Business analytics development in the food bank sector –
Phase Two Report

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1 Background
This report documents Phase Two of applied research into the innovation of food bank operations in the UK. The research is a pilot study of the NEMODE Network+ Research Call 2014. The aim of the project is to investigate the use of technology in changing food bank operations in the UK. The Phase One report details the background to the case and the organisational and technological analysis conducted to arrive at the development of business analytics for the Trussell Trust food bank network (see Hindle et al., 2015 for full details).

The context of the work is food poverty in the UK. In February 2014 the All Party Parliamentary Group on Hunger and Food Poverty commissioned a Parliamentary Inquiry into hunger and food poverty in Britain, chaired by the Bishop of Truro, Tim Thornton, and Frank Field MP. The resulting report – Feeding Britain – was launched in December 2014, based on evidence from more than 400 people across the UK (food poverty, 2014). The report estimated there are 3.5m adults who cannot afford to eat properly in the UK, 500,000 children live in families that can’t afford to feed them, and food prices have risen 47% in last ten years.

The largest food bank network in the UK is the social franchise organised by The Trussell Trust (Defra 2014). The Trussell Trust is a charity with the mission of empowering local communities to combat poverty and exclusion, and operates across the UK. The Trust reports a 40-fold increase in provision of emergency food aid between 2007-08 and 2014-15. 1,084,604 people were given three days’ emergency food and support in the year 2014-15, though these were not all unique users (http://www.trusselltrust.org/stats#our-stats-explained). In parallel with this surge in demand the number of food banks rose from 80 in January 2011 to 435 in September 2015.

The analytics development described here constitutes part of an applied research project into the use of technology in radically changing food bank operations in the UK. It is the result of action research employing Soft Systems Methodology (Checkland and Poulter 2006) and business model mapping (Osterwalder and Pigneur 2010). The project was delivered with the full involvement of the
Trussell Trust and followed a process of technology innovation developed by Dr Giles Hindle and Professor Richard Vidgen at the University of Hull (Hindle and Vidgen 2015).

## 2 Approach
The aims of the technology development for Phase 2 of the food bank project are to:

- conduct exploratory analysis of the Trussell Trust’s food bank data;
- build explanatory/predictive models using the food bank data;
- create a mapping app that gives the Trussell Trust head office (the ‘Trust’) and local food bank managers an understanding of how their users are distributed geographically and to identify the areas of greatest need.

The app development should further:

- employ free-to-use open source software so that no additional costs are incurred;
- make the tools available for others to use via the GitHub (github.com) repository
- build a prototype app that can be easily extended to include more functionality and be scaled into a production system, should the Trust so wish.

## 3 Technical architecture
The technical architecture for the food bank analytics project (FBA) is shown in Figure 1.

![Figure 1: food bank analytics (FBA) architecture](...)
2011 Census data was taken from Nomis, which is “a service provided by the Office for National Statistics, ONS, to give you free access to the most detailed and up-to-date UK labour market statistics from official sources.” (nomisweb.co.uk). A Python program was used to scrape the various census data from Nomis, resulting in 75 tables of data (see Appendix A). Census data were taken at the lowest level of granularity available, i.e., ward level (for example, within the Cheltenham local authority the College Ward is coded as E36002906).

Primary food bank data were taken from the Trust’s database as an SQL extract. The food bank data relates to the details captured when a voucher is entered into the system to record a client receiving a food package (see Appendix B). Because there is no unique client ID, it is essential to note that the voucher system records the number of food events (each visit and the number of people to be fed by that visit) and NOT the number of unique people fed. The individual visit data are then aggregated in various ways, e.g., to ward level, for the purpose of food bank modelling using R.

A file of postcode data is used to convert six-digit postcodes to latitude and longitude format for geospatial modelling.

The Google Maps distance matrix API is used to access travel times. Google provides estimates of travel time for driving using the road network, walking via pedestrian paths and pavements, bicycling via cycle paths and preferred streets, and via public transit routes. The API is free for up to 2500 calls per day and is chargeable for greater request volumes. The OpenStreetMap resource is used to provide base maps with GDAL (Geospatial Data Abstraction Library) and TopoJSON being used to format the food bank map geo shapes.

4 Descriptive analysis
Figure 2 shows actual food bank usage for the period 1 Jan 2011 – 15 Sept 2015. After rapid growth food bank usage appears to have levelled off in the years 2014 and 2015.

![Figure 2: weekly actual food bank usage](image-url)
Food bank usage spikes strongly over the Christmas and New Year period. The spike in usage requires further investigation; for example, it might be due to clients anticipating the New Year period and ensuring that they have sufficient food, it might be due to food banks closing over the New Year period (or perceptions by clients that food banks close when they might actually be open), or some combination of these and other factors.

However, while the general pattern is of levelling off (Figure 2), two notable exceptions are found: where the crisis is homelessness or where the user is of black or Asian ethnicity (Figure 3) (although visual inspection of Figure 3 suggests there is a possibility that these are also beginning to level off). Given that access to food banks is via referral agencies and that the data volumes are small, the presence of a small number of new agencies specialising, for example, in homelessness, may be sufficient to influence the trend. Equally, the change in ethnicity could be a result of differing local demographics where a newer group food banks are opening. As always, further and deeper investigation is required.

Figure 3: actual weekly food bank usage for homelessness and black or Asian ethnicity

The number of food banks opened is shown in Figure 4 with the cumulative number of food banks on the right. Food bank openings are following a classical S shape; growth begins slowly (2000 – 2010), hits a critical point where it accelerates (2011), before finally plateauing out (2014 onward).

Figure 4: food bank openings are following a classical S curve
The majority of crises are due either to benefit crises (44%) or low income (22%). In the middle of 2013 the number of benefits crises rose as a percentage of all crises—while low income crises continued to drop as a percentage of all crises (Figure 5). Note that Figure 5 shows the *composition of crises*, i.e., the proportion due to benefit crises and the proportion due to low income, rather than the absolute volume of food bank use (see Figure 2).

![Figure 5: proportion of weekly actual food bank usage related to benefit and income crises](chart.png)

Comparing regions: the proportion of clients referred for reasons of unemployment is highest in London, benefit issues are high in Yorkshire, Humber and the North West, and low income is the key reason in the North East (Figure 6). However, given that access to Trust food banks is via a referral agency these usage statistics will be influenced by the number, kind, and structure of agencies in each of the regions.
Although on average use in rural areas is about the same as in urban areas, it’s in the rural areas that we find the outliers (the top left hand corner of Figure 7) – where demand per head is greatest. This may be due to extremes of poverty and lack of amenities in rural areas or it may be a statistical anomaly. Further investigation is needed into the data around urban and rural food poverty.
5 Beneath the trend

To gain insight into the drivers of food bank use is a difficult task and one for which simple models with simple assumptions should be treated with considerable caution. For example, subject matter experts suggest that food bank usage is likely a complex mix of factors such as:

- national and local government policy – particularly, but not exclusively, in relation to benefits;
- cost of living – principally, but not exclusively, food, fuel and housing;
- prevalence and capacity of referral agencies (access to food banks is by referral only and cuts and closures of referral services will affect food bank usage);
- availability of opportunities for low-skills employment;
- prevalence and maturity of Trussell Trust food banks;
- availability of alternative emergency food provision (e.g., from food banks not affiliated with the Trust, some of which may operate on a ‘self-referral’ basis);
- cultural and social acceptability of using food banks.

To predict future use of food banks involves building a model that captures the relevant factors that drive food bank use (e.g., the list of candidate items above), to fit the model to the historical data, and then use the model to make predictions. Average growth in individual banks in the two-year period 2012-2013 was running at 36% per annum, followed by a slow down in growth in January 2014 (Figure 2). These high level trends may be a complex interaction of delays and lags in response to the rapid expansion of the number of food banks. For example, some of the growth in food bank usage may be driven by the natural maturing of food banks that opened 2011-2013, with a significant proportion of growth being driven by high levels of existing unmet need that is gradually ‘expressed’ as people slowly discover that a food bank is open in their area. We consider the impact of the food bank maturity cycle on food bank usage.

Estimating the ‘maturity curve’

Teasing apart the separate impacts of ‘time’ is notoriously hard. Typically time is thought to have three separate - but interrelated - effects: age, cohort and period.

- **Age/maturity.** It will take some time for a food bank to reach maturity because many people will only find out where a new food bank is slowly through word of mouth. Therefore, the age of the food bank since it opened will impact on food bank usage;

- **Period.** Clearly, food bank demand is also driven by events, such as the state of the economy, benefit changes, and seasonality - all of which are events that happen at points in time;

- **Cohort.** Finally, and a rather less obviously, food banks that opened at the same time might share characteristics. For example, the original generation of food banks may have opened in the areas of greatest need and thus be serving a different demographic from food banks that opened later.
The key questions that we want to answer regarding maturity are:

- Is there a maturity curve after food banks open? If it takes a period of time for food banks to get up and running, then a potential explanation for the slowdown (Figure 2) is that a large cohort of food banks are maturing at the same time.

- How much variation is there across food banks? Are they slowing everywhere?

To answer these questions we have built a model as described in Appendix 3. While various analyses have been conducted (and more are to be done), the food bank maturity curve in Figure 8 suggests that it takes about a year for a food bank to reach full maturity on average. However, the main impact occurs much faster: 75% of the impact of a new food bank has typically occurred after 5 to 6 months.

In Figure 9 the underlying trend for food bank demand (average people fed per week) is shown, when controlling for maturity, seasonality, and variation between food banks. The trend shows that demand rose steeply in the period 2012-2013 and then plateaued. Therefore, it seems that food bank maturity, i.e., the lag between opening and getting to operational capacity, does not explain the fall off in food bank demand and there is likely some other factor at play (e.g., one or more of the factors identified above). Further, there is considerable variability between food banks and it may be that growth continues in some areas of the country while leveling off and falling in others. Further work exploring the drivers of food bank use is needed.
In summary, our food bank model shows that we’d expect a food bank launched today to serve around 50 people per week, take 6 months to reach full operational maturity, and to serve double the yearly average over the Christmas/New Year period.

6 The food bank app

To enable the Trust and individual food banks to examine and interact with the data and the analytics a food bank app was developed. The app is rendered in D3, a JavaScript library for manipulating documents based on data using HTML (hyper text markup language), SVG (scalable vector graphics), and CSS (cascading style sheets): “D3’s emphasis on web standards gives you the full capabilities of modern browsers without tying yourself to a proprietary framework, combining powerful visualisation components and a data-driven approach to DOM [document object model] manipulation” (d3js.org). The app also uses the leaflet.js JavaScript mapping library and data from OpenStreetMap to create the map.

The D3 implementation can be hosted locally or on a central server and allows any user to access the app via their Web browser (Chrome, Safari, Firefox, and IE8 and above) without needing to install software and without having to learn how to use a new software environment. A single app is used by food banks and the Trust allowing the app user to zoom in and out to view the data at the level they need (e.g., an individual food bank, an urban conurbation, a region, or nationally).

The app uses actual data for 1 January 2014 - 15 September 2015 concerning client location (no personal details are accessed), food bank location and food bank voucher use. Data are further segmented by crisis type. Predicted values are generated in the analytics process using the Census data to predict where we would expect to see demand for food banks.
On opening the app the user sees a zoomable map of the UK with individual Trussell Trust food banks shown as red dots (Figure 10). On the right hand side are options that the user can change to see different views of the data. The default view is to show actual use of food banks, represented by the different depths of colouring of the wards. For example, the darkest colour in Figure 10 represents food bank usage of 4.2 visits per hundred heads of population in the period 1 January 2014 to 15 September 2015. This view provides a useful heat map of food bank usage together with the location of food banks (which can be toggled on or off). The opacity of the map can be changed to reveal or hide the underlying geography. At this level, food bank usage is related to wards, regardless of the food bank that actually served the food bank client. The app user can zoom in and out of the map looking at locations of food banks, noting patterns of dispersion, for example if there is a cluster of food banks in an area with high density of use, such as Birmingham, are those food banks working together to share resources such as storage space and logistics?

![Figure 10: actual food bank usage](image)

By using the zoom the app user can investigate local patterns of food bank use. Figure 11 shows the usage density around the Holderness Foodbank. It seems to serve a large community, with the densest usage apparently a long way away from the food bank. Is the darker area actually the area of greatest need, or are the Trust’s referral networks just stronger out there? Would an additional food bank be warranted to serve this area, or are there other emergency food providers already adequately serving that locale?
The app user can then switch to predicted need, which is calculated using data from the 2011 Census in a logistic regression model. The more than thirty independent variables in the logistic regression model include: level of economic activity, state of health, level of deprivation, number of dependent children, age of children, and occupation.

Figure 12 shows actual usage for the Holderness and Hull Foodbanks on the left and the predicted use on the right. The analysis shows that while predicted use is low, other than for Hull and Bridlington, the actual use is rather higher, possibly indicating rural poverty that is not captured in the Census data (Figure 7). This type of analysis helps the Trust ask questions about the location of their food banks and to identify areas that might require food bank provision, particularly where there are areas of high predicted food bank use that are not served by a food bank. However, as the app does not currently show non-Trust food banks it is possible that areas of high predicted use where the Trust is not represented are being served by non-Trust food banks.
To get deeper insight into the reasons that people visit food banks there is analysis of the crisis type:

- Benefit changes
- Benefit delays
- Child holiday meals
- Debt
- Delayed wages
- Domestic violence
- Homeless
- Low income
- Sickness
- Unemployed
- Other

At a ward level, of the census variables we looked at, long-term health issues and deprivation indices were the most strongly correlated with food bank usage.

When a person is issued with a voucher by an agency the agency will record a crisis type (Appendix B). This is sensitive data (some food bank users may prefer not to divulge this information) and some agencies might be more thorough than others in capturing the crisis type. Further, these crisis types may be interrelated and selecting a single ‘cause’ for a visit may be a gross over-simplification. In Figure 13 the crisis type ‘homeless’ is shown for the North Lakes food bank. Homelessness seems to be a more prevalent type of crisis here than in many other areas. This might be due to the homeless agencies that the Trust partners with being particularly good at getting their message out through their networks, or it may represent higher levels of underlying homelessness in this area. This information may also be useful to other agencies, raising the question of how data might be shared.
However, it should also be noted that the densities for homelessness are low and the patterns observed in Figure 13 may be due to small sample sizes.

Figure 13: actual food bank usage for the North Lakes, crisis type ‘homeless’

To explore individual food banks the app user can click on a food bank icon (the red dot) and see the actual reach of the selected food bank (Figure 14). Reach is calculated based on the locations of the individual food bank users served by that specific food bank. Specifically, it uses an ‘alpha hull’ routine to construct a polygon from the locations (postcodes converted into latitude/longitude) of the individual users served by a given food bank. Examination of the Holderness Foodbank reach in Figure 14 shows this food bank to be covering a wide area, with areas of highest density of use some distance from the food bank (compare with Figure 11). This raises the question of whether the food bank could be more centrally located to reduce access times for clients.
Figure 14: actual food bank reach for the Holderness Foodbank

Given a start and a finish location the Google Maps API provides estimates of drive time and walk time. The food bank app uses a 30-minute drive time and a 30-minute walk time to calculate the reach of the food bank in terms of travel time (Figure 15). The walk time area coincides well with the areas of densest food bank use for the Bridgwater Foodbank.

Figure 15: drive time reach and walking time reach for the Bridgwater Foodbank
7 Summary

The project represents a small step toward using data and data visualisations to inform decision-making and policy in the food bank sector. The graphs reproduced in this paper were part of an exploratory analysis designed to pave the way to building a visualisation tool for the Trust. The reader is reminded to be wary of reading too much into the patterns in this data. Further statistical analysis and model building would be needed to support conclusions that go beyond the merely descriptive.

Recommendations for future work

Firstly, further predictive modelling can be conducted on the core food bank data to build better models for predicting food bank usage and models that help explain how and why food banks are used. The candidate list of factors in section 5 needs further development, for example the introduction of weather data. The Bayesian models used to build the predictive models of food bank use can also be used to clean and check the data by, for example, imputing missing values and detecting inaccurate data.

Secondly, candidate extensions for the food bank app include:

- Showing data for individual food bank users (to aid local food bank planning)
- adding non-Trust food banks to the data (to aid food bank location planning)
- adding agencies that issue vouchers (to see number and type of agencies and location/distance from food bank)
- show donors (to support marketing)
- show food bank storage locations
- add local amenities and services (e.g., Citizens Advice to support signposting).

Thirdly, the Trust can consider organisational initiatives, such as:

- Data quality. Vouchers are used to record the issuing of food packages and do not capture unique users. Adding a food bank user ID would allow food packages to be associated with individuals and thus it would then be possible to count the number of unique people fed in a period. Age is currently in very coarse ranges and should have greater granularity (unique food bank user ids would allow date of birth to be captured and yet greater accuracy and granularity). However, capturing more data about food bank users must be balanced with the impact on behaviours (might this greater detail be intrusive and deter some people from using food banks?) and clear ethical guidelines and processes within the Trust concerning how data will be used.

- Enterprise systems. Voucher data is entered from a manual form with all the attendant problems of paper forms. The Trust might develop an enterprise system that would allow issuing agencies to enter data directly into a computer system that is then accessed online by the food bank fulfilling the food package. This would help ensure data completeness and accuracy. If a unique food bank user ID were added to the database then further analysis of food bank use would be possible.

- Data sharing. Firstly, there are opportunities to share data with other food banks that are not part of the Trust network. If an enterprise voucher system were developed then this
could be made available to non-Trust food banks and the voucher data pooled to provide a
more complete view of food bank use in the UK. Alternatively, a data interchange format
might be developed in XML allowing non-Trust food banks to contribute data (in return for
using the food bank app on their own data). Secondly, data might be shared with other
agencies and charities, for example with debt, housing and homelessness charities, to get
deeper insight into the causes of food poverty and to engage multiple agencies in concert.

Concluding remarks
In summary, the food bank analytics project has led to exploration of the Trust’s data and
encouraged the Trust’s management to ask questions about the meaning of that data and to reflect
on how the Trust can use data to support and implement its mission. These insights into data,
together with predictive models, can then be used to help decision-making, e.g., whether to co-
locate housing advisers with food banks that have high levels of homeless crisis in order to provide
support to clients (e.g., see Jones (2016) account of debt counselling in a food bank). The initial
analytics work has also highlighted the need for more data of better quality. In conclusion, the
analytics project represents a first step on the Trust’s transformative journey to becoming a data-
centric organisation.

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people-guidance.
Appendix A: 2011 Census data scraping
http://www.nomisweb.co.uk/census/2011/quick_statistics

Reference
Arrow pointing up Name
QS101EW Residence type
QS102EW Population density
QS103EW Age by single year
QS104EW Sex
QS105EW Schoolchildren and full-time students at their non term-time address
QS106EW Second address
QS108EW Living arrangements
QS110EW Adult lifestage (alternative adult definition)
QS111EW Household lifestage
QS112EW Household composition - People
QS113EW Household composition - Households
QS114EW Household composition (alternative child and adult definition) - People
QS115EW Household composition (alternative child and adult definition) - Households
QS116EW Household type
QS117EW People aged 18 to 64 living in a one adult household
QS118EW Families with dependent children
QS119EW Households by deprivation dimensions
QS121EW Armed Forces
QS201EW Ethnic group
QS202EW Multiple ethnic groups
QS203EW Country of birth (detailed)
QS204EW Main language (detailed)
QS205EW Proficiency in English
QS206WA Welsh language skills
QS207WA Welsh language skills (detailed)
QS208EW Religion
QS210EW Religion (detailed)
QS211EW Ethnic group (detailed)
QS212EW Passports held
QS213EW Country of birth (expanded)
QS301EW Provision of unpaid care
QS302EW General health
QS303EW Long-term health problem or disability
QS401EW Accommodation type - People
QS402EW Accommodation type - Households
QS403EW Tenure - People
QS404EW Tenure - Household Reference Person aged 65 and over
QS405EW Tenure - Households
QS406EW Household size
QS407EW Number of rooms
QS408EW Occupancy rating (rooms)
QS409EW  Persons per room - Households
QS410EW  Persons per room - People
QS411EW  Number of bedrooms
QS412EW  Occupancy rating (bedrooms)
QS413EW  Persons per bedroom - Households
QS414EW  Persons per bedroom - People
QS415EW  Central heating
QS416EW  Car or van availability
QS417EW  Household spaces
QS418EW  Dwellings
QS419EW  Position in communal establishment
QS420EW  Communal establishment management and type - Communal establishments
QS421EW  Communal establishment management and type - People
QS501EW  Highest level of qualification
QS502EW  Qualifications gained
QS601EW  Economic activity
QS602EW  Economic activity of Household Reference Person
QS603EW  Economic activity - Full-time students
QS604EW  Hours worked
QS605EW  Industry
QS606EW  Occupation (Minor Groups)
QS607EW  NS-SeC
QS608EW  NS-SeC of Household Reference Person - People aged under 65
QS609EW  NS-SeC of Household Reference Person - People
QS610EW  NS-SeC of Household Reference Person (HRP) - HRP Aged under 65
QS611EW  Approximated Social Grade
QS612EW  Year last worked
QS613EW  Approximated social grade
QS701EW  Method of travel to work
QS702EW  Distance travelled to work
QS703EW  Method of Travel to Work (2001 specification)
QS801EW  Year of arrival in the UK
QS802EW  Age of arrival in the UK
QS803EW  length of residence in the UK
Appendix B: food bank data

The data used in the analysis is taken from the food bank voucher database. Vouchers are issued by partner agencies and then redeemed by the food bank client at a food bank. Once redeemed, the voucher(s) is entered into a Web-based application by the local food bank.

<table>
<thead>
<tr>
<th>Field</th>
<th>Definition</th>
</tr>
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<tbody>
<tr>
<td>voucherNo</td>
<td>Voucher unique identifier</td>
</tr>
<tr>
<td>referringAgency</td>
<td>Agency issuing the voucher</td>
</tr>
<tr>
<td>foodbankID</td>
<td>Food bank unique identifier</td>
</tr>
<tr>
<td>date</td>
<td>Date the food bank voucher is used by the client</td>
</tr>
<tr>
<td>clientPostCode</td>
<td>Six digit post code of client (or no fixed address)</td>
</tr>
<tr>
<td>noAdults</td>
<td>Number of adults in the household to be fed by the food package</td>
</tr>
<tr>
<td>noChildren</td>
<td>Number of children in the household to be fed by the food package</td>
</tr>
<tr>
<td>crisisType</td>
<td>One of: Benefit changes, Benefit delays, Child holiday meals, Debt, Delayed wages, Domestic violence, Homeless, Low income, Sickness, Unemployed, Other</td>
</tr>
<tr>
<td>ethnicity</td>
<td>One of: White, Mixed, Asian, Black, Chinese, Other</td>
</tr>
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<td>ageGroup</td>
<td>16-24, 25-64, over 65</td>
</tr>
<tr>
<td>paidEmployment</td>
<td>Y/N</td>
</tr>
</tbody>
</table>

Notes:

1. The voucher records the number of people fed. As there is no unique client ID it is not possible to state accurately how many individual people a food bank has fed since a food bank user may make repeat visits.

2. The age categories are very coarse grained.

3. There is no database of referring agencies – unique agency IDs would allow more accurate analysis.
Appendix C: Bayesian modelling (Stan)

To start the investigation into these questions we constructed a hierarchical Bayesian negative binomial state space model using the Stan Bayesian statistical inference package (http://mc-stan.org). The key features of the model are:

- **Negative Binomial.** A count of the number of people served could be modelled as poisson distribution. However, the assumptions for poisson data are not fully met by this data set (i.e., the mean is not the same as the variance), thus the model uses a negative binomial distribution, which allows for greater dispersion.

- **Hierarchical.** The model uses data from one food bank to make inferences about others. This is particularly useful for making tighter inferences on food banks with shorter time series, such as those that have recently opened. The model estimates different means and trends for each food bank and common parameters for seasonality and the maturity curve. These elements enter the model on the log scale, so are effectively allowing seasonality to have the same underlying percentage impact across the country.

- **State Space.** The model estimates an underlying ‘state’ that evolves over time and which is theorized to give rise to the observed time series dynamics.

- **Maturity curve.** The maturity curve is estimated as a negative exponential, but with the shape parameter pooled across food banks. This allows for a gradual maturation toward the underlying base demand and for the base demand to vary by foodbank.

- **Seasonality.** Seasonality is captured over 52 weeks with Fourier terms and with additional Christmas/New Year period dummy variables.

- **Bayesian.** The model uses a full Bayesian approach to capture the high degrees of granularity and non-linearity in the data. The model is estimated using an unbalanced panel of food banks with Stan (http://mc-stan.org) and rstan (an R interface to Stan).