STATE OF HUNGER

YEAR TWO TECHNICAL ANNEX

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the trussell trust
Stop UK Hunger

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CONTENTS

1. INTRODUCTION

This technical annex accompanies the second main State of Hunger report published in May 2021. Building on the State of Hunger technical annex (Sosenko et al, 2019) it provides a more detailed description of the technical statistical analyses employed in year two of the study. For an overview of the design and implementation of the study as a whole, please refer to the technical annex that accompanied State of Hunger (Sosenko et al, 2019).

The annex is structured as follows. The next section (Section 2) provides a description of the methodology for estimating the unique households, and people that were supported by food banks in 2019/20. An overview of national household survey datasets that were analysed for the second year of the State of Hunger research is provided in Section 3. These datasets come from the Food and You survey and from the Understanding Society survey (UKHLS). The following section (Section 4) describes the methodology of the survey of people referred to food banks in the Trussell Trust network, which is the most important data source for the whole State of Hunger research programme. The remaining four sections (Sections 5-8) describe four statistical modelling exercises undertaken in the second edition of the study. Table 1 indicates the sections of the main report to which these four modelling sections correspond.

Table 1 A map of technical annex Sections 2-8 and main report sections

Technical annex section number and title	Main report section title	Main report page number
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2. ESTIMATING NUMBERS USING FOOD BANKS

In Chapter 3 of the main State of Hunger 2021 report (on p.27) summary figures are presented for the number of food banks, food parcels, and households using them, including the point that nearly half of these households used a food bank multiple times. The number of unique households who used a food bank in the Trussell Trust network in 2019/20 was calculated using the Trussell Trust's referral database. This was achieved by summing up the first occurrences of each unique client ID (which signifies a unique household). This count was decreased by 5% to adjust for repeat visits by the same household not captured under a single unique ID, i.e. a household could have moved since previously being supported and would likely be issued with a new unique ID in that situation.[1] A similar exercise was carried out to estimate the number of unique adults and children. First, for each first occurrence of the unique client id the number of parcels going to children and adults were summed. These were then both decreased by 5% and subsequently summed together to get the total number of unique people supported by food banks in the Trussell Trust network in 2019/20.

To estimate the total number of households that were supported by a food bank in the Trussell Trust network or an independent food bank (in the Independent Food Aid Network, IFAN) a further calculation was carried out using two pieces of information: that independent food banks constituted around 46% of all food banks in 2020,[2] and that the average volume of food parcels distributed among all independent food banks in Scotland is comparable to the average for food banks in the Trussell Trust network (IFAN and A Menu for Change, 2019). It was extrapolated from that, that the combined number of unique households who used any food bank in 2019/20 was around 2.5% of all households in the UK (1.35% the Trussell Trust, 1.15% independent food banks). A very slight adjustment for cross-use of the Trussell Trust and independent food banks was carried out but it did not effectively change this figure of 2.5%.[3]

1 The 5% decrease is the research teams best estimate of a correcting factor with the information available.

2 IFAN regularly updates its figures on UK-wide independent food banks. The count published on IFAN website was 994 in late January 2021. https://www.foodaidnetwork.org.uk/independent-food-banks-map

3 This adjustment was based on a question in the Wave 2 survey about receiving support from food banks outside of the Trussell Trust network. Between 2-4% of respondents to that survey said they had also received support from a food bank outside of the Trussell Trust network.

3. NATIONAL HOUSEHOLD SURVEY DATASETS ANALYSED

Food and You

Food and You is a biennial national survey with a representative sample of adults aged 16 and over. It is sponsored by the Food Standards Agency and covers England, Wales and Northern Ireland. The survey collects information about the public's reported behaviours, attitudes and knowledge relating to food safety and food issues. It also measures food insecurity using the adult version of Household Food Security Survey Module.[4]

Data from Wave 4 (2016) and Wave 5 (2018) was used (see Section 5 of this Annex). Wave 4 consisted of 3,118 interviews and fieldwork was conducted from May to September 2016. Wave 5 consisted of 2,241 interviews. Fieldwork was conducted from June to November 2018.[5]

Descriptive analyses of the pooled dataset utilised information about complex survey design, as follows: the provided population weight was used as-is; a purpose-made clustering variable was created by grouping cluster code with survey year; and a purpose-made stratification variable was analogically created by grouping stratum code with survey year. Population weights are used for obtaining the correct population profile while cluster and stratum information is used for obtaining correct confidence intervals.

UKHLS ('Understanding Society')

The UK Household Longitudinal Survey (UKHLS), widely known as 'Understanding Society' survey, is the largest longitudinal household panel study in the UK. UKHLS started in 2009 with a sample of around 40,000 households. It included most of the respondents from the predecessor survey, the British Household Panel Survey (BHPS) which ran from 1991-2009 and had around 10,000 households in it. UKHLS is a multi-topic survey. 'Core' questions are asked in every wave (edition) of the survey while other topics are covered on a periodic basis. Information is collected from all household members; parents provide information for children under 10.[6]

Participants from the main UKHLS sample were asked to complete an online survey monthly between April-July 2020 and bimonthly from September 2020. The survey attempts to interview all adult household members in each wave as well as collecting some household-level information. This survey covers the impact of the pandemic on the welfare of UK individuals, families and wider communities. Core modules include household composition, coronavirus illness, physical and mental health, loneliness and employment. Food bank use and food insecurity were asked in selected editions of the survey (see Sections 6 and 7 of this annex). The exact questions used to identify food insecurity were not the standard Household Food Security Survey Module (HFSSM) set, as described on p.20 of the Main Report, but they are believed to capture the same concept (see further discussion at the beginning of Section 6 of this report).

It is also important to note that the response rates to these special waves of UKHLS were relatively low (around 42% of the main Wave responding sample)[7]

4 See https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-us/survey-tools/

5 More details on the Food and You dataset are available at https://www.food.gov.uk/research/food-and-you

6 More information about UKHLS is available at https://www.understandingsociety.ac.uk/about/about-the-study

7 More information about this dataset can at https://www.understandingsociety.ac.uk/topic/covid-19

4. METHODOLOGY OF THE SURVEY OF PEOPLE REFERRED TO FOOD BANKS IN THE TRUSSELL TRUST NETWORK

A major survey of people referred to food banks in the Trussell Trust network was conducted over 15 January - 12 March 2020. It was a repeat of the equivalent survey conducted in State of Hunger (Sosenko et al, 2019); see the technical annex of that report for a description of the original methodology.

The aim of the survey was to collect socio-demographic information about the respondents' households and to identify their experiences in the year prior to the survey. Only one adult per household was surveyed and repeat users were only surveyed once. The survey included some questions relating to the household as a whole and some seeking an individual response from the individual completing the survey. Where we discuss demographic descriptions of people referred to food banks, we generally mean the person that took part in the survey. The actual demographics of all people supported by food banks in the Trussell Trust network might differ slightly from these demographics.

Some questions about employment activity do cover other household members. It is a convention of virtually all socio-economic and poverty research to assume that households pool their resources, so measures like income refer to the household as a whole. Strictly speaking, it is really what – using DWP terminology – would be called the 'Benefit Unit', at least where income and benefits are concerned – the householder and any partner and dependent children.

The survey was administered on tablets, with the questionnaire designed for self-completion and help available from food bank staff and volunteers. The survey was conducted at 43 food bank organisations, representing 10% of the Trussell Trust network. Nearly all of the participating food banks (40) were the same as those that took part in the survey for State of Hunger (Sosenko et al, 2019).

The food banks were originally selected using stratified random sampling with probability proportional to size, measured by the number of food parcels distributed between June 2017-May 2018. Each of the 12 regions of the UK (nine in England, Wales, Scotland, Northern Ireland) had an approximately proportional share of the sample of 43 food bank organisations, representing that region's share of food parcels distributed by the Trussell Trust. For example, four food bank organisations were sampled from a region representing 10% of the Trust's supply of food parcels.

Each region (apart from Northern Ireland) was further divided into strata using the ONS 2011 Area Classification for Local Authorities version 2. The number of strata in each region reflected the target number of food bank organisations to be sampled from that region, so a region representing 10% of the Trust's supply of food parcels was divided into four strata, each of approximately homogenous character and representing roughly 2.5% of the Trust's supply of food parcels. To illustrate, Wales had the following three strata: 'Mining legacy', 'Cities, industry & services' and 'Countryside & town'. Finally, one food bank organisation was sampled from each stratum using probability proportional to size. For practical reasons a 'de minimis' criterion was employed whereby small food bank organisations (<500 food parcels per year) were not eligible for participation, as it was judged that they would struggle to reach the target number of responses in the survey window.

This method of sampling is a common practice, and the proportionality to size means that the results can be representative of the population of people supported by food banks in the Trussell Trust network. This in turn may mean that no weighting needs to be applied to achieve this result – such a survey can be 'self-weighting'. The three new (substitute) food banks in year two were selected from the relevant strata using the same method.

Each food bank was asked to collect 30 responses, which meant that the target number of responses was over 1,100. The survey gathered 716 responses before it was terminated due to the introduction of social distancing measures. While the survey would have been self-weighting by design if the target number of responses had been reached, due to a smaller than expected number of responses, a decision was taken to weight the results, to mirror the population of all unique individuals referred to food banks in the Trussell Trust network during the survey period. An additional argument for weighting was that some survey administrators felt that people coming to the food bank with children were on average more in a rush than other service users, and hence were less likely to accept the invitation to complete the survey, resulting in some response bias. The Trussell Trust referral data was used to construct weights to ensure that the correct proportions of different age groups, household types and regions were included.

Throughout this report, results of this early 2020 State of Hunger survey are juxtaposed with results of the original survey conducted in late 2018 and a later survey 'special version' conducted in mid-2020. Because this early 2020 survey had to be weighted, for methodological consistency it was decided to also weight results of the first survey from late 2018 (which were not weighted for State of Hunger 2019). This was largely non-consequential, but in the case of a few variables, there are slight differences between late 2018 results reported here and late 2018 results reported in the previous State of Hunger report (Sosenko et al, 2019).

For a few detailed analyses that required more statistical power, data from the early 2020 survey was merged with data from the original State of Hunger survey in late 2018 (n=1,130), resulting in a combined sample of 1,846 respondents. This data was weighted using the same main weight that was used for other analyses of each of these two surveys, i.e. a composite weight of household composition and the number of food bank visits in the past 12 months. The derivation of weights is discussed further below.

The special version of the survey conducted in mid-2020, during the Covid-19 pandemic, deviated more significantly from the other two surveys in its administration and mode. This was necessitated by the changed manner of operation of food banks during this

period. People picking up food parcels from a distribution centre, or having one delivered to their home, in the same set of target areas, received a letter, inserted within their food parcel, inviting them to participate, with the offer of a small financial/ voucher as an incentive to participate.

Overall, the survey had a reduced set of questions, but some additional ones relating to the Covid-19 emergency, and was accessible via links for on-line completion, with a small number of participants taking part via a telephone interview. The demographic profile of users during this period was different. It was felt that this partially reflected the changing demographic due to the Covid-19 pandemic but may have also been due to the difference in survey method. To reflect this and improve the representativeness of the survey the data were weighted with additional variables to the main surveys (see below).

One important methodological aspect of all surveys conducted as part of the State of Hunger research programme was that they were completed only once by each respondent; those seen again at the food bank were not asked to do the survey again. Combined with the survey weight being constructed in a way consistent with this, it meant that the socio-demographic profile of people referred to food banks obtained through these surveys were not exactly the same as the profile that participating food banks saw 'on the ground' during the survey period. This is because the profile they saw was influenced by those who made repeat visits.

Because the survey was fielded for two months (and weighted accordingly), the profile presented in this report is also somewhat different from the profile of unique service users who visited a food bank over the period of a whole year (in this case, 2019/20). In general, the longer the survey data collection window (or the longer the time period used when constructing the weight), the more the profile is influenced by characteristics of infrequent users. In contrast, the shorter the survey data collection period (or the shorter the time period used when constructing the weight) – the closer we were to a weekly 'snapshot' – the more the profile is influenced by characteristics of frequent users (because the fact that they make more visits means that they have a higher chance of being captured by the survey, even when everyone is surveyed only once). The profile obtained through the State of Hunger survey sat somewhere between the weekly and the annual extremes in this regard.

No choice of data collection time window for the survey (or weight) is 'right' or 'wrong' per se. The 'snapshot' picture is more suitable if the aim is to understand drivers of crises. Because 'snapshot' surveys by design are skewed towards people who make repeat visits, drivers of chronic destitution (which necessitates repeated visits) come into better light then. If the aim is, however, to build a socio-demographic profile of unique service users over one year, using an annual weight is more appropriate (fielding a survey for several months would not be practical). The disadvantage is that the annual picture may give less emphasis to drivers of more persistent destitution.

Weighting

The purpose of weighting survey results is to ensure that the data from the sample survey has the same composition as the relevant population (all unique individuals and households who used any food bank in the Trussell Trust network in the same period as the survey period), in terms of key characteristics, particularly household composition and frequency of use of food banks. Weighting was particularly needed for the Wave 2 survey (early 2020) and for the additional survey in mid-2020 because of the interruption to fieldwork in the former case and the enforced different method of survey administration and low response rate in the latter case. Wave 1 (late 2018) survey results were retrospectively weighted for methodological consistency.

The analysis has been done using two weights. The main weight was used for the vast majority of analyses and an auxiliary weight was used in a small number of cases when the main weight was less appropriate.[8] The weights are positive numbers with a mean of 1 and are effectively separate for the three State of Hunger surveys (late 2018, early 2020 and mid-2020).

The construction of the main weight

This weight was constructed by multiplying contributing (feeding) weights (these contributing weights are described at the end of the section on weighting):

- For data from Waves 1 and 2, the weight is a product of (a) household composition weight and (b) 'the number of food bank visits over the past 12 months' weight (i.e. visits to a food bank in the Trussell Trust network by the survey respondent)
- For data from the mid-2020 State of Hunger survey, the weight is a product of (a) household composition weight, (b) age weight, (c) 'region of the UK' weight, (d) 'whether the respondent used a food bank before the Covid-19 crisis (March 2020)' weight. Note that there was no question in the mid-2020 State of Hunger survey about the number of times the respondent used a food bank, so it was not possible to construct the 'number of food bank visits over the past 12 months' weight.

The actual target values (proportions) used in building each of these weights, for each of the categories of the relevant variables, are shown in tabular form in Appendix A at the end of this annex.

The construction of the auxiliary weight

The The auxiliary weight was used in a small number of cases where there was a justified suspicion that the main weight distorted results from Wave 1 (very large differences between weighted and unweighted frequencies). The weight leaves Wave 1 results unweighted. Wave 1 was intended to be self-weighting and has a similar compositional pattern to the target population.

8 As an exception, the household composition variable within each dataset was weighted with the household composition weight (hh_weight), That was because (unusually) the referral dataset had near-complete information about household composition, and only that information was needed to weight this particular variable.

This weight was constructed in the following way:

- Records from Wave 1 were given a weight of 1.
- For data from Wave 2, the weight is a product of (a) household composition weight and (b) 'the number of food bank visits over the past 12 months' weight.
- For data from the additional (mid-2020) survey, the weight is a product of (a) household composition weight, (b) age weight, (c) 'region of the UK' weight, (d) 'whether the respondent used a food bank before the Covid-19 crisis (March 2020)' weight.

The construction of contributing / feeding weights

The following weights fed into the main weight and the auxiliary weight:

Household composition ('hh_weight', based on 5 categories); the number of food bank visits in the past 12 months ('nvisits12m_weight', based on 8 categories), age ('age_weight', based on 3 categories), region of the UK ('rgn_weight', based on 12 categories), whether the respondent used a food bank before March 2020 ('used_fb_pre_march_weight', based on 2 categories).

These weights were constructed using the following procedure:

(a) Using data from the Trussell Trust's referral database, create reference variables for the number of visits in the last 12 months, the household composition, the government office region, and whether the referred person had been supported by a food bank before March 2020. The pre-existing age variable within the database was also used;

(b) Using data from the Trussell Trust's referral database, retain records from the relevant survey period; and within that only the first instances of multiple visits by the same household;

(c)Using data from the Trussell Trust's referral database, run frequencies for the relevant variable (these results, expressed as percentage composition, are the 'target' proportions and are shown in Table A.1 in Appendix A of this technical annex);

(d) in the survey dataset, create a variable that mirrors the variable previously created in the referral dataset, in terms of values and value labels;

(e) in the survey dataset, use frequencies from step (c) to generate a weight variable. For each category of the relevant variable (e.g. age = 25-64), the weight is the proportion of the population in the referral database in a given category multiplied by the number of all records in the survey and divided by the number of records in the survey who are in that given category.

These weights are positive numbers with a mean of 1.

Derived variables

Certain variables which have been derived from a range of specific questions in the survey, and which relate to key wider benchmarks, are of particular interest, and the derivation of these is described below.

Destitution

Respondents were categorized as destitute if they met one or both of the underlying criteria: being 'destitute on essentials' and being 'destitute on income'. The definition of destitution is given in Box 3.1 on p.40 of the main State of Hunger 2021 report, based on the Joseph Rowntree Foundation studies of Destitution in the UK (Fitzpatrick et al 2020).

Respondents were tagged as 'destitute on essentials' if they lacked two or more of the six essentials. The destitution status of respondents (who lived in own accommodation) with at least one missing response on the suite of questions about essentials was categorised as missing, unless the non-missing responses indicated lacking two or more essentials. In turn, the destitution status of respondents who lived in communal accommodation or were rough sleeping with at least one missing response on the suite of questions about essentials except for the two questions about lighting and heating was categorised as missing, unless the non-missing responses indicated lacking two or more essentials.

Respondents were tagged as 'destitute on income' if they fell into one of the following categories:

- Single person with income below £70 per week (net income after housing costs)
- Couple living on their own, or a lone parent with 1-2 dependent children, with income below £100 per week
- Lone parent with more than two dependent children, or a couple living with other adults, or a couple with 1-2 dependent children, with income below £140 per week
- Couple with more than two dependent children and income below £200 per week.

Disability

The disability indicator was derived from the survey question 'Are your day-to-day activities limited because of a health problem or disability which has lasted, or is expected to last, at least 12 months?'. Those responding 'Yes, a lot' or 'Yes, a little' were categorized as having a disability. A second, analogically worded question asked about 'any other household member, including children'. Data from the first and second question were used to derive a variable indicating a household containing more than one disabled person. This definition of disability is now standard in the Census and major government surveys.

Food insecurity

A shorter, 6-item version of adult HFSSM was used to measure household food insecurity in the State of Hunger survey of people referred to food banks in the Trussell Trust network. The food insecurity score was calculated in exactly the same way as the one used by the US Department of Agriculture, an organisation that developed HFSSM. See https://www.ers.usda.gov/media/8282/short2012.pdf for details. The analysis of the Food and You data reported in Section 5 below uses the full 10-item scale.

Proportion of rental costs covered by housing allowance

Respondents who were in rental accommodation were asked how much rent they were paying and whether they were in receipt of housing allowance. Those who indicated housing allowance were further asked if (and by how much) they needed to top up their housing allowance to pay the rent. These pieces of information were combined to derive the variable indicating the proportion of rental costs covered by housing allowance.

Equivalised household income

To avoid having to ask a large number of questions about other adults (not a partner) living with the respondent, and their income, a decision was made to focus on Benefit Unit income rather than household income. (The Benefit Unit in this instance is the respondent using the food bank and any partner or dependent children). For simplicity however, the Main Report uses the term 'household income'.

Single respondents were asked about their income in the last month (after tax and National Insurance) while those living with a partner were asked about the combined income of the couple. The questionnaire also asked about the number of dependent children, including those aged 16-19 for whom the family was receiving Child Benefit. This information was combined to calculate equivalised Benefit Unit income. The modified OECD scale was used for income equivalization.

The income question collected banded information, e.g. 'between £430 - £649 in the past month (= between £100 - £149 a week)'. A continuous variable was then derived from this banded variable. Rather than choosing mid-band points, the following calculation was carried out.

The income data was cross-tabulated with household composition data and information about cell frequencies was exploited to 'shift' the mid-band value downwards or upwards, depending on the number of respondents in adjacent cells. Importantly, this 'shifting' was proportional rather than arbitrary. For example, if 20 single respondents indicated income in the band immediately below £430-£649 and 10 single respondents indicated income in the band immediately above £430-£649, the income assigned to single respondents who fell in the £430-£649 band would be proportionally shifted downwards from the mid-point, resulting in the assigned monthly income of £503 rather than £540. This method is based on a reasonable assumption that the distribution of data points within a band is not completely uniform and independent from distribution in other bands, but instead that it forms part of a larger distributional picture.

5. MODELLING OF PREDICTORS OF FOOD INSECURITY IN FOOD AND YOU POOLED 2016 AND 2018 DATA

The Food and You Survey was until recently the main UK survey which measured food insecurity using the internationally recognised HFSSM scale. Findings from this survey were used to provide a descriptive account of food insecurity in State of Hunger (Sosenko et al, 2019), along with brief reference to regression modelling of the food insecurity score. This source was revisited in this second State of Hunger study, using an additional more recent wave of data alongside the previous data, with basic survey details summarized in Section 3 above. The model described in this section is supporting evidence to the section of the main State of Hunger report (pp 78-80) which addresses risk factors and drivers of food insecurity and hunger. It is complementary to the model described in Section 6, which uses a new and more recent data source.

A bivariate analysis of factors associated with food insecurity using the HFSSM measurement, in the Food and You survey data indicated that a number of socio-demographic characteristics were statistically significantly (at the 95% level) associated with food insecurity. Modelling was subsequently carried out to investigate which of those characteristics remained significant in a multivariate context, i.e. accounting for the effects of other characteristics.

With this source, food insecurity is measured by a scale, where the score depends on the number of relevant questions answered in a way which indicated a potential problem of food insecurity. A form of regression analysis is used which is appropriate for this type of 'count' data. The model is estimating how much effect each variable has on the extent or severity of food insecurity for an individual household.

The Food and You survey had a considerably smaller sample in 2018 (2,241, Wave 5) than in 2016 (3,118, Wave 4). Since initial modelling using the 2018 data suffered from large standard errors (due to the sample being relatively small), a decision was made to perform the modelling on pooled 2016 and 2018 data (N = 5,357). The dependent variable was the raw food security score, which ranged from 0 (least food insecure) to 10 (most food insecure). The mean value of this score was 0.7, the standard deviation was 1.8, and the variable had the following distribution:

Table 2: Distribution of the food security score

	Percent, unweighted	Percent, weighted
0	79.07	79.58
1	7.04	7.12
2	3.86	4.47
3	2.99	3.07
4	1.31	1.22
5	1.36	1.24
6	1.18	1.01
7	1.33	1.00
8	0.65	0.47
9	0.50	0.34
10	0.71	0.48
Total	100.00	100.00

Source: Food and You pooled data from 2016 and 2018

Since the dependent variable has a natural upper bound, the recommended model is a generalized linear model (GLM) with family (i.e. distribution form) binomial, link function logit and the number of trials responding to the upper bound.[9] A GLM with family binomial, ten trials, and link logit was therefore employed as the modelling technique. The regression was unweighted; however, a weighted model was also fitted to make sure that coefficients remained stable. In general, while descriptive and comparative statistics should generally be weighted, in regression modelling it is a more open question, depending partly on the context, with comparison of weighted vs unweighted results a sensible check.[10]

All relevant socio-demographic variables identified in the bivariate analysis were tried in the initial, exploratory model. Unfortunately, the Food and You survey did not have information about adverse life events, lacking support, or problems with the benefit system – information which we would have liked to include and test in the model, based on State of Hunger findings (Sosenko et al, 2019 and Bramley et al, 2021). The country of the UK and gender were added as control variables.

Since the data were pooled, an indicator of survey year (2016/2018) was also included. The 'equivalised household income' variable was derived from a banded household income variable by assigning records the mid-band value and equivalising it using the OECD scale (this increased the amount of information fed into the model, as compared to the original banded income variable). Predictors not significant at the conventional 5% level were subsequently dropped (e.g. ethnicity), resulting in the final model (Table 4). Summary statistics for predictors in the final model are presented in Table 3:

9 For details about this kind of regression see section 6.3.3 in Cameron & Trivedi (2013) Regression analysis of count data (2nd ed), Cambridge: Cambridge University Press

10 See also Valliant, R., & Dever, J. A. (2018). Survey weights: A step-by-step guide to calculation. Stata Press.).

Table 3 Summary statistics for Food and You survey analysis of food insecurity

	count	mean	min	max
Age				
16-24	4022	0.05	0	1
25-34	4022	0.15	0	1
35-44	4022	0.17	0	1
45-54	4022	0.18	0	1
55-64	4022	0.17	0	1
65-74	4022	0.17	0	1
75+	4022	0.12	0	1
Decile of equivalised household income BHC	4022	4.95	1	10
Child under 16 in the household				
No	4022	0.74	0	1
Yes	4022	0.26	0	1
Living with a partner				
No	4022	0.44	0	1
Yes	4022	0.56	0	1
Employment status				
In work	4022	0.56	0	1
Retired	4022	0.29	0	1
Unemployed	4022	0.03	0	1
Other	4022	0.12	0	1
Self-reported health				
Very good	4022	0.33	0	1
Good	4022	0.43	0	1
Fair	4022	0.19	0	1
Bad	4022	0.04	0	1
Very bad	4022	0.01	0	1
Long-term health condition or illness				
No	4022	0.64	0	1
Yes	4022	0.36	0	1
Location				
Urban	4022	0.74	0	1
Rural	4022	0.26	0	1

Highest qualification				
Higher degree or postgraduate qualifications	4022	0.18	0	1
Degree, Postgrad diplomas/ Certs	4022	0.33	0	1
Diplomas in HE/other HE qual. HNC/HND/BTEC Higher	4022	0.14	0	1
A level / GCSE / Apprenticeship	4022	0.23	0	1
Other qualifications (including overseas)	4022	0.01	0	1
No qualifications	4022	0.11	0	1

Source: Food and You pooled data from 2016 and 2018

The coefficients in Table 4 below indicate the effects of given predictors and regard the predicted change in the food security score associated with a change in the predictor (either a one unit change or a change of the predictor's category versus the 'reference' group or category). For example, those living with a dependent child had a predicted food security score higher by 0.17 than those not having a dependent child in the household, while increasing the income decile by one was associated with a decrease in predicted food security score by -0.19. All predictors had the expected sign.

Note that in this model the 'survey year' dummy was significant and had a positive coefficient, meaning that, when the effect of other predictors was accounted for, there was a statistically significant increase in the level of food insecurity between 2016 and 2018. (The bivariate relationship was not statistically significant at 5% level).

Table 4: Results of a regression model predicting food security score in Food and You Survey 2016-18

	Coef.	Std. Err.	Significance (p-value)	95% Conf. Interval
Survey year				
2016	0 (Reference)			
2018	0.65	0.07	0.000	0.53,0.78
Age				
16-24	0 (Reference)			
25-34	0.17	0.08	0.036	0.01,0.33
35-44	0.05	0.08	0.518	-0.11,0.21
45-54	-0.35	0.08	0.000	-0.51,-0.19
55-64	-0.85	0.09	0.000	-1.03,-0.66
65-74	-1.4	0.15	0.000	-1.70,-1.10
75+	-2.4	0.19	0.000	-2.77,-2.02
Decile of OECD-equivalised annual household income BHC (1=lowest)	-0.19	0.01	0.000	-0.21,-0.17
Child under 16 in the household				
No	0 (Reference)			
Yes	0.17	0.05	0.002	0.06,0.27
Living with a partner				
No	0 (Reference)			
Yes	-0.67	0.05	0.000	-0.76,-0.58
Employment status				
In work	0 (Reference)			
Retired	-0.62	0.13	0.000	-0.86,-0.37
Unemployed	0.96	0.07	0.000	0.83,1.10
Other	0.16	0.06	0.004	0.05,0.27
Self-reported health				
Very good	0 (Reference)			
Good	0.49	0.06	0.000	0.37,0.61
Fair	0.88	0.07	0.000	0.74,1.02
Bad	1.18	0.09	0.000	1.00,1.36
Very bad	2.02	0.13	0.000	1.76,2.28
Long-term health condition or illness				
No	0 (Reference)			
Yes	0.4	0.05	0.000	0.30,0.49

Location				
Urban	0 (Reference)			
Rural	-0.11	0.05	0.038	-0.21,-0.01
Highest qualification				
Higher degree or postgraduate qualifications	0 (Reference)			
Degree (undergrad,inc. B.Ed.), Postgrad diplomas/Certs	0.28	0.08	0.000	0.14,0.43
Diplomas in HE/other HE qual.,HNC/HND/BTEC Higher	0.54	0.09	0.000	0.36,0.71
A level / GCSE / Apprenticeship	0.84	0.09	0.000	0.66,1.03
Other qualifications (including overseas)	0.19	0.22	0.383	-0.23,0.61
No qualifications	1.35	0.11	0.000	1.14,1.55
Constant	-2.54	0.13	0.000	-2.79,-2.29

Observations: 4,022

Pseudo R-squared = 0.31 (Efron)

Source: Food and You 2016 and 2018 (pooled)

With regards to the goodness-of-fit, there is no commonly agreed way of measuring it in a GLM.[11] One measure that has been proposed is Efron's pseudo R-squared, which is the squared correlation between the response and the fitted or predicted response. In this case the correlation was 0.557 and its square was 0.31. However, this can only be compared with similar measures and is not to be interpreted as a measure of 'how much' the model explained.

The main findings on potential drivers or risk factors from this model are that older age groups and retired people are less likely to be food insecure, along with those with partners, higher qualifications, higher income, or in work. Higher risks of food insecurity are associated with younger age, having children, unemployment, poor self-reported health and no qualifications.

11 See https://stats.idre.ucla.edu/other/mult-pkg/faq/general/faq-what-are-pseudo-r-squareds/ for an overview.

6. MODELLING OF PREDICTORS OF FOOD INSECURITY USING UKHLS JULY 2020 DATA

We also conducted modelling of predictors of food insecurity during the first Covid-19 lockdown in July 2020 using UKHLS data. This is a new source of data on both food insecurity and use of food bank and similar services, based on special waves of the main household panel survey in the UK, as described in Section 3 above. This is of value both because it is more up-to-date and covers the period of the Covid-19 pandemic and because this source has a wider range of background variables to help predict these variables. This model is reported in Table 4.10 in the main report and discussed on pp.77-80.

Similarly, to what was done using Food and You pooled data in Section 5, associations between socio-demographic characteristics and food insecurity (previously identified as statistically significant in a bivariate analysis) were tested for significance in a multivariate setting. In this case, the food insecurity indicator was reduced to a binary form and the statistical technique was a logistic regression model, the most commonly used for this kind of data. The indicator of being 'food insecure' referred to survey respondents who answered positively one or both of the following questions:

1) 'Still thinking about last week, was there a time when you or others in your household were hungry but did not eat?', combined with the reason 'Because we did not have money for food'

2) 'Still thinking about last week, did you or other adults in the household have smaller meals than usual or skip meals because you could not afford or get access to food?'

These two survey questions were very similar to two key items from the adult version of Household Food Security Survey Module – measuring severe and moderate food insecurity, respectively (see Chapter 2 of the Main Report) – except the time period (one week vs past 12 months). As such, there are strong grounds to take a positive answer to one of these questions as an indicator of food insecurity. However, it needs to be emphasized that this indicator is not identical to the indicator accepted by the State of Hunger study, which utilizes all ten HFSSM questions.

While this indicator reflected the limited questions which were asked in UKHLS, it still represented in our judgement the best way of approximating to a situation of severe food insecurity. Although it has a similar incidence to the fuller measure based on HFSSM, it is technically not exactly the same. The unweighted proportion of food insecure respondents was 2.5% (335 out of 13,457 respondents who could be categorised), the weighted proportion was 4.3% (95% CI: 3.4%-5.4%). Weighting adjusts a sample to make it more representative of the population it was designed to reflect.

The data was collected as part of the July 2020 edition of UKHLS survey, in the last week of July (see Section 3 of this annex for more details about this dataset). The sample size was 13,754, representing a 32.5% response rate relative to the main Wave responding sample.

An exploratory model was fitted first, including all variables identified through the bivariate analysis. Subsequently two predictors were dropped as non-significant (although they had the sign consistent with other State of Hunger evidence): urban-rural location, and long-term health condition. Some categorical variables (e.g. household composition) were simplified to highlight significant effects. Additional variables beyond the socio-demographic were tested, particularly a measure of 'loneliness' as a proxy for lack of informal/social support. The full model including this variable is included in the main report (Table 4.10). However, some questions remain about the interpretation of this variable, which may capture various factors which are not fully represented in this dataset or model. Therefore, to illustrate the sensitivity analyses conducted in this research we report here a variant model excluding that particular variable, as described in Table 5.

The figures in the 'Odds ratio' column indicate effect sizes. Logistic regression models predict the 'odds' of an event (probability of that even divided by one minus that probability). The odds ratio in this case is the ratio of the odds of being food insecure for a group to the odds of being food insecure for the reference group. For example, the odds of being food insecure were 48% higher for respondents who were unemployed than for respondents who were not unemployed. In the case of one continuous predictor (that does not have a reference group), the decile of household income, for a one-decile increase in household income we expected to see about 18% decrease in the odds of being food insecure. Odds ratios only take positive values, with values less than one implying a negative influence, reducing risk, while values of more than one imply a positive influence, increasing risk.

As in Section 5, two versions of the models were fit - weighted and unweighted - and upon a comparative inspection of the coefficients a decision was made to report unweighted results.[12]

12 See Valliant, R., & Dever, J. A. (2018). Survey weights: A step-by-step guide to calculation. Stata Press.

Table 5 Results of a logistic regression model predicting food insecurity status in UKHLS, 2020

	Odds ratio	Robust Std. Err.	Significance (p-value)	95% Conf. Interval
Self-reported health				
Excellent	1 (reference)	.	.	1.00,1.00
Very good	1.11	0.41	0.784	0.54,2.27
Good	2.19	0.78	0.027	1.09,4.39
Fair	4.00	1.51	0.000	1.91,8.36
Poor	6.23	2.72	0.000	2.65,14.65
Health condition				
No	1 (reference)	.	.	1.00,1.00
Yes	1.30	0.25	0.168	0.90,1.88
Decile of current weekly household income BHC (1=lowest)	0.82	0.02	0.000	0.78,0.87
Unemployed				
No	1 (reference)	.	.	1.00,1.00
Yes	1.48	0.29	0.046	1.01,2.18
Ethnicity				
Non-white	1 (reference)	.	.	1.00,1.00
White	0.51	0.11	0.001	0.34,0.77
Age				
16-24	1.28	0.49	0.518	0.60,2.72
25-34	1.73	0.44	0.031	1.05,2.84
35-44	0.76	0.19	0.271	0.46,1.24
45-54	1 (reference)	.	.	1.00,1.00
55-64	0.30	0.07	0.000	0.19,0.49
65-74	0.14	0.05	0.000	0.07,0.28
75+	0.24	0.09	0.000	0.12,0.49
Couple				
No	1 (reference)	.	.	1.00,1.00
Yes	0.57	0.10	0.001	0.42,0.80
Constant				

Observations = 8,394
Wald chi2(15) = 295.80, Prob > chi2 = 0.000
Pseudo R squared = 0.16
Source: UKHLS data from July 2020

Since logistic models belong to the family of GLMs, the model estimates from a logistic regression are maximum likelihood estimates arrived at through an iterative process. Unlike in Ordinary Least Squares regression, they are not calculated to minimize residual unexplained variance. The comment at the end of Section 5 therefore applies equally here, that there is no commonly agreed measure of model fit from a logistic regression. McFadden's pseudo R-squared (reported as default by Stata) was 0.16.

The interpretation of this model and particular effects within are discussed in the main report, pp.77-80. While the general shape of the model is similar to that described in the main report, the omission of the loneliness variable leads to a slightly less good fit to the data, and some moderate changes in the size and significance of the other variables in the model, including unemployment and couple households.

7. MODELLING OF PREDICTORS OF USING 'A FOOD BANK OR SIMILAR SERVICE' IN UKHLS APRIL 2020 DATA

This section of the annex reports modelling mentioned in Chapter 4 of the State of Hunger report, in the section 'Background driver: Lack of informal and formal support' (p.71). It was stated there that a logistic regression model of factors predicting food bank use showed that loss of informal support during the pandemic was a statistically significant predictor, accounting for the effect of other factors. This is of interest as perhaps the first example of using a major national household survey to collect indicators of food bank usage, given also the wide range of individual and household attributes in that survey which can be used in a predictive model. It is simultaneously of interest for coinciding with the first and most extreme month of lockdown in the Covid-19 pandemic.

The data used for this modelling exercise was collected as part of the UKHLS survey supplementary Covid-19 Wave in the last week of April 2020. See Section 3 of this annex for more details about this dataset. The sample size was 17,761, representing a 42% response rate (relative to the main Wave response).

The dependent variable in the model was an indicator based on the following survey question: 'How often has your household used a food bank, or similar service, in the last four weeks?'. The response options were:

- Never
- Less than four times
- Four times or more.

Respondents saying 'less than four times' or 'four times or more' were coded as 1, those who said 'never' were coded as 0, creating a binary dependent variable suitable for binary logistic regression modelling. Some people that reported using a food bank, or similar service may have done so because of non-financial reasons such as shielding.

The unweighted prevalence of reported food bank use was 1.1%, or 182 respondents out of 16,735. The weighted proportion was 1.5% (95% CI: 1.2%-2.0%). This indicates a relatively high prevalence for a monthly period, even though we know from data from the Trussell Trust and IFAN, presented in the main State of Hunger report (p.28) that April 2020 was a peak month for distribution of food parcels. That in turn suggests that special 'alternative' provision and 'similar services' were playing a strong role at that time.

A predictor of key theoretical interest - loss of informal support – was an indicator variable derived from the following survey question: 'Thinking back to earlier this year, before the outbreak of the coronavirus pandemic. How has the help and support you receive from family, friends or neighbours who do not live in the same house/flat as you changed?'. Those who ticked the answer 'I receive less help from some people who

previously helped me' were coded as 1 and those who did not choose this answer were coded as 0.

The initial model included key socio-demographic variables related to financial situation, household composition, ethnicity, health and loss of support. Subsequently the 'white ethnicity' indicator was dropped due to lack of significance (although the sign of the coefficient was consistent with findings in Section 6 above: ethnic minority respondents had higher odds of reporting food bank use than white respondents). The final model is presented in Table 6.

As in Section 6 of this annex, figures in the 'Odds ratio' column indicate effect sizes and direction. The odds ratio in this case is the ratio of the odds of having used a food bank or similar service in April 2020 for a given group to the odds of having used a food bank or similar service in April 2020 for the reference group. For example, the odds were 75% higher for respondents with a long-term health condition or illness than for respondents without it. As in Sections 5 and 6, both weighted and unweighted models were fit and a decision was made to report unweighted results.

Table 6 Results of a logistic regression model predicting food bank use in the past four weeks, UKHLS special Covid-19 Wave, April 2020

	Odds ratio	Robust Std. Err.	Significance (p-value)	95% Conf. Interval
Self-reported current financial situation				
Living comfortably	1.00 (reference	.	.	1.00,1.00
Doing alright	2.14	0.67	0.015	1.16,3.94
Just about getting by	7.84	2.40	0.000	4.31,14.28
Finding it quite difficult	20.47	6.61	0.000	10.87,38.55
Finding it very difficult	28.26	10.31	0.000	13.83,57.78
Long-term health condition or illness				
No	1.00 (reference)	.	.	1.00,1.00
Yes	1.75	0.30	0.001	1.25,2.45
Shielding				
No	1.00 (reference)	.	.	1.00,1.00
Yes	4.61	0.90	0.000	3.14,6.75
Lost informal support in the pandemic				
Not mentioned	1.00 (reference)	.	.	1.00,1.00
Mentioned	1.67	0.38	0.024	1.07,2.62
Living with a partner				
Yes	1.00 (reference)	.	.	1.00,1.00
No	1.80	0.29	0.000	1.31,2.47
Number of children under 16	1.34	0.12	0.001	1.12,1.60
Constant	0.001	0.00	0.000	0.000-0.002

Observations = 8,394
Wald chi2(15) = 295.80, Prob > chi2 = 0.000
Pseudo R squared = 0.16

Source: UKHLS data from July 2020

It is clear that the strongest predictors in this model are current financial condition, and 'shielding' status, with strong effects also from reporting a long-term health condition and not living with a partner. Those who had lost informal support during the pandemic were 67% more likely to use a food bank or similar service. The model with the 'loss of support' predictor fit the data slightly better than a model without it, based on the pseudo R-squared value (0.18 vs 0.17) as well as Akaike Information Criterion (AIC) value (1654 vs 1649).

8. PANEL MODELLING OF FOOD PARCEL UPTAKE AT LOCAL AUTHORITY LEVEL IN ENGLAND

In the second year of the State of Hunger project the research team updated the model that was originally developed in year one and reported in State of Hunger (Sosenko et al, 2019). A detailed description of the original modeling approach can be found in the technical annex to the previous report.[13] The current annex provides an overview of the original exercise and a detailed description of the update in year two.

The original modelling in State of Hunger One

As part of year one research activities, a decision was made to conduct modelling on panel data. A 'panel' refers to a data set which contains repeat observations for a set of entities, such as cities, firms, countries or individuals, or a succession of different time periods, such as years. Panel data are used with increasing frequency in economic modelling and in other disciplines. Variations are observed over both time and space/individuals/organisations, depending on the context. A range of different statistical approaches can be used with such data sets, but in many of these applications there is particular interest in approaches which focus on the variations over time periods for the same units.

It is argued that such data provide a more robust platform for making causal claims than cross-sectional data, as unobserved/unmeasured differences between cases (in our example, localities) can be controlled for by certain techniques. This may open opportunities for applying quasi-experimental techniques. Using panel data makes it possible to eliminate bias resulting from not observing causal factors that are constant over time within each panel member (e.g. geographical location or environment in the case of administrative units).[14]

A panel dataset of 325 Local Authority Districts (LAD) in England was constructed covering a period of eight years, 2011/12 – 2018/19. The dataset contained a variable for the number of food parcels distributed by food banks in the Trussell Trust network within each LAD (divided by the size of the working age population), which served as the dependent variable in the modeling, plus demographic variables, economy-related variables, housing-related variables and welfare-related variables (see Table 10 the end of this section of this annex for a complete list), which served as candidate independent variables in the modelling. All of these variables had either been or could be rationally linked to the need for food parcels, on the basis of previous research literature and initial scoping work.

13 https://www.trusselltrust.org/wp-content/uploads/sites/2/2019/11/Technical-Summary.pdf

14 See e.g. Deaton, A. (2018) The Analysis of Household Surveys: A Microeconometric Approach to Development Policy. Washington, DC: World Bank Group

Two modelling techniques, 'fixed effects' (FE) and 'first differences' (FD) were employed and compared. These techniques are relatively similar, in that they focus on relationships between year-to-year changes within each local authority, not on the cross-sectional relationships. 'Fixed effects' (FE) establish a constant term which is different for each locality but which is fixed across the period. 'First differences' treat the changes from year to year in each variable, dependent and independent, as the variables which are entered into the regression model, and is a very well-established standard procedure in time series econometrics. First differences are more robust if there is some doubt about whether some of the variables in the model are 'stationary' over the study period. Technically, FE is more efficient than FD if there is no serial correlation, while FD relies on a less demanding 'strict exogeneity' assumption than FE, hence providing more reliable results if strict exogeneity required by FE does not hold and the one required by FD holds.[15]

Candidate independent variables (the 'longlist') were examined one by one to identify ones that had simultaneously a meaningful effect on the R squared, were statistically significant and had a sizeable effect on the dependent variable. An initial FE model was then fit using 'shortlisted' variables. Variables that were not statistically significant at the conventional 5% level were subsequently dropped, with the exception of two variables where there was a theoretical reason to keep them (related to unemployment and population health). The final FE and FD models had the same set of nine predictors (see Table 7 for the FE model). The two models were consistent with regards to the direction of effects, with the exception of one of the retained non-significant theoretically-justified variables ('Number of work seekers per 1,000 working age population').

15 See Wooldridge, J.M. (2010) Econometric Analysis of Cross Section and Panel Data. 2nd ed. Cambridge, Mass: MIT Press.

Table 7 Results of a fixed effects model predicting the number of food parcels provided by food banks in the Trussell Trust network per 1,000 working age population, 325 local authorities in England, 2011/12-2018/19 (reproduced from the technical annex to Sosenko et al, 2019, Table A3.1)

	Coefficient	Robust Std Err	Significance	95% Confidence. Interval	
			(p-value)	Lower	Upper
Number of distribution centres operated by food banks in the Trussell Trust network	3.37	0.52	0.000	2.36	4.39
Real weekly value of main out-of-work benefits*	-1.52	0.47	0.001	-2.44	-0.60
Number of work seekers per 1,000 WA** population	-2.06	1.24	0.097	-4.50	0.37
Interaction of the value of main out-of-work benefits and number of work seekers per 1,000 working age population***	0.03	0.02	0.101	-0.01	0.07
Percent of working age benefit claimants on UC	0.46	0.09	0.000	0.28	0.64
Number of people on health-related benefits per 1,000 WA population****	-0.23	0.24	0.342	-0.70	0.24
Number of JSA/ESA/IS sanctions per 1,000 working age population	0.31	0.10	0.002	0.11	0.50
Number of failed PIP assessments per 1,000 working age population	0.93	0.37	0.012	0.21	1.65
Number of households subject to 'bedroom tax' per 1,000 working age population	0.68	0.13	0.000	0.41	0.94

Note: R-sq: 0.56 (within), 0.25 (between), 0.36 (overall). Rho: 0.73. F(9,324)=63. Prob > F = 0.000.

* Jobseeker's Allowance (JSA)/Employment and Support Allowance (ESA)/Income Support (IS) personal allowance, Universal Credit (UC) standard allowance.

** Working age

*** 'Work seekers' refer to JSA claimants and UC 'searching for work' claimants.

**** ESA, IB, SDA, UC 'no work requirement', UC 'preparing for work'. The two latter benefit categories contain a relatively small number of claimants without health issues, such as carers of a child aged 2. It is not possible to disaggregate these categories using publicly available data.

A few versions of the model were further tested, to address potential non-stationarity, unobserved heterogeneity and feedback from the outcome to predictors. These tests did not undermine the results of the main model.

The update of the model

In the second year of State of Hunger research the dataset was updated with relevant data that became available after the first State of Hunger report was published. To improve model fit, three changes have been made to predictors in the model, in comparison to the original model:

1. The predictor 'Number of distribution centres operated by food banks in the Trussell Trust network ' has been replaced with 'Number distribution centres operated by food banks in the Trussell Trust network per 1,000 working age population', for consistency with other predictors.

2. The predictor 'Number of work seekers per 1,000 working age population' has been replaced with 'Percent of working age population who are unemployed'.

3. The predictor 'Percent of working age population on out-of-work benefits' has been added.

Two predictors have been further dropped from the original model: 'Number of people on health-related benefits per 1,000 working age population' (non-significant in the original model but retained there as a control variable) and 'Number of failed PIP assessments per 1,000 working age population' (statistically significant in the original model but not in the updated one).

Additionally, in this second round of modelling it was concluded that a first differences (FD) model should be reported instead of the fixed effects (FE) model. The FD approach is more robust than FE if one or more variables are trending (there is temporal non-stationarity) and/or if there is endogeneity.[16] This decision reflected some changes in the data with a slightly longer series, but also further time for reflection on the balance of advantages between these techniques in this context, in the light of authoritative advice and diagnostic tests. However, again, both types of model were run and compared, and the differences are not great.

A small number of local authorities (16) were dropped in the modelling due to missing values.

As the model was extended to 2019/20, it does not cover the period of the coronavirus crisis. It therefore cannot be said whether effect sizes identified by this model 'held' during the Covid-19 period. Importantly, during the period 2011-2019 there were no economic, policy or social changes of the magnitude observed during the Covid-19 crisis. For this reason, the updated model does not provide a complete basis for predicting effects of economic, policy or other social changes during Covid-19 on the uptake of food parcels.

16 Wooldridge, J.M. (2010) Econometric Analysis of Cross Section and Panel Data. 2nd ed. Cambridge, Mass: MIT Press.

Table 8 Descriptive statistics for variables in Local Authority level panel Model A, (2011/12-2019/20.

Variable	min	max	mean	SD	N
Number of emergency food parcels distributed by food banks in the Trussell Trust network per 1,000 WA* population	0	252.57	23.27	28.89	2907
Number distribution centres operated by food banks in the Trussell Trust network per 1,000 WA population	0	0.25	0.03	0.03	2907
Real value of main income replacement benefit	62.53	67.45	65.70	1.57	2916
Percent of WA population on out-of-work benefits	2.94	24.49	8.90	3.62	2790
Percent of WA population who are unemployed	1.63	15.56	5.12	2.25	2916
Percent of claimants of WA benefits who are on UC	0	49.10	7.13	11.36	2790
Number of JSA and ESA sanctions per 1,000 WA population	0	51.86	6.89	8.36	2790
Number of households affected by 'bedroom tax' per 1,000 WA population	0	32.83	6.20	5.67	2916

* WA: working age

Table 9 Results of a regression model predicting food parcel uptake, 309 local authorities in England, 2011/12-2019/20 (Model A, first differences)

	Coef.	Robust Std. Err.	Significance (p-value)	95% Conf. Interval
Number distribution centres operated by food banks in the Trussell Trust network per 1,000 WA* population	358.30	27.80	0.000	303.78,412.82
Real value of main income replacement benefit**	-1.37	0.26	0.000	-1.89,-0.85
Percent of WA population on out-of-work benefits	-2.97	0.68	0.000	-4.31,-1.63
Interaction of the two preceding variables	-0.62	0.65	0.346	-1.90,0.67
Percent of WA population who are unemployed	0.85	0.34	0.013	0.18,1.51
Percent of claimants of WA benefits who are on UC	0.36	0.04	0.000	0.27,0.44
Number of JSA and ESA sanctions per 1,000 WA population	0.24	0.05	0.000	0.13,0.34
Number of households affected by 'bedroom tax' per 1,000 WA population	0.46	0.14	0.001	0.19,0.73
Constant	0.61	0.36	0.092	-0.10,1.32

Observations = 2,472

R squared = 0.31

* WA: working age

** UC/JSA/ESA/IS standard or personal allowance for people aged 25 or above. Weekly value adjusted for inflation. Reference year: 2011.

The size of the effect of each of these factors on food parcel uptake was as follows:

- One extra food bank would see an increase of 358 parcels (an 8% increase relative to the 2019/20 level) in a typical local authority.

- One percentage point higher unemployment would have led to 0.85 more food parcels per 1000 working age population, equivalent to an extra 107 in a typical local authority, a 2% increase of the 2019/20 level.

- One percentage point more of the working age population on working age benefits would have reduced food parcels by 2.7 per 1000, 291 in a typical local authority, or about 6.5% of the 2019/20 level.

    - A £1 increase in UC/JSA/ESA/IS standard allowance was associated with a decrease of 2.6%, or 118 food parcels in a typical local authority (relative to the 2019/20 level).

    - An increase of 10 percentage points in the proportion of claimants of working age benefits who are on Universal Credit was associated with an increase of 3.6 per 1000 in the number of food parcels, 454 in a typical local authority, an increase of 8.4% on the 2019/20 level.

- An increase of 100 in the number of benefit sanctions was associated with an increase of 24 in the number of parcels, an increase of 0.5% in a typical local authority (relative to the 2019/20 level).

- An increase in the number of households subject to removal of the spare room subsidy ('bedroom tax') of 100 was associated with an increase in the number of food parcels of 46, an increase of 1% in a typical local authority (relative to the 2019/20 level).

While there might appear to be some contradiction between the second and third of the above effects, we interpret these findings as follows. Unemployment does have some effect, as expected, in terms of increasing the risk of destitution and the need to use a food bank. However, where people are actually able to get benefit payments, this substantially reduces their risk of destitution and food bank need, allowing for their employment situation.

These findings are similar to those of the original modelling (reported in State of Hunger (Sosenko et al, 2019)), with some detailed differences. The bullet points above suggest a precision in the size of these effects which may be misleading – for each predictor variable, there is generally quite a wide confidence interval on the size of its effect, as shown in the final column of Table 9. The model is a linear model, which implies that the effect remains the same across the range, and can be scaled up and down, within reason. the relationships summarized as above may be used to give an indicative estimate of the effect of changing certain policy parameters 'other things being equal'. However, some care should be exercised if trying to predict the effect of a variable changing in value by much more than the amount by which it varied in the base data (indicated by descriptive statistics in the preceding Table 8). Care should also be exercised through recognising that, in realistic forward-looking scenarios, many other things may well not remain equal.

Model diagnostics were carried out by inspecting multicollinearity and a plot of residuals versus fitted values. The largest VIF was 5.01, substantially below the value of 10, a conventional threshold for evidence of multicollinearity. The plot of residuals versus fitted values appeared pattern-less, suggesting no obvious violations to OLS regression assumptions.

Despite this, further checks were carried out to address a potential problem of unobserved heterogeneity, which could be due to omitting a causally important variable. A variable that was not included in the model (due to lack of suitable data) but suspected to be potentially causal was the number of independent food banks (i.e. not belonging to the Trussell Trust network). The presence of independent food banks is likely to exert downward pressure on the uptake of food parcels at food banks in the Trussell Trust network, and as such it would be desirable for it to be included in the model.

While relevant longitudinal data does not exist, the research team was able to exploit data about the number of independent food banks in each local authority as of June 2019. This data was included in the model in the form of a weight, which - to some extent - fed into the model information about the relevant part of the error term. Coefficients from this weighted model (B) were very close to those from the main model (A), increasing our confidence in the validity of the main model.

A second attempt at incorporating information about independent food banks in the model took the form of adding to the model a spatial lag of the dependent variable (weighted averages of observations for the 'neighbours' of a given location). This to some extent controlled for unobserved time-varying local characteristics, of which the presence of independent food banks is one case.[17] The spatial lag predictor was not significant and the coefficients in this model (C) were very close to coefficients in the main model (A) reported in Table 9, again increasing our confidence in the validity of the main model.

Variables considered for the modelling

Table 10 lists all the variables tested within the local authority level panel modelling, including those which were not significant and not retained in the models reported. Variables marked with an asterisk were divided by the size of the working age population.

Inflation data used to calculate the real-term value was downloaded from the ONS website.[18]

The size of the working age population was sourced from NOMIS.[19]

17 See Duranton, Gobillon & Overman (2011) 'Assessing the effects of local taxation using microgeographic data', The Economic Journal, 121 (September), 1017-1046.

18 https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceindices.

19 https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=2002.

Table 10

Number of operational Trussell Trust food banks*	The Trussell Trust administrative system
number of lone parent households*	Annual Population Survey – Households with dependent children and type (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=137)
number of lone parent households*	Annual Population Survey – Households with dependent children and type (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=137)
number of people who are non-UK born*	Annual Population Survey (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=17)
number of working age people who have a disability that limits the amount or the kind of work that they can do*	Annual Population Survey (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=17)
Economy-related variables	
real gross weekly median pay (full-time workers)	Annual Survey of Hours and Earnings (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=30)
real gross weekly pay at 10th percentile (full-time workers)	Annual Survey of Hours and Earnings (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=30)
percent of employees working on a part-time basis	Annual Population Survey (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=17)
jobs density[20]	Jobs Density (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=57)
number of work seekers (number of JSA claimants combined with the number of UC claimants in the 'searching for work' category)*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; datasets 'Jobseekers Allowance' and 'People on Universal Credit')
real value of specific parts of local authority budgets (homelessness, Supporting People, mental health), £ per capita	CIPFA (https://www.cipfa.org/)
real value of main out-of-work benefits (JSA/ESA/IS personal allowance; UC standard allowance). The reference year was 2011.	McInnes (2019) Benefits Uprating 2019, Briefing Paper Number CBP 8458, London: House of Commons Library.
percent of working age population who are unemployed	Model-based estimates of unemployment (from NOMIS; https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=127)

20 The number of jobs in an area divided by the resident population aged 16-64 in that area. For example, a job density of 1.0 would mean that there is one job for every resident aged 16-64.

percent of working age population on out-of-work benefits	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Benefit Combinations'
Housing-related variables	
real private rent at 25th percentile (three versions: room, 1 bed, 2 bed), £ per month	Valuation Office Agency (https://www.gov.uk/government/collections/private-rental-market-statistics)
number of non-passported HB claimants (a proxy for HB not covering full rent)*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Housing Benefit')
number of PRS LHA claimants*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Housing Benefit')
discrepancy between the value of LHA and real private rent at 25th percentile, £ per month (three versions: room, 1 bed, 2 bed)	LHA rates from Valuation Office Agency (https://www.gov.uk/government/collections/local-reference-rents-levels-collection). Real private rent data from Valuation Office Agency (https://www.gov.uk/government/collections/private-rental-market-statistics).
Council Tax collected by LA as proportion of all collectible CT (a proxy for Council Tax arrears)	MHCLG (https://www.gov.uk/government/collections/council-tax-statistics#collection-rates-for-council-tax-and-non-domestic-rates)
number of SRS households on HB*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Housing Benefit')
Homelessness-related variables	
number of households accepted as homeless*	MHCLG (https://www.gov.uk/government/statistical-data-sets/live-tables-on-homelessness)
number of single persons accepted as homeless*	MHCLG (https://www.gov.uk/government/statistical-data-sets/live-tables-on-homelessness) 'No priority need' was used as a proxy for single applicants.
number of households in Temporary Accommodation*	MHCLG (https://www.gov.uk/government/statistical-data-sets/live-tables-on-homelessness)
Welfare-related variables	
number of claimants of ESA/IB/SDA/UC 'no work requirement'/UC 'preparing for work'*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Benefit Combinations')
number of cases of failed DLA to PIP reassessment*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'DLA to PIP Reassessments')
number of cases of unsuccessful fresh PIP assessment*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'PIP Clearances')
number of households subject to 'bedroom tax'*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Housing Benefit')
number of households subject to Benefit Cap*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Benefit Cap')
number of JSA/ESA/IS sanctions*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Sanction Decisions')
number of UC sanctions*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Sanction Decisions')

percent of UC claimants among all working age benefit claimants	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Benefit Combinations')
number of 'fit for work' outcomes of WCA*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'ESA Work Capability Assessments')
number of LHA recipients subject to SAR*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Housing Benefit')
number of SRS tenants with HB paid to claimant instead of the landlord*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Housing Benefit')
number of households subject to HB non-dependent deductions (three versions: 1+, 2+, 3+ non-dependents)*	Stat-Xplore (https://stat-xplore.dwp.gov.uk/; dataset 'Housing Benefit')

Appendix A
Detailed Table on Weighting Factors

Table A.1: Weighting targets based on analysis of Trussell Trust food voucher data for the relevant periods (column percentages)

	State of Hunger survey period		
	Late 2018	Early 2020	Mid-2020
Age			
18-24			8
25-64			88
65+			4
Household composition			
Single	49	49	44
Lone parent	20	19	18
Couple / 2+ adults	13	13	15
Couple with children	18	19	23
Number of food bank visits over the past 12 months			
1	53	45	
2	16	16	
3	10	11	
4	7	8	
5	4	5	
6	3	4	
7-9	4	6	
10+	3	5	
Region of the UK			
East			9
East Midlands			6
London			14
North East			5
North West			13
Northern Ireland			2
Scotland			10
South East			11
South West			9
Wales			7
West Midlands			9
Yorkshire and the Humber			5
Used a food bank in the Trussell Trust network before March 2020			
No			62
Yes			38

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