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DO MINIMUM WAGES INCREASE SEARCH EFFORT?

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Minimum wages often generate a perplexing set of empirical impacts, including little to no employment consequences but large wage consequences. This paper tests arguably the most promising explanation - search models of minimum wages - in a more direct manner than has been possible to date. The analysis combines extensive data on UK workers' search behaviour with quasi-experimental analysis of the UK minimum wage policy structure, including the 2016 introduction of the National Living Wage. I find robust evidence of increased labour force participation and extensive margin search in response to higher minimum wages with no corresponding change in employment rates. Evidence of decreased average search intensity is uncovered and the duration of unemployed search increases. Taken together, the unemployed search results suggest that minimum wages do impact on labour flow frictions in important ways. In contrast, no significant estimates are found for any on-the-job search moments, i.e. I find no evidence for potential concerns that higher minimum wages provide a disincentive for workers to progress up job ladders.

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Key words: Equilibrium search models, Minimum wages, Quasi-experimental analysis

JEL Classification: E24, J21, J64

1 Introduction

A perplexing pattern of empirical results, inconsistent with frictionless Walrasian models, have regularly been attributed to minimum wages. A range of studies have found small to no disemployment consequences of wage floor policies – a concurrence dubbed the 'elusive employment effect' of minimum wages by Manning (2016). At the same time, first order wage consequences for large portions of the distribution have been uncovered.[1] Minimum wages are evidently impacting on the labour market but the specific adjustment mechanisms remain unclear. More precise understanding of causal mechanisms is paramount for modelling and predicting minimum wage impacts - particularly if they are to be raised above levels previously seen - as is being touted in the United Kingdom, several US states, and other parts of the world.

This paper tests arguably the most promising answer - search models of minimum wages - in a more direct manner than has been possible to date. Using detailed data on workers' search behaviour and United Kingdom natural experiments, I directly estimate the impact of minimum wages on multiple search and labour force participation decisions of both employed and unemployed workers. The analysis uncovers new stylised facts on the responsiveness of key labour market frictions to wage floor policies that can be used in modelling minimum wage labour market impacts.

Walrasian models of labour markets predict that minimum wage policies drive firms to reduce their labour demand thus increasing unemployment. Any wage consequences will be limited to those directly impacted by the policy. Since the seminal work of Card and Krueger (1994) the majority of empirical findings have been inconsistent with such predictions. Minimal or zero adverse employment consequences are common microeconometric study results across countries as diverse as the USA (see for example Card and Krueger (2000, 2015), Dube et al. (2010), Kuehn (2016)), the UK (see Stewart (2002, 2004b,a) Dolton et al. (2015) and Dickens et al. (2015), Manning (2016)), Brazil (Engbom and Moser (2017)), New Zealand (Hyslop and Stillman (2007)) and others.[2]

While the employment consequences of minimum wages often appear minimal, their impact on the wage distribution is first order. DiNardo et al. (1996); Lee (1999); Teulings (2003); Autor et al. (2016); Engbom and Moser (2017) find significant com-

[1] See for example DiNardo et al. (1996); Lee (1999); Teulings (2003); Autor et al. (2016); Engbom and Moser (2017)

[2] It should be noted that some authors have measured negative employment consequences of minimum wages in the USA, most vocally Neumark and Wascher (2000); Neumark et al. (2007). Such results are normally generated through state-panel methodologies over many years. Other authors, such as Dube et al. (2010), argue that the negative results are a consequence of divergent residual state-level employment trends. UK research almost uniformly finds no large, significant employment consequences.

pressions of the wage distribution in response to the minimum wage. Wages are raised in the lower half of the distribution (potentially up to the 50th percentile) including for individuals not directly impacted by minimum wages. Significant wage impacts preclude the possibility that minimum wages are simply ineffective and irrelevant. That then beggars the question: what mechanisms are minimum wages impacting the labour market through and which theoretical framework is the most appropriate to use? The most promising candidate explanations of the combined wage and employment consequences stem from the search and matching literature.

Search theory's central idea is that labour markets are characterised by frictions resulting from imperfect matching of vacancies and job seekers. Firms and workers do not instantly meet and must instead search for each other in a costly process, with the corresponding search decisions a function of incentives. Equilibrium unemployment and wages are determined by solving the system of value functions for searching and employed workers, vacancies and filled positions, combined with a specified matching technology.[3] Minimum wages have potential to impact on the returns to extensive and intensive margin search decisions for both unemployed and employed job seekers.

Search theory has of course been applied to minimum wages, both theoretically and empirically. One of the first to explicitly consider minimum wages in a search context, albeit briefly, is Bontemps et al. (1999). Their model of heterogeneous workers and firms, with on-the-job search, has ambiguous theoretical employment consequences of minimum wages. Minimum wages set at a moderate level raise wages and encourage workers with high leisure values to accept jobs, reducing unemployment. If set above the lower support of job productivity, however, job destruction and increased unemployment will result.[4]

Flinn (2006) create an stationary equilibrium search and matching model in which the matching rates between firms and working are determined by vacancy creation and extensive margin search decisions (i.e. endogenous matching rates). Unlike Bontemps et al. (1999), there is no on-the-job search.[5] Heterogeneity is introduced through individuals' value of leisure and the productivity of worker-firm specific matches. A key development is the modelling the extensive margin search decision of individuals - individuals with high values of leisure can simply opt to remain separated from the labour force.

In the model, it is theoretically possible for minimum wages to increase employ-

[3]The early developments of such equilibrium unemployment models are surveyed in Mortensen and Pissarides (1999) beginning with the seminal paper Pissarides (1990)

[4]The Bontemps et al. (1999) model does not consider search effort and assumes that all workers are searching, i.e. there is no modelling of labour market inactivity.

[5]A companion paper Flinn and Mabli (2005) remains unpublished has extended the model to include on-the-job serach.

ment and welfare of both firms and workers.[6] The paper structurally estimates the theoretical model using employment data from the Current Population Survey (CPS) and firm profit data. Flinn (2006) finds that workers' bargaining power is too low in the absence of minimum wages which, under their model, implies that minimum wages are welfare improving.

Dube et al. (2016) claim a less structural approach to search and matching theory of minimum wages. Their method uses a border-discontinuity design of contiguous county pairs experiencing varying state-level minimum wage legislation. Their results suggest that minimum wages impact significantly on flows but not stocks of employment - hiring and separations are reduced. While not directly addressing search theory, Dube et al. (2016) argue that their results are consistent with job ladder models prominent in the search literature.[7]

Two comments on the minimum wage search literature can be drawn. Firstly, given data constraints, the existing work treats the search frictions themselves as a black box that are not observed, even imperfectly. As a consequence, most estimation relies on employment outcomes such as wages and employment status and imposed structure to back out hypothesised search responses indirectly. Secondly, and relatedly, the methods are restricted in how easily they can separately identify search mechanism responses. The literature has put forward a number of candidate search mechanisms, including extensive margin search decisions, on-the-job search and search intensity that may all adjust in response to minimum wages - and it is of benefit to identify which, if any, are particularly impacted.

This paper is, I believe, the first to combine explicit evidence on multiple search mechanisms and a natural policy experiment to directly estimate the impact of minimum wages on search margins. I use large survey data on both the extensive margin (searching or not searching) and intensive margin (search effort exerted) for unemployed and on-the-job job seekers.

I combine these search data with unique structure of United Kingdom minimum wage policy. The UK sets multiple minimum wages based on recipients' ages and changes in the age-structure do occur. The bulk of this paper's analysis focuses on a 2010 change in the age of eligibility for the adult minimum wage from 22 years to 21 years: overnight, the minimum wage for 21 year olds received a boost of nearly 23%. Minimum wages for other age groups changed only in line with inflation, providing

[6] A binding minimum wage encourages more individuals to search for jobs, raising employment. If workers' bargaining power in the absence of minimum wages is less than required for the Hosios condition, a binding minimum wage can improve workers' effective bargaining power. The improved bargaining position then leads to an equilibrium result that is closer to the socially optimal outcome, hence is welfare improving.

[7] Well known variants of job-ladder models are Burdett and Mortensen (1998); Bontemps et al. (1999, 2000); Flinn and Mabli (2009).

a well-identified setting for quasi-experimental analysis. A difference-in-differences identification strategy is used to estimate the treatment effect of the 23% increase in minimum wages for 21 year olds, using non-targeted age groups as controls. I also briefly discuss the well-publicised recent introduction of a fourth age category for those aged 25 years and over in early 2016. As this only represented a 7.5% boost in minimum wages, the setting is much less significant than the 2010 change.

Headline results find a large increase in minimum wages has no significant impact on employment probabilities but significantly increases the incidence of extensive margin unemployed search. Put differently, non-working individuals switch from inactivity to unemployed search, boosting labour force participation. I also find some evidence that average search intensity declines for unemployed job seekers following the minimum wage rise and unemployment durations rise. No statistically significant impacts are found for any search measure associated with on-the-job searching. Such a result suggests no evidence for a potential claim that minimum wages disincentivise progression up a job ladder.

The contributions of the paper are threefold. Firstly, and most significantly, I provide a direct test of search theory's application to minimum wages and the corresponding consequences for search and labour force participation decisions. Secondly, the analysis uncovers stylised facts that can be used to guide future search modelling of minimum wage impacts. Finally, the results allow an assessment of the consequences of the recent, highly publicised, addition of an minimum wage in the UK and the plans to ratchet up the rate overtime.

The rest of the paper is structured as follows. Section 2 outlines relevant search theory and derives testable implications for the empirical analysis. Section 3 outlines the empirical context including the UK policy environment, the data and the identification strategy used. Sections 4 through 6 present empirical results of the impact on minimum wages on the search outcomes investigated while section 7 outlines robustness checks undertaken. Finally, section 8 concludes.

2 Motivating theory

In a standard search model, unemployed workers searching for a job receive a flow value characterised by the following Bellman equation:

$$\rho V_U = b + \lambda \int_{\rho V_U} [V_E(w(\theta)) - V_U] dF(\theta) \tag{1}$$

Where b is an unemployment benefit, ρ the discount rate, and λ the probability that the worker is matched to an employer. Job offer matches have heterogeneous productivities, θ following distribution $F(\theta)$. Workers only accept employment offers that yield higher utility than their current state. As a result, there is some critical productivity value, $\hat{\theta} = \rho V_U$, for which all matches at least as great as $\hat{\theta}$ are accepted.

Workers employed at a job have the following flow value:

$$\rho V_E = w(\theta) + \eta(V_U - V_E((\theta))) \tag{2}$$

They receive a wage that is specific to the match productivity θ. With some exogenous probability η the match is terminated and the worker becomes unemployed.

Firms with a filled position receive the productivity value of the match, θ, pay wages $w(\theta)$ and face the same exogenous probability η of a terminated contract.

$$\rho V_F = \theta - w(\theta) - \eta V_F \tag{3}$$

Vacancies cost c and are filled with probability λ_V. Free-entry of vacancy creation is assumed, pushing the value unfilled vacancies to 0:[8]

$$\rho V_V = -c + \lambda_V (V_F - V_V) = 0 \tag{4}$$

The number of matches is a constant returns to scale matching technology that depends positively on the stocks of unemployed workers, u, and vacancies, v.

$$M(u, v) = M(\frac{u}{v}, 1) = vq(k) \tag{5}$$

where $k = \frac{u}{v}$ and the partial derivatives are positive $\frac{\partial M}{\partial u}, \frac{\partial M}{\partial v} > 0$.

Wages are determined through Nash bargaining between workers and firms where α is the relative bargaining power of workers.

$$w(\theta) = \underset{w}{\text{argmax}} [V_E - V_U]^{\alpha} [V_F]^{1-\alpha} \tag{6}$$

The system of the equations can be solved for the equilibrium unemployment level u:

$$u = \frac{\eta}{\eta + (1 - F(\hat{\theta}))q(k)/k} \tag{7}$$

[8]The probability the vacancy is filled is the product of the probability of a match (see equation 5) times the probability the job offer is accepted $1 - F(\rho V_U) = 1 - F(\hat{\theta})$, i.e. the probability that the productivity of the match, θ exceeds an unemployed workers reservation level

2.1 Extensive margin search decision

In the baseline search model above workers are in one of two possible states: employed or unemployed and searching for a job. In reality, many individuals are removed from the labour market (defined as not employed, not seeking employment and/or not able to work) for a variety of reasons. Binding minimum wages can only generate zero or positive employment consequences if the baseline search model is augmented to include an extensive margin search decision.

To model the phenomenon, each individual has a flow value of remaining outside the labour market and not searching, ρV_O.[9] The outside option can be conceptualised as a value of leisure, pursuing education, caring for family members and so on. The ρV_O are heterogeneous and follow some distribution Q. The only individual heterogeneity comes from the outside options - individuals are identical conditional on engaging in the labour force.

An individual decides to enter the labour market if the corresponding value of unemployed search is higher than their outside option i.e. $\rho V_U \geq \rho V_O$. The proportion of the population engaged in the labour force - the participation rate - is therefore $Q(\rho V_U)$.

Minimum wages enter the model by enforcing a lower bound of m on the feasible wage distribution. Match values less than m are unprofitable for firms and do not result in employment. Workers' reservation wage is also influenced by the presence of the minimum wage $\rho V_U(m)$.[10] Thus the critical productivity value for a successful match is the maximum of $[m, \rho V_U(m)]$.

The labour force participation rate under minimum wages becomes $Q(\rho V_U(m))$. The change in labour force participation has the same sign as the change in the value of unemployed search under minimum wages. Ex ante this is ambiguous, but the former is measurable and the latter unobservable. If labour force participation increases with minimum wages, that implies the value of unemployed search has increased.

Theoretical implication: *Higher minimum wages can only have a non-negative impact on employment if there is a corresponding increase in unemployed search. This is turn requires the values of unemployed search to be increasing in the minimum wages.*

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[9] As per Pissarides (2000) and Flinn (2006)

[10] Direct effects of minimum wages on $\rho V_U(m)$: the destruction of some lowest productivity jobs ($\theta < m$) and increased wages for those still profitable at m but previously paying less than m. Indirect effects: adjustments to the number of vacancies created and other unemployed individuals searching.

2.2 Intensive margin search decision

Unemployed search can also be impacted by the intensity with which a workers chooses to search. A job seeker can adjust their searching effort with greater search effort corresponding to a higher job-finding rate.

To model this, the job finding rate of a worker becomes a function of their search effort s_i, the aggregate search effort of all job seekers and the number of vacancies.[11] The job finding rate is increasing in individual search and decreasing in aggregate search, i.e. $\frac{\partial \lambda_i}{\partial s_i} > 0$ and $\frac{\partial \lambda_i}{\partial s} < 0$.

$$\lambda_i = \frac{s_i M(su, v)}{su} = M(s, \frac{v}{u}) \tag{8}$$

Additional search effort is costly for the individual. The cost of search, $\sigma_i(s_i)$, is modelled as a strictly increasing and convex function to ensure an interior solution.

$$\sigma_i(s_i) \text{ where } \sigma_s > 0, \sigma_{ss} \geq 0 \tag{9}$$

The value function for an unemployed worker is adapted to take into account the search intensity tradeoff. For a simplification that demonstrates the essence of the problem, all job matches are assumed homogeneous. There is therefore a single value V_E for employment and a single wage w.

$$\rho V_{Ui} = b - \sigma(s_i) + \lambda(s_i, q)(V_E - V_{Ui}) \tag{10}$$

The optimal search intensity maximises the value of unemployed search, trading off the gains of greater search (increased job finding rate) with the increased cost. The first order condition (applying the envelope theorem) is:

$$-\sigma_s(s_i) + \frac{\partial \lambda(s_i, q)}{\partial s_i}[V_E - V_{Ui}] = 0 \tag{11}$$

The partial derivative of λ is evaluated by using the functional form assumption from equation 8 and imposing a symmetric equilibrium $s_i = s$ as follows:

$$\left.\frac{\partial \lambda_i}{\partial s_i}\right|_{s_i = s} = \frac{\lambda_i}{s} \tag{12}$$

Finally we can substitute the term for $V_E - V_{Ui}$ into the first order condition to obtain an expression for optimal search intensity:

$$-\sigma_s(s_i) + \frac{w - b + \sigma(s_i)}{\rho + \eta + \lambda(s_i, q)} \frac{\lambda(s_i, q)}{s} = 0 \tag{13}$$

[11] As per Pissarides (2000).

Two possible effects of minimum can be observed through this equation. Firstly, search effort is increasing in the offered wage. Minimum wages that raise the offered wage provide a stronger incentive to find employment, increasing the return to search. Secondly, however, search effort is decreasing in the ratio of vacancies to unemployed searchers. If minimum wages increase the number of searching individuals, v/u falls, generating a congestion externality and decreasing search effort of existing searchers.

Theoretical implication: *Higher minimum wages have an ex ante ambiguous impact on search intensity. The direction of change indicates whether the (positive) wage consequences of minimum wages or the (negative) congestion externality dominates.*

2.3 On-the-job search

Minimum wages may also impact on on-the-job search and therefore job-to-job transitions up a job ladder. When including on-the-job search, the stock of job seekers is now the sum of unemployed workers and workers searching on-the-job. The matching function therefore becomes:

$$M = M(u + e, v) = M(\frac{u + e}{v}, 1) = vq(k) \tag{14}$$

Where v is the stock of vacancies, u is the stock of unemployed workers and e the stock of employed workers searching for a new job. Inverse market tightness is now $k = \frac{u+e}{v}$. For analytical tractability, it is assumed that unemployed and employed job seekers contribute equally to the matching function and have the same job finding rates.[12] The job offer rate for all job seekers is therefore $\lambda = M(u + e, v)/(u + e) = q(k)/k$.

Employed workers choose whether or not to search on-the-job. Searching provides the chance to switch to a higher productivity job but also incurs a direct cost of search, σ. These two features are traded off in the workers decision to search or not. The value function for searching, superscripted s, in job of productivity θ is:

$$\rho V_E^s(\theta) = w^s(\theta) - \sigma + \lambda \int_\theta (V_E(x) - V_E^s(\theta))dF(x) + \eta(V_U - V_E^s(\theta)) \tag{15}$$

λ is the probability of a new job offer. Only offers from jobs of greater productivity are accepted, i.e. $x > \theta$. Therefore with probability $\lambda(1 - F(\theta))$ on-the-job search results in a job-switch and resulting value change $V_E(X) - V_E^s(\theta)$. As before, a match may be terminated for exogenous reasons with probability η.

[12] Pissarides (2000)

If a workers opts not to search they save the cost σ but lose the opportunity to switch to a better job. The value function, superscripted ns, in such cases is:

$$\rho V_E^{ns}(\theta) = w^{ns}(\theta) + \eta(V_U - V_E^{ns}(\theta)) \tag{16}$$

Workers in job θ will choose to search on-the-job if the benefits of doing so outweigh the costs. The benefit is the expected gain from a new job multiplies by the probability it occurs. The cost constitute the direct search cost σ and any wage differential $w^{ns}(\theta) - w^{s}(\theta)$.[13]

$$\lambda \int_{\theta} (V_E(x) - V_E^{s}(\theta))dF(x) \geq w^{ns}(\theta) - w^{s}(\theta) + \sigma \tag{17}$$

The first order implication of binding minimum wages is the reduction in the value of switching jobs arising from compression in the wage distribution. For jobs with low values of θ, where the minimum wage binds, the current employment value is higher, and the expected gain from a new job is lower. As a consequence we are likely to see fewer job-to-job transitions in particular from low-productivity jobs. Phrased differently, there is concern that minimum wages disrupt the start of the job-ladder model.

Theoretical implication: *Higher minimum wages can reduce the incentive to progress up the job ladder, thereby reducing on-the-job search and job-to-job transitions.*

3 Empirical setting

Following the abolition of the Wage Councils in 1993, no minimum wage legislation existed in the United Kingdom until the introduction of the National Minimum Wage (NMW) in April 1999. A youth rate, applicable to those aged 18-21 was set at 83% of the adult rate and a lower rate for 16-17 year olds was introduced in October 2003. The stratified levels of minimum wages have been updated annually by a small amount, slightly altering the gap between the adult and youth rate overtime as shown in Figure 1.[14] The age categories themselves are adjusted occasionally: on October 2010 the age of eligibility for the adult minimum wage switched from 22 to 21 years old and on 1st April 2016 a fourth age category was added with those aged 25 and over.

[13] In Pissarides (2000), wages are higher for non-searchers than searchers because searching imposes the cost of a potential quit on the firm. Firms observe whether their workers are searching so can adjust the wage to recoup some of this cost.

[14] A separate minimum wage applies to individuals on apprenticeship schemes however this is not shown in the figure.

The United Kingdom collects comprehensive data on search behaviour including search methods, intensity and durations for both on-the-job and unemployed search. These data combine with a unique minimum wage policy structure to provide an advantageous setting in which to test the search theory outlined above.

Two sources of survey data are used in the analysis: the Quarterly Labour Force Survey (QLFS) and the Annual Survey of Hours and Earnings (ASHE). The QLFS is a large survey of households in the UK with detailed demographic, geographic and labour force information on approximately 100,000 individuals each quarter. The labour force data contain information on workers' labour market situation (e.g. employment status and history, wages, occupation) and search behaviour for both unemployed and employed individuals.

A limitation with the QLFS is the accuracy of the wage data arising from individual self-reporting. As a consequence, analysis is supplemented with the Annual Survey of Hours and Earnings (ASHE). The ASHE is a 1% sample of employees totaling around 150-200,000 individuals per year. The data on hours and earnings are employer reported from payroll records and response is compulsory. As a consequence it is deemed to have less measurement error than the QLFS.

3.1 Regression framework

The key empirical question is the impact of minimum wage levels and subsequent adjustment of the wage offer distribution on the three search mechanisms discussed in section 3. To identify the 'treatment effect' of minimum wages, I use difference-in-differences methodology around age-tier policy changes. For a given policy change, the age group facing a new minimum wage age-tier is compared to a suitable control age group, pre- and -post the change.

The bulk of the analysis focuses on the change in the eligibility age for the adult minimum wage from 22 years to 21 years on the 1st October 2010. The minimum wage applicable to 21 year olds jumped nearly 23% from the reduced youth minimum wage rate of £4.83 to the adult rate of £5.93 overnight. In this situation, the 'treatment' group is 21 year olds and the 'control' group used most frequently is 22-23 year olds.[15]

The baseline regression framework follows the familiar difference-in-differences functional form of equation 18.

$$Y_{igt} = \alpha_0 + \alpha_1 G_g + \alpha_2 d_t + \delta(G_g * d_t) + X'_{igt}\beta + \epsilon_{igt} \tag{18}$$

[15]Some attention is paid to the recent introduction of a fourth age tier to those aged 25 and over on 1 April 2016. The minimum wage increased from £6.70 to £7.20 (an increase of around 7.5%) - smaller in financial terms but applicable to a much larger group. Here, those aged 25 and over are the 'treatment' group and those aged 21-24 the most obvious 'control' group.

Y_{igt} is the search outcome of individual i in age-group g at time t. There are two age groups for each policy change: $g \in \{treatment, control\}$. G_g equals one if individual i is in the treatment group ($g =$ treatment) and zero otherwise, d_t equals one if time t is after the policy change and zero if before, and $G_g * d_t$ is an interaction between the two. The difference-in-differences estimate of the treatment effect is the coefficient on the interaction term, δ. Other covariates, X_{igt} can be added in as controls to improve the precision of estimation. If the difference-in-differences strategy is correctly specified controls should not alter the point estimates significantly.

Section 7 addresses in detail potential identification concerns surrounding the framework. In short, the approach passes the general tests (parallel trends, no contemporaneous policies etc) and several setting specific concerns.

4 Descriptive statistics

Tables 1 and A1 and figure 2 present descriptive statistics to give context to the core analysis. Table 1 shows fractions of the sample engaged in various labour market activities. The sample of individuals are those within 24 months of the policy change in October 2010, calculated for both the regression sample (21-23 year olds) and for the general working age population.

The labour market activities are generated from the QLFS. Unemployed refers to the International Labour Organisation definitions: to be unemployed the individuals must be actively seeking work and available to begin work. As a consequence, individuals searching for work but unavailable to work are classified as inactive. Therefore, the related 'Searching' category includes all unemployed individuals and those inactive individuals who are actively seeking work but unable to begin working. 'Not searching' is the remainder of inactive individuals. 'Education' refers to individuals who are inactive as a consequence pursuing educational activities.

Figure 2 presents a kernal density graph of the log hourly wage distribution with vertical lines for 2010 youth and adult minimum wages superimposed, calculated prior to the October adult rate change of that year.[16] The two density peaks around the minimum wage rates clearly show the impact of multiple age tiers on the distribution.

The appendix includes additional descriptives for interested readers. Table A1 discretises the wage distribution into minimum wage categories, which demonstrates that over 10% - i.e. a sizeable fraction - of 21 year olds earn below the adult minimum wage immediately prior to the policy change (where they, by law, must be paid the higher rate). Table A2 presents descriptives on search intensity variables.

[16]These are employer reported weekly wages divided by employer reported paid hours, excluding overtime for both hours and pay, all sourced from the (unweighted) Annual Survey of Hours and Earnings, 2010.

5 Unemployed search results

As discussed in the theoretical section, for minimum wages to have no employment consequences there must be an increase in unemployed search. Therefore, the core analysis begins with estimating the impact of the increased minimum wages on the probability of employment and unemployed search behaviour.

Here, I present regression results for the difference-in-differences methodology applied to the 2010 adult rate age eligibility change. The standard regression equation, as per 18, is:

$$Y_{igt} = \alpha_0 + \alpha_1 Age21 + \alpha_2 Post + \delta(Age21 * Post) + X'_{igt}\beta + \epsilon_{igt} \tag{19}$$

where Y_{igt} is some search outcomes for individual i in age group g at time t, $Age21$ the group dummy and $Post$ the time dummy. Controls X_{igt} vary by the regression and are detailed when used.

The baseline extensive margin search results asks whether non-working 21 year olds switch from not-searching (inactivity) to searching (unemployment) in response to a higher minimum wage. A set of mutually exclusive and exhaustive labour market outcomes - working, unemployed (i.e. searching) and inactive (i.e. not searching) - are constructed. A system of linear probability models, using the difference-in-differences identification, is estimated on the set of labour market outcomes.[17] Errors are clustered at the age-region level to account for non-spherical errors associated with difference-in-differences.[18] I include all individual observations 24 months either side of the policy change (1st October 2010) who are aged between 21 and 23 years of age.

Table 2 presents the baseline unemployed search results for the linear probability system. I control for individuals' sex, region of residence (defined at the NUTS2 level), the quarter of the observation, various measures of educational attainment, marital status, ethnicity and occupation.[19] I also include a variable referred to as 'proxy' which controls for whether the survey was a proxy response by a family member rather than the individual themselves.[20]

The estimated treatment effect for the probability of employment is insignificant

[17] Probit and multivariate logit models are also estimated and produce similar estimates. Given the ease of interpretation, and weaker identification requirements, the paper presents the linear probability versions.Athey and Imbens (2006) discuss the additional error structure assumptions for identification in non-linear difference-in-differences models.

[18] Bertrand et al. (2004). Age is defined in years, region is defined by the NUTS2 level geographic region of residence. This gives 117 clusters.

[19] Table A3 in the appendix presents the results without any controls - reassuringly the inclusion of controls does not change the treatment estimates.

[20] A proxy response is likely to have more measurement error.

and small, implying the higher minimum wage has no measurable impact on the propensity for 21 year olds to be in work. A zero employment consequence result is in line with most of the previous UK minimum wage literature.

Consistent with search theory, we see a corresponding significant increase in unemployed search and a decrease in search inactivity. The result should be interpreted as higher minimum wages encouraging increased extensive margin search for non-working individuals. The increase is in the order of two percentage points from a base of around twelve percentage points (from the descriptive statistics), so is therefore economically significant too.

The analysis is also repeated with two alternative variables measuring extensive margin search. Firstly, I retained the set of three labour force outcomes but redefined searching/unemployed and not searching/inactive as described in 4. Individuals who are searching for work but unavailable to work are reclassified as 'searching.' The results are unchanged. Selected tables are displayed in the appendix. Secondly, I use an entirely separate variable from the Quarterly Labour Force Survey that asks individuals, under a different question, whether they have been searching for work at any point in the last four weeks. Again, the results find an increase in extensive margin search in response to the minimum wage.

An amount of analysis was undertaken to test if the treatment estimates varied by educational attainment and region of residence. One would expect minimum wage policy to impact less educated groups more strongly than highly educated groups. One might also expect estimated impacts of minimum wages to be higher in low wage areas, where the minimum wage is more locally binding. By stratifying the sample on education and regional income levels, it was found that low education individuals are driving the baseline results for unemployed search. Put differently low educated workers appear far more impacted by the minimum wage than their highly educated counterparts. The results however did not vary by local median wages.

I also re-ran the analysis for the high profile 2016 introduction of the National Living Wage - effectively a higher minimum wage for those aged 25 and over. As discussed above in the introduction, the initial was only 7.5% although policy guidance suggests this may increase. A similar difference-in-differences analysis was undertaken around this age change and baseline results are displayed in the appendix. Only three calender quarters of data are available since March 2016, at present. To boost the sample size, 25-28 year olds are considered the 'treatment' group and 22-24 year olds the 'control' group. For no functional forms or outcome variables are significant treatment estimates obtained. I am unable to uncover any measurable impact of the policy change on these outcomes to date.

5.1 Unemployed search intensity

The above results suggest a robust increase in the number of unemployed searchers in response to the higher minimum wage for 21 year olds in 2010. The next question is to ask how this impacted on the search effort exerted by unemployed searchers.

'Effort' by its very nature is a rather intangible concept. Using the Quarterly Labour Force Survey search data, I have constructed what can be thought of as noisy measures of an individual's search effort. These are available for both unemployed job seekers and employed job seekers, searching on-the-job.

In the QLFS, individuals who have already acknowledged that they are seeking a job then list off the primary and secondary methods by which they seek a job. Fourteen different search methods are included in the tabulated results, including 'Visit a Jobcentre', 'Study situations vacant', 'Ask friends, relatives, colleagues' and 'On books at a private employment agency.' Individuals indicate their main search method followed, in decreasing order, by any other search methods they use.

The first summary measure of 'search effort' is a simple count of the number of methods an individual uses to search. The logic is that if an individual indicates that they are searching using multiple methods, they are likely to be investing more effort than if only searching with a single measure.

The majority of respondents (90%) only acknowledge one search method and there is a long tail of respondents acknowledging many search methods. In response, the second summary measure is simply a binary variable equal to one if the individual acknowledges more than one method.

The third measure categories the level of effort based on the main method acknowledged. Many of the options can be deemed 'low commitment', or passive, search methods such as 'On books of private employment agency,' 'Wait for results of application.' Others are more likely to require considerable effort exertion and can therefore be considered active search methods. For example 'Answer job advertisements,' 'Apply directly to employers.' All fourteen answers were categorised as either passive or active, with the full list in the appendix. A binary variable was created that equals one if the main search method used is active, and zero if passive.[21]

I begin by investigating the response of unemployed search intensity to the 2010 minimum wage change. Again, the baseline difference-in-differences method is used and those aged 21-23 years old and surveyed 24 months either side of the policy

[21] In response to possible concerns that measure three construction contains too much subjectivity, a fourth measure is also utilised. I regress the time spent searching for a job on the search methods used and suitable controls. More effective search methods can then be objectively identified as the ones associated with the shortest search time, ceteris paribus. Intuitively, we would expect higher effort to be associated with more rapid job finding and thus I use this fourth measure accordingly. The analysis has not yet been released into the public domain and so cannot be discussed at present.

comprise the core sample.

Tables 3 presents the initial results by estimating whether unemployed job-seekers search more intensely in response to the minimum wage change. Column one is the classic linear probability model using the binary variable 'Active' described above: 1 indicates the individual searches actively, 0 indicates the individual searches passively. The treatment effect point estimate is negative but insignificant. Column two presents another linear probability model: this time outcome Y equals one if the individual reports search using multiple methods and zero if only a single method is used. A negative and weakly significant point estimate is found. Columns three and four use the actual number of search methods reported, estimating the model with standard OLS and maximum likelihood Poisson respectively. Given the count data nature of the variable, column four is likely a better specification. Column four again finds negative and weakly significant treatment estimates.

Table 3 only includes those already searching for a job and thus is potentially susceptible to selection bias. As presented above, many individuals select into searching, from not searching, following the minimum wage change and this should be taken into account. In response, 4 present Heckman selection corrected regressions. First, a probit regression is run (entitled 'selection equation') to that equals 1 if non-working individuals select into searching. Consistent with the extensive margin search results, a significant treatment effect is estimated in the selection equation. The fitted selection equation then enters the second stage, intensive margin regression for search intensity. As is common place with Heckman selection models, an exclusion restriction is used: the variable 'Student' is included in the selection equation but not the intensive margin equation. It seems realistic that full time studying should impact on an individual's decision to search or not, but perhaps less so on how hard they search once deciding to search.

The same results are found when correcting for selection. Negative point estimates are found all around, but these are only significant for the second column: the binary variable for using multiple search methods or not. The significance of the mills lambda estimates suggests that selection is an important part of the regression fit, however excluding it does not appear to cause bias for any outcome variable investigated.

Tables A7 and A8, in the appendix, repeat the above regressions on stratifications of the sample by education and regional income. As for the extensive margin results, it appears that the negative treatment estimates are driven by low education individuals. Highly educated individuals do not have any significant treatment estimates, and the point estimates are sometimes positive. Again, no major differences between richer and poorer regions are uncovered.

5.2 Unemployed search duration

So far, the results have presented evidence of significant increases in the number of unemployed searchers and some weak evidence of decrease average search effort. I now turn to the duration of unemployed job seeking.

Tables 5 and 6 present the standard difference-in-differences regressions for self-reported unemployed job seeking durations. The data is self-reported, job-seeking information from the Quarterly Labour Force Survey. Responses are provided at the point of the survey, not at the point of finding a job, therefore the seeking is ongoing. Unfortunately, respondents are grouped into discrete time categories such as "less than one month" and "between one and three months" rather than reporting precise durations. The mid-point of each time category is taken as the estimated time spent searching for each individual respondent. Two outcome variables are used in separate instances: one is the self-reported unemployment duration (as, by definition, unemployment must involve job-seeking) which is referred to as TimeA. Respondents are separately asked how long they have been searching for a job, and this outcome variable is referred to as TimeB. TimeB is generally shorter than TimeA. Reassuringly, both responses give qualitatively identical results.

Table 5 presents pure linear regressions of the expected time spent job-seeking while Table 6 formally corrects for those selecting into searching. Significant, positive treatment estimates are found for both the selection equation (implying more individuals search in response to the higher minimum wage: consistent with previous findings) and the intensive margin duration equation. More individuals may be searching, but on average they are searching for longer. When stratified on education level (in the appendix), again the duration results appear to be mostly driven by low education individuals. Again, none of the intensive margin treatment estimates appear biased by the exclusion of a selection correction - all regressions were run with and without selection correction and no significant differences were uncovered.

5.3 Relating the unemployed search results to theory

To summarise and relate back to the search theory implications: the results have found no change in the probability of employment and the required corresponding increases in unemployed searchers. In this situation, it appears that minimum wages increase the value of unemployed searching and the corresponding increase in unemployed searchers prevents employment destruction. There is some evidence of decreased average intensity, which if robust, suggests that the congestion externality of more searchers dominates the direct effect of higher wages. Overall, the returns to search effort appear to have decreased.

Consistent with more searchers (congestion) and potentially lower search effort, the duration of unemployed search increases.

6 On-the-job search

As discussed in the theory section, search and matching models of job ladders would suggest that minimum wages may disrupt on-the-job search, and hence the job ladder, by weakening incentives to progress to higher productivity matches.

To test this theoretical implication, as before, I use a difference-in-differences identification strategy around the policy change. An individual is categorised as searching on the job if they answer affirmatively to whether or not they are looking for an additional paid job or business. If they are, they then clarify whether it is to be an additional job or a replacement job for their current position. The vast majority of respondents are looking for a replacement job - consistent with a job ladder model.

Table 7 presents baseline results linear probability models for the estimated treatment effect of the 2010 policy change on the propensity to search on the job. Columns 1 & 2 use a dependent variable Y_{igt} that refers to the default measure of on-the-job search, labelled OJS. This equals one if the individual is undertaking any form of on-the-job search. Column 3 investigates whether those individuals already searching are more likely to search for a replacement job versus an additional job following the policy change. There, 'Replace' equals one if the job they are searching for is intended to replace their existing one and zero if it is in addition to their existing job. Finally, column 4 redefines on-the-job search as only occurring if the individual is looking for a replacement job and zero if the are either not searching, or searching for an additional job. This brings the definition more in line with the notion of a job-ladder. As can be observed, all estimated treatment effects are not statistically distinguishable from zero.

Similar to the unemployed search analysis, I further investigate whether the estimated treatment effects vary by sub-populations. I interact the treatment term with educational attainment, and split the sample into high and low educated individuals, as shown in table A11 in the appendix. There is no statistical difference in the estimated treatment effects, either in the split sample or the interaction term regressions. I also test to see whether the estimated treatment effect varies by regional wages. These results are presented in appendix tables A12 and A13. Again, the answer appears to be that all regions have statistical zero estimated treatment effects.

In short, no evidence of causal impact of minimum wages on on-the-job search is uncovered, either overall or in any sub-population. It appears that, at least in this setting, higher minimum wages do not disincentivise individuals to progress up the job ladder - no significant impact on the intent to change jobs can be uncovered.

6.1 On-the-job search intensity

Despite not finding evidence that minimum wage changes impact on employed individuals' propensity to search on the job, there is a possibility that search effort changes for those already searching. Tables 8 and 9 repeat the search intensity analysis for those individuals employed and potentially searching on-the-job. The same search measures are used and, again, a mixture of regressions that include only those already searching (ignoring selection) and those that deal with selection are presented. The sample is stratified along education and regional income lines. Nowhere do I find a significant treatment estimate of minimum wages for on-the-job search intensity. It appears that any adjustment is again restricted to unemployed job seekers.

6.2 On-the-job search durations

Tables 10 and 11 repeat the durations analysis for on-the-job search durations. Only one outcome variable is available; the self-reported duration of search, equivalent to TimeB in the unemployed job-seeking analysis. No statistically significant effects are found either on the intensive or extensive margin. Again this is fully consistent with earlier on-the-job search results.

6.3 Relating on-the-job search results to theory

Interestingly, for no search outcome - probability of searching, search effort or duration of searching - do the results estimate significant impacts of minimum wages. A statistically negative result such as this is important in its own right. It should be interpreted as there being no measurable impact of minimum wages on a worker's desire to transition jobs. Here, at least, it appears that concerns over higher minimum wages incentivising individuals to remain in low productivity jobs are not substantiated.

7 Robustness checks

As for any difference-in-differences identification strategy, the underlying assumptions are tested where possible. I test the common trends identification requirement by looking for statistically significant differences in time trends between treatment and control groups prior to the policy change. I do this in a number of ways. Firstly, I regress outcomes of interest on an intercept, the treatment dummy, a collection of time dummies d_t and those time dummies interacted with the treatment group, $d_t * G_g$. Significant coefficients on the interaction terms, $\alpha_{2,\tau}$, leading up to the policy change would indicate that the treatment and control groups were diverging prior, a likely violation of the common trends assumption.

To formalise, for each outcome variable of interest, the following regression was run for 21-23 year olds, our sample of interest:

$$Y_{igt} = \alpha_0 + \alpha_1 Age21 + \sum_{\tau=-T}^{T} \beta_\tau d_\tau + \sum_{\tau=-T}^{T} \gamma_\tau (Age21 * d_\tau) + \epsilon_{igt} \tag{20}$$

These were undertaken for both annual time dummies and quarterly time dummies. When it came to quarterly regressions, seasonal fixed effects had to be taken into account. [22] Once quarterly fixed effects were included, no significant interaction terms were uncovered in the four years leading up to the policy change when all the primary outcome variables (detailed below) were tested. From five years prior, there was some measured minimal divergence which is not overly surprising given the time lag.

Analysis also checked for diverging parametric time trends by fitting separate linear and quadratic time trends for the treatment and control group. Once controlling for group fixed effects, again no statistically significant differences were uncovered in the four years leading up to the policy change.

As a further robustness check, placebo difference-in-differences regressions were run on data at alternative time periods. False interventions were generated for various time periods within a four year range either side of the true policy intervention (ensuring that the true policy intervention was not captured). None of the false interventions generated significant treatment estimates.

I was also able to test for observable composition changes in the treatment and control groups that might conflate demographic change with the policy intervention. Difference-in-differences regressions were run were with the outcome being various observable group characteristics e.g. ethnicity, gender, geographic location, educational attainment. None were found to have significant, diverging results between the treatment and control groups, which is an encouraging result. By definition, there is no way of testing changes in unobservable characteristics that may influence labour force outcomes. As I am comparing 21-23 year olds - a very narrow demographic band in the population - it seems reasonable to assume that a major unobservable change differentially affecting one group is unlikely.

There are a couple of other considerations for identification. One must be sure that the control group of 22-23 year olds is indeed a control group - they cannot be impacted by the treatment. I considered this in detail by using difference-in-differences methodology with 22-23 year olds as the treatment group, and various sets of other age groups as the relative controls. Under no specifications were significant treatment estimates on 22-23 year olds measured.

[22] More 21 year olds are in full time education than 22-23 year olds and thus significant differences in time dummies for each summer quarter (during summer break) were uncovered.

Nonetheless I also varied the age of the control group used, out of concern that 22-23 year olds might still be impacted. The results were robust to using any control group of twenty-something year olds.

In this particular setting, the treatment and impact on the results of students may be of concern. Many 21 year olds are still in formal education and the baseline results exclude labour force inactive students from the sample. To assuage concerns that this decision impacts on the results, all regressions were run including students into the analysis. For no outcome did the results change quantitatively meaningfully. Combined with the earlier findings that the results are driven by less educated individuals - i.e. those with no post-school education - this should reassure those with concerns.

Finally, there is always concern that the estimated results should instead be attributed to a concurrent policy change. I was unable to find any relevant policy change around the 2010 mark that affected 21 year olds differentially to 22-23 year olds. The majority of other age discontinuities in labour market policies kick in at 18 or 25 years old. No other policy impacts were found differentially affecting 21 year olds compared to 22-23 year olds.

As a matter of functional form robustness, all linear probability models were also run as non-linear probit and/or multivariate logit models. This did not qualitatively change the results but, naturally, decreased the ease of estimate interpretation.

8 Conclusion

Taken together, the analysis finds robust responses to minimum wages for unemployed searchers. There is a shift from inactivity (no search) towards labour force participation, specifically unemployed searching, in response to the 23% boost in minimum wages of 21 year olds in 2010. Broadly consistent with most UK research, the rise appears to have no significant impact on employment rates. The increased extensive margin search is accompanied by a corresponding increase in the average duration of unemployed search.

Surprisingly, I also find weak evidence of a decrease in average search effort for unemployed searchers. This has three potential explanations. Firstly, decreased average search effort could be due to a composition effect: marginal searchers switching into searching at a low intensity drag the average down. Alternatively, the increase in extensive search generates a congestion externality on existing searchers which in turn may decrease in their search effort. Thirdly, search intensity may play a valuable role in assisting workers to find their optimal job match. Minimum wages that increase wages for the lowest paying jobs may decrease the returns to an optimal match from the worker's point of view, discouraging costly search effort. In short, minimum wages may create an 'any job will do' mentality, reducing match qualities. Each of these three explanations has significant ramifications for labour markets, and merit further consideration.

In contrast to the unemployed search margins, no significant impacts on any measures of on-the-job search are found. No change in the propensity to search, effort of searching or duration of searching is estimated. It appears that, at least in this setting, minimum wage increases do not impact on worker's intentions to progress up the job ladder, assuaging a possible concern that minimum wage policies incentivise individuals to remain in low productivity jobs.

9 Tables and figures

Figure 1: United Kingdom Minimum Wage policy structure

	Age 25+	Age 21-24	Age 18-20	Age 16-17	% difference between youth and adult
1 April 2016	£7.20	£6.70	£5.30	£3.87	
	Age 21+		Age 18-20	Age 16-17	
1 October 2015	£6.70		£5.30	£3.87	26.4%
1 October 2014	£6.50		£5.13	£3.79	26.7%
1 October 2013	£6.31		£5.03	£3.72	25.4%
1 October 2012	£6.19		£4.98	£3.68	24.3%
1 October 2011	£6.08		£4.98	£3.68	22.1%
1 October 2010	£5.93		£4.92	£3.64	20.5%
	Age 22+		Age 18-21	Age 16-17	
1 October 2009	£5.80		£4.83	£3.57	20.1%
1 October 2008	£5.73		£4.70	£3.53	21.9%
1 October 2007	£5.52		£4.60	£3.53	20.0%
1 October 2006	£5.35		£4.45	£3.40	20.2%
1 October 2005	£5.05		£4.25	£3.00	18.8%
1 October 2004	£4.85		£4.10	£3.00	18.3%
1 October 2003	£4.50		£3.80	£3.00	18.4%
1 October 2002	£4.20		£3.50	-	20.0%
1 October 2001	£4.10		£3.50	-	17.1%
1 October 2000	£3.70		£3.20	-	15.6%
1 April 1999	£3.60		£3.00	-	20.0%

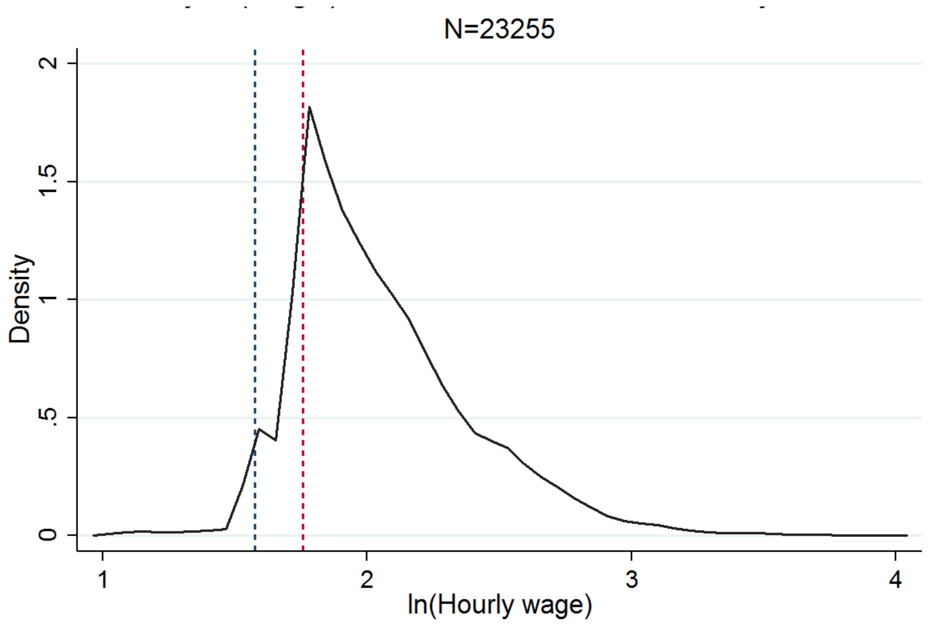
Source: Low Pay Commission

Table 1: Descriptive statistics

	21-23 year olds		16-64 year olds	
	%	N	%	N
Working	62.68	33,459	69.96	753,728
Unemployed	11.91	6,358	5.73	61,732
Student	14.32	7,645	5.47	58,918
Inactive	11.09	5,919	18.84	203,030
Total	100	53381	100	1,077,408
Not working: Searching	13.29	7,094	6.40	68,961
Not working: Not searching	10.44	5,574	18.45	198,829
Of those working:				
No on-the-job search	86.39	28,953	93.52	705,340
On-the-job search	13.61	4,561	6.48	48,848
Of those searching on the job:				
Want a replacement job	87.69	3,966	83.74	40,468
Want an additional job	12.31	557	16.26	7,855

Table presents sample percentages and counts of individuals within 24months of Oct 2010. Working, unemployed, student and inactive are mutually exclusive and exhaustive categories. Searching and Not Searching have slight definitional changes from Unemployed and Inactive. Source: Quarterly labour force survey: Secure Access.

Figure 2: Log(wage) distribution for 18-25 year olds



Kernel density plot of log hourly wage, excluding overtime. The blue and red vertical bars represent youth and adult minimum wage rates respectively. Source: ASHE 2010

Table 2: Baseline non-employed search, extensive margin results, 2010 minimum wage change

	(1) Working	(2) Unemployed	(3) Inactive
Post	-0.0222***	0.0110**	0.0112**
	(0.00588)	(0.00429)	(0.00438)
Age 21	-0.0327***	0.0269***	0.00588
	(0.00788)	(0.00602)	(0.00527)
Post*Age 21	-0.00403	0.0205**	-0.0164**
	(0.0110)	(0.00835)	(0.00744)
Constant	0.607***	0.207***	0.185***
	(0.0296)	(0.0151)	(0.0216)
Observations	45736	45736	45736
Controls	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Unemployed search intensity, 2010 minimum wage change

	(1)	(2)	(3)	(4)
Outcome:	Active	>1 methods	# methods	# methods
Estimation:	OLS	OLS	OLS	Poisson
Post	-0.0451***	0.0101	0.0292	0.0192
	(0.0153)	(0.00907)	(0.0476)	(0.0261)
Age 21	0.0298*	0.00911	0.0394	0.0267
	(0.0175)	(0.0104)	(0.0546)	(0.0299)
Post*Age 21	-0.0168	-0.0262*	-0.112	-0.0789*
	(0.0242)	(0.0144)	(0.0754)	(0.0416)
Constant	0.643***	0.234***	2.120***	0.838***
	(0.0592)	(0.0352)	(0.185)	(0.100)
Observations	6990	6990	6990	6990
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are not in work and are searching for a job. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Unemployed search intensity, 2010 minimum wage change - correcting for selection

	(1)	(2)	(3)
Outcome:	Active	>1 methods	# methods
Post	-0.0441***	0.00983	0.0237
	(0.0151)	(0.00896)	(0.0474)
Age 21	0.0299*	0.00750	0.0368
	(0.0173)	(0.0103)	(0.0545)
Post*Age 21	-0.0202	-0.0272*	-0.125*
	(0.0240)	(0.0142)	(0.0753)
Constant	0.668***	0.259***	2.291***
	(0.0597)	(0.0353)	(0.188)
Select eq.			
Post	0.0324	0.0324	0.0344
	(0.0277)	(0.0277)	(0.0278)
Age 21	0.0964***	0.0964***	0.0861***
	(0.0317)	(0.0317)	(0.0318)
Post*Age 21	0.0755*	0.0755*	0.0946**
	(0.0443)	(0.0443)	(0.0444)
Constant	0.115	0.115	0.0737
	(0.102)	(0.102)	(0.103)
Lambda	-0.0575***	-0.0371***	-0.230***
	(0.0169)	(0.0100)	(0.0527)
Observations	19922	19922	19922
Controls	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are not in work. The selection equation includes all controls and treatment variables alongside a variable for studying - the exclusion restriction. Heckman selection model estimated by two-step maximum likelihood. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Length of time searching for a job, unemployed searchers, 2010 minimum wage change

	(1) TimeA	(2) TimeA	(3) TimeB	(4) TimeB
Post	0.895	1.418**	1.265*	1.841**
	(0.703)	(0.704)	(0.714)	(0.724)
Age 21	-1.329*	-1.518**	-1.384*	-1.609**
	(0.727)	(0.616)	(0.738)	(0.632)
Post*Age 21	2.985***	2.529**	2.861***	2.394**
	(1.031)	(0.977)	(1.058)	(1.007)
Constant	[Witheld]	19.14***	[Witheld]	20.86***
		(1.875)		(2.229)
Observations	5096	5096	5087	5087
Controls	No	Yes	No	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. TimeA is unemployment searching duration, TimeB is job-seeking duration, both self-reported. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity, occupation.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Length of time searching for a job, unemployed searchers, 2010 minimum wage change - selection correction

	(1)	(2)	(3)	(4)
Outcome:	TimeA	TimeA	TimeB	TimeB
Post	3.064***	1.362*	1.275**	1.587***
	(0.547)	(0.699)	(0.565)	(0.562)
Age 21	-0.188	-1.539**	-1.340**	-1.261**
	(0.728)	(0.611)	(0.666)	(0.516)
Post*Age 21	2.905***	2.504**	2.335***	1.848**
	(0.921)	(0.974)	(0.867)	(0.839)
Constant	[Witheld]	19.43***	[Witheld]	21.85***
		(1.919)		(1.775)
Selection eq.				
Post	0.169***	0.225***	0.0330	0.0199
	(0.0277)	(0.0329)	(0.0325)	(0.0322)
Age 21	0.00249	0.0664*	0.0667	0.0660*
	(0.0378)	(0.0387)	(0.0439)	(0.0379)
Post*Age 21	0.188***	0.168***	0.102**	0.122**
	(0.0475)	(0.0559)	(0.0476)	(0.0497)
Constant	[Witheld]	0.355***	[Witheld]	0.168*
		(0.0985)		(0.0918)
athrho				
Constant	2.951***	-0.0368	-0.149***	-0.0566***
	(0.185)	(0.0293)	(0.0203)	(0.0207)
lnsigma				
Constant	2.923***	2.588***	2.641***	2.564***
	(0.0248)	(0.0251)	(0.0257)	(0.0250)
Observations	19922	19922	19922	19922
Controls	No	Yes	No	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity and occupation. TimeA refers to self-reported unemployment searching duration. TimeB is a separate self-reported measure of time spent job-seeking.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Baseline OJS

	(1) OJS	(2) OJS	(3) Replace	(4) Replace	(5) Replace
Post	0.0237***	0.0208***	0.0235***	0.0205***	0.0196
	(0.00593)	(0.00582)	(0.00473)	(0.00465)	(0.0139)
Age 21	-0.00615	-0.00456	-0.00963	-0.00765	-0.0239
	(0.00835)	(0.00783)	(0.00720)	(0.00669)	(0.0191)
Post*Age 21	0.00488	0.00576	0.00387	0.00426	-0.00864
	(0.0122)	(0.0123)	(0.0103)	(0.0104)	(0.0240)
Constant	[Witheld]	0.187**	[Witheld]	0.201**	0.993***
		(0.0933)		(0.0927)	(0.0582)
Observations	33392	33392	33354	33354	4488
Controls	No	Yes	No	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change who are in work. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity and occupation. Columns 1-2 are LPM with the dependent variable equal to one if an individual is searching for any job. Columns 3-4 are LPMs for an individual searching for a replacement job. Column 5 is, of those searching for a job, the likelihood of searching for a replacement job not an additional job.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: OJS search intensity

	(1) Active OLS	(2) >1 methods OLS	(3) # methods OLS	(4) # methods Poisson
Post	-0.0392**	-0.00326	-0.0647*	-0.0534
	(0.0161)	(0.00898)	(0.0372)	(0.0335)
Age 21	0.0317	0.00675	-0.00420	-0.00388
	(0.0210)	(0.0118)	(0.0487)	(0.0434)
Post*Age 21	-0.0161	0.00138	0.0903	0.0736
	(0.0287)	(0.0160)	(0.0664)	(0.0592)
Constant	0.333**	0.230***	1.643***	0.519*
	(0.132)	(0.0736)	(0.305)	(0.272)
Observations	4529	4529	4529	4529
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are in work and are searching for a new job. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: OJS search intensity - correcting for selection

	(1) Active	(2) >1 methods	(3) # methods
Post	-0.0256	-0.0186	0.143
	(0.0720)	(0.0405)	(0.202)
Age 21	0.0287	0.0101	-0.0501
	(0.0262)	(0.0151)	(0.0891)
Post*Age 21	-0.0123	-0.00283	0.147
	(0.0347)	(0.0201)	(0.121)
Constant	0.0655	0.531	-2.432
	(1.382)	(0.775)	(3.782)
Selection eq.			
Post	0.103***	0.103***	0.103***
	(0.0220)	(0.0220)	(0.0220)
Age 21	-0.0231	-0.0231	-0.0231
	(0.0277)	(0.0277)	(0.0277)
Post*Age 21	0.0274	0.0274	0.0274
	(0.0387)	(0.0387)	(0.0387)
Constant	-1.088***	-1.088***	-1.088***
	(0.196)	(0.196)	(0.196)
Lambda	0.167	-0.188	2.540
	(0.857)	(0.480)	(2.332)
Observations	33459	33459	33459
Controls	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are in work. The selection equation includes all controls and treatment variables. Heckman selection model estimated by two-step maximum likelihood. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Length of time searching for a job - OJS

	Baseline		By education		By regions	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Low	High	Poor	Rich
Post	1.745***	1.806***	1.892***	1.457***	1.987***	1.371**
	(0.399)	(0.395)	(0.601)	(0.475)	(0.624)	(0.574)
Age 21	-0.764*	-1.292***	-1.044*	-1.942***	-1.540***	-1.112*
	(0.441)	(0.381)	(0.539)	(0.590)	(0.532)	(0.578)
Post*Age 21	-0.721	-0.455	-0.383	-0.444	-0.329	-0.727
	(0.599)	(0.573)	(0.779)	(0.965)	(0.839)	(0.870)
Constant	[Witheld]	18.82***	26.47***	6.267***	28.73***	8.915***
		(5.078)	(7.101)	(1.916)	(8.367)	(2.447)
Observations	4503	4503	2584	1891	2206	2090
Controls	No	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. TimeA is unemployment searching duration, TimeB is job-seeking duration, both self-reported. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity, occupation. Columns include 1-2 all individuals, 3-4 split the sample by educational attainment, 5-6 by regional income.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Length of time searching for a job - OJS, selection correction

	Baseline		By education		By regions	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Low	High	Poor	Rich
Post	2.111***	-1.613	-9.262	2.681	-1.827	-1.223
	(0.332)	(3.375)	(37.17)	(2.060)	(5.016)	(4.331)
Age 21	-0.866*	-0.522	-3.555	-3.502	-2.431	3.047
	(0.457)	(1.577)	(9.820)	(2.676)	(2.103)	(6.717)
Post*Age 21	-0.641	-1.378	-2.366	-0.371	-0.527	-4.403
	(0.631)	(2.128)	(9.868)	(1.283)	(2.435)	(6.501)
Constant	[Witheld]	89.66	212.8	-12.80	88.65	78.54
		(66.39)	(616.1)	(31.10)	(76.17)	(105.2)
Selection eq.						
Post	0.111***	0.0946***	0.0955***	0.108***	0.122***	0.0600*
	(0.0206)	(0.0216)	(0.0281)	(0.0346)	(0.0312)	(0.0313)
Age 21	-0.0308	-0.0216	0.0212	-0.133**	0.0277	-0.0968**
	(0.0267)	(0.0278)	(0.0327)	(0.0554)	(0.0402)	(0.0406)
Post*Age 21	0.0238	0.0249	0.0181	0.00181	0.00492	0.0859
	(0.0377)	(0.0388)	(0.0461)	(0.0782)	(0.0556)	(0.0571)
Constant	[Witheld]	-1.030***	-0.718***	-0.618*	-0.981***	-0.690***
		(0.194)	(0.262)	(0.357)	(0.285)	(0.256)
Lambda	4.067***	-45.41	-142.1	15.13	-39.59	-53.72
	(0.150)	(42.11)	(469.0)	(24.26)	(49.66)	(80.42)
Observations	33459	33459	23593	9482	15814	15677
Controls	No	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are in work. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity and occupation. TimeA refers to self-reported unemployment searching duration. Model is a Heckman selection model estimated by two-step maximum likelihood.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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10 Appendix

10.1 Classifying active versus passive search

Active measures

1. Visit a Job Centre
2. Visit a Careers Office
3. Visit a Jobclub
4. Advertise in newspapers or journals
5. Answer job advertisements
6. Apply directly to employers
7. Look for premises or equipment (self-employment)
8. Seek any kind of permit (self-employment)
9. Try to get a loan or other financial backing (self-employment)

Passive measures

1. On books of a private employment agency
2. Study situations vacant in newspaper or journals (but not answer)
3. Wait for results of application for job
4. Ask friends, relative, colleagues or unions
5. Do anything else to find work

10.2 Additional descriptive statistics

Table A1: Position in the wage distribution, 2010, prior to minimum wage change

	Age	21	21-23	18-25	16-64
Below	%	0.66	0.75	1.43	0.91
	N	18	68	334	1,547
Youth Spike	%	2.62	0.87	2.96	0.53
	N	71	79	691	898
Between	%	7.24	2.85	5.34	1.29
	N	196	259	1,249	2,197
Adult Spike	%	11.08	10.78	10.03	4.34
	N	300	979	2,344	7,396
Above	%	78.39	84.75	80.24	92.94
	N	2,122	7,697	18,750	158,534
Total	%	100	100	100	100
	N	2,707	9,082	23,368	170,572

Table discretises the wage distribution into five groups: those earning below the youth minimum wage, those earning within ±2% of youth minimum wage, those earning between 2% above youth minimum wage to 2% below adult minimum wage, those earning within ±2% of adult minimum wage and those earning more than 2% above adult minimum wage. Sample: individuals within 24 months of Oct 2010. Spike means earning within 2% of respective minimum wage. Source: ASHE 2010.

Table A2: Descriptive statistics for search intensity

		Type of Searching		No. methods	
		Passive	Active	1	2-14
Unemployed search	N	3,963	3,105	6,410	658
	%	56.07	43.93	90.69	9.31
OJS	N	3,362	1,167	4,232	297
	%	74.23	25.77	93.44	6.56
Total	N	7,325	4,272	10,642	955
	%	63.16	36.84	91.77	8.23

Sample: 21-23 year olds, 24 months either side of policy, searching for a job

10.3 Additional results for non-employed search

Table A3 includes students in the regressions an has no controls. To meet statistical disclosure requirements of the UK Data Service, the constant is withheld.

Table A3: Baseline non-employed search extensive margin - no controls, including students

	(1) Working	(2) Unemployed	(3) Inactive	(4) Student
Post	-0.0114*	0.00736*	0.00807*	-0.00402
	(0.00675)	(0.00395)	(0.00439)	(0.00456)
Age 21	-0.0877***	0.00798	-0.00784	0.0876***
	(0.0180)	(0.00637)	(0.00591)	(0.0148)
Post*Age 21	-0.0144	0.0153**	-0.0142**	0.0133
	(0.0127)	(0.00708)	(0.00644)	(0.00927)
Constant	[Witheld]			
Observations	53381	53381	53381	53381
Controls	No	No	No	No

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

An amount of analysis was undertaken to test if the treatment estimates varied by educational attainment and region of residence. One would expect minimum wage policy to impact less educated groups more strongly than highly educated groups. Individuals were classified as high-education or low-education using QLFS information on their highest qualification. A variety of different definitions were constructed for robustness checking and all gave broadly the same results. The results presented here define low education as individuals with a highest qualification of A-level and equivalent or below and no post-school education. High education is considered to be individuals with any post-school education (i.e. above A level).

Two main approaches for testing for differential treatment estimates were used. Firstly, educational attainment was interacted with the treatment interaction term (with the education variable also included as a first order effect) using the whole sample of 21-23 year olds. Secondly, the sample was stratified into high and low education individuals and separate difference-in-differences regressions were run. Both methods gave the same story: the headline results appear to be driven by low education individuals. No statistically significant treatment effects are estimated for highly educated individuals. The second approach, using split samples, is more easily interpretable and so is shown here in Table A4.

A second additional formulation brings geography into the equation - one would expect the same minimum wage to have more significant consequences in a low wage area relative to a high wage area. The QLFS and ASHE both include numerous geographic classifications. Two sets of geographic delineations are used here: travelto-work-areas (TTWAs), commonly considered the best measure of a local labour market in the UK, and NUTS Level 2 (Nomenclature of Units for Territorial Statistics).[23] For a given set of geographical classifications, the ASHE is used to calculate the mean and median regional hourly income.[24] The local Kaitz index - the adult minimum wage divided by local average hourly wage - is calculated for each region.

Geographic variation is used in two ways, similar to the education investigation above. Firstly, I interact the local Kaitz index with the treatment interaction term ($Treatment * Age21$) and include the relevant first order effect separately. Secondly, I stratify the sample into those individuals living in below average income areas and those in above average income areas. Both approaches give the same results: no statistically significant differences in treatment effects are estimated based on regional income.

I have stratified the analysis by males and females. A large literature demonstrates that females are disproportionately affected by minimum wages and also have a greater elasticity of labour supply. A larger extensive margin search response to minimum wages for females than males would be consistent with these narratives. Unfortunately, the analysis has not yet been released into the public domain by the UK Dataservice, and so cannot be discussed at present.

[23] TTWAs are defined as: at least 75% of the area's resident workforce work in the area, and at least 75% of the people who work in the area also live in the area. There are over 200 TTWAs and some contain very small numbers of sampled individuals. As a consequence, the ASHE calculates average income with a non-negligible degree of sampling error in the small TTWAs, introducing noise into the estimates. In response, I also use a second, larger geographic definition, NUTS2. NUTS2 categorises the UK into 39 separate regions in 2010 (6 for Scotland, 2 for Wales, 1 for Northern Ireland and 30 for England).

[24] Two measures of hourly income are used: all paid income divided by paid hours worked excluding overtime and all paid income divided by hours worked including overtime.

Table A4: Unemployed search, extensive margin - by education levels

	Low education individuals			High education individuals		
	(1)	(2)	(3)	(4)	(5)	(6)
	Working	Unemp	Inactive	Working	Unemp	Inactive
Post	-0.0263***	0.0129**	0.0134**	-0.00241	0.00136	0.00105
	(0.00847)	(0.00564)	(0.00620)	(0.00913)	(0.00750)	(0.00748)
Age 21	-0.0144	0.0150**	-0.000604	-0.0733***	0.0627***	0.0107
	(0.00983)	(0.00690)	(0.00707)	(0.0163)	(0.0138)	(0.00906)
Post*Age 21	0.00239	0.0189*	-0.0213**	-0.0139	0.0208	-0.00690
	(0.0131)	(0.00976)	(0.00954)	(0.0220)	(0.0211)	(0.0143)
Constant	0.704***	0.193***	0.103***	0.737***	0.178***	0.0849***
	(0.0383)	(0.0179)	(0.0283)	(0.0318)	(0.0265)	(0.0189)
Observations	33463	33463	33463	11685	11685	11685
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change split by educational attainment. Columns 1-3 are for low education individuals, columns 4-6 for high education individuals. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Extensive margin search results - NUTS2 regions split by income

	—— Poorer regions ——			—— Richer regions ——		
	(1)	(2)	(3)	(4)	(5)	(6)
	Working	Unemp	Inactive	Working	Unemp	Inactive
Post	-0.0218**	0.00658	0.0152**	-0.0210**	0.0148**	0.00620
	(0.00878)	(0.00578)	(0.00656)	(0.00847)	(0.00660)	(0.00627)
Age 21	-0.0435***	0.0304***	0.0131*	-0.0180*	0.0226**	-0.00455
	(0.0113)	(0.00833)	(0.00780)	(0.0105)	(0.00910)	(0.00658)
Post*Age 21	0.00508	0.0177	-0.0228**	-0.0145	0.0224*	-0.00792
	(0.0139)	(0.0114)	(0.0105)	(0.0174)	(0.0127)	(0.0108)
Constant	0.572***	0.236***	0.192***	0.596***	0.174***	0.230***
	(0.0253)	(0.0149)	(0.0207)	(0.0319)	(0.0189)	(0.0247)
Observations	21701	21701	21701	21408	21408	21408
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change, split by regional income in 2010. Income measured median hourly wage, excluding overtime, of each NUTS2 region (from ASHE). Poorer (richer) regions are the 50% of NUTS2 regions with the lowest (highest) median hourly wage. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, education, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Extensive margin search results - TTWA regions split by income

	—— Poorer TTWAs ——			—— Richer TTWAs ——		
	(1)	(2)	(3)	(4)	(5)	(6)
	Working	Unemp	Inactive	Working	Unemp	Inactive
Post	-0.0230**	0.00900	0.0140*	-0.0194*	0.0118	0.00759
	(0.00973)	(0.00657)	(0.00775)	(0.0101)	(0.00826)	(0.00713)
Age 21	-0.0325***	0.0282***	0.00425	-0.0270***	0.0235***	0.00350
	(0.0103)	(0.00828)	(0.00786)	(0.00863)	(0.00746)	(0.00754)
Post*Age 21	0.0134	0.000993	-0.0143	-0.0160	0.0291**	-0.0131
	(0.0152)	(0.0126)	(0.0114)	(0.0184)	(0.0136)	(0.0121)
Constant	0.596***	0.210***	0.194***	0.442***	0.384***	0.174***
	(0.0255)	(0.0187)	(0.0257)	(0.0478)	(0.0305)	(0.0549)
Observations	20010	20010	20010	18599	18599	18599
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change, split by TTWA income in 2010. Income measured median hourly wage, excluding overtime, of each TTWA region (from ASHE). Poorer (richer) TTWAs are the 50% of TTWAs with the lowest (highest) median hourly wage. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, education, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Unemployed search intensity by education - correcting for selection

	(1) Active Low	(2) Active High	(3) >1 m. Low	(4) >1 m. High	(5) # m. Low	(6) # m. High
Post	-0.0526***	-0.0455	0.0131	0.000819	0.00722	0.0683
	(0.0183)	(0.0278)	(0.0107)	(0.0166)	(0.0555)	(0.0933)
Age 21	0.00881	0.0451	0.0244**	-0.0447**	0.101*	-0.197*
	(0.0202)	(0.0355)	(0.0118)	(0.0212)	(0.0615)	(0.119)
Post*Age 21	-0.0328	0.0464	-0.0395**	0.00424	-0.153*	-0.0686
	(0.0281)	(0.0498)	(0.0163)	(0.0297)	(0.0852)	(0.167)
Constant	0.673***	0.581***	0.285***	0.146*	2.327***	2.174***
	(0.0685)	(0.131)	(0.0399)	(0.0783)	(0.209)	(0.441)
Selection eq.						
Post	0.0489	-0.00553	0.0489	-0.00553	0.0500	0.00278
	(0.0319)	(0.0585)	(0.0319)	(0.0585)	(0.0319)	(0.0585)
Age 21	0.0884**	0.206***	0.0884**	0.206***	0.0730**	0.218***
	(0.0351)	(0.0775)	(0.0351)	(0.0775)	(0.0351)	(0.0775)
Post*Age 21	0.108**	-0.0563	0.108**	-0.0563	0.135***	-0.0634
	(0.0492)	(0.109)	(0.0492)	(0.109)	(0.0493)	(0.109)
Constant	0.330***	0.344	0.330***	0.344	0.280**	0.334
	(0.114)	(0.258)	(0.114)	(0.258)	(0.114)	(0.258)
Lambda	-0.113***	-0.0395	-0.0423***	-0.0277	-0.241***	-0.194**
	(0.0225)	(0.0285)	(0.0132)	(0.0170)	(0.0686)	(0.0958)
Observations	15375	4236	15375	4236	15375	4236
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are not in work, split by educational attainment. Low refers to individuals with a maximm of A level / High school education. High refers to individuals with some post-school education. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity. The selection equation includes all controls and treatment variables alongside a variable for studying - the exclusion restriction. Heckman selection model estimated by two-step maximum likelihood.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Unemployed search intensity by geography - correcting for selection

	(1) Active Poor	(2) Active Rich	(3) >1 m. Poor	(4) >1 m. Rich	(5) # m. Poor	(6) # m. Rich
Post	-0.115***	-0.0450**	0.0153	-0.00462	0.0773	-0.0297
	(0.0320)	(0.0201)	(0.0174)	(0.0121)	(0.0989)	(0.0636)
Age 21	-0.0126	0.0344	0.0000848	0.0101	0.0478	0.0407
	(0.0335)	(0.0211)	(0.0182)	(0.0126)	(0.104)	(0.0667)
Post*Age 21	0.0313	-0.0123	-0.0157	-0.0163	-0.0773	-0.0878
	(0.0498)	(0.0318)	(0.0270)	(0.0191)	(0.154)	(0.101)
Constant	0.709***	0.498***	0.247***	0.167**	2.345***	1.857***
	(0.106)	(0.112)	(0.0577)	(0.0671)	(0.334)	(0.353)
Selection eq.						
Post	0.0189	0.0100	0.0189	0.0100	0.0270	0.0120
	(0.0576)	(0.0368)	(0.0576)	(0.0368)	(0.0577)	(0.0368)
Age 21	0.150**	0.0715*	0.150**	0.0715*	0.123**	0.0653*
	(0.0610)	(0.0385)	(0.0610)	(0.0385)	(0.0611)	(0.0386)
Post*Age 21	-0.0381	0.0824	-0.0381	0.0824	-0.000157	0.0963*
	(0.0916)	(0.0584)	(0.0916)	(0.0584)	(0.0916)	(0.0584)
Constant	0.309*	0.460**	0.309*	0.460**	0.241	0.472**
	(0.176)	(0.202)	(0.176)	(0.202)	(0.176)	(0.202)
Lambda	-0.188***	-0.0446**	-0.0541**	-0.0383***	-0.276**	-0.245***
	(0.0446)	(0.0208)	(0.0246)	(0.0124)	(0.140)	(0.0656)
Observations	4329	12350	4329	12350	4329	12350
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are not in work, split by average income of their resident TTWA. Poor refers to the poorest half of TTWAs, rich to the richest half of TTWAs. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity. The selection equation includes all controls and treatment variables alongside a variable for studying - the exclusion restriction. Heckman selection model estimated by two-step maximum likelihood.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Length of time searching for a job - selection correction - by education

	(1)	(2)	(3)	(4)
Outcome:	TimeA	TimeA	TimeB	TimeB
Education	Low	High	Low	High
Post	2.153***	0.249	1.737*	-0.105
	(0.813)	(0.298)	(0.957)	(0.485)
Age 21	-1.220*	-0.830*	-1.629**	-0.415
	(0.688)	(0.478)	(0.767)	(0.669)
Post*Age 21	1.589	1.138	2.368*	0.427
	(1.099)	(0.743)	(1.248)	(0.931)
Constant	22.05***	10.21***	19.15***	9.840***
	(2.198)	(1.487)	(2.298)	(1.392)
Selection eq.				
Post	0.0306	-0.0185	0.186***	0.388***
	(0.0392)	(0.0768)	(0.0360)	(0.102)
Age 21	0.0411	0.118	0.0670	-0.0237
	(0.0463)	(0.0810)	(0.0478)	(0.0870)
Post*Age 21	0.145**	0.0173	0.167**	0.333**
	(0.0595)	(0.130)	(0.0652)	(0.150)
Constant	0.434***	0.0319	0.511***	0.449
	(0.111)	(0.346)	(0.117)	(0.316)
athrho				
Constant	-0.0870***	0.00446	-0.0507	-0.0711**
	(0.0280)	(0.0628)	(0.0394)	(0.0334)
lnsigma				
Constant	2.677***	1.791***	2.683***	1.774***
	(0.0253)	(0.0540)	(0.0256)	(0.0689)
Observations	15375	4236	15375	4236
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity and occupation. TimeA refers to self-reported unemployment searching duration. TimeB is a separate self-reported measure of time spent job-seeking.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Length of time searching for a job - selection correction - by region

	(1)	(2)	(3)	(4)
Outcome:	TimeA	TimeA	TimeB	TimeB
Regional income:	Poor	Rich	Poor	Rich
Post	1.235	1.514*	0.487	1.659
	(0.869)	(0.789)	(1.046)	(1.056)
Age 21	-1.234	-1.268*	-2.002**	-1.133
	(0.776)	(0.763)	(0.867)	(0.950)
Post*Age 21	2.153	2.031**	3.857**	2.010
	(1.397)	(1.028)	(1.533)	(1.261)
Constant	15.75***	16.66***	13.26***	16.45***
	(2.091)	(2.296)	(2.524)	(3.094)
Selection eq.				
Post	0.000589	0.0333	0.210***	0.250***
	(0.0495)	(0.0435)	(0.0478)	(0.0452)
Age 21	0.0712	0.0511	0.0630	0.0688
	(0.0533)	(0.0540)	(0.0590)	(0.0511)
Post*Age 21	0.112	0.132**	0.140*	0.182**
	(0.0768)	(0.0652)	(0.0805)	(0.0825)
Constant	0.324**	0.309**	0.523***	0.290**
	(0.151)	(0.130)	(0.142)	(0.131)
ρ	-0.0936***	-0.0386	-0.0713***	0.00106
	(0.0219)	(0.0324)	(0.0171)	(0.0597)
$ln(\sigma)$	2.602***	2.504***	2.627***	2.538***
	(0.0334)	(0.0389)	(0.0350)	(0.0386)
Observations	9048	9689	9048	9689
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity and occupation. TimeA refers to self-reported unemployment searching duration. TimeB is a separate self-reported measure of time spent job-seeking. Model is a Heckman Selection model, estimated by maximum likelihood.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

10.4 Additional tables for on-the-job search

Table A11: OJS by education

	OJS		Replace	
	(1)	(2)	(3)	(4)
	Low	High	Low	High
Post	0.0182***	0.0298**	0.0182***	0.0289**
	(0.00648)	(0.0132)	(0.00539)	(0.0118)
Age 21	0.00409	-0.0413**	0.00114	-0.0468***
	(0.00790)	(0.0180)	(0.00704)	(0.0164)
Post*Age 21	0.00605	0.00570	0.00475	0.00462
	(0.0130)	(0.0292)	(0.0115)	(0.0256)
Constant	0.148	0.458**	0.158*	0.484***
	(0.0914)	(0.184)	(0.0916)	(0.184)
Observations	23556	9476	23541	9453
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity and occupation.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: OJS by NUTS2 geographic split sample

	OJS		Replace	
	(1)	(2)	(3)	(4)
	Poor	Rich	Poor	Rich
Post	0.0258***	0.0136	0.0235***	0.0159**
	(0.00836)	(0.00852)	(0.00689)	(0.00658)
Age 21	0.00346	-0.0175	-0.00458	-0.0156
	(0.0106)	(0.0122)	(0.00961)	(0.00986)
Post*Age 21	0.00493	0.0152	0.00231	0.0135
	(0.0178)	(0.0179)	(0.0160)	(0.0141)
Constant	0.149	0.280**	0.172	0.273**
	(0.133)	(0.127)	(0.132)	(0.128)
Observations	15777	15650	15756	15635
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity, education and occupation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: OJS by TTWA geographic split sample

	OJS		Replace	
	(1)	(2)	(3)	(4)
	Poor	Rich	Poor	Rich
Post	0.0199**	0.0154*	0.0133	0.0219***
	(0.00906)	(0.00911)	(0.00823)	(0.00820)
Age 21	0.00824	-0.0200*	-0.00169	-0.0158
	(0.00949)	(0.0118)	(0.00846)	(0.00973)
Post*Age 21	0.00601	0.0213	0.00666	0.0126
	(0.0184)	(0.0189)	(0.0174)	(0.0151)
Constant	0.108	0.332**	0.133	0.344***
	(0.133)	(0.129)	(0.133)	(0.129)
Observations	13777	14490	13757	14479
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 21-23 year olds, 24 months either side of policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, ethnicity, education and occupation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: OJS search intensity by education - correcting for selection

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Active	Active	>1 m.	>1 m.	# m.	# m.
Education:	Low	High	Low	High	Low	High
Post	0.130	-0.0261	0.412	0.0851	1.247	0.0339
	(0.606)	(0.119)	(1.375)	(0.146)	(4.348)	(0.282)
Age 21	0.0320	0.0682	0.0936	-0.0978	0.296	-0.184
	(0.143)	(0.143)	(0.325)	(0.177)	(1.029)	(0.340)
Post*Age 21	0.0602	-0.0376	0.0926	-0.0102	0.385	0.0484
	(0.170)	(0.0522)	(0.386)	(0.0863)	(1.220)	(0.141)
Constant	-2.556	0.119	-6.230	-1.195	-18.76	-0.376
	(9.468)	(1.718)	(21.50)	(2.076)	(67.99)	(4.049)
Selection eq.						
Post	0.105***	0.118***	0.105***	0.118***	0.105***	0.118***
	(0.0285)	(0.0354)	(0.0285)	(0.0354)	(0.0285)	(0.0354)
Age 21	0.0206	-0.135**	0.0206	-0.135**	0.0206	-0.135**
	(0.0326)	(0.0554)	(0.0326)	(0.0554)	(0.0326)	(0.0554)
Post*Age 21	0.0238	0.000176	0.0238	0.000176	0.0238	0.000176
	(0.0460)	(0.0782)	(0.0460)	(0.0782)	(0.0460)	(0.0782)
Constant	-0.774***	-0.659*	-0.774***	-0.659*	-0.774***	-0.659*
	(0.264)	(0.360)	(0.264)	(0.360)	(0.264)	(0.360)
Lambda	2.114	0.174	4.800	1.027	15.18	1.259
	(6.969)	(1.321)	(15.82)	(1.579)	(50.04)	(3.101)
Observations	23593	9482	23593	9482	23593	9482
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are in work. The selection equation includes all controls and treatment variables. Heckman selection model estimated by two-step maximum likelihood. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: OJS search intensity by geography - correcting for selection

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Active	Active	>1 m.	>1 m.	# m.	# m.
Region:	Poor	Rich	Poor	Rich	Poor	Rich
Post	-0.0462	0.0444	0.00566	-0.0273	-0.108	0.150
	(0.0629)	(0.143)	(0.0402)	(0.0645)	(0.175)	(0.347)
Age 21	0.0122	-0.0160	-0.0228	0.0120	-0.0601	-0.163
	(0.0631)	(0.0876)	(0.0408)	(0.0381)	(0.176)	(0.213)
Post*Age 21	-0.0248	0.0832	0.00532	0.00484	0.111	0.313
	(0.0858)	(0.109)	(0.0563)	(0.0460)	(0.241)	(0.265)
Constant	1.227	-1.143	0.831	0.459	4.109	-2.042
	(2.037)	(2.186)	(1.234)	(1.004)	(5.586)	(5.323)
Selection eq.						
Post	0.0464	0.108***	0.0464	0.108***	0.0464	0.108***
	(0.0476)	(0.0286)	(0.0476)	(0.0286)	(0.0476)	(0.0286)
Age 21	0.0428	-0.0606*	0.0428	-0.0606*	0.0428	-0.0606*
	(0.0527)	(0.0338)	(0.0527)	(0.0338)	(0.0527)	(0.0338)
Post*Age 21	0.0504	0.0699	0.0504	0.0699	0.0504	0.0699
	(0.0806)	(0.0503)	(0.0806)	(0.0503)	(0.0806)	(0.0503)
Constant	-0.927	-0.797***	-0.927	-0.797***	-0.927	-0.797***
	(0.626)	(0.261)	(0.626)	(0.261)	(0.626)	(0.261)
Lambda	-0.497	1.130	-0.472	-0.124	-1.616	2.752
	(1.345)	(1.580)	(0.807)	(0.730)	(3.680)	(3.846)
Observations	8163	20157	8163	20157	8163	20157
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. Sample is 21-23 year olds, 24 months either side of policy change who are in work. The selection equation includes all controls and treatment variables. Heckman selection model estimated by two-step maximum likelihood. Controls included: sex, region (NUTS2 level), quarter, proxy, education, marital status, ethnicity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

10.5 2016 new age tier

Table A16: Baseline extensive margin regressions - 2016 new age tier

	(1) Working	(2) Unemployed	(3) Inactive	(4) Student
Post	0.00816	-0.00823*	0.000692	-0.000623
	(0.00813)	(0.00491)	(0.00526)	(0.00471)
Age 25+	0.0671***	-0.0200***	0.00923**	-0.0563***
	(0.00769)	(0.00395)	(0.00457)	(0.00470)
Post*Age 25+	0.00140	-0.0000717	-0.00416	0.00284
	(0.00936)	(0.00564)	(0.00657)	(0.00510)
Constant	0.410***	0.0630***	0.507***	0.0199
	(0.0827)	(0.0178)	(0.0765)	(0.0233)
Observations	47651	47651	47651	47651
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 22-28 year olds, 12 months before and 9 months after policy change. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, education, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: Baseline regressions - 2016 new age tier, excluding students

	(1) Working	(2) Unemployed	(3) Inactive
Post	0.00762	-0.00883*	0.00121
	(0.00761)	(0.00533)	(0.00570)
Age 25+	0.0216***	-0.0257***	0.00410
	(0.00626)	(0.00433)	(0.00488)
Post*Age 25+	0.00369	0.000496	-0.00419
	(0.00875)	(0.00605)	(0.00695)
Constant	0.424***	0.0655***	0.511***
	(0.0801)	(0.0196)	(0.0772)
Observations	45096	45096	45096
Controls	Yes	Yes	Yes

Standard errors in parentheses, clustered on age-region level. Sample is 22-28 year olds, 12 months before and 9 months after policy change, not excluded from labour force due to studying. Controls included: sex, region (NUTS2 level), quarter, proxy, marital status, education, ethnicity.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$