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DISCUSSION PAPER SERIES

IZA DP No. 11632

Estimating the Effect of an Increase in the Minimum Wage on Hours Worked and Employment in Ireland

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ABSTRACT

Estimating the Effect of an Increase in the Minimum Wage on Hours Worked and Employment in Ireland

On the 1st of January 2016 the Irish National Minimum Wage increased from €8.65 to €9.15 per hour, an increase of approximately six percent. We use a difference-in-differences estimator to evaluate whether the change in the minimum wage affected the hours worked and likelihood of job loss of minimum wage workers. The results indicate that the increase in the minimum wage had a negative and statistically significant effect on the hours worked of minimum wage workers, with an average reduction of approximately 0.5 hours per week. The effect on minimum wage workers on temporary contracts was higher at 3 hours per week. We found a corresponding increase in part-time employment of 2 percentage points for all minimum wage workers and 10 percentage points for those on temporary contracts. We find no clear evidence that the increase in the minimum wage led to an in-creased probability of becoming unemployed or inactive in the six-month period following the rate change.

JEL Classification: E24, J22, J23, J31, J42

Keywords: minimum wage, hours of work, employment, unemployment

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1. Introduction

On the 1st of January 2016, following recommendations from the Irish Low Pay Commission, the Irish National Minimum Wage (NMW) increased from €8.65 to €9.15 per hour, an increase of approximately six percent. This far exceeded the 0.7 percent rise in average hourly earnings for the same period (Low Pay Commission, 2016).[1] As such, employers of minimum wage workers experienced non-trivial changes to labour costs, making this a suitable setting for studying the effects of minimum wage increases on employment outcomes. Prior to this rate change, there was a period of nine years during which the minimum wage did not increase.[2] This coincided with an economic downturn, with unemployment in Ireland reaching a peak of 15 percent in 2012. However, there was a strong return to economic growth from 2013 onwards and by 2016 the unemployment rate had fallen to below eight percent. The fact that the minimum wage remained stable for several years prior to the 2016 rate change is useful as it allows us to carry out tests to ensure that our estimates are capturing effects relating to the minimum wage change, as opposed to general diverging trends among minimum wage and higher paid workers.

A priori, the expected employment effects of minimum wage changes depend on the structure of the labour market. In perfect competition, the wage elasticity of labour supply is infinite and workers earn their marginal product. In this setting, a binding minimum wage leads to a reduction in employment (Neumark and Wascher, 2008). It is important to note that this can happen in two ways, either at the extensive margin, with a reduction in the number of workers, and/or at the intensive margin, with a reduction in hours worked (Brown, 1999). However, under monopsony, the wage elasticity of labour supply is low and firms can use their market power to set wages below their perfectly competitive level. In this setting, there can be a decline in the firm's profits without a reduction in employment. Manning (2003) argues that monopsony may be more relevant in modern labour markets, however the degree of market power can vary across industries (Bachmann and Frings, 2017).

There exists a vast literature estimating the effect of minimum wage changes on employment. The results from this literature are often mixed. Recent studies which find no discernible employment effects include Dolton et al. (2015), Hirsch et al. (2015) and Baek and Park (2016). However, others find adverse employment effects (see, e.g., Neumark et al., 2004; Meer and West, 2015; Sabia et al.,

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[1] The corresponding wage increases in the wholesale and retail and hospitality sectors, which typically have a high incidence of minimum wage employment, were 1.7 percent and 0.4 percent respectively.

[2] The previous national minimum wage had been in place since July 2007. There was a temporary reduction in this rate to €7.65 per hour from February to July 2011.

2012). Despite these conflicting results, the weight of evidence tends to indicate little to no employment effects, as outlined in recent literature surveys by Schmitt (2015) and Belman et al. (2015). Dickens et al. (2015) suggest that the reason the literature often finds no employment effects is because previous work did not focus on vulnerable groups. Part-time females are the focus of study for Dickens et al. (2015) and they find that the introduction and uprating of the minimum wage in the UK is associated with negative employment effects for this group. Other studies focus on young workers, with Liu et al. (2016) and Gorry and Jackson (2017) finding negative employment effects for young workers in the US.

The literature on the impact of the minimum wage on hours worked is more limited than that relating to employment. Neumark & Wascher (2008) suggest that when reacting to changes in the minimum wage, employers may adjust the level of labour inputs by reducing the total number of hours worked across all minimum wage employees rather than making specific workers redundant. Metcalf (2008), citing oral evidence given to the UK Low Pay Commission by the British Retail Consortium and the Union of Shop, Distributive and Allied Workers (USDAW), indicates that following an uprating of the minimum wage, managers look closely at potential hours adjustments to offset rising labour costs. Consistent with this, several studies find a reduction in hours of minimum wage and low paid workers as a result of the introduction and uprating of the minimum wage (see, e.g., Stewart and Swaffield, 2008; Metcalf, 2008; Couch and Witttenburg, 2001; Neumark & Wascher, 2008; Belman et al., 2015; Neumark et al., 2004). However, others find little to no effect on hours worked (see, e.g., Zavodny, 2000; Skedinger, 2015; Dolton et al., 2010).

Given that responses to minimum wage increases may occur at both the intensive margin (hours worked) as well as the extensive margin (number of workers), we study both effects in this paper. In addition to looking at all minimum wage employees, we also focus on the sub-group of temporary contract workers. As noted by Dickens et al. (2015), certain vulnerable sub-groups may be more susceptible to adverse effects of minimum wage changes. Temporary contract workers may be particularly susceptible to cuts in hours and employment given their more precarious employment status, however this group has been overlooked to date in the minimum wage literature. While our results indicate that the 2016 increase in the minimum wage in Ireland did not lead to greater job loss among minimum wage workers, we find that average hours worked of minimum wage employees declined by approximately 0.5 hours per week. The effect for temporary contract workers was more pronounced, at approximately three hours per week. We also find an increase in part-time minimum wage employment following the rate change, coupled with a substantial decrease in involuntary part-time employment among minimum wage workers. This indicates that these workers were choosing to work part-time as opposed to simply not being able to find a full-time job. As such, while some of the hours reduction may be due to employers responding to increased labour costs, we cannot rule out the possibility that more individuals were choosing to work part-time due to the higher minimum wage.

The remainder of the paper is organised as follows. In Section 2 we describe the data used in the study and outline our strategy for identifying minimum wage and non-minimum wage workers. Sections 3 and 4 respectively analyse the impact on hours worked and the probability of job loss as a result of the 2016 minimum wage increase. Section 5 concludes.

2. Data

For our analysis we use data from the Irish Quarterly National Household Survey (QNHS). The QNHS data is collected continuously throughout the year and is the official data source for producing statistics relating to the labour force in Ireland. In addition to information relating to employment and labour force status, the dataset contains demographic and human capital related variables such as age, sex and education. However, there is no detailed information on a person's income, which poses a challenge for this study as we aim to separate minimum wage from non-minimum wage workers. While exact income data is not included, the dataset does categorize individuals into wage deciles, based on monthly take home pay, and we know the bands (in euros) corresponding to each decile.[3] This enables us to distinguish individuals likely to be impacted by the NMW change both before and after its introduction, thereby allowing us to measure the impact of the increase in the NMW on the number of hours worked and the probability of job loss.

In the QNHS, a person's information can be captured directly from the person themselves or, alternatively, via another member of the household (known as a proxy response). However, proxy responses are not permitted for the income decile questions and this explains most of the missing information. There are 124,875 employees in 2015 and 2016, of which 89,810 do not have decile information. Over 70 percent of these missing cases are due to proxy responses. There are two questions relating to hours worked in the data. The first relates to the actual number of hours worked in the reference week. The second captures the usual number of hours worked on a weekly basis by the employee, which may be calculated as the average hours over the last four weeks. When evaluating how the increase in the minimum wage affected hours worked, it is more appropriate to

[3] The income deciles are set by the CSO and are subject to revision.

evaluate the change in usual hours worked. However, in the data there is very little difference between the information contained in both questions and our results are robust to using actual hours instead of usual hours. In terms of the response rate for hours worked, over 96 percent of employees with decile data also have information on hours worked.

In Table 1 we report descriptive statistics relating to the characteristics of individuals with and without decile information for the years 2015 and 2016. While both groups are broadly similar, we observe some variation in those responding to the wage question by broad demographic characteristics. For example, males are more likely to be in the group with no decile data. We observe very little variation in these characteristics over time in both groups. Nonetheless, we account for both non-random selection as well as possible variation over time in the characteristics of our sample of employees. As noted by Bollinger et al. (2018), non-response in earnings surveys can be particularly prevalent in the tails of the earnings distribution, which is where our target group of minimum wage workers are likely to be located. In the presence of severe earnings nonresponse, selection models can be used to test the robustness of the results. For example, Bollinger and Hirsch (2013) use CPS data, which has a 30 percent nonresponse rate, and verify the robustness of their results from a wage equation using a two-step Heckman (1979) procedure. In this paper we also implement a Heckman two-step model and show the results do not differ from our baseline results. Any possible variation within groups over time is accounted for by the inclusion of additional demographic covariates within our difference-in-differences model. Given that these characteristics are quite stable over time, it is perhaps not surprising that our results are not overly sensitive to their inclusion.

2.1 Identifying minimum wage and non-minimum wage workers

When evaluating minimum wage changes, the group most affected by the change, i.e. the treatment group, are employees who were earning below the new minimum wage rate in the previous time period. For example, individuals earning below €9.15 per hour in 2015 would have had their hourly wage increased in order to comply with the 2016 minimum wage legislation. As such, in this paper when we refer to our treatment group of minimum wage workers, we are referring to those earning on or below the new (2016) minimum wage of €9.15 per hour.

Using the information available in the QNHS, we identify minimum wage and non-minimum wage workers as follows. Let *minincome* and *maxincome* denote the lower and upper wage levels respectively of the individual's wage decile. For instance, in 2016, the fifth decile of monthly wages ranges from €1,497 to €1,792.[4] We calculate a variable called *calcminwage* which represents what the individual's gross monthly income would be if they were on the minimum wage based on their usual hours of work, such that, *calcminwage = (hoursworked x €9.15) x 4.3.* For example, the monthly pay of an individual working 25 hours per week and earning the minimum wage would be 25*€9.15*4.3. Based on these variables, we know that an individual is not a minimum wage worker if *minincome* > *calcminwage*, i.e., if their lowest possible take home pay exceeds what their gross income would be if they were on the minimum wage given the number of hours that they work. Table 2 below shows some examples of individuals in the data who are categorized as non-minimum wage workers.

To identify minimum wage workers, we compare an individual's highest possible take home pay to what they would be earning (gross) if they were on the minimum wage. We categorize an individual as a minimum wage worker if *maxincome* $\leq$ *(calcminwage*1.1),* i.e. if their maximum possible take home pay is less than or equal to what they would be earning (gross) if they were on the minimum wage. We introduce a degree of flexibility by adding 10% to *calcminwage* due to the fact that we are using a person's maximum possible wage as a guide to their actual wage. Therefore, it is likely that individuals whose *calcminwage* just barely falls short of their *maxincome* are minimum wage workers and therefore should be included. Our categorisation of minimum wage workers is relatively strict given that we are using *maxincome* to identify their wage and it is likely that the actual take home pay of most workers will be lower than the maximum level in their decile.

As an example, consider an individual working 25 hours in decile 2, which, in 2016, runs from €632 to €991. This person would have a maximum monthly take home pay of €991, which is then compared to €1081, i.e., the gross earnings of a worker employed for 25 hours on the minimum wage of €9.15 per hour (+10%). In this case, the individual would be categorized as a minimum wage worker as their maximum monthly pay is approximately equal to the monthly income of a minimum wage worker given the number of hours that they work. Table 3 below shows some examples of individuals in the data who are categorized as minimum wage workers.

Note that we are comparing take home pay (*minincome* and *maxincome*) with a hypothetical value of gross pay (*calcminwage*) based on the number of hours that a person works. This does not impact our identification of non-minimum wage workers other than strengthening our assertion that these workers are definitely not minimum wage workers, as their lowest possible take home pay exceeds their hypothetical gross minimum wage. For minimum wage workers, this is also not problematic. In general, the take home pay of minimum wage workers is close to or equal to their gross wage. For

[4] This relates to monthly take-home pay.

example, a person on the minimum wage working 27 hours per week will have take home pay equal to their gross pay.[5] There will be slight differences for hours above this, however, note again that we are using *maxincome* to identify these workers, most of which will have take home pay less than this level. Despite this, we may also capture some low paid individuals whose hourly wage slightly exceeds the minimum. However, there is evidence that workers whose wages lie just above the minimum experience negative employment and hours spillover effects as a result of minimum wages (see e.g., Neumark et al., 2004).

Our identification of minimum wage workers is supported by the fact that individuals that we identify as minimum wage workers possess characteristics that have been shown in previous research to be associated with minimum wage employment.[6] In Table 4, we show the results of a linear probability model where the dependent variable equals one if the person is identified as a minimum wage worker and zero if identified as a non-minimum wage worker. The results for all workers indicate that males, Irish nationals, older people, those with higher levels of education and those with children are less likely to be minimum wage workers. Individuals working in the accommodation and food or wholesale and retail services sectors and part-time workers are more likely to be minimum wage workers. We also report separate results by gender and show that the same patterns appear for both males and females.[7]

In Table 5, we show the distribution of minimum wage and non-minimum wage workers by wage decile. It is clear that individuals in the treatment group (our minimum wage workers) are concentrated in low wage deciles, whereas individuals in the control group (our non-minimum wage workers) are concentrated in higher wage deciles. Note that virtually no minimum wage workers appear in deciles 9 and 10. As such, for our analysis, we exclude these two deciles to make the treatment and control group more comparable.[8]

A limitation of our approach relates to the fact that of all employees with hours and decile information, there are approximately 10 percent that we cannot assign a minimum wage status as they do not meet

[5] The yearly income of this person is (27*€9.15)*52=€12,846.60. Plugging this figure into the Deloitte tax calculator shows that a person on this wage has a gross income equal to their net income; http://services.deloitte.ie/tc/Results.aspx

[6] Maitre et al. (2016) analyse the characteristics of minimum wage workers in Ireland.

[7] While these results are useful in providing an overview of the characteristics associated with minimum wage employment, we should be conscious of potential collinearity between some of the variables which could affect the magnitude of the coefficients. For example, education, sector and part-time employment are likely to be correlated. In addition, while we control for a range of observable characteristics, there is likely to be unobservable traits, such as innate ability, that will also affect the probability of minimum wage employment.

[8] The results in the paper are not reliant on this exclusion.

our assignment criteria.[9] Of the 10 percent of unassignable employees, we cannot identify minimum wage workers working very low (less than 15) hours due to the large width of the lowest wage decile. For example, a minimum wage employee working 10 usual hours per week at a minimum wage level of €9.15 per hour will have a monthly salary of €393.45. However, as this falls within the first decile, which ranges from 0 to €631, we cannot assign any minimum wage individuals working 10 hours to the treatment group as *maxincome > (calcminwage*1.1)*. The problem persists for individuals working up to 14 hours per week, as the maximum qualifying criteria for identifying a minimum wage worker in this category also lies below the first decile upper range. We cannot simply assume that all first decile individuals working up to 15 hours per week are minimum wage workers as, for instance, an individual working 10 hours could earn €13 per hour and still fall within the first income decile. However, according to the Central Statistics Office Ireland (2017), this low hours group accounts for less than 20 percent of minimum wage workers in Ireland. Therefore, our analysis is reflective of approximately 80 percent of minimum wage workers.

Finally, there may be concerns related to the fact that we use hours as a dependent variable and we also use hours as part of our allocation criteria for minimum wage status in order to generate our treatment dummy variable. However, while endogeneity concerns may exist in certain scenarios where the same variable enters both sides of the regression equation, this is not problematic for our allocation criteria. We are simply using hours to calculate what a person's hypothetical minimum wage would be, which we then compare to their income decile. Consider an employee in decile 3 (€992-€1280) working 32 hours per week. Given this person's maximum possible wage is approximately equal to what they would be earning as a minimum wage worker, they are classified as a minimum wage worker (T=1). More precisely, their *maxincome (€1280) < calcminwage (€1385)*. Note that hours can increase and this does not change their minimum wage status (T=1). In fact, if hours were 33 instead of 32, then we are more certain that they are minimum wage workers. If, on the other hand, the hours for this type of person were to decrease to 30, then they are still a minimum wage worker as *maxincome (€1280) < calcminwage (€1298)*. If they decreased further to, for example, 29 hours, then we can no longer assign this worker as they meet neither criteria due to *minincome (€992) < calcminwage (€1255) < maxincome (€1280)*. This type of person would then be contained in the 10 percent of unassignable individuals for which we cannot be sufficiently certain as to their status. However, note that they would simply drop from the analysis and it would not be the case that the hours change would simultaneously affect their minimum wage status and the dependent variable. For their minimum wage status to change to T=0, this type of person would have to see an hours

[9] These are individuals where (*minincome < calcminwage*1.1 < maxincome)*

reduction from 32 hours to 22 hours per week with no corresponding decile change. However, in reality, decile and hours are not independent and a dramatic hours reduction is likely to coincide with a drop in income decile, which will, again, likely leave the treatment status unchanged at T=1. For example, if the hours drop to 25 and there is a corresponding movement from decile 3 to decile 2, then we are back at our initial assessment and the individual is still a minimum wage worker (T=1).

3. Hours Worked

We use a difference-in-differences (DiD) strategy to estimate the effect of the national minimum wage change on hours worked. This involves calculating the change in hours worked for the treatment group (minimum wage workers) in the period following the policy change compared to the period preceding the policy change, and subtracting from this the change in hours worked of the control group (the non-minimum wage workers) over the same two periods. For example, if we observe a reduction in hours worked for the treatment group and a similar reduction in hours worked for the control group, then we cannot say that the minimum wage change caused the hours reduction in the treatment group, given that the control group (of non-minimum wage workers) experienced a similar reduction. If, on the other hand, we observe a reduction in hours worked for the treatment group and no reduction (or even an increase) in hours worked for the control group, then we attribute the decline in hours worked for the minimum wage workers to the minimum wage increase. For our analysis of hours worked, we pool yearly cross-sections of data, with each year containing a minimum wage and non-minimum wage group.

The treatment effects can be estimated using standard linear regression techniques. With just two time periods, namely 2015 and 2016, the difference-in-differences estimator can be implemented with the following regression,

$$Hours_{i,t} = \beta_1 + \beta_2 Year_t + \beta 3 T_i + \beta 4 Year_t * T_i + \beta 5 X_{i,t} + \varepsilon_{i,t} \tag{1}$$

Where $Hours_{i,t}$ are the usual hours worked of worker *i* in time *t*. $Year_t$ is a dummy variable which equals one for observations in 2016 and zero for observations in 2015, Ti is a treatment dummy variable which equals one if worker *i* is a minimum wage worker and zero if a higher paid worker. The interaction term $Year_t*T_i$ is the estimated treatment effect.[10] We also include a vector of additional covariates, $X_{i,t}$, which includes age, education, gender and the number of children in the family. Including additional covariates in a difference-in-differences model controls for any potential

[10] It is straightforward to show that $\beta 4$ = [E(Hours | Year=2016, T=1) – E(Hours | Year=2015, T=1)] – [E(Hours | Year=2016, T=0) – E(Hours | Year=2015, T=0).

compositional changes within the treatment and control groups over time. Even if the treatment is independent of these covariates, it is common practice to include them in order to improve the precision of the difference-in-differences estimate.

When multiple pre-treatment time periods exist, the standard difference-in-differences model (equation 1) is often augmented to include time fixed effects, as follows,

$$Hours_{i,t} = \beta_1 + \sum_{\tau=t_2}^{T} \delta_\tau I_{\tau,t} + \beta 3 T_i + \beta 4 Post_t * T_i + \beta 5 X_{i,t} + \varepsilon_{i,t} \qquad (2)$$

Where $I_{\tau,t}$ is a dummy variable for period τ. The interaction term which gives the difference-in-differences estimate, $Post_t * T_i$, interacts the post-treatment time dummy with the treatment dummy, as in equation (1). The key assumption underlying the difference-in-differences estimator is that of parallel trends between the treatment and control groups. In the absence of any policy change, the outcomes of the treatment and control group should display similar trends over time. As noted by Mora and Reggio (2015 & 2012), the type of specification shown in equation (2) implies the existence of equivalent pre-treatment trends for the treatment and control groups. It is common for researchers to carry out placebo tests in pre-treatment years, where no policy change occurred, in an attempt to verify the parallel trends assumption (see, e.g., De Jong et al., 2011). If one obtains a significant difference-in-differences estimate in a placebo year, then this indicates that the outcomes in the treatment and control groups were diverging even before the policy change occurred. In our analysis we include three pre-treatment years, 2013, 2014 and 2015.[11] We find no statistically significant estimates in the placebo years, which supports the parallel trends assumption. An alternative to reporting results from several pre-treatment placebo years is to implement a test for common pre-treatment dynamics in the pooled model, using a method proposed by Mora and Reggio (2015 & 2012), henceforth referred to as the MR test. While a full exposition of the Mora and Reggio test is beyond the scope of this paper, the intuition behind the test is relatively straightforward. It is based on comparing the difference-in-differences estimate under the parallel trends assumption to other models which allow for the possibility of diverging pre-treatment dynamics among the treatment and control groups. In the presence of common pre-treatment dynamics, the estimates will not be statistically significantly different. We report the p-values from the MR test in our tables of results.[12] Again, all of the results are supportive of the parallel trends assumption.

[11] We do not include 2011 as a pre-treatment year as there was a temporary reduction in the minimum wage in this year. Furthermore, Ireland was in a deep recession up until 2012. A period of economic recovery began in 2013 thereby making the years from 2013 onwards more comparable. Nonetheless, our results are robust to including 2012 as a pre-treatment year.

[12] With a high p-value, we fail to reject the null hypothesis of common pre-treatment dynamics.

3.1 Hours worked results

The results from our baseline specification are shown in the first two columns of Table 6. Equation (2) is estimated for all workers as well as for temporary contract workers only. The increase in the minimum wage is shown to have a negative and statistically significant effect on the hours worked of minimum wage workers in the order of 0.5 hours per week. The results for temporary contract workers are more pronounced, indicating that the increase in the minimum wage led to a weekly reduction of approximately 3 hours per week for minimum wage workers on temporary contracts. The other coefficients reveal that being male, older and having higher education is associated with greater hours worked, while each additional child in the household reduces the weekly hours worked of the individual by approximately 1 hour. The parallel trends assumption is supported by the MR-test, which indicates common pre-treatment dynamics.

As our analysis is based on a sample of individuals for which wage decile data exists, we verify the robustness of our results using a Heckman Sample Selection Model. In the first stage regression, which models the probability that the individual is included in our sample, we use the following independent variables; gender, age, education, no. of children and nationality (Irish or non-Irish). As such, the first stage regression contains the same independent variables as our difference-in-differences model, along with the additional nationality variable. The results from the Heckman Model, shown in columns (3) and (4), are very similar to our baseline estimates.

In our analysis, wage deciles are used to allocate individuals as minimum wage or non-minimum wage workers. The fact that these deciles can change over time could potentially bias our estimates. While the deciles remained largely unchanged during the main period of interest, 2015 and 2016, there were some minor changes, typically in the order of less than one percent, to the higher wage deciles in quarter 2 of 2016. For example, in 2015 and quarter 1 of 2016, the maximum wage in decile 6 was €2,130 per month. From quarter 2 to quarter 4 of 2016, this was slightly lower at €2,117 per month. To illustrate how this could impact our estimates, consider an employee in decile 6 working 49 hours per week. In 2016 their *maxincome (€2,117)* $\leq$ *calcminwage**1.1 (€2,121), and therefore this person is classified as a minimum wage employee. However, in 2015, the *maxincome (€2,130)* just slightly exceeds the calculated minimum wage. As such, this person just falls short of meeting our allocation criteria. This means that in 2015 we cannot allocate employees in decile 6 working 49 hours per week as minimum wage employees, whereas we can in 2016. Therefore, decile changes in the pre- and post-treatment period could potentially generate shifts in the hours distribution which are due to our allocation criteria and are unrelated to the minimum wage change. We verify that changes to wage deciles are not biasing our results by estimating our difference-in-differences model on the pre- and post-treatment years, 2015 and 2016, and removing any worker whose decile-hours combination meant that they could not be allocated in both years.[13] As such, we are ensuring that any change in the hours distribution is unrelated to the impact of changing wage deciles. The results from our difference-in-differences model using the adjusted hours distribution is shown in columns (5) and (6). The estimates are very similar to our baseline and Heckman specifications. Overall, there is a reduction of 0.6 hours per week, while the reduction for temporary workers is 2.8 hours per week.[14]

The hours effect for temporary workers appears to drive the main result for the specification including all workers. Taking the adjusted hours model and excluding temporary workers yields a negative and statistically significant coefficient when no additional covariates are added. However, with the inclusion of additional control variables, the estimate loses statistical significance.[15] Therefore, our results show some evidence, albeit weak, of a decrease in hours for all minimum wage employees. However, the evidence of a negative hours effect is stronger for minimum wage workers on temporary contracts.

It should be noted that sub-minimum wage rates exist for certain categories of employees including those aged under 18, people with less than two years work experience or people who are in structured training during working hours. The sub-minimum rate for those aged under 18, for example, was €6.41 in 2016, which amounts to 70 percent of the national minimum wage.[16] However, the incidence of sub-minimum wage employment is very low. Of all individuals on or below the minimum wage, approximately 90 percent earn the minimum wage while just 10 percent earn a sub-minimum rate (CSO, 2017). Carrying out a separate analysis for sub-minimum wage workers is not currently possible as imposing such restrictions on an already limited sample size results in too few observations for any meaningful analysis. Moreover, the nature of our assignment mechanism to treatment and control groups, which is based on wage deciles, would limit our ability to precisely distinguish sub-minimum from minimum wage workers. As such, our treatment group of minimum wage workers may also include some sub-minimum wage workers. However, these workers were also subject to an increase in their hourly wage, similar to minimum wage workers, and may therefore face similar hours effects. While we cannot fully separate out sub-minimum wage workers, we carry out a robustness check which involves excluding under 18's from the analysis. These workers account for approximately one

[13] As the decile changes are small, there are just four hours-decile combinations for which we can allocate a worker in one year and not the other. These include the following: decile 4 – 35 hours, decile 6 – 49 hours, decile 7 – 56 hours, decile 8 – 66 hours. Dropping these individuals reduces our sample size from 21966 to 21638 for the full sample and from 1339 to 1316 for the temporary contract workers subsample.

[14] The adjusted hours model results are also robust to a Heckman correction.

[15] The specification which excludes temporary workers and contains the additional control variables shows a decrease of 0.34 hours per week. However, the associated p-value is 0.28.

[16] For a detailed list of sub-minimum rates, see http://www.lowpaycommission.ie/Rates/

quarter of sub-minimum wage earners (CSO, 2017). Our estimates in this age restricted specification remain unchanged in both their magnitude and statistical significance.[17]

3.2 Part-time employment

The detected fall in the number of hours worked among the treatment group can potentially be driven by at least two competing effects, (a) employers reducing the hours of individuals in receipt of the NMW in response to increased costs or (b) an increase in the proportion of individuals choosing to work part-time as a consequence of the higher rate of pay.[18] While we cannot measure the competing strength of both effects, we can use our estimation approach to assess if the change in the NMW rate was associated with a higher increase in part-time employment among the treatment group and examine any change in the motives of individuals working part-time over the period.

Table 7 shows the results of a difference-in-differences model using part-time employment as the dependent variable instead of hours worked. For brevity, we report the results from the adjusted hours distribution specification which we believe are the most reliable estimates as they rule out bias due to changes in wage deciles. However, as is the case with hours worked, our results are also robust to the baseline and Heckman Selection Models. While the dependent variable is a binary indicator of part-time status, we show results for a linear probability model, as the interaction term in nonlinear models, such as probit or logit models, are not interpretable in the same was as a standard linear regression, thereby making it difficult to interpret the difference-in-differences estimate (Karaca-Mandic et al., 2012). The results indicate that the incidence of part-time employment increased by approximately 2 percentage points more in the treatment group compared to the control group following the increase in the NMW. The corresponding estimate for minimum wage workers on temporary contracts was 11 percentage points.[19]

The QNHS data contains information on an individual's motives for working part-time. One of those responses is that the individual is working part-time as they could not find a full-time job, which gives us an indication as to the incidence of involuntary part-time employment. If, as a result of the increased minimum wage, employers impose part-time hours on individuals who would otherwise choose to work full-time, then one may expect the incidence of involuntary part-time employment to

[17] As they are virtually identical to our baseline results, for brevity we do not report these results in the paper.
[18] Specifically, the increased NMW rate will have met the reservation wage of individuals considering part-time employment.
[19] As with the hours model, the part-time model satisfies the parallel trends assumption. When placebo tests are run, we do not observe significant treatment effects. Likewise, when the baseline model is run, which includes all years of data, the MR-test is consistent with common pre-treatment dynamics.

increase following the minimum wage change. However, Table 8 indicates that the incidence of involuntary part-time work (could not find a full-time job) fell in both the control and treatment groups between 2015 and 2016. The magnitude of the decline was higher among minimum wage workers, falling from 45 percent in 2015 to 34 percent in 2016. Therefore, we cannot discount the possibility that incentive effects, whereby more individuals were choosing to work part-time by virtue of the increase in the NMW, were a potential factor in explaining some of the reduction in average hours worked among minimum wage workers.

4. Probability of Job Loss

We also adopt a difference-in-differences approach to assess the impact of the minimum wage change on the probability that a minimum wage employee becomes unemployed or inactive. However, we cannot take the same approach as that used for hours, which compares outcomes among yearly cross-sections of data. In order to evaluate job loss, we need to observe the same individual in two different time periods. Our approach involves following minimum wage workers over time to see if they experience job loss following the minimum wage increase. To do this, we exploit the longitudinal nature of the QNHS data to examine an individual's employment status in the period immediately before and immediately after the minimum wage change. We measure the extent to which the relative rate of job loss among minimum wage workers, who were observed in the data in quarter 4 2015 (before the NMW change) and again in quarter 1 of 2016 (after the NMW change), changed in the period following the increase in the NMW.[20]

Our dependent variable is a job loss dummy variable which equals one if the individual was in employment in quarter 4 2015, just before the NMW change, and unemployed or inactive following the NMW change (in quarter 1 2016). It is likely that there will be seasonal effects from quarter 4 to quarter 1 which will impact low wage workers differently to high wage workers. For example, some low wage workers may be employed on short-term contracts to cover the Christmas period (quarter 4) and will lose this job in January (quarter 1). Therefore, we cannot simply compare the rate of job loss of low wage workers with that of high wage workers as there may be seasonal differences which have nothing to do with the minimum wage. To overcome this seasonality, we again use a difference-in-differences estimator; this time we compare the difference in job loss rates in Q4 2015 – Q1 2016 between low and high wage workers, to the difference in job loss rates over the same period in the previous year, Q4 2014 – Q1 2015, when no minimum wage change occurred. For example, if we observe a high job loss rate among low wage workers relative to high wage workers for the treatment

[20] It should be noted that this job loss could be either voluntary or involuntary.

period, Q4 2015 – Q1 2016, and observe similar sized differences for Q4 2014 – Q1 2015, then it is likely that this difference is due to seasonal effects as opposed to employment effects relating to the minimum wage. However, if the higher rate of job loss for low wage workers in Q1 2016 exceeds that of the previous period (Q1 2015) then this would indicate a causal employment effect relating to the minimum wage. We estimate this difference-in-differences model with the following regression,

$$JobLoss_{i,t} = \beta_1 + \beta_2 Wave_t + \beta_3 T_{i,t} + \beta_4 X_{i,t} + \beta_5 Wave_t * T_{i,t} + \varepsilon_{i,t} \qquad (3)$$

Where $JobLoss_{i,t}$ is a dummy variable which equals one if the individual was employed in quarter 4 and unemployed or inactive in quarter 1, and zero if employed in both periods. $Wave_t$ is a dummy variable which equals one for the period Q4 2015 to Q1 2016 and equals zero for the period Q4 2014 to Q1 2015. The interaction between $Wave_t$ and T_{it} is the difference-in-differences estimate.

4.1 Job loss results

The results from our employment difference-in-differences model (equation 3) is shown in Table 9 below. The results indicate that there was no negative job loss effects following the introduction of the minimum wage in January 2016. The patterns of job loss of minimum wage workers compared to higher paid workers after the minimum wage increase was similar to patterns in previous year where no minimum wage change occurred. We observe the same results if we extend our analysis to quarter 2 of 2016. However, due to the fact that roughly 20 percent of households are replaced in each consecutive quarter of the survey, the sample sizes are too small to study beyond quarter 2. Therefore, our results are consistent with no negative employment effects up to six months following the increase in the minimum wage. However, the findings of Meer and West (2016), who use US data over the period 1975-2012, suggest that that the minimum wage will impact employment over time through changes in growth rather than an immediate drop in relative employment levels. This type of long run analysis is beyond the scope of the current paper and as such, we cannot discount the possibility of longer term employment effects.

5. Conclusion

This study assesses the impact of the increase in the minimum wage from €8.50 to €9.15 in 2016 on the hours worked, the incidence of part-time employment and the rate of job loss among minimum wage employees in Ireland. Our results indicate that the increase in the minimum wage rate resulted in an average reduction of approximately 0.5 hours per week among minimum wage workers, with a higher reduction, at approximately 3 hours per week, among those on temporary contracts. Further examination of the data reveals that the incidence of involuntary part-time work (could not find a full-time job) fell for both minimum wage and non-minimum wage workers between 2015 and 2016, with the overall magnitude of the decline being higher for minimum wage workers. Consequently, we cannot discount the possibility that incentive effects, whereby more individuals were choosing to work part-time by virtue of the increase in the NMW, were a factor in explaining the reduction in average hours worked among minimum wage workers.

Our results also indicate that the increase in the minimum wage did not lead to an increased likelihood of minimum wage workers becoming unemployed or inactive. While the relative rate of job loss of minimum wage workers was higher than non-minimum wage workers, we observed a similar pattern and similar magnitudes when looking at previous years where no change occurred in the NMW. However, Meer and West (2016), who use US data over the period 1975-2012, suggest that that the minimum wage will impact employment over time through changes in growth rather than an immediate drop in relative employment levels. Therefore, while we detect no immediate effects, we cannot rule out the possibility of longer term employment effects relating to the MW change.

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Tables

Table 1: Descriptive statistics on employees with missing and complete decile data, 2015 & 2016

	Decile data		No decile data	
	2015	**2016**	**2015**	**2016**
Age (in years)	41.6 (n=17,587)	41.7 (n=17,208)	40.1 (n=47,595)	39.9 (n=42,215)
Low education (%)	13.2 (n=17,539)	12.5 (n=16,969)	13.4 (n=45,876)	13.4 (n=40,668)
Medium education (%)	34.3 (n=17,539)	35.6 (n=16,969)	39.3 (n=45,876)	40.3 (n=40,668)
High education (%)	52.4 (n=17,539)	51.9 (n=16,969)	47.3 (n=45,876)	46.2 (n=40,668)
Male (%)	38.0 (n=17,857)	38.7 (17,208)	52.0 (n=47,595)	52.4 (42,215)
Usual hours	33.1 (n=17,223)	33.2 (n=16,537)	34.9 (n=44,838)	35.0 (n=39,855)
Part-time (%)	29.0 (n=17,857)	27.8 (n=17,208)	22.7 (n=47,595)	22.4 (n=42,215)

Source: QNHS 2015, 2016

Table 2: Examples of individuals categorized as non-minimum wage workers

Decile	Hours worked	*minincome*	*calcminwage*	Minimum wage worker
7 (€2124 - €2431)	40	€2124	€1573.80	No
5 (€1497 - €1792)	25	€1497	€983.63	No
3 (€992 - €1280)	20	€992	€786.90	No

Table 3: Examples of individuals categorized as minimum wage workers

Decile	Hours worked	*maxincome*	calcminwage (+10%)	Minimum wage worker
1 (€0 - €631)	15	€631	€649	Yes
2 (€632 - €991)	30	€991	€1298	Yes
4 (€1281 - €1496)	39	€1496	€1688	Yes

Table 4: Probability of being MW worker, 2015 and 2016

VARIABLES	All	Males	Females
Male	-0.054***	-	-
	(0.003)	-	-
Age	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)
Medium education	-0.105***	-0.064***	-0.151***
	(0.006)	(0.008)	(0.008)
High education	-0.232***	-0.157***	-0.302***
	(0.005)	(0.007)	(0.008)
Services	0.125***	0.076***	0.148***
	(0.004)	(0.007)	(0.006)
Part-time	0.035***	0.122***	0.008*
	(0.004)	(0.009)	(0.005)
Children	-0.022***	-0.021***	-0.019***
	(0.002)	(0.002)	(0.002)
Irish	-0.147***	-0.090***	-0.193***
	(0.005)	(0.007)	(0.007)
Constant	0.647***	0.488***	0.744***
	(0.010)	(0.014)	(0.014)
Observations	50,071	19,750	30,321

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Data is combined for the years 2015 and 2016. Services relates to accommodation / food and wholesale / retail

Table 5: Distribution of MW and non-MW workers by decile (2015 and 2016)

Decile	MW	non-MW
1	17.12	0
2	16.47	3.58
3	20.39	6.51
4	37.31	6.02
5	4.85	6.92
6	2.36	16.97
7	1.23	19.14
8	0.26	16.87
9	0.02	14.5
10	0	9.5

Note: Data for 2015 and 2016 are pooled and the deciles are reported.

Table 6: Effect of the minimum wage increase on hours worked

	Pooled model (2013-2016)		*Heckman Selection Model*		*Adjusted Hours Distribution Model (2015-2016)*	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Temporary contract workers only	Full Sample	Temporary contract workers only	Full Sample	Temporary contract workers only
Hours worked	-0.52**	-2.89***	-0.54**	-2.51***	-0.63**	-2.81**
	(0.240)	(0.977)	(0.242)	(0.979)	(0.299)	(1.21)
T	2.28***	4.20***	2.22***	4.03***	2.23***	4.27***
	(0.114)	(0.441)	(0.116)	(0.444)	(0.209)	(0.833)
Male	6.48***	4.40***	7.28***	5.50***	6.51***	4.18***
	(0.082)	(0.384)	(0.261)	(0.578)	(0.128)	(0.606)
Age	-0.11***	-0.11***	-0.12***	-0.214***	-0.11***	-0.074***
	(0.004)	(0.016)	(0.005)	(0.040)	(0.006)	(0.023)
High education	2.27***	5.36***	1.99***	2.05	2.46***	6.09***
	(0.132)	(0.651)	(0.159)	(1.35)	(0.204)	(0.980)
Medium education	0.72***	1.90***	0.72***	0.24	0.94***	1.75*
	(0.132)	(0.653)	(0.135)	(0.896)	(0.203)	(0.984)
No. of children	-1.04***	-1.07***	-1.06***	-1.43***	-1.03***	-1.18***
	(0.038)	(0.177)	(0.039)	(0.214)	(0.058)	(0.284)
Constant	35.57***	28.51***	39.63***	46.61***	34.27***	26.08***
	(0.241)	(1.04)	(1.26)	(6.17)	(0.366)	(1.513)
			Lambda	*Lambda*		
			-2.9	-8.3		
Year fixed effects	Yes	Yes	Yes	Yes	N/A	N/A
Common pre-treatment dynamics (MR-test)	*Yes* (*P =0.54*)	Yes (*P=0.47*)	Yes (*P=0.77*)	Yes (*P=0.28*)	N/A	N/A
Observations	49,650	3,224	49,650	3,224	21,638	1,316

Notes: Data source is the Quarterly National Household Survey. The Mora and Reggio (2015) test is implemented using the Stata *didq* module. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect of the minimum wage increase on part-time employment

VARIABLES	Full Sample	Temporary contract workers only
Part-time	0.023*	0.108**
	(0.014)	(0.055)
T	0.023***	-0.038
	(0.010)	(0.037)
Year	-0.017***	0.007
	(0.006)	(0.031)
Male	-0.221***	-0.116***
	(0.006)	(0.027)
Age	0.005***	0.005***
	(0.000)	0.001
High education	-0.162***	-0.319***
	(0.010)	0.044)
Medium education	-0.064***	-0.057
	(0.010)	(0.045)
No. of children	0.059***	0.056***
	(0.003)	(0.013)
Constant	0.195***	0.458
	(0.017)	(0.068)
Observations	21,631	1,315
R-squared	0.1145	0.1282

Table 8: Reported reasons for working part-time 2015 / 2016

	MW workers		**Non-MW workers**	
Reason	2015	2016	2015	2016
Education / training	12.0	14.3	2.8	3.9
Illness	1.7	0.7	1.8	1.4
Caring for children	18.1	17.2	33.1	31.7
Personal / family reasons	18.3	25.9	26.8	34.9
Could not find FT job	45.3	34.4	26.5	20.0
Other	4.5	7.5	8.9	8.2

Source: QNHS 2015, 2016. Individuals report only one of the reasons listed above.

Table 9: Effect of the minimum wage increase on the probability of becoming unemployed or inactive (Q4 2015 – Q1 2016)

VARIABLES	Q1 2016
Job loss	0.01
	(0.011)
T	0.02**
	(0.008)
Year	0.00
	(0.005)
Male	0.01***
	(0.005)
Age	-0.001***
	(0.0002)
High education	-0.01*
	(0.006)
Medium education	0.001
	(0.008)
No. of children	0.001
	(0.002)
Constant	0.041***
	(0.015)
Observations	3375
R-squared	0.0116