Minimum Wage and Skills:

Evidence from Job Vacancy Data

Elodie Andrieu* and Malgorzata Kuczera**

*King's College London and **Cambridge University, OECD

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Motivation

- Change in the minimum wage $\rightarrow$ increase in labour costs.
- Mechanisms to offset increases in labour costs:
  - cuts in hiring
  - layoffs
  - price rise
  - productivity
  - ...
- Focus: **productivity**
  1. hire more educated workers
  2. shift towards more high technology production
- Scarce research on impact of minimum wage on non-employment margins.

Outline

Measuring demand for skills

- We want to understand firms demand for education and tech skills requirements

- We analyse millions of UK job vacancies
  - Has there been any changes over time and across England in tech skills and education requirements advertised online?
  - What other job characteristics does education and tech skills correlate with? Does this differ amongst high and low wage postings?
  - Do employers use tech skills and education as to compensate for increase in labour costs?

This paper

- Use the framework of the minimum wage change to explore the relationship between firms' labour costs and the demand in education and tech requirements
  - Large (unexpected) announcement of the policy in July 2015
  - Effects on the characteristics of posted jobs
  - DiD strategy using variation in exposure within occupations across space and within space across occupations

- Significant heterogeneity in prevalence of low-education jobs
  - More likely in lower wage jobs and lower skilled occupation
  - More likely in Northern areas in England
  - More likely to be affected by the minimum wage policy

- Significant heterogeneity in the level of tech jobs
  - Higher wages and high-skilled jobs
  - South and mid-west regions
  - Less likely to be affected by the minimum wage policy

Related Work

- BGT data to analyse various dimensions of the labour market
  - Skill demand (Grinis, 2019 (UK); Deming and Kahn, 2018; Hershbein and Kahn, 2018; Clemens, Kahn & Meer, 2020)
  - Trade (Javorcik et al, 2020)
  - Concentration (Azar et al., 2018)
  - Flexible work arrangements (Adams-Prassl et al., 2020)
  - Covid (Andrieu et al., forthcoming and Forsythe et al., 2020)
- Minimum wage and its impact on employment
  - Card and Krueger (1994) and more
  - effects are heterogeneous across skill groups: increases wages for the low-wage occupations without reducing employment (UK: Stewart, 2004 and Manning, 2012, Germany: Dustmann et al., 2021 and the US: Black et al., 2016)
  - little evidence that the UK minimum wage has had an adverse effect on employment at an aggregated level.
- Minimum wage and its effect on other outcomes
  - recent review of existing margins see Clemens, 2021
  - flexible hour contrats (Adams-Prassl, 2020, Datta, Giupponi and Machin, 2019)
  - workers' productivity (Horton, 2018)
  - older workers and higher levels of education (Clemens, Kahn, and Meer (forthcoming))
  - gender (Dickens, Riley and Wilkinson, 2015)
- Firms responses to an increase in labour costs
  - productivity (Ku, 2021, Neumark, 2001 and Mayneris, Poncet and Zhang, 2018)

Online Job Vacancies

- Burning Glass Technologies data
  - 'Near universe' of UK online job postings from 2014-2019
  - Job description, set of skills to perform the job
  - Many other variables
  - Representative of UK labour markets (Grinis, 2017 and other studies)
- Using BGT, our paper is the first to
  - measure educational qualifications directly from the text of job ads
  - identify the tech level at the ad level, using the skill information (10,000 keywords) of the job (not pre-determined classification)

Construction of the education variable

- Goal: to retrieve all vacancies that clearly mention an education qualification from the set of BGT job adverts
- Example of an ad for a Computer Numerical Control (CNC) technician:

> *"[...] currently seeking a senior cnc technician or works engineering technician to join their team in Huyton you will be* $\boxed{\textit{hnc}}$ *or* $\boxed{\textit{btech}}$ *trained or equivalent have experience in working within a busy works engineering department the role will be responsible for maintenance across the site you will be responsible for [...]"*

- **Steps:**
  1. direct matching of keywords in the job text
  2. cleaning strategies (using context around keywords): extracting numerical values (nvq 2, nvq two), removing (e.g. degree of)
  3. classifying jobs that have a mandatory education level (using job titles)
- This ad is classified as both level 3 (BTEC) and level 4 (HNC).
  4. final cleaning strategy (detect multiple job openings in 1 ad) and create multiple variables in final database

Classifying tech ads

- Goal: to retrieve a tech level for all vacancies from the set of BGT job adverts using job description (i.e. set of keywords)

- Why?
  - some tech jobs are not in the techie occupation classification (e.g. "Data Architects", "Big data Engineers" and "Digital Marketing Data Scientist")
  - different tech levels within narrow occupation groups

- Take a supervised machine learning approach relying on an external tech classification
  1. Label all vacancies using the occupation of ads as tech and non-tech;
  2. Define keywords that are predictors of a tech job by creating 3 clusters: tech, non-tech and neutral; techiness
  3. Use pool of keywords to compute tech levels on the basis of vacancy's skills; metrics
  4. Use a logistic regression to estimate the probability of searching a tech worker; logistic
  5. Sort ads into high, medium and low tech categorise for the analysis.

Examples and accuracy

	Job Title	UKSOCCode	Probability	Predicted Class	Ad metric (mean)
1	Senior Staff Nurse	2231	0.04	0	13.25
2	Social Worker	2442	0.01	0	5.14
3	Quantity Surveyor	2433	0.05	0	15.97
4	Financial Accountant	2421	0.03	0	11.48
5	Graduate Software Developer	2136	0.99	1	90.53
6	Project Support Coordinator	4215	0.16	0	16.91
7	Collections Agent	7122	0.02	0	10.24
8	Marketing Executive	3543	0.05	0	14.86
9	Graduate/Junior Data Analyst	2135	0.88	1	59.01
10	Shop Manager	1254	0.02	0	10.37
11	Family Solicitor	2413	0.01	0	5.91
12	Electrical Engineer	2123	0.90	1	65.88
13	Post-Doc Stats Physics/Comp. Mod.	2112	0.57	1	39.36
14	Lecturer In Hospitality Management	2311	0.13	0	23.73
15	Graduate Landscape Architect	2431	0.14	0	26.75
16	Electronics Technician Medical Device	3112	0.93	1	70.07
17	Senior Loyalty Analyst	2423	0.35	0	29.64
18	Java Developer Sql Spring.	2136	0.99	1	89.24
19	1St/2Nd Line Support Engineer	3132	0.65	1	44.33
20	Sales Support/Junior Administrator	7129	0.17	0	21.64
21	Linux Technical Lead Solutions Engineer	2136	0.86	1	58.64
22	Senior Developer Sharepoint, .Net	2136	0.96	1	75.34
23	Senior It Support Analyst	3132	0.82	1	57.71
24	Senior C# .Net Developer, 80K	2136	0.97	1	78.05
25	Field Service Engineer	5249	0.54	1	49.50

- Many robustness checks:
  - alter set of keywords
  - in-sample predictions (92% of accuracy)

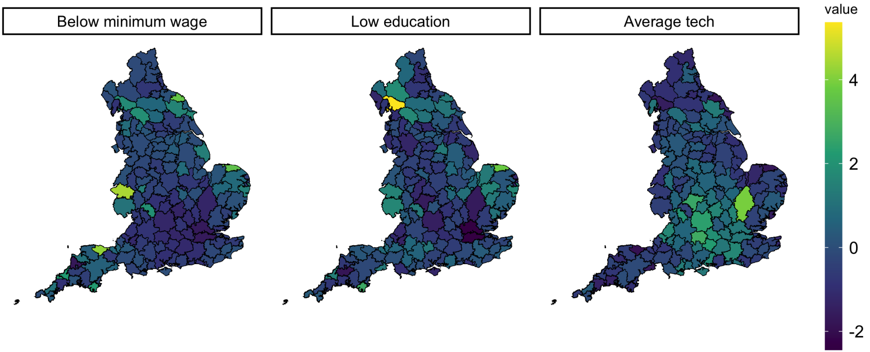
Final database for analysis

Job ID	SOC2	SOC cat.	TTWA	H. Wage	Educ.	Educ. cat.	Tech prob.	Tech cat.	others...
Posting 1	12	high	London	12	6	grad	0.80	high	...
Posting 2	65	mid	Huntingdon	8	3	non-grad	0.35	mid	...
...	...	...	...	...	...	...	...	...	...

- Variables
  - SOC2: 2-digit SOC occupation
  - SOC category: low (7-9), medium (4-6) and high (1-3) skilled
  - TTWA: Travel To Work Areas (175)
  - Hourly wage: in pounds. Removed top p1 and p99 for outliers
  - Education: from 1 to 7.
  - Education categories: graduate (levels 6 and 7) and non-graduate (others), mutually exclusive.
  - Tech probability: number between 0 and 1.
  - Tech category: low, mid and high tech jobs
  - Others: different aggregation levels of variables

Stylised facts

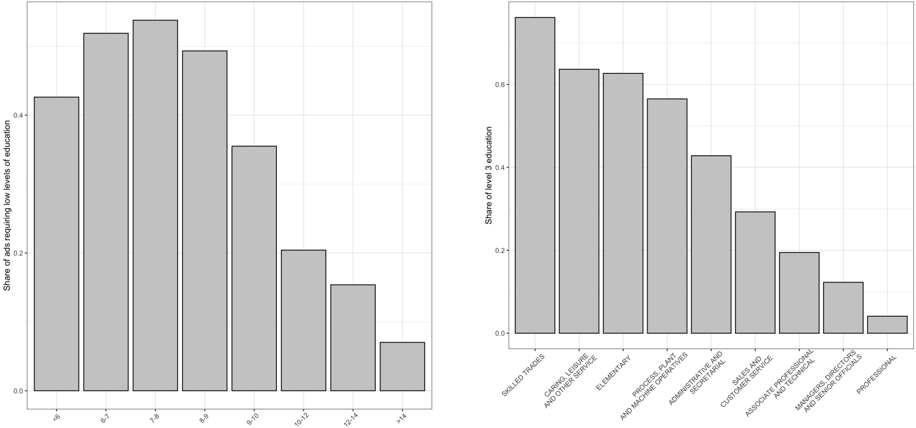
- Fact 1: In local labour markets with a high share of low-wage jobs in 2014 (before the change in policy in 2016), education requirements in online jobs postings are relatively lower.
- Fact 2: In local labour markets with a high share of low-wage jobs in 2014 (before the change in policy in 2016), technology levels in online jobs postings are relatively lower.



Notes: share of ads in TTWAs below the minimum wage, with low education requirements and technology level. Figures are computed on the sample of ads from 2014 to July 2015 as this is when the change in policy was announced.
Source: BGT 2014-2019.

Share of non-graduate vacancies

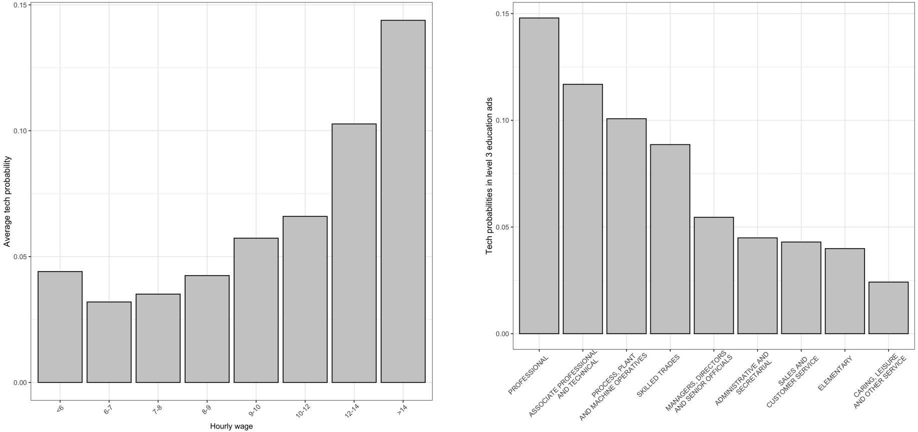
Figure: by wage group (left) and by one-digit occupations (right)



Notes: The bars show the proportion of non-graduate vacancies by wage group (left) and by one-digit occupations (right) over the 2014 to 2019 BGT sample.
Source: BGT 2014-2019.

Tech level of ads (probability of searching for a tech worker)

Figure: by wage group (left) and by one-digit occupations (right)



Notes: Left: shows the average technology probability of job postings for non-graduates by hourly wage bins. Right: shows the average technology probability of job postings at the 1-digit occupation level.
Source: BGT 2014-2019.

Minimum Wage Policy: conceptual framework

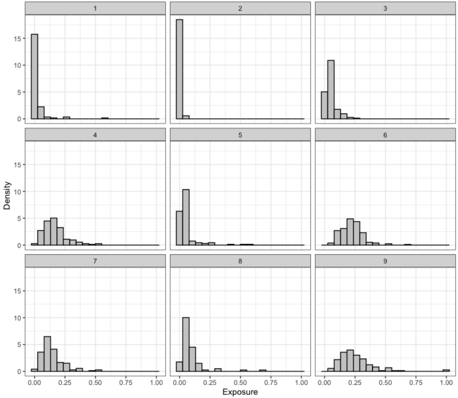
- We explore large increase in the NMW in April 2016: the minimum wage rose by 7.5% from £6.70 to £7.20.
- 10% of the labour force is concerned by a change in the minimum wage, and 25% within low and middle skilled occupations.
- The sudden increase in labour costs for firms will have an effect on the employment structure
- Different channels: layoffs, cuts in hiring, price rises, cuts in non-labour costs, and improvements in productivity
- Aim of increasing productivity: reduce the unit cost of production.
- We discuss the change in productivity:
  - labour-labour substitution: change in education requirements
  - labour-technology substitution: change in tech skills requirements

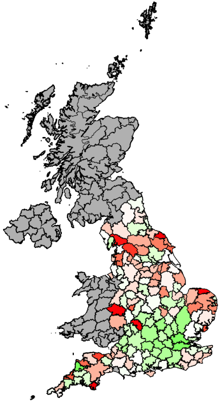
Methodology

- NMW is a national policy: use variation in exposure to the changes across occupations and TTWA
- We construct a degree of exposure measure of each occupation in each local labour markets in England
- The share of ads offering below the minimum wage in 2014 in a 2-digit occupation-location:

$$ExposureNMW_{o,l,2014} = \frac{adsHwage < \$7_{o,l,2014}}{ads_{o,l,2014}} \quad (1)$$

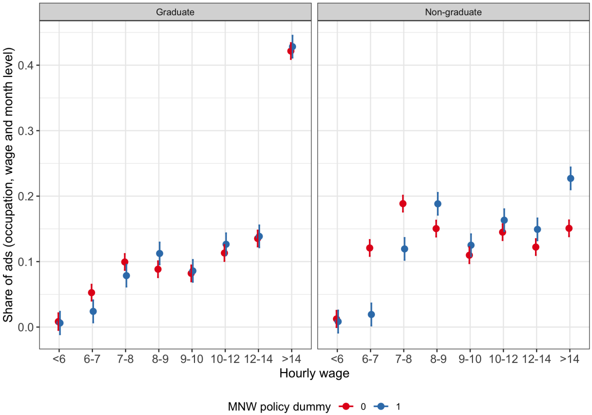
The variation in NMW bite





Notes: Panel (a): each panel shows the distribution of the share of vacancies that are paid below the NMW (minimum wage bite) for a given occupation. Panel (b): shows the spacial distribution, the greener the area, the lower the share of online ads posting wages below the minimum wage in 2014, on the contrary, the redder the larger that share is.
Source: BGT, 2014.

Minimum wage policy impact on offered wages, by education



Notes: Figure gives estimates of the treatment effect of NMW increase on wage bins within each educational group. The estimates are identified by comparing the share of vacancies in a given wage bin before and after the NMW introduction, controlling for occupation, season and time FE for each wage bin, as well as for the time between the announcement and beginning of the policy.
Source: BGT 2014-2019.

- shift at the right side of the distribution of posted wages (not for graduates)
- by occupations group; effect visible mainly in middle-low skilled fig
- graphical evidence of the compliance with the minimum wage policy

Specifications

$$S_{t,o,l} = \beta_1 NMW_{o,l,2014} * Dpolicy_t + \beta_x X + FE + \epsilon \quad (2)$$

- $S_{t,o,l}$ is the share of ads:
  - in each education category by occupation o, month-year t, TTWA l
  - in each tech level categories by occupation o, month-year t, TTWA l
- *NMW* stands for the exposure to the change in the minimum wage at the TTWA-occupation level in 2014
- *Dpolicy* is a dummy that equals 1 from April 2016 onward
- X controls for the time between announcement of the policy and its implementation in order to account for employers expectations
- *FE* are fixed effects for the occupation*TTWA, season*year
- Standard errors are two-way clustered at the occupation-year level.

Labour-labour substitution

Table: Overall occupations

	Dependent variable:			
	share of ads by month-year			
	Graduates	Graduates	Non-graduates	Non-graduates
	(1)	(2)	(3)	(4)
Exposure x treatment	0.044	0.015**	-0.062*	-0.058*
	(0.055)	(0.005)	(0.036)	(0.027)
Controls	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	Yes
Clustered se	Yr-SOC	Yr-SOC	Yr-SOC	Yr-SOC
Observations	110,263	110,100	114,186	114,088
Adjusted R^2	0.085	0.566	0.276	0.696

Notes: Fixed effects: Year*SOC-season and TTWA. Standard errors are clustered at the Year-SOC level. *p$<$0.1; **p$<$0.05; ***p$<$0.01.

- Increase the share of ads requiring a graduate qualification and decrease in ads requiring non-graduate education Parallel trends

Labour-labour substitution - middle and low skilled occupations

Table: Low and middle skilled occupations

	Dependent variable:			
	share of ads month-year			
	Graduates	Graduates	Non-graduates	Non-graduates
	(1)	(2)	(3)	(4)
Exposure x treatment	0.004	0.001	-0.095***	-0.062**
	(0.068)	(0.032)	(0.016)	(0.023)
Controls	Yes	Yes	Yes	Yes
Fixed effects	No	Yes	No	Yes
Clustered se	Yr-SOC	Yr-SOC	Yr-SOC	Yr-SOC
Observations	27,074	27,074	36,799	36,799
Adjusted R^2	0.010	0.392	0.106	0.377

Notes: Fixed effects: Year*SOC-season and TTWA. Standard errors are clustered at the Year-SOC level. *p<0.1; **p<0.05; ***p<0.01.

- Effect are concentrated at the bottom of the skill distribution. Parallel trends
- Robust: no effects of the policy at the top of the skill distribution
- Separating effects between high exposed vs low exposed location

Labour-technology substitution

Table: Impact of the minimum wage on the demand for higher tech workers

	Dependent variable:		
	Share of high tech ads		
	Overall	High-skilled occ	low-med skilled occ
	(1)	(2)	(3)
Policy announcement	0.007	0.0003	0.026**
	(0.009)	(0.011)	(0.012)
Exposure x treatment	0.143**	0.241	0.170**
	(0.060)	(0.192)	(0.065)
time*TTWA-SOC FE	Yes	Yes	Yes
Clustered SE	yes	yes	yes
Observations	53,990	43,730	10,260
Adjusted R^2	0.372	0.400	0.258
Note:			*p<0.1; **p<0.05; ***p<0.01

- The minimum wage policy increases the demand for ICT workers overall
- This increase was entirely driven by the low-medium skilled occupations vacancies
- The estimate for high-skilled occupations is non-significant, suggesting that our results are not capturing a structural shift across the skill distribution Parallel trends

Robustness and limits

- Robustness:
  - We use LFS employment data to construct the exposure measure - at a higher level of aggregation due to the number of observations.
  - Placebo break in the data: estimates are non-significant.
- The change in graduates supply and share of people with more tech skills during our period of analysis, using job postings partly corrects for that.
- The change in the composition of firms that hire in labour markets (e.g. firms stopped hiring)
- Conclusion for job-seekers: they face an increase in education and tech level requirements from employers.

Conclusion

- Our work examines the drivers of education and tech requirements including adjustment to higher labour costs
- We document the response to a labour cost increase using an unexpected change in the minimum wage policy.
- Results show a higher national minimum wage led to a decrease in the share of non-graduate ads and an increase in tech requirements in low and middle skilled occupations.
- In line with recent studies showing that to compensate labour cost increase, firms are increasing productivity.
- Up-skilling effect.

From a policy perspective

- Minimum wage policies aim at supporting low-income: where most effects are captured.
- The targeted population might be harmed by the policy change.
- Existing studies show no aggregate effect on employment, need to be conscious of changes in hiring patterns.
- Future research using the text in the add could look at non-wage compensation: opportunities for training and access to insurance.
- Spatial inequalities.

Thank you !

Techie occupations

4-digit SOC code	Title
2122	Mechanical engineers
2123	Electrical engineers
2124	Electronics engineers
2126	Design and development engineers
2127	Production and process engineers
2133	IT specialist managers
2134	IT project and programme managers
2135	IT business analysts, architects and systems designers
2136	Programmers and software development professionals
2137	Web design and development professionals
2139	Information technology and telecommunications professionals n.e.c.
2150	Research and development managers
3112	Electrical and electronics technicians
3113	Engineering technicians
3131	IT operations technicians
3132	IT user support technicians
5242	Telecommunications engineers
5245	IT engineers

Notes: First column is the occupational code of the SOC classification, and the second column is the title of the occupation.

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External tech classification

- Classification by Harrigan et al. (2018)
- "techies": occupations that are "closely related to the installation, management, maintenance, and support of ICT, as well as product and process design and longer-term R&D activities" techie

Techiness of a keyword

- *Techiness* of a keyword (x_k): the proportion of techie occupations in the whole set of ads where k appears
- K-means clustering to classify keywords into techie, neutral and non-techie clusters with pre-determined centroids:
  - 0 (100;0): 0% techie (non-techie cluster)
  - 0.5 (50;50): 50% techie (neutral cluster)
  - 1 (0;100): 100% techie (techie cluster)
- Example of clusters: wordclouds
- Output at this stage is that for each keyword we have:
  - its "techiness"
  - its cluster number
- accuracy in predicting ICT occupations based on mean techiness: 89%

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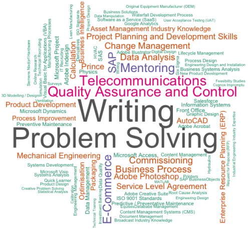
Examples of neutral (top-left), techie (top-right) and non-techie (bottom-left) keywords



Notes: Samples of around top 100 most frequent distinct keywords collected from English online vacancies and classified using context mapping and clustering. A couple of very frequent keywords are dropped from the plot for scaling issues. Size and color are by frequency of being posted.

Source: BGT 2014-2019. back

From tech skills to tech ads

- An ad in BGT data is a set of keywords
- For each online job vacancies skills: merge techiness and cluster number

Job ID	Skills	Techiness x_k	Cluster c
Posting 1	Skill 1	x_1	c_1
Posting 1	Skill 2	x_2	c_2
Posting 1	Skill 3	x_3	c_3
Posting 1	Skill 4	x_4	c_4
Posting 2	Skill 1	x_1	c_1
Posting 2	Skill 5	x_5	c_5
Posting 2	Skill 6	x_6	c_6
Posting 2	Skill 7	x_7	c_7
...	...	...	...

- Compute multiple metrics at the ad level: mean, median, min, max and share of techie keywords

Job ID	Mean	Median	Min	Max	Share
Posting 1	Mean$(x_k, k \in j_1)$	Med$(x_k, k \in j_1)$	Min$(x_k, k \in j_1)$	Max$(x_k, k \in j_1)$	S_1
Posting 2	Mean$(x_k, k \in j_2)$	Med$(x_k, k \in j_2)$	Min$(x_k, k \in j_2)$	Max$(x_k, k \in j_2)$	S_2
...	...	...	...	...	...

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From tech ads to hiring a tech worker

- Difficult to interpret the metrics computed above
- Difficult to define the threshold for a low, medium and high tech ad
- We compute the probability that the employer is looking for a tech worker using a logistic link function:

$$logit(\theta_i) = log\left(\frac{\theta_i}{1-\theta_i}\right) = \beta_0 + \beta_{x_i} X_i \qquad (3)$$

  where θ_i is the probability of looking for a techie for online job posting i and $X_i \in \{Mean_i, Med_i ...\}$ are the different metrics for online job posting i.

- Preferred specification is when $\beta_{x_i} X_i = \beta_1 mean\_tech_i + \beta_2 max\_tech_i$
- We use the estimated relationship to predict probabilities of being a tech ad on the whole sample table back main

Logit results for preferred specification

Table: Logit regression

	Dependent variable:
	techies_reshef
techie_mean	0.077***
	(0.0002)
techie_max	0.024***
	(0.0001)
Observations	7,748,298
Note:	*p<0.1; **p<0.05; ***p<0.01

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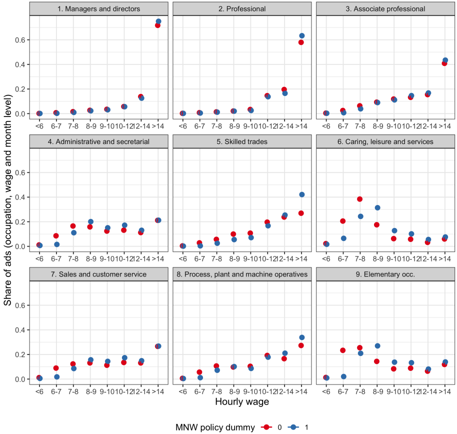
Minimum wage policy impact on posted wages, by occupation categories



Notes: Figure gives estimates of the treatment effect of NMW increase on wage bins within each occupation group. The estimates are identified by comparing the share of vacancies in a given wage bin before and after the NMW introduction, controlling for occupation, season and time FE for each wage bin, as well as for the time between the announcement and beginning of the policy.
Source: BGT 2014-2019.

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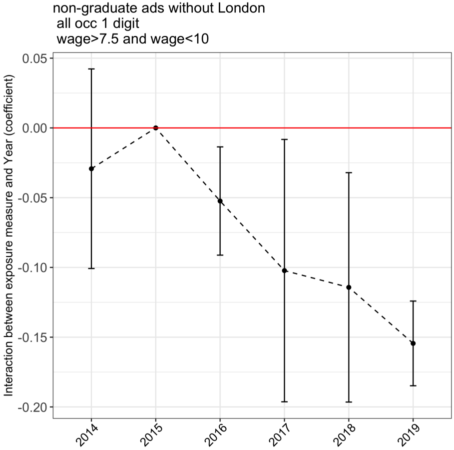
Parallel trends



Source: BGT 2014-2019.

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Parallel trends

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