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The impact of the NLW on automation on businesses – with a focus on automation

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1. Introduction

The purpose of this project is to explore the extent to which firms' responses to recent increases in the National Living Wage (NLW) vary by the estimated opportunity for capital-labour substitution (automatability). There are many ways in which firms can adjust to minimum wage increases, for example by improving productivity, substituting away from labour inputs in the production process towards machines (capital), accepting lower profits, or raising prices.[1] It is likely that some industries with a high proportion of minimum wage workers, for example retail, are more able to adopt technology such as robots, in contrast to other industries such as social care. The increased coverage of minimum wage rates does not necessarily mean that low-skilled workers will suffer adversely. While technology may replace certain jobs, it can also create new jobs that are complementary to that technology. A greater understanding of how different industries are responding to the increased bite of the NLW in terms of technology adoption provides vital information for the LPC evidence base.

Aitken, Dolton and Riley (2018) find evidence of negative employment effects in the retail industry, following the introduction of the NLW in 2016, and this is one industry where firms may have significantly substituted labour for capital as a result of minimum wage increases. Forth, Paczos, Riley and Davies (2020), using a dataset compiled from a matched sample of firms observed in the Labour Market Outlook (LMO) survey[2] and company accounts data in Financial Analysis Made Easy (FAME),[3] find some evidence that firms may have increased their capital investment in response to the NLW. This project builds on these insights and undertakes a more extensive analysis of the FAME dataset to study businesses responses to the NLW in more detail, with a particular focus on the heterogeneity of any response according to the prospects of automation.

Previous work in the UK, for example Riley and Rosazza Bondibene (2015, 2017), Draca, Machin, and Van Reenen (2005, 2011), and Bernini and Riley (2016) have examined how minimum wages have affected firm productivity and profitability. It is widely-recognised that technology is particularly suitable to displacing labour that performs routine tasks (Autor Levy and Murnane, 2003; Black and Spitz-Oener, 2010; Acemoglu and Autor, 2011; Goos et al., 2014). Lordan (2019) addresses the issue of how minimum wage changes affect employment opportunities in automatable jobs in the UK. She uses individual level data from the UK Labour Force Survey (LFS) and examines how minimum wage changes affect the type of work available for low-skilled workers. Lordan and Neumark (2018) undertake a similar analysis for the US. Aaronson and Phelan (2017) also analyse the susceptibility of low-wage employment to technological substitution and provides some evidence that firms may automate routine jobs in response to a minimum wage increase, reducing employment

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[1] See Forth, Paczos, Riley and Davies (2020) for recent survey evidence on firm responses to minimum wage increases.
[2] The LMO is conducted by the Chartered Institute of Personnel and Development (CIPD).
[3] A UK wide dataset available from Bureau van Dijk. FAME contains financial data on the population of UK registered companies.

opportunities for workers in routine jobs. In contrast to Lordan (2019), Lordan and Neumark (2018) and Aaronson and Phelan (2017), who all use worker level data, our work uses firm level data, and attempts to uncover how firms adjust to increases in minimum wage rates.

Finally, with the spread of artificial intelligence (AI) and robots, there is a burgeoning literature on how robots are affecting labour markets, for example Graetz and Michaels (2018) who find that robots did not significantly reduce total employment. In contrast Acemoglu and Restrepo (2017) find evidence of job losses as a result of robot adoption across US labour markets. In France, Acemoglu, LeLarge, and Restrepo (2020) find robot adoption coincides with declines in the share of production workers at industry level, although firms adopting robots increase total employment.

2. Data

We use FAME (Financial Analysis Made Easy), a UK wide commercial dataset available from Bureau van Dijk. Fame contains data on the population of UK registered companies. A drawback is that many companies' data items are missing; although there are reporting requirements for the largest companies, these are particularly light for smaller companies. Importantly, it covers non-manufacturing firms where many low-wage workers are employed. The FAME data is currently available from 2002 to March 2019. In the current study, we use data from 2009-2017. We don't use data for 2018 or 2019, as we do not have complete data for those years, as explained further below.

We map various occupation-level measures of automatability to the LFS/APS to create industry level estimates of automatability, which are then matched to firms in FAME using industry codes. Further details on the specific measures – and the source data that are used to derive them – are given later.

3. Difference-in-difference estimates of firm outcomes

The approach we take to identify the effects of minimum wage increases is similar to previous studies. We use a difference-in-differences (DiD) approach as has been used by Riley and Rosazza Bondibene (2015, 2017), Bernini and Riley (2016), and Draca et al. (2005, 2011). This quasi-experimental setting allows us to compare various firm outcomes (e.g. changes in employment or productivity) in firms that were more affected by the introduction of the NLW, compared with those that were less affected.

We focus on longitudinal balanced-panel models, selecting firms for the treatment and control groups based on their average labour costs in a particular year (before the policy change), as discussed further below. We then track outcomes for these two groups up to *n* years later. We first estimate the impact of the NLW on firm outcomes without considering the role of automation, before turning to the influence of automation in the next step. Formally, we estimate the impact of the NLW in a standard DiD framework as:

$$y_{ijt} = \alpha + \gamma(Post_t * NLW_{it}) + \beta X_{ijt} + \gamma Z_{jt} + \delta_i + T_t + \varepsilon_{ijt} \qquad (1)$$

where y_{ijt} is the outcome of interest for firm i in industry j at time t (for example average labour costs, capital stock or capital/labour ratio). NLW_{it} is a dummy variable equal to one if the firm is in the treatment group and zero otherwise. $Post_t$ is an indicator of the post-NLW announcement period. The interaction between $Post_t$ and NLW_{it} captures the difference-in-differences estimate of the effect of the NLW on outcome y_{ijt}. The vector X_{ijt} contains controls for time-varying firm characteristics intended to account for differences between firms unrelated to the NLW. The vector Z_{jt} contains controls for time-varying industry characteristics intended to account for differences between industries unrelated to the NLW.

This includes 2-digit industry-year fixed effects. δ_i are firm specific fixed effects capturing any time-invariant firm characteristics, and the T_t are a set of year dummies that pick-up time-varying factors that influence treatment and control firms in the same way. ε_{ijt} is a random error term, and the rest are parameters to be estimated.

We then extend equation (1) to include a further interaction term to examine the effect of the NLW introduction across industries that have greater or lesser degrees of automatability:

$$y_{ijt} = \alpha + \gamma(Post_t * NLW_{it}) + \gamma_{Auto}\left(Post_t * NLW_{it} * Auto_j\right) + \eta Auto_j + \zeta\left(NLW_{it} * Auto_j\right) + \beta X_{ijt} + \gamma Z_{jt} + \delta_i + T_t + \varepsilon_{ijt} \qquad (2)$$

$Auto_j$ indicates the probability of automation in each industry *j.* The three-way interaction captures the extent to which the industry level probability of automation affects outcomes such as capital intensity to a greater or lesser extent in NLW-affected firms.

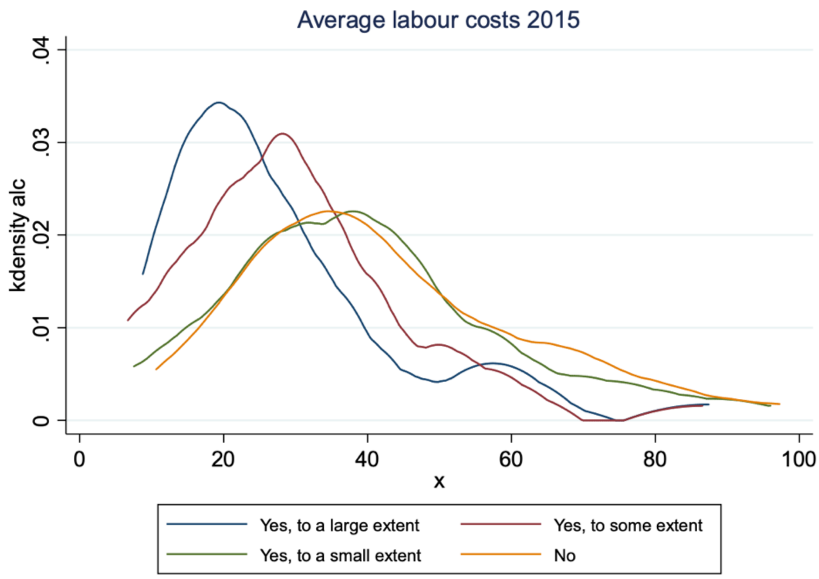
Prior to testing for any effects of the NLW on firm outcomes it is important to see whether we observe a change in the firm average wage distribution following the introduction of the NLW and subsequent upratings. This can be done by estimating equation (1) for the change in log average wages. These checks also provide evidence as to the validity of the definition of our firm treatment group.

4. Defining treatment and control groups

The main difficulty with firm-level analysis of minimum wage impacts is defining a suitable set of firms to allocate to the treatment and control groups. Following previous studies, we base the identification of treated companies in the sample on the average wage per worker, using this as a proxy for the proportion of low-paid workers in the firm. FAME has a figure for total remuneration that can be divided by the total number of employees to calculate an average wage or labour cost for the firm. We use the LMO-FAME linked sample analysed by Forth et al. (2020) to identify the level of average labour costs at which exposure to the NLW is likely to be greatest. This prior analysis suggests that many of the exposed firms have average labour costs of around £20,000 per head, whereas for non-exposed firms the average is around £40,000 per head, this is shown in

Figure 1.

Figure 1: Distribution of average labour costs by degree of exposure to the NLW



Source: Forth et al. (2020).

We explore a range of treatment and control groups and present results based on two definitions. The first definition defines the treated group as firms with average annual labour costs (ALC) between £15,000 per head – £25,000 per head, and the control group as firms with ALC between £26,000 per head – £45,000 per head. The second definition defines the treated group as firms with ALC between £15,000 per head – £25,000 per head, and the control group as firms with ALC between £30,000 per head – £45,000 per head. Draca et al. (2011) has shown that minimum wage workers were concentrated in firms with low average labour costs when the NMW was introduced in 1999, suggesting that average wages were a reasonable (though imperfect) means of identifying firms' exposure to the NMW then. Riley and Rosazza Bondibene (2017) show this continued to be the case a decade later.

5. Defining the pre-NLW ('policy off') and post-NLW ('policy on') periods

The NLW was announced in July 2015 and came into force in April 2016. Most firms have financial years that run from April – March. Our main specification then identifies the pre-NLW period ('policy off') as 2013 – 2015 and the post-NLW period ('policy on') as 2016 – 2017.[4] The assumption is that there were no substantive anticipatory effects.

We do not use data for 2018. This is because we only have accounts data from firms who filed in December 2018/19 (for previous years, we have those who file in December and those who file in March). As a result, we find that a substantial share of firms who are present in our balanced panel prior to 2018 drop out in that year. The 'sample exit' rates in Table 1 show that exit rates that are much higher (over 20%) for the 2018 sample compared with previous years (around 10%), and in addition there is evidence of a differential reporting effect for the treated firms compared with the control firms. For this reason, we end our observation period in 2017 and do not use data for 2018.

[4] 2013 here refers to the 2013/14 financial year, and similarly for other years stated in the text

Table 1: Exit rates for the 2011-2015 and 2013-2018 samples

2011-2015									
	Total sample			Control			Treated		
Exit year	2014	2015		2014	2015		2014	2015	
% firms that exit	8.13	11.55		8.32	11.37		7.76	11.88	
2013-2018									
	Total sample			Control			Treated		
Exit year	2016	2017	2018	2016	2017	2018	2016	2017	2018
% firms that exit	11.45	8.14	26.38	11.71	8.40	22.43	10.96	7.63	33.96

Note: exit can occur because the firm exits the population or because it fails to report in a given year, even though it is still trading.

Table 2 shows summary statistics for the treatment and control groups in the first year of the post-NLW period within our main experiment. We use a balanced panel rather than an unbalanced panel as this allows us to compare the same firms before and after the policy change. Firms in the balanced sample have to appear in all five years of the treated or control sample period, whereas in the unbalanced sample firms may appear once or more. Table 3 is the equivalent to Table 2 and shows the treated and control samples for the unbalanced sample. In the control group, the median firm in the balanced panel is slightly larger and more capital intensive than in the full unbalanced sample. In the treatment group, the median firm in the balanced panel is again slightly larger than in the full unbalanced sample. Table 4 shows the distribution of industries for the 2016-2017 control and treatment period for both the balanced and unbalanced sample. The table shows that while the distribution of industries differs across the control and treated samples, the distribution of industries appears very similar across the balanced and unbalanced samples. Table A1 in the Appendix shows a similar pattern for the treatment and control groups in the 2013-2015 period.

Table 2: Summary statistics for the balanced treated and control samples (2016)

	2016					
	Control sample			Treated sample		
	mean	st. dev.	median	mean	st. dev.	median
Average labour costs (£'000s)	35.4	14.2	34.4	20.9	5.1	20.8
Employment	417.1	3,341.5	94.0	588.5	5,087.5	91.0
Labour productivity (£/head)	52.1	30.6	45.8	27.6	17.0	24.5
Capital per head (£/head)	79.8	258.5	29.0	46.2	113.5	18.9
Capital (£)	53,773	691,049.1	2,882	47,663.3	862,297.7	1,898
Profit margins (%)	0.22	1.21	0.24	0.16	0.69	0.15
Obs.		4,105			2,330	

Table 3: Summary statistics for the unbalanced treated and control samples (2016)

	2016					
	Control sample			Treated sample		
	mean	st. dev.	median	mean	st. dev.	median
Average labour costs (£'000s)	35.5	13.0	34.5	21.2	6.3	20.9
Employment	364.4	2,862.5	88.0	636.4	9,226.4	85.0
Labour productivity (£/head)	52.1	33.3	45.6	28.1	18.1	24.7
Capital per head (£/head)	80.8	274.0	27.5	48.0	118.8	18.3
Capital (£)	49,938	583,291.2	2,559.0	48,094.3	906,219.5	1,760.0
Profit margins (%)	0.22	1.28	0.24	0.17	0.93	0.15
Obs.		5,911			3,251	

Table 4: Distribution of Industries in the balanced and unbalanced treated and control samples (2016-2017)

Control Sample (2016-2017)	Balanced sample		Unbalanced sample	
SIC section	Freq.	Percent	Freq.	Percent
Accommodation and Food Service Activities	130	2	200	2
Administrative and Support Service Activities	744	9	1,208	10
Arts, Entertainment and Recreation	240	3	330	3
Construction	638	8	939	8
Electricity, Gas, Steam and Air Conditioning Supply	8	0	22	0
Human Health and Social Work Activities	532	6	651	5
Information and Communication	351	4	554	5
Manufacturing	2,288	28	3,186	27
Other Service Activities	231	3	349	3
Professional, Scientific and Technical Activities	660	8	1,183	10
Transportation and Storage	476	6	680	6
Water Supply; Sewerage, Waste Management	103	1	162	1
Wholesale and Retail Trade; Repair of Motor Vehicles	1,809	22	2,458	21
Total	8,210	100	11,922	100
Treated Sample (2016-2017)	Balanced sample		Unbalanced sample	
SIC section	Freq.	Percent	Freq.	Percent
Accommodation and Food Service Activities.	455	10	646	10
Administrative and Support Service Activities	375	8	565	9
Arts, Entertainment and Recreation	374	8	479	7
Construction	76	2	117	2
Electricity, Gas, Steam and Air Conditioning			5	0
Human Health and Social Work Activities	1,264	27	1,563	24
Information and Communication	139	3	220	3
Manufacturing	542	12	765	12
Other Service Activities	280	6	381	6
Professional, Scientific and Technical Activities	139	3	311	5
Transportation and Storage	106	2	170	3
Water Supply; Sewerage, Waste Management	31	1	44	1
Wholesale and Retail Trade; Repair of Motor Vehicles	879	19	1,219	19
Total	4,660	100	6,485	100

Note: Samples presented here cover two years, 2016-2017.

Trend-adjusted difference-in-difference estimates

As a placebo test, we estimate equation (1) for alternative 'treatment' years and find statistically significant and positive wage effects, which suggests we are picking up the effects of annual increases in the NMW in the 'policy off' period. As a result of this we estimate trend-adjusted version of equations (1) and (2) to abstract from wage increases in previous years. Our trend-adjusted DiD estimates than capture the effect of the NLW increase over and above the increases in wages found in earlier years.

We estimate the trend-adjusted DiD by subtracting the estimates from a placebo period from estimates derived from the experiment period outlined above. This placebo period is 2011 – 2015 (where 2011 – 2013 is the policy off period, and 2014 – 2015 is the policy on period).

We then conduct a placebo test where we shift the trend-adjusted DiD back in time. We use data for 2011 – 2015 (2014 – 2015 policy on) for the placebo experiment period, and subtract from these estimates the estimates using data for the period 2009 – 2013 (2012 – 2013 policy on). The finding of any significant effects would cast doubt on the validity of our main identification strategy using the trend-adjusted DiD.

6. Control variables

Firm level controls include the following:

- Whether the firm is foreign owned, an exporter, and whether the firm is young (less than 6 years old).

Industry level time-varying controls include:

- There will be large differences in the competitive environment that firms operate in and this is likely to affect how firms respond to minimum wage increases. To take into account differences in competition we include the Herfindahl–Hirschman Index, a measure of market concentration.
- The ongoing Brexit process has led to uncertainty that will affect the investment decisions of firms differently; our results will be biased if this is correlated with the probability of automation and we do not control for this uncertainty. Bloom et al. (2019), in a survey of UK firms, finds that the decision to leave the EU has led to a large and long-lasting increase in uncertainty, and that the anticipation of Brexit reduced investment by 11% in the three years following the June 2016 referendum. We include industry level controls to capture differences in uncertainty across industries. Exposure to uncertainty from Brexit can be measured by the importance of exports and the share of EU migrant workers, for example. Some industries have a high proportion of immigrants working in them, for example 42% of the immigrants working in retail trade in 2019 were from the EU. To control for differential industry level exposure to EU migrant labour we therefore include the share of EU immigrants as a proportion of all workers in each industry derived from the Annual Population Survey. Using ONS input output tables we derive measures of direct and indirect exposure to EU exports. Direct exposure is measured as the ratio of exports to the EU by industry over industry output. The indirect measure takes into account the extent of intermediate sales that ultimately appear in exports to the EU. Both the direct and indirect measures are highly correlated, and we include only the direct measure in the regression analysis.

7. Defining automatability

We consider several different approaches to measuring the scope for automation within different industries. Autor, et al. (2003) first proposed a task-based framework for analysing the implications of technological change on the demand for skills. The task-based approach has been developed and widely used for example by Autor and Dorn (2013) and Autor et al. (2015). In this framework, a routine task intensity (RTI) index is derived that splits tasks into three types: (1) tasks that are easily routinised because they follow precise, well-defined procedures – tasks that can be performed both by computer capital and low-skill workers; (2) “abstract” tasks - creative, problem-solving, and coordination tasks that are more difficult to automate; and (3) “manual” tasks - many low-education occupations – service occupations in particular – rely heavily on “manual” tasks such as physical and interpersonal activities. An RTI in each 3-digit occupation can be defined as:

$$RTI_k = \ln\left(T_k^R\right) - \ln\left(T_k^M\right) - \ln\left(T_k^A\right) \qquad (3)$$

where T_k^R, T_k^M, T_k^A are the levels of routine, manual and abstract task inputs for occupation k measured at the 3-digit level. We use an RTI measure, similar to that used by Lordan (2019) who uses questions from the UK Skills and Employment Surveys/British Skills Survey (BSS) to create a measure that is very similar to the Autor and Dorn (2013) and Autor et al. (2015) versions. Lordan (2019) estimates equation (3) for 3-digit SOC (2000) codes based on standardized responses to the following questions, and then matched to LFS data:

- Routine tasks are measured as the response to the question ‘How often does your work involve short repetitive tasks’. Responses are ‘never’, ‘rarely’, ‘sometimes’, ‘often’ or ‘always’.
- Manual tasks are measured as the response to ‘how much variety is there in your job?’ Responses are ‘a great deal’, ‘quite a lot’, ‘some’, or ‘none at all.’
- Abstract tasks are measured as the response ‘would you say the importance of analysing complex problems in depth is ‘essential’, ‘very important’, ‘fairly important’, ‘not very important’, or ‘not at all important.’

We replicate this approach using pooled data from the 2012 BSS. We estimate an RTI index for each four-digit occupation and match this to the Annual Population Survey (APS) to derive an aggregate indicator for each industry, which we then match to FAME.

In contrast to the task-based approach, Frey and Osborne (2013) try to estimate the susceptibility of employment to computerisation by classifying occupations in the US by asking experts about the technological potential for automation in the near future. As a result, the study suggests that 47% of all people employed in the US are working in jobs that could be performed by computers or algorithms within the next 10 to 20 years. This approach has been criticised as occupations usually consist of a bundle of tasks not all of which may be easily automatable (Autor, 2014, 2015). Autor and Handel (2013) also show that the even within occupations, the heterogeneity of tasks performed at different workplaces appears to be huge.

Arntz, Gregory, and Zierahn (2016) estimate the risk of automation for jobs in 21 OECD countries based on the approach of Frey and Osborne (2013), while relaxing one of their main assumptions. In their task-based approach, Arntz et al. (2016) use PIACC (Programme for the International Assessment of Adult Competencies) data that surveys task structures across OECD countries. They find the share of jobs at risk of automation to be about 9% on average across OECD countries. The ONS (2019) have produced a modified version of the Arntz et al. (2016) methodology for 2011 and 2017 and have published automation probabilities for each four-digit SOC category. We match the four-digit SOC estimates of automatability that ONS provide to individuals in the Annual Population Survey (APS) to get a probability of automation for each job. We then aggregate up to industry level in the same way as for the RTI measure described above.

Josten and Lordan (2019) and Dechezleprêtre et al. (2020) both introduce new measures of automatability based on patent data. This approach likely has a better chance of identifying jobs that will be automatable in the next decade if the volume of patents in an area is high. Josten and Lordan (2019) start with the classification produced by Autor and Dorn (2013) and Autor et al. (2015) which is backward looking and captures the jobs that have already been automated. From this classification they re-classify 201 jobs that were classified as non-automatable, distinguishing between jobs that are expected to be fully automatable, jobs that are polarised automatable and jobs that are not expected to be automatable. They describe polarised automatable as those where patent technology has had some success, but it is thought that it will lead to polarisation, with humans being needed where a personal interaction holds real value and robots being used where it does not. To determine if a technology is actively being developed as a substitute for that occupation they search Google Patents. We take the occupation-level estimates of automatability produced by Josten and Lordan (2019), and again we match them to individuals in the APS and aggregate up to industry level.

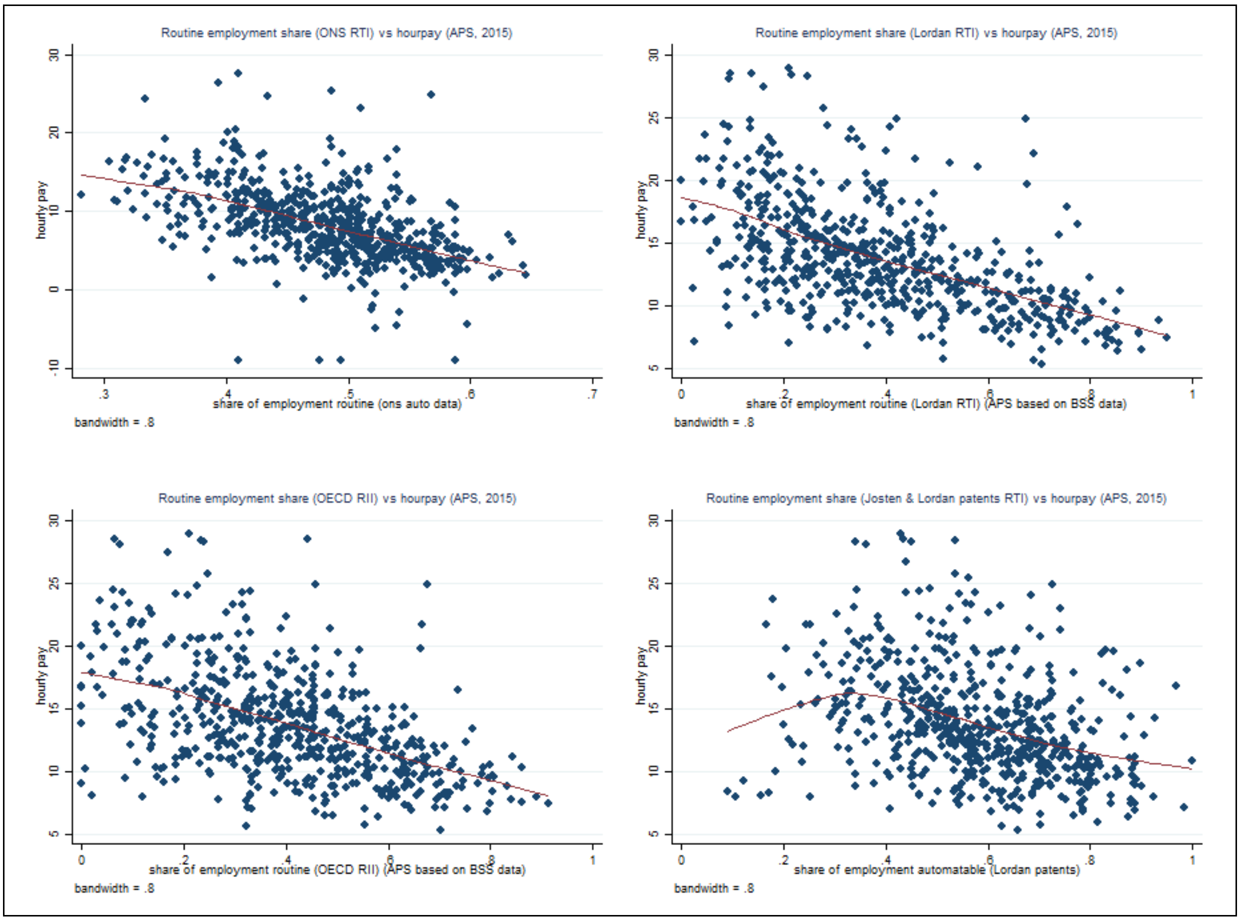
Finally, Marcolini et al. (2016) propose a new measure of routine content of occupations, called the Routine Intensity Indicator (RII), built on data from the OECD PIAAC survey. The measure is derived from information about the extent to which workers can modify the sequence in which they carry out their tasks and decide the type of tasks to be performed on the job. It is based on individual-level information on what workers actually do, rather than expert opinion, and does not assume that the content of tasks is time invariant. The index takes into account sequentiability (ability to choose the sequence of tasks involved), flexibility (ability to change content of work or how this is carried out), planning own activities, and organising own work time. We construct a version of this based on similar questions asked in the British Skills Survey. The index can be constructed at occupation or industry level.

In summary we use the following measures of automatability:

- A measure based on the ONS/OECD task-based approach.
- A task-based RTI measure based on Lordan (2019).
- The patent-based measure from Josten and Lordan (2019).
- A routine intensity indicator (RII) similar to Marcolini et al. (2016).

Figure 2 shows the share of routine employment at industry level against hourly wages for 2015 in the Annual Population Survey, and illustrates that as we would expect, wages are lower in industries that have higher potential for automatability.

Figure 2: Measures of automatability plotted against hourly wages in the Annual Population Survey



8. Results for firm outcomes

Table 5 reports results from our trend-adjusted difference-in-differences estimates of the effect of the NLW on firm outcomes. Table 6 presents placebo results, and then in Table 7 we present the results including the interaction with the automation indices.

In Table 5, we consider effects on firms' average labour costs, employment, labour productivity (value added per head), capital per head, capital stock and profitability (EBITDA margin). The treatment period is 2013 – 2017 (policy on 2016 – 2017), and the control period is 2011 – 2015 (policy on 2014 – 2015). We report effects estimated on two samples. Column (1) shows the results using a Treated/Control definition of ALC between £15k-25k for the treated and £26k-45k for the control. Column (2) shows the results using a definition for the control group of ALC between £30k-45k. In column (1) we find a 1.7 percent increase in average labour costs as a result of exposure to the NLW, and in column (2) a 2.1 percent increase. Both of these are statistically significant at the 5% level. We do not find statistically significant effects of the NLW on any of the other firm outcomes except profit margins, where we find evidence of a small negative effect significant at the 10% level.

Table 5: Trend-adjusted difference-in-differences estimates of the effects of the NLW

		(1)	(2)
		T 15-25 C 26-45	T 15-25 C 30-45
Average labour costs	Coeff	0.017**	0.021**
	se	0.007	0.007
Employment	Coeff	-0.003	-0.014
	se	0.036	0.041
Labour productivity	Coeff	0.005	0.004
	se	0.012	0.013
Capital per head	Coeff	0.051	0.053
	se	0.058	0.059
Capital	Coeff	0.035	0.041
	se	0.069	0.078
Profit margins	Coeff	-0.012*	-0.013*
	se	0.007	0.007
Obs		68,385	56,674

Note: Firm outcome variables are estimated using the inverse hyperbolic sine transformation,[5] except profit margins. 2-digit industry-year effects included. Statistical significance ***1%, **5%, *10%.

Table 6 presents our results of our placebo test using a trend adjusted DiD. The treatment period is 2011 – 2015 (policy on 2014 – 2015), and the control period is 2009 – 2013 (policy on 2012 – 2013). The results show that we find no statistically significant effects on any of our firm outcomes which gives us some reassurance that we have a valid experiment.

[5] The inverse hyperbolic sine is defined as $\log\left(y + (y^2+1)^{\frac{1}{2}}\right)$ and is defined at zero and for negative values. It can be interpreted in the same way as a standard logarithmic dependent variable.

Table 6: Trend-adjusted placebo difference-in-differences estimates of the effects of the NLW

		(1) T 15-25 C 26-45	(2) T 15-25 C 30-45
Average labour costs	Coeff	-0.004	-0.001
	se	0.006	0.006
Employment	Coeff	0.024	0.025
	se	0.035	0.039
Labour productivity	Coeff	0.003	0.007
	se	0.011	0.012
Capital per head	Coeff	-0.034	0.051
	se	-0.033	0.056
Capital	Coeff	-0.014	-0.010
	se	0.067	0.074
Profit margins	Coeff	0.006	0.011
	se	0.006	0.007
Obs		72,245	59,590

Note: Firm outcome variables are estimated using the inverse hyperbolic sine transformation, except profit margins. 2-digit industry-year effects included. Statistical significance ***1%, **5%, *10%.

Table 7: Trend-adjusted differences-in-differences estimates of γ_{Auto}

		ONS routine		RTI		RII		Patents	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		T 15-25	T 15-25	T 15-25	T 15-25	T 15-25	T 15-25	T 15-25	T 15-25
		C 26-45	C 30-45	C 26-45	C 30-45	C 26-45	C 30-45	C 26-45	C 30-45
Average labour costs	Coeff	-0.070	-0.080	0.003	0.002	-0.025	-0.023	0.000	-0.012
	se	0.094	0.089	0.030	0.030	0.027	0.025	0.033	0.033
Employment	Coeff	-0.383	0.512	-0.016	-0.006	-0.098	-0.091	-0.012	0.007
	se	-0.351	0.545	0.165	0.182	0.145	0.152	0.179	0.203
Labour productivity	Coeff	0.047	-0.007	0.018	0.010	0.003	-0.003	0.016	0.012
	se	0.168	0.172	0.054	0.057	0.048	0.048	0.059	0.064
Capital per head	Coeff	0.128	0.749	0.071	0.092	0.016	0.022	0.141	0.176
	se	0.191	0.796	0.241	0.265	0.213	0.222	0.262	0.296
Capital	Coeff	0.015	0.980	0.088	0.147	0.018	0.038	0.119	0.343
	se	0.139	1.042	0.315	0.347	0.278	0.291	0.174	0.388
Profit margins	Coeff	0.058	0.028	0.008	-0.001	0.025	0.025	0.018	0.003
	se	0.094	0.100	0.030	0.033	0.027	0.028	0.033	0.037
Obs		68354	56648	68330	56635	68330	56635	68354	56649

Note: Firm outcome variables are estimated using the inverse hyperbolic sine transformation, except profit margins. 2-digit industry-year effects included. Statistical significance ***1%, **5%, *10%.

Table 7 then presents our results of γ_{Auto} from our trend-adjusted differences-in-differences version of equation (2). We present the results using 4 different measures of automatability, and for each of these measures we show the results using our two definitions of the treatment and control groups. Columns (1)-(2) shows the results using the ONS task based routine measure. Columns (3)-(4) the results using a standard RTI measure. Columns (5)-(6) the results using a routine intensity indicator (RII) based on Marcolin et al. (2016). Finally, Columns (7)-(8) present the results using the patent-based measure from Josten and Lordan (2019). The results show that irrespective of our treatment/control group definition and regardless of which automatability measure we use, we fail to find any statistically significant effects of variation in industry level automatability on firm outcomes depending on NLW exposure.

9. Summary

We use a difference-in-differences specification, based on firm-level panel data from FAME, to explore the extent to which firms' responses to recent increases in the National Living Wage (NLW) vary by the estimated opportunity for capital-labour substitution (automatability).

In our baseline specification, we find that average labour costs increased by around 2 percentage points more in firms that were more exposed to the NLW (those with average labour costs in the range £15,000-£25,000) than in otherwise-similar firms that were less exposed to the NLW (those with average labour costs in the range £26,000-£45,000). We also find that profit margins fell by around 1 percentage point more in exposed firms, although this result is on the borderline of statistical significance at the 10 per cent level. We find no statistically significant effects of the NLW on employment, productivity, capital stocks or the capital-labour ratio. The results are very similar if we use an alternative definition of less-exposed firms which requires them to have average labour costs in the range £30,000-£45,000.

We then add an interaction term to our baseline specification in order to investigate whether the effects of the NLW vary by the estimated opportunity for automation within the industry to which each firm belongs. A variety of estimates of automatability exist in the literature and so we use four alternative measures, to ensure that any results are not driven by the particular features of one indicator. Irrespective of our definition of treatment and control groups, and regardless of which measure of automatability we use, we find no statistically significant interaction effect between industry-level automatability and NLW exposure for any of our chosen firm outcomes.

These findings do not necessarily mean that the NLW has no differential effect of any kind according to the degree of automation potential within the industry. However, any such effect, if it does exist, has not been detectable in our sample, which suggests that it is not large and pervasive. It could be that a localised effect is present in some particular industries – perhaps those which are already reasonably capital intensive and have some past experience of automation or those in which the potential for automation is particularly high. This would suggest a non-linear effect, which could be investigated in further work.

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Appendix

Table A1: Distribution of Industries in the balanced and unbalanced treated and control samples (2013-2015)

Control Sample (2013-2015)	Balanced sample		Unbalanced sample	
SIC section	Freq.	Percent	Freq.	Percent
Accommodation and Food Service Activities	196	2	345	2
Administrative and Support Service Activities	1,132	9	2,180	10
Arts, Entertainment and Recreation	360	3	529	2
Construction	951	8	1,669	8
Electricity, Gas, Steam and Air Conditioning	9	0	33	0
Human Health and Social Work Activities	797	6	1,046	5
Information and Communication	520	4	1,071	5
Manufacturing	3,434	28	5,849	27
Other Service Activities	347	3	632	3
Professional, Scientific and Technical Activities	1,011	8	2,062	10
Transportation and Storage	712	6	1,218	6
Water Supply; Sewerage, Waste Management	152	1	261	1
Wholesale and Retail Trade; Repair of Motor Vehicles	2,694	22	4,590	21
Total	12,315	100	21,485	100
Treated Sample (2013-2015)	Balanced sample		Unbalanced sample	
SIC section	Freq.	Percent	Freq.	Percent
Accommodation and Food Service Activities	682	10	1,129	10
Administrative and Support Service Activities	569	8	1,033	9
Arts, Entertainment and Recreation	561	8	745	7
Construction	112	2	215	2
Electricity, Gas, Steam and Air Conditioning			5	0
Human Health and Social Work Activities	1,894	27	2,553	23
Information and Communication	209	3	419	4
Manufacturing	818	12	1,408	13
Other Service Activities	416	6	613	5
Professional, Scientific and Technical Activities	206	3	541	5
Transportation and Storage	159	2	301	3
Water Supply; Sewerage, Waste Management	48	1	71	1
Wholesale and Retail Trade; Repair of Motor Vehicles	1,316	19	2,216	20
Total	6,990	100	11,249	100