Food hardship in the US during the pandemic: What can we learn from real-time data?*

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Abstract

We study the potential effect of the declaration of the state of emergency, the beginning and end of the stay-at-home orders, and the one-off Economic Impact Payments on food hardship in the United States during the first wave of the coronavirus pandemic. We use daily data from Google Trends for the search term "foodbank" and document the development of a hunger crisis, as indicated by the number of individuals who need to locate a food pantry through the internet. The demand for charitable food handouts begins to decrease once families start receiving the stimulus payments, but the biggest fall comes when economic activity resumes after the lifting of the lockdown orders. Our estimates indicate that the increased need for emergency help among vulnerable families lasted for at least 10 weeks during the first wave of the pandemic, and we argue that real-time data can be useful in predicting such urgency.

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1 Introduction

The impact of the COVID-19 pandemic on poverty will be devastating around the world (Sumner et al., 2020; Palomino et al., 2020). And the United States will be no exception. Yet it may take a long time before researchers can actually measure the full consequences of the pandemic for vulnerable households, largely because of the unavailability of data. Surveys that were operating in the field during the COVID-19 outbreak had to abruptly terminate all face-to-face interviews.[1] While efforts are being made to keep collecting face-to-face content remotely, the questions that could not be adapted have been dropped (Sastry et al., 2020). In addition, the quality of data collected from surveys during the pandemic is of some concern, on account of the negative effects on response rates, the unrepresentative random sub-samples (as the virus has affected different socio-economic groups differently), comparability of data at different points during the pandemic, respondents' self-selection, etc. (Schaurer and Weiß, 2020). Data from multiple surveys is also expected to be made available to researchers with a substantial delay. But if we are to design effective policies to help those most in need, then an accurate diagnosis of the economic situation of families is a matter of urgency.

The main objective of this study is to analyze the potential for real-time data to provide a prompt diagnosis of the effects of the pandemic — and the sudden halt of economic activity — on one of the most extreme consequences of poverty: food hardship. With that objective in mind, we use daily data from Google Trends for the search terms "foodbank" and "food pantry." The assumption is that families in need may potentially use the internet to locate the closest foodbank available, once they run out of goods in their pantries. They might also want to know about opening days and hours and generally how the system works. We want to analyze the extent to which web search intensities for those terms can be a leading indicator of subsequent demand for charitable food and ascertain whether real-time data can serve as an alternative to survey data for poverty analyses. The ultimate goal is to document the effects of the pandemic — and of the measures imposed to stop its spread — on the ability of families to provide food for their members. We focus on data relative to the US, one of the richest countries in the world, with high levels of food insecurity.[2]

According to data from the US Department of Agriculture, in 2019, 10.5% of households in the US (35.2 million individuals) suffered food insecurity.[3] That is, at times during the year, these households were uncertain of having (or were unable to acquire) enough food to meet the needs of all their members, because they did not have sufficient money or other resources. Some 6.4% of US households qualify as low food secure and 4.1% as very low food secure. In the former case, households obtain sufficient food only by employing a number of strategies, such as eating less varied diets, participating in food

[1] For example, in the US, two major supplements to the Panel Study of Income Dynamics (PSID) — the Child Development Supplement and the Transition into Adulthood Supplement — were in the field during the pandemic outbreak and had to cancel all interviews. The same was true of Europe. The most important data source for the study of poverty in Europe, the European Union – Statistics on Income and Living Conditions, suspended data collection during the first wave of the pandemic, given the impossibility for its interviewers to go into families' homes. Eurostat has suggested that countries either postpone/prolong the fieldwork or move from face-to-face to telephone interviewing (Eurostat, 2020).

[2] We use the term "food hardship" throughout the paper when discussing our foodbank search intensity measure from Google Trends. We refer to "food insecurity" only in those instances in the paper where the standard definition of food insecurity in the United States is used. We would like to thank a referee for suggesting such use of both terms.

[3] See http://www.ers.usda.govwww.ers.usda.gov for further details.

assistance programs or resorting to food pantries. In very low food secure households, the eating patterns of one or more members have been disrupted and food intake has been reduced at times during the year because of insufficient money. The prevalence of the problem is even higher in households with children (13.6%), in single-mother households (28.7%), in black, non-Hispanic households (19.1%), and in Hispanic households (15.6%). Also there is considerable heterogeneity across states, with the lowest prevalence in New Hampshire (6.6%) and the highest in Mississippi (15.7%) — see Figure A.1 in the Appendix.

Despite such high levels of prevalence, and according to the same data source, 2019 was the eighth year in a row that food insecurity had declined, from a peak in 2011 of 14.9% of US households. That year, 2019, was also the first year that food insecurity prevalence was statistically significantly below the pre-recession levels of 2007 — see Figure A.2 in the Appendix. However, the outbreak of the pandemic has abruptly changed this trend. Schanzenbach and Pitts (2020a), using data from the Census Bureau's Household Pulse Survey, document the fact that food insecurity at least doubled among all households and tripled among households with children during the first weeks of the pandemic. Estimates for the increase in food insecurity since the beginning of the pandemic vary depending on the definition of food hardship, the data source used, and the period of analysis, yet the escalation in the need for charitable food is beyond doubt in the great majority of studies (Bauer et al., 2020; Feeding America, 2020; Niles et al., 2020; Raifman et al., 2020; Gundersen et al., 2021).[4]

Our paper contributes to three strands of literature. First, we enrich the growing research into the short-term effects of the pandemic on economic well-being and poverty (Chetty et al., 2020; Dang et al., 2020; Han et al., 2020; Cicala, 2021; Crossley et al., 2021). Second, our results extend previous findings on the diverse impact of the different interventions undertaken to stop the spread of the virus (Kong and Prinz, 2020; Baek et al., 2020). We study the causal effect on the number of searches for "foodbank" of three events: the announcement of the state of emergency; the beginning of the stay-at-home orders; and the end of the lockdowns. These were all declared on different dates across the nation's states. Importantly, we also contribute to analysis of the effects of policies implemented to mitigate the negative effects of the pandemic. In particular, we analyze the effect of the one-off Economic Impact Payments (EI Payments) under the CARES Act, by which adults in low-income families received a one-time payment of $1200, plus $500 for each dependent child under the age of 16. Interestingly enough, the great majority of payments were received by low-income families on 15 April (Chetty et al., 2020).[5] Finally, we contribute to the literature that discusses the extent to which (ready available) real-time data serves as a tool to predict economic phenomena, and whether such a tool can be used for sound policy design (Nuti et al., 2014; Jun et al., 2018).

We document the development of a hunger crisis in the US during the first wave of the coronavirus pandemic, as indicated by the number of individuals needing to locate a foodbank through the internet. The demand for charitable food becomes less apparent once families start receiving the stimulus payments; but the main decline comes once economic activity resumes, with the lifting of the lockdowns. Our estimates indicate

[4]Ahn and Norwood (2021) are the only ones claiming that food insecurity only increased among households with children, and not in all households. In the next section, we provide a literature review of the most recent studies on food insecurity.

[5]Annual income needed to be less than $150,000 for married couples, with the household head's income less than $112,500; annual income for single filers had to be below $75,000. However, families with any immigrant adult without a Social Security number were ineligible (Bitler et al., 2020).

that the increased need for emergency help among vulnerable families lasted at least 10 weeks during the first wave of the pandemic. Our findings suggest that real-time data can be useful in forecasting the increased need for charitable food — partly among individuals who have to find information on foodbanks for the first time. The policy implications of our findings are very important, because food hardship has short- and long-term consequences in several domains — it is associated with worst health at all ages, including fatigue and reduced immune response (Gundersen and Ziliak, 2015); chronic diseases (Seligman et al., 2009); psychological problems and mental disorders (Hamelin et al. 2002; Davison et al., 2015; Burke et al., 2016); and increased future healthcare costs.[6]

This paper is organized as follows. After this introduction, Section 2 provides a literature review of recent papers that have analyzed the impact of the coronavirus outbreak on food insecurity in the US. Section 3 presents the data used, its advantages and limitations. Section 4 details our identification strategy. Section 5 presents our main findings and some robustness checks. Section 6 discusses the usefulness of Google Trends data for the purposes of our analysis, by comparing it with information on food insecurity trends from contemporaneous surveys and with trends on one of its leading causes, unemployment. Finally, there are some conclusions.

2 Literature review

There are a handful of studies that analyze the short-term impact of the pandemic on food insecurity in the US.[7] Bitler et al. (2020) use the COVID Impact Survey and the National Health Interview Survey (NHIS) to compare food insecurity rates over time. They estimate that the prevalence increased by 12 percentage points between 2018 and April 2020 (from 11% to 23%). Low-income families with children have been hardest hit: their food insecurity rates rose from 13% in 2018 to 34% in April 2020 — an increase of 21 percentage points. The authors argue that the rise in food insecurity is explained by the rise in unemployment and food prices. Additionally, and taking data from the COVID Impact Survey, the authors estimate that 6.8% of the respondents had received food from a food pantry in the seven days prior to the interview (8.3% among households with children), which is far above the previous peak of 2.8% in 2014 (estimated using the Current Population Survey – Food Security Supplement). The authors conclude that despite the measures taken by the US government — extending and increasing unemployment insurance and Supplemental Nutrition Assistance Program (SNAP) payments, introducing a new program to replace missing school meals (Pandemic-Electronic Benefit Transfer – P-EBT) and sending cash relief payments (EI Payments) — food insecurity has increased.

In a similar vein, Schanzenbach and Pitts (2020b) analyze data from the COVID Impact Survey and estimate that food insecurity had doubled overall and tripled among households with children by the end of April 2020, relative to predicted rates for March.

[6]See also Alaimo et al. (2001), Jyoti et al. (2005), and Howard (2011) for the effect of food insecurity on children's development and academic outcomes, and Case et al. (2005) and Currie (2009) for the long-term consequences of poor health during childhood.

[7]Part of the literature has also been devoted to analysis of the impact of the coronavirus pandemic on poverty and income loss in the US. In this respect, some studies document an important deterioration in the situation of vulnerable families (Dang et al., 2020; Belot et al., 2021; Parolin and Wimer, 2020), while others actually conclude that, thanks to the support packages, poverty was alleviated during the first wave of the pandemic (Han et al., 2020; Ganong et al., 2020).

They also document that 7% of respondents reported having received assistance from a food pantry in the week prior to the interview. The figure jumps to 10% when individuals who said they had applied or tried to apply for food pantry assistance are included.[8] Additional estimates using other sources of data can be found in Schanzenbach and Pitts (2020a) and (2020c). Ziliak (2021) compares the December Supplements of the Current Population Survey up to 2019 and the Census Bureau's Household Pulse Survey for 2020, and shows that food insecurity tripled between 2019 and July 2020 (from 3.4% to 10.8% among the adult population).[9] In comparison, during the Great Recession the rate only rose from 3.6% in 2007 to 4.9% in 2009 (and peaked at 5.1% in 2014). The author also documents an increase in the percentage of low-income adult individuals receiving charitable food: up from 9.1% in 2019 to 14.5% in June 2020 — a total increase of 59%. These figures are well above those of the Great Recession, when there was an increase of only 26% between 2007 and 2009.

Other studies have also analyzed the impact of the changes in social assistance programs and unemployment benefits on food insecurity in the US since the outbreak of the pandemic. Bauer et al. (2020) study the effect of the P-EBT program, which provides families with a voucher to purchase groceries for an amount equal to the value of school meals missed from the start of the school closures at the end of the 2019/20 school year. The authors estimate a reduction in household food insecurity levels of 6 percentage points two weeks after the P-EBT is paid out to vulnerable families with children. Using data from the Understanding Coronavirus in America survey, Raifman et al. (2020) analyze the impact of the expansion of unemployment insurance benefits in terms of both size and scope. Their results indicate that receipt of unemployment insurance is associated with a 30% decline in food insecurity among low-income households that suffered job loss during the first wave of the COVID-19 pandemic.[10]

Despite the timely relevance of the aforementioned studies, research on trends in food insecurity since the pandemic outbreak is not without its limitations — mostly because of the need to rely on survey data. It is often the case that trends need to be estimated from different data sources that use different approximations and definitions of food insecurity and also different reference periods (Ziliak 2021; Schanzenbach and Pitts, 2020c). Sample sizes are at times relatively small (Raifman et al., 2020) or are very selective (e.g. families that were below a certain percentage of the official poverty line prior to the pandemic), thus leaving aside individuals that became poor during the first wave of the pandemic. Also, most surveys started to collect data weeks after the first COVID-19 diagnosed case. For example, the first wave of Understanding Coronavirus in America (UCA) lasted from 1 April to 28 April, the US Census Bureau's Household Pulse Survey started collection in the days from 23 April to 5 May, and the COVID Impact Survey took place from 4 May to 10 May — thus, preventing analysis of the very first impact of the pandemic on food insecurity. Additionally, data does not always cover the whole nation, but only certain regions or cities (e.g. the COVID Impact Survey), it necessarily relies on self-reporting, which is prone to bias, and it may reach researchers only with a substantial delay.[11] In

[8] As explained by the authors, these figures are likely to underestimate the share of the population that interacts with food pantries, because surveys exclude the homeless population and likely under-represent those with unstable housing.

[9] When considering adults who report having sufficient food but not enough variety, the percentage escalates from 18.6% to 44.2% (Ziliak, 2021).

[10] For a previous analysis of the effect of public assistance on food insecurity, see Borjas (2005), Ratcliffe et al. (2011) and Shaefer and Gutierrez (2013).

[11] One of the most important databases for the analysis of food insecurity in the US, the December

the next sections, we explore the use of (readily available) data from Google Trends to document changes in food insecurity.[12]

3 Data

We use daily data from Google Trends for the search terms "foodbank," "food bank" or "food pantry" for all the states in the US for the period 1 January to 30 June 2020. Data is provided by Google as a search intensity measure that goes from 0 to 100 — being 0 the smallest proportion among the queried terms within a given region and a time frame and 100 being the highest proportion.[13] Given that we extract three queries, we compute a unique dependent variable "search" which contains the highest daily value among the three terms.[14] Figure 1 shows the search intensity index trend. As can be seen, while Google Trends searches for "foodbank" were relatively low and stable during the first weeks of 2020, the outbreak of the pandemic meant a sudden upsurge in the number of searches — being particularly intense eight weeks after the Centers for Disease Control and Prevention (CDCP) first public alert about the coronavirus and one week before the declaration of the state of emergency at the national level (issued on 13 March 2020). The search intensity index escalates rapidly with the stay-at-home orders and until mid-April — with only a slight decrease at the end of March, coinciding with end-of-the-month payments. The maximum is reached in the second week of April, when a clear downward trend commences — probably because vulnerable families start to receive the one-off EI Payments (see below for more detail).

[Place Figure 1 here]

If we take a longer time frame, the data indicates that the search intensity peak in April 2020 was quite unique in the time that Google Trends data has existed. Figure 2 shows the monthly data for the search term "foodbank" since January 2004 and up until June 2020. While there are peaks throughout the period, particularly in the winter months and during the Great Recession, none gets even close to the peak of April 2020, potentially indicating the severity of the need for charitable food brought about by the measures imposed to stop the pandemic.[15]

Supplement of the Current Population Survey, will only provide data relative to 2020 in the second half of 2021.

[12] Google search intensity data has been used to forecast multiple economic indicators: private consumption (Vosen and Schmidt, 2011); motor vehicles and travel purchases, unemployment benefit claims and consumer confidence (Choi and Varian, 2012); job searches (Baker and Fradkin, 2017), etc. Since the coronavirus outbreak, the use of Google search intensity data has grown exponentially to study mental well-being (Brodeur et al., 2021); economic anxiety (Fetzer et al., 2021); unemployment claims (Kong and Prinz, 2020), etc. None of the reviewed literature though contains any analysis of food insecurity using data from Google Trends. At a very descriptive level, Mayasari et al. (2020) analyze the frequency of use in Google Trends of terms related to lifestyle behaviors, nutrients and herbs and, briefly, also food insecurity. They determine in which countries of the world searches for terms such as "food bank," "free meal," or "turmeric" are more common.

[13] More details regarding the computation of the search intensity measure can be obtained from Google Support at https://support.google.com/trends/answer/4365533?hl=en

[14] Throughout the paper, we will simply refer to "foodbank."

[15] Food insecurity is seasonal in many contexts, as in the winter months many vulnerable families have to choose between paying for heating costs or food (Bhattacharya et al., 2003; Nord and Kantor, 2006). Also see Lombe et al. (2018) for an analysis of the impact of the Great Recession on increased food insecurity in the US.

[Place Figure 2 here]

Importantly for our analysis and our identification strategy, Google Trends provides the index by geographical area (in our case, we extract data at the state level). Figure 3 shows the search intensity trend for all the states, along with the declaration of the state of emergency in each state (solid line), the beginning of the stay-at-home orders (if any) (dash), 15 April, when a large number of low-income families received a payment via the CARES Act (short dash) and the end of the lockdown (long dash).[16] While there is considerable heterogeneity across the states, an increase in the search intensity measure for "foodbank" occurs in all of them after the start of the pandemic, reversing in most states around mid-April.

[Place Figure 3 here]

It is relevant to highlight at this point that the Google Trends search index is constructed from randomly selected subsets of total search data. Although all queries are stored, Google Trends randomly samples each search and uses only a fraction of the total searches for a term to build the index.[17] Sampling is done daily, which complicates the replication of previously downloaded data (Nuti et al., 2014). If one wants to get data from different samples, one needs to wait only a day for the sampling to change. To ensure that our results do not depend on this sampling process, we extracted data on 30 different days. Figure A.3 in the Appendix shows that the trends that we can derive in each extraction are very close to one another. The same is true for the results.

The advantages of using Google Search data for our analysis are that: (i) it allows an analysis almost in real time (data is available with a delay of 36 hours); (ii) in our case, it permits the analysis of a phenomenon that affects individuals often not well represented in surveys; (iii) data is not affected by the stigma or shame that may arise in interviews; and, (iv) it possibly captures individuals who need to resort to charitable food for the first time given the sudden economic shock brought about by the pandemic.[18] As for the limitations of Google Search, we need to bear in mind that: (i) older individuals are less likely to use internet to find information than are younger individuals — therefore, our results may not be representative of the elderly population; (ii) heterogeneous effects cannot be analyzed; and, (iii) we do not know exactly why a term is being sought.[19] However, given

[16]See also Table A.1 in the Appendix for the exact dates.

[17]When computing the index, Google Trends also excludes minority searches, those that have a low search volume, duplicate or repeated searches from the same user performed in a short period of time and searches with special characters, such as apostrophes. It is insensitive to capital letters. This way, the level of interest is not artificially affected by, for instance, typing errors.

[18]Niles et al. (2020) estimate that one food insecure household in three can be classified as newly food insecure since the coronavirus pandemic outbreak.

[19]That said, the Pew Research Center (2021) indicates that internet users include 99% of adults aged between 19 and 29 years; 98% of those aged 30–49; 96% of those aged 50–64; and 75% of people aged 65 and over. By race and gender, the percentages are indistinguishable. Together with age, income and education are the main sources of unequal internet use. Only 86% of adults who earn less than $30,000 use the internet, whereas the percentages are higher for people earning $30,000–49,999 (91%), $50,000–74,999 (98%), and $75,000 or more (99%). As for educational attainment, 71% of people with less than a completed high-school education use the internet, compared to 86% of those with only a completed high-school education, and 98% of college graduates. Moreover, Google had 88.1% of the search engine market share in the United States in 2020. We also actually considered searches in languages other than English, in order to see if we could predict increased need by population subgroup, but the volume of searches was not sufficiently large.

the relevance of this last point, we have investigated it by taking advantage of the Google Trends comparative search tool, which allows several search terms to be introduced at the same time and information to be gleaned about their relative importance within the same period and context. Figure 4 compares the search intensity measures for "foodbank near me" and "foodbank donation." While the search intensity measure for "foodbank near me" is very similar to the trend presented in Figure 1 and used throughout our analysis, the search intensity measure for "foodbank donation" is stable and very low, indicating that the vast majority of searches were not done by individuals willing to donate food, but rather by those who needed to obtain charitable food.[20]

[Place Figure 4 here]

4 Identification strategy

We use three different strategies to identify the causal effect of the four interventions we are interested in (the declaration of the state of emergency, the beginning and end of the lockdowns and the one-off EI Payments): (i) a difference-in-differences (DID) approach; (ii) regression discontinuity design with difference-in-differences (RDD-DID); and, (iii) an event study.

Regarding the DID estimation, we exploit the fact that each state declared each "intervention" (event) on a different date. At the same time, we compare the search intensity measure pre- and post-lockdown in 2020 to the search intensity measure on the same dates in 2019 (and 2018 for robustness) within the same state. Thus, our identification strategy relies on the differences in timing of the lockdown between states and the within-state comparison of Google searches before and after the same dates in different years. For example, in the case of the lockdowns, our specification would be as follows,

$$S_{ir} = \alpha L_{ir} \cdot Year_i + \beta L_{ir} + \gamma X_{ir} + \mu_r + \rho_i + \epsilon_{ir} \tag{1}$$

where i refers to a given day and r refers to a state. S_{ir} is the daily search intensity measure for the term "foodbank." L_{ir} is an indicator variable that takes the value 1 on the days after the lockdowns were declared, and 0 otherwise (both in 2019 and 2020). $Year_i$ equals 2020. Our parameter of interest is α which captures the causal effect of the event on the intensity of searches. The variable X_{ir} includes controls for the accumulated number of deaths by COVID-19 (per million) and the accumulated number of diagnoses (also per million). Finally, the model includes fixed effects for state (μ_r), for year, for week, and for weekday (summarized in ρ_i). Results are weighted by the population in each state, and standard errors are robust and clustered at the day level.[21]

We complete our DID results with an estimation of the immediate structural break of each intervention, by adopting an RDD combined with the DID strategy, as presented

[20] Additionally, Google Trends offers the possibility to know the most common searches that include a given term. We tried with "food bank" (two words) for the same period of analysis throughout the US and found that "food bank near me," "food near me," and "the food bank" were the three most common searches that included "food bank" — which is reassuring. Figure A.4 in the Appendix shows the list of the 25 most common terms and the associated search intensity index. Moreover, search data for "food stamps" and "SNAP," which can be regarded as an alternative proxy for the need for charitable food, provided a similar trend to that shown in Figure 1 — see Figure A.5 in the Appendix.

[21] We have also checked our results when clustering our standard errors at the state level and when we use a double cluster at the state and day level. Our main conclusions do not depend on such a choice.

above. We compare these estimated breaks to those for 2019, thus creating an RDD-DID. The goal is to obtain the immediate effect in the few days around each announcement, rather than the average effect of all pre-announcement observations on all post-announcement observations, which is what the DID results provide (Brodeur et al., 2021). Formally,

$$S_{ir} = \alpha L_{ir} \cdot Year_i + \beta L_{ir} + \lambda D_{ir} \cdot (L_{ir} \cdot Year_i)\delta D_{ir} \cdot ((1 - L_{ir}) \cdot Year_i) + \theta D_{ir} \cdot L_{ir} + \eta D_{ir} \cdot (1 - L_{ir}) + \gamma X_{ir} + \mu_r + \rho_i + \epsilon_{ir} \tag{2}$$

where i refers to a given day and r refers to a state (as above). D_{ir} is the distance in days from, in this example, the lockdown — being negative for the days before the lockdown and positive for the days after. This running variable is interacted with the lockdown to allow for different effects on both sides of the cutoff. In the main results, we use a polynomial of order 1 and the same fixed effects and controls as in equation (1), while in the robustness checks we use polynomials of higher order.

As for the event study, we take the four weeks prior to an intervention and the four weeks after (both in 2019 and in 2020), while we set to 0 the exact week of the intervention. The fourth week before the intervention ($k = -4$) is the week of reference. Formally,

$$S_{ir} = \sum_{k=-3}^{k=4} \alpha_k^n L_{kr} \cdot Year_i + \sum_{k=-3}^{k=4} \beta_k^n L_{kr} + \gamma^n X_{ir} + \mu_r^n + \rho_i^n + \epsilon_{ir}^n \tag{3}$$

For example, when $k = 2$, α_2 is going to inform us of the effect of a lockdown two weeks after its implementation and in comparison to the fourth week before ($k = -4$). The same number of fixed effects and controls as in equations (1) and (2) are included. Population weights and robust standard errors clustered at day level are used. We run an additional exercise for $k = [-4, +16]$.

5 Results

Table 1 presents the results of the DID estimations for the four interventions of interest during the first wave of the coronavirus pandemic: the declaration of the state of emergency (columns 1 to 2), the beginning of the lockdowns (columns 3 to 4), the one-time EI Payments (columns 5 to 6), and the end of the lockdowns (columns 7 to 8). For each intervention, we show first results that consider only fixed effects, while in the adjacent column we present results that also include population weights and controls.[22] Each panel presents results for a relevant period of the intervention (detailed in the first row), to take into account the fact that the different events took place in a sequential manner.

The results indicate an important increase in the search intensity for "foodbank" as a result of both the declaration of the state of emergency and the stay-at-home orders (relative to the pre-pandemic search patterns), with coefficients that range between 19.15 and 27.19, depending on the specification. Thus, while both interventions were efficient in terms of stopping the spread of the coronavirus, they meant an increase in the number of families that needed to resort to charitable food. Instead the one-off EI Payments that most low-income families received on 15 April mark the beginning of a declining trend.

[22] In order to save space, we do not show results that consider fixed effects and population weights but no controls, as they are very similar to the results that include controls. These results are available from the authors on request.

The associated coefficient to the policy for the period between 1 April and 30 April is not statistically meaningful, indicating that the decreased need to look for charitable food after the payments just compensated for the increase associated with the lockdowns. With the end of the stay-at-home orders, and as the economy resumed its activity, the search intensity measure for "foodbank" declined substantially, as indicated by the negative coefficients in columns 7 and 8.

[Place Table 1 here]

The previous results are confirmed by Table 2, which provides the results for the RDD-DID estimation of the immediate break caused by each intervention in the days surrounding it.[23] The first column refers to the specification relative to the state of emergency; the second column refers to the lockdown; the third column refers to the one-time EI Payments; and the fourth column refers to the end of the stay-at-home orders. The results indicate once more that the immediate effect of the declaration of the state of emergency and the lockdowns was to increase the search intensity measure for "foodbank" — with the effect particularly strong after the declaration of the state of emergency. By contrast, we find an immediate negative effect for the end of the lockdowns naturally associated with a certain increase in economic activity.

[Place Table 2 here]

Event study estimates inform us not only of the direction of the effect of each intervention, but also the duration of each event. Figure A.6 in the Appendix shows the results when we consider the four weeks before and the four weeks after each event, while Figure 5 provides estimates for the four weeks before the state of emergency until the end of June. The results indicate that the increase in the search intensity measure in Google Trends starts with the declaration of the state of emergency by each state and continues with the stay-at-home orders. The peak is reached five weeks after the declaration of the state of emergency when all the states that were to declare a lockdown had done so. The one-off EI Payments were received in all states within five to seven weeks following declaration of a state of emergency; at this point, a clear downward trend starts and continues until week 11, during which searches for "foodbank" are not statistically different from those in the reference period. Altogether, though, the search intensity measure was above the level in the reference period for 10 weeks after declaration of the state of emergency.

[Place Figure 5 here]

Our findings document the development of a hunger crisis in the US during the first wave of the coronavirus pandemic, as indicated by the number of individuals who needed to locate a foodbank through the internet. Charitable food demand starts to decline once families begin to receive the stimulus payments, but the main fall comes once economic activity resumes, with the lifting of the lockdowns. Our estimates indicate that the increased need for emergency help among vulnerable families lasted at least 10 weeks during the first wave of the pandemic.

[23] An advantage of RDD-DID is that results are not restricted to an arbitrarily chosen time period, as in the DID estimates presented above.

5.1 Robustness checks

We confirmed our main findings with a number of robustness checks that are summarized here. First, and following Brodeur et al. (2021), we rescaled the search intensity index to take account of the fact that the absolute number of searches may be different in 2019 and 2020. As daily searches can only be obtained for a period of less than nine months, they propose to use weekly data for the period 2019 to 2020 to rescale the dependent variable. Our main conclusions remain unchanged when we do that — likely because of the use of fixed effects by year. Second, we ensured that our results do not depend on the comparison between 2019 and 2020 exclusively, so we have included in our sample daily search data from 2018, too. When we do that, the coefficients increase slightly, while the statistical significance remains at the same level. Furthermore, we confirmed that 2019 serves well as a "control" year in our specifications, by running our models for a sample that includes exclusively data from 2018 and 2019, and by simulating a scenario whereby the different interventions occurred on the same dates, but in 2019. Figure A.7 in the Appendix shows that none of the event study coefficients are statistically significant in this placebo exercise. Third, we transformed our dependent variable into logarithms to obtain the same (qualitative) findings. The same is true when we consider a hurdle model that accounts for the number of zeros in our dependent variable. Fourth, and following Adda (2016) and Qiu et al. (2020), we added to our controls the daily average temperature in each state, using data from the National Oceanic and Atmospheric Administration (NOAA).[24] Our results are nearly identical to those presented in Table 1. Finally, we ran our RDD-DID specifications by including a polynomial of order 2: we obtain smaller positive coefficients regarding the declaration of the state of emergency and the beginning of the lockdowns, and a stronger negative impact for the end of the stay-at-home orders. The level of significance is the same as presented in Table 2 for all coefficients.

6 Can we really learn to study food insecurity from Google Trends?

The previous section showed the impact of the different interventions on food hardship during the first wave of the pandemic proxied by search intensity data. In this section, we consider how reliable such data is in predicting demand for charitable food. First, we do that by considering the extent to which data on food hardship from Google Trends is comparable to that obtained from contemporaneous surveys. And, second, we study the extent to which search intensity data correlates with changes in unemployment, one of the most important causes of food insecurity in the present context (Bitler et al., 2020; Restrepo et al., 2021).

With the first objective in mind, we take data from the longitudinal survey Understanding Coronavirus in America run by the University of Southern California Center for Economic and Social Research (CESR). This online survey collects data about attitudes, beliefs, experiences, and behaviors around the pandemic, and also (since the beginning of April) information on food insecurity.[25] The great advantage of the Understanding

[24]We computed daily temperature by extracting the information from all the weather stations across the US and averaging it by state and date.

[25]Note that, for example, the Census Bureau's Household Pulse Survey, which contains information on food insecurity, only started data collection in the fourth week of April, and thus does not allow analysis of the very first impact of the coronavirus outbreak. In the case of the COVID Impact Survey, only one

Coronavirus in America dataset for the purposes of our analysis is that it contains daily data: panelists are assigned to answer on a specific day within each 14-day wave. We proxy the daily level of food insecurity with all the positive answers to three questions: 1) "In the past seven days, were you worried you would run out of food because of a lack of money or other resources?", 2) "In the past seven days, did you eat less than you thought you should because of a lack of money or other resources?", and 3) "In the past seven days, did you go without eating for a whole day because of a lack of money or other resources?". The respondents can declare "yes," "no," or "unsure." In this last case, we assume the answer to be negative. Figure 6 shows the high correlation between the prevalence of (daily and weekly) food insecurity and the corresponding search intensity index for "foodbank," highlighting the usefulness of web search data to predict demand for charitable food.[26]

[Place Figure 6 here]

Second, if Google search intensity data is useful in monitoring the development of a hunger crisis in a given context, one would expect such data to be correlated with one of the leading causes behind the upsurge in food insecurity since the coronavirus pandemic began, and that is, undoubtedly, unemployment. Thus, we download data from the Economic Tracker (of the Opportunity Insights organization) on the number of initial weekly Unemployment Insurance (UI) claims, which we plot together with the search intensity data for "foodbank" at the national level.[27] Figure 7 shows that the correlation between the two variables is high, with UI claims peaking two weeks before the search intensity measure for "foodbank" reaches its maximum.[28] Given the delays in the actual receipt of the benefits, it is not surprising that those newly unemployed and with no savings need to resort to a foodbank soon after losing their jobs. Both variables decline at a similar rate from the month of April onwards.

[Place Figure 7 here]

The two exercises highlight the usefulness of real-time data for the purposes of our analysis — by underscoring its comparability with data from high-frequency surveys and by pointing out its correlation with leading indicators of family need, such as unemployment. The great advantage of real-time data from Google Trends is that it is free and readily available to any researcher, policymaker, practitioner, or NGO manager.

7 Concluding remarks

This study documents the development of a hunger crisis in the United States during the first weeks of the coronavirus pandemic. We show large increases in the daily number of individuals who searched the internet for the term "foodbank," which, we argue, proxies the need to resort to charitable food during the period. The results indicate that the declaration of a state of emergency, the beginning of the lockdowns in each state, and the abrupt halt in economic activity all imposed a burden on families in need that could

week in April, one in May, and one in June are covered.

[26] The correlation between the two variables is 0.73 for daily data and 0.89 for weekly data.

[27] See http://tracktherecovery.orgwww.tracktherecovery.org

[28] We use initial claims, rather than continued claims, because the search intensity data for "foodbank" is likely to reflect new poor (as argued above), in association with unemployment entries.

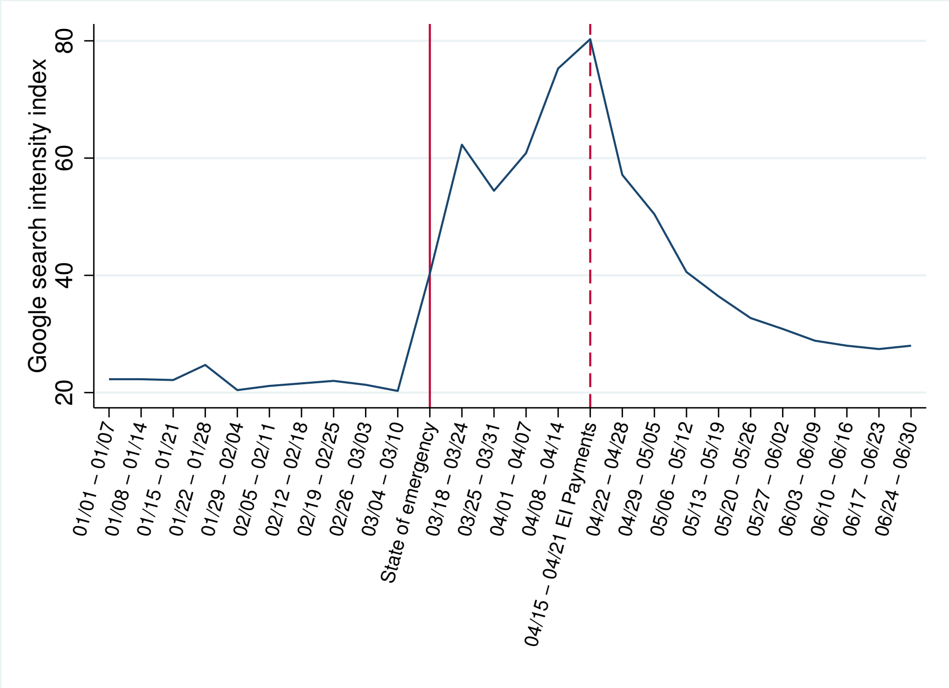
not feed their members from their own resources. The one-time EI Payments under the CARES Act, and particularly the end of the stay-at-home orders, led to an improvement in the situation. Our estimates from an event study indicate that the urgent need for charitable food during the first wave of the pandemic lasted for 10 weeks.

Hunger is difficult to measure. It is often suffered by hard-to-reach populations with unstable housing. It is sometimes endured in silence, because of stigma and shame. As a result, surveys are likely to under-report the extent of the problem. In this paper, we argue that, despite all its limitations, Google search intensity data for terms associated with hunger can be used as an additional tool to study trends in food insecurity. Figure A.8 in the Appendix shows that Google Search real-time data also predicts well the increased demand for charitable food associated with the second and third waves of the pandemic.[29] More broadly, this paper highlights the value and importance of having access to readily available real-time data for important indicators of well-being. The early detection of emergency need can help public officials and NGOs mount a more effective response.

Future additional research will need to confirm our findings in terms of food hardship and the usefulness of real-time data for the analysis of other dimensions of economic distress. Food hardship is just one dimension of severe deprivation, and resorting to a foodbank is only one of the strategies that families in need undertake to cope with falling income. Forthcoming studies should analyze the usefulness of our approach when times are less extraordinary than those brought about by a pandemic. Furthermore, we need a better understanding of how real-time data, most likely capturing the short-run effect of a sudden economic shock, can serve to complement other measures of food scarcity derived from surveys.

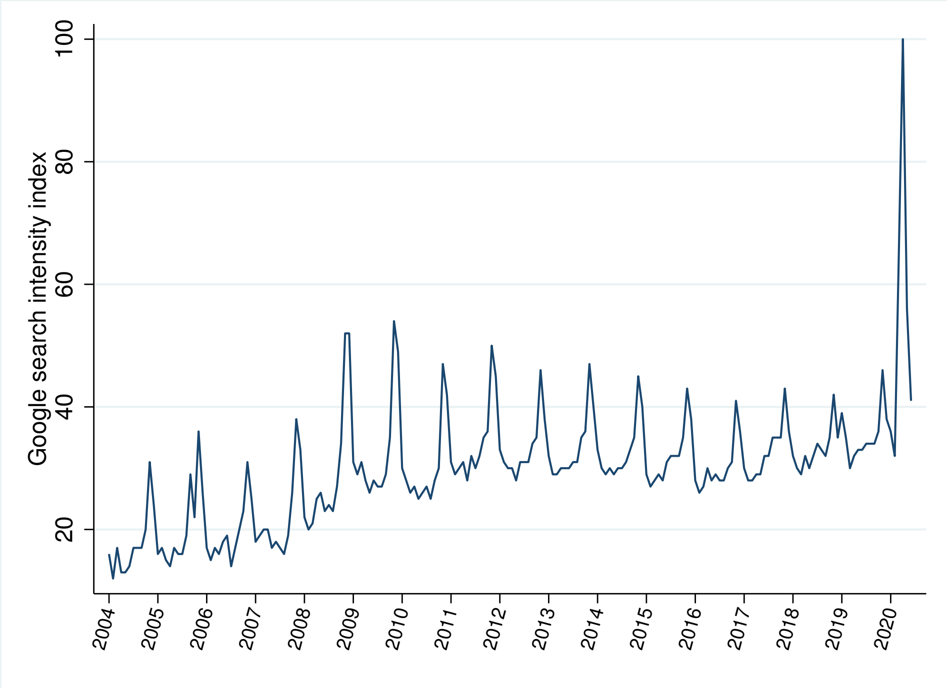
[29]Notably, the search intensity measure for "foodbank" did not reach the levels of the first wave.

Figure 1: Weekly average of the search intensity index for "foodbank" in Google Trends, US, 1 January – 30 June 2020



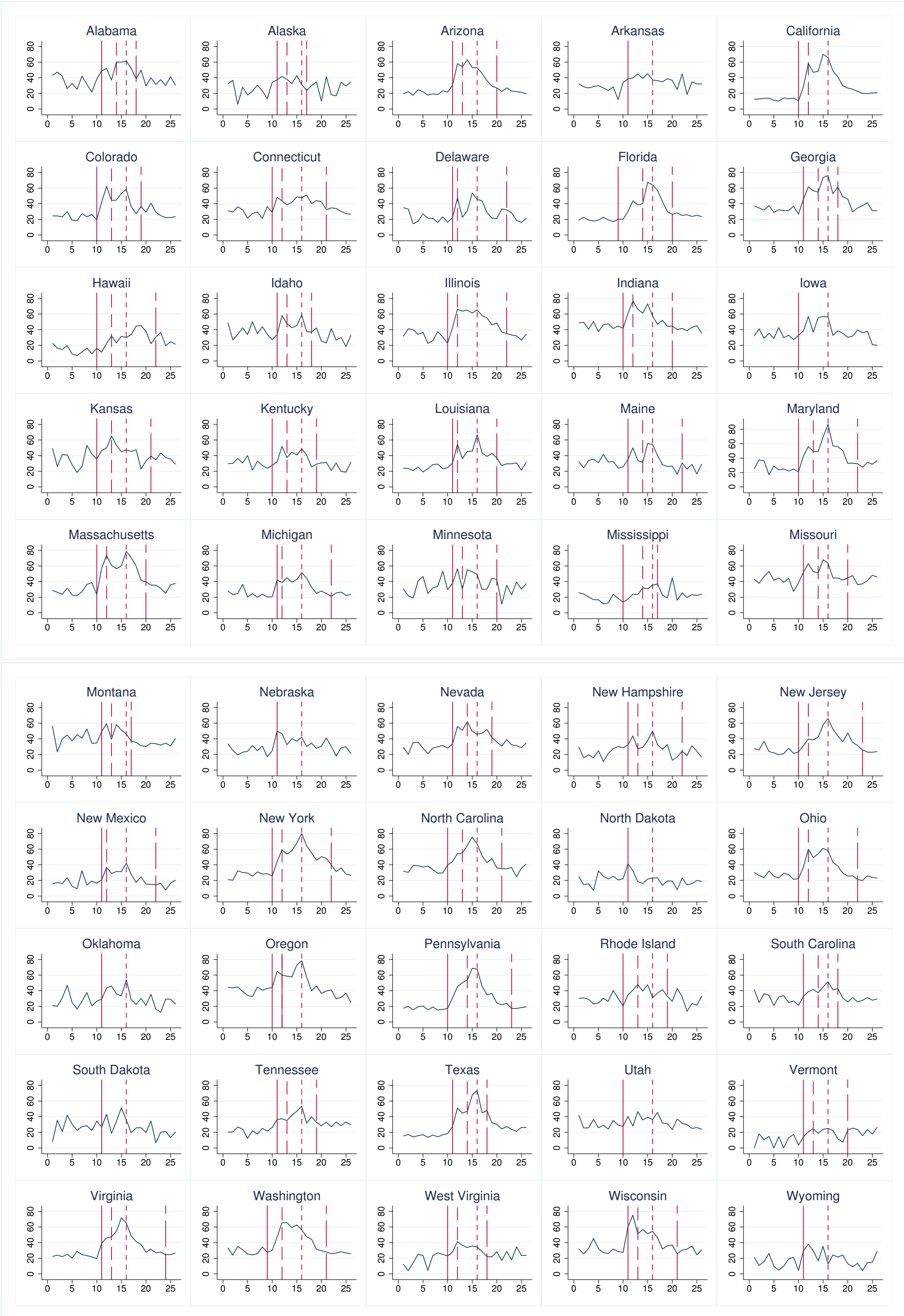
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data downloaded on 1 October 2020.
Source: Authors' computation using data from Google Trends.

Figure 2: Monthly search intensity index for "foodbank" in Google Trends, US, January 2004 – June 2020



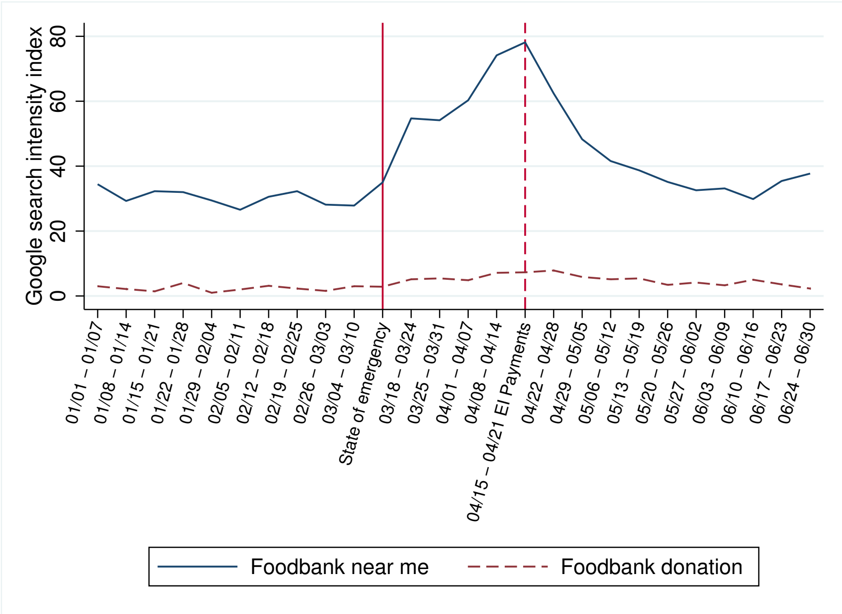
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data downloaded on 19 November 2020.
Source: Authors' computation using data from Google Trends.

Figure 3: Weekly average of the search intensity index for “foodbank” in Google Trends by state, US, January – June 2020



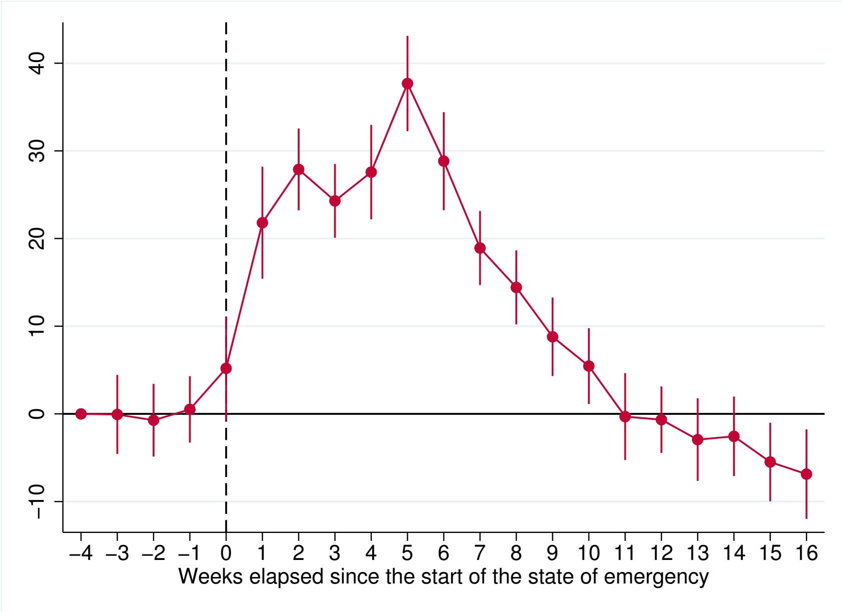
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Emergency state (solid line), beginning of lockdown (dash), EI Payments (short dash) and end of lockdown (long dash). Data downloaded on 1 October 2020.
Source: Authors’ computation using data from Google Trends.

Figure 4: Weekly average of the search intensity index for "foodbank near me" and "foodbank donation" in Google Trends (comparative search), US, 1 January – 30 June 2020



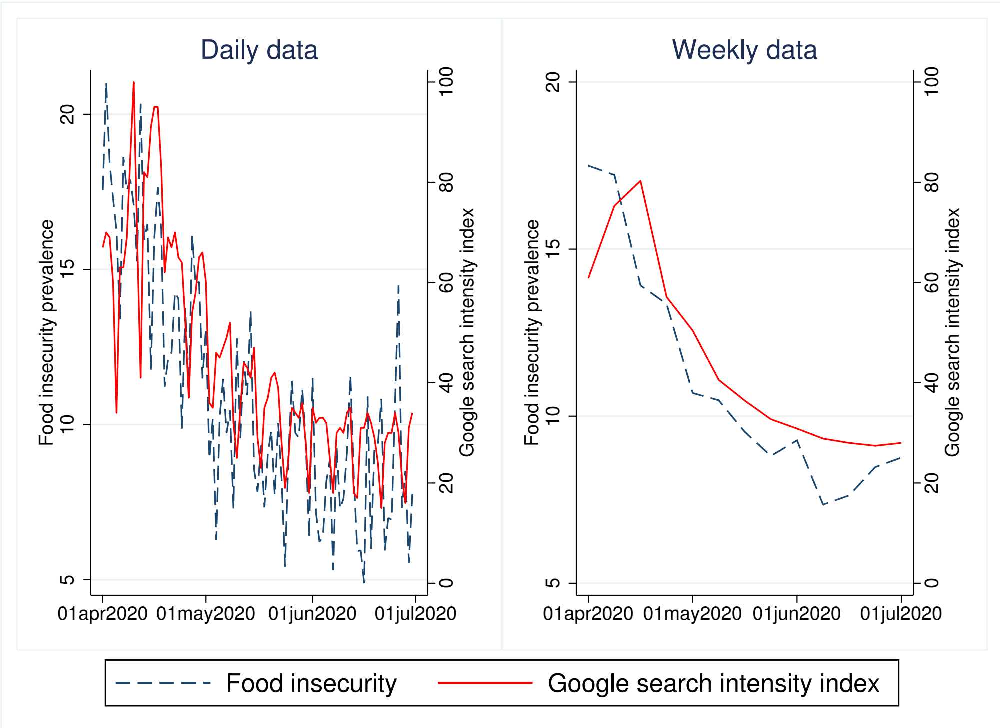
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data downloaded on 20 October 2020.
Source: Authors' computation using data from Google Trends.

Figure 5: Event study results for the search intensity index for "foodbank" in Google Trends, US, 1 January – 30 June 2020



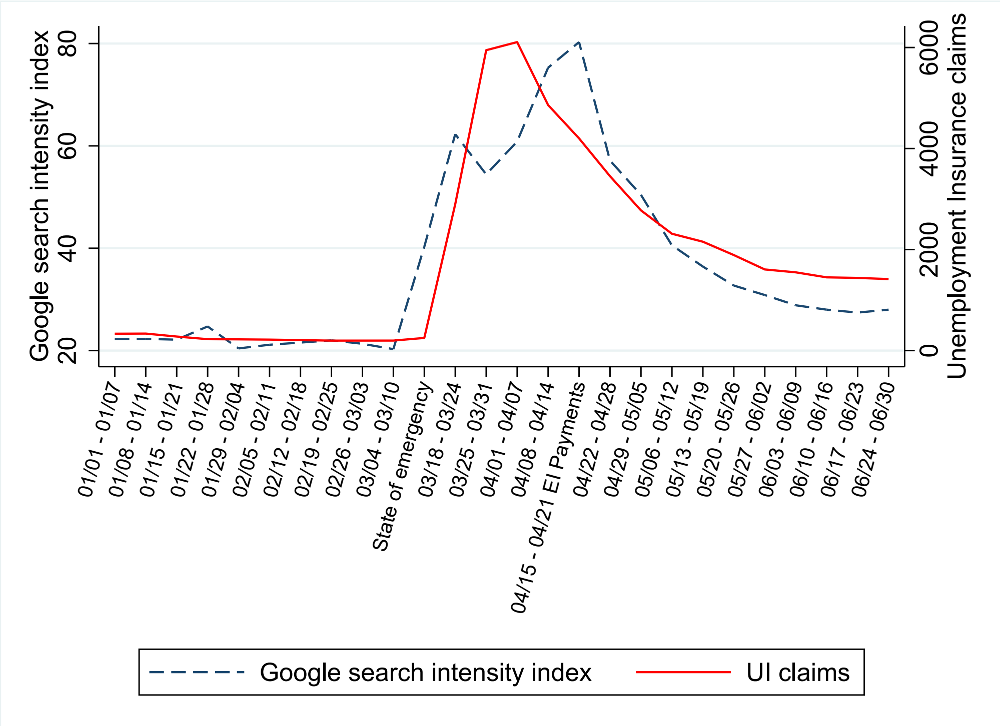
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Beginning of the lockdown [1, 5]; EI Payments [5, 7]; End of lockdown [6, 13]. Controls are the accumulated number of deaths per million individuals and the accumulated number of diagnoses per million individuals. Weights contain total population in the state in 2019 from the United States Census Bureau. Robust standard errors have been clustered at day level. Vertical lines show confidence intervals at 95%.
Source: Authors' computation using data from Google Trends.

Figure 6: Search intensity index for "foodbank" and prevalence of food insecurity according to Understanding Coronavirus in America, daily (left) and weekly data (right), April – June 2020, US



Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame.
Source: Authors' computation using data from Google Trends and Understanding Coronavirus in America.

Figure 7: Weekly average of the search intensity index for "foodbank" in Google Trends and initial unemployment insurance claims, January – June 2020, US



Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data on unemployment insurance claims is per thousand.
Source: Authors' computation using data from Google Trends and the unemployment insurance claims from the Economic Tracker (Opportunity Insights) and the Department of Labor.

Table 1: Difference-in-difference results for the declaration of the state of emergency (columns 1–2), the beginning of the lockdowns (columns 3–4), the one-off Economic Impact Payments (columns 5–6) and the end of the lockdowns (columns 7–8) on the daily search intensity measure for "foodbank," US, 1 January – 30 June 2020

	1 January – 15 April		1 January – 15 April		1 April – 30 April		15 April – 30 June	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Emergency*Year	19.15***	24.62***						
	(1.47)	(2.01)						
Lockdown*Year			18.98***	27.19***				
			(1.91)	(2.28)				
Stimulus*Year					-2.59	-4.09		
					(2.63)	(3.76)		
End*Year							-7.49***	-8.41***
							(1.59)	(1.87)
State FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Week FE	yes	yes	yes	yes	yes	yes	yes	yes
Weekday FE	yes	yes	yes	yes	yes	yes	yes	yes
Weights	no	yes	no	yes	no	yes	no	yes
Controls	no	yes	no	yes	no	yes	no	yes
Observations	10450	10450	10450	10450	3000	3000	7650	7650

Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Controls are the accumulated number of deaths per million individuals and the accumulated number of diagnoses per million individuals. Weights contain total population in the state in 2019 from the United States Census Bureau. Robust standard errors are shown in parentheses and have been clustered at day level. ***p $<$ 0.01; **p $<$ 0.05; *p $<$ 0.1.

Table 2: RDD-DID results for the state of emergency, beginning and end of the lockdown, and the stimulus payments on the daily search intensity measure for "foodbank," US, 1 January – 30 June 2020

	State of emergency (1)	Beginning of lockdown (2)	Stimulus payment (3)	End of lockdown (4)
Emergency*Year	32.63^{***}			
	(2.73)			
Lockdown*Year		20.84^{***}		
		(3.14)		
Stimulus*Year			-3.43	
			(2.84)	
End*Year				-11.55^{***}
				(3.50)
State FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Week FE	yes	yes	yes	yes
Weekday FE	yes	yes	yes	yes
Weights	yes	yes	yes	yes
Controls	yes	yes	yes	yes
Observations	18000	15120	18000	14400

Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Controls are the accumulated number of deaths per million individuals and the accumulated number of diagnoses per million individuals. Day zero in each event is dropped from the specification. Weights contain total population in the state in 2019 from the United States Census Bureau. Robust standard errors are shown in parentheses and have been clustered at day level. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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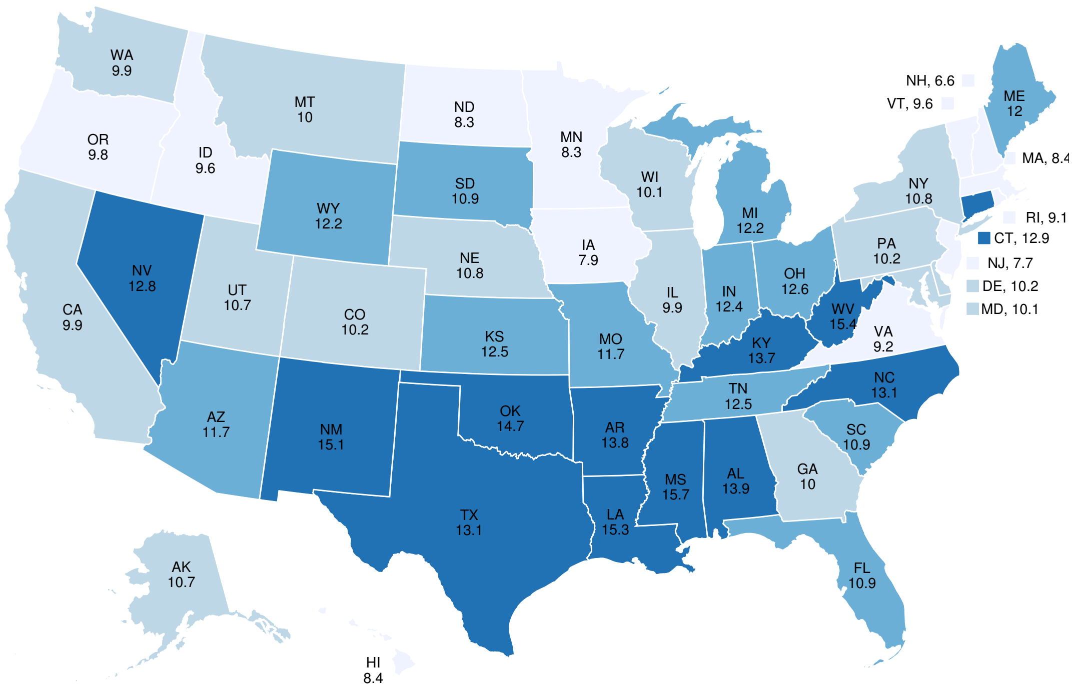
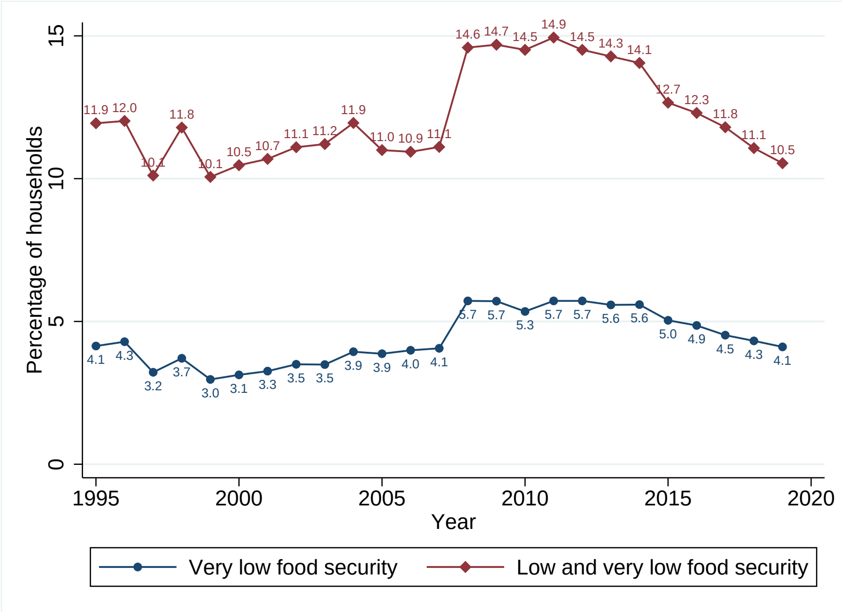
A Appendix

Figure A.1: Percentage of low food secure households in the US, 2019



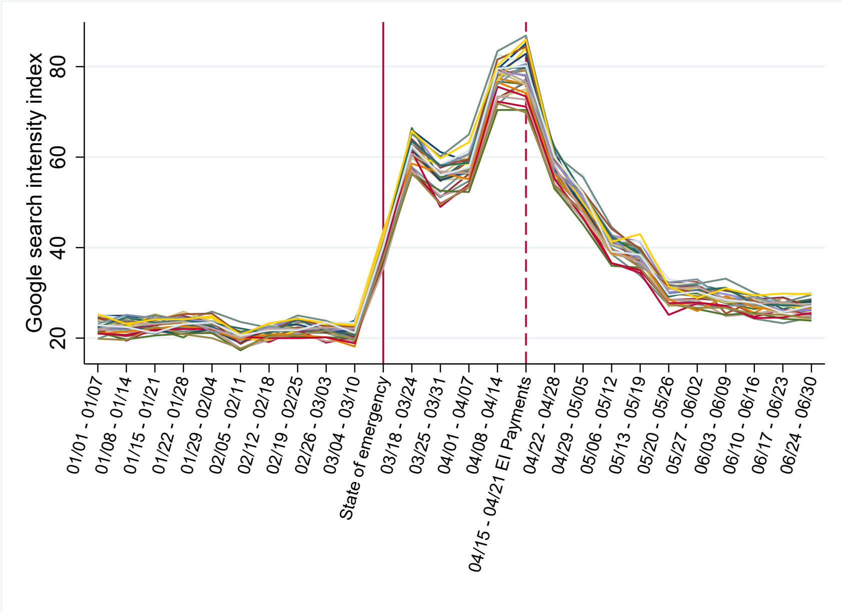
Source: Data is from the Economic Research Service of the United States Department of Agriculture.

Figure A.2: Percentage of low food secure households and very low food secure households in the US, 1995–2019



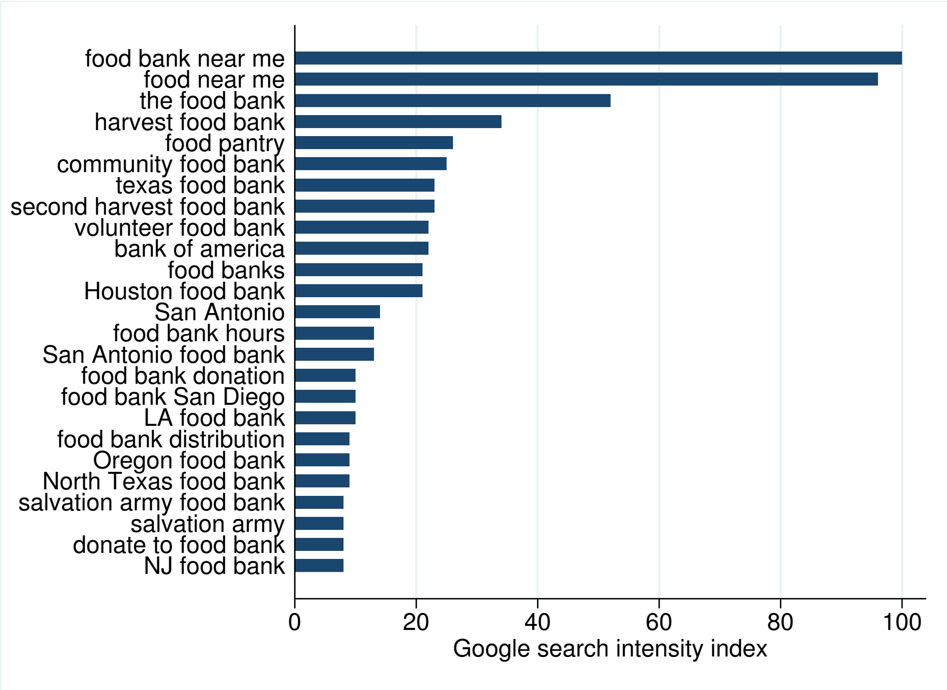
Source: Data is from the Economic Research Service of the United States Department of Agriculture.

Figure A.3: Weekly average of the search intensity index for "foodbank" in Google Trends, data from 30 different extractions, US, 1 January – 30 June 2020



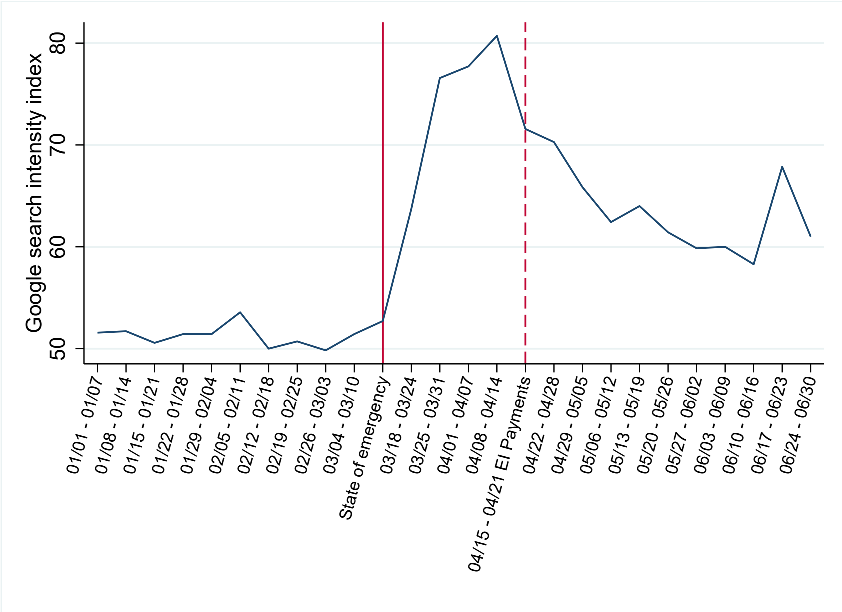
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data downloaded between 23 June 2021 and 22 July 2021.
Source: Authors' computation using data from Google Trends.

Figure A.4: Most common related terms searched in Google Trends that include "food bank," US, January – June 2020



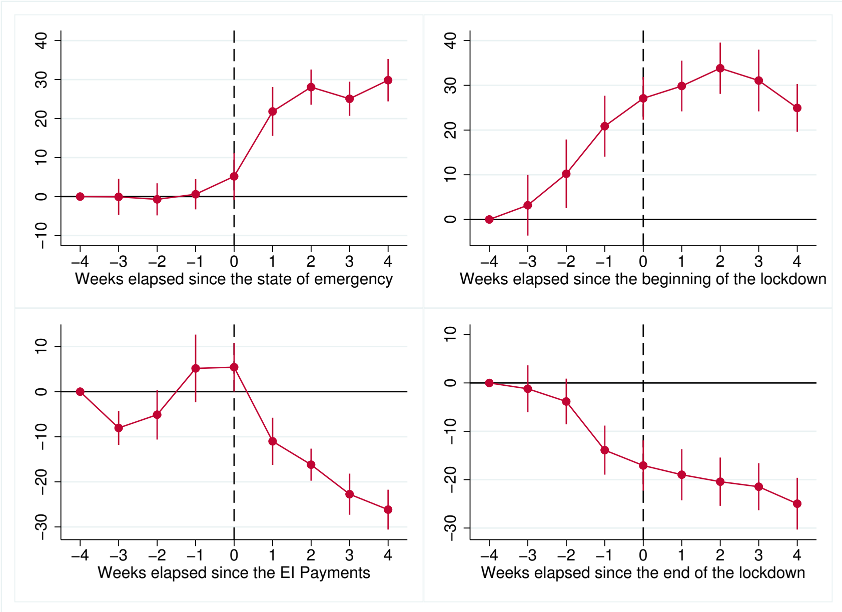
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data downloaded on 5 March 2021.
Source: Authors' computation using data from Google Trends.

Figure A.5: Weekly average of the search intensity index for “food stamps” and “SNAP” in Google Trends, US, 1 January – 30 June 2020



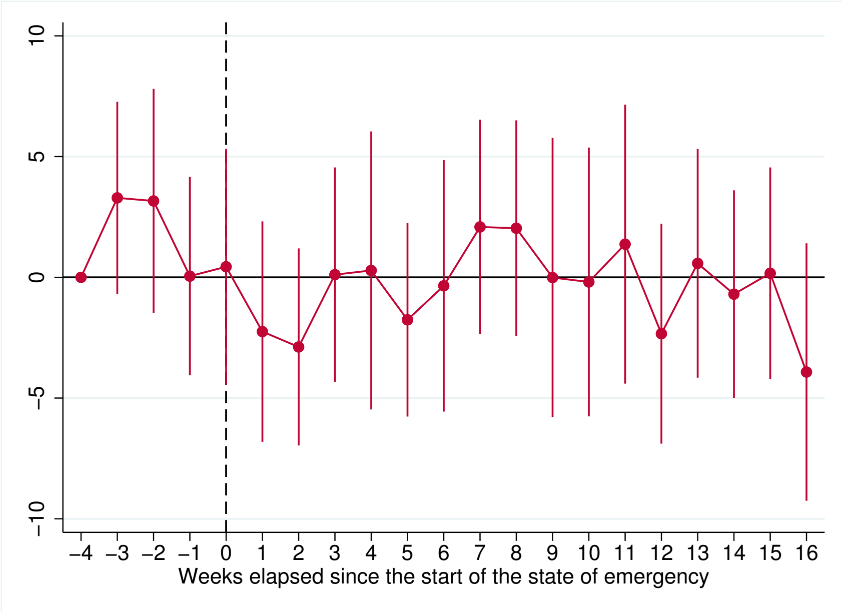
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data downloaded on 19 July 2021.
Source: Authors’ computation using data from Google Trends.

Figure A.6: Event study results for the search intensity index for “foodbank” in Google Trends, US, 1 January – 30 June 2020



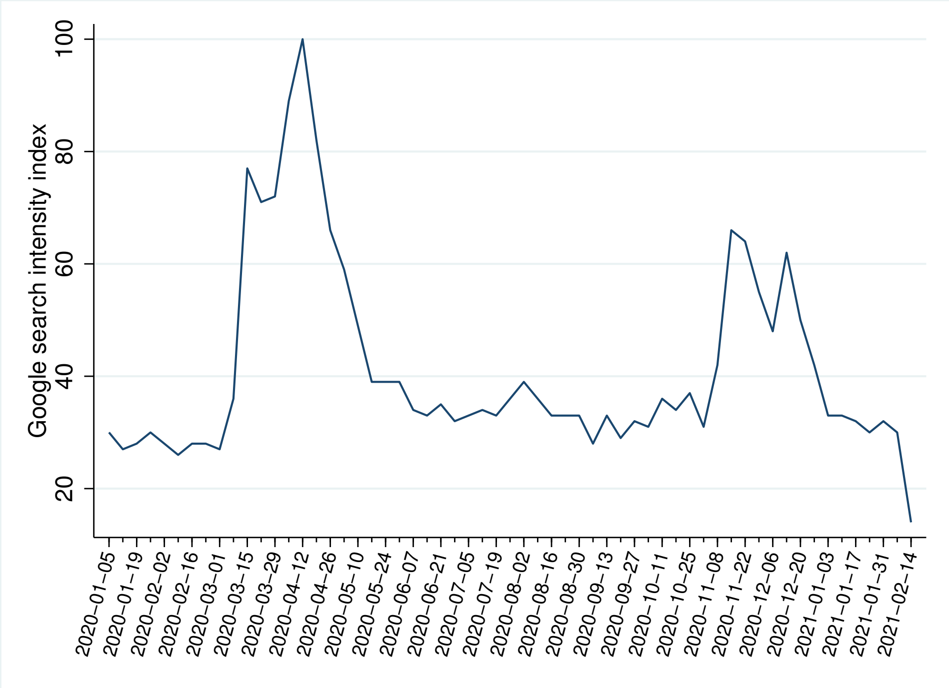
Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Controls are the accumulated number of deaths per million individuals and the accumulated number of diagnoses per million individuals. Weights contain total population in the state in 2019 from the United States Census Bureau. Robust standard errors have been clustered at day level. Vertical lines show confidence intervals at 95%.
Source: Authors’ computation using data from Google Trends.

Figure A.7: Event study results for the search intensity index for "foodbank" in Google Trends, placebo exercise, 2018–2019, US



Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Weights contain total population in the state in 2019 from the United States Census Bureau. Robust standard errors have been clustered at day level. Vertical lines show confidence intervals at 95%.
Source: Authors' computation using data from Google Trends.

Figure A.8: Weekly average of the search intensity index for "foodbank" in Google Trends, US, 1 January 2020 – 7 February 2021



Note: Google search intensity index goes from 0 to 100 indicating the popularity of a given term within a region and time frame. Data downloaded on 17 February 2021.
Source: Authors' computation using data from Google Trends.

Table A.1: Dates of the state of emergency declaration and beginning and end of the stay-at-home orders by state by 30 June 2020, United States

State	State of emergency	Beginning of the stay-at-home order	End of the stay-at-home order
Alabama	13/03/2020	04/04/2020	30/04/2020
Alaska	11/03/2020	28/03/2020	24/04/2020
Arizona	11/03/2020	31/03/2020	15/05/2020
Arkansas	11/03/2020	-	-
California	04/03/2020	19/03/2020	-
Colorado	10/03/2020	26/03/2020	09/05/2020
Connecticut	10/03/2020	23/03/2020	20/05/2020
Delaware	12/03/2020	24/03/2020	31/05/2020
Florida	01/03/2020	03/04/2020	18/05/2020
Georgia	14/03/2020	03/04/2020	30/04/2020
Hawaii	04/03/2020	25/03/2020	31/05/2020
Idaho	13/03/2020	25/03/2020	30/04/2020
Illinois	09/03/2020	21/03/2020	29/05/2020
Indiana	06/03/2020	24/03/2020	18/05/2020
Iowa	09/03/2020	-	-
Kansas	09/03/2020	30/03/2020	22/05/2020
Kentucky	06/03/2020	26/03/2020	11/05/2020
Louisiana	11/03/2020	23/03/2020	16/05/2020
Maine	15/03/2020	02/04/2020	31/05/2020
Maryland	05/03/2020	30/03/2020	01/06/2020
Massachusetts	10/03/2020	24/03/2020	18/05/2020
Michigan	11/03/2020	24/03/2020	01/06/2020
Minnesota	13/03/2020	27/03/2020	17/05/2020
Mississippi	04/03/2020	03/04/2020	27/04/2020
Missouri	13/03/2020	06/04/2020	18/05/2020
Montana	12/03/2020	28/03/2020	26/04/2020
Nebraska	13/03/2020	-	-
Nevada	12/03/2020	01/04/2020	09/05/2020
New Hampshire	13/03/2020	27/03/2020	01/06/2020
New Jersey	09/03/2020	21/03/2020	09/06/2020
New Mexico	11/03/2020	24/03/2020	31/05/2020
New York	07/03/2020	22/03/2020	28/05/2020
North Carolina	10/03/2020	30/03/2020	22/05/2020
North Dakota	13/03/2020	-	-
Ohio	09/03/2020	23/03/2020	29/05/2020
Oklahoma	15/03/2020	-	-
Oregon	08/03/2020	23/03/2020	-
Pennsylvania	06/03/2020	01/04/2020	05/06/2020
Rhode Island	09/03/2020	28/03/2020	08/05/2020
South Carolina	13/03/2020	07/04/2020	04/05/2020
South Dakota	13/03/2020	-	-
Tennessee	12/03/2020	31/03/2020	11/05/2020
Texas	13/03/2020	02/04/2020	30/04/2020
Utah	06/03/2020	-	-
Vermont	16/03/2020	25/03/2020	15/05/2020
Virginia	12/03/2020	30/03/2020	10/06/2020
Washington	29/02/2020	23/03/2020	31/05/2020
West Virginia	04/03/2020	24/03/2020	03/05/2020
Wisconsin	12/03/2020	25/03/2020	26/05/2020
Wyoming	12/03/2020	-	-

Source: Data obtained from the Economic Tracker (of the Opportunity Insights organization).