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**Labour demand in the UK during the COVID-19 pandemic:
evidence from online job postings**

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Jeremy Smith (Head of the Department of Economics, University of Warwick) and Michael Ward
(Head of the Department of Economics, Monash University)

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Labour demand in the UK during the COVID-19 pandemic: evidence from online job postings

Štěpán Vácha*

Abstract

The COVID-19 pandemic hit the labour market significantly through its impact on human health. This paper uses job posting data to measure the effect of the pandemic on labour demand in the UK throughout 2020, including estimates of recovery. It demonstrates the advantage of using online job vacancies to monitor the labour market compared to lagged estimates or surveys used by the Office for National Statistics (ONS). The labour demand shock is found to be of a similar size to those reported in the US or Sweden. Total weekly vacancies posted online were down by 39% during the first wave and 12.5% in the second half of 2020, representing a significant, but not full recovery. The significance and size of the shock vary among different industries of the economy. All industries except Human health & social work activities have seen a significant drop in job postings due to the pandemic, with the Accommodation & food service activities sector being hit the most. Although the ONS estimates have grasped the main impact of the pandemic on vacancies, using real-time data can provide the policymakers with a much-needed timely information when dealing with a shock like the global health pandemic.

J230 Labor Demand, Labor Economics, Labor Market Data, COVID-19

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Online appendix and code can be found at github.com/stepva/rae-warwick

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1 Introduction

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, changed the year 2020 in a way no one could conceive. It brought with itself an economic crisis in many aspects different from the previous downturns like the Great Depression of the 1930s or the Great Recession from 2007 onwards. The pandemic critically hit the human part of our economy, whether it is directly through health issues or indirectly through a lockdown and other measures put in place, disrupting the labour market in an unprecedented way (Campello et al. 2020). The collapse of the labour market, participation rates and employment is also much faster and deeper than in the Great Recession (Bell & Blanchflower 2020).

In order to better understand and assess the impact of COVID-19 on the labour market, specifically in the United Kingdom, in my research, I use actual job postings data to see when and how the UK demand for labour changed with the spread of the virus in the country, comparing different sectors of the economy. My dataset comes from Burning Glass Technologies, a private sector company scraping the online job posting universe. Although job adverts on the internet do not account for all job adverts in the country and are estimated to be biased towards higher-skilled jobs, they are strongly correlated with the number of total vacancies, providing a useful measure of the overall demand in the labour market (Javorcik et al. 2019, Forsythe et al. 2020).

Using this data allows for deeper and more thorough research compared to the data and reports published by the British Office for National Statistics (ONS) which does not work with actual job adverts and postings but rather with estimates based on their Vacancy Survey of businesses. This survey is sent to employers every month. The ONS publishes the results later using usually 3-month moving averages, therefore only providing a bigger picture without the possibility of seeing the change weekly. As Bell and Blanchflower noted in May 2020, “UK data from the ONS is less timely and unable to signal high frequency changes in the UK labour market. Hence it is more difficult for us to present a contemporary view of UK trends.” (Bell & Blanchflower 2020, p. R52)

The ONS report *Vacancies and jobs in the UK: April 2020* released on April 21st last year, more than a month after the start of the pandemic, only worked with estimates up to March 6th, prior to any coronavirus related measures taken (ONS 2020a). This is a significant lag in important results and findings, as the presence of a negative labour demand shock was at the time of publishing already being noticed by week-by-week data. With continuous time series of job postings in real-time, actual job advert data can improve the current labour market monitoring system and capture the impact of crises sooner (almost in real-time) (Hayashi & Matsuda 2020), which is vital for policymakers to understand what industries are affected the most and how to appropriately respond to the shocks (Adrjan & Lydon 2020).

This research contributes to the growing literature of using job postings data rather than their estimates to analyse the labour market and further applying this approach to the COVID-19 pandemic in different countries (see Literature Review 2). It also allows for a comparison of actual job postings data with the estimates from the Office for National Statistics, showing how accurate the Vacancy Survey actually is.

2 Literature Review

Research around the labour market and specifically how it changes and behaves during an economic recession is improving and growing with every new crisis. The last one, often called the Great Recession, started in 2007 as a financial crisis, which “quickly evolved into a global jobs crisis” (Islam & Verick 2010, p. 3). While examining the impact and adjustment process of the

labour market during the crisis, Arpaia & Curci (2010) note, claiming evidence from surveys, that the increase of unemployment rates was caused by a lack of demand for labour, a fall in the job vacancy rate, and not by a mismatch between vacant posts and workers.

In recent years, studying the labour demand has moved to more advanced techniques with larger amounts of naturally occurring data easily available – with actual job postings, rather than surveys. Thurgood et al. (2018) use 8 years of vacancies data from Reed, the largest employment agency in the UK, with a machine learning model to develop new classifications of occupations and show a different structure of the labour market than was thought by official statistics. They think of this type of data as complementing the traditional survey-based datasets (Thurgood et al. 2018) and argue that they represent an explicit measure of the economic activity (Turrell et al. 2019). Although Grinis (2017) uses a similar technical methodology to look at the difference between STEM and non-STEM occupations and the skills and knowledge employers require, vacancy data is being used mainly to estimate shifts in labour demand – Javorcik et al. (2019) uses online job postings data scraped from multiple sites and a fixed effects, difference-in-difference model approach to successfully show a change in labour demand caused by trade uncertainty provoked by the Brexit vote in 2016. This methodology is being used in almost every similar research paper.

When focusing on the COVID-19 crisis, researchers use different types of vacancy data. Campello et al. (2020) use a database of job openings from more than 50,000 employers to report a sharp decline in corporate hiring during the pandemic. With more advanced and specific data, the research can go even further. Marinescu et al. (2020) combine job vacancy numbers with job applications data from Glassdoor, a job search engine, to show that job applications in the US did not decrease as much as the vacancy listings, indicating an increase in the number of applications per job. A similar approach was taken for Sweden by Hensvik et al. (2020), where they take advantage of data which included the number of clicks on every job ad, finding differences in clicks-per-vacancy for those occupations allowing for a work from home or those classified as resilient to the health crisis compared to the rest.

However, this data is not available everywhere and the majority of researches relies on job postings numbers only. These could be either collected by a national institution, as in Norway (see Holgersen et al. (2020)), or scraped from multiple different sites, which is done for example by Burning Glass Technologies (BGT). Their data was used by Javorcik et al. (2019) in the above-mentioned paper, and Forsythe et al. (2020) are the first to use it for analysing the labour market deterioration in the US during the spring months of the pandemic. However, Forsythe et al. (2020) only use basic time-series statistics without any further regressions. Outside of data scraped from multiple sites, such as from BGT, researchers often use data from single job postings sites and agencies. Those regularly used in Europe and the US are for example Glassdoor (Marinescu et al. 2020), Reed (Arthur 2020) or Indeed (Adrjan & Lydon 2020). Hayashi & Matsuda (2020) from the Asian Development Bank have used the same approach to look at the labour market during COVID-19 in Bangladesh and Sri Lanka through their local job postings sites.

My research contributes to this literature by using data collected by Burning Glass Technologies for the United Kingdom, where the majority of analyses of the demand for labour during COVID-19 comes from the survey-based data from the Office for National Statistics, with the exception of Arthur (2020) who uses data from a single employment agency but lacks any econometric method as it is not an economic paper.

3 Research Question & Data

In this research I am answering the question of how the labour demand in the United Kingdom changed with the COVID-19 pandemic in 2020, specifically looking at the number of job postings online and using those as a proxy for a labour demand in different industries and the country as a whole. The industries I am looking at are based on the UK Standard Industrial Classification (SIC) Hierarchy sections, which represent 21 different industries of the British economy (see the online appendix for the full list of SIC sections).

3.1 Dataset

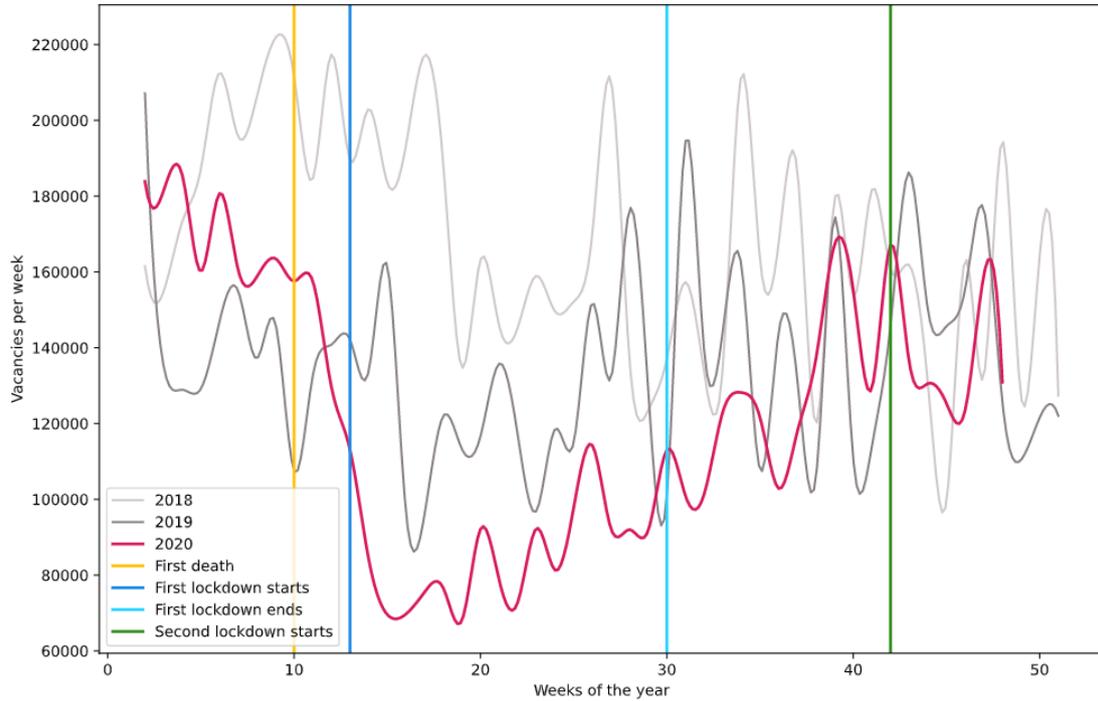
My dataset comes from Burning Glass Technologies and contains weekly unique job postings numbers for the United Kingdom for the past three years, from the first week of 2018 until the 29th of November 2020 (week 48). This represents 152 weeks of data covering a total of 21,480,303 vacancies posted to online sources, an average of 141,317 per week. Approximately one-third of the job postings are classified by the SIC code and are therefore split into 18 different industry sections. The total number of vacancies with the industry code is 7,661,747, or 36% of the whole dataset (see the online appendix for total numbers of job postings for all industries). Having weekly data not only for the pandemic year 2020 but also for the two previous years allows me to control for seasonality and to work with a larger set of “pre-COVID” weeks.

3.2 Total vacancies

The first look at the dataset offers an idea of the drop in job postings after the pandemic took on. This can be seen on Figure 1, which shows the weekly number of total vacancies posted online in the UK for the years 2018, 2019 and 2020. I have decided to omit the first and last weeks of the years because they do not consist of all seven days and due to the way BGT collects the data they contain an accordingly lower number of vacancies in the week and are therefore outliers. On the chart, we can thus see weeks 2 to 51 for 2018 and 2019, and weeks 2 to 48 for 2020. I have also highlighted four important events related to the pandemic. Those are the first confirmed death to COVID-19 in the UK, which occurred on 5th of March 2020; the beginning of the first lockdown, which I put on 23rd of March when prime minister Boris Johnson announced the “stay-at-home” order; the end of the first national lockdown – since restrictions easing was going on during the month of June 2020, the day highlighted on the graph is 23rd of June, when the prime minister announced further relaxing of restrictions. Although the national lockdown ended, local lockdowns were being put in place and the so-called “second wave” of the pandemic in the country started. The last highlighted date is the 5th of November, on that day last year the second national lockdown officially came into force in England as a response to the worsening of the situation.

Figure 1 not only indicates the drop which occurred in the spring of 2020, but it also shows how volatile the weekly number of vacancies is during the “normal” years. We can see similar seasonal patterns in the data from 2018 and 2019, although at the same time there is a difference between those two during the first half of the year, while they seem to stabilize and equalize later on. This confirms the need for a larger data set when comparing pre-COVID and post- or during-COVID vacancy numbers. For example, Forsythe et al. (2020) use only the first two months of 2020, that is January and February, as a comparison. As Holgersen et al. (2020) note, this approach of using only the first two months of the year as “normal” strongly assumes a constant level of vacancies over the pre-pandemic years, which cannot be concluded from the figure. They then proceed to use 2019 data, while I am using both 2019 and 2018, the past two

Figure 1: Weekly job postings with highlighted COVID-19-related events

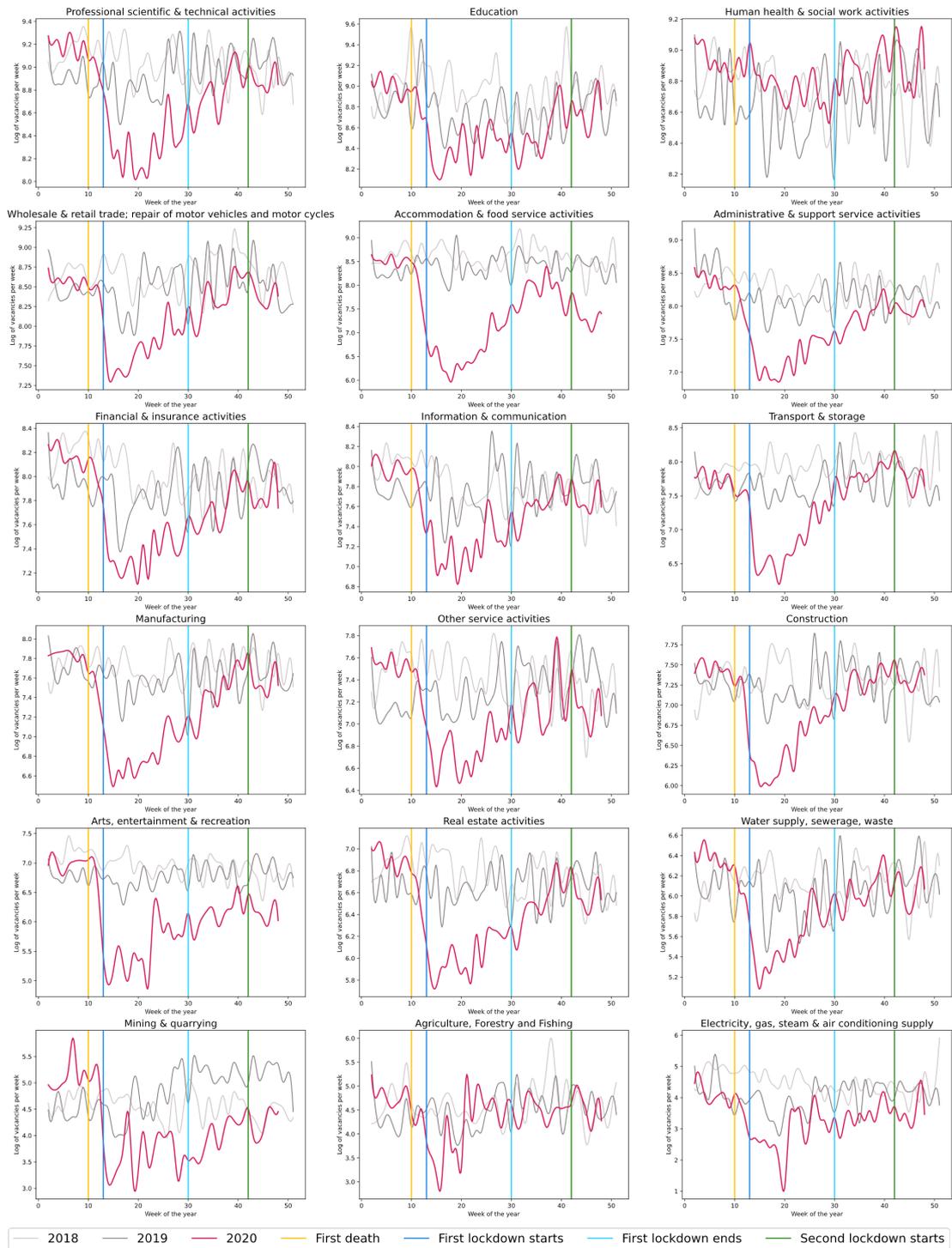


years, as a “counterfactual” assumption of what would have happened in 2020 if it was not for the pandemic (see Methodology 4). This improves the results as it accepts seasonal fluctuations which occur not only in the labour market as a whole but mainly in particular industries related to education, construction or tourism.

3.3 Different industries

The second figure, 2, shows the differences in the reaction to the pandemic projected to job postings among 18 different industries, sorted by the total number of vacations over the full dataset, including the same four highlighted events as in the first figure. The natural log scale offers a better relative comparison between the years and there are significant differences among the industries immediately visible. Some industries, such as Education or Human health & social work activities, the two larger sectors, have not seen a large relative drop in vacancies after the beginning of the pandemic. On the other hand, there are industries with a massive relative fall in job postings which has not recovered yet, those include Accommodation & food service activities or Arts, entertainment & recreation. The recovery of different industries is also interesting, as some of them, namely the smallest ones – Agriculture, Forestry and Fishing or Electricity, gas, steam & air conditioning supply – seem to have seen a faster recovery of the job postings numbers than for example Transportation & storage, Real estate activities or Administrative & support service activities.

Figure 2: Logs of weekly job postings over the years for different industries



4 Methodology

To estimate the effect of the COVID-19 pandemic on online job postings in the UK, I am using a difference-in-difference model of week-by-week time-series panel data combined with fixed effects. My dependent variables are the actual number of weekly job postings and the natural logarithm of those, both for total values and for different industries. This is a very similar model to the one used by Hensvik et al. (2020) when estimating the change in job search during the COVID-19 in Sweden. A similar difference-in-difference model was also used by Javorcik et al. (2019) when estimating the effect of the Brexit vote on labour demand. In my case, the years 2018 and 2019 serve as a control group and 2020 as a treatment group.

4.1 Overall and First wave models

The main model takes the form of:

$$\ln(Postings_{y,w}) = \alpha + \delta(After_w \times Y2020_y) + \gamma_y + \gamma_w + \epsilon_{y,w} \quad (1)$$

where $Postings$ is the number of job postings in a week w of year y , either for the whole market or for a particular industry; $After$ is a dummy variable taking the value one if the week w is number 11 or higher and zero otherwise (for weeks 2-10), as week 10 of 2020 has seen the first COVID-19 death in the UK occur, as explained above; $Y2020$ is a dummy variable taking the value one if the year y is 2020 and zero otherwise (for years 2018 and 2019); and γ_y and γ_w are year and week fixed effects, respectively.

This model captures the effect of COVID-19 on online job postings in the UK as the difference-in-difference variable estimates the change before and after week 10 in 2020 compared to the previous two years. I use this model with slight alterations to estimate the effect both on the actual number of job postings (using $Postings$ as my dependent variable) and the log of those (using $\ln(Postings)$ instead), and independently for each of the 18 different industries, as I expect differences in the reaction to COVID-19 between them, already indicated by Figure 2. A similar approach was taken by Hensvik et al. (2020) and allows me to compare the industries between themselves and see which have been hit more severely by the pandemic when looking from the labour demand point of view.

I use two alterations of the above-explained model which come purely from the ability to have a dataset with more weeks in 2020 compared to Hensvik et al. (2020), Holgersen et al. (2020), or Forsythe et al. (2020). I look both at the full COVID-19 period available in my data, that is weeks 11 to 48 of 2020, and independently of that only at the so-called “first wave” of the pandemic, represented by the first national UK lockdown, which lasted until week 30 of 2020 and can be seen highlighted on Figures 1 and 2. For that model, I use a “shorter” dataset for the control years 2018 and 2019, which ends in weeks number 30 for both years. These results are then more relevant for a comparison with other papers or the Office for National Statistics and are also expected to show a larger drop in the vacancies. The first model, which looks at the whole COVID-19 period includes a visible recovery but at the same time contains a start of the second wave with a second national lockdown.

4.2 Recovery phase model

Finally, making use of a longer time period available in my dataset, I am also estimating the recovery of the job postings numbers for the whole market and different industries. For this, I am using a simple difference-in-difference model for weeks 31 to 48 for the three years. Those are the weeks after the first national lockdown ended in the UK (the “recovery phase”), with

2020 as the treatment to see the difference in the level of job postings after the first pandemic wave compared to the same time in previous years:

$$\ln(\text{Postings}_{y,w}) = \alpha + \beta Y_{2020_y} + \psi_{y,w} \quad (2)$$

with job postings numbers for weeks 31-48 in years 2018, 2019 and 2020 as my dependent variable and a dummy variable Y_{2020} indicating if the year $y = 2020$ or otherwise. The recovery of vacancies is another metric often used by the ONS in the reports and provides a further picture of the differences between the industries and how they were able to recover from the COVID-19 negative shock.

Combination of both time series analysis and difference-in-difference regression with a much broader and higher-frequency dataset for UK job postings fills the gap in the literature and provides a useful measure of the change in labour demand. It covers almost the whole year of 2020, the first pandemic wave, and also indicates a level of recovery in vacancies posted for the labour market and different industries separately.

5 Results

5.1 The whole labour market

The effect of the COVID-19 pandemic on job postings in the whole labour market overall, as of late November last year, is -29%. When looking at the period of the first lockdown, the decrease in weekly vacancies is deeper, -39% or -57,768 in absolute numbers (see Table 1 for full results). This is a very similar result to what Hensvik et al. (2020) reported in Sweden, where they estimated the reduction in the inflow of vacancies to be at 40%, although their dataset only covered the time period up to mid-April. Similarly, Forsythe et al. (2020) observe a 44% decline in weekly postings in the US for a period from mid-March to late April. Due to the way the reports by Office for National Statistics are constructed, it is difficult to find a comparable period in them – however, in July, they write that “after vacancies decreased by approximately 60% between March and May, there has been a small increase in June” (ONS 2020e). That would mean that the decrease in the first lockdown is estimated by the ONS to be much larger than what actual job postings data suggest. Regarding the “recovery phase”, the weeks after the first national lockdown has ended, I find that the level of vacancies was still at 87.5% of the previous years, indicating some, but not full recovery for the British labour demand, which is in line with ONS report from December: “vacancies have continued to recover in September to November 2020 [...] but still remain below the pre-coronavirus (COVID-19) pandemic levels” (ONS 2020b).

5.2 Different industries

As can be seen from Figure 3 or Table 2, there is a difference in the effect of COVID-19 on vacancies between the different sectors and industries represented in the British economy. The first particularly interesting industry is Human health & social work activities, which did not experience a statistically significant drop in job postings due to the pandemic. In the post-lockdown period, it has also seen a significant rise in the vacancies compared to previous years by 16%. This comes from the increased need for hospital and first-aid workers due to the pandemic. In July, ONS reported that this sector was the largest in the economy at that time and accounted for almost a third of all vacancies (ONS 2020e) – a slightly larger proportion than in my dataset, although it is still the largest sector there with almost a quarter of that

period’s vacancies. This result also coincides with the findings of Hensvik et al. (2020), who report the health sector occupations to be among the most resilient to the pandemic together with education, although they do find a statistically significant drop in Sweden, nevertheless.

Table 1: Difference-in-difference estimates for the whole labour market

	Overall model		First wave model	
	ln(Postings)	Postings	ln(Postings)	Postings
After×Y2020	-0.3449*** (0.0891)	-41,247** (12,152)	-0.4999*** (0.0819)	-57,768*** (11,525)
R^2 overall	0.3198	0.2853	0.5044	0.4224
Observations	141		87	
Recovery phase model				
	ln(Postings)	Postings		
Y2020	-0.1334** (0.051)	-19,572** (7,297)		
R^2 adj	0.094	0.1		
Observations	57			

*Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, standard errors in parentheses.*

Overall and First wave models based on equation 1, Recovery phase on equation 2.

Education, the second biggest industry, is another sector that has seen a relatively smaller decrease in labour demand compared to the others, with the COVID-19 effect estimated to “just” -37% in the first wave and -32% overall, second-lowest after Human health & social work activities. Perhaps due to the summer holidays, its recovery has not been as fast as in other sectors and for example, the ONS mentions this industry only in the report from October, noting a good recovery over the past three months (ONS 2020*d*). The change of the labour demand in Professional scientific & technical activities, usually the largest industry, has been relatively higher with vacancies down by half in the first lockdown and by 41% overall.

On the other end of the spectrum from Human health & social activities sit industries which were severely affected by the pandemic – the largest overall declines in vacancies are seen in Mining & quarrying (-73%), Accommodation & food service activities (-74%) and Arts, entertainment & recreation (-62.5%). The latter two are industries where, as Hensvik et al. (2020) reports as well, the social-distancing restrictions and “stay-at-home” measures have the highest impact, especially the closure of pubs, restaurants, sports events and fitness facilities. For Mining & quarrying, the third smallest industry in the UK, it was likely the combination of COVID-19 restrictions with the continuous decline of the importance of coal in the British economy, closure of mines and the turn to net-zero emissions or a coal-free economy. Neither Hensvik et al. (2020) for Sweden nor Forsythe et al. (2020) for the US report any COVID-19 effect for this industry, although Holgersen et al. (2020) find a drop of 78% in vacancy postings in Mining & quarrying in 2020 compared to 2019 for Norway and report the exact same three industries to be hit the most by the pandemic.

Figure 3: Effect of COVID-19 on the number of weekly vacancies for different industries

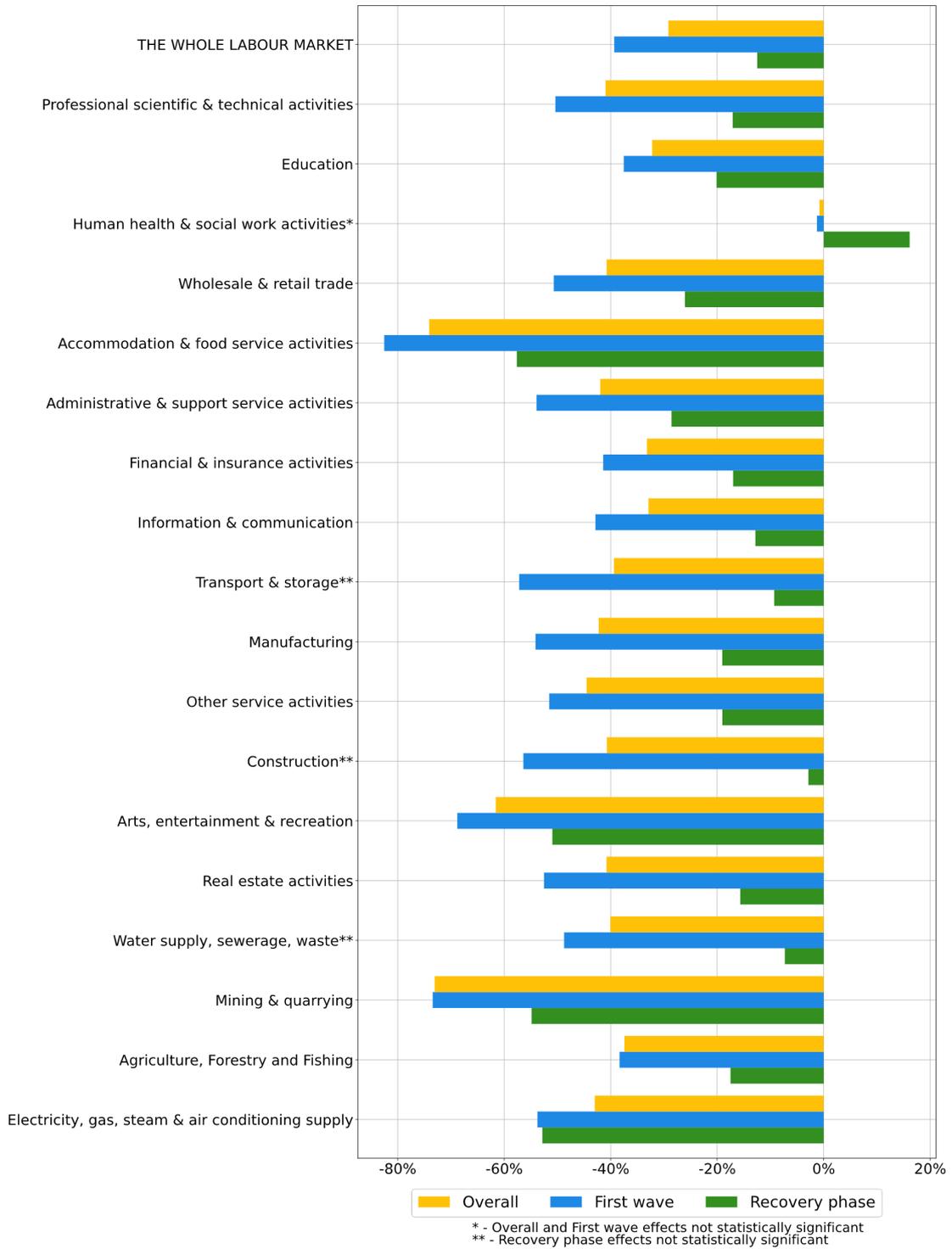


Table 2: Difference-in-difference estimates for different industries

		Overall model	First wave model	Recovery phase model	
		ln(Postings)	ln(Postings)	ln(Postings)	
Professional scientific & technical activities	After×Y2020	-0.5273*** (0.0972)	-0.7008*** (0.0921)	Y2020	-0.1873*** (0.05)
	R ² overall	0.3508	0.553	R ² adj	0.191
Education	After×Y2020	-0.3889*** (0.0872)	-0.4708*** (0.0915)	Y2020	-0.2245*** (0.068)
	R ² overall	0.3053	0.4098	R ² adj	0.152
Human health & social work activities	After×Y2020	-0.008 (0.0831)	-0.0128 (0.0825)	Y2020	0.1496** (0.056)
	R ² overall	-0.0075	-0.006	R ² adj	0.098
Wholesale & retail trade; repair of motor vehicles & motorcycles	After×Y2020	-0.5237*** (0.1188)	-0.7071*** (0.1272)	Y2020	-0.3018*** (0.073)
	R ² overall	0.3588	0.577	R ² adj	0.222
Accommodation & food service activities	After×Y2020	-1.3507*** (0.1712)	-1.7448*** (0.164)	Y2020	-0.8587*** (0.085)
	R ² overall	0.6736	0.8062	R ² adj	0.643
Administrative & support service activities	After×Y2020	-0.5442*** (0.1252)	-0.7749*** (0.1324)	Y2020	-0.3366*** (0.061)
	R ² overall	0.4695	0.6257	R ² adj	0.347
Financial & insurance activities	After×Y2020	-0.4034*** (0.0914)	-0.5346*** (0.0934)	Y2020	-0.1865*** (0.049)
	R ² overall	0.373	0.5149	R ² adj	0.194
Information & communication	After×Y2020	-0.3991*** (0.1011)	-0.5599*** (0.1007)	Y2020	-0.1373** (0.054)
	R ² overall	0.3202	0.4893	R ² adj	0.09
Transport & storage	After×Y2020	-0.5008*** (0.1426)	-0.8484*** (0.1334)	Y2020	-0.0976 (0.067)
	R ² overall	0.2597	0.5928	R ² adj	0.019
Manufacturing	After×Y2020	-0.5494*** (0.1043)	-0.7791*** (0.0946)	Y2020	-0.2114*** (0.062)
	R ² overall	0.417	0.6922	R ² adj	0.161
Other service activities	After×Y2020	-0.5893*** (0.1078)	-0.7247*** (0.0962)	Y2020	-0.2111*** (0.066)
	R ² overall	0.2383	0.4215	R ² adj	0.142
Construction	After×Y2020	-0.5231*** (0.14)	-0.8301*** (0.1374)	Y2020	-0.0292 (0.065)
	R ² overall	0.1957	0.527	R ² adj	-0.014
Arts, entertainment & recreation	After×Y2020	-0.9565*** (0.1348)	-1.1652*** (0.1429)	Y2020	-0.7125*** (0.057)
	R ² overall	0.6693	0.7135	R ² adj	0.737
Real estate activities	After×Y2020	-0.524*** (0.1009)	-0.7451*** (0.0934)	Y2020	-0.1704*** (0.054)
	R ² overall	0.4105	0.6539	R ² adj	0.14
Water supply, sewerage, waste	After×Y2020	-0.5121*** (0.1113)	-0.6684*** (0.1176)	Y2020	-0.0758 (0.06)
	R ² overall	0.0902	0.3409	R ² adj	0.011
Mining & quarrying	After×Y2020	-1.3121*** (0.1827)	-1.3253*** (0.2071)	Y2020	-0.7953*** (0.109)
	R ² overall	0.2336	0.3037	R ² adj	0.483
Agriculture, Forestry and Fishing	After×Y2020	-0.4689*** (0.177)	-0.4835** (0.202)	Y2020	-0.1924* (0.104)
	R ² overall	0.0152	0.0748	R ² adj	0.041
Electricity, gas, steam & air conditioning supply	After×Y2020	-0.5619** (0.2164)	-0.7713*** (0.2314)	Y2020	-0.7517*** (0.098)
	R ² overall	0.3523	0.3979	R ² adj	0.508
Observations		141	87	Obs.	57

Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, standard errors in parentheses. Overall and First wave models based on equation 1, Recovery phase on equation 2.

The Arts, entertainment & recreation and Accommodation & food service activities sectors have also not seen much of a recovery, which is another metric where industries differ a lot. The first lockdown came with the largest drop – estimated to -69% and -82.5%, respectively for the two – and although there has been some recovery, the labour demand in those sectors was still more than 50% lower than in the previous years, with no sight of improvement coming with the second lockdown and a winter period. This is partly in line with the ONS estimates from November, which suggests 49.4% lower vacancies in the Arts, entertainment & recreation sector, although a more severe 67.1% lower level for the Accommodation industry (ONS 2020*c*).

Industries that have seen a statistically significant drop in the vacancies posted in the British online universe and at the same time their recovery are Transportation & storage and Construction sectors. During the first lockdown, they “lost” 57% and 56% of vacancies, respectively, but both sectors recovered, with the labour demand in the Transportation & storage industry being 9% lower in the “recovery phase” compared to previous years and just 3% for Construction, lowest of all industries – with this effect not being statistically significant in either case. ONS estimates confirm this incredible recovery, even mentioning a year-by-year increase towards the end of 2020 (ONS 2020*d,b*), while it has not been captured by other papers due to the range of their data. The third industry showing a similar pattern of a large drop followed by a quick recovery, although it being one of the smallest industries, is Water supply, sewerage, waste. The combination of the three mentioned sectors offers a possible explanation for why that is, as they are often considered to be “essential industries” (as used by both Hensvik et al. (2020) or Forsythe et al. (2020)) and require the necessary workforce even amidst a pandemic. Both Hensvik and Forsythe also find a smaller COVID-19 effect on labour demand for these “essential industries”. Electricity, gas, steam & air conditioning supply would also fall into that category, but it still remained at levels far below the previous years, not seeing a recovery.

6 Conclusion

This undergraduate research paper aims to show the advanced and latest methods which are being used to change the way we monitor and analyse the labour market in real-time and with that, using actual online job postings data from the UK, estimate and explain the impact of the global COVID-19 pandemic on the British demand for labour during most of 2020. It also offers a brief comparison of the results to those produced by the Office for National Statistics, coming from estimates based on a monthly survey of businesses.

I report a sharp decline in labour demand, represented by online vacancies, across the whole market in the UK due to COVID-19 which is similar in size to those in other developed economies. The decline is, as results show, very industry-specific. Although almost all industries in the British economy experienced a significant fall in job postings during the first wave of the pandemic, with the notable exception of Human health & social work activities, they differ strikingly in the way they recovered after that time period. Particularly concerning is the impact on the Arts, entertainment & recreation and Accommodation & food service activities industries, which comes from the nature of the pandemic which brought with itself a closure of their businesses and strict stay-at-home orders.

Although the ONS estimates have grasped the main impact of the pandemic on vacancies, reporting similar levels of decreases and recoveries especially in the most “extreme” industries, they seem to have overexaggerated the overall drop for the whole market. The main issue with the ONS reports is, however, the lag with which they are published and the way in which they are presented using the three-month averages. On the other hand, using modern methods and real-time data might help policymakers significantly when working with a shock like this one.

Those can include not only job postings numbers for industries as shown in this paper but other metrics such as regional distribution of vacancies (used by Forsythe et al. (2020) or Javorcik et al. (2019)), user clicks on job ads (leveraged by Hensvik et al. (2020)), description of the posts (shown by Arthur (2020)) and many more. Certain data sets provided by Burning Glass Technologies also contain information about specific occupations or regions, which gives a much better insight into the impact of the crisis on labour demand. Those were not available in my dataset, but it is something to be considered for further research.

As of now, in April 2021, more than a year after the first COVID-19-related death, the pandemic is still present, and the labour market is still experiencing weakness. With a second and third wave shifting the labour market dynamics again and further hitting industries like Arts, entertainment & recreation or Accommodation & support service activities, which do not have a simple way to react to the restrictions, the effect is even more industry-specific than before. However, as Forsythe et al. (2020) concluded, simply lifting the restrictions is not likely to heal the damage experienced by the economy and the labour market. The key to being able to react to these shocks and recover from them quickly and smoothly in the future lies in the understanding of their impact on the labour market as soon as possible. The current pandemic provides an excellent opportunity to develop a long-term labour market tracking system and analysis based on actual data, rather than lagged estimates or surveys.

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