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Minimum Wage and Employment:
Escaping from the Parametric
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Abstract

Parametric regression models are often not flexible enough to capture the true relationships as they tend to rely on arbitrary identification assumptions. Using the UK Labor Force Survey, we estimate the causal effect of national minimum wage (NMW) increases on the probability of job entry and job exit by means of a non parametric Bayesian modelling approach known as Bayesian Additive Regression Trees (BART). This procedure is simple, flexible and it does not require ad-hoc assumptions about model fitting, number of covariates and how they interact. We find that the NMW exerts a positive and significant impact on both the probability of job entry and job exit. Although the magnitude of the effect on job entry is higher, the overall effect of NMW is ambiguous as there are lot of more employed workers. This can explain the insignificant effect found in the previous studies based on aggregate macroeconomic data. Furthermore, the causal effect of NMW is higher for young workers and in periods of high unemployment and they have a stronger impact on job entry decisions. However, no significant interactions were found with gender and worker qualifications.

Keywords: BART, causal inference, difference-in-difference, matching regression.

JEL Codes: C23, C11, C14, J3, J4.

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1 Introduction

The most characteristic feature regarding the literature on the causal impact of the minimum wage on employment is the complete lack of consensus. Neumark and Washer (2007) compile an extensive survey of previous research and conclude that the minimum wage exerts an adverse impact on employment of low-skilled workers and a non significant impact on total employment. However, a meta-analysis on this issue conducted by Card and Krueger (1995) and the subsequent correction by Doucouliagos and Stanley (2008) both find that although there is a wide range of results in the previous research, the overall mean is consistent with a non significant impact of the minimum wage on employment output once the publication selection bias is accounted for.

The reason for the wide range of findings is the fact that the results hinge dramatically on ad hoc assumptions about the parametric specification of the empirical model and on the definition of the control group in the analysis. This is corroborated in the highly insightful and interesting discussion in a series of papers by Allegretto et al. (2011, 2013), Dube et al. (2010), and Neumark et al. (2014) in a state-level panel analysis for the US. Therefore, Dube et al. (2010) and Allegretto et al. (2011) suggest that it is essential to control for spatial heterogeneity in order to estimate the impact of the minimum wage in a panel data setting. In particular, they propose to include two types of local controls consisting of: 1) jurisdiction-specific linear time trends; and 2) interactions between time dummy variables for sets of neighboring states or neighboring counties so they could be used as controls to determine the impact of the minimum wages. Subsequently, Neumark et al. (2014) criticize these measures on the grounds that there are other non-linear ways of controlling for unobserved trends and that this approach excludes other potential controls apart from those for the neighboring regions. Crucially, the parametric form of the model appears to be critical determinant of whether a significant or insignificant impact of minimum wage on state employment is obtained.

Aggregation bias can be a potential second problem of the literature discussed above as an aggregate data might mask the real effect of minimum wage at the individual level. This paper

uses the UK Labor Force Survey to estimate the causal impact of the UK national minimum wage (NMW) on employment using a non parametric Bayesian modelling approach known as the Bayesian Additive Regression Trees (BART henceforth) that was originally developed by Chipman et al. (2010) and applied to the analysis of causal inference by Hill (2011). This procedure shares some similarities with standard matching estimation strategies, see for example Abadie and Imbens (2006), as it compares unemployment-to-employment and employment-to-unemployment transitions of individuals affected by the NMW with a similar individual whose salary is not affected but it is sufficiently close to those in the treatment group. However, this procedure has important advantages over other more traditional parametric specifications. Among them, it does not require any type of hypothesis over the covariates to be included in the model, the ability to consider a large number of regressors and to estimate any type of interactive effects between the treatment variable and any other variable in the analysis, or the way this methodology copes with missing values without the necessity of dropping them from the sample. Thus, under the BART model, for each treated individual the definition of the closest untreated individual and the interactions between the different clusters of individuals and time or and any other relevant covariate is not constrained to follow any ad-hoc parametric function.

This paper is closely related to at least three previous works that estimate the impact of the NMW on employment at the individual level using micro-data. Stewart (2004) and Dickens and Draca (2005) study the impact of the NMW by applying the difference-in-difference regression techniques to the UK Labor Force Survey data, finding that the NMW does not have a significant adverse effect on employment. In both cases, the treated group are workers whose salary must be modified due to the NMW change while the control group are workers whose salary is not affected by the NMW change but it is very close to those affected by it. In particular, Stewart (2004) analyzes how the introduction of the UK NMW in 1999 and their subsequent changes in 2000 and 2001 has affected the employment-to-employment transition. Dickens and Draca (2005) follow a similar approach for the NMW increases in October 2003

but they extend the analysis to consider the separate effect of the NMW on job entry and job exit decisions. For the US, Sabia et al. (2013) also use a difference-in-difference approach to estimate the effect of an increase in the minimum wage in New York on low skilled individual employment. They find that the minimum wage has a negative impact on employment that is robust to using different control groups: neighbor states, high skilled workers or a synthetic control group. Unlike these papers, we do not study the impact of NMW for a specific number of years but the impact of all the NMW changes since its introduction in 1999. Moreover, we follow a matching estimation that can be interpreted as being similar to a regression that puts more weight on observations that are very similar to the treatment and control groups. As we will discuss later, this has important advantages for the reliability of the estimation results. Finally, the approach used in this paper allows us to identify the most relevant interactions of the NMW effect with other variables such as gender, age, qualifications and business cycle without the necessity of proposing a parametric specification.

To preview the results, we find that the NMW exerts a positively significant impact on both the probability job entry and job exit. Although the magnitude of the effect on job entry is larger, the overall effect of NMW is ambiguous as there are a lot of more employed workers than the number of the unemployed. This could explain the insignificant effect found in the previous work based on aggregate macroeconomic estimations. We find that the causal impact interacts with workers' age and business cycle such that the effect is stronger for younger workers and in high unemployment periods. Other variables such as gender or qualifications do play an important role in these interactions.

In the next section, we present the data used. Sections 3 and 4 discuss methodological approaches used for analyzing the labor-market impact of the minimum wage and explain the main features of the BART model, respectively. Empirical results are shown and discussed in section 5. The final section summarizes our findings and offers some conclusions.

2 Data

Our analysis is based on the UK Labour Force Survey (LFS). The LFS is a quarterly nationally-representative survey of households across the UK. Each quarterly file contains information on approximately 60 thousand households and over 100 thousand individuals aged 16 and above. Each household is retained in the survey for five consecutive quarters, with one-fifth of households replaced in each wave. The survey contains detailed demographic and socio-economic information on the respondents, including, importantly, their labour market outcomes. Since the NMW was introduced in April 1999, we use all quarterly datasets available since April-June 1999 to October-December 2011, pooling all available LFS waves during this period. In order to have a sufficient number of observations, we include all individuals aged between 16 and 40.

The UK NMW features three different age-dependent rates: the 16-17 years old rate, the youth rate (applying to those aged 18-21¹), and the adult rate.² Historically, the youth rate was set some 35% higher than the 16-17 rate while the adult rate exceeds the youth rate by around 20%. The LFS reports the date of birth of every respondent and also the date the survey was carried out. By comparing these two dates, we can determine the precise age of each respondent on the day of the survey.³ We therefore know whether a particular individual is below or above the age threshold at which they become eligible for a different (higher) NMW rate. Furthermore, we do not analyze the effects of differences between the different age-specific NMW rates but instead consider the regular annual increases that apply to all rates.

¹ The upper limit for the youth rate has been lowered to 20 from October 2010. Where relevant, our analysis takes this change into account.

² A fourth rate, for apprentice workers, was introduced in October 2010 (we do not consider those subject to this rate in our analysis). No minimum wage applies to those who belong to one of the few exemptions such as members of the armed forces, volunteers, students on work placements, workers living in the
ces.

³ The precise date of birth is not available in the publicly released LFS datasets. We are grateful to the Office for National Statistics for making the restricted release of the LFS available to us.

3 Methodological Considerations

We analyze the effect of the national minimum wage increases on employment by going beyond the difference-in-difference and the matching estimation methodologies traditionally used for this purpose. We start by explaining the difference-in-difference and matching models and then outline why and how our approach differs from them.

The difference-in-difference methodology involves comparing the changes in the outcomes (such as employment) after a NMW change for the treatment and control groups. Consider the impact of NMW on the probability of job loss. The treatment group comprises workers whose wages have to go up in the wake of an annual NMW increase because the new NMW rate is higher than their current wage. The wages of those in the control group should be close to but just above the new rate so as not to have to change.

More specifically, the treatment group can be defined as the individuals whose wages meet the following condition:

$$nmw_t < w_{it} < nmw_{t+1} \quad (1)$$

where nmw_t is the (age-dependent) NMW rate in effect at time t while w_{it}

where the dependent variable is the probability that individual i is unemployed conditional on being employed in the preceding quarter, D_i is a dummy variable denoting individuals belonging to the treatment group, included on its own and in interaction with the gap between individual i and the NMW. X_{it} collects all remaining covariates (individual socio-economic characteristics and time effects). An analogous equation can be estimated for the probability of remaining employed conditional on employment in the previous quarter. In line with the standard practice, equation (1), and in particular the coefficient estimates of the first two terms, are interpreted as capturing the differentiated effect of the minimum-wage increase on the probability of becoming unemployed for the treated individuals relative to those in the control group.

A similar approach can be used to estimate the impact of NMW on the probability of job entry. In this case the equation to estimate is

$$P(y_{i,t+1} = 1 | y_{i,t} = 0) = \alpha + \beta_1 D_i + \beta_2 X_{it} + \epsilon_{it} \quad (3)$$

A particular problem presents itself here in the fact that we do not have any previous wage information for those who only enter into employment after the NMW increase. In other words, we do not know whether those entering into employment after the increase would have earned more or less than the minimum wage before the increase. Dickens and Draca (2005) define the treatment group as those whose earnings are less than or equal to the (age-relevant) new NMW rate and the control group as those who earn up to c percent above the NMW:

$$\text{Treatment group: } y_{i,t} \leq \text{NMW}_{t+1} \quad (4)$$

$$\text{Control group: } y_{i,t} < \text{NMW}_{t+1} < (1+c)\text{NMW}_{t+1} \quad (5)$$

A somewhat uncomfortable implication of this specification is that the treatment group now includes also those who earn less than the NMW (recall that there are specific cases when this is allowed, for example for apprentices). An alternative specification would entail constructing the treatment group as including only those who earn the minimum wage after the NMW increase.

analyses is the use of a Bayesian regression model known as BART. As in all Bayesian models, we need a likelihood function defined for a set of parameters, θ , and a prior distribution $\pi(\theta)$. The likelihood function, $L(Y|X, D, \theta)$, is obtained from the following additive regression model, where the mean of Y is determined from the sum of estimated models for the response variable:

$$E(Y) = \sum_{j=1}^M f_j(x; \theta_j) \quad (6)$$

where

enhanced from a theoretical point of view by a recent paper by Petrone et al. (2013). As explained by Hill (2011), the results of this type of analysis are robust with respect to prior modifications.

Using the priors specified above it is possible to simulate samples of the posterior distribution with a non-excessive computational effort using Markov Chain Monte Carlo (MCMC), more specifically using Metropolis Hastings within Gibbs. This means that the simulation algorithm alternates Gibbs steps (as the one that is necessary to simulate θ^2) and Metropolis Hastings steps when the conditional distributions for the remaining parameters are not available in a closed form expression. In particular, the distribution used to update the values of θ and θ^2 consists of adding/dropping a terminal node and changing a split variable or a split point with the probabilities specified in Chipman et al. (2010). Once the posterior distribution of $\theta = (\theta_1, \dots, \theta_k, \theta^2_1, \dots, \theta^2_k)$ has been obtained, the predictive distribution for the probability of job exit is:

$$P(\text{job exit} | \theta) = \int P(\text{job exit} | \theta, \theta^2) P(\theta^2 | \theta) d\theta^2$$

5 Results

As an initial analysis, we show in Table 1 the results of a probit model for job entry and job exit as specified in Equations (1) and (2) as a function of the dummy variable for the treatment along with a set of covariates.⁵ In this regression λ is set to be 0.1 but the results are qualitatively similar when we consider $\lambda = 0.3$, $\lambda = 0.5$ and $\lambda = 1$. The last row of Table 1 indicates that the

be vulnerable to NMW increases. Besides, the interactive effect is clearly stronger in job entry. In Figure 4, we consider the interaction with the highest attained qualification. The graphs reveal that this is not a relevant factor to explain differences in the causal impact of NMW either for job entry or job exit. Finally, Figure 5 presents the interaction with the regional business cycle measured using the unemployment rate. Interestingly, this interaction effect is very different for the two labor-market flows: the minimum-wage effect on

Figure 2 NMW Increases, Job Exit/Entry and Gender

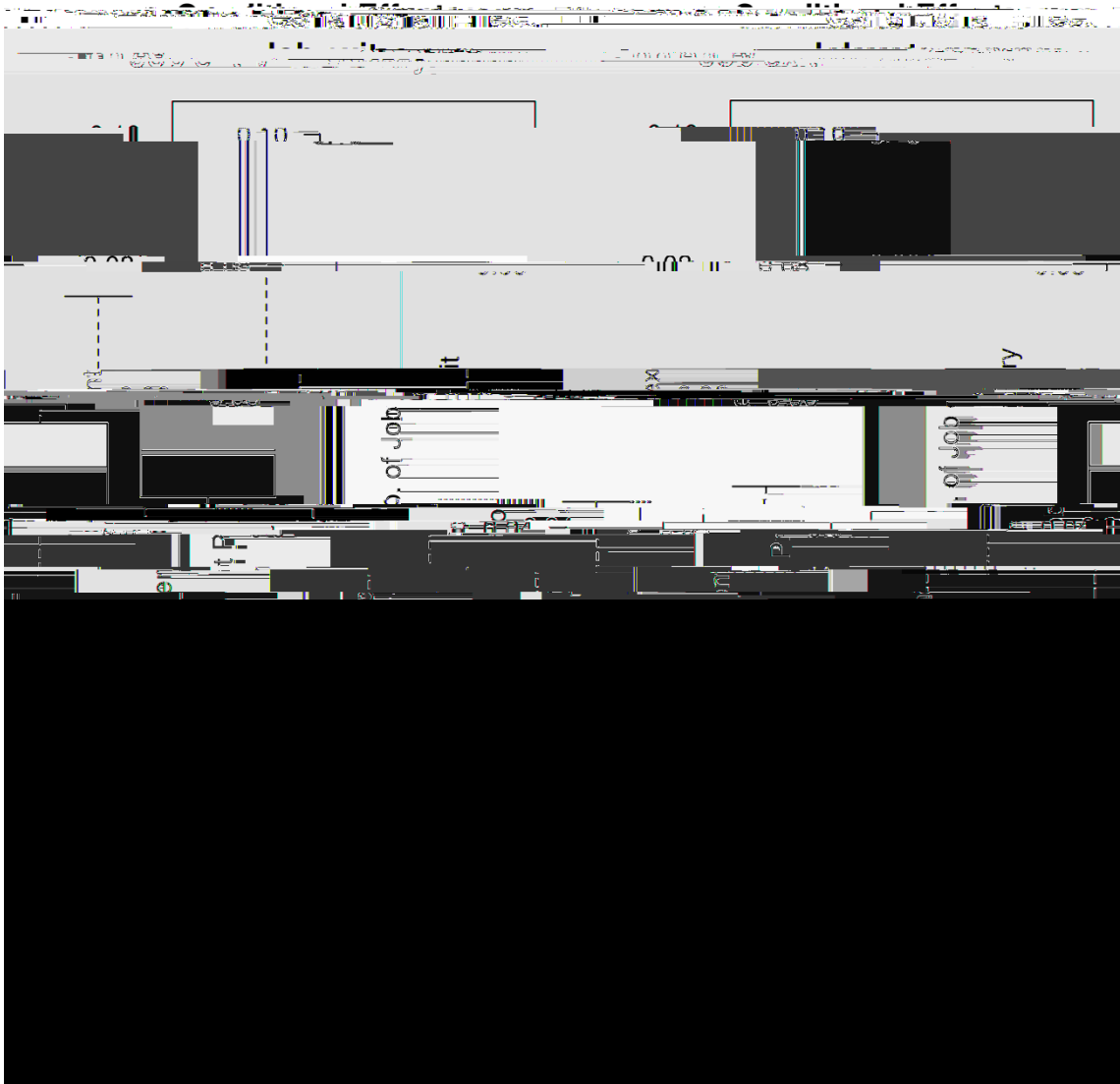


Figure 3 NMW Increases, Job Exit/Entry and Age

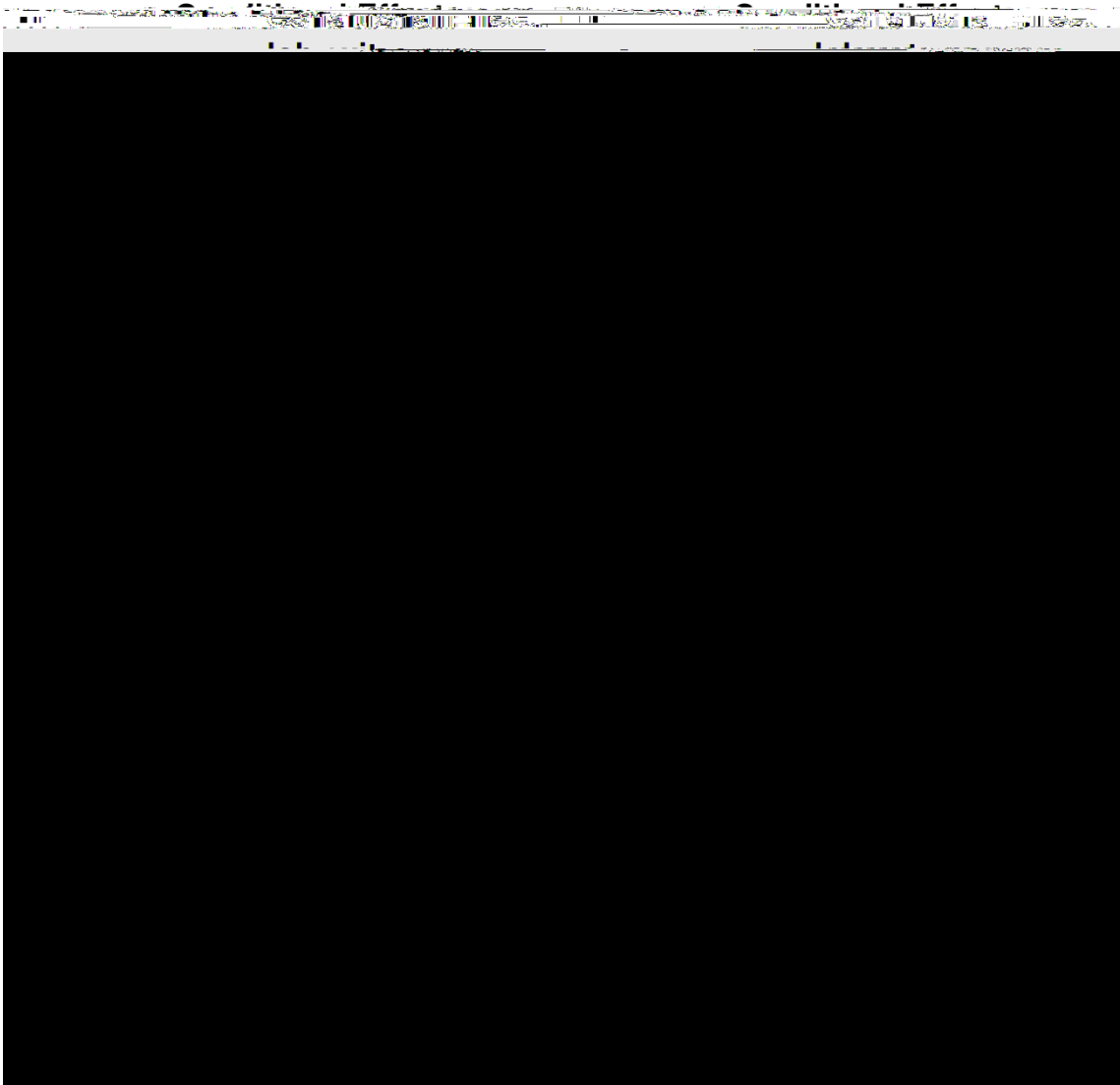
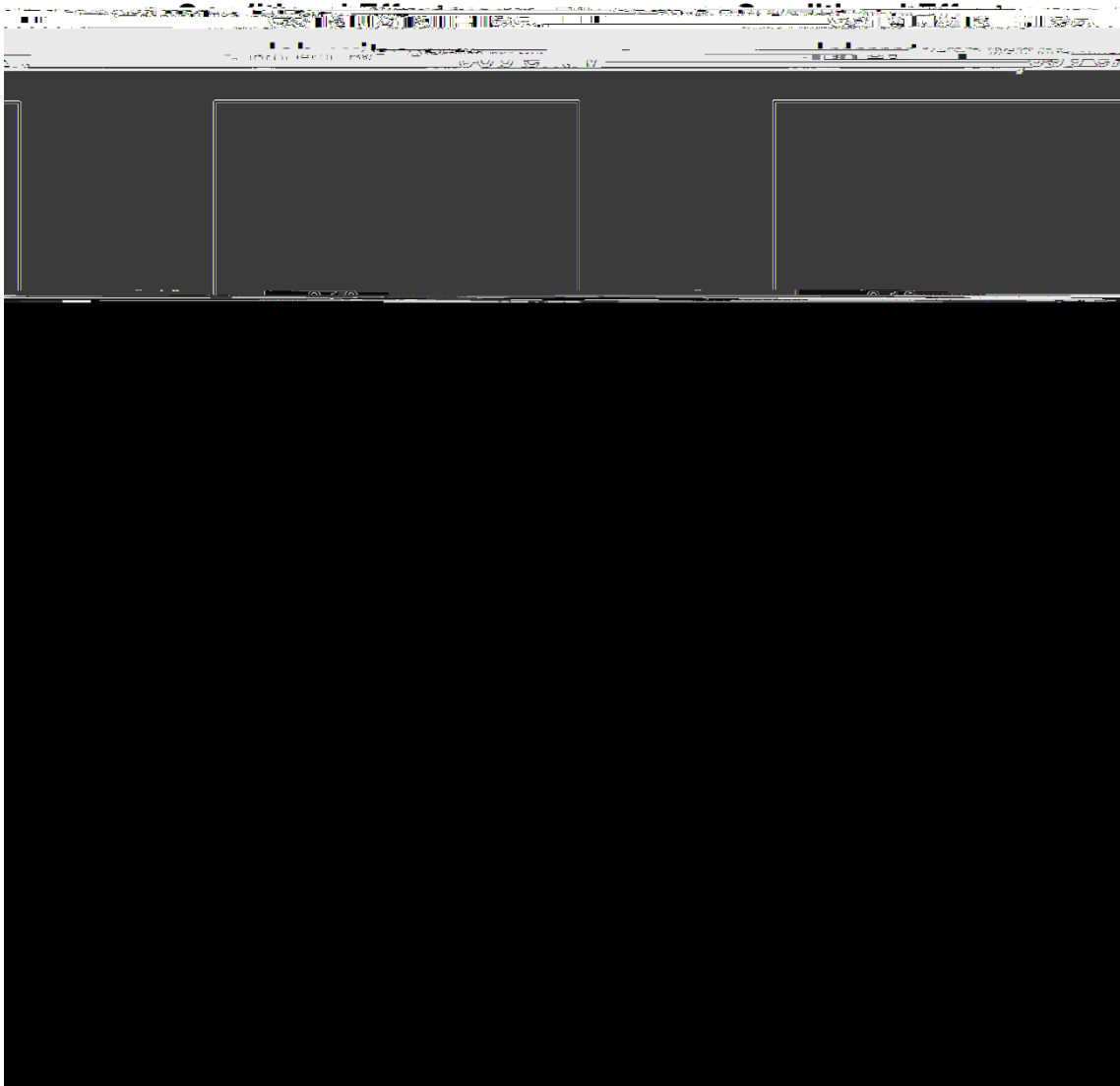


Figure 4 NMW Increases, Job Exit/Entry and Qualifications



Notes: 1 Degree or equivalent, 2 Higher education, 3 GCE A Level or equivalent, 4 GCSE grades A-C or equivalent, 5 Other qualifications, 6 No qualification, 7 Don't know

the impact on job entry being relatively stronger (given that there are fewer unemployed than employed workers, the absolute size of the flows cannot be readily compared). The causal effect of NMW is found to be higher for young workers and in periods of high unemployment; both of these interactions are more prominent for job entry than for job exit. However, no significant interactions were found with gender and worker qualification. Overall, the effect of NMW is stronger for job entry than for job exit.

Our paper opens new lines of research that can be explored in subsequent works. For example, this fully flexible approach could be adapted to deal with some of the most recent discussion in the literature about the importance of the econometric specification on estimating the effect of minimum wage using panel data models in US states. Also, it could be used to estimate the possible interactions between the federal minimum wage and the state minimum wages, as done by Baskaya and Rubinstein (2012), without the necessity of estimating two different models.

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