



Assessing the Relationship Between Emergency Food Assistance and Social Vulnerability During the COVID-19 Pandemic

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Abstract

Food insecurity is a major public health challenge that is associated with negative health outcomes in wealthy countries. In US urban areas, food banks and pantries played an expanded role in providing emergency food assistance and addressing food insecurity during the COVID-19 pandemic. This study seeks to determine if socially vulnerable neighborhoods are more likely to receive emergency food assistance during this pandemic, after controlling for distance to emergency food distribution sites and spatial clustering. The study area is El Paso County, Texas—an urban area on the US-Mexico border. Dependent variables represent both coverage and intensity of emergency food transfers (EFTs) from local food banks and pantries during November 2020, at the census tract level. Independent variables are derived from the widely used Social Vulnerability Index (SVI) developed by the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry. Our statistical analyses are based on multivariable generalized estimating equations that account for spatial clustering and proximity to emergency food distribution sites. Results indicate that both coverage and intensity of EFTs are significantly greater in neighborhoods with higher social vulnerability and proximity to emergency food distribution sites, but lower in neighborhoods that are more vulnerable in terms of housing and transportation. Our findings highlight the significance of neighborhood-level social factors in influencing access to the emergency food network during a public health crisis and have important implications for government agencies and nonprofit organizations associated with public health and emergency preparedness in US urban areas.

Keywords Social Vulnerability · Spatial regression · COVID-19

Introduction

Among the social determinants of health, food insecurity—when people lack the resources to access sufficient food for a healthy life (Coleman-Jensen et al., 2018)—is a major public health challenge that affects two billion people in the world (FAO et al., 2020). Even in some high-income countries, food insecurity impacts over 15% of the population (Pollard & Booth, 2019). Food insecurity is associated with many negative health outcomes in wealthy countries, including some acute conditions and poor general health among children (Drennen et al., 2019; Kimbro & Denney, 2015; Thomas et al., 2019), the development and progression of chronic disease among adults (Banerjee et al., 2017; Essien et al., 2016; Laraia, 2013), and poor mental health (Afulani et al., 2020; Maynard et al., 2018).

The novel coronavirus (COVID-19) pandemic brought severe financial challenges to many households in high-income countries, introducing food insecurity to some households and increasing its severity for others (Fitzpatrick et al., 2021; Kent et al., 2020; Wolfson & Leung, 2020). In the US, where the provision of social services is often delegated to non-governmental actors (Mettler, 2011; Morgan & Campbell, 2011), the emergency food network—which includes nonprofit food banks and pantries (Campbell et al., 2011)—played an expanded role in providing food assistance during the pandemic (Blackmon et al., 2021; Zack et al., 2021). In US urban areas, food banks and pantries found innovative ways to efficiently distribute emergency food assistance amidst a health crisis (Blackmon et al., 2021; Bublitz et al., 2021; Cavaliere et al., 2021; Zack et al., 2021).

Empirical evidence suggests that there was increased utilization of emergency food assistance in the US during the COVID-19 pandemic. National surveys indicate that food pantry use increased during the early months of the pandemic, particularly among households that recently became food insecure (Ohri-Vachaspati et al., 2020). Multiple studies on Vermont demonstrated an increase of up to 68% in the use of food pantries during the pandemic (Niles et al., 2020a, b). However, one study on predominantly African-American residents in an US urban area (Pittsburgh) found no significant change in food bank usage after the start of the pandemic (Dubowitz et al., 2021).

A pressing question for public health is whether emergency food assistance reached socially vulnerable neighborhoods in US urban areas during the COVID-19 pandemic. The evidence generated to answer this question has important implications for policymakers and practitioners. Residents of socially vulnerable neighborhoods face multiple challenges—such as transportation insecurity and long distances (Curran & Armenia, 2021; El-Geneidy et al., 2016)—to access emergency food assistance at food banks and pantries (Fong et al., 2016), and these challenges likely are more severe during a health crisis (Zack et al., 2021). If residents of socially vulnerable neighborhoods in urban areas were unable or unwilling to access emergency food assistance during the pandemic, then policymakers and practitioners can expect more adverse short- and long-term health outcomes related to food insecurity in these vulnerable areas.

Some studies analyze who receives emergency food assistance in urban areas of high-income countries (Daponte et al., 1998; Fong et al., 2016; Hosler et al., 2021;

Prayogo et al., 2018), but almost all of this research examines individual- or household-level factors in non-crisis time periods. Another study sought to determine whether proximity to supermarkets influences the number of phone calls for food assistance before the COVID-19 pandemic (Janda et al., 2021a). Other studies examined access to emergency food providers during the COVID-19 pandemic (Bertmann et al., 2020; Janda et al., 2021b), but did not analyze differences in the reception of emergency food assistance. The social characteristics of neighborhoods that received greater emergency food assistance during a public health crisis have not been examined in adequate detail. Moreover, most of the available research does not consider proximity to emergency food distribution sites in urban areas.

To address these limitations, our study uses original data on locations of emergency food recipients and locally derived generalized estimating equation models to determine if socially vulnerable neighborhoods are more likely to receive emergency food assistance in El Paso County—an urban county in Texas, USA—during the COVID-19 pandemic. The food insecurity rate was 14.6% in El Paso County in 2019, the most recent year of data that is available (Gundersen et al., 2021). Previous studies have documented significant racial/ethnic disparities in food insecurity during the pandemic, with Hispanic and African-American households experiencing higher rates of food insecurity compared to white households (Niles et al., 2021; Schanzenbach & Pitts, 2020). Our central research question is framed as follows: does social vulnerability predict reception of emergency food assistance at the neighborhood level, even after controlling for distance to food bank and pantry sites and spatial clustering? The data for this study comes from all five of the emergency food providers that served residents of El Paso County in November 2020 and includes 77,881 emergency food transfers to households that provided complete and correct home address information.

Data and Methods

The study area for this research comprises El Paso County—the westernmost county in the state of Texas located on the US-Mexico border. With a total population of 839,238, El Paso County is the sixth largest county in Texas. Almost 83% of county residents are Hispanic, 21% are below the poverty level, and the median household income is \$48,903 (American Community Survey, 2019). Nearly 81% of the county population resides in the City of El Paso—the sixth largest city in Texas and the second largest city in the US Southwest.

This study of emergency food assistance reception encompasses households in El Paso County that received emergency food transfers (EFTs) from the local food bank and pantries during November 1 to 30, 2020. We selected the month of November, because it was the most recent data available and we wanted to provide the latest results for local community leaders. We obtained the street addresses of these households from their respective emergency food distribution sites and used *ArcGIS Desktop 10.8.1* software to geocode their home locations. Out of a total of 87,417 recipients in this county, we excluded 9,536 (10.9%) households because of incorrect addresses, ineligible entries, or errors in locating their home addresses. Our analysis

Table 1 Variable definitions and descriptive statistics

Variables	Definition and Measurement	Min	Max	Mean	SD
<i>EFT</i> (emergency food transfers) <i>Coverage</i> : Proportion of households receiving EFTs at least once: November 1 to 30, 2020	Number of households with at least one EFT divided by total households in census tract	0.02	0.95	0.19	0.12
<i>EFT Intensity</i> : Ratio of total EFTs to households: November 1 to 30, 2020	Total EFTs in census tract divided by total households in the census tract	0.02	1.69	0.34	0.23
CDC/ASTDR Social Vulnerability Index (SVI)	Overall SVI based on combining all themes	0.00	1.00	0.50	0.29
SVI Theme 1: Socioeconomic status	% Below Poverty Level % Unemployed Per Capita Income % Age 25 or older with no high school diploma	0.00	1.00	0.50	0.29
SVI Theme 2: Household composition & disability	% Age 65 or older % 17 or younger % Single parent household	0.00	1.00	0.50	0.29
SVI Theme 3: Minority status & language	% Minority % Age 5 or older speak English less than well	0.00	1.00	0.50	0.29
SVI Theme 4: Housing and transportation	% Multi-Unit structures % Mobile homes % Crowding (more people than rooms) % Households without a Vehicle % In institutionalized group quarters	0.00	1.00	0.50	0.29
Good Access to food distribution site	33% or less of tract area lying outside 1-mile buffer around food assistance distribution sites	0.00	1.00	0.06	0.24
Some Access to food distribution site	33–67% of tract area lying outside 1-mile buffer around food assistance distribution sites	0.00	1.00	0.06	0.23
Low Access to food distribution site (treated as reference group)	67% or more of tract area lying outside 1-mile buffer around food assistance distribution sites				

NOTE: N=160 tracts in El Paso County with population greater than 0

thus includes 77,881 EFT recipient households in the month of November 2020, with 43,391 households in the county receiving EFTs at least once. We formulated dependent variables that represent both the coverage breadth and intensity depth of EFTs at the neighborhood (census tract) level. EFT *coverage* was measured as the proportion of households in the tract that received EFTs at least once, and EFT *intensity* was measured as the ratio of total EFTs to the total number of households in a given tract. For both these measures, the household counts for each tract were derived from the 2018 American Community Survey (ACS) five-year estimates. Summary statistics for these variables are provided in Table 1 and maps depicting their spatial distributions are shown in Fig. 1.

Our independent variables focus on social vulnerability characteristics of census tracts, based on the Social Vulnerability Index (SVI) developed by the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry—CDC/ASTDR (CDC/ASTDR, 2021). While this SVI was developed to assist

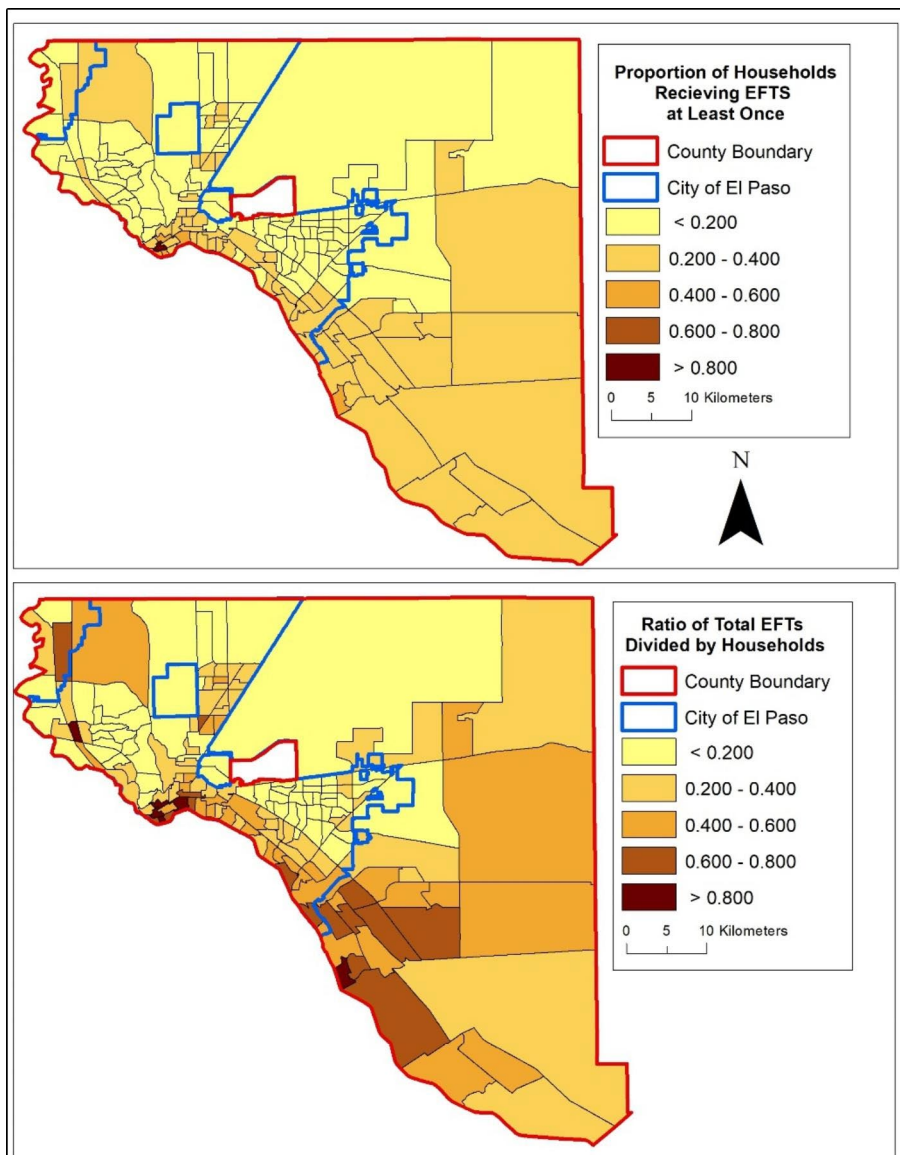


Fig. 1 Emergency food transfers (EFTs) by census tract in El Paso County, Texas: November 1 to 30, 2020

public health officials and local planners identify communities that need support for emergency events such as severe weather, disease outbreaks, or chemical exposure (Flanagan et al., 2018), this index has been used to analyze public health disparities (Karaye & Horney, 2020; Lehnert et al., 2020) and food insecurity (Ware et al., 2021). The CDC/ASTDR SVI utilizes US Census and ACS data to determine the relative social vulnerability of every county and census tract. Specifically, each county and tract is ranked using 15 variables grouped into four themes; these themes and vari-

ables are listed in Table 1. For each US state, the CDC/ASTDR SVI dataset provides a tract-level score (percentile ranking) for each theme, as well as a composite overall SVI score that combines all themes. For tracts in El Paso County, we downloaded scores for the overall SVI and its four themes from the latest (2018) version of the CDC/ASTDR SVI, and recalculated the percentile rankings so that scores ranged from 0 to 1, with 1 representing the highest level of social vulnerability in this county. The names and descriptive statistics for the SVI variables are summarized in Table 1.

Our analysis also includes tract-level categorical variables representing distance to emergency food distribution sites as control variables. During the study period, there were five emergency food distribution sites (one food bank and four food pantries) operating in El Paso County. Following the US Department of Agriculture (USDA)'s recommendation for assessing proximity, we used *ArcGIS* software to construct one-mile buffer zones around each of the five emergency food distribution sites used in November 2020. This one-mile Euclidean distance is commonly used to assess the proximity dimension of food access to a full-service supermarket in US urban areas (USDA, 2009, 2015; Wilde et al., 2014). We defined emergency food access for each tract using the USDA (USDA, 2009) criteria for the Food Access Research Atlas, based on the percentage of tract area lying outside the one-mile buffer around these food distribution sites, such that: *low access* equals 67% or more, *some access* equals to 34 to 66%, and *good access* equals 33% or less, of the tract area outside this one-mile buffer (Bacon & Baker, 2017). After classifying all tracts in El Paso County into these three categories, we created two dummy variables (good access and some access) to serve as control variables, as shown in Table 1.

Multivariable models based on generalized estimating equations (GEEs) were used to analyze the relationship between emergency food assistance (*coverage* and *intensity*) and relevant independent variables. GEEs extend the generalized linear model to account for clustered data (Nelder & Wedderburn, 1972), in addition to relaxing several assumptions of traditional regression models (e.g., normality). Recent research suggests that GEEs based on theoretically informed clusters are more suitable for analyzing socio-spatial disparities compared to other approaches such as spatial autoregressive models, mixed models with random effects, and multilevel modeling approaches (Collins et al., 2015; Chakraborty, 2020; Chakraborty et al., 2021).

For estimating a GEE model, it is necessary to define clusters of observations (e.g., census tracts) based on the assumption that observations within a cluster are correlated, and observations from different clusters are independent (Garson, 2013). After experimentation with several variables from the 2018 ACS, the median decade of housing construction (ranges from "1940–1949" to "2010 or later) associated with each tract was selected to define clusters. The median age of housing stock corresponds to the urban developmental context within with households are nested, and has been utilized as a clustering variable in previous studies that used GEEs for analyzing social inequalities in other metropolitan areas of Texas (Collins et al., 2015; Chakraborty, 2019, 2020; Chakraborty et al., 2019). This cluster definition resulted in 8 census tract clusters for El Paso County, with the number of tracts per cluster ranging from 2 to 34.

GEEs also require the specification of an intra-cluster dependency correlation matrix (Garson, 2013). The 'independent' correlation matrix was selected for the

results reported here, since this specification yielded the best statistical fit based on the QIC (quasi-likelihood under the independence model criterion). To improve model fit, several different distributions (e.g., normal, gamma, and inverse Gaussian) appropriate for non-zero continuous dependent variables were evaluated using logarithmic and identity link functions. The gamma distribution with identity link function was chosen for all GEEs since this model specification provided the best fit based on the QIC value. Statistical significance of independent variables in our GEEs were estimated using two-tailed p -values from the Wald Chi-square test.

For each dependent variable, the first set of multivariable GEE models (Models 1 and 2) includes the overall SVI score for each tract, while the second set (Models 3 and 4) contains separate independent variables for the four SVI themes. All variables were standardized before inclusion in the GEE models and standardized coefficients are provided to compare the relative contribution of each independent variable. To check for multicollinearity, the multicollinearity condition index (MCI) was calculated for the combination of variables included in the GEE model. The MCI was found to be smaller than 10.0 for all models, indicating the absence of serious collinearity problems among the independent variables.

Results

The spatial distributions of EFT coverage and intensity in El Paso County are depicted as classified choropleth maps in Fig. 1, where census tracts are grouped into five classes based on the values of each variable. The first map represents the proportion of households receiving EFTs at least once, and the second map portrays the ratio of total EFTs divided by households for each tract. For both these variables, tracts with relatively higher values (>0.6) can be observed near downtown El Paso, as well as in specific locations along the southern county border outside the City of El Paso. Both EFT coverage and intensity are considerably smaller (<0.2) in less populated tracts located in the northeastern part of El Paso County.

The multivariable GEE model results for each dependent variable are summarized in Tables 2 and 3, respectively. In Table 2, the overall SVI score is positively and significantly associated with EFT coverage ($p < 0.001$), in both the absence (Model 1) and presence (Model 2) of variables representing access to emergency food distribution sites. Tracts with both good access and some access to emergency food distribution sites indicate significantly higher proportions of households that received at least one EFT ($p < 0.01$), compared to those with low access. When the overall SVI score is replaced by the four SVI themes in Model 3, two of these themes (socioeconomic status and minority status/language) reveal positive and significant relationships with EFT coverage ($p < 0.001$) and one theme (housing/transportation) shows a significantly negative association ($p < 0.001$). When access to emergency food distribution sites are considered in Model 4, three of the four SVI themes (socioeconomic status, household composition/disability, and minority status/language) indicate a significantly positive association ($p < 0.001$), while one theme (housing/transportation) yields a significantly negative association ($p < 0.001$) with EFT coverage. Compared to tracts with low access to food distribution sites, those with good access and some

access indicate significantly higher EFT coverage ($p < 0.01$), after controlling for SVI themes.

In Table 3, the overall SVI score shows a positive and significant association with EFT intensity ($p < 0.001$), in both Models 1 and 2. Tracts with good access and some access to food distribution sites have significantly higher total EFTs/household ratios ($p < 0.05$), compared to those with low access. In Model 3, only one SVI theme (minority status/language) reveals a positive and significant coefficient ($p < 0.05$). When access to emergency food sites is included in Model 4, three SVI themes (socioeconomic status, household composition/disability, and minority status/language) show a significantly positive association ($p < 0.001$), while the housing/transportation theme again indicates a significantly negative association ($p < 0.001$) with EFT intensity. Compared to those with low access, tracts with good access and some access to food distribution sites have significantly higher EFT intensity ($p < 0.05$), after controlling for all SVI themes.

The spatial distribution of standardized residuals from our complete GEE model (i.e., Model 4 in Tables 2 and 3) is depicted as classified choropleth maps in Fig. 2. On these maps, tracts shaded in orange or red indicate locations where actual values of EFT coverage or intensity are larger than what the GEE model predicted. Tracts shaded in light or dark blue are locations where the actual values of EFT coverage or intensity are smaller than those predicted by the GEE model. Both maps show that several orange or red tracts are located near an emergency food assistance site, thus confirming the importance of geographic proximity to these sites in influencing EFT coverage or intensity. The blue tracts represent neighborhoods with unusually lower levels of EFTs that cannot be explained on basis of social vulnerability or distance to food assistance sites; these food insecure areas deserve more attention from local government or non-profit organizations.

Contributions and Policy Implications

Our findings reveal that social vulnerability is a very strong predictor of emergency food assistance reception in El Paso County, Texas, at the neighborhood (tract) level. Both coverage and intensity of EFTs are significantly greater in neighborhoods with higher social vulnerability, even after controlling for distance to emergency food distribution sites and spatial clustering in the data. When individual themes or components of social vulnerability are examined, we found significantly higher coverage and intensity of EFTs in neighborhoods that are more vulnerable in terms of socioeconomic status, household composition and disability, and minority status and language difficulty, but less vulnerable in terms of housing and transportation characteristics. Minority status and language difficulty is the only social vulnerability theme that is consistently and positively associated with both EFT coverage and intensity, in all our multivariable models. Although the housing and transportation theme indicated a significantly negative relationship with both EFT coverage and intensity, lower EFTs in neighborhoods characterized by multifamily rental housing, institutional group quarters, and zero-vehicle households potentially reflect a larger support network and greater food sharing in these areas, as well as limited access to

Table 2 Generalized estimating equations (GEEs) for predicting proportion of households receiving EFTs at least once, November 2020

	MODEL 1			MODEL 2			MODEL 3			MODEL 4		
	Beta	SE	p-value	Beta	SE	p-value	Beta	SE	p-value	Beta	SE	p-value
Constant	0.185	0.014	<0.001	0.177	0.014	<0.001	0.183	0.001	<0.001	0.171	0.007	<0.001
Overall CDC/ASTDR SVI	0.081	0.009	<0.001	0.080	0.008	<0.001						
SVI Theme 1							0.026	0.011	0.020	0.021	0.003	<0.001
SVI Theme 2							0.012	0.009	0.146	0.015	0.004	<0.001
SVI Theme 3							0.055	0.007	<0.001	0.059	0.005	<0.001
SVI Theme 4							-0.005	0.005	0.268	-0.011	0.001	<0.001
Good access to food site				0.098	0.037	0.008				0.127	0.048	0.009
Some access to food site				0.035	0.011	0.001				0.067	0.005	<0.001
QIC	39.562			40.107			40.838			30.021		

NOTE: N = 160 census tracts. Model specifications are gamma with identity link with an independent correlation matrix with controls for clustering in terms of median decade of housing stock (8 clusters). SE is standard error and QIC is Quasi Likelihood under Independence Model Criterion. All p-values are based on Wald Chi-Square test

Table 3 GEEs for predicting ratio of total EFTs to households, November 2020

	MODEL 1			MODEL 2			MODEL 3			MODEL 4		
	Beta	SE	p-value	Beta	SE	p-value	Beta	SE	p-value	Beta	SE	p-value
Constant	0.332	0.026	<0.001	0.318	0.014	<0.001	0.017	0.001	<0.001	0.308	0.007	<0.001
Overall CDC/ASTDR SVI	0.152	0.017	<0.001	0.150	0.008	<0.001						
SVI Theme 1							0.037	0.020	0.068	0.031	0.003	<0.001
SVI Theme 2							0.022	0.015	0.116	0.026	0.004	<0.001
SVI Theme 3							0.110	0.012	<0.001	0.117	0.005	<0.001
SVI Theme 4							-0.004	0.008	0.662	-0.018	0.001	<0.001
Good access to food site				0.153	0.065	0.018				0.210	0.048	0.015
Some access to food site				0.075	0.027	0.006				0.127	0.005	<0.001
QIC	42.560			44.238			43.075			32.710		

NOTE: N = 160 census tracts. Model specifications are gamma with identity link with an independent correlation matrix with controls for clustering in terms of median decade of housing stock (8 clusters). SE is standard error and QIC is Quasi Likelihood under Independence Model Criterion. All p-values are based on Wald Chi-Square test

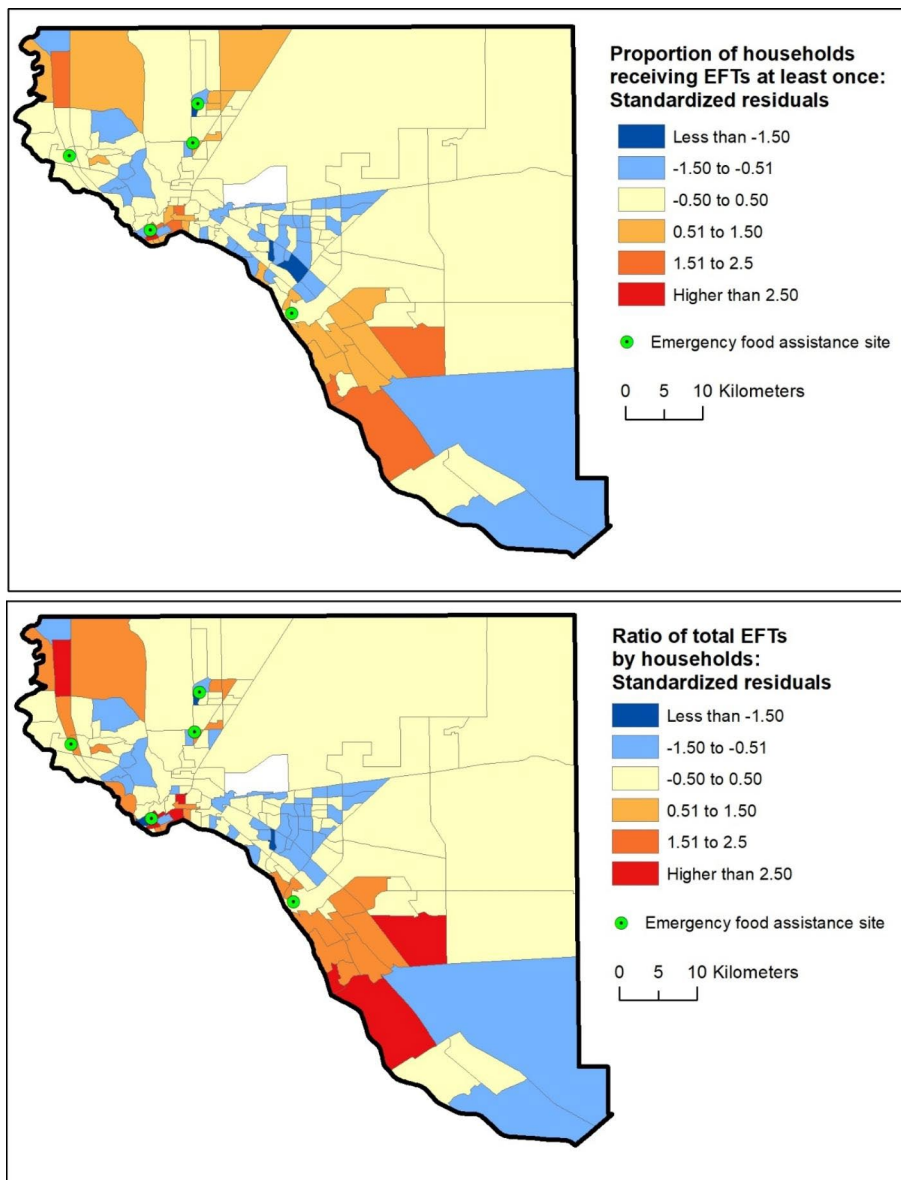


Fig. 2 Standardized residuals by census tract from generalized estimating equations (Model 4 in Tables 2 and 3) for predicting EFT coverage and intensity, respectively, in El Paso County

EFTs for households without automobiles. With regards to distance from emergency food distribution sites, neighborhoods with good and moderate access indicated higher levels of emergency food assistance reception compared to those with low access, after controlling for their social vulnerability characteristics. Overall, these results suggest that socially vulnerable neighborhoods and neighborhoods in closer

proximity to emergency food distribution sites are more likely to receive EFTs in El Paso County during a health crisis.

There are multiple potential explanations for these results. The historical isolation of socially disadvantaged residents in US cities, sustained by practices such as redlining, can lead to greater inequality across neighborhoods (Goldsmith & Blakely, 2010; Nardone et al., 2020). In socially vulnerable and economically disadvantaged neighborhoods, there likely will be greater need for emergency food assistance, which may contribute to higher EFT demand and reception during the COVID-19 pandemic. In addition, because transportation costs influence demand (Tyagi, 2004), neighborhoods proximate to emergency food distribution sites are likely to experience greater demand for EFTs. The lower transportation and time costs remove potential barriers to accessing emergency food distribution sites, which also may help explain why the housing and transportation theme is the only social vulnerability theme that is negatively associated with EFT reception. Furthermore, news coverage during the pandemic focused on the challenges and severe needs of disadvantaged community members, along with their deservingness of emergency food assistance (Mejia et al., 2022). This news coverage could contribute to higher EFT reception in socially vulnerable neighborhoods, by increasing awareness of available resources and reducing stigma among local residents.

This study makes two major contributions to applied research on public health. First, by uncovering that socially vulnerable neighborhoods are more likely to receive emergency food assistance in El Paso County during the pandemic, it suggests that the emergency food network can play a key role in slowing, or at least not exacerbating, health disparities across urban neighborhoods amidst a public health crisis. While previous research finds that household needs matter in decisions on whether to use a food pantry in non-crisis times (Daponte et al., 1998; Fong et al., 2016; Hosler et al., 2021; Prayogo et al., 2018), this study shows that social vulnerabilities at the neighborhood level matter during a health crisis.

Second, the study expands our understanding of which neighborhoods are socially vulnerable during a health crisis. While previous research emphasizes proximity to the supermarket (Hosler et al., 2021; Janda et al., 2021), our study demonstrates that longer distances to the emergency food distribution site create food access challenges. This finding adds to previous literature on food assistance deserts (Curran & Armenia, 2021; Waity, 2016) by showing that proximity to emergency food distribution sites matters for accessing food during a public health crisis.

These contributions to applied research have important implications for local policymakers and leaders of urban emergency food networks in the US. Because the CDC/ASTDR SVI is found to be a strong predictor of receiving emergency food assistance during the pandemic, policymakers can use this finding to better assist socially disadvantaged community members in future crises. In times of crisis, emergency food demand may increase rapidly, and there may not be enough time (or it may be physically impractical) to launch a comprehensive or detailed analysis to determine the geography of this changing demand. Consequently, policymakers must make rapid decisions about funding and emergency food distribution with limited information, and there is a high risk of selecting locations for emergency food distribution sites that are not effective in serving socially disadvantaged residents. This

study suggests that the CDC/ASTDR SVI can be a low-cost and effective prediction tool for policymakers in crisis settings, which in turn can help policymakers advance evidence-based strategies to minimize distance to emergency food distribution sites.

Moreover, when policymakers and leaders of emergency food networks are looking to identify additional vulnerable neighborhoods that may not be accessing or receiving food during a public health crisis, food assistance deserts and neighborhoods with higher transportation vulnerability are promising targets. Although socially vulnerable neighborhoods generally are more likely to receive emergency food assistance during the pandemic, some socially vulnerable neighborhoods receive less food assistance than others. The socially vulnerable neighborhoods that are located further away from the emergency food distribution sites or otherwise have high transportation vulnerability face barriers to receiving food assistance, and policymakers and nonprofit leaders can target awareness campaigns to reach residents in these vulnerable neighborhoods. The finding on spatial and transportation barriers to accessing emergency food assistance therefore can lead to more efficient, evidence-based policies aimed at serving vulnerable populations during a crisis.

Our findings also have important implications for gentrification and the “suburbanization of poverty” (Kneebone & Garr, 2010). As living costs in neighborhoods change, some EFT recipients may be forced to move further away from service providers and may lose access to crucial services such as EFTs. These changes put additional pressure on emergency food providers to track the current geography of emergency food assistance, thus adding to their high workload and responsibilities. Active collaborations between emergency food providers and academic researchers with expertise in spatial analysis can help study changes in emergency food assistance, identify newly vulnerable neighborhoods, and inform public policy (Janda et al., 2021b).

Finally, the findings have important implications for racial/ethnic health disparities in the US. Food insecurity has strong negative effects on health, and previous research demonstrates that Hispanic households have higher rates of food insecurity compared to white households (Niles et al., 2021; Schanzenbach & Pitts, 2020). The findings presented here on El Paso County—a predominantly Hispanic community—indicate that socially vulnerable neighborhoods are more likely to receive EFTs during the pandemic, which over time could potentially address ethnic disparities related to COVID-19 (Lopez et al., 2021). The strong positive relationship between higher language vulnerability and EFT reception at the neighborhood level is particularly encouraging. If socially vulnerable neighborhoods in Hispanic communities continue to gain access to emergency food moving forward, then this sustained access may help reduce other ethnic health disparities in the future. More research is needed, however, to examine whether these findings hold in other Hispanic communities in the US.

While this study represents an important starting point for analyzing the relationship between social vulnerability and emergency food assistance, it is important to consider two limitations. First, we used census tracts as units of analysis since social vulnerability information was not available at smaller resolutions and for households receiving EFTs, in particular. The aggregated tract-level indicators enabled us to examine neighborhood-level associations, but cannot be used to clarify how

much emergency food assistance actually reached socially vulnerable residents in these neighborhoods. Future research will seek to address this issue through the use of structured surveys and semi-structured interviews conducted at the household level. Second, our analysis was based on emergency food assistance data for a single month (November 2020). Future work will explore additional data on EFTs in El Paso County over a longer timeframe during the COVID-19 pandemic and examine month-to-month variations that we were unable to analyze in this study.

Conclusions

This study demonstrates that, during the COVID-19 pandemic, social vulnerability can be used to predict the reception of emergency food assistance at the neighborhood level in El Paso County, Texas. Neighborhoods in closer proximity to emergency food distribution sites also are more likely to receive emergency food assistance. Our findings thus highlight the significance of neighborhood-level social and spatial factors in influencing access to the emergency food network amidst a public health crisis. The results have important implications for government officials and nonprofit organization leaders who are in charge of public health and emergency preparedness in US urban areas. During a public health crisis, the CDC/ASTDR SVI can help determine neighborhood-level demand for emergency food assistance. Moreover, neighborhoods in food assistance deserts and those with higher transportation vulnerability may need to be targeted with more support services, so that residents can access and receive emergency food assistance.

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Data Availability The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Code Availability All study code is available upon request to the corresponding author.

Statements and declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

Ethics approval This study was reviewed and approved by the UTEP Institutional Review Board (Protocol 1671400-1) on October 19, 2020, with the action of Exempt.

Consent to participate Not applicable.

Consent for Publication Not applicable.

References

- Afulani, P. A., Coleman-Jensen, A., & Herman, D. (2020). Food insecurity, mental health, and use of mental health services among nonelderly adults in the United States. *Journal of Hunger & Environmental Nutrition*, 15(1), 29–50
- American Community Survey (ACS) (2019). Quick Facts: El Paso County, Texas. <https://www.census.gov/quickfacts/fact/table/elpasocountytexas,elpasocountycolorado/PST045219>
- Bacon, C. M., & Baker, G. A. (2017). The rise of food banks and the challenge of matching food assistance with potential need: Towards a spatially specific, rapid assessment approach. *Agriculture and Human Values*, 34(4), 899–919
- Banerjee, T., Crews, D. C., Wesson, D. E., Dharmarajan, S., Saran, R., Burrows, N. R., Saydah, S., & Powe, N. R. (2017). Food insecurity, CKD, and subsequent ESRD in US adults. *American Journal of Kidney Diseases*, 70(1), 38–47
- Bertmann, F., Belarmino, E. H., Wentworth, T., Biehl, E., Neff, R., & Niles, M. T. (2020). Food access through school meals and food pantries during COVID-19: Early findings from Vermont. *College of Agriculture and Life Sciences Faculty Publications*. <https://scholarworks.uvm.edu/calsfac/22/>
- Blackmon, L., Chan, R., Carbral, O., Chintapalla, G., Dhara, S., Felix., P., Jagdish, A., Konakalla, S., Labana, J., McIlvain, J., Stone, J., Tang, C. S., Torres, J., & Wu, W. (2021). Rapid development of a decision support system to alleviate food insecurity at the Los Angeles regional food bank amid the COVID-19 pandemic. *Production and Operations Management*, 30(10), 3391–3407
- Bublitz, M. G., Czarkowski, N., Hansen, J., Peracchio, L. A., & Tussler, S. (2021). Pandemic reveals vulnerabilities in food access: Confronting hunger amidst a crisis. *Journal of Public Policy & Marketing*, 40(1), 105–107
- Campbell, E., Hudson, H., Webb, K., & Crawford, P. B. (2011). Food preferences of users of the emergency food system. *Journal of Hunger & Environmental Nutrition*, 6(2), 179–187
- Cavaliere, B., Drew, C., & Martin, K. (2021). Food bank drive-through distribution during COVID-19: A reflective essay. *Journal of Agriculture Food Systems and Community Development*, 10(2), 135–145
- Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry (CDC/ASTDR) (2021). Social Vulnerability Index. <https://www.atsdr.cdc.gov/placeandhealth/svi/index.html>
- Chakraborty, J. (2019). Proximity to extremely hazardous substances for people with disabilities: A case study in Houston, Texas. *Disability and Health Journal*, 12(1), 121–125
- Chakraborty, J. (2020). Unequal proximity to environmental pollution: An intersectional analysis of people with disabilities in Harris County, Texas. *The Professional Geographer*, 72(4), 521–534
- Chakraborty, J., Collins, T. W., & Grineski, S. E. (2019). Exploring the environmental justice implications of Hurricane Harvey flooding in Greater Houston, Texas. *American Journal of Public Health*, 109(2), 244–250
- Chakraborty, J., McAfee, A., Collins, T. W., & Grineski, S. E. (2021). Exposure to Hurricane Harvey flooding for subsidized housing residents in Harris County, Texas. *Natural Hazards*, 106(3), 2185–2205
- Coleman-Jensen, A., Rabbitt, M. P., Gregory, C. A., & Singh, A. (2018). *Household food security in the United States in 2017, ERR-256*. US Department of Agriculture, Economic Research Service

- Collins, T., Grineski, S., Chakraborty, J., Montgomery, M., & Hernandez, M. (2015). Downscaling environmental justice analysis: Determinants of household-level hazardous air pollutant exposure in Greater Houston. *Annals of the American Association of Geographers*, 105, 684–703
- Curran, E., & Armenia, A. (2021). Food assistance deserts in Central Florida: Identifying service gaps using spatial analysis. *Journal of Applied Social Science*, 15(1), 95–106
- Daponte, B. O., Lewis, G. H., Sanders, S., & Taylor, L. (1998). Food pantry use among low-income households in Allegheny County, Pennsylvania. *Journal of Nutrition Education*, 30(1), 50–57
- Drennen, C. R., Coleman, S. M., de Cuba, S. E., Frank, D. A., Chilton, M., Cook, J. T., Cutts, D. B., Heeren, T., Casey, P. H., & Black, M. M. (2019). Food insecurity, health, and development in children under age four years. *Pediatrics*, 144(4), e20190824
- Dubowitz, T., Dastidar, M. G., Troxel, W. M., Beckman, R., Nugroho, A., Siddiqi, S., Cantor, J., Baird, M., Richardson, A. S., Hunter, G. P., Mendoza-Graf, A., & Collins, R. L. (2021). Food insecurity in a low-income, predominantly African American cohort following the COVID-19 pandemic. *American Journal of Public Health*, 111(3), 494–497
- El-Geneidy, A., Levinson, D., Diab, E., Boisjoly, G., Verbich, D., & Loong, C. (2016). The cost of equity: Assessing transit accessibility and social disparity using total travel cost. *Transportation Research Part A*, 91, 302–316
- Essien, U. R., Shahid, N. N., & Berkowitz, S. A. (2016). Food insecurity and diabetes in developed societies. *Current Diabetes Reports*, 16, 79
- FAO, IFAD, UNICEF, WFP, & WHO (2020) *The state of food security and nutrition in the world 2020. Transforming food systems for affordable healthy diets*. Rome: FAO.
- Fitzpatrick, K. M., Harris, C., Drawve, G., & Willis, D. E. (2021). Assessing food insecurity among US adults during the COVID-19 pandemic. *Journal of Hunger & Environmental Nutrition*, 16(1), 1–18
- Flanagan, B. E., Hallisey, E. J., Adams, E., & Lavery, A. (2018). Measuring community vulnerability to natural and anthropogenic hazards: The Centers for Disease Control and Prevention's Social Vulnerability Index. *Journal of Environmental Health*, 80(10), 34–36
- Fong, K., Wright, R. A., & Wimer, C. (2016). The cost of free assistance: Why low-income individuals do not access food pantries. *The Journal of Sociology & Social Welfare*, 43(1), 71–93
- Garson, G. D. (2013). *Generalized linear models and generalized estimating equations*. Asheboro, NC: Statistical Associates Publishers
- Goldsmith, W. W., & Blakely, E. J. (2010). *Separate societies: Poverty and inequality in U.S. cities, second edition*. Philadelphia: Temple University Press
- Gundersen, C., Strayer, M., Dewey, A., Hake, M., & Engelhard, E. (2021). *Map the meal gap 2021: An analysis of county and congressional district food insecurity and county food cost in the United States in 2019*. Feeding America
- Hosler, A. S., Cong, X., & Alharthy, A. (2021). Food pantry use and its association with food environment and food acquisition behavior among urban adults. *Journal of Hunger & Environmental Nutrition*, 16(3), 356–369
- Janda, K. M., Dominguez, D. S., Ranjit, N., Hoelscher, D. M., Price, A., & van den Berg, A. (2021a). Mapping food insecurity-related 2-1-1 calls in a 10-county area of Central Texas by zip code: Exploring the role of geographic food access, urbanicity and demographic indicators. *Journal of Community Health*, 46, 86–97
- Janda, K. M., Hood, R., Price, A., Night, S., Marty, W. E., Rohlich, A., Hanson, K., Espinoza, M., & van den Berg, A. E. (2021b). Examining food insecurity and areas with unmet food needs during COVID-19: A geospatial, community-specific approach. *Journal of Agriculture Food Systems and Community Development*, 10(3), 55–67
- Karaye, I. M., & Horney, J. A. (2020). The impact of social vulnerability on COVID-19 in the US: an analysis of spatially varying relationships. *American Journal of Preventive Medicine*, 59(3), 317–325
- Kent, K., Murray, S., Penrose, B., Auckland, S., Visentin, D., Godrich, S., & Lester, E. (2020). Prevalence and socio-demographic predictors of food insecurity in Australia during the COVID-19 pandemic. *Nutrients*, 12(9), 2682
- Kimbro, R. T., & Denney, J. T. (2015). Transitions into food insecurity associated with behavioral problems and worse overall health among children. *Health Affairs*, 34(11), 1949–1955
- Kneebone, E., & Garr, E. (2010). The suburbanization of poverty: Trends in metropolitan America, 2000–2008. Metropolitan Policy Program at Brookings. http://www.hartfordinfo.org/issues/wsd/region/Brookings_Poverty_Report.pdf
- Laraia, B. A. (2013). Food insecurity and chronic disease. *Advances in Nutrition*, 4(2), 203–212

- Lehnert, E. A., Wilt, G., Flanagan, B., & Hallisey, E. (2020). Spatial exploration of the CDC's Social Vulnerability Index and heat-related health outcomes in Georgia. *International Journal of Disaster Risk Reduction*, 46, 101517
- Lopez, L., Hart, L. H., & Katz, M. H. (2021). Racial and ethnic health disparities related to COVID-19. *Journal Of The American Medical Association*, 325(8), 719–720
- Maynard, M., Andrade, L., Packull-McCormick, S., Perlman, C. M., Leos-Toro, C., & Kirkpatrick, S. I. (2018). Food insecurity and mental health among females in high-income countries. *International Journal of Environmental Research and Public Health*, 15(7), 1424
- Mejia, P., Mahmood, H., Perez-Sanz, S. B., Garcia, K., & Dorfman, L. (2022). "People like us": News coverage of food assistance during the COVID-19 pandemic. *Health Equity*, 6(1), 367–374
- Mettler, S. (2011). *The submerged state: How invisible government policies undermine American democracy*. Chicago, IL: University of Chicago Press
- Morgan, K. J., & Campbell, A. L. (2011). *The delegated welfare state: Medicare, markets, and the governance of social policy*. Oxford, England: Oxford University Press
- Nardone, A., Chiang, J., & Corburn, J. (2020). Historic redlining and urban health today in U.S. cities. *Environmental Justice*, 13(4), 109–119
- Niles, M. T., Beavers, A. W., Clay, L. A., Dougan, M. M., Pignotti, G. A., Rogus, S., Savoie-Roskos, M. R., Schattman, R. E., Zack, R. M., Acciai, F., Allegro, D., Belarmino, E. H., Bertmann, F., Biehl, E., Birk, N., Bishop-Royse, J., Bozlak, C., Bradley, B., Brenton, B. P., & Yerxa, K. (2021). A multi-site analysis of the prevalence of food insecurity in the United States, before and during the COVID-19 pandemic. *Current Developments in Nutrition*, 5(12), nzab135
- Niles, M. T., Belarmino, E. H., & Bertmann, F. (2020a). COVID-19 impacts on food security and systems: A third survey of Vermonters. *College of Agriculture and Life Sciences Faculty Publications*. <https://scholarworks.uvm.edu/calsfac/27>
- Niles, M. T., Josephson, A. L., Bertmann, F., Belarmino, E. H., & Neff, R. (2020b). COVID-19 and food insecurity impacts: A follow up Vermont study. *College of Agriculture and Life Sciences Faculty Publications*. <https://scholarworks.uvm.edu/calsfac/26>
- Nelder, J. A., & Wedderburn, R. W. (1972). Generalized linear models. *Journal of the Royal Statistical Society: Series A (General)*, 135(3), 370–384
- Ohri-Vachaspati, P., Acciai, F., Martinelli, S., Harper, K., Bertmann, F., Belarmino, E. H., Neff, R., & Niles, M. T. (2020). Food assistance program participation among US households during the COVID-19 pandemic. <https://keep.lib.asu.edu/items/244>
- Pollard, C. M., & Booth, S. (2019). Food insecurity and hunger in rich countries—it is time for action against inequality. *International Journal of Environmental Research and Public Health*, 16(10), 1804
- Prayogo, E., Chater, A., Chapman, S., Barker, M., Rahmawati, N., Waterfall, T., & Grimbale, G. (2018). Who uses foodbanks and why? Exploring the impact of financial strain and adverse life events on food insecurity. *Journal of Public Health*, 40(4), 676–683
- Schanzenbach, D. W., & Pitts, A. (2020). Food insecurity in the Census Household Pulse Survey tables. Institute for Policy Research Rapid Research Report. <https://www.ipr.northwestern.edu/documents/reports/ipr-rapid-research-reports-pulse-hh-data-1-june-2020.pdf>
- Thomas, M. M. C., Miller, D. P., & Morrissey, T. W. (2019). Food insecurity and child health. *Pediatrics*, 144(4), e20190397
- Tyagi, R. K. (2004). Technological advances, transaction costs, and consumer welfare. *Marketing Science*, 23(3), 335–344
- US Department of Agriculture (USDA), Economic Research Service (2009). Access to affordable and nutritious food: Measuring and understanding food deserts and their consequences. https://www.ers.usda.gov/webdocs/publications/42711/12716_ap036_1_.pdf
- US Department of Agriculture (USDA) (2015). Food Access Research Atlas. <https://www.ers.usda.gov/data-products/food-access-research-atlas/go-to-the-atlas/>
- Waity, J. F. (2016). Spatial inequality in access to food assistance in Indiana. *Sociological Inquiry*, 86(1), 103–126
- Ware, L. J., Kim, A. W., Pioreschi, A., Nyati, L. H., Taljaard, W., Draper, C. E., Lye, S. J., & Norris, S. A. (2021). Social vulnerability, parity and food insecurity in urban South African young women: The healthy life trajectories initiative (HeLTI) study. *Journal of Public Health Policy*, 42, 373–389
- Wilde, P., Llobrera, J., & Ver Ploeg, M. (2014). Population density, poverty, and food retail access in the United States: An empirical approach. *International Food and Agribusiness Management Review*, 17, 171–186

- Wolfson, J. A., & Leung, C. W. (2020). Food insecurity and COVID-19: Disparities in early effects for US adults. *Nutrients*, *12*(6), 1648
- Zack, R. M., Weil, R., Babbin, M., Lynn, C. D., Velez, D. S., Travis, L., Taitelbaum, D. J., & Fiechtner, L. (2021). An overburdened charitable food system: Making the case for increased government support during the COVID-19 crisis. *American Journal of Public Health*, *111*, 804–807

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