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The economic impacts of the UK's eat out to help out scheme

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Abstract
We evaluate the economic impacts of the UK's Eat Out to Help Out (EOTHO) scheme on the food service sector. EOTHO subsidised the cost of eating out, with a 50% discount Mondays to Wednesdays in August 2020. We exploit the spatial variation in take-up using a continuous difference-in-differences approach and an instrumental variables strategy. We measure the effect on footfall using mobility data from Google and on employment using job posts from Indeed. Our estimates indicate that a one standard deviation increase in exposure to the EOTHO scheme increased footfall in retail & recreation by 2%-5%, and job posts in the food preparation & service industry by 6%-8%. These effects are transitory, and we do not find evidence of large spillover benefits to non-recreational activities or other sectors.

Key words: consumption subsidy, covid-19, instrumental variables, footfall, job posts
JEL: C36; H29; H32; J23; L83

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1. Introduction

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 policies.[1] Among these, the Eat Out to Help Out (EOTHO) scheme, run during August 2020, aimed to boost demand and protect jobs in the food service sector (UK Government, 2020b, 2020c). Participating businesses in EOTHO received government support to offer a discount on food and non-alcoholic drinks consumed on the premises. Over 160 million subsidised meals were served, costing government £849 million (UK Government, 2020d).

We assess some of the economic impacts of the EOTHO scheme on the food service sector. Given the programme's objectives, its duration (one month), and data availability, our focus is on footfall and recruitment, for which we have timely data at an appropriate frequency. 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 data on footfall from Google and on 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 a one standard deviation increase in exposure to EOTHO increased footfall in retail & recreation by 2%-5%. Similarly, a one standard deviation increase in exposure to the EOTHO scheme increased job posts in the food preparation & service industry by 6%-8%.[3] The effect on footfall does not persist beyond the duration of the scheme. The impact on job posts lasted a few weeks beyond the end of the programme.

Overall, our findings suggest that the policy only 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

[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 – among businesses participating in EOTHO (UK Government, 2020d). The interplay between EOTHO and the Job Retention Scheme may have attenuated the effect on hiring.

in restaurant bookings concentrated between Mondays and Wednesdays in August (Statista, 2020). We also find increased demand for jobs in the food preparation & service sector. Note that our indicator measures the flow of job adverts; therefore, a transitory effect on job posts could still imply a permanent increase in the number of employees. Unfortunately, we do not know if job posts resulted in individuals being hired, or if any changes in employment were permanent or temporary. However, we find suggestive evidence that more intensive use of EOTHO is not associated with higher employment in September 2020, relative to September 2019 levels. We do not find evidence of large spillover benefits to other industries in terms of recruitment.

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 the intensity of treatment being exogenous (the conditional independence assumption). We provide evidence to support the validity of our main identifying assumption. We show there is no evidence of diverging pre-trends for each of the outcomes we consider. We also use an instrumental variables (IV) strategy as we may still be concerned that the intensity of treatment could vary across LADs due to unobservable factors correlated with local labour markets and mobility patterns. Specifically, we instrument the intensity of treatment with the number of restaurant chains, thus, exploiting the fact that restaurant chains are likely to have made centralised decisions on whether to participate in the programme. Our 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. 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 vacancies (job posts) and footfall. 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 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

[4] Chetty et al. (2020) exploit real time data to track 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.

depend on footfall and social gatherings. This paper is also closely related to the literature on the labour market effects of fiscal incentives to increase consumption (Kosonen, 2015; Benzarti and Carloni, 2019).

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

2. Background and data sources

Businesses participating in EOTHO received government support to offer a 50% discount, up to £10 per person, on food and non-alcoholic drinks consumed on the premises. Support was available for discounts offered from Monday to Wednesday from the 3rd of August to the 31st of August 2020 (UK Government, 2020b). The EOTHO subsidy aimed to increase demand for the food preparation & service industry.

This paper focuses on two relevant indicators – footfall and job posts – that should capture the increase in demand for food services and provide a proxy for the economic impact of the scheme. These two daily indicators are available at the Local Authority District (LAD) level and represent the best data available for considering the economic impacts. In principle, it may be possible to directly assess effects on employment, turnover and survival when the relevant data becomes available in the Inter Departmental Business Register (towards the end 2023). Although this would require the government to be willing to identify subsidised firms in that data. Even then, the IDBR only has quarterly data which may be too long a period to properly capture the effects of EOTHO as we will show below.

2.1 Data on the EOTHO scheme

We use publicly available data on businesses that participated in the programme to construct different measures of the intensity of treatment of the programme by LAD. Application to the scheme opened at the end of July and closed at the end of August.[5] During this period, HM Revenue and Customs' (HMRC) used a GitHub repository to

[5] Establishments in the UK could sign up if they were registered as a food business with the relevant local authorities (on or before the 7th of July 2020) 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).

collect details of participants in the programme when establishments registered for the scheme. The repository remains publicly available on the GitHub website.[6] This source includes information on the date of registration for the scheme, name of the business, and full address including the postcode. The source provides the same information for each participating outlet, regardless of whether they are an independent business or part of a restaurant chain. There were around 52,000 establishments registered by 3 August, when the discount was first available, increasing to over 62,000 by the end of the scheme on 31 August (Figure A.1 in the Appendix). We merge the repository with ONS Postcode Directory data (ONSPD) and aggregate at the LAD level.

Official statistics for the scheme were published in the first quarter of 2021. This release includes information on the total number of outlets that made a claim to the EOTHO scheme by LAD. These figures exclude restaurant chains with more than 25 participating outlets which are included in the GitHub data. There is a strong correlation in the number of participant outlets by LAD in data from HMRC's GitHub repository and these official statistics (Figure A.2). In any case, we also report estimates using the official numbers as the intensity of treatment and show that the results are the same as when using the GitHub data.

2.2 Data on outcomes

2.2.1 Footfall

We measure footfall, using daily data for LADs, which is available online from Google on mobility.[7] Data is reported as a percentage change relative to a pre-pandemic reference date (the median of the period between 3 January and 6 February 2020). We create an index using the reference period as the base.[8] Google published data on categories that are useful for measuring social distancing efforts, as well as access to essential services. The data is split into six categories based on the destination of trips - retail & recreation, supermarket & pharmacy, parks, public transport, workplaces and residential. 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

[6] See https://github.com/hmrc/eat-out-to-help-out-establishments.
[7] COVID-19 Community Mobility Reports: https://www.google.com/covid19/mobility/. The following nine LADs were excluded from the analysis as the mobility data contained missing values for more than 25 days: Ceredigion, Clackmannanshire, Isle of Anglesey, Isles of Scilly, Merthyr Tydfil, Na h-Eileanan Siar, Orkney Islands, Rutland and Shetland Islands.
[8] Low sample sizes mean that Google data can be missing for some areas in some days. To address this issue, we imputed around 7.5% of our sample using the average value of the previous two days and the subsequent two days for each location.

also test whether the programme affected trips to other types of outlets by looking at footfall in the supermarket & pharmacy category.[9] 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. We will discuss the implications of this for our results in Section 5.

2.2.2 Job adverts

We use daily data on job posts from Indeed to measure the number of job adverts across time in each LAD. All job adverts posted on Indeed's website include a location field. Employers are not required to use a standardised format - the information provided can be the full address, a partial postcode or a broader geographical area like the name of the town or city. Using the information provided by employers, Indeed identifies the LAD of each job advert. Job posts can usually be allocated to a LAD, except in cases when the advert only includes the name of a city which contains more than one LAD. In these cases, Indeed allocates job adverts to a LAD, which is usually that with the highest proportion of employment in the relevant city.[10] We exclude these eight LADs, given that number of adverts in these LADs is inaccurate by construction, although results are very similar when including them.

The data available to us corresponds to the rate of growth relative to a pre-pandemic reference date – the 1st of February in each year (2019 and 2020). As with the mobility data we create an index using the reference period as the base for each year.[11] We focus on the impact on job posts in the food preparation & service category as it comprises adverts that are more likely to reflect restaurants responding to any increased demand generated by the scheme.[12] We also extend the analysis to measure the effect on job posts in all sectors except food preparation & service, and hospitality & tourism.[13] One limitation of using data on job posts is that some of these may not translate into actual

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

[10] These correspond to Birmingham, Camden, Glasgow City, Lambeth, Manchester, Nottingham, Portsmouth, and Westminster.

[11] The following five LADs were excluded from the analysis as job adverts were not common and only posted on a few dates: Isles of Scilly, Nah-Eileanan Siar, Orkney Islands, Shetland Islands, and East Renfrewshire. As with the mobility data, low sample sizes mean this data can be missing for some areas in some days. We imputed 0.3% of our sample using the average value of the previous two days and the subsequent two days for each location.

[12] 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.

[13] 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.

jobs. The data is also only representative of a subset of food establishments that advertise positions through online channels, and potentially larger businesses that are more likely to have capacity to hire more staff. Again, we will discuss potential implications for our results in Section 5.

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. Given this, we focus on estimating the effect of intensity of treatment rather than considering treatment and control groups. To do this, we employ a continuous difference-in-differences strategy that exploits spatial variation in the number of participating outlets in the scheme across locations in the UK. This involves a before-and-after comparison across LADs with different intensity of the treatment measured by the number of participating outlets (at the total level and per capita). Identification relies on the exogeneity of the spatial variation in the intensity of treatment after controlling for confounding factors such as local shocks. Clearly this is quite a strong identifying assumption as firms opt into the scheme, so the intensity of treatment may vary across LADs due to unobservable factors correlated with local labour markets and mobility patterns – e.g., the ability of firms to survive after lockdown measures were introduced. To deal with these concerns, we construct an instrument for the intensity of treatment by exploiting the fact that some restaurant chains with regional or national presence made centralised decisions on whether to participate in the EOTHO scheme. These decisions will affect the intensity of treatment but should be independent of local labour market conditions and mobility patterns.

3.1 Intensity of treatment of the scheme

Our empirical strategy exploits the fact that the take-up of the scheme varies widely across LADs, so the intensity of treatment differs. 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 or with aspects which are uncorrelated with our outcomes (e.g., lack of programme awareness). Our main measures for the intensity of treatment are based on the number of participating outlets.[14] We construct two measures

[14] We exclude 19 businesses that participated in the scheme (0.03% of the total number of participants) given that the reported postcode is incorrect, and thus we could not allocate them geographically to a LAD.

by LAD using: i) the number of establishments registered as participating in HMRC's GitHub repository on the last day of August 2020; and ii) the same number of participating outlets but per capita.[15]

The most natural measure of the intensity of treatment would be the share of restaurants that participated in the scheme. The closest we can get to this is the take-up rate of the scheme in each LAD as the number of establishments in EOTHO divided by the total number of businesses in the food and beverage sector. Across the UK, this ranges from 13% to 64%, with an average of 33% among LADs (Figure A.3). However, we only consider this as a robustness check and not our main intensity of treatment since it is unclear which is the correct total establishment figure that should be considered (i.e., if all outlets or only those eligible and opened in August 2020) and either would introduce a large measurement error for several reasons. First, the data on total number of outlets by LAD and sector is only available for March 2020, and take-up is likely to underestimate programme participation given many firms went out of business after March 2020. Then, any choice of the sector for the total number of firms in the denominator would be inaccurate as most but not all participating establishments belong to the food and beverage sector.[16] Moreover, we also cannot obtain a precise number of eligible outlets given some were not eligible as they did not have space for consuming food and non-alcoholic drinks on the premises.

Figure 1 (panel A on the left) shows substantial variation in the logarithm of the number of participating outlets, with the distribution across LADs approximating a normal distribution. Panel A on the right presents the spatial distribution of the intensity of treatment.[17] A similar pattern is observed when looking at per capita numbers of participating outlets (Figure 1 panel B). Across the UK, many eligible businesses did not use the scheme. Participation on EOTHO ended up being less than half of what the UK government had anticipated.[18] This is surprising given that the food sector had been struggling after lockdown measures were introduced. However, the low demand for the

[15] In a robustness check we measure intensity allowing for variation in the number of establishments registered within the month of August 2020, as described below.

[16] According to official figures, 79% of establishments belong to the food and beverage sector (2007 SIC sector 56). See https://www.gov.uk/government/statistics/eat-out-to-help-out-statistics.

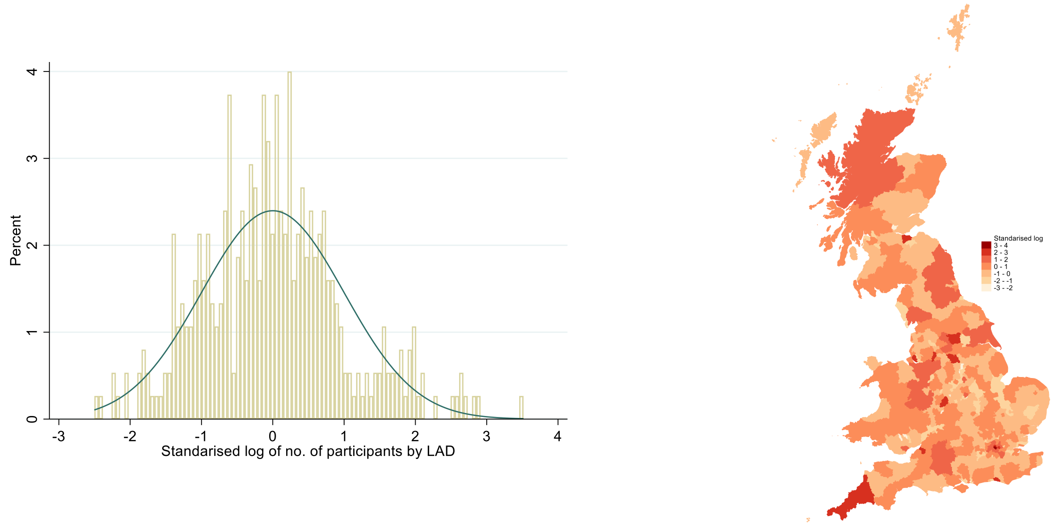
[17] These measures have been standardised to ease interpretation, so the distributions are centred around zero. LADs located in the North and South-West of the UK had higher participation rates in the EOTHO programme.

[18] 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.

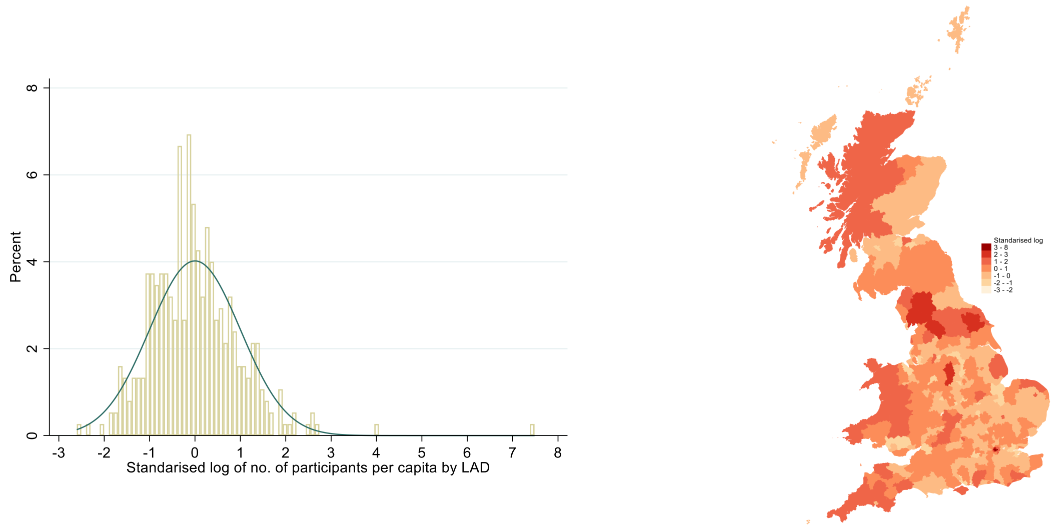
EOTHO scheme is in line with low uptake of other types of interventions such as business support programmes.[19]

Figure 1. Variation in the number of participating outlets

A) Number of participating outlets



B) Number of participating outlets per capita



Note: The left-hand panels plot a histogram and smoothed density plot for our measures of the intensity of use of the scheme for all LADs across the UK. The right hand panels map the same data – the darker the color on the map, the higher the intensity. Source: Author calculations using data from ONS, HMRC and HMRC's GitHub repository.

We consider four alternative measures for the intensity of treatment as robustness checks. First, we obtain the number of participating outlets at the end of August 2020 but using the official figures from HMRC, which only include firms with 25 or fewer participating outlets.[20] Eligible businesses could decide to participate after the EOTHO

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

[20] Restaurant chains with more than 25 participating outlets were not required to provide details of each establishment, including full address, when making a claim to the EOTHO scheme. Thus, HMRC was not able to allocate outlets of these businesses to a LAD and, as a result, official figures disaggregated by LAD exclude firms with more than 25 outlets.

programme was launched. As a result, the number of establishments registered increased with time in all locations during August 2020. So, we obtain a version of our two main intensity measures (number of participating outlets at the total level and per capita) that vary during the month of August. We also consider a time-varying take-up rate of the scheme – i.e., number of establishments in EOTHO divided by the total number of businesses in the food and beverage sector as of March 2020.

3.2 The empirical model

We first use a continuous-treatment difference-in-differences (DiD) model that compares outcomes for LADs before-and-after the introduction of EOTHO as a function of the intensity of treatment. To deal with the potential non-randomness of the scheme uptake, we instrument for the intensity of treatment using the number of restaurant chains (see Appendix for details on the data we use), as discussed below. Our DiD estimating equation is the following:

$$\ln(y_{it}) = \alpha_i + \eta_t + \gamma_{rt} + \beta(I_i \times post_t) + \varepsilon_{it} \qquad (1)$$

where (y_{it}) is one of several outcome variables in LAD i and in day-week t. We include additive LAD fixed effects (α_i), week and day fixed effects (η_t), and week-by-region or counties (NUTS1 or NUTS2) dummies (γ_{rt}). I_i is the continuous and time-invariant intensity of treatment measure for each LAD. $post_t$ 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 on outcomes conditional on the fixed effects. The LAD fixed effects account for time-invariant unobservable factors at the LAD level, while week and day fixed effects account for time-varying factors common to all LADs. The week-by-region or counties fixed effects capture local economic shocks, shocks related to the spread of the disease across UK areas and effects of local measures implemented to mitigate the spread of COVID-19. In our most complete specification, we further include LAD-specific linear trends by calendar week to account for potential differences in trends across LADs. This approach relies on the assumption that any pre-existing trends across differently exposed LADs are linear and would have evolved at the same rate in the absence of the scheme.

The main identification concern is that OLS will give biased estimates if participation levels are not randomly distributed across LADs. This will be the case if there are underlying unobservable factors (e.g.., different perceptions of the risk of being infected) correlated with outcomes and explaining differences in the intensity of treatment across LADs. We employ an instrumental variables approach to deal with these concerns. For this, we use information on restaurant chains, which usually refer to a group of establishments with presence in multiple locations that share the same name and concept (Figure A.4 and Table A.1 in the Appendix). We instrument the intensity of treatment with the number of restaurant chains in each LAD (our main instrument). There are two alternative instruments we could consider for each LAD. First, we could consider take-up rate for restaurant chains – i.e., number of establishments from restaurant chains in EOTHO divided by the total number of businesses in the food and beverage sector. This alternative suffers from the same issues described above for the intensity of treatment (i.e., measurement error and lack of data on total number of eligible outlets), so we do not consider it further. A second alternative is the number of establishments from restaurant chains in each LAD. We use this measure as a robustness check since it is more likely to be correlated with the size and income of LADs. It may also be measured with error as some establishments from the same restaurant chain in the same location could be eligible while others are ineligible if they do not have a dine-in option.

Our instrument exploits the fact that many restaurant chains appear to have made centralised decisions on whether to participate in the programme. For these chains, the decision to participate in EOTHO is likely to be independent of local labour market conditions, providing us with an exogenous source of spatial variation. The validity of our instrument relies on restaurant chains making the same decision on programme participation for all their outlets rather than decisions by establishment, according to local economic conditions. That is, for each chain, we need either all outlets registered to participate on the scheme or none of them.[21] Table A.2 suggests that many restaurant chains did make centralised decisions regarding the participation of all their establishments in the EOTHO scheme. To construct the table, we obtain the share of outlets participating in EOTHO from their total number of establishments. This share is likely to be underestimated since we have no data on whether outlets were eligible in August 2020 (i.e., were open and had a dine-in option). This means that totals may include outlets that were ineligible for EOTHO. From the list of 80 most popular restaurants chains, 5 have a take up rate above 85% and 56 of them below 15%, which means that

[21] This is less likely to be the case among restaurant chains that operate a franchise business model, which often have a decentralised decision-making process.

three quarters of these restaurant chains appear to have taken a mainly centralised decision. Although, as always, it is impossible to directly test the exclusion restriction, the table provides suggestive evidence that supports it.

This empirical strategy most obviously provides an estimate of the local average treatment effect caused by variation in the number of chain restaurants that participate. However, it will provide an estimate of the average treatment effect (ATE) (rather than the local average treatment effect) if our instrument is correlated with take-up for non-chain restaurants due to spillovers. That is, if non-chain outlets are more likely to apply for the scheme if they observe surrounding chain restaurants (their competitors) participating.[22] Table A.3 presents the first-stage of the IV estimates, showing a high correlation between the intensity of treatment and the instrument (see also Figure A.5). To look for evidence of spillovers we split the sample of participants between outlets from restaurant chains and establishments from non-chains. From the total number of around 62,000 outlets participating in EOTHO, over 4,000 are part of one of the 80 most popular chains in the UK. Table A.4 and Table A.5 present the first-stage estimates using an intensity of treatment measured by only the number of chain and non-chain participating outlets, respectively. In both cases, we obtain positive and statistically significant estimates at the 1% level. As we would expect, the F-statistics are larger for participation of outlets from restaurant chains compared to our main sample, which includes all establishments (Table A.3). More importantly, the estimates from Table A.5 suggest that the presence of restaurant chains induces non-chain outlets to participate in the programme, thus, providing evidence on spillovers in the take up of the scheme. This suggests our empirical strategy should provide an estimate of the average treatment effect.

4. Results

Our analysis concentrates on the first post-lockdown period – that is, from the last week of June 2020 – to exclude weeks with mobility restrictions. We also focus on LADs from Primary Urban Areas (PUAs).[23] To explain why, we start by analysing longer-term trends of footfall and job posts for LADs from PUAs and non-PUAs (Figure A.6 and A.7). For

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[22] Outlets that participated in the scheme put a sticker in the front door to show that they were offering the discount. Also, participating outlets actively advertised the discount via social media.

[23] 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/.

footfall, PUAs and non-PUAs present a similar trend from the beginning of 2020 until mid-July 2020, when the latter group begins diverging and having a faster return to pre-pandemic levels, besides a higher level of footfall for the rest of 2020. We see a similar pattern for job posts. That is, a faster return to pre-pandemic levels and a higher index in non-PUAs compared to PUAs after mid-July 2020. The different trend between these groups could be associated to an heterogenous impact of the pandemic on the economy, given that is easier to follow social distancing and other safety measures in (more) rural areas. Further, Google does not recommend comparing their mobility data between urban and rural regions. Thus, our analysis focuses on LADs located in PUAs.

Figure A.8 presents the footfall trend for PUAs in the UK with footfall split by category. We see 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 early November. Figure A.9 shows the trend of job posts in 2020 by category for LADs from PUAs. As with job posts, we observe a large drop in the number of job posts, with the lowest point around mid-May. The index suggests that the food preparation & service sector was severely affected by the crisis, and that the recovery only began after lockdown restrictions were relaxed.

4.1 Baseline estimates: footfall and job posts

We focus on two outcomes: the natural logarithm of the footfall index and of the job post index. We consider two (standardised) intensity measures: the natural logarithm of total and per capita number of participating outlets. Table 1 presents the average treatment effect of the EOTHO programme on footfall in the retail & recreation category (Panel A) for the weeks in which the discount was available, and on job posts in the food preparation & service category (Panel B).

The DiD estimates from estimating equation 1 are reported in the first three columns (1 to 3). The IV estimates are reported in the next three columns (4 to 6). We consider three specifications in each case, including different area by time fixed effects to account for i) local policy measures related to the pandemic; and ii) area-specific shocks associated to the evolution of the pandemic. We first include region-by-week fixed effects (columns 1 and 4), then we replace these by county-by-week fixed effects (columns 2 and

5).[24] Finally, we also add district-specific linear trends (columns 3 and 6), which is our preferred specification as it better accounts for local pandemic-related shocks. As explained in the previous section, our main estimates are based on two different measures of the intensity of treatment (presented as separate rows in Table 1), which are standardised to ease interpretation.

Table 1. Impact of EOTHO on footfall and job posts

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Footfall [(a)]						
Intensity: Log of outlets in EOTHO	0.038***	0.035***	0.013***	0.049***	0.051***	0.022***
	(0.005)	(0.005)	(0.003)	(0.006)	(0.006)	(0.004)
F-statistic	N/A	N/A	N/A	225	196	171
Intensity: Log of outlets in EOTHO per capita	0.039***	0.042***	0.010***	0.076***	0.088***	0.040***
	(0.004)	(0.005)	(0.003)	(0.010)	(0.010)	(0.008)
F-statistic	N/A	N/A	N/A	50	89	71
Panel B: Job posts [(b)]						
Intensity: Log of outlets in EOTHO	0.027	0.048**	0.032*	0.059**	0.080***	0.072***
	(0.019)	(0.021)	(0.017)	(0.028)	(0.029)	(0.024)
F-statistic	N/A	N/A	N/A	129	104	96
Intensity: Log of outlets in EOTHO per capita	0.010	0.035	0.023	0.093**	0.129***	0.127***
	(0.018)	(0.026)	(0.017)	(0.047)	(0.048)	(0.045)
F-statistic	N/A	N/A	N/A	34	49	36
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: The table presents DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variables are the natural logarithm of the footfall index and job post index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Panel A of Table 1 reports results looking at the impact of the programme on footfall in retail & recreation to quantify to what extent EOTHO increased the number of people visiting establishments in this category. All estimates are positive and statistically significant at the 1% level. The estimates from our most complete DiD specification (column 3) range between 1.0% and 1.3%. IV estimates suggest larger effects (column 6), such that a one standard deviation increase in the number of participants in the scheme

[24] Overall, we observe larger coefficients among specifications that include county-by-week fixed effects compared to those with region-by-week fixed effects. This could be due to local policy shocks having a larger role within a smaller geography (i.e., counties) relative to broader areas (i.e., regions), and the spatial correlation in the spread of COVID-19 – i.e., LADs in the same county may have observed a similar evolution of the pandemic and, as a result, similar containment measures.

led to an increase in footfall of between 2.2% and 4.0% across PUAs in the UK. The larger IV estimates suggest a downward bias in the OLS that seems reasonable as unobservable confounders (e.g., fears of infection) are likely to be negatively correlated with both footfall and the likelihood that restaurants felt it was worthwhile participating in the scheme. Breaking down by days (Table A.6) this effect mainly comes from increased footfall on Tuesdays (1.4%) and Wednesdays (2.3%) in August, which is when the discount was available. We find evidence of displacement from Mondays (-2.3%) to Tuesdays-Wednesdays. The scheme had no significant impact between Thursdays and Sundays.

Next, we examine the effects on job posts. Panel B of Table 1 captures how firms reacted to the increase in the demand for food and restaurant services. The estimates from our preferred DiD specification (column 3) range between 2.3% and 3.2%, with one of them not being statistically significant (for outlets per capita as the intensity of treatment). Our IV estimates show larger impacts, with estimates being statistically significant in our two intensities considered. From our preferred IV specification (column 6), the results indicate that a one standard deviation increase in the exposure to the EOTHO scheme increased job posts by between 7.2% and 12.7%. As expected, IV estimates seem larger than OLS, for similar reasons as discussed for footfall above. The EOTHO scheme led to higher activity in the labour market in the form of job adverts and recruitment efforts across PUAs in the UK.

We also measure the effect of EOTHO on footfall in the supermarket & pharmacy category to understand if the programme affected trips to other types of outlets. Table A.7 presents the results, which indicate a negative effect of between -3% and -1% on this category. This suggests there was a small displacement effect from supermarket & pharmacy to retail & recreation activities. We extend the analysis by 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 were spillover effects to other industries. Table A.8 presents the results of this exercise. We conclude the programme had a small effect (around 1.7%) on job posts in other sectors during the period of analysis, but demand mainly increased in the food preparation & service sector.

4.2 Dynamic treatment effects

We can also consider dynamic effects of the programme on footfall and job posts. To do this, we replace the interaction of our treatment intensity with the dummy for the four-week period the scheme was active ($I_i \times post_t$ in equation 1) by the interaction of the intensity with week dummies to obtain weekly estimates for the impact of the programme.

We focus on the main measure on the intensity of use of the programme (the number of outlets in EOTHO) and present the results for the other two intensities in the Appendix (Figure A.10). We use our preferred specification, which includes county-by-week fixed effects and district-specific time trend. Since we include district fixed effects, we need to omit one week – we choose week 31 (the week before the scheme went live), so all estimates are relative to that week. As well as allowing us to consider the timing of effects, this exercise also provides evidence on the common trend assumption as we report estimates for four weeks before the discount was available.

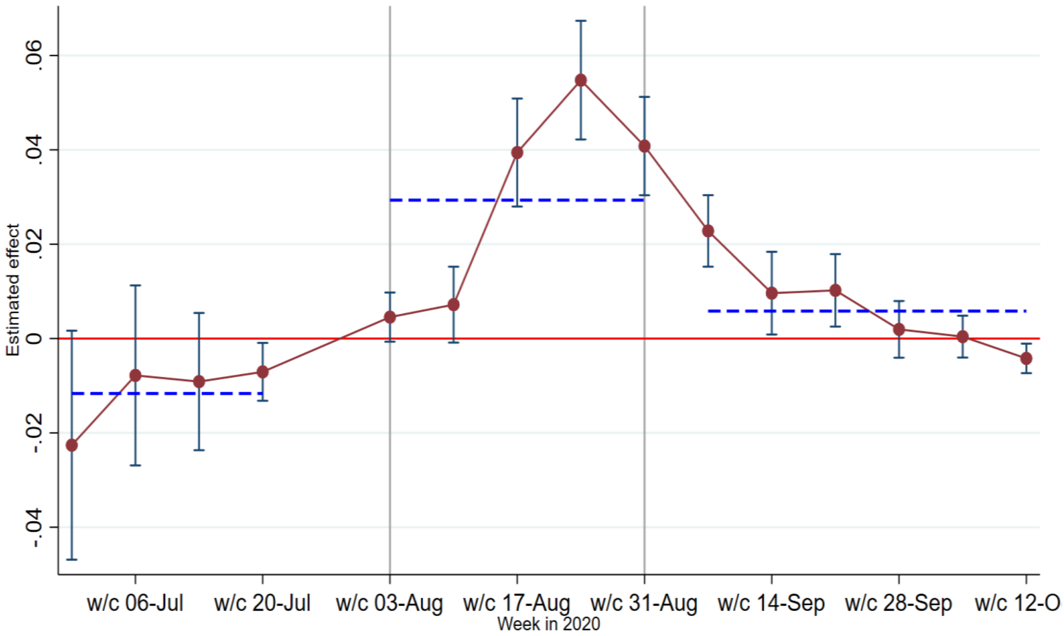
Panel A of Figure 2 presents an event study graph with the weekly estimates for footfall in the retail & recreation category. This allows us to assess the impact of the EOTHO programme on footfall over time – i.e., before, during and after the scheme was live. Grey lines highlight the weeks in which the EOTHO scheme was live, while the vertical black lines depict 95% confidence intervals. The estimates in the weeks prior to the start of the programme suggest no obvious pre-trend prior to the start of the scheme. Consistent with this, the p-value obtained from a joint test for the equality of coefficients for the pre-scheme weeks commencing 6, 13, and 20 July 2020) is 0.61. Although such pre-trend tests may suffer from low power, calculations following Roth (2020) suggest our test is not under-powered under a plausible violation of the common trend assumption.[25]

The point estimates for footfall are positive, but marginally insignificant in the first two weeks of the scheme. The estimates jump sharply and become significant in the second half of the month. These coefficients capture the net effect of the scheme as the discount was only available from Monday to Wednesday. The effect on footfall starts decreasing towards the end of the scheme, with estimates becoming statistically insignificant in the last week of September and in subsequent weeks. Figure A.10 presents the event study graphs using the two alternative measures for the intensity of treatment. Overall, these results suggest the scheme increased footfall but mainly during the month of August 2020.

[25] We are worried about positive pre-trends where higher mobility rates pre-EOTHO may drive more exposure to EOTHO (e.g., because restaurants in areas which get lots of tourists respond to seasonal increases in footfall by signing up to EOTHO). Given this concern, we construct the slope and the constant of a hypothesised pre-trend using the point estimate for one week pre-EOTHO (first lag) and the lower bound of the confidence interval for two weeks pre-EOTHO (second lag). Follow Roth (2022) we compute the power of the pre-trend test under this plausible linear violation of the common trend assumption and get a power of .93 (for footfall) and 0.99 (for job postings) well-above 0.8 widely used as a recommended benchmark.

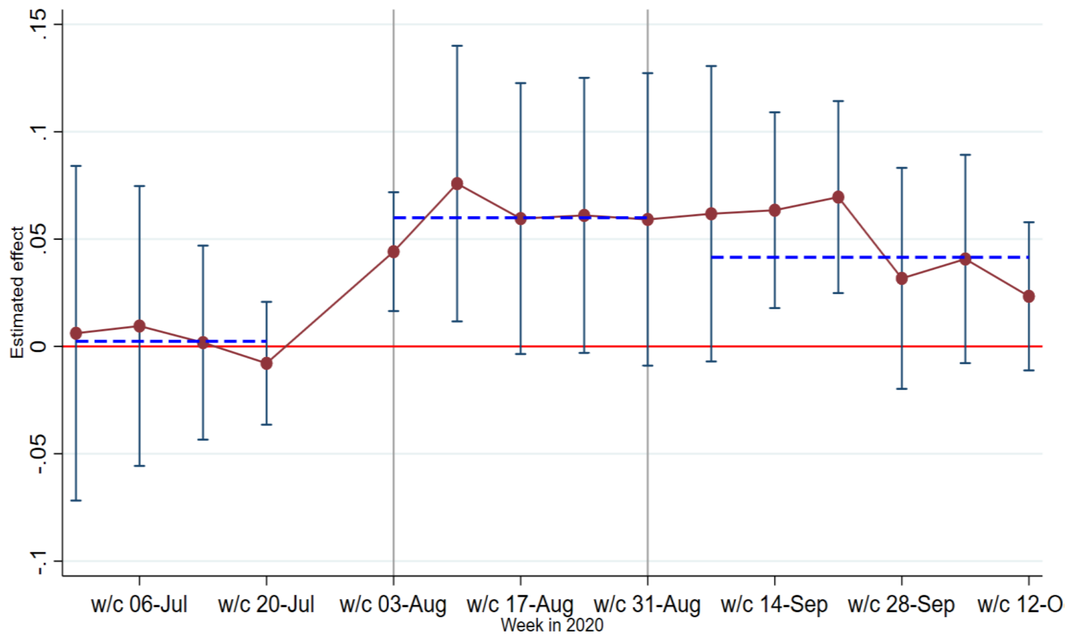
Figure 2. Dynamic treatment effects

A) Footfall



Note: Weekly estimates for the effect of EOTHO on footfall using data at the LAD level. The estimates were obtained from our preferred DiD specification with the intensity of use of the scheme measured using the log number of outlets in EOTHO (panel A, column 3 of Table 1). The vertical black lines depict 95% confidence intervals. The vertical grey lines highlight the weeks in which the EOTHO scheme was live.

B) Job posts



Note: Weekly estimates for the effect of EOTHO on job posts using data at the LAD level. The estimates were obtained from our preferred DiD specification with the intensity of use of the scheme measured using the log number of outlets in EOTHO (panel B, column 3 of Table 1). The vertical black lines depict 95% confidence intervals. The vertical grey lines highlight the weeks in which the EOTHO scheme was live.

Panel B of Figure 2 presents the weekly estimates for the effect of EOTHO on job posts in the food preparation & service category. In line with what we observed for footfall, the job posts estimates are not statistically different from zero before August, again suggesting no obvious pre-trend prior to the start of the scheme. The p-value from a joint test for the equality of coefficients using the first four lags is 0.93.[26] The point estimates are positive and significant from the beginning of August when the EOTHO scheme went live (3 August 2020). The coefficient is stable while the scheme is active and for three weeks after the scheme ended, although the statistical significance fluctuates over the eight-week period for which these effects are seen. We observe a similar pattern for the effect on job posts when considering the alternative measures on the intensity of use of the programme (Figure A.10).

One interpretation of these patterns is that there was some hiring early on in anticipation of the increase in footfall (which might make sense given many establishments would have been operating with lower staffing levels) and some hiring late on reflecting the overall increase in demand because of EOTHO. Overall, our results suggest a positive, but transitory, effect on both footfall and job posts due to the EOTHO scheme. However, a transitory increase in job posts could still imply a permanent increase in the number of employees. In the Appendix, we analyse the effect of EOTHO on employment using annual data (for the month of September in each year) at the LAD level for the food and services sector (2007 SIC sector 56). The estimates suggest no effect on employment although this comes with a strong caveat: compared to our daily data on footfall and job posts, the main limitation for this outcome – given the frequency of the data publicly available – is the lack of information for the period just before the scheme started. This precludes before-and-after comparisons within the same year and meaning we cannot consider the differential economic impact of COVID-19 pre-EOTHO.

4.3 Robustness checks

Our estimates for both footfall and job posts are robust to the use of alternative measures for the intensity of treatment and several sensitivity checks.

First, we use the number of participating outlets at the end of August 2020 but using the official figures from HMRC, which excludes firms with more than 25. Our IV estimates suggest a similar effect of 2.2% and 7.3% on footfall and job posts respectively

[26] As mentioned in the previous footnote, the power of the pre-trend test is 0.99 under a plausible linear violation of the common trend assumption (constructed in the same way as for footfall).

(Table A.9). Second, we construct a time-varying version of our two main intensity measures (number of participating outlets at the total level and per capita) as eligible businesses could decide to participate once the EOTHO scheme was live. The IV results are also similar: between 3.3% and 4.8% for footfall, and between 9.3% and 10.4% for job posts (Table A.10).

Next, we consider a time-varying measure of take-up as the intensity of treatment of the programme. Specifically, we define this as the number of establishments registered in EOTHO divided by the total number of businesses in the food and beverage sector (2007 SIC sector 56), from the UK business counts of March 2020. The results also indicate a positive and significant impact for the EOTHO scheme on footfall and job posts (Table A.11). To cross check our comparison of footfall and job post estimates we obtain estimates using the same sample of LADs as used for job posts. The IV results indicate a similar effect with an increase in footfall of between 3% and 4% from a one standard deviation increase in exposure to the EOTHO scheme (Table A.12).

A concern specific to our results for job posts is that they might be affected by the seasonal pattern of hiring. The increase in the number of job posts in the month of August could be driven by the summer seasonal pattern, as restaurants, cafes and pubs in some regions tend to hire more staff to meet a higher demand for their services. 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, and the interplay with the scheme (e.g., seasonal outlets opening, hiring people, and then applying for EOTHO). Regardless, we include another robustness check considering seasonality. For this, the dependent variable corresponds to the index in 2020 relative to 2019. The IV coefficient for job posts from our preferred specification is similar, (column 6 from Table A.13), suggesting there is not a seasonal pattern that could affect our estimates. Mobility data from Google is not publicly available for 2019, so an equivalent analysis is not possible for footfall.

For the IV results, we can also consider two variations of our instrument. Instead of using the number of restaurant chains as an instrument, we first obtain the total number of establishments from these restaurant chains in each LAD. The IV coefficients are relatively similar for the number of outlets in EOTHO as our measure of intensity. The results suggest an effect of 2%-4% footfall in the retail & recreation category, and 6%-7% on job posts in the food preparation & service category from a one standard deviation increase in exposure to the EOTHO scheme (columns 2 and 3 from Table A.14). In Table A.15, we also consider reduced-form estimates derived by replacing the intensity of treatment measure with our baseline instrument (the number of restaurant chains), with results showing significant effects on both footfall and job posts. Also, we run an additional check for the IV strategy. We calculate the instrument in the same way (i.e., number of restaurant chains present in each LAD), but we focus on restaurant chains that appear to have made a centralised decision on whether to participate in the programme. More specifically, we exclude 19 restaurant chains with a take up rate of EOTHO between 15% and 85% according to Table A.2. The F-statistics from the first-stage are larger when using this revised version of our instrument, yet point estimates are almost unchanged compared to our main results (Table A.16).

To further support the validity of our DiD approach and results, we conduct a placebo test measuring the effect of the EOTHO programme on job posts but in 2019. To do this, we replicate Panel A in Table 1 but using the data on job posts from a year previous to the implementation of EOTHO. We consider the same ten calendar weeks in 2019, from 29 June to 6 September. Table A.17. presents the results. Our DiD estimates are reported in the first three columns, while IV estimates in the last three columns. All the estimates are statistically insignificant. Moreover, all the coefficients oscillate around zero. The point estimates from our preferred specifications are also small and close to zero; 0.5% and 0.9% from the DiD and IV approach, respectively. The results from this placebo test reinforce the validity of our empirical strategy, given that the EOTHO scheme was indeed not implemented in August 2019. Mobility data from Google is not publicly available for 2019, so an equivalent analysis is not possible for footfall.

The final concern we address is that our estimates could result from different pre-treatment trends in the outcome variable across LADs with different exposure to the scheme. To allow for this, we also obtain estimates considering changes in our outcome variables (instead of levels) as well as controlling for changes in the same outcome variable but from a four-week pre-treatment period. Specifically, our dependent variables for job posts and footfall capture changes between the week commencing 27 July 2020 (the week before the scheme went live) and the week commencing 24 August 2020 (the last full week in which the scheme was live). We do this by comparing the same day of the week in these two periods. In the same way, we control for changes in the pre-intervention period; that is, between the week commencing 29 June 2020 (five weeks before the scheme went live) and the week commencing 27 July 2020 (one week before the scheme went live). The results are presented in Table A.18. We still observe a positive and significant effect on both footfall and job posts, with effects ranging between 5.7% and 8.6% for footfall, and between 5.6% and 8.4% for job posts.

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 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. The scheme also increased 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. Unfortunately, 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 large 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 severe disruption to the economy.

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Appendix

I. Data on restaurant chains

Our instrument for the take-up of the EOTHO scheme requires data on the number of establishments from restaurant chains in each LAD.

To construct this, we use a list of the 80 most popular restaurant chains –according to customers' perceptions– in the UK from YouGov (Table A.1).[27] This includes cafes, food stores, pubs, and restaurants. From this list, we exclude 3 chains that offer food but not meals (Ben's Cookies, Millie's Cookies and Krispy Kreme). Then, we obtain the location of each establishment from every restaurant chain by web scraping the name and address of outlets from information publicly available on Yell.com.[28] In this way, we create a database with the list of outlets across the UK from the most popular restaurant chains.

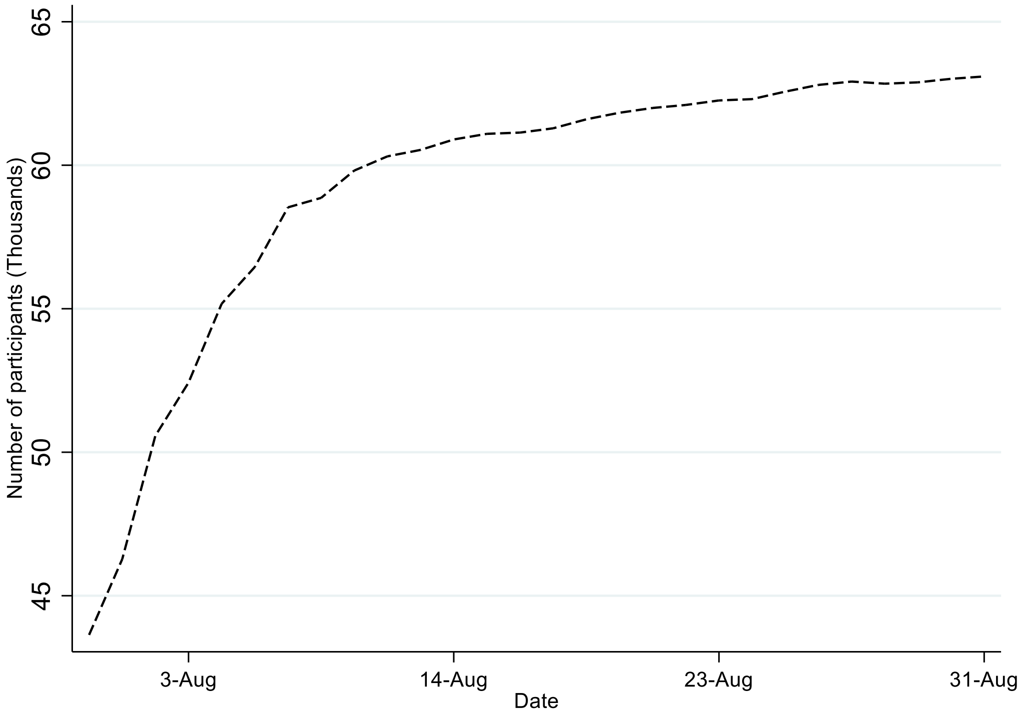
We aggregate the data at the LAD level, obtaining the number of chains present in each location, as well as the total number of outlets from restaurant chains (Figure A.3). On average, LADs across the UK have 16 restaurant chains (from the list of the most popular) and 39 establishments from these chains.

[27] YouGov is an international research data and analytics group specialised in market analysis and brand perception. See yougov.co.uk.

[28] Yell is a top-leading UK online business directory that has systematically covered the name and location of more than 2.9 million businesses since 1996.

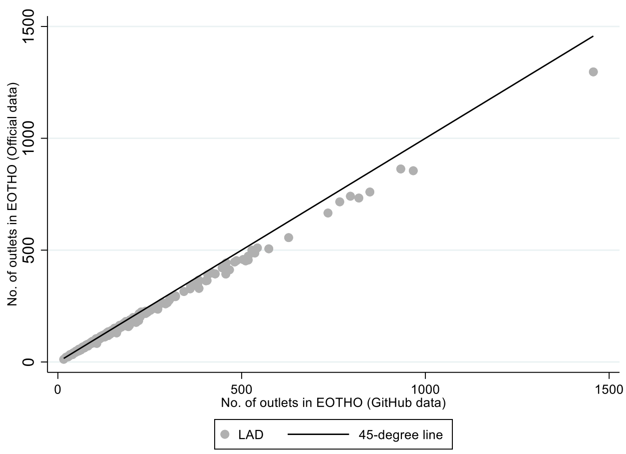
II. Figures

Figure A.1. Number of participants in the EOTHO scheme



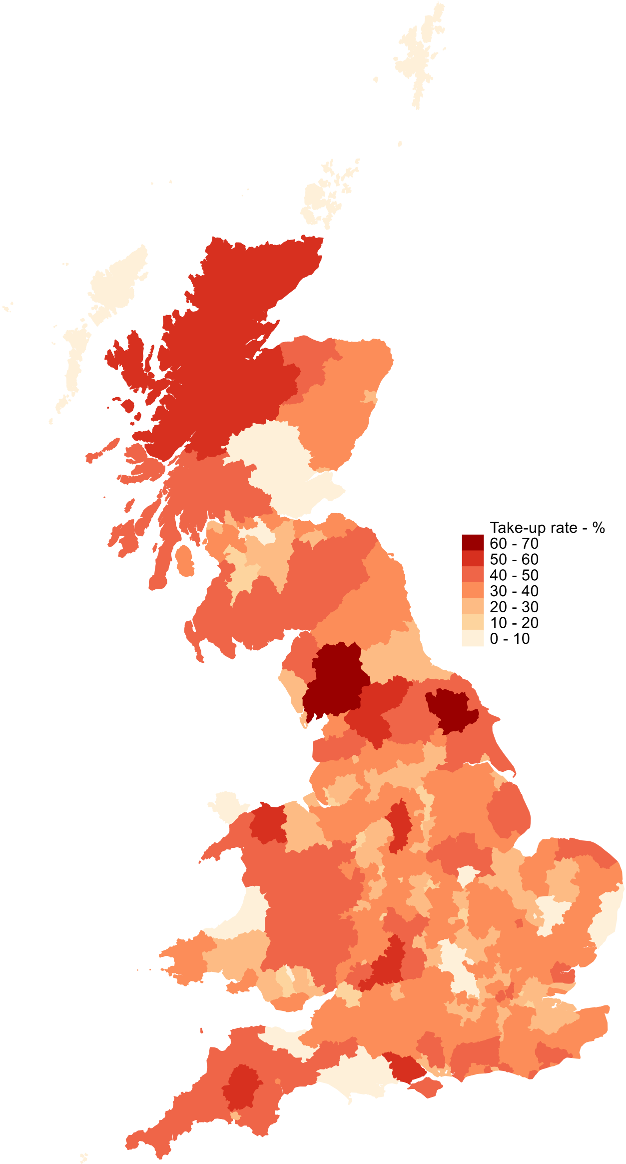
Note: The figure shows the evolution of the total number of food establishments that enrolled in EOTHO. Source: Author calculations using data from HMRC's GitHub repository.

Figure A.2. Number of participants in EOTHO by source of the data



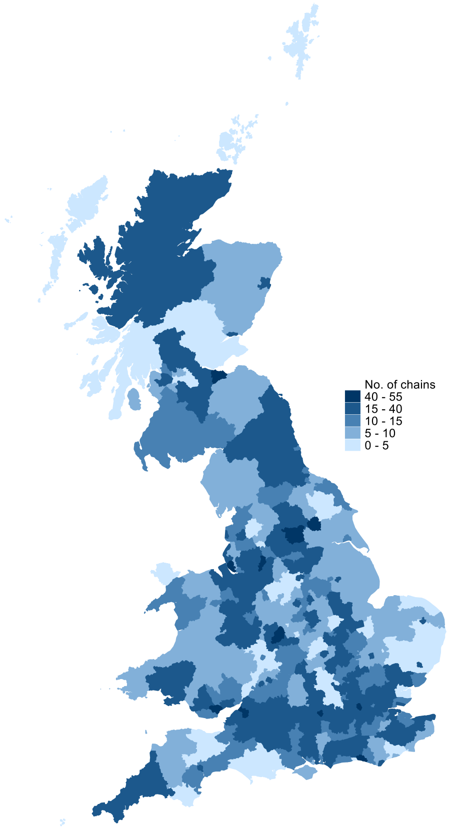
Note: Scatterplot for the number of outlets in the EOTHO scheme from the Gib Hub data against the number of participants in the official data. Source: Author calculations using data from HMRC and HMRC's GitHub repository.

Figure A.3. Variation in take-up across the UK



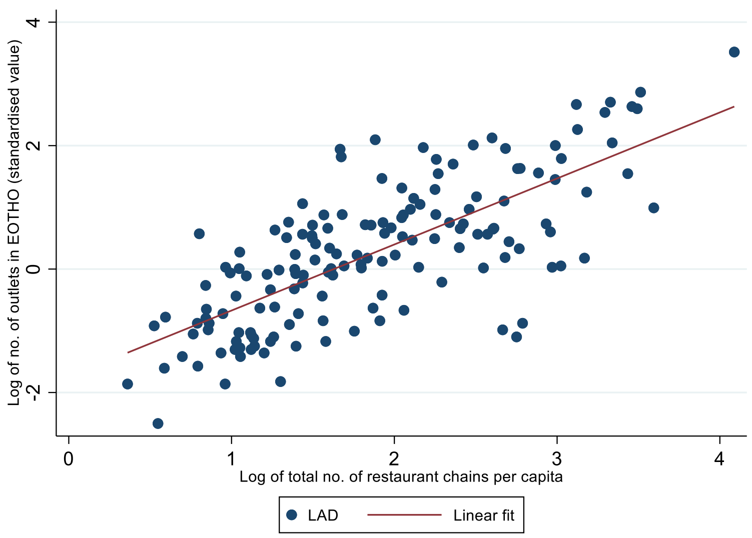
Note: Map showing the take-up rate by the end of the scheme on 31st August 2020 for every LAD in the UK. The darker the color, the higher the take-up rate. Source: Author calculations using data from HMRC's GitHub repository.

Figure A.4. Number of restaurant chains by LAD



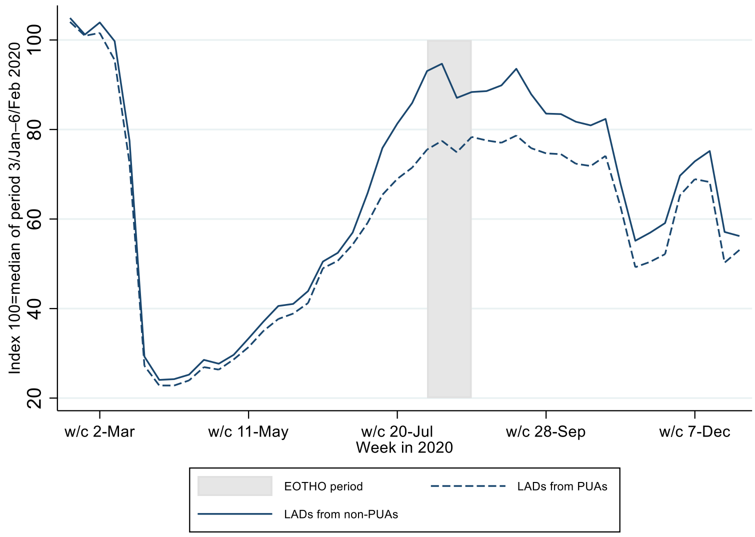
Note: Map showing the number of restaurant chains in each LAD from the list of 80 most popular chains in the UK. Source: Author calculations using data from YouGov and Yell.

Figure A.5. Restaurant chains and intensity of treatment



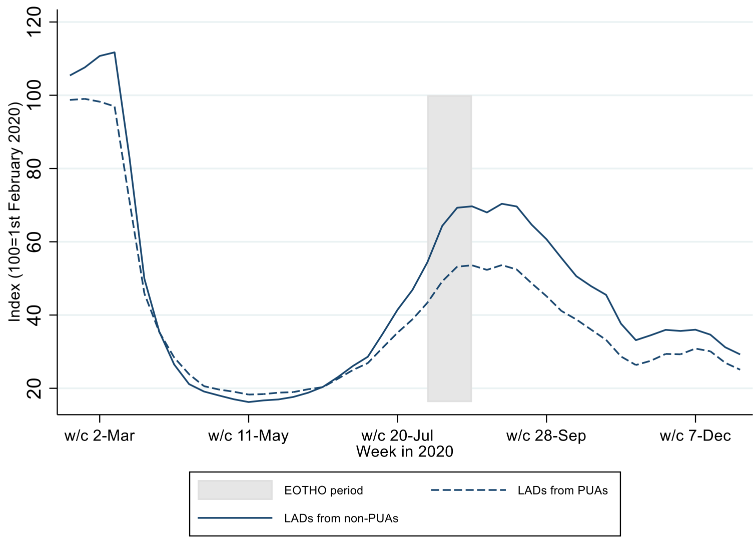
Note: The scatterplot provides a visualisation of the relationship between the number of restaurant chains per capita and our main measure of intensity of use of the scheme (the log number of outlets in EOTHO) across LADs from PUAs. Source: Author calculations using data from HMRC's GitHub repository, ONS, YouGov and Yell.

Figure A.6. Footfall pattern by type of LAD



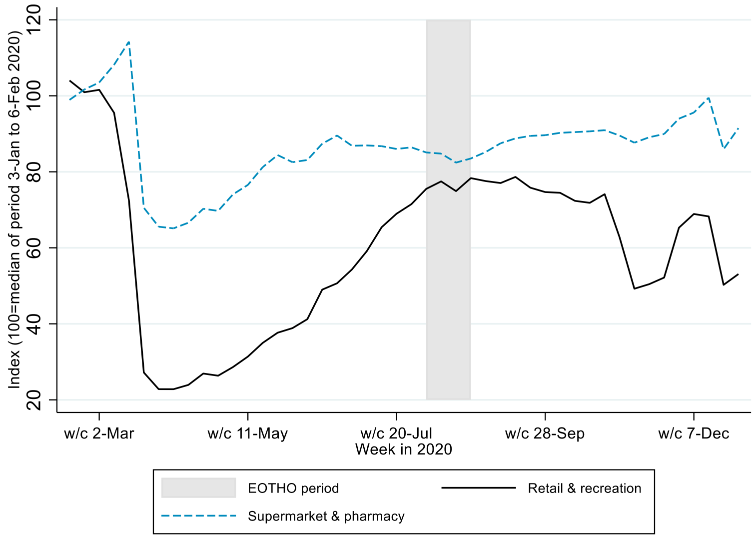
Note: Weekly average of the footfall index across LADs for PUAs and non-PUAs. The shaded area corresponds to the period in which the EOTHO scheme was live. Source: Author calculations using data from Google.

Figure A.7. Job posts pattern by type of LAD



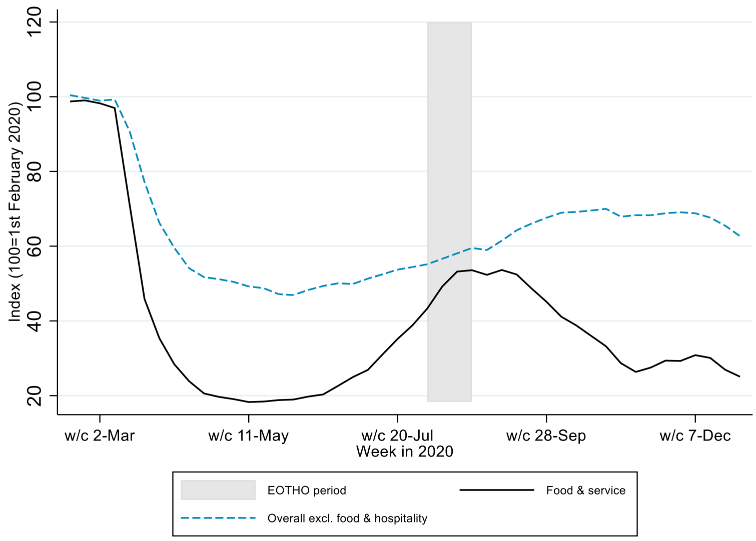
Note: Weekly average of the job post index across LADs for PUAs and non-PUAs. The shaded area corresponds to the period in which the EOTHO scheme was live. Source: Author calculations using data from Indeed.

Figure A.8. Footfall pattern by Google mobility category



Note: Weekly average of the footfall index across LADs from PUAs in the UK for the retail & recreation and supermarket & pharmacy categories. The shaded area corresponds to the period in which the EOTHO scheme was live. Source: Author calculations using data from Google.

Figure A.9. Job posts pattern by Indeed category

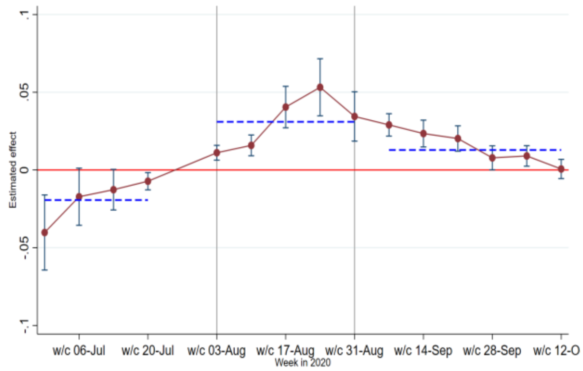


Note: Weekly average of the job post index across LADs from PUAs in the UK for food preparation & service and all sectors except food preparation & service, and hospitality & tourism. The shaded area corresponds to the period in which the EOTHO scheme was live. Source: Author calculations using data from Indeed.

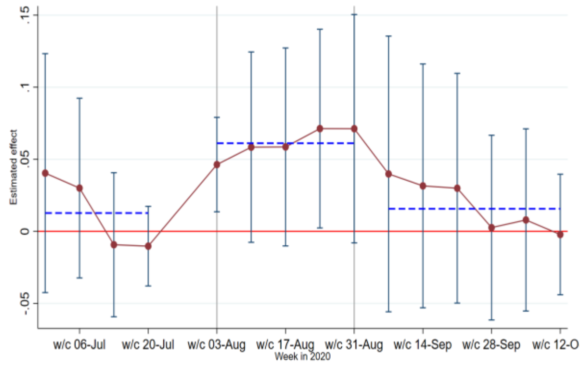
Figure A.10. Event study graphs with alternative measures on the intensity of treatment

Panel A: Log of outlets in EOTHO per capita

Footfall

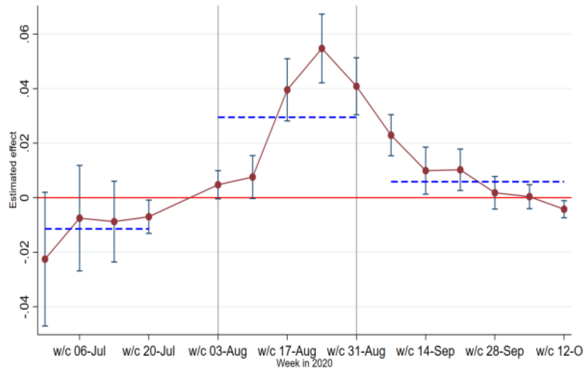


Job posts

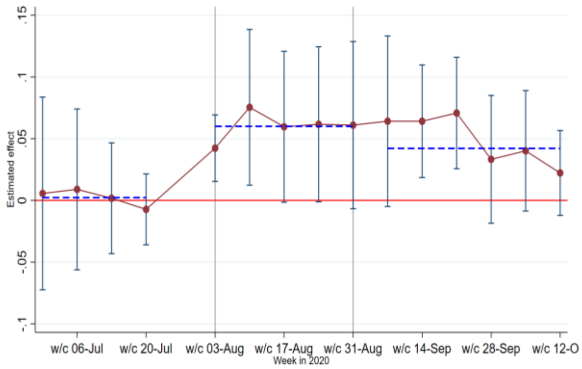


Panel B: Log of outlets in EOTHO (from official figures)

Footfall



Job posts



Note: Weekly estimates for the effect of EOTHO on job posts and footfall using data at the LAD level and alternative measures of intensity of treatment. The estimates were obtained from our preferred DiD specification (column 3 in Table 1). The vertical black lines depict 95% confidence intervals. The vertical grey lines highlight the weeks in which the EOTHO scheme was live.

III. Tables

Table A.1. List of the 80 most popular restaurant chains in the UK

Name of the restaurant chain	
Aberdeen Angus Steakhouse	Las Iguanas
All Bar One	Little Chef
Ask Italian	Loch Fyne Restaurant
Beefeater Grill	Mc Donald's
Bella Italia	Meat & Shake
Ben's Cookies	Miller & Carter
Brasserie Blanc	Millie's Cookies
Brewers Fayre	Nando's
Burger King	Papa John's Pizza
Byron	Patisserie Valerie
Caffe Nero	Pizza Express
Chicken Cottage	Pizza Hut
Chipotle Mexican Grill	Planet Hollywood
Chiquito	Pret a Manger
Coffee Republic	Prezzo
Costa Coffee	Shake Shack
Cote Brasserie	Shakeaway
Debenhams Restaurant	Sizzler
Domino's Pizza	Sizzling Pubs
EAT	Slug & Lettuce
Five Guys	Spudulike
Flaming Grill	Starbucks Coffee
Flat Iron	Stonehouse Pizza & Carvery
Franco Manca	Strada
Frankie & Benny's	Subway
Fuji	Supervalu
Gaucho	TGI Friday's
Giraffe Restaurant	Taco Bell
Gourmet Burger Kitchen	Toby Carvery
Greggs	Tortilla
Hard Rock Cafe	Upper Crust
Harry Ramsden's	Wagamama
Harvester	Wahaca
Honest Burgers	Walkabout
Hungry Horse	Wasabi Sushi & Bento
Itsu	West Cornwall Pasty & Co
Jamie's Italian	Wild Bean Cafe
Jimmy Chung's	Wimpy
KFC	YO! Sushi
Krispy Kreme	Zizzi

Source: Author calculations using data from yougov.co.uk.

Table A.2. Share of participating outlets in EOTHO from the total number of establishments for the 80 most popular restaurant chains in the UK

Restaurant chain	Share (%)	Restaurant chain	Share (%)
Brasserie Blanc	100	Wagamama	1
Flat Iron	100	Cote Brasserie	1
Gaucho	100	Harvester	1
McDonald's	99	Miller & Carter	1
Debenhams Restaurant	95	West Cornwall Pasty & Co	1
Wimpy	82	Pizza Hut	1
Taco Bell	75	Nando's	0
Hard Rock Café	75	Aberdeen Angus Steakhouse	0
KFC	69	Ask Italian	0
Subway	69	Beefeater Grill	0
Giraffe Restaurant	67	Ben's Cookies	0
Shake Shack	54	Brewers Fayre	0
Wasabi	52	Byron	0
Spudulike	36	Caffe Nero	0
Strada	33	Flaming Grill	0
Costa coffee	31	Franco Manca	0
Chipotle Mexican Grill	30	Gourmet Burger Kitchen	0
Itsu	28	Greggs	0
Starbucks	28	Honest Burgers	0
Meat & Shake	25	Hungry Horse	0
Burger King	23	Jamie's Italian	0
Wahaca	22	Jimmy Chung's	0
Chicken Cottage	22	Krispy Kreme	0
Coffee Republic	16	Las Iguanas	0
Papa John's Pizza	14	Little Chef	0
Fuji	13	Millie's Cookies	0
EAT	13	Pizza Express	0
Frankie & Benny's	10	Planet Hollywood	0
Loch Fyne Restaurant	8	Prezzo	0
Bella Italia	6	Shakeaway	0
Harry Ramsden's	5	Sizzler	0
Tortilla	5	Slug & Lettuce	0
Upper Crust	4	Stonehouse Pizza & Carvery	0
All Bar One	3	Supervalu	0
Domino’s pizza	3	TGI Friday's	0
Five Guys	3	Toby Carvery	0
Pret a Manger	2	Walkabout	0
Patisserie Valerie	2	Wild Bean Café	0
Sizzling Pubs	2	YO! Sushi	0
Chiquito	1	Zizzi	0

Note: For each restaurant chain, the table presents the share of establishments participating in EOTHO, using the number of outlets that appear in HMRC’s GitHub repository and the total number of outlets from Yell.com. The share is likely to be underestimated since the total number of establishments is not restricted to eligible outlets (i.e. outlets that were open during the period of analysis and had a dine-in option). Source: Author calculations using data from YouGov, Yell and HMRC’s GitHub repository.

Table A.3. First stage of IV estimates

	(1)	(2)	(3)
Panel A: Footfall [(a)]			
Intensity: Log of outlets in EOTHO	0.068***	0.066***	0.059***
	(0.005)	(0.005)	(0.004)
F-statistic	225	196	171
Intensity: Log of outlets in EOTHO per capita	0.043***	0.038***	0.032***
	(0.006)	(0.004)	(0.004)
F-statistic	50	89	71
Panel B: Job posts [(b)]			
Intensity: Log of outlets in EOTHO	0.060***	0.057***	0.050***
	(0.005)	(0.006)	(0.005)
F-statistic	129	104	96
Intensity: Log of outlets in EOTHO per capita	0.038***	0.036***	0.029***
	(0.006)	(0.005)	(0.005)
F-statistic	34	49	36
Day, week & LAD fixed effects	Yes	Yes	Yes
Area by week fixed effects	Region	County	County
LAD-specific linear trends	No	No	Yes

Note: OLS results estimated using data at the LAD level for PUAs and ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variable is the respective intensity. The reported coefficients correspond to the interaction between the number of restaurant chains and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.4. First stage of IV estimates only for chain outlets

	(1)	(2)	(3)
	Panel A: Footfall [(a)]		
Intensity: Log of chain outlets in EOTHO	0.055***	0.057***	0.053***
	(0.004)	(0.003)	(0.003)
F-statistic	240	318	327
Intensity: Log of chain outlets in EOTHO per capita	0.037***	0.039***	0.036***
	(0.005)	(0.004)	(0.004)
F-statistic	65	75	88
	Panel B: Job posts [(b)]		
Intensity: Log of chain outlets in EOTHO	0.052***	0.052***	0.048***
	(0.004)	(0.003)	(0.003)
F-statistic	157	226	245
Intensity: Log of chain outlets in EOTHO per capita	0.036***	0.039***	0.035***
	(0.005)	(0.005)	(0.004)
F-statistic	47	56	64
Day, week & LAD fixed effects	Yes	Yes	Yes
Area by week fixed effects	Region	County	County
LAD-specific linear trends	No	No	Yes

Note: OLS results estimated using data at the LAD level for PUAs and ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variable is the respective intensity. The reported coefficients correspond to the interaction between the number of restaurant chains and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,780 observations and 154 clusters; in panel (b) 10,150 observations and 145 clusters.

Table A.5. First stage of IV estimates only for non-chain outlets

	(1)	(2)	(3)
	Panel A: Footfall [(a)]		
Intensity: Log of non-chain outlets in EOTHO	0.067***	0.064***	0.057***
	(0.005)	(0.005)	(0.005)
F-statistic	202	170	150
Intensity: Log of non-chain outlets in EOTHO per capita	0.041***	0.035***	0.030***
	(0.006)	(0.004)	(0.004)
F-statistic	44	71	56
	Panel B: Job posts [(b)]		
Intensity: Log of non-chain outlets in EOTHO	0.059***	0.056***	0.049***
	(0.005)	(0.006)	(0.005)
F-statistic	114	88	81
Intensity: Log of non-chain outlets in EOTHO per capita	0.035***	0.033***	0.026***
	(0.007)	(0.005)	(0.005)
F-statistic	29	38	27
Day, week & LAD fixed effects	Yes	Yes	Yes
Area by week fixed effects	Region	County	County
LAD-specific linear trends	No	No	Yes

Note: OLS results estimated using data at the LAD level for PUAs and ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variable is the respective intensity. The reported coefficients correspond to the interaction between the number of restaurant chains and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.6. Extension: impact of EOTHO on footfall by day of the week

	Mon (1)	Tue (2)	Wed (3)	Thu (4)	Fri (5)	Sat (6)	Sun (7)
			Panel A: DiD estimates [(a)]				
Intensity: Log of outlets in EOTHO	-0.020***	0.011***	0.020***	0.001	0.001	-0.002	0.003
	(0.006)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
			Panel A: IV estimates [(a)]				
Intensity: Log of outlets in EOTHO	-0.023***	0.014***	0.023***	-0.001	0.001	-0.005	0.002
	(0.007)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Day, week & LAD FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area by week FE	County	County	County	County	County	County	County
LAD-specific linear trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variable is the natural logarithm of the footfall index for the relevant day of the week. The reported coefficients correspond to the interaction between the intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 1,500 observations and 150 clusters.

Table A.7. Impact of EOTHO on footfall in the supermarket & pharmacy category

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Footfall [(a)]			
Intensity: Log of outlets in EOTHO	0.001	0.001	-0.010***	-0.009***	-0.011***	-0.031***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
F-statistic	N/A	N/A	N/A	225	196	171
Intensity: Log of outlets in EOTHO per capita	0.005***	0.006***	-0.001	-0.014***	-0.018***	-0.056***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.006)	(0.009)
F-statistic	N/A	N/A	N/A	50	89	71
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June to 6 September. The dependent variable is the natural logarithm of the footfall index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters.

Table A.8. Impact of EOTHO on overall job posts excluding food preparation & service and hospitality & tourism

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Job posts [(a)]			
Intensity: Log of outlets in EOTHO	-0.017***	-0.012**	0.001	-0.002	0.005	0.017***
	(0.005)	(0.006)	(0.004)	(0.008)	(0.007)	(0.005)
F-statistic	N/A	N/A	N/A	129	104	96
Intensity: Log of outlets in EOTHO per capita	0.016	0.018	0.008	-0.003	0.008	0.029***
	(0.017)	(0.014)	(0.006)	(0.013)	(0.011)	(0.010)
F-statistic	N/A	N/A	N/A	34	49	36
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June to 6 September. The dependent variable is the natural logarithm of the job post index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,220 observations and 146 clusters.

Table A.9. Robustness check: using official figures from HMRC

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Footfall [(a)]						
Intensity: Log of outlets in EOTHO (from official figures)	0.038***	0.035***	0.013***	0.049***	0.051***	0.022***
	(0.005)	(0.005)	(0.003)	(0.006)	(0.006)	(0.004)
F-statistic	N/A	N/A	N/A	220	194	169
Panel B: Job posts [(b)]						
Intensity: Log of outlets in EOTHO (from official figures)	0.027	0.047**	0.030*	0.059**	0.080***	0.073***
	(0.019)	(0.021)	(0.017)	(0.028)	(0.029)	(0.024)
F-statistic	N/A	N/A	N/A	220	194	169
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: The table presents DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variables are the natural logarithm of the footfall index and job post index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.10. Robustness check: using a time-varying measure of intensity

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Footfall [(a)]						
Intensity: Log of outlets in EOTHO	0.073***	0.063***	0.031***	0.101***	0.097***	0.033***
	(0.010)	(0.009)	(0.006)	(0.011)	(0.010)	(0.006)
F-statistic	N/A	N/A	N/A	713	901	1,091
Intensity: Log of outlets in EOTHO per capita	0.002	0.004	0.007	0.025***	0.037***	0.048***
	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
F-statistic	N/A	N/A	N/A	44	76	73
Panel B: Job posts [(b)]						
Intensity: Log of outlets in EOTHO	0.060**	0.081***	0.054***	0.109**	0.130***	0.093***
	(0.027)	(0.025)	(0.015)	(0.052)	(0.046)	(0.028)
F-statistic	N/A	N/A	N/A	428	549	714
Intensity: Log of outlets in EOTHO per capita	0.012	0.011	0.016	0.078**	0.100***	0.104***
	(0.012)	(0.015)	(0.015)	(0.036)	(0.038)	(0.039)
F-statistic	N/A	N/A	N/A	30	39	38
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: The table presents DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variables are the natural logarithm of the footfall index and job post index. The reported coefficients correspond to the interaction between the timing varying intensity measures and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.11. Robustness check: using take-up as the measure of intensity

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Footfall [(a)]						
Intensity: Take-up of EOTHO	-0.124	-0.286	-1.240***	13.06***	12.24***	10.61***
	(0.473)	(0.395)	(0.263)	(4.304)	(3.620)	(2.906)
F-statistic	N/A	N/A	N/A	10	12	23
Panel B: Job posts [(b)]						
Intensity: Take-up of EOTHO	0.431	0.161	1.024	13.18	16.72**	26.90**
	(1.270)	(1.296)	(1.031)	(8.074)	(8.383)	(10.68)
F-statistic	N/A	N/A	N/A	9	9	25
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: The table presents DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variables are the natural logarithm of the footfall index and job post index. The reported coefficients correspond to the interaction between the intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.12. Robustness check: restricting the sample for footfall to match that used for jobs.

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Footfall [(a)]						
Intensity: Log of outlets in EOTHO	0.040***	0.037***	0.014***	0.056***	0.060***	0.025***
	(0.006)	(0.006)	(0.003)	(0.007)	(0.007)	(0.006)
F-statistic	N/A	N/A	N/A	129	104	96
Intensity: Log of outlets in EOTHO per capita	0.039***	0.041***	0.010***	0.089***	0.097***	0.044***
	(0.004)	(0.006)	(0.017)	(0.015)	(0.014)	(0.012)
F-statistic	N/A	N/A	N/A	34	49	36
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: The table presents DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variable is the natural logarithm of the footfall index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,220 observations and 146 clusters.

Table A.13. Robustness check: impact of EOTHO on job posts in 2020 relative to 2019

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Job posts (a)			
Intensity: Log of outlets in EOTHO	0.037*	0.047**	0.027	0.053*	0.068**	0.067***
	(0.020)	(0.020)	(0.017)	(0.029)	(0.028)	(0.025)
F-statistic	N/A	N/A	N/A	129	104	96
Intensity: Log of outlets in EOTHO per capita	0.015	0.028	0.020	0.085*	0.110**	0.117**
	(0.020)	(0.026)	(0.015)	(0.047)	(0.045)	(0.047)
F-statistic	N/A	N/A	N/A	34	49	36
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: The table presents DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June to 6 September. The dependent variable is the natural logarithm of the job post index in 2020 relative to 2019. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,220 observations and 146 clusters.

Table A.14. Robustness check: using number of establishments from restaurant chains as the instrument

	IV estimates		
	(1)	(2)	(3)
	Panel A: Footfall (a)		
Intensity: Log of outlets in EOTHO	0.046***	0.041***	0.019***
	(0.007)	(0.006)	(0.003)
F-statistic	49	57	63
Intensity: Log of outlets in EOTHO per capita	0.058***	0.069***	0.033***
	(0.008)	(0.008)	(0.007)
F-statistic	30	32	35
	Panel B: Job posts (b)		
Intensity: Log of outlets in EOTHO	0.045	0.063**	0.067***
	(0.028)	(0.029)	(0.021)
F-statistic	85	75	85
Intensity: Log of outlets in EOTHO per capita	0.058	0.086*	0.097***
	(0.045)	(0.045)	(0.035)
F-statistic	10	20	18
Day, week & LAD fixed effects	Yes	Yes	Yes
Area by week fixed effects	Region	County	County
LAD-specific linear trends	No	No	Yes

Note: The table presents IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variables are the natural logarithm of the footfall index and job post index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.15. Reduced-form estimates

	(1)	(2)	(3)
	Panel A: Footfall [(a)]		
No. of restaurant chains	0.003***	0.003***	0.001***
	(<0.001)	(<0.001)	(<0.001)
Adjusted R-squared	0.881	0.897	0.915
	Panel B: Job posts [(b)]		
No. of restaurant chains	0.004**	0.005***	0.004***
	(0.002)	(0.002)	(0.001)
Adjusted R-squared	0.829	0.849	0.889
Day, week & LAD fixed effects	Yes	Yes	Yes
Area by week fixed effects	Region	County	County
LAD-specific linear trends	No	No	Yes

Note: The table presents OLS results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variables are the natural logarithm of the footfall index and job post index. The reported coefficients correspond to the interaction between the number of restaurant chains and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.16. Robustness check: using the number of restaurant chains with a centralised decision as the instrument

		IV estimates	
	(1)	(2)	(3)
	Panel A: Footfall [(a)]		
Intensity: Log of outlets in EOTHO	0.050***	0.051***	0.021***
	(0.006)	(0.006)	(0.004)
F-statistic	226	206	183
	Panel B: Job posts [(b)]		
Intensity: Log of outlets in EOTHO	0.061**	0.081***	0.070***
	(0.028)	(0.029)	(0.023)
F-statistic	131	106	99
Day, week & LAD fixed effects	Yes	Yes	Yes
Area by week fixed effects	Region	County	County
LAD-specific linear trends	No	No	Yes

Note: The table presents IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2020 to 6 September 2020. The dependent variables are the natural logarithm of the footfall index and job post index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,850 observations and 155 clusters; in panel (b) 10,220 observations and 146 clusters.

Table A.17. Robustness check: impact of EOTHO on job posts in 2019

	DiD estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Job posts [(a)]			
Intensity: Log of outlets in EOTHO	-0.010	0.001	0.004	0.005	0.012	0.005
	(0.010)	(0.012)	(0.007)	(0.012)	(0.014)	(0.009)
F-statistic	N/A	N/A	N/A	129	104	96
Intensity: Log of outlets in EOTHO per capita	-0.005	0.007	0.002	0.009	0.019	0.009
	(0.008)	(0.010)	(0.008)	(0.019)	(0.022)	(0.016)
F-statistic	N/A	N/A	N/A	34	49	36
Day, week & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by week fixed effects	Region	County	County	Region	County	County
LAD-specific linear trends	No	No	Yes	No	No	Yes

Note: The table presents DiD and IV results estimated using data at the LAD level for ten calendar weeks from 29 June 2019 to 6 September 2019. The dependent variable is the natural logarithm of the job post index. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for dates in which the scheme was live. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 10,220 observations and 146 clusters.

Table A.18. Robustness check: Controlling for a four-week pre-trend

	DiD estimate (1)	IV estimate (2)
	Panel A: Footfall [(a)]	
Intensity: Log of outlets in EOTHO	0.057***	0.086***
	(0.007)	(0.011)
Four-week pre-trend	-0.147**	-0.181***
	(0.057)	(0.066)
F-statistic	N/A	245
	Panel B: Job posts [(b)]	
Intensity: Log of outlets in EOTHO	0.056*	0.084**
	(0.031)	(0.042)
Four-week pre-trend	-0.412***	-0.411***
	(0.084)	(0.083)
F-statistic	N/A	125
County & day fixed effects	Yes	Yes

Note: DiD and IV results estimated using data at the LAD level. The dependent variable corresponds to the difference in the natural logarithm of the respective index between the week commencing 27 July 2020 (the week before the scheme went live) and the week commencing 24 August 2020 (the last full week in which the scheme was live) for each day of the week. The pre-trend corresponds to the difference in the natural logarithm of the respective index between the week commencing 29 June 2020 (five weeks before the scheme went live) and the week commencing 27 July 2020 (one week before the scheme went live) for each day of the week. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 1,085 observations and 155 clusters; in panel (b) 1,022 observations and 146 clusters.

IV. Impact on employment

Although our results suggest an effect on job posts, they do not measure the direct impact on employment. A positive and transitory effect on job posts could still imply a permanent increase in the number of employees. In this subsection we analyse the effect of EOTHO on employment. We use data on the total number of employees, as well as full-time and part-time employees, in the food and service sector (2007 SIC sector 56), by LAD from the Business Register and Employment Survey (BRES).

The information on employment corresponds to a snapshot in time from the month of September of each year and for the period between 2015 and 2020. In this way, the data from 2019 provides information before the pandemic, while 2020 covers the month immediately after the EOTHO scheme ended. Compared to our daily data on footfall and job posts, the main limitation for this outcome – given the frequency of the data publicly available – is the lack of information for the period just before the scheme started. This precludes before-and-after comparisons within the same year and meaning we cannot consider the differential economic impact of COVID-19 pre-EOTHO. Another challenge is how the interaction with other schemes (e.g., furlough scheme) may have affected employment figures.

However, measuring the effect on employment could give a sense of longer-term effects of the policy. Table A.19 presents the estimates from our preferred DiD and IV specifications for the total number of employees, as well as for full-time and part-time employees. The DiD and IV coefficients indicate a small but negative and significant effect on the total number of employees, driven by a decline in full-time employment, with no significant effect on part-time employees. A one standard deviation increase in the number of participants in EOTHO led to a 1.6%-3.8% decrease in the total number of employees in the food and services sector among PUAs in the UK.

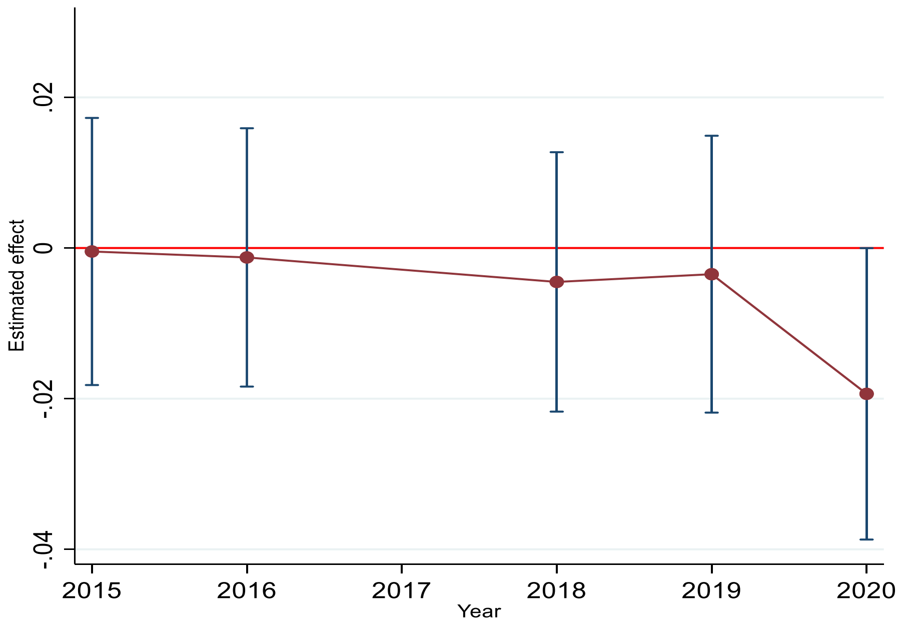
For total number of employees, Figure A.11 contains the event study graph from our preferred DiD specification and using the number of outlets in EOTHO as the measure of intensity of treatment. We observe that coefficients are close to zero across the years prior to 2020, with 2017 being the omitted year. Our estimates indicate that while the EOTHO scheme led to higher activity in the labour market in terms of job adverts more intensive use of EOTHO is not associated with higher employment in September 2020, relative to September 2019 levels (although, as discussed above, considerable caution is needed here given issues with the timing of the employment data).

Table A.19. Impact of EOTHO on employment

	DiD estimates			IV estimates		
	Total employees (1)	Full-time employees (2)	Part-time employees (3)	Total employees (4)	Full-time employees (5)	Part-time employees (6)
Panel A: Employment indicators [(a)]						
Intensity: Log of outlets in EOTHO	-0.017**	-0.029***	-0.014	-0.024**	-0.048***	-0.014
	(0.008)	(0.009)	(0.009)	(0.011)	(0.013)	(0.013)
F-statistic	N/A	N/A	N/A	196	196	196
Intensity: Log of outlets in EOTHO per capita	-0.016**	-0.021**	-0.013	-0.038**	-0.075***	-0.022
	(0.007)	(0.011)	(0.008)	(0.017)	(0.021)	(0.019)
F-statistic	N/A	N/A	N/A	89	89	89
Year & LAD fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Area by year fixed effects	County	County	County	County	County	County

Note: The table presents DiD and IV results estimated using annual data at the LAD level for the month of September for the period 2015 to 2020. The dependent variable is the natural logarithm of the respective employment indicator. The reported coefficients correspond to the interaction between the respective intensity and a dummy equal to 1 for the year 2020. N/A: Not applicable. Standard errors in parentheses clustered at the LAD level; *** p<0.01, ** p<0.05, * p<0.1. Results in panel (a) use 882 observations and 147 clusters.

Figure A.11. Impact of EOTHO on employment



Note: Annual estimates for the effect of EOTHO on total employees using data at the LAD level for the month of September in each year. The estimates were obtained from our preferred DiD specification with the intensity of use of the scheme measured using the log number of outlets in EOTHO (column 1 of Table A.19). The vertical black lines depict 95% confidence intervals.

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