

# Flexible Work Arrangements in Low Wage Jobs

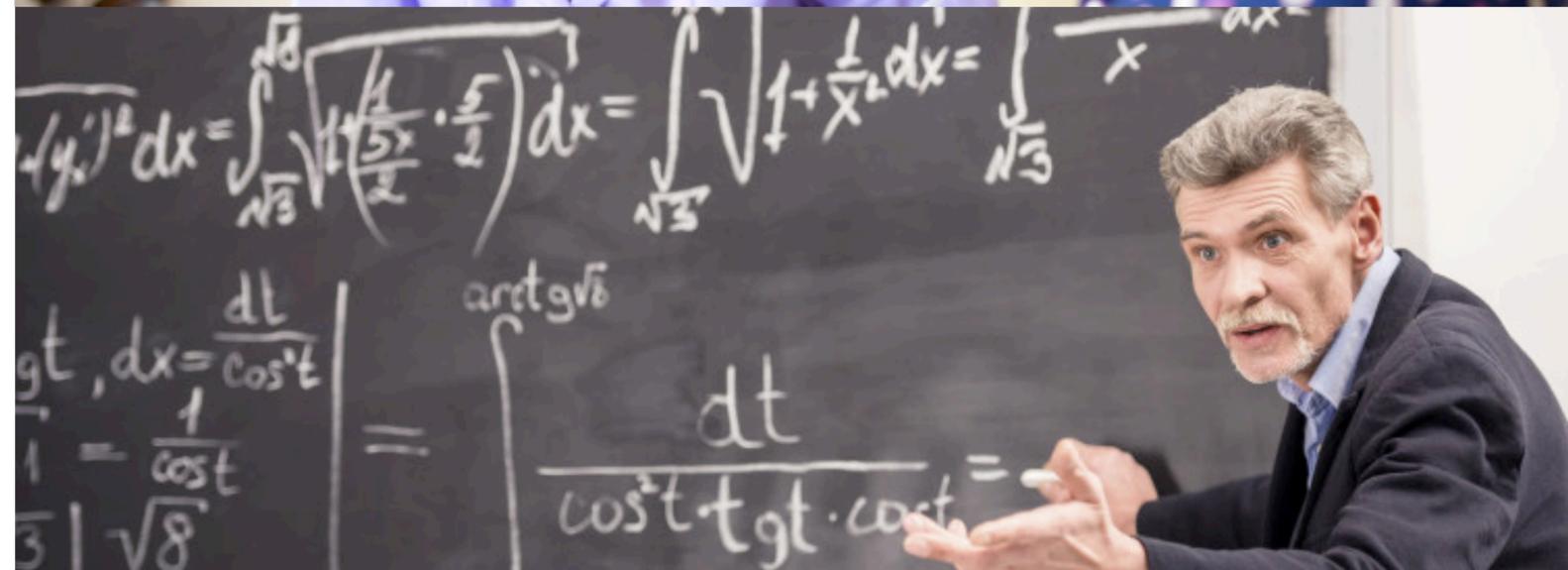
## Evidence from Job Vacancy Data

Matthias Qian, 5th of November 2020  
Jointly with Abi Adams, Maria Bolgova and Tom Waters



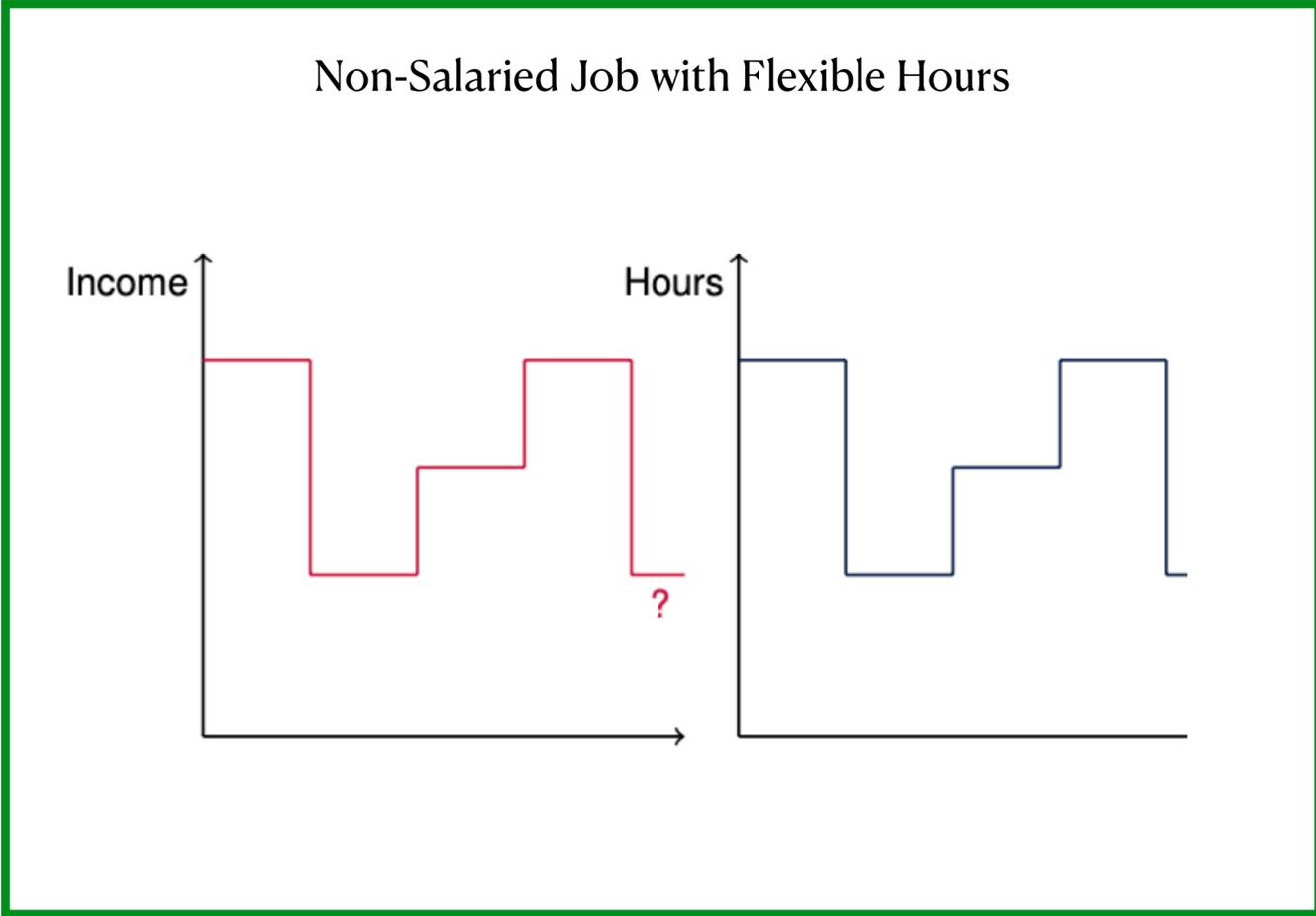
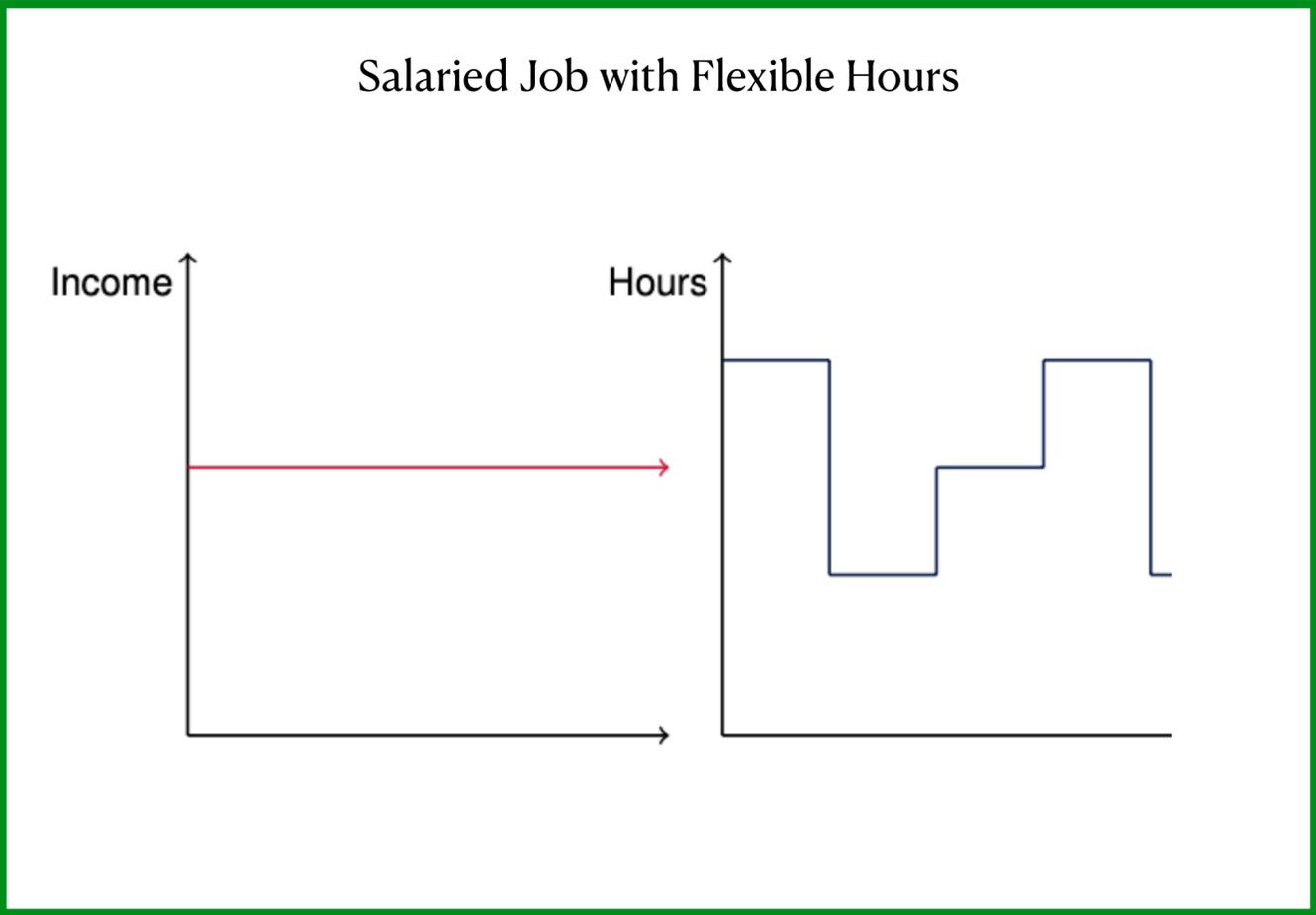
**INDUSTRIAL  
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UK Research  
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# Our goal is to measure two types of schedule flexible jobs



# Related Literature

Measurement of alternative work arrangements and zero hours contracts challenging. Existing work has therefore focused on bespoke surveys or particular sectors where specialist data exists:

- Datta et al (2019): focus on social care which has good employer-employee data
- CEP 2018 survey: cannot be used to understand changes over time
- Adams-Prassl et al (2020): Covid-surveys ask about control of hours

Growing literature using job vacancy data in order to analyse the labour market, some in real-time:

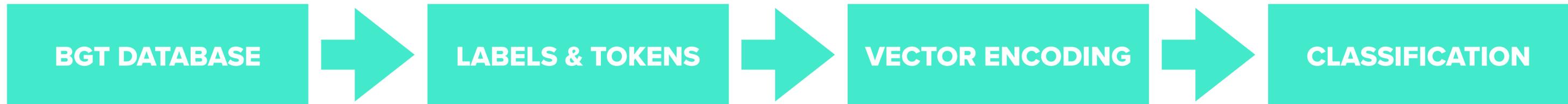
- Demand for skill: Hershbein & Kahn (2018); Deming & Kahn (2018); Clemens, Kahn & Meer (2020)
- Response of hiring strategies to public policy reform: Duchini et al (2020); Marinescu (2017)
- Shocks: Javorcik et al (2020); Forsythe et al (2020)

# The four take-aways for my talk

1. **Machine learning** as powerful technology to measure schedule flexibility
2. In UK **schedule flexible jobs are on the rise** since 2014
3. Why? Due to desire of employers to **reduce labour cost** for low skilled workers
4. During COVID-19, schedule flexibility as vital **margin of adjustment for firms**

Measuring schedule flexibility from job ads benefits  
from machine learning

# Natural language processing with supervised machine learning



We measure schedule flexibility based on vacancy text

- The full vacancy text of 50,240,650 Burning Glass Technologies (BGT) job ads
- BGT scrapes 7500 job board and company webpages

Limitations:

- Not all jobs are advertised online
- We consider only what firms state in advert rather than realised arrangement
- Not 1-to1 mapping between characteristics of vacancies & filled jobs: not all vacancies are filled & terms might be negotiated
- Jobs posted online disproportionately professional and ~30-40% missing wage info

Manually annotate 6,500 vacancies to create training data set for supervised machine learning approach

- assign 1 if vacancy contains flagged information
- assign 0 otherwise

We label for permanent, temporary, full time, part time, schedule flexible, salaried and non-salaried jobs

We tokenise at a word level (1-grams) to build parsimonious and interpretable machine learning models

We limit our vocabulary to the most frequent 5000 tokens. To improve precision and recall, we add frequently used 2-grams and 3-grams used to characterise schedule flexible, salaried, etc jobs

VECTOR ENCODING

We encode the text as numbers using the Binary Count Vectoriser. The use of TF-IDF vectoriser and word vectors did not increase the performance of classifiers

The Binary Count Vectoriser represents our corpus of vacancy text in our training data as a matrix

flexible	1	0	...	1
maternity	1	1	...	0
fixed term	0	1	...	0
:	:	:	:	:
permanent	0	0	...	1

The matrix represents all numbers as 'ntkn' tokens and excludes words on the stop word list

CLASSIFICATION

We use the Logistic Classification model due to be tractable and well established within the economics literature

Deep learning methods doesn't improve the classification accuracy

We use LASSO regularisation to do feature selection to select words from the vocabulary which are relevant for classification

The tuning parameter for the LASSO regularisation is determined with grid search and cross validation

To evaluate the performance, we draw repeated balanced samples from the annotated data and compute precision, recall and the F-score on the test data

*“As this is a Bank position to **provide cover as and when we need it**, such as for annual leave or sick leave, the hours and days you work will vary.”*

*“They are looking for a dynamic Solicitor, Legal Executive or Licensed Conveyancer to join at this incredibly exciting time to work flexibly/from home.*

*You will be given the platform to succeed and take care of your clients, whilst benefiting from flexible working from home!*

*This could suit someone looking to return to work after maternity leave, or **someone looking for flexibility around their working hours/ wanting to choose their own working hours!**”*

*“What we offer:*

*\* Competitive rates of pay- holiday pay, all out of pocket expenses paid including mileage. You should be able to earn £60-£82 per 6 hour day, based on interviews achieved*

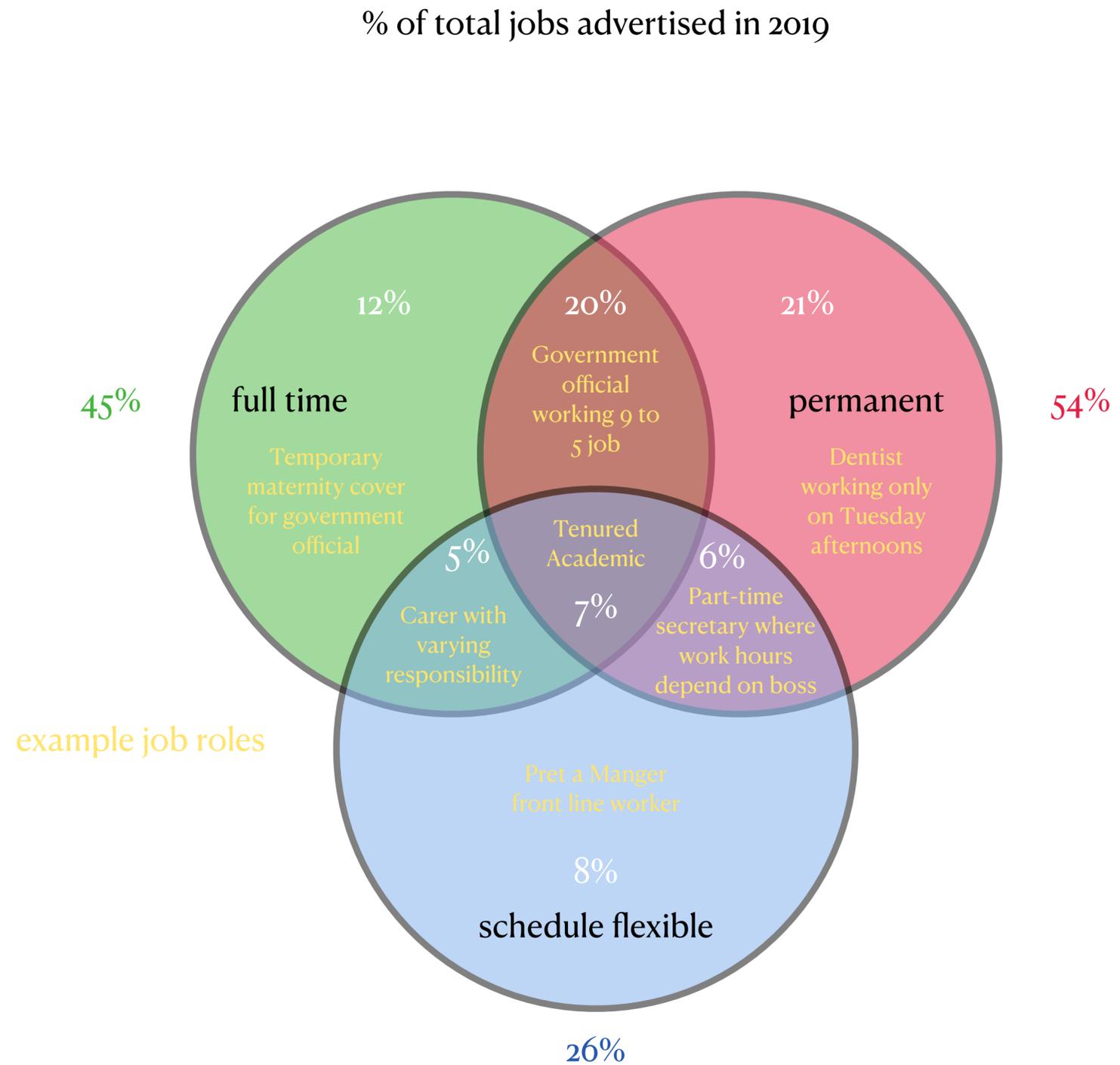
*\*Ad hoc working- which allows flexibility and choice”*

**The largest improvement (19%) from the machine learning model compared with keywords based classification is for schedule flexibility**

<b>Contract type</b>	<b>Logistic Regression Model</b>			<b>Improvement to keywords</b>		
	<b>Precision</b>	<b>Recall</b>	<b>F</b>	<b>Precision</b>	<b>Recall</b>	<b>F</b>
Schedule flexible	0.8540	0.8083	0.8303	0.0005	0.4399	0.1855
Permanent	0.9294	0.9736	0.9510	0.0471	-0.0067	0.0223
Full-time	0.9162	0.8881	0.9019	0.1898	0.2236	0.1314

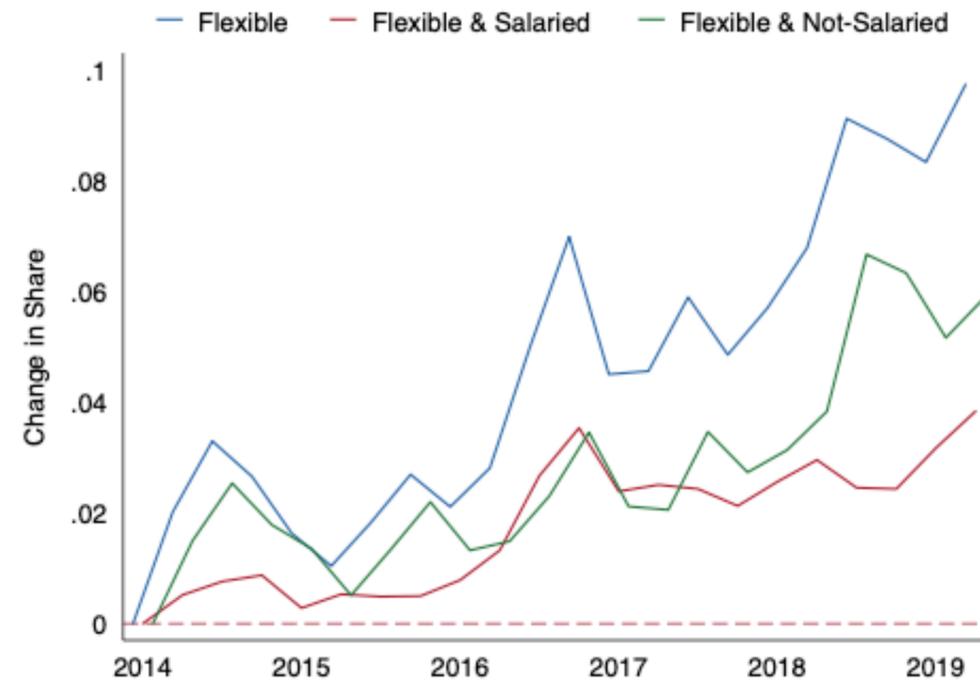
In UK we observe strong increase in the prevalence of job ads for schedule flexible positions

**The prevalence of contract types as advertised in job ads**

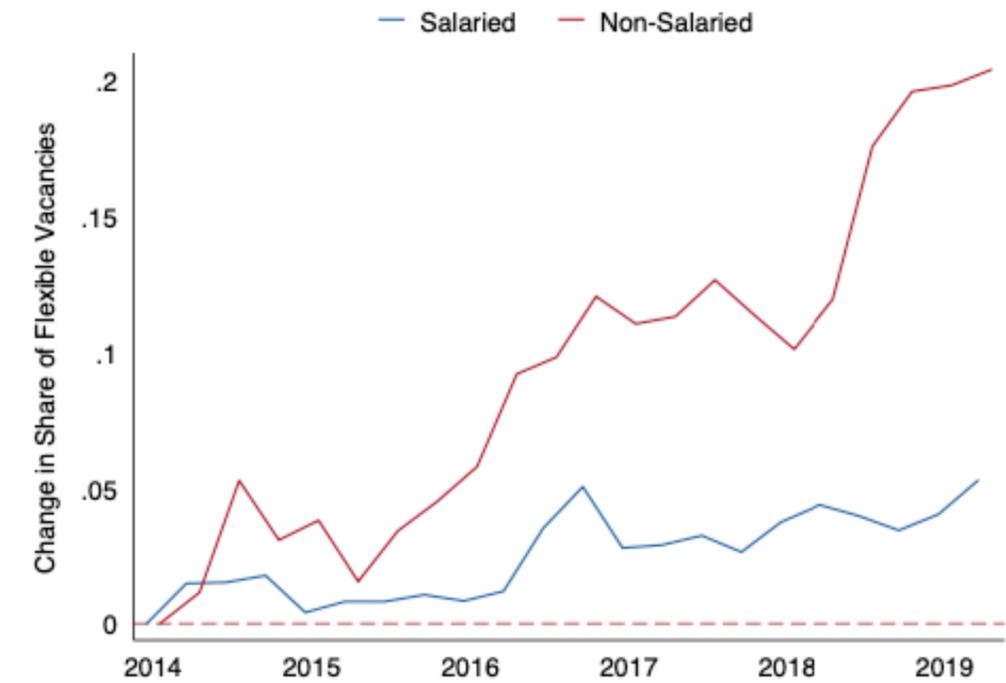


**Schedule flexibility  
experienced  
popularity among  
employers from 2014  
to 2019**

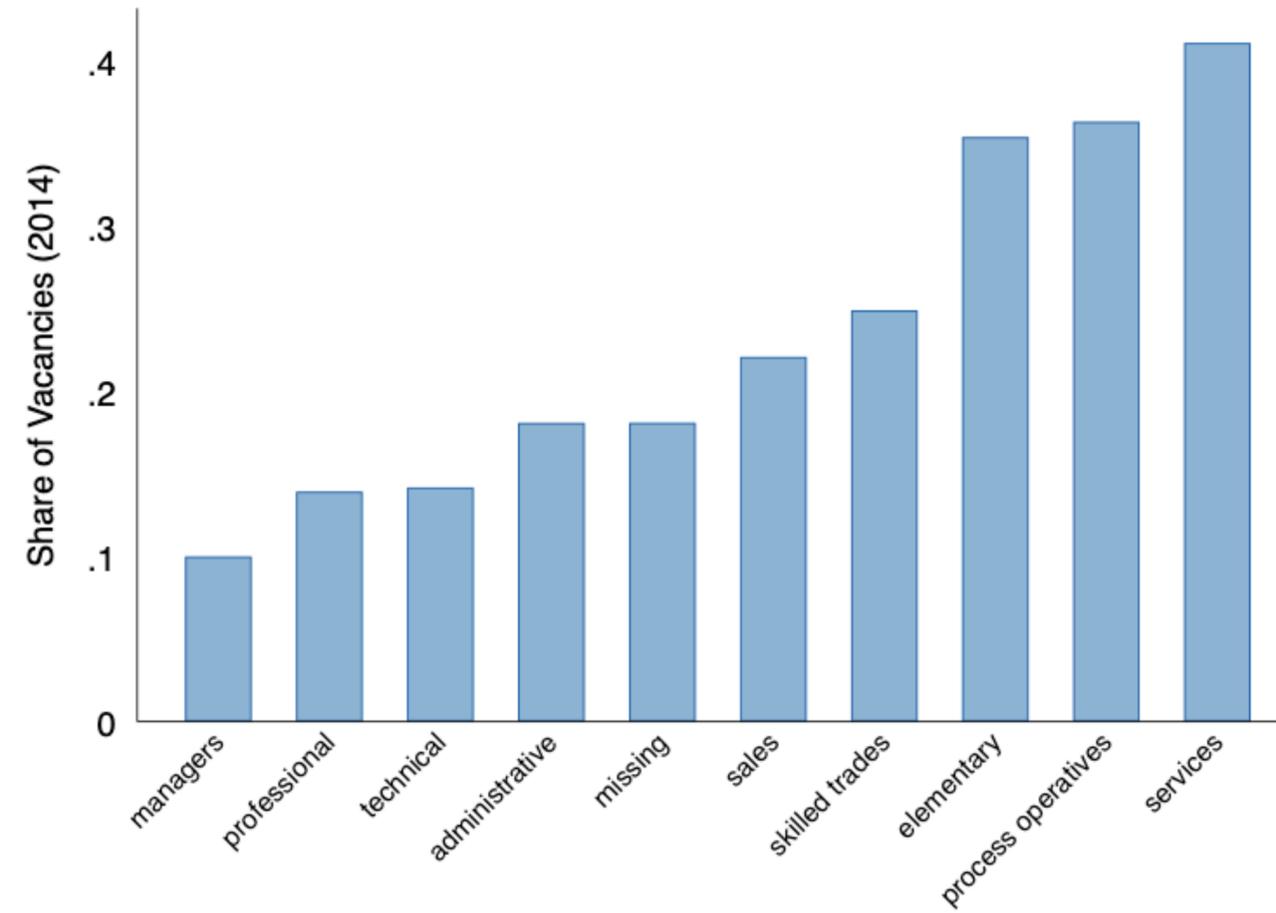
**All Vacancies**



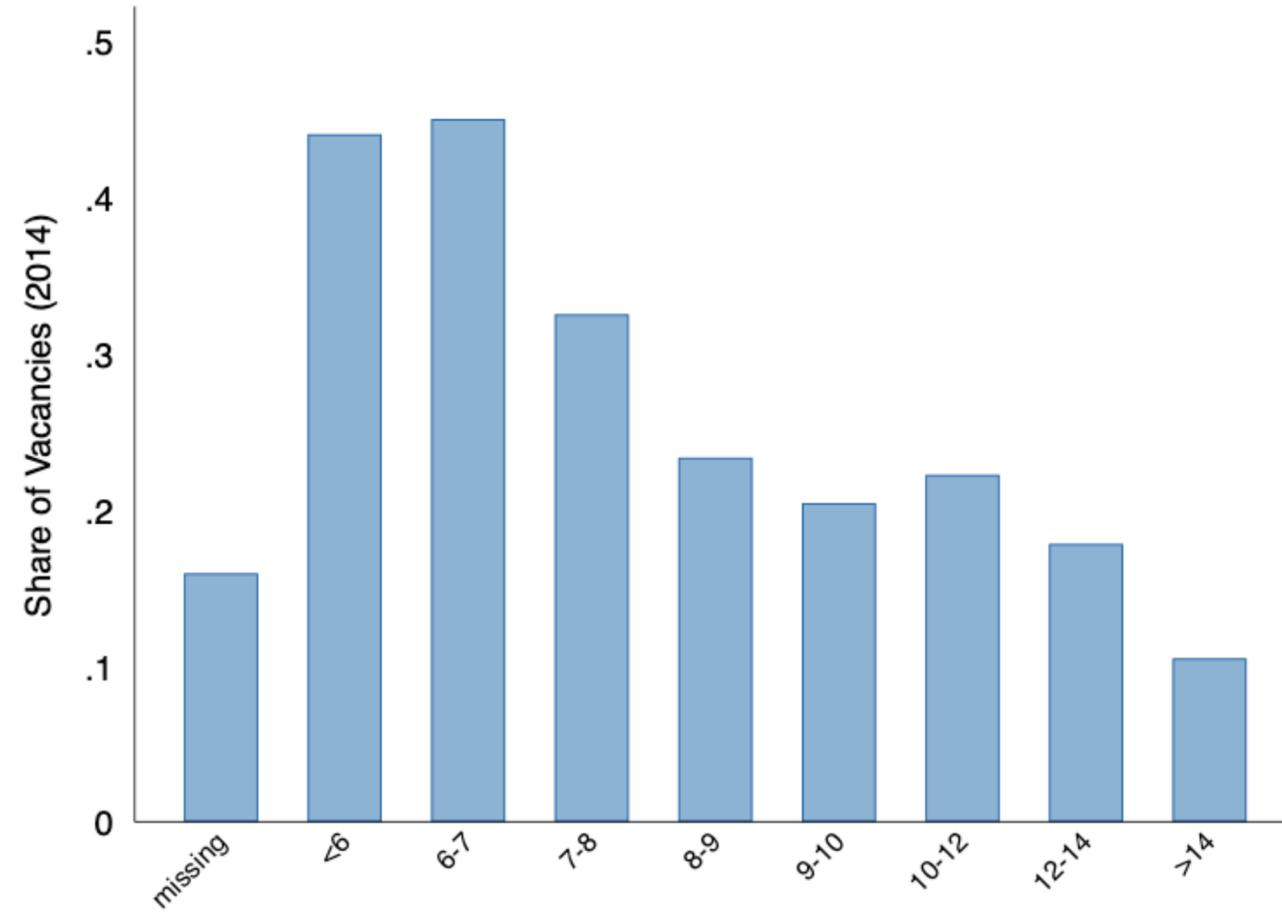
**By Salary Type**



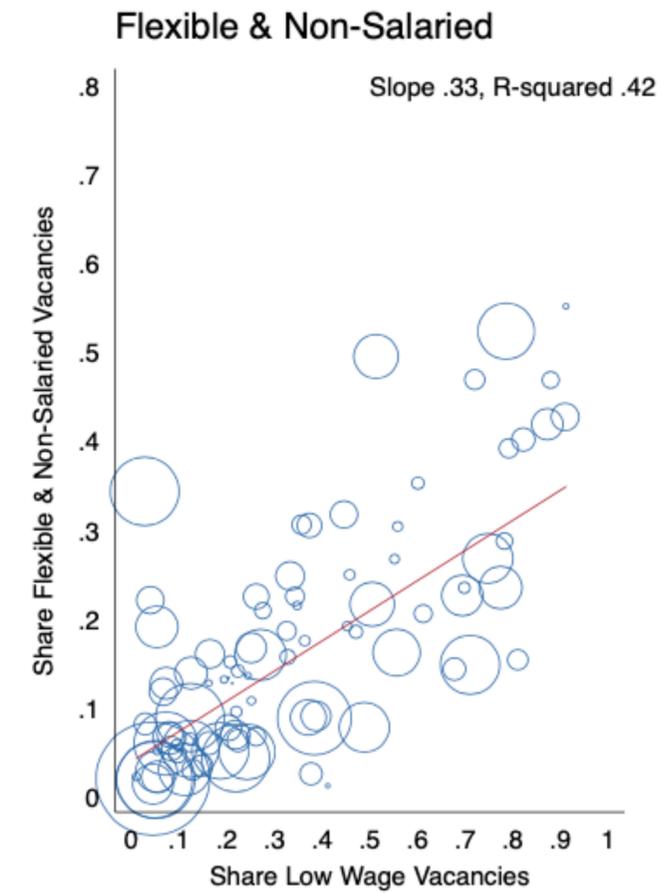
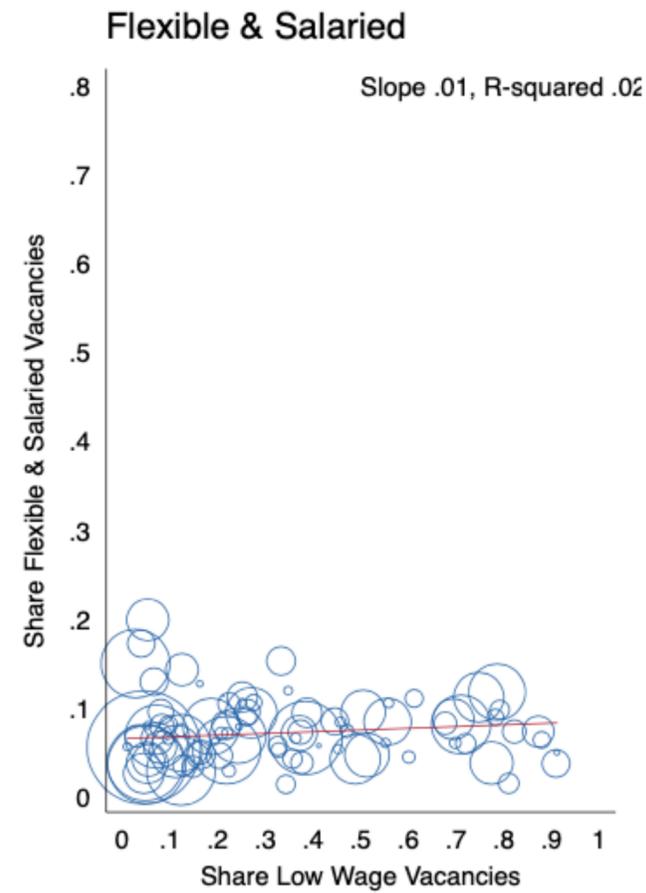
**Services with highest prevalence in schedule flexibility: “Humans as a service”**



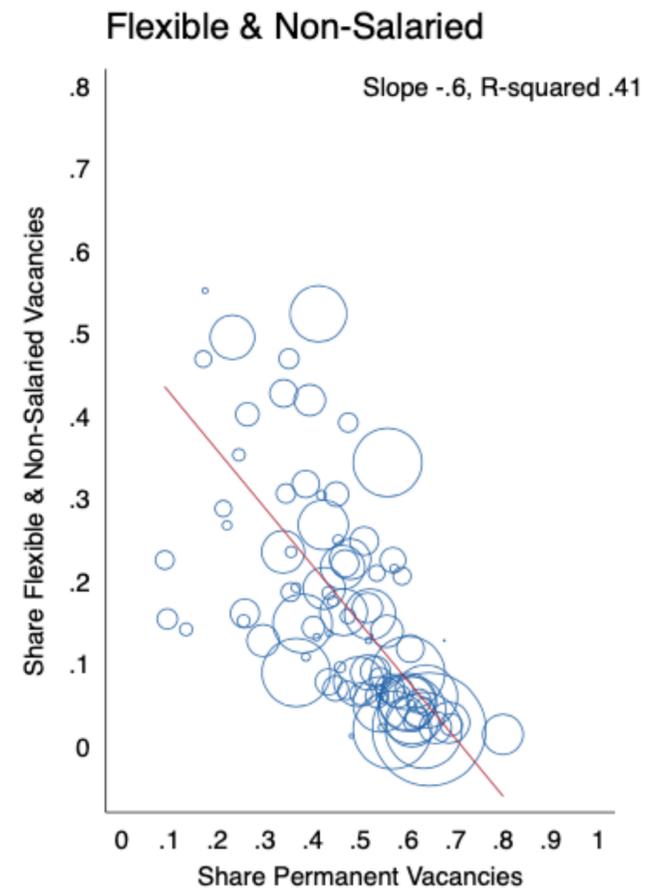
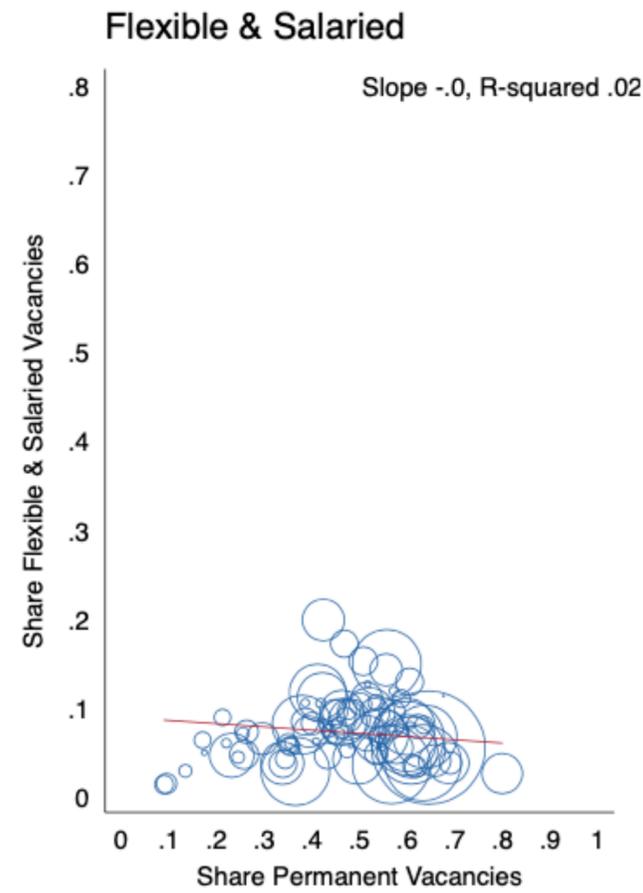
**Low-wage jobs with  
highest prevalence of  
schedule flexibility**



**Prevalence of low wage vacancies correlated with flexible, non-salaried vacancies but not with flexible, salaried vacancies**



**Prevalence of permanent vacancies negatively correlated with flexible, non-salaried vacancies but not with flexible, salaried vacancies**



We explain the rise with the desire of employers to reduce labour cost for low skilled workers

“We strongly support the National Minimum Wage and want to see further real-terms increases in the next Parliament. We accept the recommendations of the Low Pay Commission that the National Minimum Wage should rise to £6.70 this autumn, on course for a Minimum Wage that will be over £8 by the end of the decade.”

Conservative Party Manifesto, April 14<sup>th</sup> 2015.

“I am today introducing a new national living wage. We will set it to reach £9 an hour by 2020. The new national living wage will be compulsory. Working people aged 25 and over will receive it. It will start next April at the rate of £7.20. The Low Pay Commission will recommend future rises that achieve the Government’s objective of reaching 60 percent of median earnings by 2020.”

Budget Speech, July 8<sup>th</sup> 2015.

“I’ve talked to several chief executives and been surprised by the impact on their profits.  
In one [big] company, it would wipe out all of their profits”

Paul Drechsler, CBI President, September 2015.

**In April 2016, the UK transitioned to a living wage arrangement**

Table: level of minimum of hourly wages in the United Kingdom

Year	Age				
	25 and over	21 to 24	18 to 20	Under 18	Apprentice
April 2019 to March 2020	£8.21	£7.70	£6.15	£4.35	£3.90
April 2018 to March 2019	£7.83	£7.38	£5.90	£4.20	£3.70
April 2017 to March 2018	£7.50	£7.05	£5.60	£4.05	£3.50
October 2016 to March 2017	£7.20	£6.95	£5.55	£4.00	£3.40
April 2016 to September 2016	£7.20	£6.70	£5.30	£3.87	£3.30
	21 and over		18 to 20	Under 18	Apprentice
2015	£6.70		£5.30	£3.87	£3.30
2014	£6.50		£5.13	£3.79	£2.73

**We use the bunching approach with our diff-in-diff regression specification**

$$Y_{ocwt} = \sum_w \delta_w \text{After}_{wt} * \text{Exposure}_{oc} + \alpha_{ot} + \beta_{ct} + \epsilon_{ocwt}$$

occupation    county    wage    time

minimum wage bite:  
proportion of vacancies in  
SOC3-county in  
2014 that paid less  
than £7

Table: Regression analysis, impact of national living wage, aggregate specification

	Flexible (1)	All Flexible & Non-Salaried (2)	Flexible & Salaried (3)	Non-Salaried (4)	Salaried (5)
<i>Panel (a): Linear Specification</i>					
Exposure x Treatment	0.1769*** (0.0164)	0.1920*** (0.0160)	-0.0177*** (0.0065)	0.1847*** (0.0165)	0.1341*** (0.0147)
<i>Panel (b): Categorical Specification</i>					
Low Exposure	0.0181*** (0.0025)	0.0134*** (0.0021)	0.0053*** (0.0010)	0.0269*** (0.0028)	0.0083*** (0.0014)
Medium Exposure	0.0444*** (0.0050)	0.0426*** (0.0049)	0.0040** (0.0018)	0.0484*** (0.0054)	0.0272*** (0.0036)
High Exposure	0.0534*** (0.0059)	0.0582*** (0.0059)	-0.0057** (0.0023)	0.0586*** (0.0065)	0.0380*** (0.0050)

low exposure: .5 to 0.75 percentile, medium exposure: median 0.75 to 0.9, high exposure: 0.9 and above

Figure: Impact on Proportion of Flexible jobs

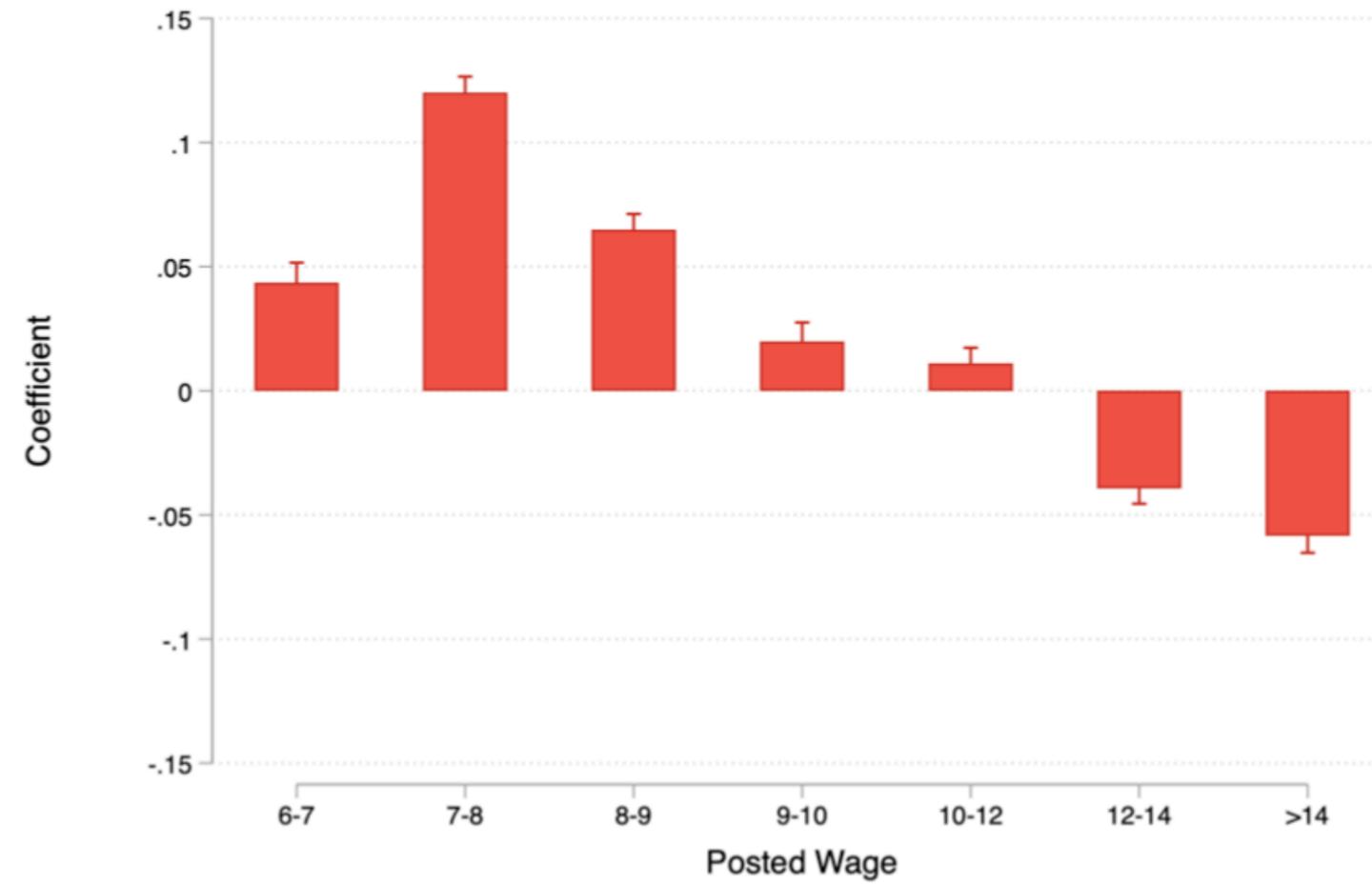
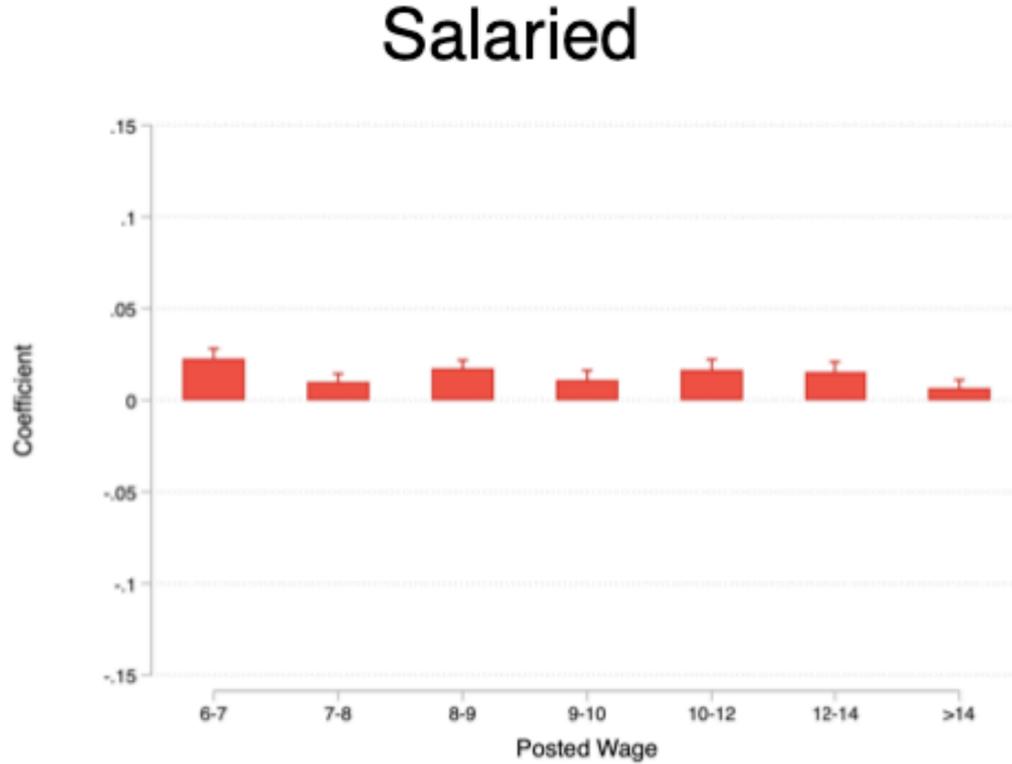
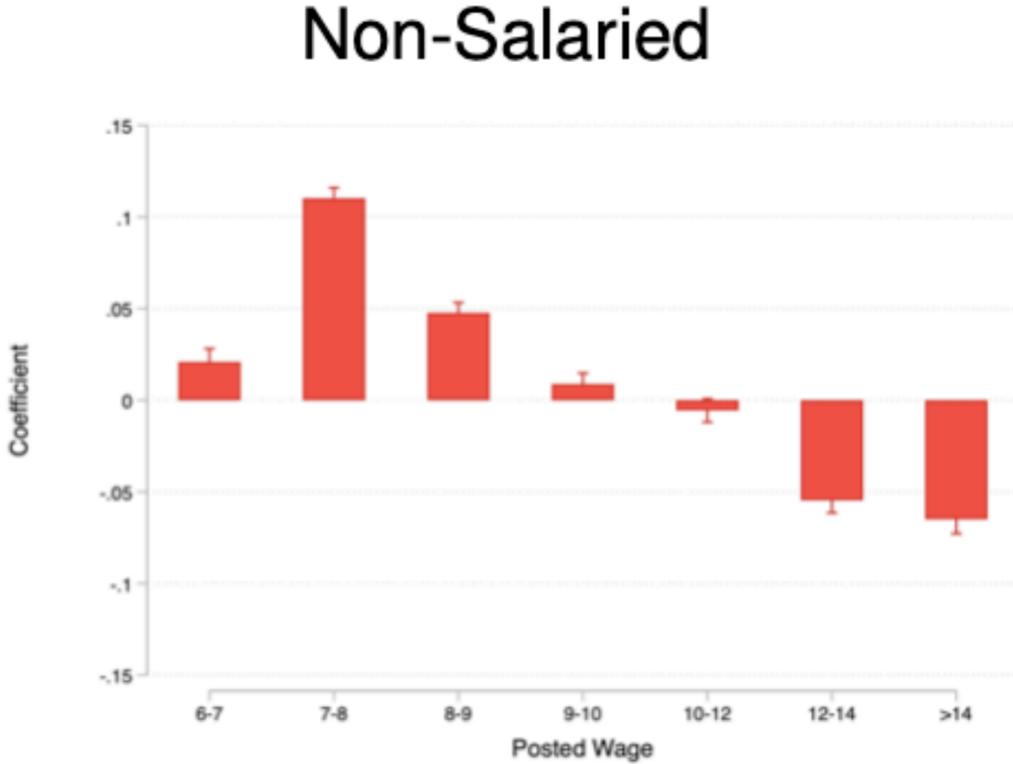


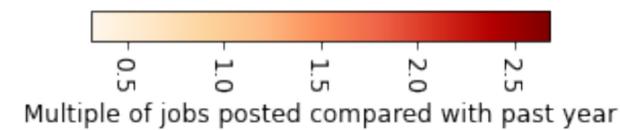
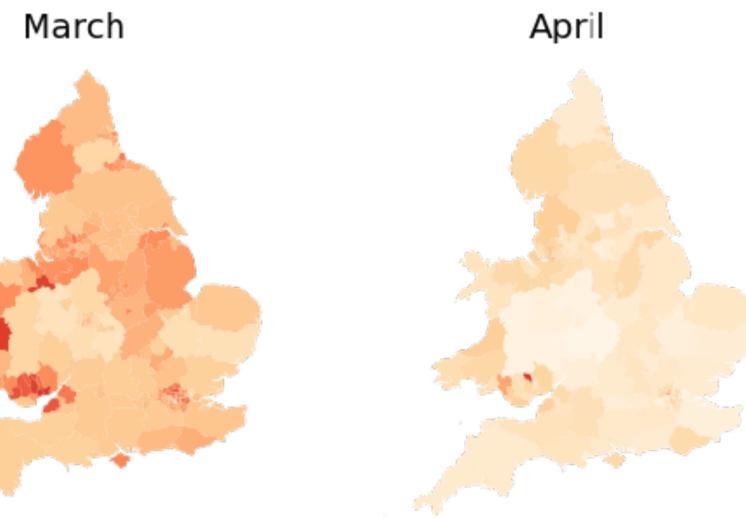
Figure: Impact on Flexible Vacancies



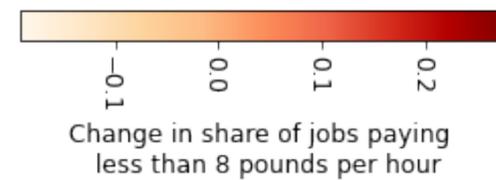
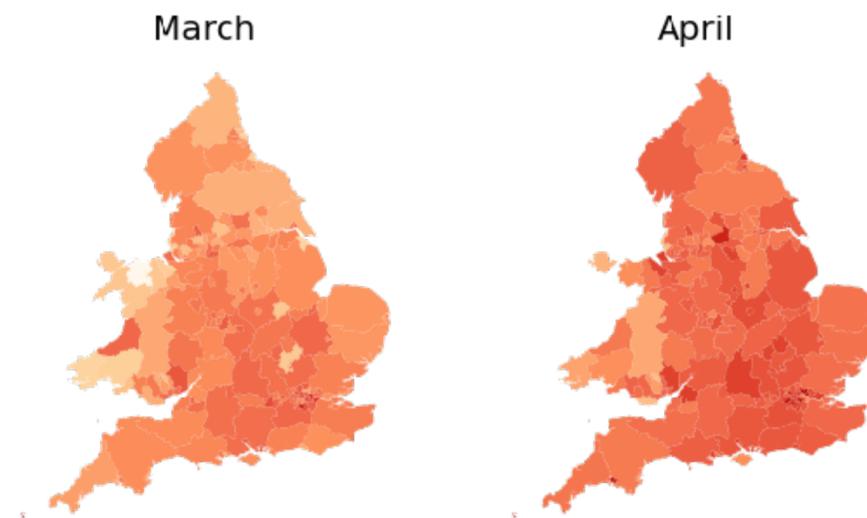
During COVID-19 the use of schedule flexible jobs surged temporarily

# Margin of firm adjustment to COVID19: fewer jobs, less pay, more schedule flexibility

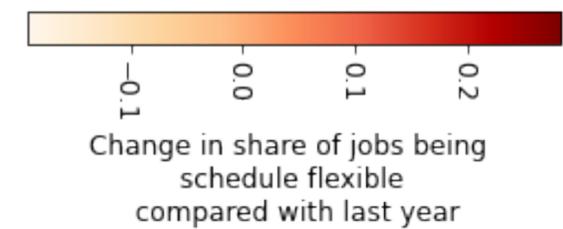
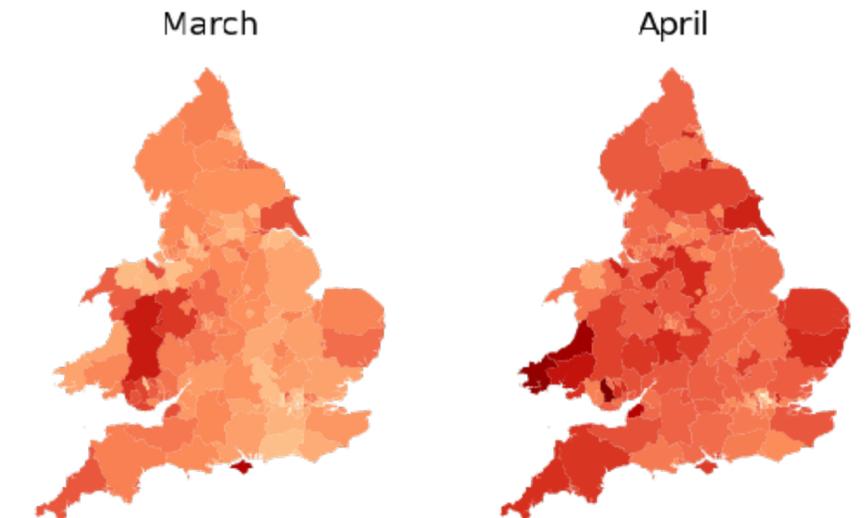
**fewer jobs**



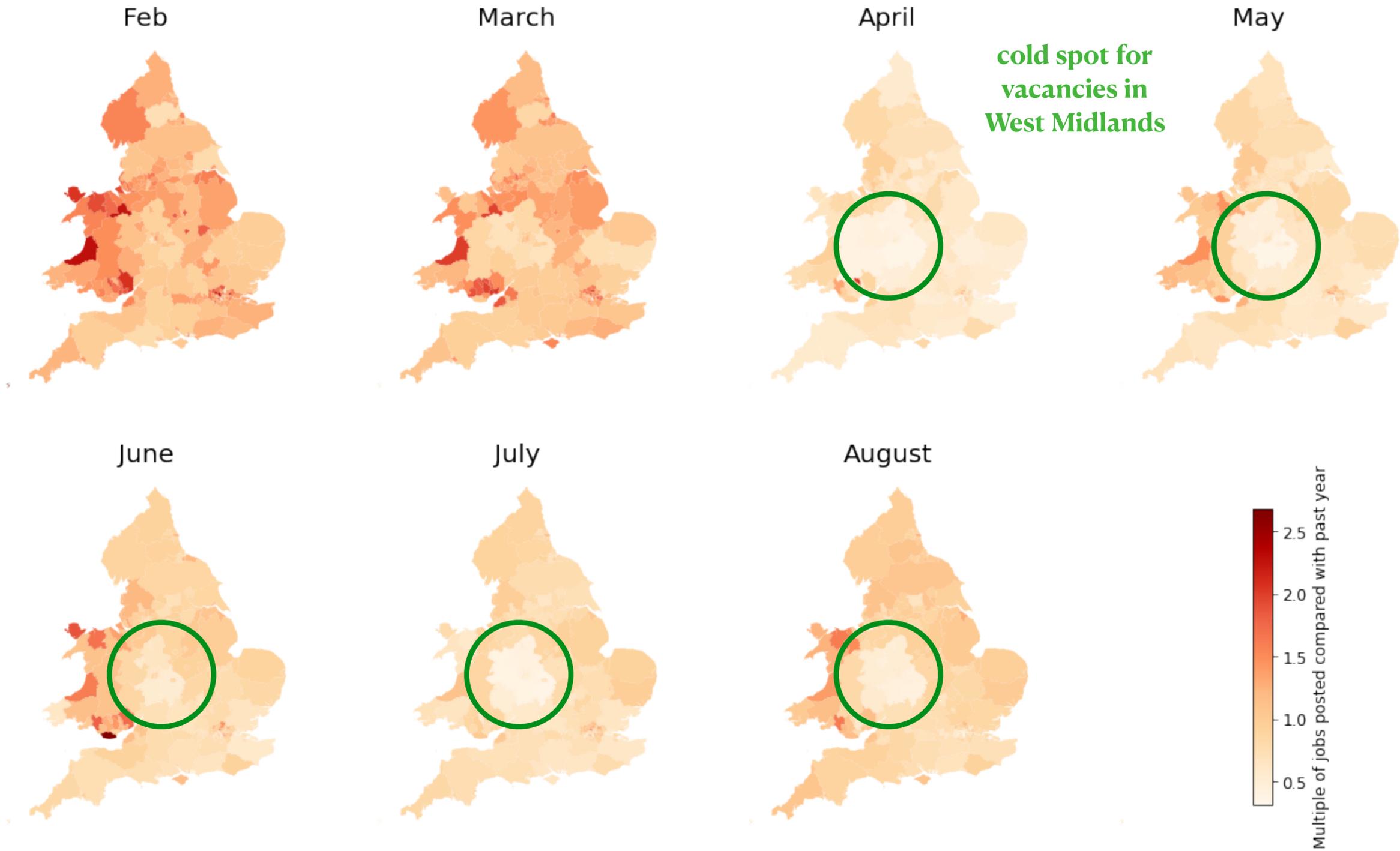
**less pay**



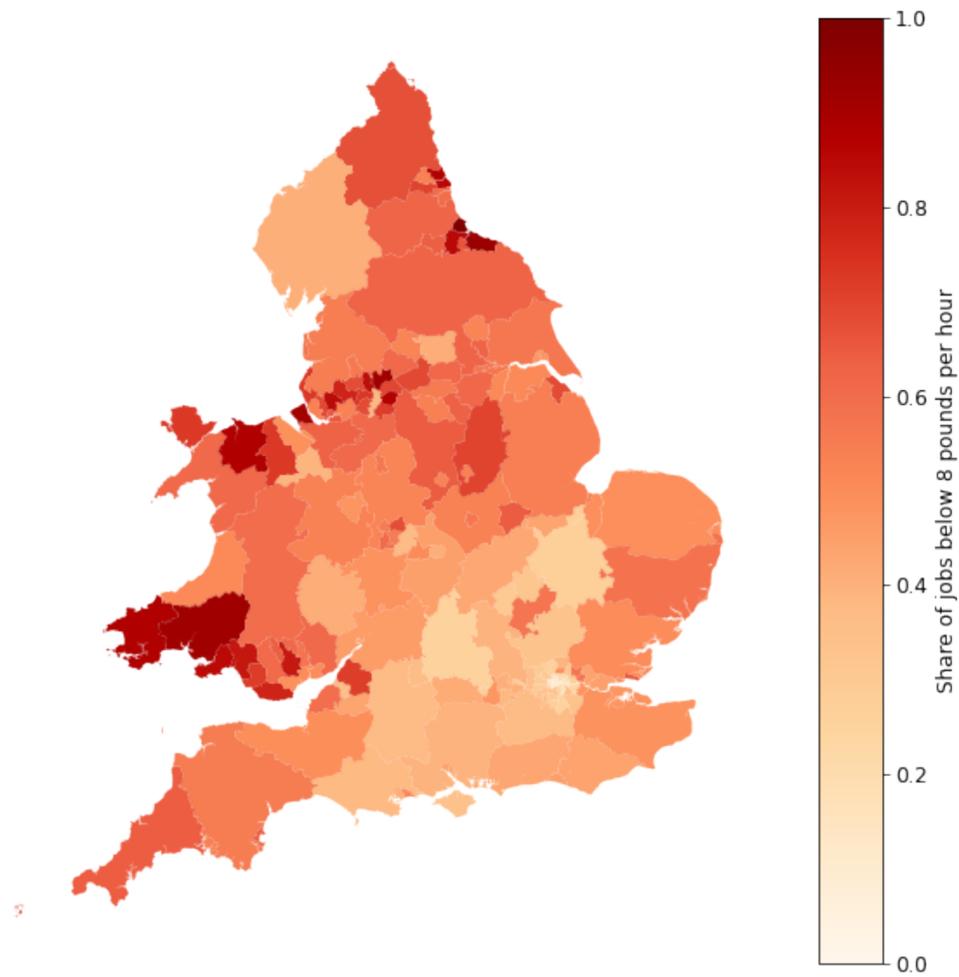
**more schedule flexibility**



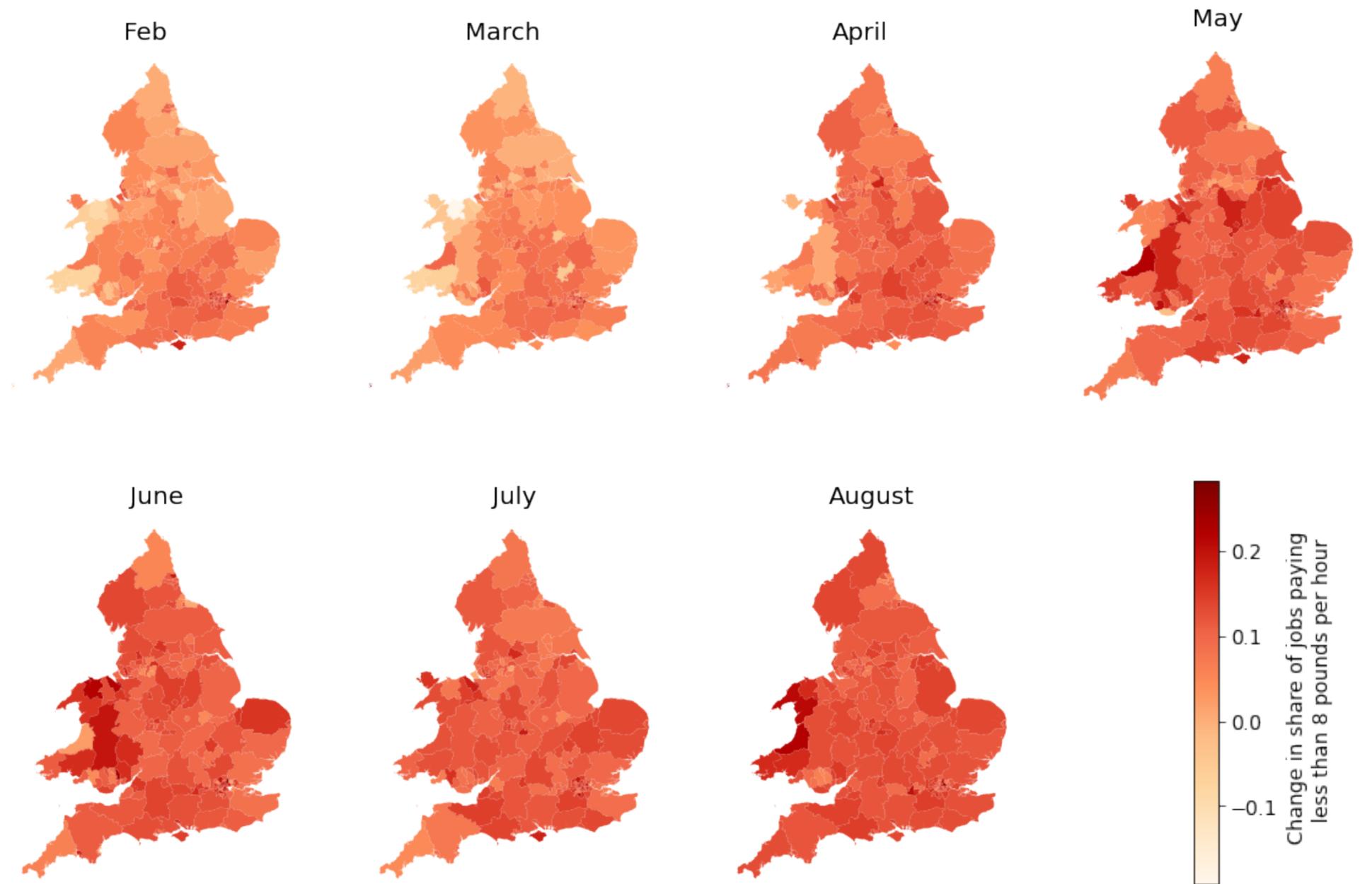
# Margin of firm adjustment to COVID-19: fewer jobs



**prevalence of low paid work (2019)**



**margin of firm adjustment to COVID19: salaries**



# Margin of firm adjustment to COVID19: schedule flexible

