.088	-0.322**	-0.216***
	(0.208)	(0.134)	(0.141)	(0.144)	(0.064)
R-squared			0.757		
Number of observations			7,540		

Notes: All models also include the counterfactual wage gap, cell and year dummies. Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Table 24

Pseudo-panel regressions by age group with low-wage sample – job entry change

Variable	Age group of dependent variable				
	16-17	18-20	21-24	25-30	31-64
Wage gap for 16-17	-0.068	0.010	-0.052	-0.062	-0.014
	(0.088)	(0.044)	(0.044)	(0.043)	(0.018)
Wage gap for 18-20	-0.672**	0.177	0.083	-0.095	0.068
	(0.276)	(0.160)	(0.152)	(0.149)	(0.062)
Wage gap for 21-24	0.518**	-0.069	-0.263	0.038	0.010
	(0.255)	(0.157)	(0.179)	(0.170)	(0.072)
Wage gap for 25-30	0.083	0.264	-0.041	-0.105	0.034
	(0.279)	(0.176)	(0.190)	(0.191)	(0.077)
Wage gap for 31-64	0.625	0.002	-0.012	-0.272	-0.307**
	(0.413)	(0.257)	(0.276)	(0.279)	(0.122)
R-squared			0.473		
Number of observations			7,354		

Notes: All models also include the counterfactual wage gap, cell and year dummies. Standard errors are shown in brackets. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.