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Recovering from the first Covid-19 lockdown: Economic impacts of the UK's Eat Out to Help out scheme

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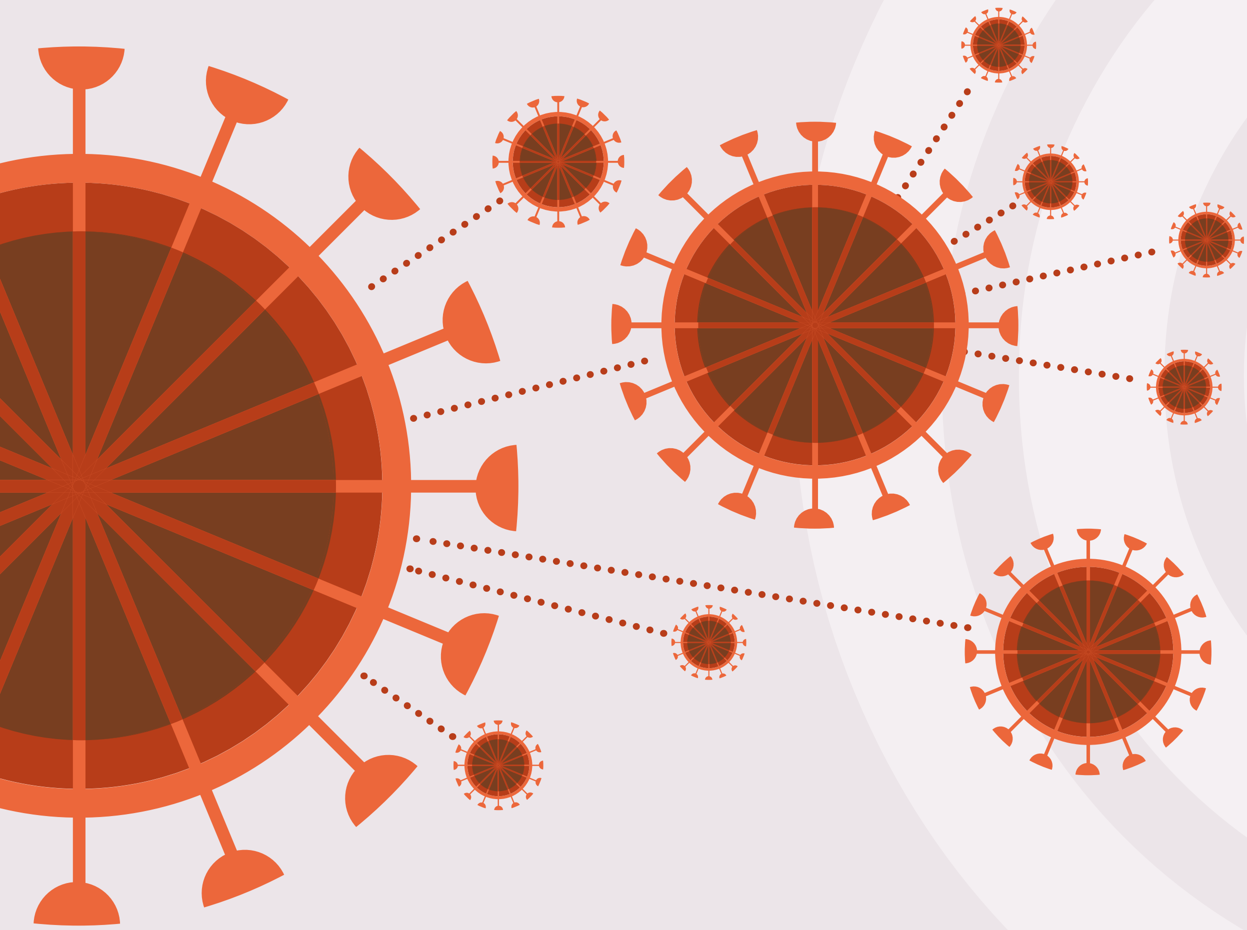

The London School of Economics and Political Science

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CEP COVID-19 ANALYSIS

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Summary

- The hospitality sector was particularly hard-hit by restrictions introduced to stop the spread of COVID-19. The Eat Out to Help Out (EOTHO) scheme –implemented in August 2020 after the 1st national lockdown had ended– aimed to boost demand and protect jobs in the food service sector. Participating businesses in EOTHO offered a 50% discount from Monday to Wednesday, up to £10 per person, on food and non-alcoholic drinks consumed on the premises.

- To capture some of the effects from the policy, we look at footfall using daily mobility data from Google and employment using daily data on job posts from Indeed UK. Our empirical strategy relies on the observed spatial variation in uptake of the scheme. We exploited this variation comparing locations with different take-up before and after the introduction of the policy.

- The results indicate that EOTHO induced higher footfall (by 5%-6%) associated with recreational activities, concentrated on specific days when the discount was available (Mondays to Wednesdays in August). However, the programme failed to encourage people to go out for other purposes and to eat out after the discount ended.

- EOTHO also increased recruitment in the food preparation & service sector. We observe an increase in the number of jobs posts (by 7%-14%) on the Indeed website. We do not find evidence of an increase in the number of job posts in other industries, suggesting the effect on recruitment was concentrated on food establishments. As this indicator measures the flow of job adverts, a transitory effect on job posts could still imply a permanent increase in the number of employees.

- Over 160 million meals were claimed by the end of September 2020, with government spending £849 million on the policy. Data limitations as well as the interaction between different policies complicate any cost-benefit calculation of the programme. On top of that, there is evidence indicating the increase in footfall due to EOTHO had an adverse effect on new COVID-19 cases. Thus, any economic gains from the scheme may have come at the cost of more infections. Further research –using administrative data– is needed to assess the overall cost-effectiveness of EOTHO.

1. Introduction

The COVID-19 pandemic severely impacted economic activity. The hospitality sector was particularly hard-hit by lockdown measures introduced to stop the spread of COVID-19 (Chronopoulos, et al., 2020; Golec, et al., 2020; Carvalho, et al. 2020; Coibion et al., 2020; Baker et al., 2020; Bounie et al., 2020; Althoff, et al. 2020). To mitigate the economic effects, the UK government introduced a variety of policy instruments, including those set out in Plan for Jobs.[1] Among them, the Eat Out to Help Out (EOTHO) scheme aimed to boost demand and protect jobs in the food service sector (UK Government, 2020c). Participating businesses in EOTHO offered a 50% discount, up to £10 per person, on food and non-alcoholic drinks consumed on the premises. The discount was available from Monday to Wednesday from 3 August to 31 of August 2020 (UK Government, 2020b). Over 160 million meals were claimed by the end of September 2020, with government spending £849 million on the programme (UK Government, 2020d).

We assess some of the economic impacts of the EOTHO scheme on the food service sector. Given the programme's objectives and data availability, our focus is on footfall and recruitment. An increase in the demand for food services is likely to be reflected in higher levels of footfall in recreational activities and more jobs posts as restaurants, pubs and cafes may hire more staff. To capture these effects, we use available data on footfall from Google and job posts from Indeed and compare locations with different levels of take-up before and after the introduction of the policy.[2]

The results indicate that, given the average take-up of the scheme across the UK, footfall in the retail & recreation category increased by 5%-6% across the week, an effect driven by Mondays, Tuesdays and Wednesdays. The effect on footfall does not persist beyond the duration of the scheme. Similarly, given average take-up, jobs posts in the food preparation & service industry increased by 7%-14%.[3] The impact on job posts lasted a few weeks beyond the end of the programme. As this indicator measures the flow of job adverts, a transitory effect on job posts could still imply a permanent increase in the number of employees.

[1] The package of measures included a furlough scheme (Job Retention Bonus), a reduction of value added tax (VAT) and the Eat Out to Help Out scheme, among other programmes to support and create jobs. See https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/898421/A_Plan_for_Jobs__Web_.pdf.

[2] Mobility data from Google can be found at https://www.google.com/covid19/mobility/ . Job posts correspond to adverts published by businesses on Indeed's website, see https://www.hiringlab.org/uk/.

[3] Official figures from HMRC show a reduction in the number of businesses that furloughed employees in August –through the Coronavirus Job Retention Scheme– who also participated in EOTHO (UK Government, 2020d). The interplay between EOTHO and the Job Retention Scheme may have attenuated the effect on hiring.

Overall, our findings suggest that the policy induced higher footfall associated with recreational activities on specific days when the discount was available. It did not encourage people to go out for other purposes or to eat out once the scheme ended. The results on footfall are in line with data from OpenTable, pointing to a transitory increase in restaurant bookings concentrated between Mondays and Wednesdays in August (Statista, 2020). The programme also increased the demand for jobs in the food preparation & service sector. We do not know if job posts resulted in individuals being hired, or if any changes in employment were permanent or temporary. We do not find evidence of spillover benefits to other industries.

As not all eligible businesses participated in the programme, there were spatial differences in take-up. We exploit this spatial variation through a continuous difference-in-differences (DiD) approach comparing locations with different take-up levels, 'the intensity of treatment', before and after the programme. Our empirical strategy relies on take-up being exogenous (the conditional independence assumption). We provide evidence to support the validity of our main identifying assumption. Although our main econometric specification considers a continuous take-up variable, we show there are no systematic differences in socio-economic characteristics between cities with take-up above and below the median. Second, we show there is no evidence of diverging pre-trends for each of the outcomes we consider. Third, our specifications include region dummies interacted with week dummies to control for local shocks, as well as several time-varying and time-invariant characteristics. The results are robust to different specifications and sensitivity checks.

To the best of our knowledge, this is the first study focused on assessing the economic impact of the EOTHO scheme using a quasi-experimental methodology and timely indicators. This paper is closely related to the literature on the labour market effects of fiscal incentives to increase consumption (Kosonen, 2015; Benzarti and Carloni, 2019). It contributes to the literature analysing the impact of policies that are intended to speed up economic recovery after COVID-19 lockdowns (Chetty at al. 2020).[4] Our findings suggest that the programme had a limited effect on footfall and vacancies (job posts). Further research, using administrative data, is needed to assess whether the scheme increased employment, turnover and chances of survival for businesses. Worryingly, Fetzer (2020) concludes that the programme was responsible for between 8 and 17 percent of new COVID-19 cases, thus accelerating the second wave of infections in the UK. This is in line with Glaeser et al. (2020), who find that the

[4] Chetty et al. (2020) exploit real time data to tracks economic activity in the US. They find that State-ordered reopening only had a small effect on employment and spending. In contrast, cash transfers to low-income households increased spending, although this did not benefit the most affected businesses.

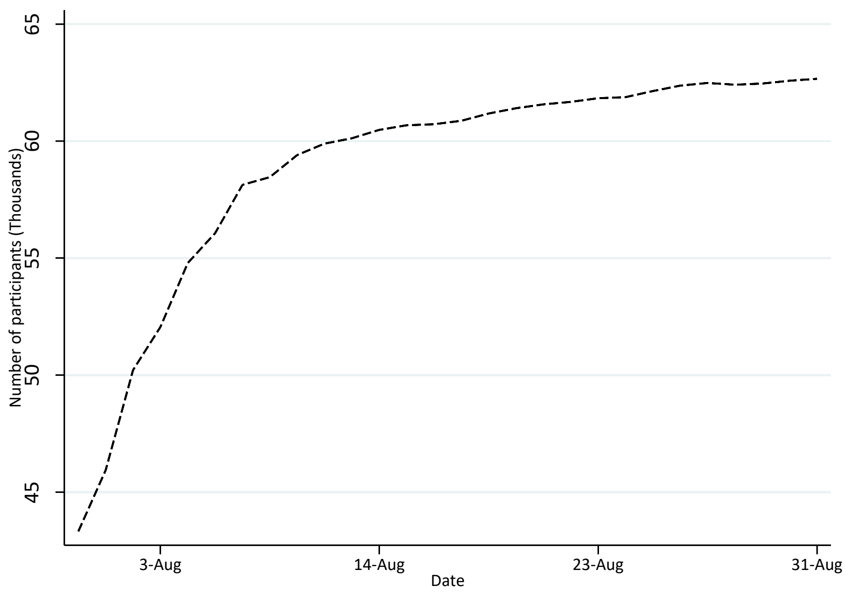
reopening of States in the US misled consumers to believe that eating out was safe again. Thus, any economic gains from EOTHO may have come at the cost of more infections as these sectors depend on footfall and social gatherings.

The paper is structured as follows: The next section describes our data sources and trends. In Section 3, we present the variation in participation in the EOTHO scheme and the empirical strategy. Section 4 presents our results and robustness checks. The last section discusses the findings and presents our conclusions.

2. Data sources

The EOTHO subsidy aimed to increase the demand for food services, which could be reflected in a larger number of customers and an increase in sales. In addition, the increase in the demand could induce businesses to hire more staff. Given the programme's objectives and available data, this paper focuses on two timely indicators: footfall and job posts. These two indicators are likely to capture the upward shift in the demand for food services and provide a proxy for the economic impact of the scheme. They do not capture long term effects on employment, turnover and survival of businesses.

Figure 1. Number of participants in the EOTHO scheme



Note: The figure presents the evolution of the total number of food establishments that enrolled in EOTHO. Source: Authors' calculation with data from HMRC's GitHub repository.

The analysis relies on data from three main sources. First, we use publicly available data from HM Revenue and Customs' (HMRC) GitHub repository on businesses that participated in the programme.[5] The information includes date of registration for the scheme and full address for each participating establishment. We use this registry to construct a measure of programme take-up.[6] Application to the scheme opened at the end of July and closed at the end of August.[7] There were around 52,000 establishments registered by 3 August, which is when the discount was first available to customers, increasing to over 62,000 by the end of the scheme on 31 August (Figure 1).

To measure footfall, we use daily data from Google on mobility, which is collected from users who provided consent to share their location history. The data available online is presented as a percentage change relative to a pre-pandemic reference date –the median of the period between 3 January and 6 February 2020– obtained separately for each day of the week in each location. The lowest level of aggregation corresponds to local authority districts (LADs) in the UK.[8] We create an index using the reference period as the base and impute around 7.5% of our sample since the information released by Google contains gaps due to low sample size across various locations in specific days.[9] The data is split into six categories based on the destination of trips.[10] Our analysis focuses on footfall in the retail & recreation category which includes visits to restaurants, cafes, shopping centres, theme parks, museums, libraries, and cinemas. We also test whether the programme affected trips to other types of outlets by looking at footfall in the supermarket & pharmacy category.[11] The footfall data is unlikely to be representative of the UK since only a subset of the population uses Google and consents to share their location history. As a result the data could be biased towards younger people and population with higher incomes, who may also be more inclined to go out in response to EOTHO. If this is the case, our results may overestimate the overall impact of EOTHO.

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[5] See https://github.com/hmrc/eat-out-to-help-out-establishments. HMRC published data in October on the number of participants in the scheme by parliamentary constituency (PC). Yet, the information was removed after identifying errors when linking some establishment with PCs. However, we observe a high correlation between the data released in October and that from HMRC's GitHub repository.

[6] HMRC released updated data at the end of November. We cannot use this information as it is not disaggregated by location: our approach exploits cross-sectional variation of take-up.

[7] Establishments in the UK could sign up as long as they were registered as a food business with the relevant local authorities (on or before the 7th of July) and had eat-in space within the premises. Businesses needed to register online and had to wait seven days from registration date to make a first claim (UK Government, 2020b).

[8] The following eight local authority districts were excluded from the analysis since the mobility data contained missing values in more than 25 days: Ceredigion, Clackmannanshire, Isle of Anglesey, Merthyr Tydfil, Na h-Eileanan Siar, Orkney Islands, Rutland and Shetland Islands.

[9] Data gaps are imputed using the average value of the previous two days and the subsequent two days for each location.

[10] Google published data on categories that are useful for measuring social distancing efforts, as well as access to essential services. The six categories are retail & recreation, supermarket & pharmacy, parks, public transport, workplaces and residential.

[11] This category includes trips to supermarkets, food warehouses, farmers markets, speciality food shops, and pharmacies.

To measure employment, we use daily data on job posts from Indeed, capturing the flow of job adverts across time in each city. The data available to us is a trend that is based on a seven-day moving average of the number of job posts aggregated by Primary Urban Area (PUA).[12] The data corresponds to an index with reference to the 1 February in each year (2019 and 2020). We focus on the impact on job posts in the food preparation & service category as it comprises adverts that are more likely to be affected by an increase in the demand from eating out due to the scheme.[13] We also extend the analysis to measure the effect on job posts in all sectors except food preparation & service, and hospitality & tourism.[14] One limitation of using data on job posts is that some of these may not translate into actual jobs. Moreover, the data is only representative of a subset of food establishments that advertise positions through online channels. Data on job posts from Indeed may be biased towards larger businesses, which are also more likely to have capacity to hire more staff. If that is the case, our results may overestimate the overall effect of the programme.

We complement the analysis by including time-varying variables such as the lockdown stringency index from the University of Oxford (Hale, Webster et al. 2020), new COVID-19 cases, the number of people claiming benefits due to unemployment (i.e. claimant count) and the number of employees furloughed through the Coronavirus Job Retention Scheme. We also consider time-invariant socio-economic characteristics of LADs and PUAs from the Annual Population Survey (e.g. population, unemployment rate, qualifications of the population, percentage of employees by industry and size of businesses) and Gross Domestic Product (GDP) per head from the Office for National Statistics (ONS).

Our analysis concentrates on the post-lockdown period –that is, from the last week of June until the third week of October 2020– although we first look at the longer-term trends. Figure A.1 in the Appendix presents the footfall trend for the UK in each category. We restrict the analysis to LADs from Primary Urban Areas as Google does not recommend comparing mobility data between urban and rural regions. We observe a sharp drop in footfall after lockdown measures were introduced in mid-March, followed by a slow recovery which started to accelerate after lockdown restrictions were relaxed –on the 4th of July– until August. Footfall

[12] PUAs are defined as the built-up area (i.e. the physical footprint) of cities, which aims to capture the concentration of economic activity. There are 63 primary urban areas in the UK. For further technical details see the following: https://www.centreforcities.org/the-changing-geography-of-the-uk-economy/.

[13] The food preparation & service category includes positions like chef, server, line cook, bar staff, kitchen assistant, cook, sous chef, kitchen team member, head chef and bartender, among others.

[14] We also exclude hospitality & tourism given that official figures indicate around 8.2% of businesses that participated in the programme belong to this sector. See UK Government (2020D). The hospitality & tourism category includes positions like porter, hotel receptionist, hospitality manager, concierge, floor staff, hotel manager, hospitality team member, travel consultant, event staff, and event producer, among others.

did not reach pre-lockdown levels until the end of October 2020. Figure A.2 shows the trend of job posts in 2020 by category. As with footfall, we see a large drop in the number of job posts, with the lowest point around mid-April. The index suggests that the food preparation & service sector were severely affected by the crisis, and that the recovery only began after lockdown restrictions were relaxed.

3. Empirical strategy

The EOTHO scheme was implemented at the same time across the UK. All establishments registered as a food business before the 7th of July 2020 were eligible to apply. Therefore, our main challenge in identifying the impact of the scheme is to obtain a suitable comparison group. We employ a continuous difference-in-differences strategy that exploits the spatial variation of take-up of the scheme across locations in the UK. That is, we do a before and after comparison between LADs/PUAs with different levels of take-up as a different intensity of treatment. We consider two outcomes: footfall and job posts. Our identifying assumptions relies on the exogeneity of the spatial variation in take-up after controlling for several confounding factors such as local shocks.

3.1 Take-up of the scheme

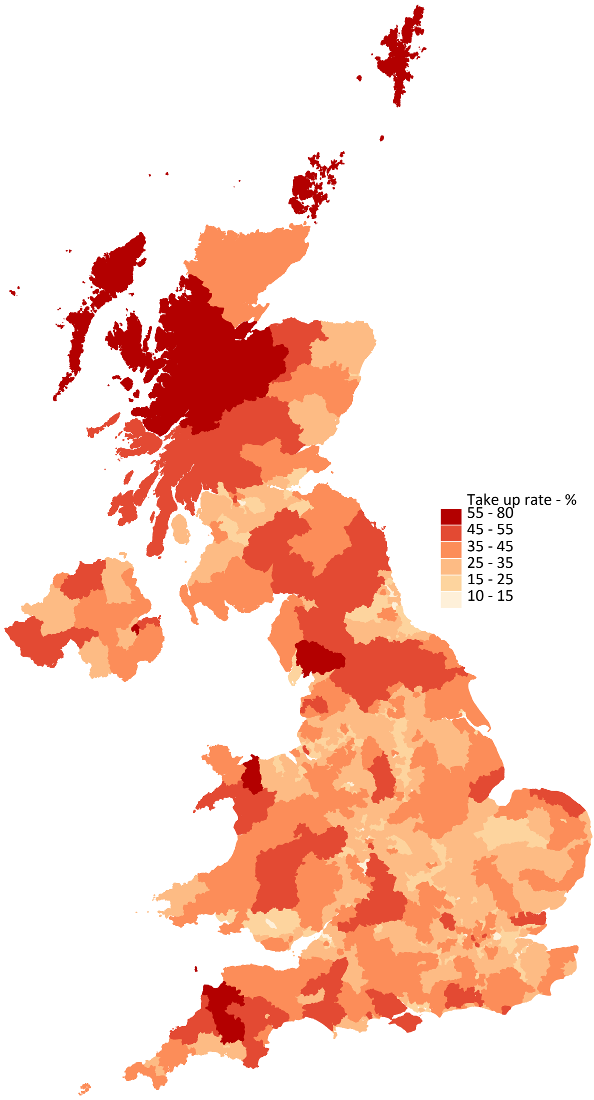
We construct a measure of take-up in each LAD/PUA using the number of establishments registered as participating in EOTHO with HMRC on the last day of August (numerator) divided by the total number of business in the food and beverage sector (2007 SIC 56), using the most recent data of the UK business counts from March 2020 (denominator).[15] According to the November official figures, around 80% of the business registered in the programme belong to the food and beverage sector.[16] The take-up rate may be subject to measurement error if lockdown measures had an heterogeneous impact on the food industry across locations. We mitigate this concern by focusing on regional comparisons (i.e. within-region variation) through the inclusion of LAD or PUA fixed effects as well as UK region dummies interacted with time effects.

Figure A.3 in the Appendix shows substantial variation in take-up, with a distribution across LADs close to a normal distribution. The average and median take-up is 24%-25%, which is relatively low given that the food sector had been struggling after lockdown measures

[15] We exclude 452 businesses that participated in the scheme (0.8% of the total number of participants) given that the reported postcode is incorrect, and thus we could not allocate them geographically to a LAD.
[16] See https://www.gov.uk/government/collections/hmrc-coronavirus-covid-19-statistics#eat-out-to-help-out-scheme.

were imposed. In addition, there is no LAD with take-up higher than 50%. Our measure of take-up is likely to underestimate participation in the programme. Some establishments that went out of business after March 2020 and those that decided to remain closed during August are considered in the denominator of our measure. Overall, take-up of the scheme ended up being less than half of what the UK government had anticipated.[17] The low demand for the EOTHO scheme is in line with low uptake of other types of interventions such as business support programmes.[18]

Figure 2. Variation in take-up across the UK



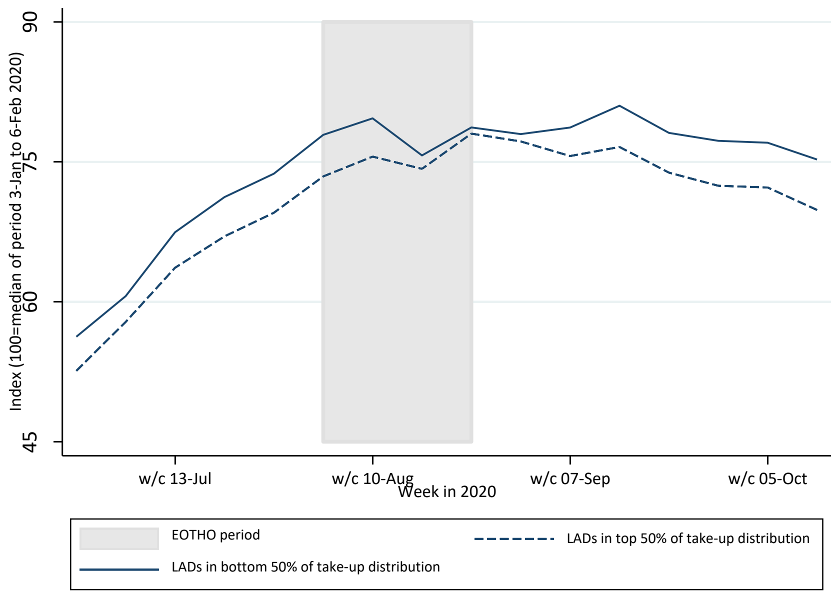
Note: The figure presents the take-up rate by the end of the scheme on 31 August 2020 for every parliamentary constituency in the UK. The darker the color, the higher the take-up rate. Source: Authors' calculation with data from HMRC's GitHub repository.

[17] The UK government aimed to support around 130,000 businesses with the EOTHO scheme. See https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/898421/A_Plan_for_Jobs__Web_.pdf .

[18] See https://www.gov.uk/government/publications/research-to-understand-the-barriers-to-take-up-and-use-of-business-support.

Figure 2 presents the spatial distribution of take-up, with the highest rates in the North and South West of the UK. The level of take-up of a location may depend on factors that are directly associated with footfall, economic activity, an idiosyncratic component of the location and/or with aspects which are uncorrelated with our outcomes (e.g. lack of programme awareness). Even though our main econometric specification considers a continuous take-up variable, capturing the intensity of treatment, we compare groups of cities with high (above the median) and low (below the median) take-up across several dimensions before the onset of the COVID-19 pandemic. Table A.1 in the Appendix contains the results, which suggest few systematic differences between these two groups on key characteristics, such as population, GDP per capita, unemployment and size of businesses. Overall, socio-economic characteristics are relatively balanced across take-up groups. We find differences on 8 out of 32 indicators; three of them statistically significant at the 10% level, three at the 5% level, and the remaining two at the 1% level. Some of the confounders that could drive these differences may be captured by the LAD or PUA fixed effects as well as region dummies interacted with time effects. Nevertheless, we conduct a robustness check including these eight time-invariant characteristics –that are statistically different– interacted with week dummies in the econometric specification.

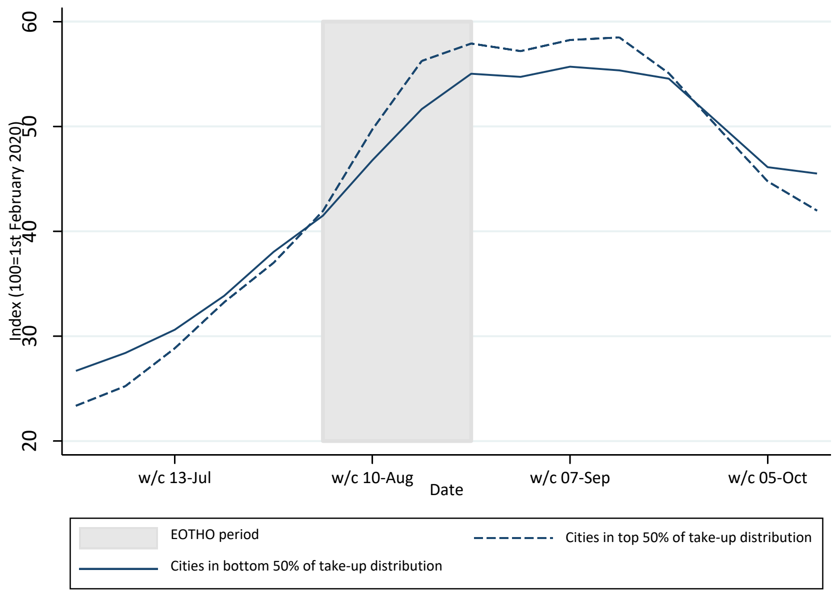
Figure 3. Footfall index for retail & recreation by take-up group



Note: The figure presents the weekly average of the footfall index for the groups of LADs with take-up above and below the median. The shadowed area corresponds to the period in which the EOTHO scheme was live. Source: Authors' calculation with data from Google.

We also inspect the trend of footfall and job posts across locations with high and low take-up, as unobservable confounding factors may be reflected on different pre-programme trends for locations with different take-up. Figure 3 shows a stable difference for the footfall index between groups in the weeks before August, and a similar difference a few weeks after the scheme ended. The graph suggests that there are no systematic differences between groups over time. Figure 4 presents the index for job posts by take-up group, which might suggest a pre-trend. In the next section we show that this visual impression is misleading. When we formally test for pre-trends –by estimating the effect in the weeks before the start of the programme and presenting an event study graph for each outcome– we find no evidence of diverging pre-trends. Despite this, we adopt a cautionary approach and control for pre-trends in our econometric specifications.

Figure 4. Indeed job post index for food preparation & service by take-up group



Note: The figure presents the weekly average of the job post index for the groups of PUAs with take-up above and below the median. The shadowed area corresponds to the period in which the EOTHO scheme was live. Source: Authors' calculation with data from Indeed.

3.2 Estimating equation

Our difference-in-differences estimates are obtained from the following econometric specification:

$$\ln(y_{it}) = \eta_w + \eta_d + \gamma_i + (\eta_w * \gamma_r) + \beta(Post_t * Takeup_i)$$

$$+\varphi T_{it} + \theta(\chi_i * \eta_w) + \delta' Z_{it} + \delta I_{ct} + \omega C'_{im} + \varepsilon_{it}$$

where i refers to local authority district (LAD) or primary urban area (PUA), t to date, d to day, w to week number in 2020, m to month, r to region (PUA or NUTS1) and c to country. We consider two outcome variables (y_{it}) the footfall index (at the LAD level) and the job post index (at the PUA level).

We include week fixed effects (η_w) and day fixed effects (η_d) to account for time-varying factors common to all locations, LAD or PUA fixed effects (γ_i) to consider time invariant unobservable factors at the LAD or PUA level, and week by region (PUA or NUTS1) dummies $(\eta_w * \gamma_r)$ which capture local economic shocks, shocks related to the spread of the disease across UK regions and local measures implemented to mitigate the spread of COVID-19. $Takeup_i$ is the continuous and time-invariant take-up measure for each LAD/PUA and $Post_t$ is a dummy taking the value of one during the dates in which the scheme was live (from 3 August to 31 August), and zero otherwise. Our coefficient of interest is β which captures the impact of the programme.

In our most complete specification, we further include a daily linear pre-trend for each LAD/PUA (T_{it}) to control for potential differences in pre-treatment trends across locations. We also add time invariant characteristics of LADs/PUAs (natural logarithm of total population and GDP per capita) interacted with the week dummies (χ_i), which control for different trends across locations in these characteristics. Further, we include the following set of time-varying covariates, which could affect footfall and the labour market independently of the programme and that are not captured by the time or location fixed effects: i) daily dummies for bank holidays and extended lockdowns, and daily number of new COVID-19 cases in each LAD/PUA (Z_{it}); ii) the daily lockdown stringency index at the country level (I_{ct}); and iii) the monthly number of furloughed employees as a percentage of total of eligible employees, and claimant counts as a percentage of population aged 16 to 64 in each LAD/PUA (C_{im}).

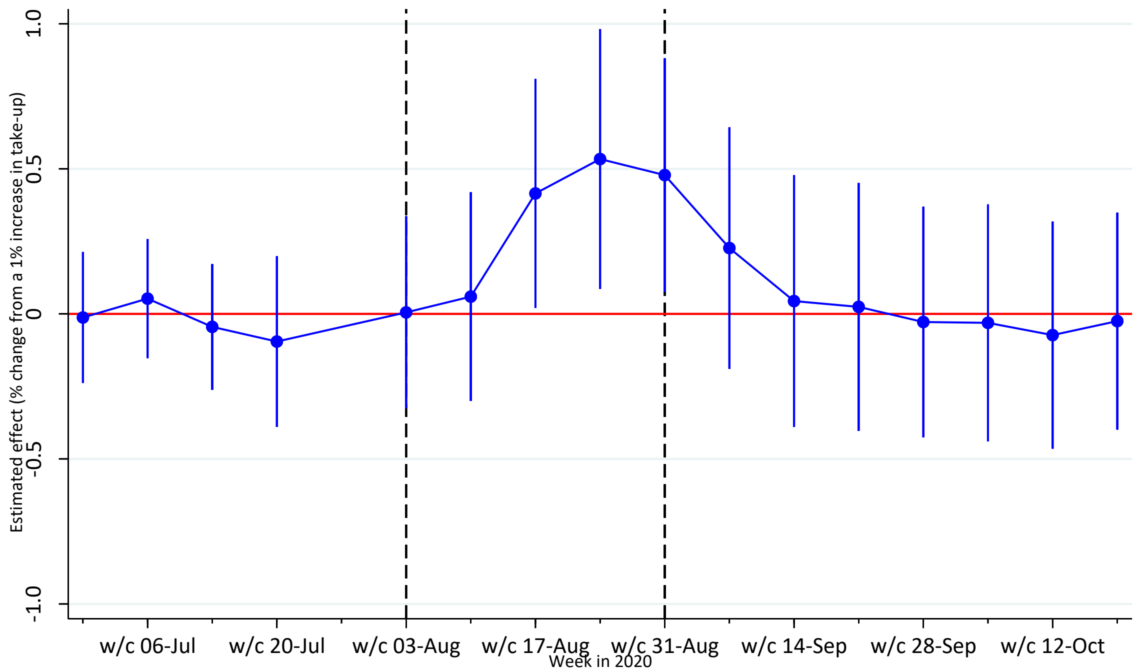
4. Results

We first discuss the results on footfall in retail & recreation to explore to what extent the programme increased the number of people visiting establishments in this category. We then present the results for job posts in the food preparation & service category. Finally, we discuss our robustness checks.

4.1 Footfall

Figure 5 presents an event study graph with the weekly estimates for footfall in the retail & recreation category using our basic specification, which only includes fixed effects. This allows us to understand the impact of the EOTHO programme on the outcome variable over time. The vertical blue lines depict 95% confidence intervals. Before the start of the scheme on 3 August, the estimates are not statistically significant. That is, we do not find evidence of diverging pre-trends prior to the start of the scheme. Footfall increases with the start of the programme (Figure 5). The fourth week of August (commencing on the 24 August) was the last full week in which the subsidy was available, with the discount only available on Monday 31 August in the following week. The effect on footfall decreases after the end of the programme, as estimates become statistically insignificant.

Figure 5. Event study graph for footfall in retail & recreation



Note: The figure presents weekly estimates for the average impact of EOTHO on footfall from our basic specification, which only includes fixed effects. The vertical blue lines depict 95% confidence intervals. The vertical dotted lines highlight the weeks in which the EOTHO scheme was live.

Table 1 reports estimates corresponding to our difference-in-differences coefficient of interest (β) which captures the effect of the EOTHO scheme in the period when the programme was live. For both footfall and job posts, we estimate five different specifications, progressively including the different set of controls described in the previous section. All five specifications include our continuous and time-invariant measure of take-up intensity, which was created using information on participants from the last day of the programme (31 August). All the estimates for the effect on footfall are positive and statistically significant at the 1% level. Our most complete specification (column 5) suggests that a 1% increase in take-up of EOTHO led to a 0.23% increase in footfall in retail & recreation.

Given the average take-up of 25% across the UK, our estimates indicate an increase in footfall among PUAs of around 5.7% (column 5). This effect mainly comes from increased footfall on Mondays (12.0%), Tuesdays (7.5%) and Wednesdays (8.1%) in August, which is when the discount was available (Table A.2 in the Appendix). The scheme had a small effect on Thursdays and no significant impact between Fridays and Sundays. We do not find evidence of displacement from Thursdays–Sundays to Mondays–Wednesdays.

Table 1. Estimates for the effect of EOTHO on footfall

	(1)	(2)	(3)	(4)	(5)
	Google footfall index in retail & recreation				
Take-up of EOTHO	0.249*** (0.034)	0.243*** (0.041)	0.247*** (0.046)	0.242*** (0.049)	0.228*** (0.050)
Baseline fixed effects	Yes	Yes	Yes	Yes	Yes
Pre-trend	No	Yes	Yes	Yes	Yes
$\chi_i * \eta_w$	No	No	Yes	Yes	Yes
Z_{it} and I_{ct}	No	No	No	Yes	Yes
C_{im}	No	No	No	No	Yes
Observations	18,445	18,445	18,445	18,445	18,445
Clusters	155	155	155	155	155
Adj. R-squared	0.880	0.886	0.890	0.891	0.891

Note: Estimates for the natural logarithm of the index. Baseline fixed effects refer to fixed effect for the day, week, LAD and the interaction of week and PUA. Standard errors in parentheses are clustered at the LAD level.; *** p<0.01, ** p<0.05, * p<0.1.

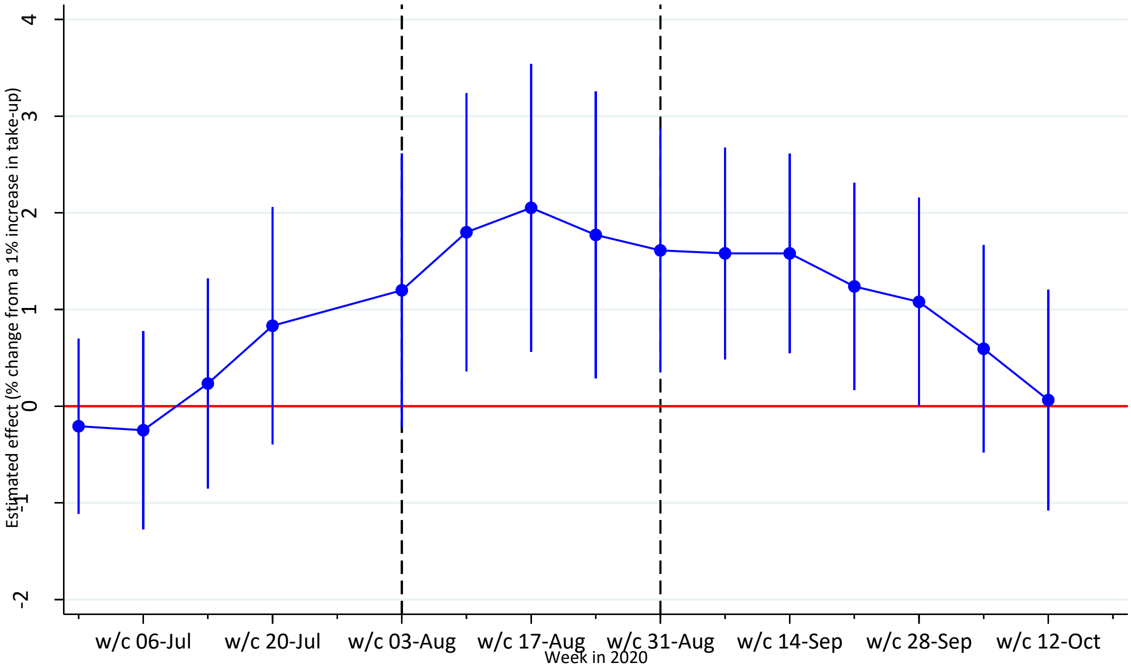
In addition, we test whether the effect persisted beyond the duration of the scheme. After the end of the programme, the estimates become statistically insignificant again (Figure 5). The effect is relatively similar (6.1%) when we consider the cumulative effect from the start of the policy until the week commencing 19 October (column 1 from Table A.3 in the Appendix). This suggests the scheme increased footfall but only during the month of August.

The EOTHO scheme incentivised people to eat out and aimed to increase their confidence for visiting other places. We test for this second channel by looking at trips to other types of outlets. Figure A.4 in the Appendix shows the event study graph for footfall in the supermarket & pharmacy category, with the weekly estimates obtained from our most complete specification. The results indicate a null effect of the programme on this category.

4.2 Job posts

Figure 6 presents the weekly estimates for the effect of EOTHO on job posts in the food preparation & service category, using our basic specification with fixed effects. The estimates are not statistically different from zero before August, further validating the empirical strategy. The point estimates do start increasing from mid-July, which coincides with the date when the EOTHO scheme was announced (8 July). It may be that some businesses started to recruit in anticipation of increased demand due to the scheme although these effects are not statistically significant.

Figure 6. Event study graph for job posts in food preparation & service



Note: The figure presents weekly estimates for the average impact of EOTHO on job posts from our basic specification, which only includes fixed effects. The vertical blue lines depict 95% confidence intervals. The vertical dotted lines highlight the weeks in which the EOTHO scheme was live.

Table 2 presents the corresponding estimates for take-up of the scheme in the food preparation & services category during the period when the discount was available. As described above, we present five different specifications. The results indicate the EOTHO scheme led to an increase of 14.0% (column 5) in the number of job posts across PUAs, given the average take-up of 25% across the UK.

The programme continued to have a positive effect on the number of job posts for a few weeks after the scheme had ended until late September (Figure 6). After that, the estimates become insignificant. The estimated cumulative effect from the start of the scheme until the week commencing 19th of October is around 19% (column 1 from Table A.4 in the Appendix). It is important to note that our estimates do not capture levels of employment directly. A transitory effect on job posts could still imply a permanent increase in the number of employees. Further research using administrative data is needed to assess the effect on employment.

We also extend the analysis measuring the effect of the policy on the number of job posts in all sectors except food preparation & service, and hospitality & tourism. This allows us to understand whether there are spillover effects to other industries. Figure A.5 in the

Appendix presents the weekly coefficients in the event study graph from our most complete specification. We conclude the programme had no effect on job posts in other sectors in the whole period of analysis, ultimately suggesting demand only increased in the food preparation & service sector.

Table 2. Estimates for the effect of EOTHO on job posts

	(1)	(2)	(3)	(4)	(5)
	Indeed job post index in food preparation & service				
Take-up of EOTHO	0.499*** (0.166)	0.522*** (0.170)	0.521*** (0.169)	0.552*** (0.184)	0.561*** (0.196)
Baseline fixed effects	Yes	Yes	Yes	Yes	Yes
Pre-trend	No	Yes	Yes	Yes	Yes
$\chi_i * \eta_w$	No	No	Yes	Yes	Yes
Z_{it} and I_{ct}	No	No	No	Yes	Yes
C_{im}	No	No	No	No	Yes
Observations	7,056	7,056	7,056	7,056	7,056
Clusters	63	63	63	63	63
Adj. R-squared	0.930	0.934	0.934	0.934	0.935

Note: Estimates for the natural logarithm of the index. Baseline fixed effects refer to fixed effect for the day, week, PUA and the interaction of week and NUTS1 region. Standard errors in parentheses are clustered at the PUA level.; *** p<0.01, ** p<0.05, * p<0.1.

4.3 Robustness checks

Our estimates for both footfall and job posts are robust to several sensitivity checks. As mentioned above, we modify our specification and include eight time-invariant characteristics that are statistically different pre-intervention across take-up groups (locations with take-up above and below the median) interacted with the week dummies. Given the average take-up across the UK, the estimated effect is similar (around 5%) on footfall in retail & recreation, while smaller (around 7%) on job posts in the food preparation & service sector (column 2 from both Table A.3 and Table A.4 in the Appendix).

Next, we consider a measure of take-up that varies during the month of August. Eligible businesses could decide to participate after the EOTHO programme was launched. As a result, take-up increased with time in all locations in the weeks when the scheme was live. We estimate our most complete specification using this continuous and time-varying measure of take-up. The DiD coefficients are relatively similar, suggesting an effect of 5% on footfall in the retail & recreation category (column 3 from Table A.3 in the Appendix) and around 15% on job posts in the food preparation & service category (column 3 from Table A.4 in the Appendix).

We also estimate our most complete specification using a discrete measure of take-up, which is equal to one in locations with take-up above the median and zero otherwise. In this case, we consider locations with take-up below the median as a control group, ultimately underestimating the effect of the policy, given that these LADs/PUAs also participated in the programme.[19] Consistent with this, the DiD coefficients are positive and statistically significant, but indicate an effect between 30% and 50% smaller compared to results presented in previous subsections. The estimates suggest an impact of 3% on footfall in the retail & recreation category and 10% on job posts in the food preparation & service category (column 4 from both Table A.3 and Table A.4 in the Appendix).

We conduct two robustness checks with different data and sample for footfall. We estimate the effect from our most complete specification but using the raw footfall index without imputing data gaps. The result suggests a similar effect with an increase in footfall of around 5% given the average take-up (column 5 from Table A.3 in the Appendix). Similarly, we use a sample comprised of all LADs (from PUAs and non-PUAs). Table A.5 in the Appendix presents the footfall estimates for all five specifications. Coefficients are positive, slightly larger and significant at the 1% level.

Finally, we consider the seasonal pattern of hiring. An increase in the number of job posts in the month of August could also be driven by the summer seasonal pattern, as some restaurants, cafes and pubs in some regions tend to hire more staff to meet a higher demand for their services. However, it is not clear to what extent this seasonal pattern is present in 2020, given the demand and supply shocks experienced due to the COVID-19 pandemic. In any case, we include another robustness check considering seasonality. For this, the dependent variable corresponds to the index in 2020 relative to 2019. Mobility data from Google is not publicly available for 2019, so an equivalent analysis is not possible for footfall. The DiD coefficient for job posts is around one third smaller (column 5 in Table A.4 in the Appendix), suggesting there could be a seasonal effect. This indicates an impact of the programme on job posts of around 9.5%.

5. Discussion and conclusions

The economic effects of the COVID-19 pandemic and subsequent lockdown measures played out unequally across sectors. Industries that rely heavily on footfall and social interactions were directly and severely affected by these restrictions. The food service industry is among these

[19] The group of LADs with take-up below the median have an average take-up rate of 18%.

sectors as businesses were ordered to close with the purpose of stopping the spread of the infection. The UK's EOTHO scheme aimed to protect jobs and partly restore consumer confidence for visiting places by subsidising the cost of eating out Mondays to Wednesdays in August 2020.

We find that the programme increased footfall in the recreation & retail category. This effect is concentrated on days when the discount was available (Mondays to Wednesdays in August). The policy failed to encourage people to go out for other purposes and to eat out after the discount ended. Also, we observe an increase in the number of jobs posts on the Indeed website in the food preparation & service category. This effect was also temporary, only lasting until the end of September. The available data does not allow us to assess whether job posts resulted in increased employment, or if any changes in employment were permanent or transitory. We do not find evidence of spillover benefits to other industries.

Our results could overestimate the effect of the programme given that our data is unlikely to be representative of the population and business in the UK. The footfall data (from Google) could be biased towards younger people and populations with higher incomes, who may also be more inclined to go out. In the same way, job posts (from Indeed) may be biased towards larger businesses, which are also more likely to have capacity to hire more staff. Hence, our coefficients of both footfall and job posts could be upward biased and may correspond to upper bound estimates.

Several questions remain unanswered due to lack of more comprehensive, representative and complementary data on EOTHO. First, we do not know if the jobs posts effectively materialised into new jobs, and if they did, whether the new hires retained their employment after the EOTHO programme ended. We also do not know whether the overshoot of demand effectively led to higher turnover or if it increased the probability of firm survival. Finally, there is no publicly available information that allows assessment of the price effects and spending behaviour of EOTHO, which would be helpful to provide some insights on deadweight and the distortions introduced by the subsidy. A descriptive analysis from the ONS suggests that consumer inflation would have been around 0.9% in August 2020 without EOTHO and the VAT reductions scheme, compared to the actual rate of 0.5% (Office for National Statistics, 2020). Future research, using administrative data, could provide answers to some of these questions.

All the issues previously described, as well as the interaction across different schemes, complicates any cost-benefit calculation of the programme. On top of that, Fetzter (2020) finds that the increase in footfall also had adverse effects on local COVID-19 infections. Further research is needed to assess the overall cost-effectiveness of EOTHO and similar programmes for boosting aggregate demand and supporting the economic recovery after COVID-19 lockdowns.

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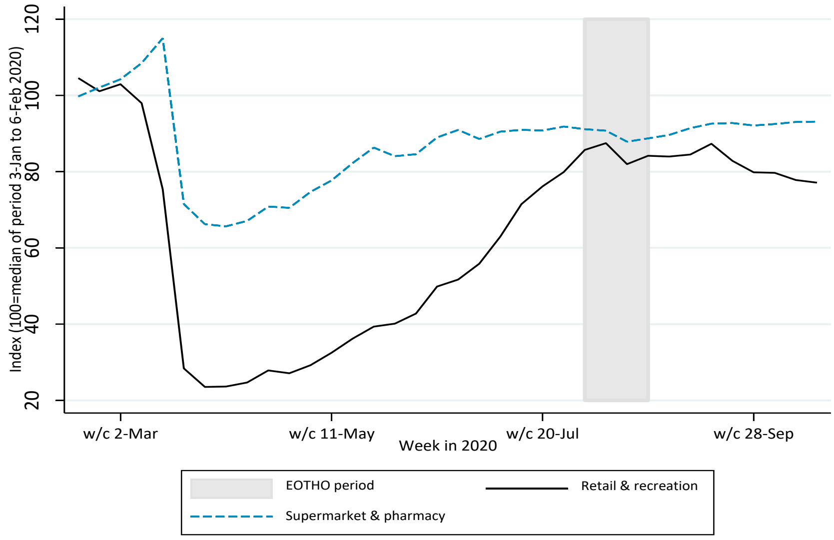
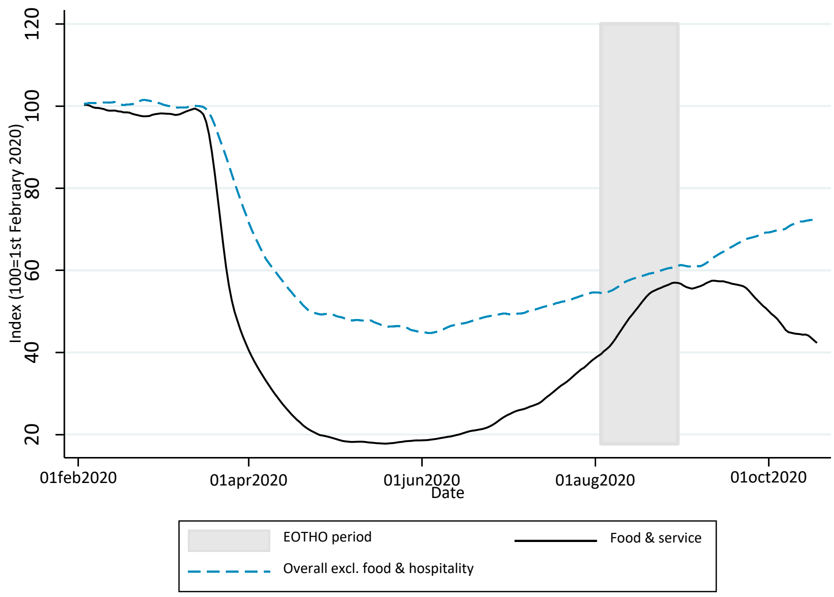
Appendix

Figure A.1. Footfall pattern by Google mobility category



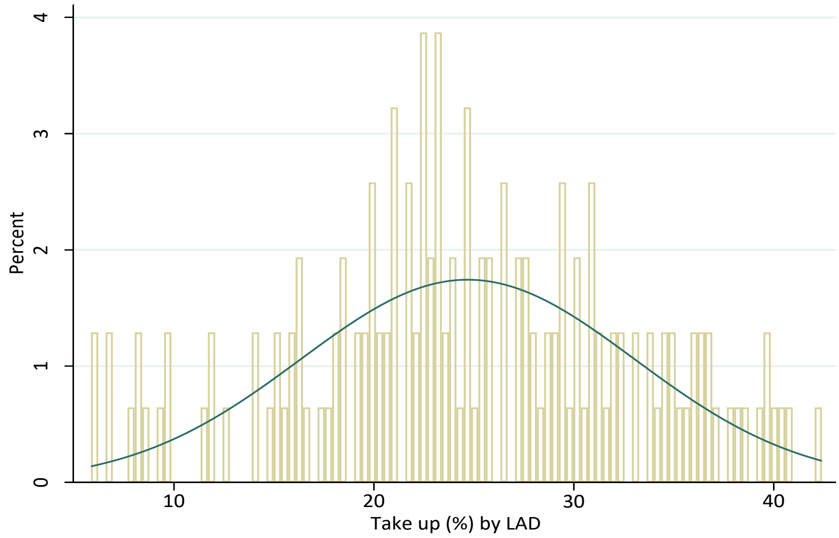
Note: The figure presents the weekly average of the footfall index across LADs in the UK for retail & recreation and supermarket & pharmacy. The shadowed area corresponds to the period in which the EOTHO scheme was live. Source: Authors' calculation with data from Google.

Figure A.2. Job posts pattern by Indeed category



Note: The figure presents the weekly average of the job post index across LADs in the UK for food preparation & service and all sectors except food preparation & service, and hospitality & tourism. The shadowed area corresponds to the period in which the EOTHO scheme was live. Source: Authors' calculation with data from Indeed.

Figure A.3. Distribution of take-up across LADs



Note: The figure presents the distribution of the take-up rate by the end of the scheme on 31 August across LADs in the UK. Source: Authors' calculation with data from HMRC's GitHub repository

Table A.1. Balance of cities in the top vs. those in the bottom 50% of the take-up distribution

Socio-economic indicator	Mean cities in bottom 50%	Mean cities in top 50%	Diff.	Obs.
Total population (natural logarithm)	12.58	12.85	0.28	63
Employment rate - pop. aged 16-64	75.88	72.46	-3.43	63
Unemployment rate - pop. aged 16+	4.41	4.33	-0.08	63
Current GDP per head (natural logarithm)	10.34	10.34	0.00	63
% of pop. with no qualifications	7.87	8.56	0.69	63
% of pop. with NVQ 1 only	11.03	10.58	-0.45	63
% of pop. with NVQ 2 only	17.15	15.57	-1.58*	63
% of pop. with NVQ 3 only	18.03	16.98	-1.06	63
% of pop. with NVQ 4+ only	34.84	37.58	2.74	63
Share of business with 0-9 employees	0.82	0.82	0.00	63
Share of business with 10-49 employees	0.14	0.15	0.00	63
Share of business with 50-249 employees	0.03	0.03	0.00	63
% of emp. in Agriculture, forestry & fishing	0.28	0.49	0.21*	63
% of emp. in Mining & quarrying	0.40	0.05	-0.35	63
% of emp. in Manufacturing	9.55	8.15	-1.40	63
% of emp. in Electricity & gas	0.59	0.46	-0.13	63
% of emp. in Water supply	0.80	0.72	-0.08	63
% of emp. in Construction	4.65	4.18	-0.46	63
% of emp. in Wholesale & retail trade	15.61	15.20	-0.41	63
% of emp. in Transportation & storage	6.43	4.06	-2.38***	63
% of emp. in Accommodation & food service	6.14	7.07	0.94**	63
% of emp. in Information & communication	3.59	3.56	-0.03	63
% of emp. in Financial & insurance activities	2.65	3.48	0.83	63
% of emp. in Real estate activities	1.41	1.74	0.33***	63
% of emp. in Professional, scientific/technical	7.13	7.23	0.11	63
% of emp. in Administrative & support activities	9.89	8.59	-1.30*	63
% of emp. in Public administration & defence	4.26	5.01	0.75	63
% of emp. in Education	8.42	10.27	1.85**	63
% of emp. in Human health & social work activities	14.25	15.23	0.99	63
% of emp. in Arts, entertainment & recreation	2.14	2.47	0.33**	63
% of emp. in Other service activities	1.79	1.87	0.08	63

Note: We do not include the equivalent comparison by take-up groups for LADs given the lack of available data on socio-economic indicators at this level. Socio-economic indicators from March 2020. For Belfast indicators were considered from the overall Northern Ireland due to data availability. *** p<0.01, ** p<0.05, * p<0.1.

Table A.2. Estimates for the effect of EOTHO on footfall by day of the week

	Monday (1)	Tuesday (2)	Wednesday (3)	Thursday (4)	Friday (5)	Saturday (6)	Sunday (7)
	Google footfall index in retail & recreation						
Take-up of EOTHO	0.477*** (0.072)	0.301*** (0.085)	0.325*** (0.090)	0.136* (0.077)	0.114 (0.074)	0.038 (0.072)	0.096 (0.077)
Baseline fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\chi_i * \eta_w$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Z_{it} and I_{ct}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
C_{im}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,006	2,006	2,006	2,006	2,006	2,006	2,006
Clusters	155	155	155	155	155	155	155
Adj. R-squared	0.942	0.950	0.953	0.966	0.967	0.961	0.949

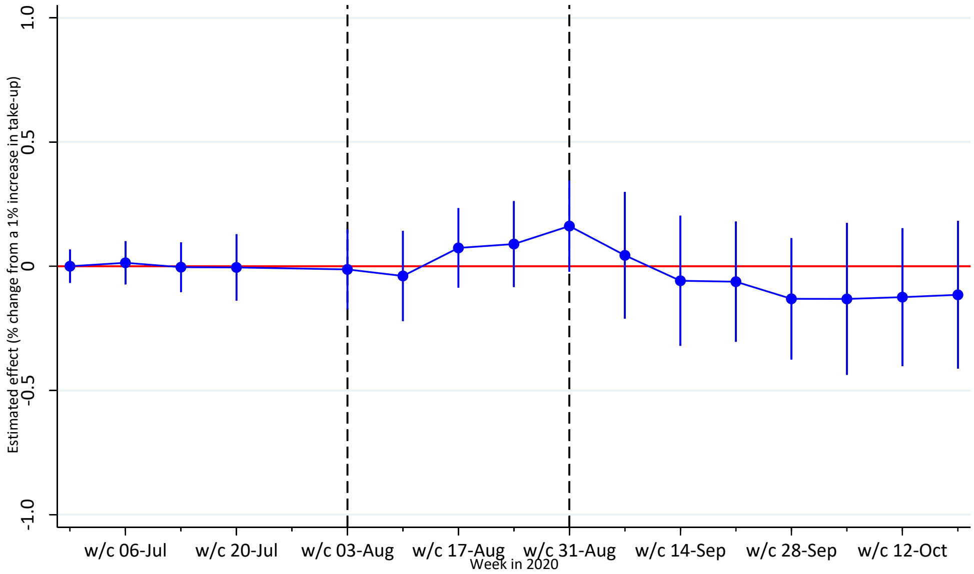
Note: Estimates for the natural logarithm of the index. Baseline fixed effects refer to fixed effect for the day, week, LAD and the interaction of week and PUA. Standard errors in parentheses are clustered at the LAD or PUA level.; *** p<0.01, ** p<0.05, * p<0.1.

Table A.3. Extensions and robustness checks for footfall estimates

	Cumulative effect until October (1)	Modified specification (2)	Time varying take-up measure (3)	Discrete take-up measure (4)	Non-imputed data (5)
	Google footfall index in retail & recreation				
Take-up of EOTHO	0.242*** (0.081)	0.187*** (0.039)	0.215*** (0.051)	0.030*** (0.010)	0.201*** (0.056)
Baseline fixed effects	Yes	Yes	Yes	Yes	Yes
Pre-trend	Yes	Yes	Yes	Yes	Yes
$\chi_i * \eta_w$	Yes	No	Yes	Yes	Yes
Z_{it} and I_{ct}	Yes	Yes	Yes	Yes	Yes
C_{im}	Yes	Yes	Yes	Yes	Yes
Extended set of interactions	No	Yes	No	No	No
Observations	18,445	18,088	18,445	18,445	17,049
Clusters	155	152	155	155	155
Adj. R-squared	0.890	0.879	0.891	0.882	0.950

Note: Estimates for the natural logarithm of the index. Baseline fixed effects refer to fixed effect for the day, week, LAD and the interaction of week and PUA. Extended set of interactions corresponds to the matrix of time invariant characteristics multiplied by each week dummy for the natural logarithm of GDP per capita, population, share of population with NVQ 2, share of employment in agriculture, forestry & fishing, transportation & storage, accommodation & food service, real estate activities, administrative & support activities, in education and in arts, entertainment & recreation. Standard errors in parentheses are clustered at the LAD; *** p<0.01, ** p<0.05, * p<0.1.

Figure A.4. Event study graph for footfall in supermarket & pharmacy



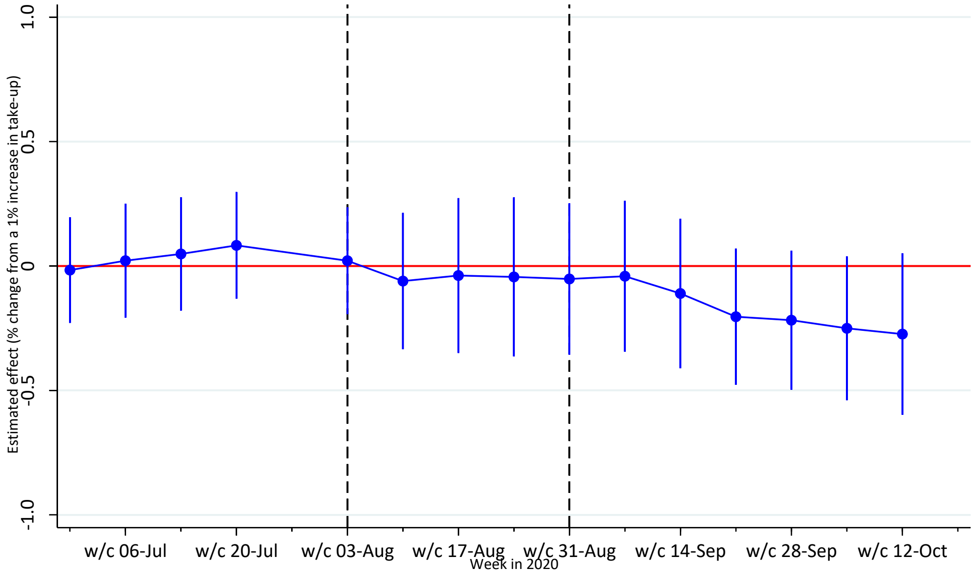
Note: The figure presents weekly estimates for the average impact of EOTHO on footfall from our most complete specification. The vertical blue lines depict 95% confidence intervals. The vertical dotted lines highlight the weeks in which the EOTHO scheme was live.

Table A.4. Extensions and robustness checks for job posts estimates

	Cumulative effect until October (1)	Modified specification (2)	Time varying take-up measure (3)	Discrete take-up measure (4)	Index in 2020/2019 (5)
	Indeed job post index in food preparation & service				
Take-up of EOTHO	0.773** (0.349)	0.263*** (0.092)	0.605*** (0.191)	0.099** (0.039)	0.379** (0.186)
Baseline fixed effects	Yes	Yes	Yes	Yes	Yes
Pre-trend	Yes	Yes	Yes	Yes	Yes
$\chi_i * \eta_w$	Yes	Yes	Yes	Yes	Yes
Z_{it} and I_{ct}	Yes	Yes	Yes	Yes	Yes
C_{im}	Yes	Yes	Yes	Yes	Yes
Extended set of interactions	No	Yes	No	No	No
Observations	7,056	6,944	7,056	7,056	7,056
Clusters	63	62	63	63	63
Adj. R-squared	0.935	0.955	0.935	0.933	0.936

Note: Estimates for the natural logarithm of the index. Baseline fixed effects refer to fixed effect for the day, week, PUA and the interaction of week and NUTS1 region. Extended set of interactions corresponds to the matrix of time invariant characteristics multiplied by each week dummy for the natural logarithm of GDP per capita, population, share of population with NVQ 2, share of employment in agriculture, forestry & fishing, transportation & storage, accommodation & food service, real estate activities, administrative & support activities, in education and in arts, entertainment & recreation. Standard errors in parentheses are clustered at the PUA level.; *** p<0.01, ** p<0.05, * p<0.1.

Figure A.5. Event study graph for overall job posts excluding food preparation & service and hospitality & tourism



Note: The figure presents weekly estimates for the average impact of EOTHO on job posts from our most complete specification. The vertical blue lines depict 95% confidence intervals. The vertical dotted lines highlight the weeks in which the EOTHO scheme was live.

Table A.5. Estimates for the effect of EOTHO on footfall for all LADs (including PUAs and non-PUAs)

	(1)	(2)	(3)	(4)	(5)
	Google footfall index in retail & recreation				
Take-up of EOTHO	0.259*** (0.031)	0.269*** (0.031)	0.265*** (0.033)	0.266*** (0.033)	0.259*** (0.033)
Baseline fixed effects	Yes	Yes	Yes	Yes	Yes
Pre-trend	No	Yes	Yes	Yes	Yes
$\chi_i * \eta_w$	No	No	Yes	Yes	Yes
Z_{it} and I_{ct}	No	No	No	Yes	Yes
C_{im}	No	No	No	No	Yes
Observations	43,911	43,911	43,911	43,911	43,911
Clusters	370	370	370	370	370
Adj. R-squared	0.847	0.848	0.851	0.851	0.852

Note: Estimates for the natural logarithm of the index. Baseline fixed effects refer to fixed effect for the day, week, LAD and the interaction of week and county. Standard errors in parentheses are clustered at the LAD.; *** p<0.01, ** p<0.05, * p<0.1.

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