The Rate Of Substitution Between Low Pay Workers and The National Minimum Wage.

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Abstract

We study the effect of the National Minimum Wage (NMW) on the workforce composition, in terms of distinct age groups with similar qualifications, within the low paying sectors of the economy. Our interest is in the degree of substitutability between labour inputs (young and old employees) in the production process. We find evidence that both the introduction and regular uprating of the NMW have a significant effect on determining observed changes in average wages for age groups older than 16-17 years of age. However, our results show that the effects of the NMW and its uprating on the sectoral cost of labour are rather weak and we conclude that, if any, the influence of the NMW has to be small and limited to the very young (16-17 year olds) or the 18-20 year olds. We estimate the elasticity of substitution, between 18-20 year olds and old workers, to be around 0.2-0.5, which would imply significant complementarity (or at least argue against perfect substitution) between younger and old employees.

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1. Introduction

The consequences of operating minimum wage laws on overall employment are debated on both theoretical and empirical grounds (Hamermesh, 1993[5]; Manning, 2003[7]; Metcalf, 2006[8]; Neumark and Wascher, 2008[10]) and the arguments in favour or against a minimum wage are well understood. The effects of the minimum wage on the composition of the workforce have been studied less. Our interest here is to study how the minimum wage over time has affected the relative share of the old (55+) and the young (16-22) workers in the working population. As the proportion of older workers in the British workforce (and indeed in most OECD countries) is increasing, we believe that the issue merits further attention. This paper estimates elasticities of substitution between young (16-22) and old (55+) low-pay employees in Britain, using the introduction (in 1999) and yearly up-rating of the UK national minimum wage.

The participation rate of workers over 50 has been increasing steadily since 2001. The Office of National Statistics (ONS) headline statistics show that the employment rate for 50-64 year-olds has increased from 58.8% in 1997 to 62% in 2001 to 66.1% in 2012. The corresponding rate for 25-49 year-olds has remained relatively stable at around 80%. Unlike that of the other age groups, the employment rate of the 50-64 year-olds is larger in 2010 and thereafter than it was before the 2008 recession. Simultaneously, since 2009, the unemployment rate for 50-64 year-olds has risen by 1.8 percentage points from 3.0% to 4.8%, while the rate for 18-24 year-olds has gone up by 6.9 percentage points from 12.4% in 2008 to 19.3% in 2012[1].

The theoretical prediction of the standard (competitive) model of the labour market in the presence of a minimum wage floor is clear: if the minimum wage is set above the market clearing wage, employment declines. The reduction in employment is determined by the distance between the competitive wage and the legal minimum and the elasticity of the demand for labour. Following Marshall's rules of derived demand, the greater (1) the elasticity of substitution between capital and labour and (2) the elasticity of demand for the firm's (industry/sector's) output, the more elastic labour demand is. Furthermore, (3) the elasticity of labour demand increases with labour's share in total costs i.e. when labour accounts for much of the production cost, thus a wage rise will result in a substantial rise in the marginal cost of output with a corresponding increase in the price and a subsequent fall in demand, which would lead to employment losses. Since the minimum wage is expected to affect more certain parts of the workforce, in practice younger workers in low skill occupations, firms could mitigate the impact on total costs by substituting younger for old workers (labour-labour substitution). Hence the substitution rate between labour groups becomes important to assess the effect of the minimum wage on labour market outcomes.

[1] Department for Work and Pensions (August 2012) Older Worker Statistical Information Booklet 2012: Official Statistics.

The first Low Pay Commission report (Low Pay commission, 1998[?])[2] suggests that the effective design of the alternative national minimum wage (NMW) rates was based on the comparison of the average productivity of low skill workers, which means that the difference in NMW rates reflects differences in the marginal product between workers of different ages. This approach recognises the difficulty of assuming homogeneous labour (in the competitive model) and uses differential wage structures to 'protect' (young) workers in the low-paying sectors where the minimum wage bite (the minimum wage as a percentage of median earnings) is expected to be stronger. It follows that once such productivity differences are accounted for, the two types of labour are assumed to be close (perhaps perfect) substitutes. We suggest that this assumption requires further study.

The sparse empirical evidence points to complementarity rather than substitutability between young and older labour in production (Gruber and Wise, 2010[4]; Kalwij et al, 2010[6]). A methodological challenge facing any such study is to account for country-specific labour market institutions. A recent OECD (2013)[11] study attempts to address this issue by controlling for policies such as employment protection, collective bargaining coverage and unemployment insurance generosity as well as broader macroeconomic conditions in a model of 25 OECD member countries over the period of 1997-2011. The results suggest either no crowding-out of young workers when the em-

[2] In the UK, the Low Pay Commission is the body which formally advises the government on the level and structure of the minimum wage since its inception in 1999

ployment of the old increases or moderate increases. This is consistent with the complementarity of the two types of labour. Labour market institutions such as minimum wage mandates are, however, not controlled for.

Apart from a limited number of empirical papers on the UK experience, which present implied elasticities of substitution between "young" age groups (see Hamermesh, 1993 [5], and Metcalf, 2006[8], for a review of empirical evidence for the UK and Neumark and Wascher, 2008[10], for an extensive review of evidence from the US and other countries), we are not aware of any study, which looks at the elasticity of substitution between young and old (55+) labour to date in the presence of minimum wages. Our study thus seeks to fill this gap in the literature by explicitly estimating the elasticity of substitution between older workers and young labour groups as these are defined by the youth sub-minimum wage rates, namely, under 18, 18 to 21 (20 since 2010), 21 (until 2010) and 22+ (21+ since 2010) and old (55+) employees resulting from minimum wage increases.

In this paper we study the rate of substitution between age groups within the low paying occupations in the UK following Metcalf's (2006)[8] advice that focus should be on low-paying sectors where the NMW bite is likely to be stronger in order to discern any effects, rather than on aggregate employment where the latter are likely to be masked by the limited extent of the NMW bite. We employ a Constant Elasticity of Substitution (CES) framework where the introduction of the NMW, its regular up-rating and the evolution of its design provide us with (arguably) exogenous variation to the relative price structure between younger and old workers. Our data comes from the UK Quarterly Labour Force Survey (LFS) and the Annual Survey of Hours and Earnings (ASHE) over the period 1997 to 2010. Estimates from each data source are compared for robustness. The results suggest substantial complementarities in production of workers of different age groups - or, at least, argue against perfect substitutability.

The remainder of the paper is organised as follows: section II presents our model and empirical strategy, while the next section (III) describes the construction of the datasets and the ratios of interest. Section IV discusses estimates of both the reduced form and structural equations. The final section concludes.

2. The Model

We are interested in the degree of substitutability between labour inputs (young and old employees) in the production process, and by extension in the effect of the NMW on (low-pay) workforce composition. We consider the within occupational group age wage differential, i.e. the difference between the average wage of two age groups, and relate it to the relative employment size of each group.

Besides the different types of labour (young and old workers), the production function involves other inputs, which we simply collect within an aggregate called capital, K. We further assume that the production function depends on young and old labour through a labour aggregate, L_{yo}, as well as the size of the rest of the labour force (the 'middle aged' group), L_{ma}. We therefore assume that the production function in occupation c at time t takes the form:

$$Q = F_{ct}(K, L_{yo}, L_{ma}) \tag{1}$$

where the young/old aggregate is defined as a CES aggregate and satisfies:

$$L_{yo}^{\rho} = \theta_{ct} L_{y}^{\rho} + L_{o}^{\rho} \tag{2}$$

where $-\infty \leq \rho \leq 1$ is a function of the elasticity of substitution σ between the two types of labour with $\rho = 1 - \frac{1}{\sigma}$ (or equivalently $\sigma = \frac{1}{1-\rho}$). The first order conditions for L_y and L_o are:

$$p\frac{\partial F}{\partial L_{yo}}\frac{\partial L_{yo}}{\partial L_{y}} = w_y \tag{3}$$

$$p\frac{\partial F}{\partial L_{yo}}\frac{\partial L_{yo}}{\partial L_{o}} = w_o \tag{4}$$

Efficient allocation implies that the marginal rate of substitution should equal the inputs' relative prices, hence, leaving $\frac{\partial F}{\partial L_{yo}}$ unspecified, we obtain (after taking logarithms),

$$\ln\frac{w_y}{w_o} = \ln\theta_{ct} + (\rho - 1)\ln\frac{L_y}{L_o} \tag{5}$$

where we allow the relative marginal productivity, measured by θ_{ct}, to depend on the occupation and the time period.

This specification is simple, it suggests that the within occupation log wage young/old differential depends on the (logarithm of the) relative utilisation of the two inputs. This relationship holds under more general conditions. Clearly it holds, if the labour and products markets are competitive, however, it would also hold when the product market is not competitive, or in some instances, when the labour markets are not competitive. In this latter case the imperfection on the labour markets amounts to a wage "mark down" which is proportional between labour input groups and is independent of the relative size of the input groups (as would be the case if each labour supply exhibit constant wage elasticity). This relative robustness to market structure is a further advantage of this approach, which is identical to the Constant Elasticity of Substitution (CES) model used in other contexts, but with similar objectives, by Card (2001)[3] and Borjas (2003)[2]. The parameter of the (logarithm of the) relative utilisation of the two inputs identifies directly the elasticity of substitution (within the young/old aggregate).

The parameter ρ measures the substitution between young and old workers keeping the size of the young/old aggregate constant. This is the quantity of interest (given the assumption concerning the technology we make) to determine the role that technological choices can play to evaluate the effect of an intervention designed to substitute between labour of distinct generations of workers. The specification remains straightforward since it is linear in the parameters of interest.

Equation (5) can be expressed as a relationship between $\ln \frac{L_y}{L_o}$ and $\ln \frac{w_y}{w_o}$ but also between $\ln \frac{L_y}{L_o}$ and $\ln \frac{w_y L_y}{w_o L_o}$, and so we have (in terms of first differences),

$$\Delta \ln \frac{L_y}{L_o} = \Delta \ln \theta'_{ct} - \sigma \Delta \ln \frac{w_y}{w_o} \tag{6}$$

and

$$\Delta \ln \frac{L_y}{L_o} = \Delta \ln \theta'_{ct} + \frac{1}{\rho} \Delta \ln \frac{w_y L_y}{w_o L_o} \tag{7}$$

Hence, equations (6) and (7), each specifies a structural model linking relative employment to relative wages and relative wage bills, between young and old workers, respectively.

Given the restrictions on the technology, σ must be positive. In particular, values for $\frac{1}{\rho}$ between 0 and 1 are not consistent with a positive value for σ. The quantities $\Delta \ln \theta_{ct}$ measure the relative marginal productivities and depend on the occupation and time period. The variables on the RHS and the LHS of equations (6) or (7) are endogenously determined in equilibrium (i.e. the equilibrium on the labour market determines both quantities and prices). However, the introduction of the NMW as well as its yearly uprating and the definition of two additional group specific minimum wage rates (the 16-17 Year Olds Rate and the Apprentice Rate) provide exogenous sources of variability to the wage or wage bill and therefore suggest instrumental variables for the relative size of the cost of labour to the firm. We assume that the change from one period to the next of the wage differentials or of the relative wage bills depends on the proportion of workers in occupation c measured in period $t-1$ who are paid a wage between the NMW in effect at time $t-1$ and the NMW that will apply at time t. We denote these quantities $Prop[w_{c,t-1,y}, w_{c,t,y}; t-1]$ and $Prop[w_{c,t-1,o}, w_{c,t,o}; t-1]$ for young and old workers, respectively. Since the minimum wage for young workers and old workers takes different values, we measure two distinct proportions. Clearly, in the absence of demand side reactions these proportions should be mechanically correlated with increases in total cost (measured by the wage bill) or increases in the average/marginal cost (measured by the average wage), which follow the introduction or the regular uprating of the minimum wage. Therefore, we can rewrite (6) and (7) as:

$$\Delta \ln \frac{w_y}{w_o} = \gamma_{0t} + \gamma_y Prop[w_{c,t-1,y}, w_{c,t,y}; t-1] + \gamma_o Prop[w_{c,t-1,o}, w_{c,t,o}; t-1] \quad (8)$$

and

$$\Delta \ln \frac{w_y L_y}{w_o L_o} = \delta_{0t} + \delta_y Prop[w_{c,t-1,y}, w_{c,t,y}; t-1] + \delta_o Prop[w_{c,t-1,o}, w_{c,t,o}; t-1] \quad (9)$$

These two equations play the role of the reduced form equations, which determine the wage differentials and the relative wage bills in response to a change in the national minimum wage. Equations (6) and (7) on the one hand and (8) and (9) on the other, imply that the reduced form equation for the change in the relative employment size takes the same general form:

$$\Delta \ln \frac{L_y}{L_o} = \beta_{0t} + \beta_y Prop[w_{c,t-1,y}, w_{c,t,y}; t-1] + \beta_o Prop[w_{c,t-1,o}, w_{c,t,o}; t-1] \quad (10)$$

Finally note that when the two inputs are complements in production, i.e. whenever $\sigma = 0$ or equivalently when $\rho = -\infty$, equations (6) and (7) suggest that the relative employment size is determined independently of the relative wages or the relative wage bills. Hence, we can feasibly observe a case where the relative wage and the relative wage bill depends on the changes to the NMW, while the reduced form for the relative employment size does not respond to a change of the NMW.

Recent theoretical and applied developments in empirical economics (as they are discussed for example in Angrist and Pischke, 2008) argue that for the effects of economic policy to be rationalised in this modelling framework, the effect of the exogenous variables must not only be statistically significant across all reduced form equations but also 'sufficiently' significant for subsequent IV estimates of the structural relationships to be informative.

In practical terms, this means that we can conclude that the policy has had sizeable effects on the outcome of interest, if the test statistics summarising the explanatory power of the proportion affected by the change in the NMW i.e. the $F-$statistics for the test of the hypothesis that the instruments can be excluded from the reduced form equations take values greater than, at least, 10 (Stock and Watson, 2010[12], give this rule of thumb, see also Angrist and Pischke, 2008, for a discussion in an empirical applied context and a theoretical justification). Finally, although we expect data produced from ASHE to be of higher quality than the data produced from the LFS, our conclusion will be strengthened, if the inferences drawn from both data sources agree.

To sum up our modelling approach, in the first stage, we estimate the reduced form equations (8), (9) and (10) using OLS, where we also test the validity of the instruments. We then proceed with Instrumental Variables (IV) estimation of the structural relationships (6) and (7) using 2SLS. We compare these with estimates obtained from LIML estimation as a robustness check.

3. Data

The raw data comes from the quarterly UK Labour Force Surveys (LFS) and the Annual Survey of Hours and Earnings (ASHE) from 1997 to 2010. LFS respondents are interviewed for five consecutive quarters. Our approach is to merge the four quarters of any calendar year into an annual dataset. Since 1997, respondents have been asked to state their wages in waves 1 and 5 i.e. the first and last quarter they would be surveyed. For every annual dataset, we keep only those individuals with reported wage information and thus no individual will be sampled twice in any one year – the fifth time an individual is interviewed cannot, by construction, be in the same calendar year as his/her previous interviews.

The ASHE dataset collects information on about 1% of employees in the UK directly from employers and national Insurance records. There are two discontinuities in the ASHE dataset within our sample period. In 2004, information (additional surveys) on employees starting a new job between January and April (survey reference date) was included. In 2006, large businesses that return their data electronically ("special arrangements")to the Office for National Statistics (ONS) were treated as a separate stratum in the ASHE[3]. We include the new stratum in year 2004 and exclude the new stratum in year 2006. This means that we maintain a steady number of homogeneous individuals in the yearly data with the least possible loss of information.

[3]ONS (2004[**?**], 2011[**?**])

We assign individuals to distinct cells using definitions of low-pay and major occupational groups according to the Standard Occupation Classification frameworks of 1990 and 2000. In some instance there is no direct correspondence between the two frameworks of classification. We use definitions followed by the UK Low Pay Commission as well as the ONS. Table 6 in the appendix summarises the low-pay occupation definitions/groups[4] we use and our bridging strategy between SOC 1990 and 2000.

Our regional classification uses the former[5] Government Offices for the Regions (GORs) classification[6]. We group workers into five age bands, namely 16 to 17 year olds ("very young"), 18 to 20 year olds ("young"), 21 year olds, 22 to 54 year olds ("middle aged") and 55+ year olds ("old"). This classification is based on the National Minimum Wage Rates' groups i.e. the Adult rate (for those 22+; 21+ from 1 October 2010), the Development rate (for those 18-21; 18-20 from 1 October 2010) and the 16-17 Year Olds rate.

[4]Retail, Hospitality, Social Care, Food Processing, Leisure, Travel and Sport, Cleaning, Agriculture, Security, Childcare, Textiles and Clothing, Hairdressing, Office Work.

[5]The GSS Regional and Geography Committee have agreed that from 1 April 2011, the former GORs should be simply referred to as 'Regions'.

[6]North East, North West, Yorkshire and the Humber, East midlands, West midlands, East of England, London, South East, South West, Wales, Scotland, (LFS sample only) Northern Ireland and Outside the UK. Northern Ireland data is owned by the Department for Trade and Investment (www.detini.gov.uk) and is not included in ASHE. Data for employees outside the UK not available due to ASHE's sampling design. We include Merseyside with the North West in 1997 as well, for consistency.

Individuals on the Apprenticeship rate (from 1 October 2010) could potentially be identified in the LFS sample but not in the ASHE sample, however, since our LFS sample only extends to the first quarter of 2010 we cannot identify those on apprenticeship rates.

The pooled panel over the 14 years, from 1997 to 2010, results in a total of 1,077,693 individual observations from the LFS, and 2,146,394 individual observations from the ASHE, which are collapsed into 5,292 and 5,964 synthetic observations, respectively. These numbers of observations are the result of collapsing the datasets by occupation c, $c = 1, \ldots, 12$; region r, $r = 1, \ldots, 12$ (11 for ASHE since it does not hold information on Northern Ireland); age band i, $i = 1, \ldots, 5$ and year. The implied total of synthetic observations, 10,080 for the LFS and 9,240 for the ASHE is far greater to our usable sample due to missing values, which we do not impute, thus ending up with a balanced pseudo panel of 378×14, from the LFS, and 426×14, from the ASHE, mean observations. By grouping individuals in cells that are sufficiently 'large' we bypass problems of measurement errors, pertinent in pseudo panels. Verbeek and Nijman (1993)[13] argue for cell sizes in excess of 100 individuals even though this number could be lower, if sufficient homogeneity between respondents in each period cell exists. The latter (individual homogeneity across periods) could also alleviate problems of estimator efficiency loss, when cell sizes are large. In our samples we have a large number of, arguably, homogeneous individuals.

By letting L_y and L_o give the number (count) of young and old employees[7], respectively, in cell (c, r, t), the ratio of young to old workers for each resulting group is then simply $l_{y/o} = \frac{L_y}{L_o}$. For the wage measure, we use variables HOURPAY (gross hourly pay) from the LFS, and HE (average hourly earnings) from the ASHE, and for weekly earnings we use variables GRSSWK (gross weekly pay in main job) from the LFS and GPAY (average gross weekly earnings) from the ASHE. The wage and wage bill ratios are then simply defined, as $w_{y/o} = \frac{w_y}{w_o}$ and $w^*_{y/o} = \frac{w_y L_y}{w_o L_o}$, respectively. All averages are weighted by the original dataset sampling weights.

Figure 1 presents means of the (log) ratios of interest over the sample period for the LFS and ASHE respectively. Notably, LFS data are more volatile in comparison to ASHE data, however, both datasets exhibit similar trends in all ratios. For the wage ratio, both samples suggest an initial upward trend suggesting that the average wage of the 'young' relative to that of the old has been growing faster until around 2002 for 18-20 and 21 year olds (2005 for 16-17 year olds). After that time, the average wage of the 16-17 and 21 year olds appears to grow slower in the LFS sample, while we observe a decline in the average wage (in comparison to the old) of the 21 year olds, and a continued but steadier than before, wage growth for the 18-20 year olds in the ASHE sample.

We trust that ASHE holds higher quality wage data (drawn from payroll records as opposed to being self-reported as in the LFS) and therefore are

[7]We have also constructed the employment ratio using the number of usual hours worked by young and old workers. The main conclusions remained unaltered.

more inclined to accept conclusions drawn from it. This could be due to a sample feature, namely, while ASHE wage data for 2010 covers the entire year, LFS wage information for 2010 is based on the first quarter (the latest available at the time of writing). LFS wage data could be higher then reflecting, for example, holiday bonuses.

From the ASHE data, the average wage ratio suggests that recently, very young workers are paid much less than old workers (large negative average ratio) and even though there was a considerable reduction in the difference in earnings until about 2005, a widening of this gap starts from then on and continues until the end of the sample period. The 18 to 20, and the 21 year olds are paid more than the very young relative to old workers and the latter less than the former relative, again, to old employees. We also observe that the average wage ratios of the 18-20 and 21 year old workers appear to be converging towards the later part of our sample.

It is noteworthy that very young workers (16-17 year old) appear to have experienced a reduction in their hourly wage relative to that of old workers at the same time as the introduction of the 16-17 year olds NMW rate (Oct 2004). However, for the 18-20 and 21 year olds, the 2001 increase in the NMW development rate pushed wages up by almost 10%. Thereafter, as the relative NMW uprating was smaller, the growth rate for these age groups appears to have been reduced. The extension of the adult rate to the 21 year olds from October 2010 can explain the sharp increase in wages of that group relative to those of old workers which we observe in the LFS.

The employment ratios for all three 'young' age groups follow a clear downward trend, suggesting that old workers, increasingly, take up more of the workforce. Notice in particular the large drop of the very young relative to old workers suggested by the LFS data. This could, of course, be attributed to a number of reasons such as, *inter alia*, increased participation rates in higher and further education among the young, increased participation of old workers in the labour force, or a combination of the two.
The relative labour cost ratios follow negative evolutions too. The ratio of the wage bill follows the employment ratio pattern in both datasets, suggesting that the relative labour cost of "young" age groups has been decreasing over time meaning that even though relative average wages may have been increasing, as the data seems to suggest (at least initially), the reduction in the number of young workers employed has brought the overall cost of employing young workers down relative to the cost of employing older workers. LFS data is again more volatile, but the overall pattern is clear.

Finally, we explore the variability of the log ratios by running OLS regressions on the complete set of occupation, region and year dummies. Table 1 summarizes F statistics on the joint significance of each set of dummies in turn. Overall, the results suggest that for all age groups, there exists significant variation across occupations and regions over time (in both samples). It is striking, however, that the year dummies do not seem to have much joint explanatory power for the wage bill ratios and the employment ratios (the

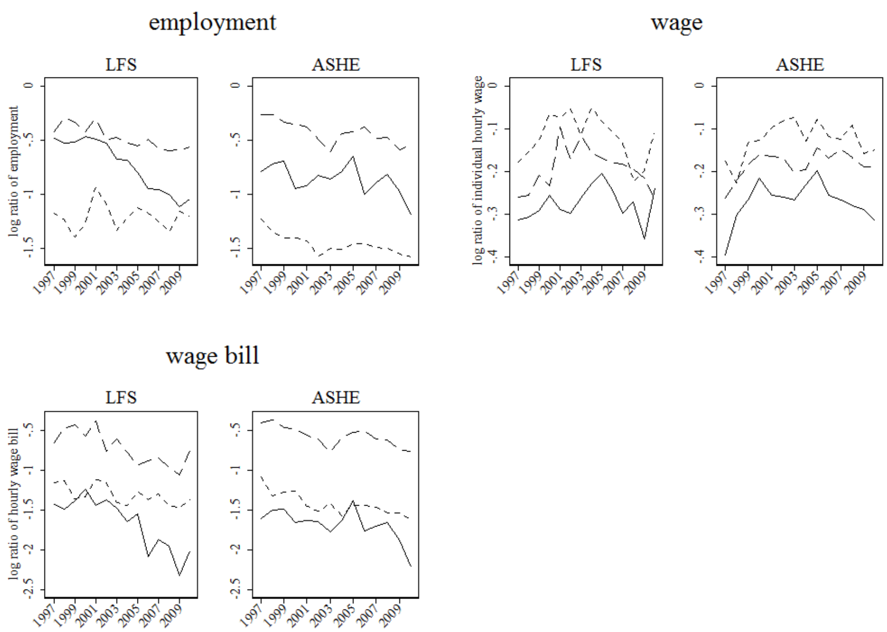

Figure 1: For the top left panel (employment), we take the ratio of individuals (count) of each 'young' age group to the 55+ age group over regions and occupations and plot over time. For the top right (wage) and bottom left (wage bill) panels we take the ratio of 'young' to old workers averaged over regions and occupations and plot over time. The continuous line shows the evolution of the ratio of the 16-17 year old group relative to the older workers' group. The long dash lines shows the evolution of the ratio of the 18-20 year old relative to older workers. Finally the short dash line shows the evolution of the ratio of the 21 year old relative to older workers.

evidence is more marginal for the wage ratios). We note that the regional dummies do not systematically explain the variability of the relative wage ratios for the 21 year old age group (LFS), or the relative employment ratios for the 18 to 20 year old (ASHE).

4. Results

The question of interest to policy makers concerns the effect of the introduction and the uprating of the NMW on the composition of the workforce. This amounts to deciding whether the different age related NMW rates have a significant effect on the number of young workers relative to the number of older workers and whether they had a significant effect on the relative wage rate and the relative wage bill. Given the economic model we described earlier, the policy question can be expressed in terms of the reduced form equations which relate the outcomes of interest - the change in the logarithm of the relative wage, wage bills and (labour) group size, to the exogenous variables - to the proportion of young and old workers affected by the future introduction or uprating of the NMW.

Table 2 presents parameter estimates of the reduced form equations (8), (9) and (10) for each age group relative to the old workers group within a particular low-pay occupation, region and year. Starting from the top panel, which presents estimates for the average hourly wage, we observe that the proportion of young workers receiving a wage between the current NMW

Table 1: OLS Regressions of log Ratios on Ocupation, Region and Year dummies

		LFS								ASHE							
		all		occupation		region		year		all		occupation		region		year	
	Age Group	$F-$stat	$p-$val	$F-$stat	$p-$val	$F-$stat	$p-$val	$F-$stat	$p-$val	$F-$stat	$p-$val	$F-$stat	$p-$val	$F-$stat	$p-$val	$F-$stat	$p-$val
$\ln(w_{i/o})$	16-17 year old	3.6224	0.0000	16.5844	0.0000	2.1645	0.0154	1.1398	0.3230	5.2354	0.0000	22.6556	0.0000	2.8550	0.0018	1.5388	0.0998
	18-20 year old	5.1547	0.0000	10.6170	0.0000	3.1231	0.0004	2.8212	0.0006	7.6730	0.0000	15.2458	0.0000	4.5091	0.0000	2.0162	0.0168
	21 year old	1.7125	0.0137	2.9966	0.0114	1.2186	0.2722	1.5276	0.1045	2.5860	0.0000	3.2095	0.0013	2.9827	0.0010	1.9330	0.0236
	22-54 year old	2.8879	0.0000	5.0854	0.0000	2.2561	0.0101	1.3378	0.1834	5.7509	0.0000	11.5455	0.0000	2.0238	0.0277	3.0568	0.0002
$\ln(w^*_{i/o})$	16-17 year old	32.8063	0.0000	136.2298	0.0000	2.7234	0.0021	3.1476	0.0002	48.8668	0.0000	226.3178	0.0000	3.5300	0.0002	1.2330	0.2521
	18-20 year old	41.6822	0.0000	132.1460	0.0000	4.3932	0.0000	1.9617	0.0211	87.9625	0.0000	279.4679	0.0000	2.2196	0.0148	1.3246	0.1915
	21 year old	8.6166	0.0000	42.1661	0.0000	4.1402	0.0000	0.6267	0.8319	49.2315	0.0000	174.1313	0.0000	3.6312	0.0001	1.2649	0.2286
	22-54 year old	24.3593	0.0000	56.6595	0.0000	3.3274	0.0002	7.0745	0.0000	56.5613	0.0000	122.0220	0.0000	4.9735	0.0000	7.9068	0.0000
$\ln(l_{i/o})$	16-17 year old	95.7852	0.0000	372.9392	0.0000	3.0165	0.0007	1.6757	0.0631	84.9527	0.0000	437.6334	0.0000	3.2853	0.0004	0.6726	0.7905
	18-20 year old	102.9694	0.0000	360.4313	0.0000	6.8958	0.0000	0.6537	0.8089	145.2741	0.0000	476.7309	0.0000	1.3033	0.2235	1.0293	0.4199
	21 year old	22.5305	0.0000	89.8099	0.0000	14.7268	0.0000	0.7254	0.7384	65.1485	0.0000	233.5023	0.0000	5.6097	0.0000	0.6226	0.8365
	22-54 year old	36.1304	0.0000	81.2370	0.0000	5.0591	0.0000	8.2236	0.0000	63.2461	0.0000	121.3290	0.0000	9.6087	0.0000	8.7971	0.0000

Source: LFS and ASHE data supplied by the Secure Data Service.

and next period's NMW,has a positive and statistically significant effect on the change in the log ratio of hourly wages. This result is consistent across datasets. Similarly, the effect of the proportion of old workers affected has a significant negative effect on the change in the log ratio of hourly wages, with the exception of the 21 year old group in ASHE (negative but insignificant). The F-statistics suggest that our instruments contribute significantly to the explanation of the observed change of the relative wages. The computed F statistics are 'large' for all age groups apart from the very young (16-17 year old), which are below the rule of thumb threshold of 10 Based on these estimates, the introduction (and the regular uprating) of the NMW explains around 10% of the variability of the relative average wage over time between occupations and regions.

The middle panel of Table 2, reports the estimated effects on changes of the relative wage bill. Estimates from both the LFS and ASHE broadly produce the same pattern of significance, a larger than average proportion of a younger group paid at an hourly wage between the current NMW and next period's NMW is associated with a larger change in the relative wage bill, while a larger than average proportion of old workers affected is associated with a smaller change in the relative wage bill. The F-statistics, which characterise the "strength" of the association, with the exception of the 21 year old group, are larger in the LFS than in the ASHE sample. Overall, we find that the introduction and the year on year uprating of the minimum wage, explains around 5% to 10% of the overall variance of the relative wage bill.

Concerning the relative employment size (bottom panel of Table 2), the significant estimates are the exception rather than the rule. For the very young (16-17 year old), the two proportions of workers affected by the uprating of the minimum wage seem to have a significant effect on the ratio of employment in the LFS sample, however, this result is not reproduced in the ASHE sample. Furthermore, for the 18-20 year old, the proportion of 'young' workers affected by the NMW change has a significant negative effect on relative employment in the LFS sample and a significant positive effect in the ASHE sample, which casts doubts over the robustness of this estimated effect. For the 21 year olds, we again obtain estimates of opposite direction from each dataset but statistically insignificant in both. If we consider the middle aged group, with the exception of the proportion of the old affected in the ASHE sample, we observe that none of the parameter estimates are significant.

We also test in each case the null hypotheses that the sum of the effects of the proportion affected by the uprating of the NMW in the younger and old group is equal to zero. For the relative wage rate, we reject the null hypothesis, at conventional levels, in all cases across datasets. For our wage bill measure, we cannot reject the hypothesis of opposite effects of the proportions of young and old workers affected on the relative cost of labour for the very young group (16-17 year old) in the LFS sample. When it comes to the relative employment size, however, we have to accept the hypothesis that the effect of the uprating is exactly balanced for the very young in the ASHE sample, and the 21 and 22-54 year old in both the LFS and ASHE samples. This suggests that the differential uprating of the age related NMW rates affect more directly the outcome of these age groups, which is perhaps expected for the 21 year olds given that these workers are more likely to be affected by any NMW upratings.

Our results so far suggest that the introduction and uprating of the NMW has had a significant effect on the determination of wages and wage bills, while the NMW had no systematic effect on the evolution of relative employment (i.e. in terms of the employment size of younger workers age groups relative to the employment size of old workers). Hence, one of the usual requirements for the application of Instrumental Variables (IV) methodology is apparently not satisfied – the candidate instruments should be significant in the reduced form equations for all endogenous variables whether they are on the RHS or the LHS of the structural equation of interest (see Angrist and Pischke, 2008 [1], for a discussion). This conclusion is not sensitive to the presence or absence of the outliers in the reduced form [8]. However, if two inputs are complements in production i.e. whenever $\sigma = 0$ or $\rho = -\infty$, the reduced form equations 8, 9 and 10 suggest that the relative employment size should be determined independently from the relative wages or the relative wage

[8] We investigate the sensitivity of the estimates to the presence of extreme observations in the samples. We run the first stage regressions by excluding extreme values from our samples by calculating the Cook's Distance and using the conventional 4/n threshold as a cut-off point. Even though some of the estimated effects are slightly larger in magnitude, the significance and signs of the coefficients are unaltered. These estimates are available from the authors upon request.

Table 2: Reduced Form Equation Estimates (OLS)

	LFS				ASHE			
	16-17 year olds	18-20 year olds	21 year olds	22-54 year olds	16-17 year olds	18-20 year olds	21 year olds	22-54 year olds
$\Delta \ln(w_{i/o})$								
$Prop[w_{t-1,y}, w_{t,y}; t-1]$	0.291*	0.580**	0.616**	0.415**	1.057**	1.171**	1.265**	0.941**
	(0.149)	(0.047)	(0.089)	(0.061)	(0.473)	(0.093)	(0.124)	(0.185)
$Prop[w_{t-1,o}, w_{t,o}; t-1]$	-0.455**	-0.539**	-0.386**	-0.445**	-1.411**	-0.752**	-0.567	-1.070**
	(0.117)	(0.072)	(0.156)	(0.034)	(0.413)	(0.171)	(0.363)	(0.096)
N	420	818	366	1545	455	1058	807	1579
$F(H_o : \gamma_y = \gamma_o = 0)$	9.692	106.9	27.36	106.8	6.971	86.82	52.44	65.57
$Prob > F$	0.0000780	8.94e-42	9.85e-12	4.32e-44	0.00105	1.48e-35	4.40e-22	4.65e-28
$F(H_o : \gamma_y + \gamma_o = 0)$	3.811	150.3	47.84	47.03	4.996	159.1	104.7	25.82
$Prob > F$	0.0516	9.98e-32	2.36e-11	1.02e-11	0.0259	5.29e-34	3.83e-23	0.000000420
$\Delta \ln(w^*_{i/o})$								
$Prop[w_{t-1,y}, w_{t,y}; t-1]$	-0.212	0.398**	0.626**	0.572**	2.112**	0.767**	0.652**	0.641*
	(0.467)	(0.170)	(0.258)	(0.184)	(1.016)	(0.249)	(0.295)	(0.377)
$Prop[w_{t-1,o}, w_{t,o}; t-1]$	-1.143**	-0.792**	-0.676	-0.515**	-1.281	-0.762	1.547*	-0.124
	(0.367)	(0.259)	(0.450)	(0.104)	(0.886)	(0.491)	(0.924)	(0.196)
N	420	819	366	1547	455	1059	809	1579
$F(H_o : \delta_y = \delta_o = 0)$	4.925	7.737	4.162	16.91	2.663	5.727	4.263	1.488
$Prob > F$	0.00772	0.000471	0.0164	5.46e-08	0.0709	0.00336	0.0144	0.226
$F(H_o : \delta_y + \delta_o = 0)$	0.207	5.506	5.911	9.654	4.323	9.458	4.875	2.897
$Prob > F$	0.650	0.0192	0.0156	0.00192	0.0382	0.00216	0.0275	0.0890
$\Delta \ln(l_{i/o})$								
$Prop[w_{t-1,y}, w_{t,y}; t-1]$	-0.924**	-0.195**	-0.158	-0.0401	-0.445	0.365**	0.284	-0.174
	(0.277)	(0.096)	(0.161)	(0.119)	(0.714)	(0.183)	(0.209)	(0.310)
$Prop[w_{t-1,o}, w_{t,o}; t-1]$	-0.549**	0.0565	0.0403	0.105	-0.891	0.284	1.093	0.610**
	(0.220)	(0.148)	(0.297)	(0.067)	(0.623)	(0.415)	(0.792)	(0.161)
N	426	855	387	1592	455	1063	818	1579
$F(H_o : \beta_y = \beta_o = 0)$	8.440	2.194	0.486	1.287	1.495	2.250	2.034	7.165
$Prob > F$	0.000257	0.112	0.615	0.276	0.225	0.106	0.131	0.000799
$F(H_o : \beta_y + \beta_o = 0)$	11.18	4.174	0.958	0.113	0.388	3.981	1.855	0.314
$Prob > F$	0.000908	0.0414	0.328	0.737	0.533	0.0463	0.174	0.575

Cluster-robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$

Note: All models include occupation, region and year dummies.

Source: LFS and ASHE data supplied by the Secure Data Service.

bills.

Table 3, presents the estimated structural parameters from Instrumental Variables (IV) estimation. The specification always controls for occupation, region and macro effects although these estimated parameters are not included in the output. We report overidentification test statistics, which assess whether the exclusion of one of our two instruments from the structural equation is supported by the data. When more instruments than endogenous variables are available, a test of overidentifying restrictions is possible. The test assumes that one instrument is valid and then tests for the validity of all other instruments i.e. whether the instruments are uncorrelated with the error term in the second stage. It should be noted that the $J-$statistic is reliable only when the instruments are not weak, as determined by the first stage results($F-$statistics greater than, say, 10). We accept this hypothesis in almost all models except the cases of the relative average wages and relative cost of labour on relative employment of the very young in the LFS sample, and the relative cost of labour of the very young, the 21 year old and middle age workers on relative employment in the ASHE sample. In these instances, the computed $J-$statistics suggest that the models are either overidentified (since we have one endogenous variable and two excluded instruments) or the instrument have little relevance.

Just-identified 2SLS is approximately unbiased. However, even then, when the instruments are weak (the first stage is in actuality zero) the es-

Table 3: 2SLS IV Estimates

	LFS				ASHE			
	16-17 year olds	18-20 year olds	21 year olds	22-54 year olds	16-17 year olds	18-20 year olds	21 year olds	22-54 year olds
$\Delta\ln(l_{i/o})$ on $\Delta\ln(w_{i/o})$								
$-\sigma$	0.293	-0.241*	-0.162	-0.220*	0.372	-0.185	-0.325	-0.527**
	(0.416)	(0.141)	(0.250)	(0.133)	(0.407)	(0.178)	(0.209)	(0.150)
θ	0.106	-0.448	0.194	-0.0792	-0.230**	0.0952	0.0211	-0.0504
	(0.207)	(0.436)	(0.251)	(0.084)	(0.099)	(0.126)	(0.251)	(0.072)
N	420	818	366	1545	455	1058	807	1579
r^2	0.0632	0.0219	0.0640	0.00889	0.0693	0.0297	-0.0140	-0.0310
$J-$statistic	13.46	1.044	0.00329	0.0901	2.122	0.0511	3.127	1.277
$Prob > J$	0.000244	0.307	0.954	0.764	0.145	0.821	0.0770	0.258
$\Delta\ln(l_{i/o})$ on $\Delta\ln(w^*_{i/o})$								
$\frac{1}{\rho}$	0.495**	-0.182	-0.138	-0.154	0.0420	-0.0321	0.165	-0.555
	(0.158)	(0.178)	(0.253)	(0.128)	(0.285)	(0.250)	(0.242)	(0.752)
θ	-0.0896	-0.584	0.241	-0.0738	-0.220*	-0.00441	-0.0297	-0.100
	(0.172)	(0.525)	(0.305)	(0.098)	(0.131)	(0.086)	(0.145)	(0.142)
N	420	819	366	1547	455	1059	809	1579
r^2	0.322	-0.441	-0.218	-0.334	0.195	-0.0321	0.286	-1.430
$J-$statistic	9.460	1.644	0.0273	0.0345	3.398	0.270	5.026	5.236
$Prob > J$	0.00210	0.200	0.869	0.853	0.0653	0.603	0.0250	0.0221

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$

Note: All models include occupation, region and year dummies.

Source: LFS and ASHE data supplied by the Secure Data Service.

timates may suggest a causal relationship when it is in fact absent. For overidentified models, the estimates are biased with the bias being an increasing function of the number of instruments. Given our concerns about the validity of the instruments, based on the first stage results, we also obtain limited information maximum likelihood estimates (LIML) which are approximately median-unbiased and robust in the presence of weak instruments and overidentification . Table 4 presents LIML estimates comparable to those from we obtain using 2SLS in Table 3.

For our structural model linking relative employment to the relative average wage, equation (6), the 2SLS and LIML results are broadly similar, which alleviates our concerns over the strength of the instruments used. Given our model specification, the negative of the coefficient estimate on the difference of the log ratio of average wages between young and old workers provides a measure of the elasticity of substitution, $\sigma \geq 0$. The parameter of interest is negative and statistically significant for the young (18-20 year old) in the LFS sample at the 10% level, implying the elasticity of substitution to be 0.2 (LIML estimate), while for the same age group the estimate from the ASHE sample is also negative yet insignificant. The only other significant estimate is that for the middle age group (22-54 year old), which implies the elasticity of substitution between workers of that group and old workers ranges between 0.2 and around 0.5 (depending on whether we use the LFS or ASHE estimate). In either case we conclude that the estimated elasticity of substitution argue in favour of some significant complementarity (or at least against perfect substitution) between the 18-20 year old and the 55+

Table 4: LIML IV Estimates

	LFS				ASHE			
	16-17 year olds	18-20 year olds	21 year olds	22-54 year olds	16-17 year olds	18-20 year olds	21 year olds	22-54 year olds
$\Delta \ln(l_{i/o})$ on $\Delta \ln(w_{i/o})$								
$-\sigma$	0.103	-0.242*	-0.162	-0.220*	0.440	-0.185	-0.336	-0.531**
	(0.723)	(0.142)	(0.250)	(0.133)	(0.444)	(0.178)	(0.212)	(0.151)
θ	0.157	-0.448	0.194	-0.0792	-0.230**	0.0952	0.0218	-0.0505
	(0.263)	(0.436)	(0.251)	(0.084)	(0.101)	(0.126)	(0.252)	(0.072)
N	420	818	366	1545	455	1058	807	1579
r^2	0.0438	0.0216	0.0640	0.00888	0.0460	0.0297	-0.0159	-0.0325
$J-$statistic	13.39	1.043	0.00329	0.0901	2.098	0.0511	3.125	1.276
$Prob > J$	0.000253	0.307	0.954	0.764	0.147	0.821	0.0771	0.259
$\Delta \ln(l_{i/o})$ on $\Delta \ln(w^*_{i/o})$								
$\frac{1}{\rho}$	0.905**	-0.242	-0.140	-0.154	-0.306	-0.0491	-0.204	-2.863
	(0.455)	(0.199)	(0.254)	(0.129)	(0.532)	(0.257)	(0.447)	(3.475)
θ	-0.317	-0.596	0.242	-0.0738	-0.333	-0.00582	-0.0747	-0.374
	(0.330)	(0.561)	(0.305)	(0.098)	(0.214)	(0.087)	(0.208)	(0.510)
N	420	819	366	1547	455	1059	809	1579
r^2	-0.407	-0.641	-0.222	-0.336	-0.517	-0.0678	-0.430	-16.87
$J-$statistic	7.808	1.542	0.0273	0.0344	2.595	0.266	3.671	1.994
$Prob > J$	0.00520	0.214	0.869	0.853	0.107	0.606	0.0554	0.158

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$

Note: All models include occupation, region and year dummies.

Source: LFS and ASHE data supplied by the Secure Data Service.

age group and between the 22-54 year old and the 55+ year old group.

Looking at the estimates of model (7), describing the relationship between relative employment and the wage bill measure, we find that for the 16-17 year old group, the 2SLS and LIML estimates are rather different, especially from the LFS sample, suggesting our instruments for that age group are weak. The coefficient estimates imply that $\sigma < 0$, which is not admissible (in our specification values of $1/\rho$ between 0 and 1 are not consistent with a positive value of σ. These results reinforce our concerns raised following the J test over the validity of these estimates. For the rest of the age groups, we fail to obtain any statistically significant result from either dataset or estimator, however, the estimated effects have the 'correct' (negative) sign. The exception is the LIML estimate from ASHE for the 21 year olds, which is positive and less than unity.

We consider 0 as an estimate of the elasticity of substitution which the data does not reject, and we conclude that the evidence presented in Tables 3 and 4 is consistent with complementarity between younger age groups and the old age group. We also observe that estimates obtained for the middle aged (22-54 year old) group, relative to old workers, are consistently insignificantly different from zero, which we again interpret as suggestive of complementarity between the two age groups. This is also a conclusion we reach from the analysis of the reduced form equations i.e. the NMW has a significant, consistent effect on the changes of the relative average wage within low-pay occupation, region and year but it has no effect on the labour force age composition.

We further check the validity of our results by estimating confidence sets robust to weak instruments following the suggestion of Mikusheva and Poi (2006)[9], who argue that in IV regression with a single endogenous variable and potentially weak instruments, the conventional (Wald-type) inferential statistics are unreliable. Table 5 presents results for each age group and dataset, which are valid whether the instruments are weak or strong. We report the Anderson-Rubin (AR) and conditional likelihood ratio (CLR) confidence sets, as well as $p-$values for the hypotheses of the coefficient of the relative average wage and the relative cost of labour being equal to zero and one. The authors note that if the instruments are weak, the Anderson-Rubin confidence set could be $(-\infty, +\infty)$ or empty $(\emptyset)$.

In our model linking the change in relative average employment to the change in relative average wage, the coefficient of the change in the relative average wage is a direct measure of the elasticity of substitution between 'young' and old workers, hence accepting the hypothesis of $\sigma = 0$ ($\rho = -\infty$) means we have to accept that the two types of labour are perfect complements in production.

The results from the LFS sample suggest that we cannot reject the hypothesis of perfect complementarity of 'young' and old labour $\sigma = 0$ except (based on the conditional likelihood test) for the 16-17 year olds and the 18-20 year olds but at the 10% significance level for the latter. The ASHE sample does reject this hypothesis for the middle age group (22-54) and (based on the Anderson-Rubin test) for the 21 year olds. This result is in line with our

Table 5: Coverage Corrected Confidence Intervals and Conditional $p-$values

			LFS				ASHE			
	Age Group	Test	CI_L	CI_U	$p-$value for $H_o : \sigma = 1$	$p-$value for $H_o : \sigma = 0$	CI_L	CI_U	$p-$value for $H_o : \sigma = 1$	$p-$value for $H_o : \sigma = 0$
$\Delta \ln(l_{i/o})$ on $\Delta \ln(w_{i/o})$	16-17 year old	Conditional LR	-2.8670	2.1115	0.2562	0.8939	-0.4927	1.8942	0.3097	0.3320
		Anderson-Rubin	$\emptyset$		0.0008	0.0016	-0.4708	1.8415	0.2143	0.2251
	18-20 year old	CLR	-0.5359	0.0382	0.0000	0.0906	-0.5481	0.1711	0.0000	0.3069
		AR	-0.5782	0.0766	0.0000	0.1440	-0.6391	0.2583	0.0000	0.5771
	21 year old	CLR	-0.7220	0.3556	0.0001	0.5365	-0.7856	0.0829	0.0000	0.1161
		AR	-0.8764	0.4850	0.0003	0.8220	-0.7270	0.0316	0.0000	0.0640
	22-54 year old	CLR	-0.4916	0.0442	0.0000	0.1025	-0.8507	-0.2408	0.0000	0.0003
		AR	-0.5587	0.1071	0.0000	0.2508	-0.8881	-0.2102	0.0000	0.0008

			LFS				ASHE			
	Age Group	Test	CI_L	CI_U	$p-$value for $H_o : \sigma = \infty$	$p-$value for $H_o : \sigma = 0$	CI_L	CI_U	$p-$value for $H_o : \sigma = \infty$	$p-$value for $H_o : \sigma = 0$
$\Delta \ln(l_{i/o})$ on $\Delta \ln(w^*_{i/o})$	16-17 year old	Conditional LR	-0.9950	0.2391	0.8595	0.0276	$-\infty$	$+\infty$	0.0093	0.4838
		Anderson-Rubin	$\emptyset$		0.0247	0.0016	$-\infty$	$+\infty$	0.0046	0.2251
	18-20 year old	CLR	-1.0220	0.0500	0.0000	0.1245	-1.2255	0.3037	0.0000	0.8435
		AR	-1.1432	0.0654	0.0000	0.1426	-2.0492	0.3535	0.0000	0.8624
	21 year old	CLR	-1.6539	0.2358	0.0001	0.5552	-8.2356	0.3395	0.0000	0.5987
		AR	-3.6043	0.2968	0.0001	0.8220	-2.3954	0.2566	0.0000	0.1479
	22-54 year old	CLR	-0.5116	0.0544	0.0000	0.1696	$-\infty$	$+\infty$	0.0000	0.0005
		AR	-0.6474	0.0943	0.0000	0.3781	$-\infty$	$+\infty$	0.0000	0.0008

Source: LFS and ASHE data supplied by the Secure Data Service.

IV estimates, which use conventional Wald-type confidence intervals, thus suggesting that our instruments are not weak. On the other hand, the hypothesis of $\sigma = 1$ is rejected for all age groups across datasets except in the case of the 16-17 year olds (according to the CLR test in the LFS sample and both tests in the ASHE sample). This implies that while firms adjust the age composition of their workforce in response to wage changes with respect to young and old workers, employment of very young workers is not affected. In this context then, while NMW upratings may affect 18+ year old workers, they have no detrimental effect on 16-17 year old employees.

Looking at the wage bill measure, we get largely similar results, accepting the null hypothesis of $\sigma = 0$ for all age groups apart from the very young (16-17 year old) in the LFS sample and the middle aged (22-54 year old) in the ASHE sample. Further, we reject the hypothesis of $\sigma = \infty$ across all samples and age groups except for the very young again in the LFS (using the CLR test). The evidence is quite consistent, at least for the very young (16-17 year old) to old comparison. For the 22-54 year old we observe a different pattern, based on the LFS, we reject $\sigma = 1$ and $\sigma = \infty$, but not $\sigma = 0$. Based on ASHE, however, we reject either null hypothesis $\sigma = 0$ or 1 or ∞.

Our IV estimates (Table 3) suggest that $\sigma = 0.527$ (wage) or $\sigma = 0.357$ (wage bill), although it is not significant in the latter case. Nevertheless, if we look at the implied confidence interval (Table 5) based on the wage bill specification, we see that we would accept all possible values generated. This is not the case with the wage specification- in that case the confidence interval suggests that σ (for middle aged relative to old workers) is between 0.2 and 0.9. The wage data suggest that for the other groups acceptable values are between 0 and 0.7, which implies complementarity. Using the wage bill information, for the 18-20 year old and the 21 year old we have confidence intervals (for $1/\rho$), which would suggest that σ is between 0 and 0.555 for the 18-20 year old, and between 0 and 0.892 for the 21 year old. We therefore reach the conclusion that young and old workers exhibit substantial complementarities.

5. Conclusion

We analyse data from 1997 to 2010 drawn from the LFS and the ASHE with a view to characterising the effect of the different NMW age-based rates and their uprating on the relative wages and the age related employment structure among low-pay occupations. Our analysis suggests that, if anything, the introduction and uprating of the NMW has a significant effect on the determination of wages and wage bills, while the NMW has no systematic effect on the evolution of relative employment. The evidence points in the direction of substantial, if not perfect, complementarity between the young age groups (18-20 year old and 21 year old) and old workers (more than 55 year old). This in turn, suggests that the differences of the NMW between age groups may not matter much when it comes to determining the labour force composition. In that sense, the current structure of the minimum wage appears innocuous. However, the evidence we report shows that the regular upratings of the NMW has a significant effect on the relative wages between younger and old workers.

Disclaimer

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Appendix

Table 6: Definitions of Low-Paying Occupations by SOC2000 and SOC1990 Codes.

Low-Paying Occupation	$SOC2000^{(2)}$	$SOC1990^{(3)(4)}$
Retail	1234, 5496, 711, 7125, 721, 925	178, 720, 721, 722, 730, 731, 732, 790, 791, 792, 954, 959
Hospitality	5434, 9222-9225	620, 621, 622, 951, 952, 953
Social care	6115	644
Employment Agencies	n/a	n/a
Food Processing	5431-5433, 8111	580, 581, 582, 800, 801, 802, 809
Leisure, travel and sport	6211, 6213, 6219, 9226, 9229	630, 699, 875, 999
Cleaning	6231, 9132, 923	670, 671, 956, 957, 958
Agriculture	5119, 9111, 9119	900, 902, 903
Security	9241, 9245, 9249	615, 619, 955
Childcare	6121-6123, 9243, 9244	650, 651, 659
Textiles and clothing	5414, 5419, 8113, 8137	553, 556, 559
Hairdressing	622	660, 661
Office work	4141, 4216, 9219	460, 461, 462

Source: LFS and ASHE data supplied by the Secure Data Service.

Notes:

(1) n/a is not applicable.

(2) Low-paying occupation definitions (SOC 2000) provided by the UK Low Pay Commission. Low Pay Commission report 2010, Appendix 4: Review of the Low-paying sectors, Table A4.1, p. 243.

(3) Adapted from data from the Office for National Statistics licensed under the Open Government Licence v.1.0: OOSS User Guide 2000: 22, Occupational Information Unit, Office for National Statistics.

(4) Some relationships were adapted from: Elias, P., and Purcell, K. (2004) “SOC(HE) A classification of occupations for studying the graduate labour market”, Researching Graduate Careers Seven Years On; Research Paper No. 6, Warwick Institute for Employment Research, Table A3, p. 40.