STATE OF HUNGER

Technical Annex

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the trussell trust
Stop UK Hunger

Contents

INTRODUCTION

This technical annex accompanies the first main State of Hunger report published in November 2019. It provides a more detailed description of quantitative research methods and statistical analyses employed by the study. The first two sections of this technical annex consider the design and implementation of two surveys undertaken by the study: a survey of people referred to Trussell Trust food banks and a survey of agencies making referrals to Trussell Trust food banks. The following two sections describe the modelling exercises conducted as part of the study, namely a logitudinal modelling and cross-sectional modelling of factors driving demand for food parcels at local authority level.

1. METHODOLOGY OF THE MAIN FOOD BANK USER SURVEY

The most significant strand of the State of Hunger study is an annual food bank user survey, for people referred to food banks in the Trussell Trust network across the UK. This survey builds on the recent work of Loopstra and Lalor (2017).

The survey aims to cover 10% of organisations belonging to the Trussell Trust network (428 in June 2018). In Year 1, 43 organisations were selected, using stratified random sampling with probability proportional to size. Each of 12 regions of the UK (9 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 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 (PPS; Stata function 'samplepps'). 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 (see below).

Where the sampled food bank organisation had up to five food banks (venues distributing food parcels), one of the venues was randomly chosen (PPS) to host the survey. Opinion of food bank managers on the suitability of each venue was sought and if the randomly selected venue was thought to not be suitable (for logistical or other reasons) the random sampling was repeated. In food bank organisations with more than five venues, two venues were selected to host the survey, using the same procedure.

Ten of the originally sampled 43 food bank organisations declined to participate and were substituted. Substitutes were selected (PPS) from the same stratum as the food bank that has declined. One organisation had to cancel its participation at short notice and was not substituted due to lack of time.

Each selected food bank organisation was asked to survey 30 service users. In cases where two venues were selected, each venue was asked to return 15 completed questionnaires.

This survey design ensured that the sample was approximately self-weighting. Although slight differences in the probability of being sampled could be corrected via a weight, a decision was taken not to do so, in order to not increase standard errors.

The survey was administered by food bank staff and volunteers, who had been trained face-to-face by the research team. A 'Survey Handbook' was also produced as a support tool for survey administrators.

The survey was conducted on tablet devices and designed for self-completion, with help available from food bank staff and volunteers. A leading industry application called ODK Collect was used to place the questionnaire onto the tablet devices. The application can work without an Internet connection.

The survey questionnaire was cognitively tested on 11 food bank users in two Trussell Trust food banks, one in England and one in Scotland. Several organisations and individuals also provided valuable feedback on the content of the questionnaire. A decision has been taken to not allow respondents skip key questions (for routing purposes and to minimise missing data). Where it was felt that the respondent may not want to answer the question, or may not know how to answer it, response options 'don't know' or 'prefer not to say' were offered.

Survey administrators were instructed that the following types of people were not eligible for the survey:

- People **under the age of 18.**
- People who arrived at the food bank **in obvious distress** or who appeared to have a **cognitive impairment** that would not enable them to self-complete a questionnaire.
- People who arrived at the food bank under the influence of **alcohol or drugs.**
- People who **behave aggressively** at the food bank.
- People with **language or literacy barriers** that could not be overcome.
- People who had **already completed the questionnaire** in a previous food bank session.
- People who came in to **collect a food parcel for someone else.**
- People who **do not have a referral voucher.**

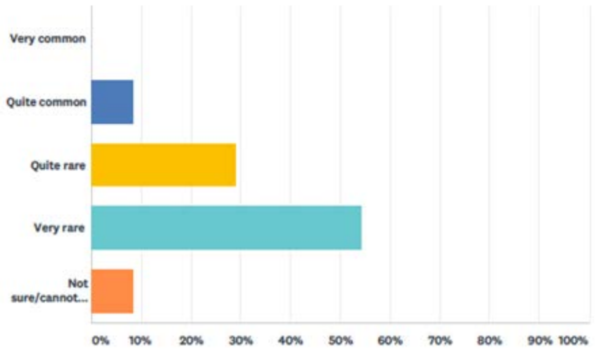
Selection bias was avoided by instructing survey administrators to approach the next available service user coming into the food bank. This instruction ensured that survey administrators did not have a choice of which service user to approach and thus the selection process was as close to random as possible.

The survey was carried out predominantly over October to November 2018. Some food banks which did not manage to reach the target by early December continued data collection until January 2019. The survey resulted in 1,130 responses which represented 90% of the target of 1,260 (42 food bank organisations each returning 30 completed questionnairs).

To review the delivery of the food bank user survey, the administrators at participating food banks completed a follow-up survey. In year one, slightly over half (57%) of survey administrators participated in this supporting survey.

The survey of administrators asked how frequently a person referred to a food bank was found ineligible for the survey, and on what grounds. Responses to questions 12-14 (presented below) suggested little evidence of systematic selection bias, with only two people indicating that ineligibility was quite common and almost 80% saying most people took part. Three of the nine respondents identifying ineligible respondents said some of their service users were found ineligible due to language barriers, though, suggesting that the survey estimate of the proportion UK-born should be corrected slightly downwards.

Q12 How common was it that service users were ineligible to take part in the survey?



Q13 What were the main reasons behind ineligibility? (Type ‘1’ next to the reason you believe was the most common, ‘2’ next to the second most common reason, etc. You can rank as many or as few reasons from this list as you wish).

ANSWER CHOICES	AVERAGE NUMBER	TOTAL NUMBER	RESPONSES
Language barriers	3	21	8
Literacy barriers	3	15	6
Cognitive impairment barriers	3	19	6
Client under the age of 18	9	17	2
Client too distressed to take part	4	18	5
Client under the influence of alcohol or drugs	6	22	4
Client behaving aggressively	7	21	3
Client already completed the questionnaire in a previous food bank session	5	20	4
Client was collecting a parcel for someone else	3	15	5
Client did not have a voucher	4	12	3
Total Respondents: 9			

Q14 How would you describe refusals, did...

ANSWER CHOICES	RESPONSES	
Most eligible people take part	78.26%	18
About half of those asked who were eligible take part	17.39%	4
Less than half of those asked who were eligible take part?	0.00%	0
Not sure/cannot say	4.35%	1
Total Respondents: 23		

2. SENSITIVITY TESTS FOR THE SURVEY OF REFERRAL AGENCIES

INTRODUCTION

The State of Hunger research aims to conduct one referral agency survey each year, in selected Local Authority areas. This note examines the characteristics of the sample of respondents taking part in the referral agency surveys, compared with the profile of referral agencies according to Trussell Trust voucher data for 2018-2019 for the 13 case study locations from which returns were received, to identify any potential types of bias that might impact on the survey results.

Initially it was planned to sample referral agencies but due to constraints relating to GDPR the invitation to fill in the survey had to be issued to all referral agencies. Again, due to GDPR this was done by food bank managers, on behalf of the research team.

SAMPLE DESIGN

The choice of case study areas was guided by the analysis of the Trussell Trust voucher data, data from the main survey of people referred to food banks, and external data. From the outset, we aimed to sample six of the ten case studies in areas that suffer from high unemployment / weak economic growth and, at the same that time, that have been relatively strongly affected by post-2010 welfare reforms and austerity. A further two case study areas were planned in areas with moderate unemployment and moderate impact of welfare reforms / austerity. The last two case study areas were to be towards the least disadvantaged end of the spectrum in those respects. By employing this design, we were aiming to have a sample that represents varying combinations of these pressures.

To inform the case study design , we have used the following indicators from the DWP's Stat-Xplore service (relating to Jan-Nov 2018 or latest point in time, whichever was more relevant): number of failed PIP (re)assessments; number of households affected by Benefit Cap; number of households affected by 'bedroom tax'; number of sanctions (UC, JSA, ESA, IS); number of Universal Credit claimants; number of episodes of being found 'fit for work' at Work Capability Assessment; number of households subject to HB non-dependant deductions;

number of HB claimants subject to Shared Accommodation Rate (all divided by the size of the working age population), real-term LA budget for 2017/18 as % of the 2010/11 value (data obtained from CIPFA); Council Tax minimum payment level (data obtained from counciltaxsupport.org).

Beyond welfare reform / austerity, we have expanded the selection criteria by including unemployment and homelessness. Unemployment relates to economic (rather than policy) factors potentially underlying food bank use. High prevalence of homelessness among food bank users has been one of the main findings from the food bank user survey and therefore it made sense to make it a selection criterion. We have used NOMIS data for unemployment rate at LA level and 'core homelessness' data for homelessness rate at LA level.[1]

To make all those different measures comparable, we have converted them to 'z scores'. Using z scores is a way of standardizing for differences in size of units and degree of variation. Having developed an overall score for each LA (its mean z score from all measures) we sorted them and selected authorities from the top, middle and bottom of the range which had significant Trussell Trust food bank presence and which represented a range of regions/countries. We also aimed at case study areas to represent a good mix of areas where the rollout of Universal Credit was already advanced in late 2017 and areas where it had been happening more slowly.

While effort was made to select case studies in a way that maximised opportunities for comparative analyses of drivers, we should emphasise that findings from the survey – however suggestive - should be treated as qualitative in character.

SAMPLE SUBSTITUTION

The online survey of referral agencies was launched in mid-March 2019 and respondents were given one month to complete the questionnaire. By the middle of April it was decided to boost the number of local authorities involved, as returns had been received from only 6 of the 10 locations, despite reminders. A further 6 'reserve' local authorities were added to the sample. These further 6 'back-up' local authorities were selected to closely match those local authorities that had not yet received returns.

By the end of the extended survey period (mid-June), 306 survey returns had been received from 13 local authorities. The results presented in the report are not weighted to take account of the different size of local authorities. It was agreed to conduct 'sensitivity testing' to consider how the respondent profile compared with the profile of referral agencies that formed the overall population of referral agencies who could have taken part.

RESPONDENT AGENCIES PROFILE

The sample of 306 responding referral agencies is a small proportion of the total number of referrals agencies according to the Trussell Trust referral data, with over 2,800 agencies making referrals across the 13 LAs where the responding agencies were based.

[1] Bramley, G. (2017) Homelessness projections: Core homelessness in Great Britain, London: Crisis.

Table A2.1 Profile of responding referral agencies compared with all Trussell Trust referral agencies in the 13 case study areas (whether area best, worst or middle on the spectrum)

Position of the area on the spectrum	Number participating in the survey	% participating in the survey	All referral agencies in case study areas	% of all referral agencies in case study areas
Worst	187	61	2,079	74
Middle	86	28	584	21
Best	33	11	157	6
Total	306	100	2,820	100

The profile of responding agencies across the 13 cases study LAs taking part in the survey was weighted more towards locations that were in the middle or best areas according to the sample analysis outlined earlier – 61% of referral agencies surveyed were in the worst LAs compared with 74% of all agencies making referrals to the Trussell Trust food banks.

The profile of the type of agency that responded to the survey is shown below, again compared with the Trussell Trust referral database for the 13 case study LAs.

Table A2.2 Profile of responding referral agencies compared with Trussell Trust voucher data (type of organisation)

Referral agency type	Number participating in the survey	% participating in the survey	All referral agencies in case study areas	% of all referral agencies in case study areas
Charity	58	19	586	21
Church	21	7	182	6
Community group	5	2	248	9
Statutory agency	141	46	1,528	54
Voluntary agency	81	26	276	10
Total	306	100	2,820	100

The table above shows that statutory organisations were under-represented in the respondent sample, compared with the total referral population, making up 46% of responses but 54% of all referral organisations. Voluntary agencies were over-represented in the referral survey, with 26% of respondents compared with just 10% of all referral agencies.

In order to understand what impact the under-representation of the 'worst' areas and statutory agencies and the over-representation of voluntary agencies might have, we conducted analysis of some key results.

Table A2.3 Reported change in number of people needing 3+ referrals in the previous 6 months

	Position of the area on the spectrum			
	Worst	**Middle**	**Best**	**Total**
Significant increase	31%	8%	13%	23%
Slight increase	32%	46%	65%	40%
No change	25%	26%	16%	24%
Slight decrease	3%	3%	0%	3%
Significant decrease	1%	0%	0%	0%
Don't know/ cannot say	7%	17%	7%	10%
Total	100%	100%	100%	

Respondents in the worst areas were more likely to say that there had been a significant increase in the numbers needing multiple referrals to the food bank over the previous 6 month period, while those in the best areas were more likely to say there had been a slight increase and less likely to say there had been no change or a decrease. Analysis by referral agency type showed no significant differences between the perceptions of statutory and voluntary agencies on the increase or decrease in multiple referrals.

Looking at key drivers, those in the worst areas gave significantly higher scores in a number of key areas (bold highlights significant differences).

Table A2.4 Average impact scores across different drivers of food bank use by LA type

	Position of the area on the spectrum			
	Worst	**Middle**	**Best**	**Total**
Limited or restricted access to local support services	1.06	.78	.63	.94
People experiencing problems with their benefits	1.78	1.80	1.48	1.75
Benefit levels are too low to make ends meet	1.40	1.11	1.07	1.28
Benefits - Limited/ restricted access to public funds for migrants/ refugees	1.30	1.21	.89	1.24
Costs - Rent levels	.95	1.08	1.04	.99
Costs - Food, gas/electricity, and other essentials	1.26	1.07	1.17	1.20
Unemployment / underemployment	1.57	1.16	1.10	1.41
Low wages	1.32	1.18	1.14	1.26
Temporary/insecure work contracts	1.33	1.05	1.00	1.22
Physical health problems	.96	.98	.67	.93
Mental health problems	1.47	1.55	1.21	1.46
Substance abuse issues	1.25	.95	1.00	1.14
Eviction	1.31	.98	.70	1.16

Homelessness	1.35	1.29	1.00	1.30
Other housing issues	1.08	1.05	.60	1.02
Relationship breakdown (spouse/partner)	1.07	1.06	.45	1.00
Other family breakdown	.79	.98	.27	.78
Domestic abuse	1.07	1.02	.42	.98
Bereavement	.46	.32	.00	.37
Other adverse life events	.93	.92	.58	.89

Mean scores: higher scores indicate higher perceived impact

Referral agencies in the 'worst' LAs gave significantly higher impact scores than those in the middle or best areas on restricted/limited services, benefits being too low to make ends meet, unemployment and eviction as having an important impact on food bank use.

Referral agencies in the 'best' areas gave significantly lower scores on 'problems with benefits' as a key driver of food bank use, compared with those in the middle and worst areas, but this was still the driver with the highest overall score.

Relationship breakdown, family breakdown and domestic abuse were significantly less commonly identified as key drivers of food bank use among referral agencies in the best areas.

Comparing types of referral organisation showed far less difference in the perceived impact of different issues on food bank use. Only for domestic violence and substance misuse were there significant differences, with churches less likely to identify these as key drivers and charities and community groups more likely to. There were not significant differences among statutory and voluntary agencies.

CONCLUSIONS: THE LIKELY IMPACT OF BIAS

The analysis above shows that the sample was slightly skewed towards referral agencies in middle and better areas and towards voluntary rather than statutory referral agencies.

On balance, under-representing referral agencies in the worst areas may reduce the overall perceived impact of benefits and other economic factors such as unemployment and low income. However, benefit impacts are universally the most important issue identified across all types of area so this does not impact on the key messages emerging.

Under-representing statutory agencies and over-representing voluntary agencies would appear to have less impact as there are few significant differences between agencies of different types

3. LONGITUDINAL MODELLING

This section presents an analysis based on a panel dataset of local authorities observed over time. We believe that this represents the most effective way of estimating the effects of different factors, including policy and administrative measures, on the key outcomes of interest in this study. Such panel-based analyses, where one can observe a large group of individuals, geographical or organisational units over a set of points in time, have become the method of choice in many social and economic studies which seek to provide evidence to support or refute claims about what factors may be influencing key outcomes of interest. The sequencing of observations in time provides more convincing evidence that such associations may reflect causal influences than the more traditional correlations over space, which are more vulnerable to problems of 'ecological fallacy' and multicollinearity.

THE DATASET

A panel dataset of 325 Local Authority Districts (LAD) in England was constructed covering the period of eight years, 2011/12 – 2018/19.[2] The dataset contains a variable for the number of Trussell Trust food parcels distributed in each LAD (divided by the size of the working age population) plus demographic variables, economy-related variables, housing-related variables and welfare-related variables (see the end of Section 3 for a complete list). All of these variables have either been or could be rationally linked to the demand for food parcels.

Two versions of the dataset were constructed, a monthly one and an annual (financial year) one. Since the majority of DWP data on Stat-Xplore comes as monthly data, the advantage of the monthly dataset is that the data is exploited as much as possible, i.e. there is no loss of information. The disadvantage is that variables in the dataset that take an annual form, such as rent levels, need to be disaggregated into monthly equivalents. This has been done in a linear fashion. While it is a defensible strategy, the assumption about the linear distribution of values over the course of a year is a strong one.

A reverse challenge with the annual version of the dataset is that monthly and quarterly values need to be aggregated into annual values, resulting in some loss of information. This has been done by taking the mean, although an option of selecting September values (roughly the middle of the financial year) was also tested. On balance, using the annual dataset entails discarding some information but avoids making a strong assumption about the linear distribution of annual values over the course of a year. The modelling results presented in the report come from the analysis of the annual dataset, although modelling on the monthly dataset has also been done as a sensitivity test (see below).

[2] Northern Ireland could not be included since DWP data does not cover it. Scotland has introduced some mitigation measures related to Welfare Reform and thus it has been decided to not include it, as doing otherwise would mean comparing 'apples with pears'. Wales has not been included as many housing and economy-related variables used in the model would require using Wales-specific datasets, which could not be done due to time constraints.

CHOICE OF MODELLING TECHNIQUE AND THE MODELLING PROCEDURE

The main criterion for selecting a modelling technique was to avoid relying on statistical assumptions that would be hard to defend, and specifically assumptions underlying the random effects model. It was therefore decided that fixed effects (FE) and first differences (FD) will be the key modelling techniques. The FE estimator is more efficient than FD one if the assumption about the lack of serial correlation holds, but the FD estimator provides more valid results when that assumption does not hold. Both models have the limitation that they cannot estimate the effect of variables which vary across local authorities but not over time (whether because they are unchanging factors, or because of limitations in available data). Thus they cannot explain why particular localities have very high or low rates of food parcel demand across the decade; the kind of analysis reported in Section 4 is more relevant to that question. However, since we are mainly interested in explaining change, the FE and FD panel models are clearly appropriate.

We started with a FE model. We firstly examined candidate variables (the ‘longlist’) 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 outcome variable. We also plotted the distribution of each candidate variable over time and examined the plots.

We then fitted an initial FE model using ‘shortlisted’ variables. At this point multicollinearity was examined (some variables were collinear to a degree but not to the point where it would create issues). Next, variables that were not statistically significant at the conventional 5% level were dropped, with the exception of two variables that were deemed to be key control variables (the number of workseekers and the number of claimants of health-related benefits). We also made sure that dropping variables did not entail major changes in coefficients of the retained variables. This resulted in a model which had one more variable (Benefit Cap) than the model presented in Table 4.1.

We then checked robustness of the FE model by comparing the results with results from a FD model. The test was positive with the exception of the Benefit Cap variable and the ‘number of workseekers’ variable, both of which had a different sign under FD. The Benefit Cap variable was dropped from the FE model but the ‘number of workseekers’ was retained as it was an important control variable. Without the Benefit Cap variable the FE and FD models were in agreement on all variables apart from the ‘number of workseekers’ one. A judgment was made that this inconsistency was non-consequential for the validity of the rest of the model. Tables A3.1 and A.3.2 present results of the FE and the FD model respectively (Table A3.1 reproduces Table 4.1 from the main report).

Table A3.1 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

				95% confidence interval	
	Coefficient	Robust Std Err	Significance (p- value)	Lower	Upper
Number of Trussell Trust food banks	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 working age 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.

* JSA/ESA/IS personal allowance, UC standard allowance.

** '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.

Table A3.2 Results of a first difference model predicting the number of Trussell Trust food parcels per 1,000 working age population, 325 local authorities in England, 2011/12-2018/19

				95% confidence interval	
	Coefficient	Robust Std Err	Significance (p- value)	Lower	Upper
Number of Trussell Trust food banks	3.90	0.35	0.000	3.22	4.57
Real weekly value of main out-of-work benefits*	-0.33	0.16	0.040	-0.64	-0.02
Number of work seekers per 1,000 working age population	0.28	0.11	0.009	0.07	0.48
Interaction of the value of main out-of-work benefits and number of work seekers per 1,000 working age population**	0.00	0.08	0.982	-0.16	0.16
Percent of working age benefit claimants on UC	0.24	0.06	0.000	0.11	0.37
Number of people on health-related benefits per 1,000 WA population***	-0.21	0.15	0.156	-0.51	0.08
Number of JSA/ESA/IS sanctions per 1,000 working age population	0.17	0.06	0.008	0.05	0.30
Number of failed PIP assessments per 1,000 working age population	0.37	0.18	0.044	0.01	0.73
Number of households subject to 'bedroom tax' per 1,000 working age population	0.73	0.11	0.000	0.52	0.93

Notes: R-sq: 0.31. F(9,2265) = 48. Prob > F = 0.000.

* JSA/ESA/IS personal allowance, UC standard allowance

** ESA, IB, SDA, UC 'no work requirement', UC 'preparing for work

To calculate the effect size of the 'real value of main out-of-work benefits', we used the 'margins' command in Stata and set the values of all other variables to their means. Following standard convention, robust standard errors were used to take account of underlying clustering within LADs. We were also conscious that the empirical results may be influenced by potential nonstationary dynamics over time, and likewise, potential failure to satisfy the spatial granularity condition. Therefore, we studied time and spatial plots of key variables to investigate this issue. Further, we validated the results using common correlated effects (a now standard methodology originally developed by Hashem Pesaran)[3], which we discuss further below, and are reasonably satisfied with the robustness of our base findings.

[3] Pesaran, M. H. (2006) "Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure", Econometrica, vol. 74(4), pp. 967-1012.

We have tested a few variations of the model. These included:

a) Fitting the model reported in Table 4.1 to a sub-group of 218 LADs where there was no more than one independent (non-Trussell Trust) food bank in June 2019. The presence of such food banks could have a confounding effect. The model returned higher coefficients (same signs):

Table A3.3. Results of a fixed effects model predicting the number of Trussell Trust food parcels per 1,000 working age population, 218 local authorities in England with no or low presence of independent food banks, 2011/12-2018/19

				95% confidence interval	
	Coefficient	Robust Std Err	Significance (p- value)	Lower	Upper
Number of Trussell Trust food banks	3.86	0.63	0.000	2.61	5.10
Real weekly value of main out-of-work benefits*	-1.12	0.61	0.067	-2.32	0.08
Number of work seekers per 1,000 working age population	0.03	1.78	0.987	-3.48	3.53
Interaction of the value of main out-of-work benefits and number of work seekers per 1,000 working age population**	0.00	0.03	0.954	-0.05	0.06
Percent of working age benefit claimants on UC	0.54	0.11	0.000	0.32	0.77
Number of people on health-related benefits per 1,000 WA population***	-0.39	0.32	0.221	-1.02	0.24
Number of JSA/ESA/IS sanctions per 1,000 working age population	0.41	0.14	0.004	0.13	0.68
Number of failed PIP assessments per 1,000 working age population	1.55	0.50	0.002	0.56	2.55
Number of households subject to 'bedroom tax' per 1,000 working age population	0.99	1.19	0.000	0.61	1.37

Notes: R-sq: 0.62 (within), 0.23 (between), 0.38 (overall). Rho = 0.74. Rho: 0.74. F(9,217) = 72. Prob > F = 0.000.

* JSA/ESA/IS personal allowance, UC standard allowance

** ESA, IB, SDA, UC 'no work requirement', UC 'preparing for work

b) Fitting the model reported in Table 4.1 with an additional variable for one year's lag on the number of food banks, to take account of the fact that it a newly open food bank may be initially quiet. That additional variable was nearly-significant (p=0.07) and the coefficient was much smaller (b=0.43) than the coefficient for that variable without a lag (b=2.4). There were no major changes of coefficients of other variables in the model and those that were statistically significant in the reported FE model remained significant.

c) Fitting the model reported in Table 4.1 with an additional variable for the proportion of working age population who have a disability that limits the amount or the kind of work that they can do. We opted not to include it in the main model as 2013 is the earliest year covered by that variable, meaning that the first two years of the panel would be lost. That variable had a positive sign (b=0.08), which underlies our interpretation put forward in Chapter 4, although it was not quite significant (p=0.19).

d) Fitting a dynamic model. An additional variable for one year's lag on the outcome variable was added to the model reported in Table 4.1. Due to the so-called Nickell bias, the Arellano-Bond estimator was used instead of FE (Stata function 'xtabond').[4] That additional lag variable was non-significant (p=0.44).

e) Fitting the model reported in Table 4.1 with added cross-section averages of all variables. This addresses the issue of potential cross-section dependence by eliminating differential effects of unobserved common factors (Pesaran, 2006). Since this 'common correlated effects' estimator is suitable for moderate to large T panels, we have used the monthly dataset. We have additionally included three lags of the supply variable (number of food banks) to allow for 'bedding in' of new food banks. All of the variables had the same sign as reported in Table 4.1 and coefficients were of a similar order of magnitude as in Table 4.1 (e.g. percent on UC: 0.017; sanctions: 0.017; failed PIP assessments: 0.066; 'bedroom tax': 0.047. When multiplied by 12 (months), the results are 0.21, 0.21, 0.80, 0.56). Stata function 'xtcce' was used.

Variables considered for the modelling included:

(variables marked with an asterix were divided by the size of the working age population)

a) demographic controls and other controls:

- number of operational Trussell Trust food banks
- number of lone parent households*
- number of people who are non-UK born*
- number of working age people who have a disability that limits the amount or the kind of work that they can do*
- dummy for December (monthly dataset only; there is a strong seasonal effect related to Christmas)

b) economy-related variables:

- real gross weekly median pay (full-time workers)
- real gross weekly pay at 10th percentile (full-time workers)
- percent of employees working on a part-time basis

[4] Arellano, M., and Bond S. (1991) "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", Review of Economic Studies, 58: 277–297.

- jobs density[5]
- number of JSA claimants combined with the number of UC claimants in the 'searching for work' category*
- real value of specific parts of local authority budgets (homelessness, Supporting People, mental health), £ per capita
- real value of main out-of-work benefits (JSA/ESA/IS personal allowance; UC standard allowance). The reference year was 2011.[6]

c) housing-related variables:

- number of households in PRS*
- real private rent at 25th percentile (three versions: room, 1 bed, 2 bed), £ per month
- number of non-passported HB claimants (a proxy for HB not covering full rent)*
- number of PRS LHA claimants*
- discrepancy between the value of LHA and real private rent at 25th percentile, £ per month (three versions: room, 1 bed, 2 bed)
- Council Tax collected by LA as proportion of all collectible CT (a proxy for Council Tax arrears)
- number of SRS households on HB*

d) homelessness-related variables:

- number of households accepted as homeless*
- number of single persons accepted as homeless*
- number of households in Temporary Accommodation*

e) Welfare-related variables:

- number of claimants of ESA/IB/SDA/UC 'no work requirement'/UC 'preparing for work'*
- number of cases of failed DLA to PIP reassessment*
- number of cases of failed fresh PIP assessment*
- number of households subject to 'bedroom tax'*
- number of households subject to Benefit Cap*
- number of JSA/ESA/IS sanctions*
- number of UC sanctions*
- percent of UC claimants among all working age benefit claimants

[5] 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.

[6] Two versions of this variable were created and tested: one with the official CPI inflation and one with inflation calculated specifically for low-income households. Living Costs and Food survey data for 2011 to 2017/18 was employed to calculate the latter. Low-income households were selected as follows: respondents in the bottom quintile of equivalised household income were divided into two halves in terms of equivalised expenditure, and the bottom half was selected as the target population (10% of the survey sample). The results presented in the report refer to this version of the variable. The other version, using official CPI, was also statistically significant (p=0.002) and had a slightly lower coefficient (-1.25) under the model reported in Table A3.1.

- number of 'fit for work' outcomes of WCA*
- number of LHA recipients subject to SAR*
- number of SRS tenants with HB paid to claimant instead of the landlord*
- number of households subject to HB non-dependent deductions (three versions: 1+, 2+, 3+ non-dependents)*

4. SUPPLEMENTARY POOLED CROSS-SECTIONAL MODELLING AT LAD LEVEL

While the panel modelling described in Section 3 above is of greatest value in highlighting evidence of what factors which are changing over time, particularly benefit system factors and economic conditions, appear to have significant impacts on food bank demand, it cannot provide any explanation for variations across different localities in the general level of demand. Therefore, as a complementary exercise, we also looked at the systematic patterns in variation across localities in the general level of demand, averaged over the most recent years, to see what factors were most associated with high general levels of demand.

Quite a large number of variables were considered for inclusion but having regard to the degree of collinearity between many of these it was decided to group these into main factors using factor analysis. Three groups of variables were subject to factor analysis: these are characterised as relating to economic conditions (including labour market), housing (including some demographic and homelessness variables) and destitution (including complex needs and migrant related variables). The factor analysis involved first taking principal components, rotating these to find more interpretable factors (i.e. clearly related to particular variables), and selecting the first three factors in each group.

Table A4.1 shows the patterns in scores on these factors, alongside the relative numbers of food parcels and food bank food banks, across the nine GOR regions of England. It can be seen that the level of food parcel demand is highest in the North East, a region with slightly more than average number of food banks, but mainly notable for high scores on unemployment and related indicators, high scores on destitution and complex needs, and low scores on earnings and related variables. It is also a region characterised by low housing demand and low demographic/housing growth. The North

West also scores quite high on food parcels and has similar characteristics to the North East, but to a less marked extent. Yorkshire and the Humber region has relatively low food parcel demand, but this may be associated by the lower presence of Trussell Trust food banks as well as less unemployment and less destitution. London also has both low food parcel demand and low supply of food banks; while unemployment is quite high, London also has high earnings/ incomes, high housing demand, lower general destitution but more destitution associated with migrants.

Table A4.1 Food parcels and food banks and eight general socio-economic factors by region, England 2013-18

Government Office Region	TT food parcels	TT food banks	Econ 1 Unem	Econ 2 Earnings	Econ 3 JobDens	Housing 1 Unafford	Housing 2 Low Dem	Housing 3 Change Dem	Destit 1 SMD & Gen	Destit 2 Migrant
North East	10.406	0.0058	0.922	-0.857	0.088	-0.457	1.436	-0.699	1.135	-0.677
Yorks & Humber	3.999	0.0037	0.095	-0.685	0.158	-0.528	0.576	-0.212	0.421	-0.334
North West	7.193	0.0060	0.336	-0.783	0.290	-0.405	0.804	-0.153	1.050	-0.294
East Midlands	5.203	0.0054	-0.347	-0.598	0.073	-0.502	0.241	0.031	-0.076	-0.400
West Midlands	6.270	0.0056	0.397	-0.308	0.069	-0.238	0.531	0.240	0.357	=0.198
South West	6.063	0.0048	-0.711	-0.464	0.127	-0.386	-0.462	-0.93	-0.243	-0.401
East of England	5.902	0.0069	-0.667	0.142	-0.161	-0.220	-0.567	0.183	-0.460	-0.352
South East	5.424	0.0052	-0.735	0.527	-0.309	-0.263	-0.868	0.036	0.-707	-0.299
London	3.985	0.0032	0.707	1.630	-0.346	1.847	-0.424	-0.004	-0.553	1.798
Total	5.731	0.0051	0.017	0.038	-0.29	0.048	0.003	-0.018	-.007	0.040
Universal Credit workseekers	1.365	0.370	0.000	7.783						
Sanctions - legacy or UC	0.230	-0.055	0.344	-0.948						

Notes: Food parcels and food banks are per 100 households; data are annual by LA and year (2013-18), excluding authorities with very low/zero number of food banks and/or parcels; remaining variables are standardised factor scores from a factor analysis of variables grouped into three main categories: economic, housing, and destitution/SMD/migrancy. (SMD stands for 'Severe and Multiple Disadvantage'). All variables entered into factor analysis were per 100 households or other appropriate ratio measures. Factor analyses and descriptive table are weighted by relative number of households in local authority.

[7] See Fitzpatrick, S., Bramley, G., Sosenko, F., Blenkinsopp, J., Johnsen, S., Littlewood, M., Netto, G. and Watts, B. (2016) Destitution in the UK, York: Joseph Rowntree Foundation

Pooled OLS regression was conducted, with the number of food parcels distributed by the Trussell Trust being the outcome variable, while predictors included the number of Trussell Trust food banks and predicted scores on eight factors (three economy-related, three housing-related and two destitution-related). The results for the period 2016-18 shown in Table A4.2 indicate that nearly half of the total variance is explained, with most variables statistically significant. This shows that there is quite a strong supply effect, with areas with more food banks having more parcels taken up, as expected. Areas that have higher unemployment rates have somewhat lower take-up, in agreement with results of fixed effects modelling. Areas of high housing pressure (such as through high unaffordability and homelessness) have substantially more take-up of parcels, while there is a particularly strong relationship with the factors which measure or proxy destitution (in general, and also that part related to complex needs). Areas of particularly low housing demand have marginally lower food parcel take-up, as do areas of demographic and housing growth.

Of the specific benefit and policy factors, people on partial LHA and people on UC for workseekers seem to be significantly positively related to food parcel take-up. However, there seems to be a negative relationship with 2+ non-dependent deductions from HB and, more marginally, with the Benefit Cap. The sanctions variable (legacy and UC combined) is not significant in this model, which refers to the period 2016-18. It may be argued that issues like NDDs and the Benefit Cap are less relevant to destitution/extreme poverty, because they tend to affect either larger households who can share resources, in the former case, or households who only stand to lose a minority part of their income. This contrasts with issues like UC, with its long waiting period and scope for extensive deductions, or some of the more extreme LHA cases. Running a similar model for the earlier period 2013-15 shows a somewhat less good fit, but also some differences, which are generally in line with expectations.

[8] It may be argued that there is a potential two-way relationship here, with areas with more problems getting more food banks and food banks; however, regression tests show that the relationship that way is weaker.

[9] Where the variable 'number of workseekers per 1,000 working age population' had a negative coefficient – see Table 4.1.

[10] The 'low demand' variable is a composite factor reflecting indicators of low demand (e.g. vacancies, low prices) as discussed in Bramley & Pawson (2002) and is not quite statistically significant.

Table A4.2 Pooled cross sectional regression model for food parcels (per 100 households); local authorities annual data 2016-2018

Variable	**Coefficient B**	**Std Coeff Beta**	**Signif**	**t-stat**
(Constant)	2.794		0.000	5.135
Number of Trussell Trust food banks	440.599	0.418	0.000	12.379
factor score econ 1 unem -emprate etc	-0.608	-0.157	0.051	-1.956
factor housing 1 rents unaffordability	0.958	0.264	0.000	3.557
factor housing 2 low demand	-0.368	-0.100	0.163	-1.396
factor housing 3 change demand	-0.409	-0.098	0.008	-2.667
factor Desit 1 SMT destit gen destit	1.781	0.502	0.000	-4.868
2+ non-dependent deductions HB	-3.374	-0.389	0.000	-4.868
Partial LHA	0.520	0.227	0.000	4.299
Benefit cap	-2.044	-0.086	0.089	-1.704
Universal Credit workseekers	1.365	0.370	0.000	7.783
Sanctions - legacy or UC	0.230	-0.055	0.344	-0.948

Dependent variable: food parcels /100 households, weighed by relative number of households

Model Summary

Model	**R**	**R Square**	**Adjusted R Square**	**Std Error of the Estimate**
1	.697[a]	0.485	0.474	2.87308
	Sum of squares	**degr frdm**	**Mean square**	**F**
Regression	3818.542	11	346.686	41.999
Residual	4044.748	490	8.255	
Total	7858.291	501		

Note: excludes authorities with no or limited numbers of food banks or parcels (per 100 households).

Pooled OLS regression was conducted, with the number of food parcels distributed by the Trussell Trust being the outcome variable, while predictors included the number of Trussell Trust food banks and predicted scores on eight factors (three economy-related, three housing-related and two destitution-related). The results for the period 2016-18 shown in Table A4.2 indicate that nearly half of the total variance is explained, with most variables statistically significant. This shows that there is quite a strong supply effect, with areas with more food banks having more parcels taken up, as expected. Areas that have higher unemployment rates have somewhat lower take-up, in agreement with results of fixed effects modelling. Areas of high housing pressure (such as through high unaffordability and homelessness) have substantially more take-up of parcels, while there is a particularly strong relationship with the factors which measure or proxy destitution (in general, and also that part related to complex needs). Areas of particularly low housing demand have marginally lower food parcel take-up, as do areas of demographic and housing growth.

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