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Book

Estimating the effect of an increase in the minimum wage on hours worked and employment in Ireland

Reference: McGuinness, Séamus/Redmond, Paul (2018). Estimating the effect of an increase in the minimum wage on hours worked and employment in Ireland. Dublin : Economic and Social Research Institute.
doi:10.26504/bkmnext354.

April 2018

ESTIMATING THE EFFECT OF AN INCREASE IN THE MINIMUM WAGE ON HOURS WORKED AND EMPLOYMENT IN IRELAND

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LOW PAY COMMISSION

ESRI ECONOMIC & SOCIAL RESEARCH INSTITUTE

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Available to download from www.esri.ie

ISBN 978-0-7070-0454-9

DOI https://doi.org/10.26504/bkmnext354

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ACKNOWLEDGEMENTS

The work carried out in this report was funded by the Low Pay Commission. We would like to thank all individuals within the Commission who provided assistance during the project and provided us with valuable comments on earlier drafts of the report. In particular, we would like to thank Dr Donal de Buitléir, Professor Donal O'Neill, Mary Mosse and Máire Ni Chuirc, as well as Brian Ring of the Central Statistics Office. We would also like to thank the Central Statistics Office for access to the data used in the study. Finally, we are grateful to Alan Barrett who provided comments on an earlier draft.

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EXECUTIVE SUMMARY

- On 1 January 2016, the Irish minimum wage (MW) increased from €8.65 to €9.15 per hour, an increase of approximately 6 per cent. Using data from the Quarterly National Household Survey (QNHS) for the years 2015 and 2016, we estimate the effect of the increase in the minimum wage on the hours worked and likelihood of job loss among low paid workers using a difference-in-differences estimator.
- We generate a treatment group of MW workers and a control group consisting of higher paid non-MW workers using wage decile and hours worked data. Individuals in the treatment group possess characteristics which have been shown in previous research to be associated with minimum wage workers; the treatment group contains a relatively high proportion of females, people with low levels of education, non-Irish nationals, services sector workers, part-time workers and young people. As expected, individuals in the treatment group are concentrated in low wage deciles, whereas individuals in the control group are concentrated in higher wage deciles.
- The QNHS data contain hours and decile information on 33,760 employees, of which we can allocate 28,511 (84 per cent) to either a treatment or control group. Due to data constraints, we cannot allocate 5,249 workers (16 per cent of the sample) as there is too much uncertainty relating to their minimum wage status. This uncertainty relates to the fact that we are working with wage decile data as opposed to precise wage values. A relatively large proportion of these unassignable employees work low hours. This means that the sample of employees used in this study may not precisely reflect the hours distribution of the full population of workers in Ireland.
- 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. This was primarily driven by the large hours effect for minimum wage workers on temporary contracts who experienced a weekly reduction of approximately 3.5 hours.
- Our analysis indicates that the results did not occur as part of a general downward trend in hours worked by MW workers in the Irish labour market over time. When the same tests were carried out using data for preceding

years for which no change in the minimum wage rate occurred, no effect was detected.

- Further analysis indicates that the incidence of part-time (PT) employment increased by approximately three percentage points more in the treatment group (MW workers) compared to the control group (non-MW workers) following the increase in the MW. The increase in the incidence of PT employment was approximately 15 percentage points higher among temporary minimum wage workers relative to non-minimum wage temporary workers.
- Descriptive analysis reveals that while the incidence of involuntary PT work (could not find a FT job) fell in both the control and treatment groups between 2015 and 2016, the absolute decline was higher in magnitude in the treatment group compared to the control group.
- We cannot discount the possibility that incentive effects, whereby more individuals were choosing to work part-time by virtue of the increase in the minimum wage, were a factor in explaining the observed reduction in average hours worked among minimum wage workers following the increase in the rate.
- Both the descriptive and econometric evidence points to some volatility over time in the rate of job loss among low waged and minimum wage workers, with no consistent evidence that the increase in the NMW rate in 2016 caused an increase in the proportions of such workers becoming unemployed or inactive.

SECTION 1

Overview

On 1 January 2016, following recommendations from the Irish Low Pay Commission, the Irish minimum wage increased from €8.65 to €9.15 per hour, an increase of approximately 6 per cent. In making their recommendations, the Low Pay Commission took into account the broader economic conditions within the Irish labour market at the time, including the strong economic recovery, growing employment and average wage increases across the economy as a whole. In the year to Quarter 1, 2016, Average Hourly Earnings increased by 0.7 per cent (Low Pay Commission, 2016). 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 per cent and 0.4 per cent respectively. While the increase in the minimum wage, at 6 per cent, was higher than the average wage increases across the economy, it is important to note that, prior to this increase, the minimum wage in Ireland had remained relatively unchanged for the previous nine years.[1]

Using data from the Quarterly National Household Survey (QNHS) for the years 2015 and 2016, we estimate the effect of the increase in the minimum wage on both the hours worked and likelihood of job loss among minimum wage workers using a difference-in-differences estimator. We find that the increase in the minimum wage had a negative and statistically significant impact on the hours worked of low paid workers, with a weekly reduction of approximately one hour. We split the sample based on the type of contract, temporary or permanent, and find a relatively large impact for temporary workers in the order of 3.5 hours per week. However, further examination of the data reveals that at least some of the observed effect may be attributed to an increase in voluntary PT employment among minimum wage workers, suggesting that the decline in average hours among the treatment group may have been driven, at least to some extent, by an increase in the incentive to work part-time following the rate rise. Our results are robust to both placebo tests for years where no change in the MW rate occurred and various alternative specifications. We do not find evidence that the increase in the minimum wage led to a rise in the rate of job loss among minimum wage workers.

[1] 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.

In the absence of precise wage data in the QNHS, we use information relating to a person's wage band and the number of hours they usually work in order to evaluate whether they are minimum wage workers. The response rate for the decile question is relatively low. Despite this, we are left with a sample of 33,760 employees for which hours and decile information exists. Of this sample, we can allocate 28,511 (84 per cent) to either a treatment or control group using our assignment mechanism which is based on a person's decile and hours worked data. However, due to data constraints, which are outlined in detail in Section 3, our estimator focuses on the impact of the change on minimum wage employees working in excess of 14 hours per week, which, according to CSO (2017), accounts for approximately 80 per cent of minimum wage workers.[2] Therefore, while clear data limitations exist in relation to Irish wage data, the results in this paper represent the best evidence available, given these data constraints, on the impact of changes to the minimum wage.

The remainder of the paper is structured as follows. In Section 1.1 we outline some of the main findings from the minimum wage literature relating to employment and hours effects of minimum wage changes. In Section 2 we describe the data and in Section 3 we give a detailed explanation of the strategy used to identify minimum wage from non-minimum wage workers. Section 4 presents some broad descriptive statistics relating to the average hours worked of minimum wage and non-minimum wage workers. Section 5 explains the difference-in-differences (DiD) methodology we use in the paper and Section 6 presents the results relating to the effect of the minimum wage on hours worked. In Section 7 we show results relating to the employment effects of the minimum wage change. Finally, Section 8 concludes.

1.1 PREVIOUS LITERATURE

Before examining the empirical evidence on the effects of minimum wage changes, it is useful to briefly consider the predicted effects from the two broad theoretical models of the labour market which underpin minimum wage analyses. The model of a perfectly competitive labour market predicts that a binding minimum wage, which is a minimum wage above the market clearing wage, will lead to negative employment effects. This is as a result of labour demand falling short of supply due to the higher wage. It is important to note that employment effects can manifest themselves 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, in the monopsony model, there is one employer who has a degree of market power which allows them to keep wages below the perfectly competitive wage rate. If a minimum wage is set

2 See CSO (2017) for distribution of MW workers by hours worked.

that is above the monopsony wage rate, but lower than (or equal to) the perfectly competitive wage, then the monopsony model predicts an increase in employment. Manning (2003) argues that monopsony may be more relevant in modern labour markets.

There exists a vast literature examining the effect of minimum wage changes on employment outcomes, however the results are mixed. Some recent studies which find no discernible employment effects include Dolton et al. (2015), Hirsch et al. (2015) and Baek and Park (2016). However, others have found negative employment effects associated with minimum wage increases especially among certain segments of the population. 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. Dickens et al. (2015) study one of the most vulnerable groups, part-time females, and find that the introduction and uprating of the minimum wage in the UK is associated with negative employment effects for this group of workers. Liu et al. (2016) find negative employment effects for the youngest workers in the US, namely those aged 18 and under, with no significant effect for 19-24 year olds. Similarly, Gorry and Jackson (2017), using US data, find that increases in the minimum wage can lead to increases in youth unemployment. While the minimum wage literature can often provide conflicting results, several surveys and meta-analyses of the recent literature conclude that the weight of evidence point to no, or very little, negative employment effects associated with minimum wages (see, e.g., Schmitt 2015; Doucouliagos and Stanley, 2009; De Linde Leonard et al., 2014).

A separate strand of the literature addresses whether the minimum wage is an effective policy tool for tackling inequality and poverty. Again, there are mixed results. Autor et al. (2016) and Dolton et al. (2010) find that a minimum wage can reduce inequality in the lower half of the wage distribution for the US and the UK respectively. Garnero et al. (2015) find that statutory minimum wage rates in Europe are associated with lower levels of wage inequality. However, MaCurdy (2015) and Logue and Callan (2016) find that minimum wages are inefficient for boosting the incomes of poor families, as a relatively high percentage of the earnings benefit goes to families in the top half of the income distribution.

The literature on the impact of the minimum wage on hours worked is more limited than that relating to employment. Nonetheless, several studies exist and, again, as is typical with minimum wage studies, the results are mixed. Some evidence suggests 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 Wittenburg, 2001; Neumark and Wacsher, 2008; Belman et al., 2015). Neumark and Wacsher (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) also provides useful insights into the practicalities of hours adjustments in firms as a result of minimum changes. 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), Metcalf (2008) highlights that for one major retailer, aggregate hours allocation is based on predicted turnover. Managers are allocated a fixed percentage of that turnover for the wage bill and therefore an uprating of the minimum wage will lead managers to look closely at potential hours adjustments. However, other research finds little to no effect on hours worked as a result of minimum wage changes (see, e.g., Zavodny, 2000; Skedinger, 2015; Dolton et al., 2010).

SECTION 2

The data

Our central problem in attempting to measure the impact of changes in the national minimum wage (NMW) is that we have no reliable earnings data for the period. The primary source of contemporaneous earnings information for Ireland has been the National Employment Surveys, however this series was discontinued in 2010 and has not been replaced. The only other reliable source of income information remaining for Ireland is EU-SILC, however no data are currently available beyond 2015 and, in addition, the Irish sample size is relatively small. For our analysis we use data from the Quarterly National Household Survey (QNHS) for all quarters in 2015 and 2016. The QNHS data are collected continuously throughout the year and the QNHS is the official data source for producing statistics relating to the labour force in Ireland. We use annual, as opposed to quarterly datasets, as they average out seasonal variation and generate larger sample sizes. 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 significant challenge for this study as we aim to separate minimum wage from non-minimum wage workers. While exact income data are not included, the dataset does categorise individuals into wage deciles for a subset of respondents, based on monthly take home pay, and we know the bands (in Euro) corresponding to each decile. This enables us to distinguish individuals likely to be impacted by the national minimum wage (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 on employment. Nevertheless, the approach is not without its limitations, specifically, the broad range of the lowest decile wage band does not allow us to accurately identify minimum wage employees working less than 15 hours per week.

We began our inspection of the data by examining both the completeness and adequacy of our two key variables, i.e., income decile and hours worked. With respect to income decile there is a lot of missing decile data; specifically of the 124,875 employees recorded in 2015 and 2016 in the QNHS, 89,810 did not provide an answer to this question. 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. Of the 89,810 cases with no decile data, 64,442, or just over 70 per cent, are due to proxy interviews. The fact that we have income information on 28 per cent of our sample is not particularly problematic provided that (a) we have retained a sufficient amount of observations that enables us to generate reliable estimates and (b) the pattern of non-response is relatively random with respect to the underlying population of employees. While we observe some variation in those responding to the wage question by broad demographic characteristics, specifically males were less likely to answer (see Appendix Table A1), a simple linear probability model of non-response suggests that differences in the characteristics of respondents and non-respondents explain only 2 per cent of the observed non-response rate. This suggests that the subset of employees who provided wage decile information do not vary substantively from non-respondents.

In terms of the sample of employees that have provided information on income decile, over 96 per cent also provided information on hours worked. However, closer examination of the data reveals that the response rate on hours varied by income decile; specifically, the non-response rate was higher within the lower income deciles, which will also tend to contain high proportions of individuals who are either in receipt of the minimum wage and/or work relatively low hours. Table 1 demonstrates that the rate of non-response with respect to hours falls from almost 10 per cent in the first decile to below 3 per cent in the fifth decile and above. The pattern of non-response suggests that our treatment group is likely to under-represent minimum wage employees who work low hours. Given that the control group will tend to be more heavily represented within the higher deciles, it is unlikely that this group's composition will be heavily affected by the missing hours' information. In a later section we check the robustness of our estimates to this issue by re-estimating our model on a dataset that replaces the missing observations of hours worked with imputed values.

TABLE 1 NON-RESPONSE OF USUAL HOURS DATA BY INCOME DECILE 2015/2016

Decile	Mean	N
1	0.097	2,389
2	0.071	3,600
3	0.054	2,785
4	0.047	3,352
5	0.030	3,915
6	0.020	4,290
7	0.021	4,750
8	0.021	4,131
9	0.018	3,529
10	0.024	2,324
Total	0.037	35,065

Source: QNHS 2015, 2016.

SECTION 3

Our identification strategy

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 bottom decile of monthly wages ranges from €0 to €631. 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 the number of hours that they work. This is based on usual hours worked which is provided in the QNHS, 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 categorised as non-minimum wage workers.

TABLE 2 EXAMPLES OF INDIVIDUALS CATEGORISED AS NON-MINIMUM WAGE WORKERS

Decile	Hours worked	*minincome*	*calcminwage*	Minimum wage worker
7 (€2,124 - €2,431)	40	€2,124	€1,573.80	No
5 (€1,497 - €1,792)	25	€1,497	€983.63	No
3 (€992 - €1,280)	20	€992	€786.90	No

Source: Quarterly National Household Survey.

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 categorise 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 per cent to *calcminwage* due to the fact that we are estimating *calcminwage* based on usual hours worked and using a person's maximum possible wage as a guide to their actual wage.[3] Therefore, it is likely that individuals whose *calcminwage* just barely falls short of their *maxincome* are minimum wage workers and therefore

[3] We carry out some sensitivity analysis by varying the 10 per cent flexibility rule. Specifically, we use *calcminwage*1.2* and *calcminwage*1* and find the results are robust to these alternative measures.

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. For example an individual working 25 hours in Decile 2, which in 2016 runs from €632 to €991, would have a maximum monthly take home pay of €991, which is then compared to €1,081, i.e., the gross earnings of a worker employed for 25 hours on the minimum wage of €9.15 per hour (+10 per cent). In this case, the individual would be categorised 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 categorised as minimum wage workers.

TABLE 3 EXAMPLES OF INDIVIDUALS CATEGORISED 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	€1,298	Yes
4 (€1,281 - €1,496)	39	€1,496	€1,688	Yes

Source: Quarterly National Household Survey.

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 example, a person on the minimum wage working 27 hours per week will have take home pay equal to their gross pay.[4] 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, it is likely that we will also capture some low paid individuals whose hourly wage slightly exceeds the minimum. However, some studies have documented spill-over effects to these types of workers from a minimum wage increase, and existing studies often estimate the impact on the hours worked of low paid individuals, as opposed to just minimum wage workers (see e.g., Stewart and Swaffield, 2008).

[4] 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.

Individuals in the treatment group possess characteristics that have been shown in previous research to be associated with minimum wage workers. In Appendix Table A2 we show the results of a linear probability model where the dependent variable equals one if the person is identified as a MW worker and zero if identified as a non-MW worker. The results indicate that males, Irish, older people, those with high 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. Furthermore, in Appendix Table A3, we show the distribution of MW and non-MW workers by wage decile. It is clear that individuals in the treatment group (our MW workers) are concentrated in low wage deciles, whereas individuals in the control group (our non-MW workers) are concentrated in higher wage deciles.

3.1 LIMITATIONS OF THE APPROACH

The QNHS data contain hours and decile information on 33,760 employees, of which we can allocate 28,511 (84 per cent) to either a treatment or control group. However, a limitation of the approach relates to our inability to allocate 5,249 employees (16 per cent of the sample). Due to the large width of the lowest wage decile, we cannot assign individuals working very low hours, specifically less than 15 hours per week, to the treatment group. For example, a minimum wage employee working ten usual hours per week at a 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 ten hours to the treatment group as *maxincome > (calcminwage*1.1)*.[5] The problem persists for individuals working up to 14 hours per week in Decile 1, as the calculated minimum wage also lies below the upper income range in the first decile. We cannot simply assume that all first decile individuals working up to 15 hours per week belong to the treatment group as, for instance, an individual working ten hours could earn €13 per hour and still fall within the first income decile. These types of employees account for 26 per cent of the 5,249 unassignable workers.

A similar issue arises in some of the higher deciles, where we are unable to assign certain individuals to either a treatment or control group. For example, the income band in Decile 2 is €632-€991, which means we cannot allocate employees working 20 hours in Decile 2 to the treatment or control group, as their *maxincome* (€991) > *calcminwage*1.1* (€866) > *minincome* (€632). Similarly, in Decile 5, where the income range is €1,497-€1,792, we cannot allocate

[5] The income deciles are set by the CSO and are subject to revision. From 2015-2016, the period used to study the effect of the minimum wage change, the wage bands were relatively stable. In previous years, from 2012 to the first half of 2014, the upper band in each of the wage deciles was approximately 15 per cent higher.

employees working 40 hours per week as *maxincome* (€1,792) > *calcminwage*1.1* (€1,731) > *minincome* (€1,497). When reporting usual hours worked, a relatively large number of employees typically list 20 or 40 hours per week and therefore, in addition to the 1-14 hours group, the 20 and 40 hours groups represent a relatively large percentage of the unassignable employees. This can be seen in Table 4 below which shows the distribution of the 5,249 unassignable employees by decile and hours worked.

TABLE 4 DISTRIBUTION OF THE ASSIGNABLE WORKERS

Decile	Hours range	Unassignable employees (%)
1	1-14	26
2	17-22	33
3	26-29	3
4	33-34	1
5	39-40	37
6	46-49	1
7	54-55	0
8	65	0
9	80	0

Source: Quarterly National Household Survey.

It is important to note that our analysis does not exclude the employees working in the hours ranges shown in Table 4. For example, while we cannot assign employees working 1-14 hours in Decile 1 to the treatment group, an employee whose hours fall within this range in higher deciles can be allocated to the control group. Similarly, while we cannot assign an individual working 17 hours in Decile 2, an individual working 17 hours in Decile 1 would be assigned to the treatment group while an individual working 17 hours in a higher decile would be assigned to the control group. Nonetheless, if the unassignable employees in Deciles 1 and 2 are disproportionately made up of minimum wage workers, then their exclusion will result in a slightly higher average hours worked of minimum wage workers in our sample relative to the total population. If the individuals working 39-40 hours in Decile 5 are disproportionately non-minimum wage workers, then their exclusion will lead to a slight reduction in the average hours worked of the non-minimum wage workers in our sample. These two effects will have an equalising impact on the average hours worked of both treatment and control groups, making the average hours worked of minimum wage and non-minimum wage workers in our sample quite similar.

Out of the sample of 28,511 employees, 4,621 (or 16 per cent) are allocated into the treatment group. Maître et al. (2016), using the Irish Survey of Income and Living Conditions (SILC) dataset, estimates that 14 per cent of individuals earn below €10 per hour. As we are assigning individuals to the treatment group using a threshold of €9.15 + 10 per cent, this equates to a wage of €10.06 per hour and, as such, our estimate is broadly in line with that of Maître et al. (2016).

Table 5 compares the distribution of our 2015 and 2016 treatment and control groups by hours worked with a comparable distribution based on a minimum wage question that was included within the 2016 QHNS waves.[6] It should be noted that both approaches use different strategies to identify both categories of workers (control and treatment) and that differences in the sampling approach can potentially result in different incidences and associated distributions. For example, Kelly and McGuinness (2017) show that the estimated minimum wage incidence in Ireland in 2009 varied from 1.9 per cent, on a measure based on wage estimates similar to ours, to 7.2 per cent based on a direct employee question which was similar to that applied in the 2016 QNHS, demonstrating that different individuals may be identified as minimum wage workers under subjective and objective estimation approaches. In addition, the new QNHS direct question contains a very high percentage of proxy responses which could impact the estimated incidence of minimum wage employment using this measure.

Notwithstanding the different measurement approach and the truncated nature of our sample data, the distribution of our treatment group by hours worked does not seem unreasonable. Under both measurement approaches the incidence of the minimum wage fell between the 20-29 and 30-34 hours categories, then increased in the 35-39 hour category, before declining consecutively in the last two hours categories. However, a better comparison can be made by imposing the same truncation present in our sample on the 2016 QNHS MW distribution, which we do in the final column of Table 5.[7] This shows that our MW sample more closely reflects that of the one reported in the QNHS; however our distribution has a lower share in the 20-29 hours category which, as discussed above (see Table 4), relates to difficulties allocating individuals working 20 hours in Decile 2, a large proportion of which may be minimum wage workers. The control group distribution, unsurprisingly given the relatively small incidence of the MW, closely follows that of the non-MW QNHS group.

6 We use the hourly distribution of hours published in Table 8A of the Central Statistics Offices QNHS National Minimum Wage Series Q4 2016 (published April 2017).

7 This is achieved by removing all observations in the 0-9 category and 50 per cent of the observations in the 10-19 category.

TABLE 5 DISTRIBUTION BY HOURS WORKED OF 2015 AND 2016 TREATMENT AND CONTROL GROUPS USING ALTERNATIVE IDENTIFICATION APPROACHES

	Sample distribution 2015 and 2016		QNHS distribution 2016		
	MW	Non-MW	MW	Non-MW	Standardised QNHS MW
1 to 9	0	0.6	8	1.1	0
10 to 19	9.7	6.9	23.1	5.2	14.2
20 to 29	14.2	16.5	26.1	11.7	32.5
30 to 34	9.3	8.2	5.6	5.6	6.9
35 to 39	37.3	38.3	18.4	35.7	23.0
40 to 44	19.1	21.4	15.1	27.1	18.8
45+	10.3	8.2	3.7	13.5	4.6

Source: Quarterly National Household Survey.
Note: The sample distribution is based on the methodology of assigning minimum wage workers outlined above. The QNHS Distribution 2016 comes from CSO (2017).

In light of the difficulties in allocating some individuals, we carry out a detailed analysis of the characteristics of these omitted workers, comparing them to the characteristics of employees in the treatment and control groups. We have seen that the unassignable employees are predominantly low-hours workers who will be disproportionately made up of young people, including students working part-time, and this is reflected in the descriptive statistics.[8] On average, the unassigned workers are relatively young, work low hours and have low levels of education (see Table 6). While it is true that the average characteristics of the unassigned workers more closely resemble those of the treatment group (minimum wage workers), we cannot simply assume that all of these individuals belong to the treatment group as it is possible that some of these could be earning far in excess of the minimum wage. Therefore, the benefit of our approach relates to the strictness of our criteria in allocating individuals to the treatment and control groups, i.e., we only allocate individuals for which the data are sufficiently clear as to whether they are minimum wage or non-minimum wage workers. However the cost of this approach is that we are left with a small percentage of our sample (16 per cent) for which we are not sufficiently confident as to which group they belong and therefore remain unassigned.

[8] A part-time worker is an employed person whose normal hours of work are less than those of comparable full-time workers.

TABLE 6 CHARACTERISTICS OF UNASSIGNED WORKERS COMPARED TO THE TREATMENT AND CONTROL GROUPS

Characteristic	Unassigned workers	Treatment group	Control group
Age (in years)	41.3	39.2	42.2
Hours worked	24.8	35.1	34.6
Low education	24.5%	19.2%	8.9%
Medium education	60.7%	61.3%	45.8%
High education	14.8%	19.6%	45.3%

Source: Quarterly National Household Survey.

SECTION 4

Descriptive statistics

The difference-in-differences strategy is based on estimating the change in hours worked for the treatment group over the two time periods and subtracting from this the change in hours worked of the control group over the same two periods. In Table 7 we show the average hours worked and incidence of part-time employment for the treatment group (MW workers) and the control group (non-MW workers) in the two time periods (2015 and 2016). The first point to note is that while, as expected, the treatment group in both periods contains a higher share of part-time workers, the average hours worked in the treatment group is marginally higher than the control. This difference is due to the absence of data on minimum wage employees working very low hours in the treatment group, which has the effect of raising the mean value of hours worked considerably. From 2015 to 2016, the average hours worked of MW workers decreased from 35.353 hours to 34.718 hours. However, over the same period, the hours worked of the non-MW workers increased from 34.461 hours to 34.724 hours. This is indicative of a potential treatment effect.

To demonstrate the impact of data truncation on the samples, Table 8 looks at the effect of re-assigning non-assigned individuals working 10-14 hours, located in the first income decile, to the treatment group. While we acknowledge that this will incorrectly assign an unknown number of individuals, the table shows that were we able to accurately identify MW employees working low hours, the data would show the control group to have much higher average hours and a much lower incidence of part-time employment compared to the treatment group.

Finally, to ensure a greater degree of comparability between our control and treatment groups, we exclude individuals in the 9th and 10th deciles on the basis that virtually no MW workers are located in these deciles. The lack of any treatment group members in the highest wage deciles indicates that it is not appropriate to include such individuals as members of the comparison group. Table 9 shows that, due to the fact that virtually all workers in Deciles 9 and 10 are full-time, this exclusion has the effect of decreasing the mean hours of the control group, while increasing the part-time share of the control group (compare Table 7 to Table 9).

TABLE 7 DESCRIPTIVE STATISTICS FOR MW AND NON-MW WORKERS (ALL DECILES INCLUDED)

	MW workers		Non-MW workers	
	2015	2016	2015	2016
Usual hours worked	Mean 35.353 Min 15 Max 98	Mean 34.718 Min 15 Max 98	Mean 34.461 Min 1 Max 90	Mean 34.724 Min 3 Max 90
Part-time work (%)	26.7%	28.9%	21.2%	19.6%

Source: QNHS 2015, 2016.

TABLE 8 DESCRIPTIVE STATISTICS FOR MW AND NON-MW WORKERS WHEN WE INCLUDE NON-ASSIGNED PEOPLE IN DECILE 1 WITH 10-15 HOURS AS MW WORKERS (NO DECILE RESTRICTION)

	MW workers		Non-MW workers	
	2015	2016	2015	2016
Usual hours worked	Mean 32.31 Min 10 Max 98	Mean 31.61 Min 10 Max 98	Mean 34.46 Min 1 Max 90	Mean 34.72 Min 3 Max 90
Part-time work (%)	35.8%	38.2%	21.2%	19.6%

Source: QNHS 2015, 2016.

TABLE 9 DESCRIPTIVE STATISTICS FOR MW AND NON-MW WORKERS (EXCLUDING DECILES 9 AND 10)

	MW workers		Non-MW workers	
	2015	2016	2015	2016
Usual hours worked	Mean 35.353 Min 15 Max 98	Mean 34.694 Min 15 Max 98	Mean 32.729 Min 1 Max 60	Mean 33.124 Min 3 Max 60
Part-time work (%)	26.7%	28.9%	27.2%	25.2%

Source: QNHS 2015, 2016.

SECTION 5

Estimation methodology

We employ a difference-in-differences (DiD) approach to estimate the impact of the increased minimum wage on hours worked. This approach is based on estimating the change in hours worked for the treatment group over the two time periods and subtracting from this the change in hours worked of the control group over the same two periods (hence the description of the approach as difference-in-differences). If the hours worked in the treatment group decreased by more than the control group, this may be indicative of a treatment effect.

More formally, the treatment group is comprised of minimum wage workers and the control group is comprised of non-minimum wage workers as defined above. We compare the hours worked of the treatment group in 2015, before the increase in the minimum wage, to the hours worked in 2016, after the introduction of the increased minimum wage. However, this alone does not lead to a causal interpretation relating to the change in the minimum wage. 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. It is possible that a general decline in hours worked can occur across the labour force for reasons other than the minimum wage change. If 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 MW workers to the minimum wage increase.

While the minimum wage increased in January 2016 from €8.65 to €9.15 per hour, our treatment group is any worker, in either year, who earned below the 2016 minimum wage of €9.15. This is to capture the causal effect of the increased minimum wage, not only on minimum wage workers in both periods, but also on workers who were not MW workers in 2015 but became MW workers in 2016.

The time periods cover the full years of 2015 and 2016. Including full years of data allows us to achieve a sufficiently large sample for the treatment group in order to allow for meaningful analysis. Moreover, it overcomes any issues which may relate to seasonal effects arising from comparing different quarters in both years. There are a total of 22,778 observations (see Table 10).

TABLE 10 NUMBER OF OBSERVATIONS IN TREATMENT AND CONTROL GROUPS (BELOW DECILE 9)

Year	Treatment group	Control group	Ratio (treatment / control)
2015	2,521	9,116	0.28
2016	2,099	9,042	0.23

Source: QNHS 2015, 2016.

The DiD estimator (Equation 1) involves regressing the hours worked on a year dummy (which equals 1 if 2016 and equals 0 if 2015), a treatment dummy *T* (equals 1 for minimum wage workers and 0 for non-minimum wage workers) and an interaction term.

$$Hours = \beta 1 + \beta 2 Year + \beta 3 T + \beta 4 Year * T + \varepsilon \qquad (1)$$

The coefficient on the interaction term (β4) is the estimate of the treatment effect, i.e., the impact of the change in the rate of the NMW on the number of hours worked by minimum wage employees. It should be noted that in a standard MW estimation, β3 would normally be negative, indicating that the treatment group tend to work fewer hours than the control group; however, the truncated nature of our MW sample combined with our exclusion of individuals in the 9th and 10th decile from our control group means that in our case the coefficient will tend to be marginally positive.

SECTION 6

Results

The results are shown in Table 11 below. Column 1 shows the results from estimating Equation 1 above and Column 2 includes additional control variables including; age, sex, education and number of children in the home, as this may affect the number of hours worked. The results indicate that the increase in the minimum wage had a negative and statistically significant effect on the hours worked of minimum wage and low wage workers, with an average reduction of approximately one hour per week for all employees in the sample. This is similar to results by Stewart and Swaffield (2008) who found that the introduction of a minimum wage in the UK resulted in a reduction in the hours worked of low paid workers by between one and two hours per week. Including the controls in Specification 2 reduces the estimate to 0.66 hours per week, and this remains statistically significant. The other coefficients in Specification 2 reveal that being male and having higher education is associated with increased hours worked, while each additional child in the household reduces the weekly hours worked of the individual by approximately one hour.

TABLE 11 DIFFERENCE-IN-DIFFERENCES RESULTS

	(1)	(2)	(3)
Variable	**No additional covariates**	**Covariates added**	**Temporary contracts**
Treatment effect	-1.054***	-0.655**	-3.33***
	(0.339)	(0.329)	(1.220)
T	2.62***	2.36***	4.67***
	(0.232)	(0.229)	(0.878)
Year	0.395***	0.331***	0.288
	(0.137)	(0.126)	(0.667)
Male		6.40***	3.88***
		(0.124)	(0.596)
Age		-0.104***	-0.059**
		(.007)	(0.024)
High education		2.51***	6.45***
		(0.231)	(0.948)
Medium education		1.44***	3.14***
		(0.208)	(0.888)
No. of children		-0.972***	-1.08***
		(0.059)	(0.271)
Constant	32.729***	33.960***	24.94***
	(0.100)	(0.404)	(1.50)
Observations	22,778	22,424	1,373
R-squared	0.009	0.150	0.1049

Source: Quarterly National Household Survey.
Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. As outlined in Equation (1), the variables *T* and *Year* are dummy variables to indicate the treatment group and treatment period respectively.

In Column 3 of Table 11 we focus on workers with temporary contracts. The effect of the increase in the minimum wage appears to have a relatively large effect on low paid temporary workers, with a weekly reduction of approximately 3.5 hours.[9] The large hours effect for temporary workers also appears to drive, to some degree, the main result for the specification including all workers. If we exclude temporary workers from our specification in Column 1 of Table 11, the coefficient reduces from -1.05 to -0.75, yet remains statistically significant at the 5 per cent level.[10] If temporary workers are excluded from the specification in Column 2, the estimate changes from -0.66 to -0.34 and loses statistical significance.[11] Therefore, our results show some evidence of a decrease in hours for all minimum wage employees. However, the evidence of a negative hours effect is much 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 of 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 per cent of the national minimum wage.[12] However, the incidence of sub-minimum wage employment is very low. Of all individuals on or below the minimum wage, 85 per cent earn the minimum wage while just 15 per cent 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 employment and hours effects. While we cannot fully separate out sub-minimum wage workers, we carry out a robustness check which involves excluding under-18s from the analysis. According to CSO (2017), approximately one-quarter of sub-minimum wage workers report that the reason they earn a sub-minimum rate is due to being under 18. Therefore excluding under-18s will further limit the number of sub-minimum wage workers in our treatment group. Doing this makes no difference to our results. Our estimates remain almost unchanged in both their magnitude and statistical significance.

9 As noted in Section 3, our strategy for identifying minimum wage workers incorporates a degree of flexibility by adding 10 per cent to the *calcminwage* variable. We carry out sensitivity analysis by varying the degree of flexibility to 20 per cent and 0 per cent. The results are robust to these changes. Specifically, for 20 per cent, the coefficient for temporary workers is -3.31 (p-value 0.014) and for 0 per cent it is -2.60 (p-value 0.018).

10 The p-value is 0.031.

11 The specification which excludes temporary workers shows a decrease of 0.34 hours per week. However the associated p-value is 0.264.

12 For a detailed list of sub-minimum rates, see www.lowpaycommission.ie/Rates.

6.1 PLACEBO TESTS

We carry out placebo tests by estimating the model for years in which no change occurred in the minimum wage. If we were to observe effects similar to those found in Table 11 for years in which no change occurred, this would call into question any causal interpretation of the results in Table 11. The results of the placebo tests are shown in Table 12 for the following year pairings; 2012-2013, 2013-2014 and 2014-2015.[13] As we can see, the coefficient which indicates the treatment effect is not statistically significant in any of the years, and the sign fluctuates from positive to negative depending on the year. The results from the placebo tests support the view that increasing the NMW influenced the hours worked of minimum wage employees in a causal way in 2016.

TABLE 12 PLACEBO TESTS

	2012-2013		2013-2014		2014-2015	
VARIABLES	Pooled	Temp	Pooled	Temp	Pooled	Temp
Treatment	-0.154	-0.0907	-0.346	-1.194	0.183	0.727
	(0.298)	(0.970)	(0.298)	(0.992)	(0.307)	(1.071)
T	2.670***	4.655***	2.548***	4.724***	2.113***	3.949***
	(0.212)	(0.676)	(0.220)	(0.705)	(0.211)	(0.734)
Year	0.239**	0.371	-0.191*	-0.559	-0.778***	-0.476
	(0.0995)	(0.546)	(0.109)	(0.582)	(0.121)	(0.640)
Male	6.461***	4.913***	6.480***	4.608***	6.428***	3.400***
	(0.0984)	(0.469)	(0.106)	(0.499)	(0.115)	(0.543)
Age	-0.124***	-0.163***	-0.119***	-0.142***	-0.113***	-0.0451**
	(0.00521)	(0.0197)	(0.00569)	(0.0214)	(0.00620)	(0.0222)
Medium education	0.816***	2.874***	0.569***	2.158**	1.064***	3.221***
	(0.164)	(0.775)	(0.183)	(0.871)	(0.197)	(0.857)
High education	2.153***	4.601***	2.163***	4.905***	2.218***	6.355***
	(0.163)	(0.752)	(0.185)	(0.869)	(0.219)	(0.923)
Children	-0.989***	-0.756***	-1.047***	-1.000***	-1.113***	-1.246***
	(0.0482)	(0.226)	(0.0525)	(0.229)	(0.0564)	(0.252)
Constant	35.76***	29.79***	35.88***	29.66***	35.52***	25.21***
	(0.299)	(1.185)	(0.341)	(1.374)	(0.378)	(1.454)
Observations	32,543	2,202	27,863	1,900	24,714	1,625
R-squared	0.160	0.134	0.161	0.124	0.159	0.101

Source: Quarterly National Household Survey.
Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. As outlined in Equation (1), the variables *T* and *Year* are dummy variables to indicate the treatment group and treatment period respectively.

[13] We stopped at 2011 as there was a temporary reduction on the minimum wage during this year.

6.2 IMPUTATION

In order to assess the impact of the higher rate of non-response to the question on hours among workers in the bottom two income deciles, we imputed values for the missing observations based on an hours worked model that controls for age, gender, education, occupation and sector. The results are shown in Appendix Table A4. The estimated treatment effects decreased only marginally and lost none of their statistical significance. Moreover, the estimated values of $\beta 3$, the coefficient associated with the group variable *T*, fell in all three model specifications as a result of slightly better data coverage among low hour workers. We also ran models for the placebo years using the imputation method (Appendix Table A5). The treatment coefficients are not statistically significant for any of the placebo years.

6.3 CONTROL GROUP RESTRICTIONS

As stated, we cannot assign individuals working 14 hours or less to the MW category. As a robustness check, we re-estimate the model with individuals working less than 15 hours also removed from the control group (Appendix Table A6). The treatment coefficients remain negative and statistically significant. The treatment coefficient is not statistically significant for the placebo years (Appendix Table A7).

6.4 PUSH OR PULL EFFECT?

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.[14] While we cannot measure the competing strength of both effects, we can use our estimation approach to assess if the change in the MW rate was associated with a higher increase in PT employment among the treatment group and examine any change in the motives of individuals working part-time over the period.

Table 13 shows the results of a difference-in-differences model on part-time employment, as opposed to hours worked. While the dependent variable is a binary indicator of part-time status, we show results for a linear probability model. The interaction term in a probit model is not interpretable in the same way as a standard linear regression, which can make it difficult to interpret the

[14] Specifically, the increased NMW rate will have met the reservation wage of individuals considering part-time employment.

difference-in-differences estimate.[15] The results indicate that the incidence of PT employment increased by approximately 3 percentage points more in the treatment group compared to the control group following the increase in the MW. The increase in the incidence of part-time employment was approximately 15 percentage points higher among temporary MW workers relative to non-MW temporary workers. This model again passes all placebo tests for 2012-2013, 2013-2014 and 2014-2015, suggesting that the 2016 increase in the NMW rate exerted a positive causal influence on the rate of part-time employment.

TABLE 13 PART-TIME DIFFERENCE-IN-DIFFERENCES WITH DECILE RESTRICTION (LINEAR PROBABILITY MODEL)

	(1)	(2)	(3)
Variable	Part-time	Part-time	Part-time
Treatment effect	0.0425***	0.0265*	0.140**
	(0.0148)	(0.0146)	(0.0553)
T	-0.00527	-0.00402	-0.0650*
	(0.00996)	(0.00997)	(0.0384)
Year	-0.0199***	-0.0165***	-0.0129
	(0.00652)	(0.00610)	(0.0307)
Male		-0.223***	-0.106***
		(0.00538)	(0.0268)
Age		0.00445***	0.00448***
		(0.000292)	(0.00108)
Medium education		-0.0877***	-0.132***
		(0.00972)	(0.0407)
High education		-0.193***	-0.353***
		(0.0106)	(0.0430)
Children		0.0548***	0.0494***
		(0.00282)	(0.0132)
Constant	0.272***	0.236***	0.526***
	(0.00466)	(0.0182)	(0.0683)
Observations	22,778	22,424	1,373
R-squared	0.001	0.114	0.113

Source: Quarterly National Household Survey.
Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. As outlined in Equation (1), the variables *T* and *Year* are dummy variables to indicate the treatment group and treatment period respectively.

Table 14 indicates that the incidence of involuntary PT work (could not find a FT job) fell in both the control and treatment groups between 2015 and 2016, with the overall magnitude of the decline being higher in the treatment group compared to the control group. Consequently, we cannot discount the possibility that incentive effects, whereby more individuals were choosing to work part-time

[15] See Karaca-Mandic et al. (2012) for a detailed analysis of interaction terms in non-linear models. However, in our analysis, a probit model generates almost identical results (available from the authors).

by virtue of the increase in the MW, were a factor in explaining the reduction in average hours worked among MW workers following the increase in the minimum wage.

TABLE 14 REPORTED REASONS FOR WORKING PART-TIME 2015 / 2016

	MW workers		Non-MW workers	
Reason	**2015**	**2016**	**2015**	**2016**
Education / training	12.01	14.36	2.88	4.29
Illness	1.72	0.69	1.88	1.49
Caring for children	18.10	17.30	31.68	30.71
Personal / family reasons	18.25	25.95	26.70	34.91
Could not find FT job	45.40	34.26	27.75	20.37
Other	4.52	7.44	9.11	8.22

Source: QNHS 2015, 2016.

SECTION 7

Employment

In order to assess the impact of the minimum wage on employment, we exploit the longitudinal nature of the QNHS to measure the extent to which the rate of relative job loss among low waged individuals, who were observed in the data in both Quarters 4 and 1, increased in the period following the increase in the NMW in 2016.[16] Due to attrition rates and the fact that we are conditioning on just two quarters of data means that our sample sizes are relatively small. This becomes particularly problematic as we move beyond Quarter 1 as more individuals are dropped from consecutive samples. As such, we report the results comparing Quarter 4 to Quarter 1.[17] 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.

A job loss dummy variable is created which equals one if the individual was in employment in Quarter 4 and unemployed or inactive in Quarter 1. There will likely 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 temporary 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 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 for the same quarters in previous years. For example, if we observe a high job loss rate among low wage workers relative to high wage workers for the treatment period, Q4 2015 – Q1 2016, and observe similar sized differences in previous years, for example Q4 2014 – Q1 2015, then this may be 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 previous periods (e.g., Q1 2013, Q1 2014 and Q1 2015) then this would indicate a causal employment effect relating to the minimum wage.

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16 It should be noted that this job loss could be either voluntary or involuntary.

17 We extended our analysis to Quarter 2 and found similar results. We do not extend the analysis beyond Quarter 2 as the sample size becomes too small.

We examine the employment effect using the following three definitions of low pay versus higher pay;

- Employees in ISCO 5 (sales and protective services) compared to employees in ISCO 1-4 (managers, professionals, associate professionals, clerical workers).
- Employees in Decile 1 compared to employees in Deciles 2 to 10.
- Minimum wage workers compared to non-minimum wage workers based on our assignment methodology outlined earlier in the paper.

While it is true that the first two categories broadly reflect low paid and non-low paid workers, the categorisation is not precise; specifically, there will be individuals on relatively high rates of hourly pay in both ISCO 5 and in Decile 1. As such, we consider the third comparison, minimum wage to non-minimum wage workers, as representing the most accurate measure of the policy change on employment outcomes. Descriptive evidence from Q4 / Q1 comparisons over the period 2012 to 2016, Tables 15a-15c, indicates that the rate of job loss was higher among each of the low paid groups in all periods. For instance, between Q4 2012 and Q1 2013 4.79 per cent of ISCO 5 employees became unemployed or inactive compared to 2.05 per cent of workers in ISCO 1-4, a difference of 2.74 per cent. The key question for our analysis relates to whether the rate of employment loss increased in a significant way after the introduction of the higher NMW rate in Q1 2016? The descriptive evidence is somewhat inconclusive in that while the rate of relative job loss among the low income groups did appear to increase in Q4 2015 to Q1 2016, relative to the difference that occurred a year earlier, the rate does not look dissimilar to others which occurred in other periods prior to the rate change.

We test formally, again using a difference-in-differences model, whether the increase in the rate of job loss among low waged workers was significantly higher in the period following the introduction on the NMW increase (Q4 2015 to Q1 2016) compared to the same period in the years preceding the change.[18] To estimate the difference-in-differences model, we run the following regression,

$$LostJob = \beta_1 + \beta_2 2016 + \beta_3 T + \beta_4 2016 * T + \varepsilon \qquad (2)$$

where *LostJob* is a dummy variable which equals one if a person is employed in Quarter 4 and unemployed or inactive in Quarter 1, and zero if the person is

[18] One could take the same approach to look at hours worked, by replacing job loss with changes in hours worked as the dependent variable. However, this would address a different question to the one examined in this paper, as it would focus on changes in hours worked of MW workers who were working in both periods. As such, it ignores any structural employment changes relating to new employees. Moreover, the sample size issues mentioned earlier would be even more problematic as we would have to condition on MW workers who are both employed and in MW jobs in both periods.

employed in both periods. The variable *2016* is a dummy variable which equals one for the period Quarter 4 2015 to Quarter 1 2016, and zero for previous time periods. The variable *T* is a treatment dummy which equals one if the person is a minimum wage / low paid worker and zero otherwise. Finally, 2016*T, which is an interaction term between the time and treatment dummy variables, gives the estimated treatment effect.

The results for the three alternative definitions of low pay are shown in Tables 16a-16c. The difference-in-differences result essentially tests whether the averages shown in Tables 15a-15c are statistically significantly different. For example the coefficient in Column 1 of Table 16a of 0.0146 is equal to the difference between the two statistics in Table 15b (6.40-4.94=1.46).

The results show a statistically significant positive treatment effect only for the model comparing ISCO 5 and ISCO 1-4 workers in 2016 to the previous two years (2015 and 2014). No treatment effect was detected in the model comparing Decile 1 workers with those in Deciles 2 to 10 or in the three MW models. In total, only two of the nine coefficients are statistically significant. However, if we estimate the model for placebo years, where no MW change occurred, some of the results appear statistically significant. For example, in the occupation based model, placebo comparisons of 2015 to 2013 and 2014 to 2013 both yield statistically significant results. The existence of positive and significant coefficients in placebo periods casts doubt on the causal influence of any statistically significant effect found for the treatment period. In summary, there is no consistent evidence that the increase in the NMW rate in 2016 caused an increase in the proportions of such workers becoming unemployed or inactive.

TABLE 15A JOB LOSS RATES FOR ISCO 5 COMPARED TO ISCO 1-4

Time Period	ISCO 5 – sales / protective services (% unemployed / inactive *t+1*)	ISCO 1-4 – managers, professionals (% unemployed / inactive *t+1*)	Difference
Q4 2015 – Q1 2016	4.49	1.53	2.96
Q4 2014 – Q1 2015	3.51	2.00	1.51
Q4 2013 – Q1 2014	4.33	2.32	2.01
Q4 2012 – Q1 2013	4.79	2.05	2.74

Source: Quarterly National Household Survey.

TABLE 15B JOB LOSS RATES FOR DECILE 1 COMPARED TO DECILES 2-10

Time Period	Decile 1 workers (% unemployed / inactive *t+1*)	Deciles 2-10 workers (% unemployed / inactive *t+1*)	Difference
Q4 2015 – Q1 2016	8.38	1.98	6.40
Q4 2014 – Q1 2015	6.87	1.93	4.94
Q4 2013 – Q1 2014	8.38	2.76	5.62
Q4 2012 – Q1 2013	6.84	2.24	4.60

Source: Quarterly National Household Survey.

TABLE 15C JOB LOSS RATES FOR MW COMPARED TO NON-MW WORKERS

Time Period	MW (% unemployed / inactive *t+1*)	Non-MW (% unemployed / inactive *t+1*)	Difference
Q4 2015 – Q1 2016	4.68	1.19	3.49
Q4 2014 – Q1 2015	3.85	1.49	2.21
Q4 2013 – Q1 2014	5.39	1.69	3.70
Q4 2012 – Q1 2013	2.76	1.66	1.52

Source: Quarterly National Household Survey.

TABLE 16A DIFFERENCE-IN-DIFFERENCES EMPLOYMENT RESULTS: Q1 2015 AND Q1 2016

	(1)	(2)	(3)
Variable	Bottom decile model	Occupation[19] model	MW model
Treatment effect	0.0146	0.0144***	.0128
	(0.0157)	(0.00538)	(.0103)
T	0.0493***	0.0152***	0.0221***
	(0.0103)	(0.00358)	(0.0068)
2016	0.000490	-0.00461	-0.0001
	(0.00431)	(0.00292)	(0.0043)
Constant	0.0193***	0.0200***	0.0125***
	(0.00282)	(0.00195)	(0.0028)
Observations	5,475	15,852	4,447
R-squared	0.009	0.005	0.007

Source: Quarterly National Household Survey.
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. As outlined in Equation (2), the variables *T* and *2016* are dummy variables to indicate the treatment group and treatment period respectively.

[19] Robust to the inclusion of control variables and robust standard errors; age, gender, education, number of children.

TABLE 16B DIFFERENCE-IN-DIFFERENCES EMPLOYMENT RESULTS: Q1 2014 AND Q1 2016

	(1)	(2)	(3)
Variable	Bottom decile model	Occupation model	MW model
Treatment effect	0.00773	0.00954*	-0.00216
	(0.0161)	(0.00561)	(0.0112)
T	0.0562***	0.0200***	0.0370***
	(0.00928)	(0.00368)	(0.00724)
2016	-0.00772*	-0.00789***	-0.00494
	(0.00467)	(0.00303)	(0.00463)
Constant	0.0276***	0.0232***	0.0169***
	(0.00293)	(0.00200)	(0.00293)
Observations	6,056	16,293	4,767
R-squared	0.010	0.005	0.009

Source: Quarterly National Household Survey.
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. As outlined in Equation (2), the variables *T* and *2016* are dummy variables to indicate the treatment group and treatment period respectively.

TABLE 16C DIFFERENCE-IN-DIFFERENCES EMPLOYMENT RESULTS: Q1 2013 AND Q1 2016

	(1)	(2)	(3)
Variable	Bottom decile model	Occupation model	MW model[20]
Treatment effect	0.0180	0.00219	0.01963
	(0.0150)	(0.00561)	(0.0147)
T	0.0460***	0.0274***	-0.0049
	(0.00853)	(0.00371)	(0.0037)
2016	-0.00259	-0.00514*	0.0152*
	(0.00427)	(0.00304)	(0.0088)
Constant	0.0224***	0.0205***	0.0168***
	(0.00259)	(0.00203)	(0.0025)
Observations	6,473	15,970	5,104
R-squared	0.009	0.007	0.005

Source: Quarterly National Household Survey.
Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. As outlined in Equation (2), the variables *T* and *2016* are dummy variables to indicate the treatment group and treatment period respectively.

[20] Not significant with controls and robust standard errors; age, sex, education, number of children.

SECTION 8

Summary

This study uses QHNS data to assess the impact of the increase in the minimum wage from €8.65 to €9.15 in 2016 on the hours worked, the incidence of PT employment and the rate of job loss among minimum wage employees. Data limitations have resulted in our analysis being restricted to MW employees working more than 14 hours per week, as well as limiting our ability to allocate certain groups of employees in higher deciles, working greater numbers of hours, to either a treatment or control group. Specifically, the QNHS data contain hours and decile information on 33,760 employees, of which we can allocate 28,511 (84 per cent). Of the unallocated employees, approximately 60 per cent work 22 hours per week or less. As such, there may be a disproportionate number of low hourly wage workers in the unallocated group. Therefore, while we use strict allocation criteria, in that we do not allocate employees for which we are not sufficiently confident as to their minimum wage status, our inability to allocate a large number of low-hours workers means that our sample may not accurately reflect the hours distributions of the full populations of minimum wage and non-minimum wage employees.

Our results indicate that the increase in the MW in 2016 resulted in a decrease in hours worked for minimum wage workers. This was primarily driven by minimum wage workers on temporary contracts, who experienced an average reduction of approximately 3.5 hours per week. Our results are robust to both placebo tests for years where no change in the MW rate occurred, and various alternative specifications.

We also test for the presence of employment effects related to the minimum wage increase. Both the descriptive and econometric evidence points to some volatility over time in the rate of job loss among low waged and minimum wage workers, with no consistent evidence that the increase in the NMW rate in 2016 caused an increase in the proportions of such workers becoming unemployed or inactive.

Our results show that there was a large decrease in involuntary PT work (could not find a FT job) in 2015 and 2016 among minimum wage workers. Therefore, while observed falls in hours are generally attributed to employers reducing the hours of existing employees as a result of higher labour costs, we cannot rule out the possibility that more individuals were choosing to work part-time due to the increased minimum wage. Given this, and the lack of any negative employment effect there is little solid evidence to support the view that the 50 cent increase in the national minimum wage rate that came into effect on 1 January 2016 had any immediate large adverse impacts on Irish workers.

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APPENDIX

TABLE A1 DESCRIPTIVE STATISTICS ON EMPLOYEES WITH MISSING AND COMPLETE DECILE DATA, 2015 AND 2016

Variable	Decile data	No decile data
Age (in years)	41.63	40.02
Male (%)	38.3	52.2
Low education (%)	12.9	13.4
Medium education (%)	50.5	52.4
High education (%)	36.6	34.2
Usual hours	33.14	34.97
Part-time (%)	28.4	22.6

Source: QNHS 2015, 2016.

TABLE A2 PROBABILITY OF BEING MW WORKER

Variables	MW
Male	-0.0535***
	(0.00449)
Age	-0.00456***
	(0.000234)
Medium education	-0.121***
	(0.00896)
High education	-0.242***
	(0.00910)
Services	0.129***
	(0.00691)
Part-time	0.0151**
	(0.00598)
Children	-0.0242***
	(0.00188)
Irish	-0.131***
	(0.00773)
Constant	0.637***
	(0.0162)
Observations	28,121

Source: Quarterly National Household Survey.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Services relates to accommodation/food and wholesale/retail.

TABLE A3 DISTRIBUTION OF MW AND NON-MW WORKERS BY DECILE

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

Source: Quarterly National Household Survey.

TABLE A4 IMPUTED HOURS MODEL

	(1)	(2)	(3)
Variable	No additional covariates	Covariates added	Temporary contracts
Treatment effect	-0.952***	-0.579*	-3.127***
	(0.329)	(0.319)	(1.110)
T	2.103***	1.927***	3.502***
	(0.226)	(0.222)	(0.810)
Year	0.366***	0.287**	0.176
	(0.136)	(0.125)	(0.644)
Male		6.397***	3.938***
		(0.123)	(0.558)
Age		-0.0954***	-0.0573***
		(0.00641)	(0.0218)
Medium education		1.547***	2.959***
		(0.204)	(0.790)
High education		2.719***	6.416***
		(0.227)	(0.858)
No. of children		-0.924***	-0.977***
		(0.0577)	(0.259)
Constant	32.66***	33.35***	24.79***
	(0.0971)	(0.396)	(1.357)
Observations	23,697	23,325	1,531
R-squared	0.005	0.143	0.095

Source: Quarterly National Household Survey.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A5 IMPUTED HOURS PLACEBO TESTS

	2012-2013		2013-2014		2014-2015	
Variable	Pooled	Temp	Pooled	Temp	Pooled	Temp
Treatment	-0.173	0.293	0.0560	-1.699*	0.215	-0.235
	(0.243)	(0.864)	(0.327)	(0.950)	(0.476)	(1.226)
T	2.548***	4.238***	1.130***	2.497***	0.993***	0.707
	(0.171)	(0.614)	(0.214)	(0.669)	(0.254)	(0.710)
Year	0.150	-0.334	0.242**	0.646	-0.306***	0.582
	(0.104)	(0.539)	(0.104)	(0.536)	(0.109)	(0.567)
Male	6.918***	4.959***	6.567***	4.951***	6.308***	3.872***
	(0.0969)	(0.455)	(0.104)	(0.481)	(0.110)	(0.517)
Age	-0.109***	-0.118***	-0.120***	-0.134***	-0.126***	-0.0880***
	(0.00518)	(0.0201)	(0.00550)	(0.0207)	(0.00586)	(0.0228)
Medium education	0.920***	2.356***	0.372**	1.743**	0.767***	2.069**
	(0.162)	(0.696)	(0.178)	(0.794)	(0.188)	(0.810)
High education	2.816***	5.422***	1.993***	4.473***	1.566***	4.583***
	(0.162)	(0.660)	(0.179)	(0.783)	(0.208)	(0.892)
Children	-0.937***	-0.900***	-1.056***	-1.101***	-1.131***	-1.309***
	(0.0477)	(0.204)	(0.0514)	(0.216)	(0.0540)	(0.231)
Constant	33.99***	26.86***	35.89***	29.19***	36.77***	28.79***
	(0.302)	(1.187)	(0.331)	(1.321)	(0.353)	(1.419)
Observations	34,061	2,494	29,624	2,153	26,229	1,778
R-squared	0.170	0.132	0.155	0.105	0.151	0.081

Source: Quarterly National Household Survey.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A6 OVER 14 HOURS RESTRICTION RESULTS: 2015-2016

	(1)	(2)	(3)
Variable	No additional covariates	Covariates added	Temporary contracts
Treatment effect	-0.898***	-0.542*	-3.342***
	(0.336)	(0.325)	(1.198)
T	1.851***	1.724***	3.508***
	(0.230)	(0.226)	(0.860)
Full 2016	0.239*	0.204*	0.256
	(0.128)	(0.117)	(0.627)
Male		6.088***	3.642***
		(0.118)	(0.576)
Age		-0.0825***	-0.0361
		(0.00617)	(0.0240)
Medium education		1.192***	3.681***
		(0.200)	(0.888)
High education		2.314***	7.112***
		(0.219)	(0.940)
Children		-0.952***	-0.902***
		(0.0562)	(0.258)
Constant	33.50***	34.05***	24.86***
	(0.0911)	(0.382)	(1.473)
Observations	22,228	21,883	1,307
R-squared	0.005	0.145	0.099

Source: Quarterly National Household Survey.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A7 OVER 14 HOURS RESTRICTION PLACEBO TESTS

	2012-2013		2013-2014		2014-2015	
Variable	Pooled	Temp	Pooled	Temp	Pooled	Temp
Treatment	-0.186	0.377	0.0225	-1.370	0.764	0.472
	(0.240)	(0.898)	(0.334)	(1.018)	(0.505)	(1.422)
T	2.961***	4.436***	1.867***	3.080***	1.729***	1.657**
	(0.169)	(0.647)	(0.218)	(0.710)	(0.260)	(0.769)
Year	0.238**	-0.175	0.149	0.0785	-0.326***	0.305
	(0.0981)	(0.532)	(0.0976)	(0.523)	(0.102)	(0.550)
Male	6.184***	4.435***	5.889***	4.142***	5.722***	2.987***
	(0.0935)	(0.462)	(0.0997)	(0.490)	(0.104)	(0.527)
Age	-0.0991***	-0.119***	-0.109***	-0.139***	-0.109***	-0.0696***
	(0.00499)	(0.0229)	(0.00528)	(0.0236)	(0.00553)	(0.0250)
Medium education	0.732***	2.554***	0.306*	2.205**	0.464**	2.982***
	(0.159)	(0.767)	(0.173)	(0.875)	(0.182)	(0.891)
High education	2.330***	5.522***	1.695***	4.877***	1.247***	5.249***
	(0.158)	(0.708)	(0.173)	(0.853)	(0.199)	(0.948)
Children	-0.912***	-0.881***	-0.994***	-0.999***	-1.070***	-1.286***
	(0.0462)	(0.220)	(0.0495)	(0.227)	(0.0520)	(0.230)
Constant	34.92***	29.04***	36.63***	31.38***	37.23***	29.33***
	(0.290)	(1.309)	(0.318)	(1.457)	(0.334)	(1.503)
Observations	31,237	2,037	27,377	1,770	24,497	1,491
R-squared	0.170	0.148	0.154	0.113	0.151	0.079

Source: Quarterly National Household Survey.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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ISBN **978-0-7070-0454-9**

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