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# Understanding how low-socioeconomic status households cope with health shocks: An analysis of multi-sector linked data

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## Abstract

Low-socioeconomic status (SES) households have little income or wealth to buffer against the negative impacts of an adverse health event (*health shock*) among adult household members. However, these households may employ a variety of other coping strategies such as receiving help from family, friends, and social services. Administrative data from a non-profit food distribution center, electronic medical record (EMR) data from a safety-net healthcare system, and publicly available residential appraisal data were linked to provide insight into these coping strategies. Three broad types of coping strategies were examined: changes in household structure, residential mobility, and utilization of social services. Of 3,235 households, 20.2% had at least one adult member who experienced a health shock. These households were more likely to gain additional adult household members and employed household members, were more likely to move residence and to move distances greater than one mile, and were less likely to visit the food distribution center after the shock.

### Keywords

Health shocks; food insecure; coping; health disparity

## 1. Introduction

Households and individuals of lower socio-economic status (SES) are more likely to suffer from poorer health and have fewer resources to buffer against the negative effects of poor health (Smith and Kington 1997). As a result, unexpected adverse health events can be particularly devastating for low-income households because they can disrupt employment, create new household economic needs (i.e. healthcare costs), and increase household work loads (i.e. providing care for the unhealthy household member). Despite the known challenges for low-income families when household members fall into poor health, relatively little is known about household coping strategies. We know that for higher income families, adverse health events often lead to depleation of savings (Semyonov, Lewin-Epstein, and

Maskileyson 2013, Smith 1998, Van Doorslaer et al. 1997). However, for households with little or no savings and income, coping strategies are likely to be more diverse.

Because coping strategies of low-SES households have not been explicitly examined, there are few recommendations for how policy makers or social service organizations might best intervene to provide assistance following adverse health events. This gap in the research is, in part, a result of insufficient data to measure how poor health impacts the lives of those for whom wealth and income were scant prior to an adverse health event. We will address this gap by linking robust, unique administrative and clinical data sets to better understand coping strategies employed by low-SES households when an adult household member experiences an adverse health event. Specifically, we relied on unexpected adverse health events, (e.g., *health shocks*), experienced by adult patients in a safety net healthcare system as a source of exogenous variation to understand how health impacted household composition changes, employment, housing mobility, and utilization of social services.

## 2. Background

### Health and Household Socio-economic Status

Income is negatively correlated with health within every age category (Smith and Kington 1997, Smith 2004), and this correlation is robust across a sample of 16 developed countries (Semyonov, Lewin-Epstein et al. 2013). A consistent association between SES and health is common and consistent in numerous studies and across diverse populations, places, and health outcomes. People of lower SES or who live in neighborhoods characterized by lower SES are more likely to have poorer health (Marmot, Stansfeld et al. 1991, Blackman and Masi 2006, Drewnowski, D. Rehm et al. 2007, Peek, Cargill et al. 2007).

However, the causal mechanism for this correlation has long been debated (Adler and Ostrove 1999). Evidence from multiple studies suggests a bidirectional causal pathway from poor health to lower SES (Deaton 2008, Van Doorslaer et al. 1997) and vice versa, from low SES to poorer health (Adams, Hurd et al. 2003, Smith 2005). For example, poor health leads to lower SES if chronic or acute health conditions limit workforce participation and, in turn, this process results in job loss. Low SES leads to poorer health if households have limited access to health resources and exhibit suboptimal health behaviors (i.e. disengage in preventive health care, avoid regular doctor visits, or eat unhealthy diets).

The relationship between SES and health also varies across the life cycle. In middle- and older-aged adults, poor health is realted to lower household SES (Smith and Kington 1997, Smith 1998, Heckman and Smith 1999) because new adult adverse health events lead to less employment, income and wealth (Smith 2004). Additionally, children living in low-SES households experience poorer health outcomes in adulthood (Smith 2004, Currie 2008, Currie and Almond 2011). Household SES particularly impacts the health of household members during childhood and early adulthood when income and wealth trajectories are being established (Condliffe and Link 2008). Thus, when an adult household member experiences poor health, household SES may decline. This decline in household SES may in turn impact the health of children in the household and their long-term health trajectories. Therefore, the effects of poor health and low-SES are compounded within the household.

## Adverse Health Events and Health Shocks

Understanding the frequency and impact of adverse health events experienced by adult household members is critical to designing strategies to improve the well-being of all individuals living in low-SES households. Adverse health events exist along a continuum based upon the degree to which they can be anticipated and prevented. For example, adverse health events resulting from natural disasters (e.g., tornado, earthquake, tsunami) are largely unpreventable and may be generally considered exogenous to other individual preventive health behaviors. However, hypoglycemia in a diabetic patient caused by failure to take prescribed medication or follow a prescribed diet may be considered highly preventable and is endogenously related to the patient's behavior. In the medical literature, adverse health events such as hospitalizations are characterized as either preventable and non-preventable based upon whether access and utilization of primary care could have theoretically prevented the hospitalization (Parchman and Culler 1999).

Researchers have utilized adverse health events as an exogenous source of variation in order to identify the causal impact of adverse health events. These events, often referred to as a *health shock*, produce a quasi-experimental framing wherein treated patients experience health shocks and untreated patients do not. However, this causal identification strategy relies upon correctly characterizing health shocks such that they are truly exogenous events (Smith 2004).

While researchers largely agree on the validity of the quasi-experimental design, there is significant heterogeneity in how health shocks are defined. For example, studies utilizing data from the Health and Retirement Study or the Panel Study of Income Dynamics have defined health shocks as onset of acute or chronic conditions such as heart problems, stoke, cancer, lung disease or diabetes and/or changes in self-rated health or hospitalizations (Wu 2003, Berkowitz and Qiu 2006, Condliffe and Link 2008, Lee and Kim 2008, Conley and Thompson 2011, Bradley, Neumark et al. 2012, Kim, Yoon et al. 2012). Other studies have used databases such as the National Highway Traffic Safety Administration to identify car crash victims (Doyle Jr 2005). Others have analyzed household survey data to study change in self-reported health status or indicence of chronic physical or mental health problems (García-Gómez 2011) as a measure of health shocks. Clearly, these different characterizations of health shocks differ in terms of the extent to which the adverse health events may be considered strictly exogenous and this is a known limitation of the literature.

## Coping Strategies

Despite this discrepency, robust evidence suggests that health shocks tend to be most severe among low-SES households and those without private health insurance (Berkowitz and Qiu 2006, Lee and Kim 2008, Conley and Thompson 2011, Kim, Yoon et al. 2012, Curtis, Corman et al. 2013). However, we know little about how low-SES households who have little income or wealth cope with health shocks. Very low-SES households are under-represented in previous work because the literature has largely focused on the impact of health shocks on income and wealth. Moreover, many prior survey studies face limitations in recruitment of these populations. However, some studies have examined coping strategies among the food insecure, a particular subset of the low-SES population. The food insecure are individuals or households without reliable access to a sufficient quantity of affordable, nutritious food.

Studies examining food insecure populations suggest that adverse health events can impact low-income households far beyond depletion of household financial resources. For example, maternal post-partum depression was associated with a large increase in household food insecurity (Noonan, Corman et al. 2014). An adverse health event to an adult family member may cause job loss, increased expenses for healthcare, and high recurring expenses to obtain medication (Smith 2004). Additionally, households experiencing these challenges are also more likely to report food insecurity (Edin, Boyd et al. 2013). In qualitative work, researchers have found that prior to cutting back on food, household members engage in multiple coping strategies. These included relying upon social networks to meet family needs, turning to non-profit food distributors, and engaging in strategic shopping patterns to stretch limited financial resources (Edin, Boyd et al. 2013).

Finally, researchers have also documented coping strategies used by households who experience income volatility. These strategies include accessing savings, increased utilization of credit, and reliance on public benefit programs (Andersen, Austin et al. 2015). Notably, low-SES households can engage in these coping strategies in creative ways. For example, households with little savings of their own often access the savings of friends or family members, seek help from informal savings circles (especially among immigrant populations), or make early withdrawals from retirement savings accounts. Additionally, access to credit from traditional sources can be limited for low-SES households, thus they often turn to non-traditional lenders such as pay-day loans.

Across multiple domains, the extant literature suggests that key coping strategies are related to either seeking help among family and friends or seeking help from social service organizations. Empirically, we might observe coping strategies related to seeking help from family and friends by observing changes in household composition. Coping strategies related to seeking help from social service organizations may be observed on both the intensive (quantity of help received during a visit to a service provider) and extensive (number of visits to service providers) margins. Finally, we might observe increases in food insecurity or changes in residential address as either a failure of the primary coping strategies or as a coping strategy itself. For example, a household member may report food insecurity because they are cutting meal sizes in order to devote resources to improving health of the sick adult wage earner; or a family may cut meal size because they have exhausted all other possible alternatives (Edin, Boyd et al. 2013). Similiarly, household members may double-up; that is, move-in with extended family to provide extra help with household caregiving; or they may move-in with extended family because of eviction (Ahrentzen 2003).

## 2. Data and Methods

### 2.1 Data Sources

To estimate the impact of health shocks on policy-relevant outcomes, we linked 3 datasets: (a) Crossroads Community Services administrative data, Parkland Health and Hospital

System (b) Electronic Medical Record data, and (c) Dallas Central Appraisal District (DCAD) housing appraisal data.

**(a) Crossroads Community Services (>5,500 households annually)—**Crossroads Community Services (hereafter "Crossroads") is the largest non-profit food distributor in Dallas County, Texas and distributed over 2.6 million pounds of food to 15,787 individuals in 2014. Crossroads maintains a robust, longitudinal database comprising data from their low-SES (<185% federal poverty line) clients. The database includes client and household-level measures of demographic and socioeconomic information, residential location, food selection, and service utilization.

**(b) Parkland EMR (~65,000 records annually)—**Parkland Health and Hospital System (hereafter "Parkland") is one of the largest integrated safety-net health care systems in the US, and reports 1.5 million patient encounters annually. Parkland consists of a 900-bed hospital, specialty clinics, and 12 community-oriented primary care clinics that collectively provide comprehensive inpatient, outpatient, specialty and primary care for under- and uninsured, low income Dallas County residents. Parkland uses the state-of-the-art comprehensive system-wide Epic EMR system (Epic Systems Inc., Verona, WI). Parkland EMR data include patient-, provider-, clinic-, and system- level data incorporating both medical and non-medical data (e.g., demographic, health conditions, medical procedures and tests, and healthcare utilization data). Because Parkland is an intergrated health system and the only safety-net provider in Dallas County, it has nearly complete coverage for low-income under- or un-insured adult county residents.

**(c) Dallas Central Appraisal District Data (>650,000 parcels)—**Publicly available appraisal data (appraisal value, home characteristics, and parcel location) for Dallas County, Texas were obtained from the local tax authority, the Dallas Central Appraisal District (DCAD). Appraisal data are recorded annually for each housing parcel (n>630,000).

### 2.2 Sample

The analytic sample includes all households in the Crossroads administrative database with: (1) more than 1 Crossroads visit occurring in the two-year study window of December 1, 2013-November 30, 2015, (2) Crossroads visits spanning a minimum of 180 days, and (3) at least one household member who was an established Parkland patient. Households with one established Parkland patient were defined as having at least one inpatient or outpatient encounter with Parkland during 2004-2015.

### 2.3 Variables

Dependent variables, derived using Crossroads and DCAD data, measure three distinct types of household coping strategies as identified in the extant literature: utilization of Crossroads food assistance, household composition changes, and changes in residential address. Our measure of Crossroads utilization is based upon changes in utilization along the extensive margin and was the Crossroads visit rate, defined as the number of visits to receive charitable food assistance within the study window divided by the number of months in the study window. Measures of household composition changes included a change in the number of adults in the household and whether or not a household gained an employed (full or part time) adult. Households were characterized as gaining an employed adult if they both gained an additional adult household member and there was an additional adult household member employed. Measures of residential address change included whether or not the household moved residence and whether or not a household moved a long distance (more than one mile). Moves were determined by comparing geocoded addresses at the first and last Crossroads visit in the study window.

Our primary independent variable, the presence of a health shock between Crossroads visits, was obtained from the Parkland EMR. Health shocks occurring between the first and last Crossroads visit in the study window were identified using EMR data. We modeled the effect of health shocks on dependent variables by considering occurrence of a health shock to any adult household member. Separately, we modeled health shocks occurring to the head of household and to other adult household members (non-head of household) among a subsample of households with >1 adult household member (hereafter, the “multiple-adult subsample”). The head of the household was defined as the client who is the primary household member responsible for selecting and transporting food for the household during visits to Crossroads.

To generate unbiased estimates of health shock effects on subsequent behavior, we identified exogenous shocks that were likely to be uncorrelated with changes in patient behavior (e.g., such as sudden uptake of preventive services). To satisfy these restrictions, we limited our characterization of health shocks to emergency department visits for clinical encounters (e.g., not for the purpose of medication refills) for conditions that are not potentially preventable. We excluded potentially preventable visits using diagnosis codes (i.e., ICD-9) following a standardized approach common in the health services literature (Parchman and Culler 1999). Following this approach, preventable conditions include, for example, asthma or hypertension (which can be managed by patient adherence to maintenance therapies).

Other covariates were obtained from Crossroads and Parkland EMR data. Covariates drawn from Crossroads data included: household size, presence of children (<18 years of age) in the household (yes/no), number of household members employed full or part time (continuous), and for the head of household: age (continuous), sex (male/female), race/ethnicity (Hispanic, Black, White/other), marital status (no/yes), and highest level of education obtained (some high school, high school graduate, college graduate). We controlled for the length of time between the two Crossroads visits during which a health shock could have occurred. EMR covariates included the total number of outpatient visits (from 2012-2015) and type of healthcare insurance (uninsured/charity care, Medicaid, Medicare, other/unknown). Presence of children, employment, marital status were measured based on the values provided at the first Crossroads visit within the study window.

### 2.4 Analytic Methods

**(a) Linking Administrative Data Sets—**Address histories for each of the eligible households were geo-coded following a hierarchical geo-coding process comprising 3 levels: (1) parcel, or cadastral, information (Murray, Grubesic et al. 2011) (2) ESRI's StreetMap Premium product (ESRI and Tele Atlas 2012), and (3) Google application program interface (API). Each address was passed to the cadastral address locator first, and the un-matched addresses from the cadastral-level geocoding results were passed to the StreetMap address locator. Any un-matched addresses from the street-level geocoding results were then passed to the Google API for the final geocoding. A total of 8,165 addresses were geocoded; 63.2% (N=5,159) matched at the cadastral level, 29.4% (N=2,399) matched at the street-level, and 7.4% (N=607) matched with the Google API.

The second and third geocoding levels produce coordinates that correspond to the middle of streets; these coordinates were adjusted to the nearest parcel. Some coordinates (N=746) corresponded to parcels associated with more than one DCAD account, and subsequently, more than one parcel value. For these parcels, Crossroads addresses were matched to a single DCAD account if text from the second line of the address provided adequate unit-level information to match a DCAD account associated with a unit. If the second line of the address did not provide adequate unit-level information then the account with the highest property value was chosen. For accounts with equal value, the account with the most appropriate building use (e.g., residential) description was chosen. For the analytic sample, 100% of the provided addresses were matched to a DCAD parcel through one of the 3 hierarchical geocoding levels.

We matched Crossroads data to EMR data using the following criteria: (1) 100% match on date of birth (DOB) and (2) fuzzy match on patient name. The ‘STRINGDIST’ command in R was used to match first and last name, or to match a similar full name (van der Loo 2014). If two or more Parkland patients matched on DOB and fuzzy name, then ties were broken by a 100% match on zip code (i.e., if any of the EMR zip codes matched any of the Crossroads zip codes).

**(b) Multivariate Analysis—**We estimated three multivariate regression models for each dependent variable. The models differed in terms of how the health shock variable was defined. We examined household-adult health shocks in the full analytic sample by defining the health shock as 1 or more health shocks experienced by any adult household member during the study window (hereafter a “household-adult health shock”). In the multiple-adult subsample, the health shock variable was defined differently in 2 separate models. In the first multiple-adult subsample model, the health shock variable was defined as 1 or more health shocks experienced by the adult head of household during the study window (herafter a “head health shock”). In the second multiple-adult subsample model, the health shock variable was defined as 1 or more health shocks experienced by a non-head adult household member during the study window (hereafter “non-head health shock”). We examined head and non-head health shocks only in the multiple-adult subsample to facilitate a comparison of how households cope when different types of adult members experience poor health.

Crossroads visiting frequency was modeled as a continuous dependent variable and parameter estimates were obtained using ordinary least squares regression. Ordered logistic regression was used to estimate parameters for models with change in number of adult household members as the dependent variable. Finally, logistic regression models were estimated for all binary dependent variables.

# 3. Results

## 3.1 Data Linkage Results

The analytic sample included all households represented in the Crossroads administrative database from December 1, 2013 through November 30, 2015. The initial Crossroads data included 71,349 visits to a food distributor by 10,840 unique individuals residing in 7,588 households. Only records with more than 1 Crossroads visit, and with a Crossroads history spanning more than 179 days, were included in the analytic sample to facilitate measurement of change in behavior associated with coping strategies. The final Crossroads sample comprised 4,471 households. Of these, 3,696 (83%) were engaged in the Parkland Health System, defined as having at least 1 adult household member with a Parkland encounter during 2004-2015. 100% of the matched household addresses were geocoded to a DCAD parcel using the methods described previously.

## 3.2 Descriptive Analysis

Summary measures for variables included in the linked analytic sample are provided in Table 1. Household size varied from 1 to 14 members, and included 0 to 3 employed adults. More than one-third (37%) included children. For each household, the individual who most often visited Crossroads to obtain food is identified as the head of household. Average head of household age is 47 years, and 32% are married. Half (51%) of the head of households have a high school degree or more education. Thus, 49% of the households in our sample have a head who has less than a high school education. The sample is primarily Non-Hispanic Black (53%) or Hispanic (33%).

Household-adult health shocks occurred in 20% of the full sample. Most households lacked insurance (52%). The average Crossroads utilization rate was 0.85; in other words, households visited Crossroads for food slightly less than once per month. In the full analytic sample, 38% of households had a Crossroads utilization rate of 1 or greater, indicating that they visited Crossroads at least once per month during the study window. On average, household health system participation amounted to 26 outpatient encounters per household between 2012 and 2015. Among households that experienced changes in the number of adult members, more households gained (12.6%) than lost (3.4%) adult members. Additionally, 3.7% of the sample gained an employed adult member and 8.2% moved during the study window.

Table 1 describes the multiple-adult subsample (n=1,151). For this subsample, head health shocks occurred in 16.9% of households and non-head health shocks occured in 12.2% of households. In comparison with the full analytic sample, households in the subsample are larger and the proportion of households with children is higher. The mean age of household head is comparatively younger, and the subsample includes more Hispanic households (61%) than Non-Hispanic Black (29%) households. Heads of households in the subsample were less educated than in the full sample. Within the multiple adult household sample, there were slightly more changes in the number of adults in the household during the study period and residential mobility was slightly higher (9.6% of households moved). Crossroads utilization rate and health system participation (i.e., number of medical encounters) were lower for the subsample.

### 3.3 Multivariate Regression Results

Table 2 presents estimates for multivariate least squares regression models examining the impact of health shocks on Crossroads visiting rate. A household-adult health shock in the full sample model (first column, Table 2) is associated with a lower Crossroads utilization rate, but has no significant association with the Crossroads utilization rate in the multiple adult household sub-sample (second and third columns, Table 2). Across all models, households with an older head and a higher number of employed adults visited Crossroads more frequently, while Hispanic households visited less frequently than non-Hispanic households. Additionally, in the Household-Adult Shock model, households with a married head of household visitted less frequently.

The relationship between health shocks and household compositional changes were measured by examining (1) changes in the number of adults in the household via ordered logistic regression, and (2) additions of an employed adult household member using logistic regression (Table 3). A household-adult health shock in the full sample (first 2 columns, Table 3) and a non-head health shock in the multiple-adult subsample (columns 5 and 6, Table 3) are associated with both an increase in the number of adults and increased odds of gaining an employed adult household member. The effect sizes are noteworthy, particularly when examining a health shock to a non-head adult household member: households are nearly twice as likely to gain any adults and to gain employed adults when there is a health shock to a non-head adult household member. Interestingly, there are no statistically significant relationships between household composition and head health shocks.

Other strong correlates of changes in household composition include the presence of children in the household and race/ethnicity (Table 3). In the household-adult shock models, households are 4.5 times more likely to add adult household members and twice as likely to add an employed adult if there are children present. Considering only the multiple adult subsample, when a shock occured to a head or non-head, households are twice as likely to add adult household members when there are children, but there is no significant relationship between presence of children and adding employed adults. In contrast, race/ethnicity is more strongly associated with adding employed adults. Compared to non_Hispanic households, Hispanic households are nearly 8 (full sample) or 5 (multiple adult subsample) times more likely to add employed adults.

Health shocks are also associated with change in residential address (Table 4). In the full sample, households experiencing a health shock are 2 times more likely to move and to move a distance greater than 1 mile compared to households that do not experience a health shock. In the multiple adult subsample, estimated effect sizes are similar when a health shock is experienced by the head of household, but parameter estimates are not statistically significant in models examining non-head health shocks. Most other covariates are not related to residential address changes, with the exception of household head age (among all models, decreased likelihood of moving and moving long distances), race/ethnicity (for the full sample only, Hispanic households are more likely to move, but not move long distances), household size (for the full sample only, larger households are more likely to move and move longer distances), and employed adults (for the full sample only, households with more employed adults are less likely to move and move longer distances). Finally, among all models, those with longer study windows are more likely to move.

## 4. Discussion

We found that household-adult health shocks are related to a number of coping behaviors including decreased Crossroads utilization, changes in household composition (i.e. an increase in adults and an increase in employed adults), and an increased likelihood of residential moves as well as moving longer distances. Additionally, our results are suggestive of interesting correlates between coping behaviors and household demographics that likely can influence the direction of future research agendas. Hispanic households and households with children are much more likely to add adults and add employed adults.

When comparing results for head vs non-head health shocks in the multiple adult subsample, we found evidence for different coping strategies that vary depending upon which household adult endured the health shocks. When non-head adults experience health shocks, the household is more likely to “double up”—taking on additional adult members to distribute expense and care burdens. When the head of the household's health is affected, households are more likely to move and move longer distances.

### 4.1 Value of multi-sector data linkages

Multi-sector data linkages provide numerous advantages because they provide a shared goal and vision that can help to unite diverse stakeholders. Our analysis demonstrates the power of linked data from the social-service, health, and housing sectors to improve our understanding of how households manage food, employment, and housing resources to cope with an adverse health event. Previous work in this area has relied on changes in income or wealth measures (Wu 2003, Berkowitz and Qiu 2006, Condliffe and Link 2008, Lee and Kim 2008, Kim, Yoon et al. 2012). Wealth and income measures may be less relevant for understanding the impacts of health shocks for our low SES population, who are largely unemployed and have very low income. People of higher wealth and income (even marginally), whom are not in this sample, have the luxury of spending wealth or income *before* they need to do things like seek social services, double up, or move.

Linked data from multiple safety-net systems improves equitable representation in research and reduces the research burden for vulnerable populations. Low SES populations frequently provide an array of data to social service providers, yet are often under-represented in research. For example, many Crossroads clients have filled out extensive applications to qualify for a host of social services (e.g., WIC, SNAP, Social Security, Section 8 housing); middle- and upper- income families are not burdened with providing such information. Many agencies require routine re-certification wherein data are collected longitudinally. In addition, non-profit agencies are increasingly collecting or sharing additional data from clients in order to fulfill funder obligations or to meet criteria for claiming evidence based programming. Increased utilization and linkage of these data can improve representation of low SES populations in research. Moreover, utilization of EMR data to ascertain health status bypasses the use of respondent surveys for primary data collection, which entail significant response burden, can be adversely impacted by low response rates and bias, and is often cost-prohibative.

Utilizing administrative non-profit data provides significant advantages for researchers wishing to understand vulnerable populations. Linking EMR data to additional sources of social, behavioral, and economic data has tremendous potential for transdisciplinary health research. Parallel efforts in the health services literature have long acknowledged the power of EMR data linkages to improve health outcome research (Bradley, Penberthy et al. 2010). However, these efforts have been characterized as tehnnologically challenging and hard to manage due to the required interfacing between multiple independent organizations, often with competing needs, regulatory rules, and goals (Bradley, Neumark et al. 2012)(Bradley, Neumark et al. 2012). Our work suggests these challenges may be overcome through fostering collaborative multi-sector relationships. These relationships may be centered around shared goals and mutual benefits resulting from greater data integration. Widespread adoption of EMRs in the U.S. will make future multi-sector data linkages with healthcare partners potentially feasible across many communities.

Non-profit organizations also benefit from non-profit data linkages. For example, they can benefit from collaboration with researchers if those collaborations exist for the sake of long-term shared vision and goals. Our study is an example of the benefits that such a long-term investment can yield. The study authors have formed the Community Assistance Research Iniative (CARE) to work alongside non-profit agencies to increase their capacity for collecting and learning from their administrative data. In turn, non-profits can leverage newfound data to evaluate service provision, report quality metrics and benchmarks to funders, and to guide future innovations in program development, implementation, and evaluation.

Multi-sector linked data analysis presents advantages over alternative research designs. Significant investments of time and relationship-building are needed to establish trust in order to recruit participants for traditional cross-sectional and cohort research designs. Moreover, in these designs, response rates—particularly for low-SES populations—are often low and attrition is high. Administrative data, in contrast, can be embedded in service provision and response rates can be exceptionally high. The robust data collection at Crossroads highlighted herein leverages the long-established trust that the organization has with their clients to ensure data collection efficiency and quality. Notably, many administrative data sources present an additional advantage in that they are continually collecting data. In our linked data, DCAD housing appraisal data are released yearly and Crossroads administrative and Parkland EMR data continue to accrue. Thus data are available to researchers on a rolling basis.

### 4.2 Fostering Transdisciplinary Research with Multi-Sector Data Linkages

While each stakeholder may have unique applications for the linked data, the data linkage endeavor in itself is a shared goal and can provide incentive for all parties to work together. In turn, engaging multiple stakeholders in the data collection, analysis, linkage and sharing process ensures development of meaningful data that can be deployed by all partners. In our case, CARE has served as a conduit between institutions and between researchers from diverse backgrounds. With the assistance of academic researchers, the non-profit agencies affiliated with CARE have increased their capacity for collecting and learning from their administrative data. Additionally, with the assistance of non-profit leaders, the researchers affiliated with CARE have developed more actionable research focuses.

Our study benefits from strengths drawn from public health, economics, and an understanding of the situations faced by low-income families. Economics literature provides a robust framework for characterizing exogenous health shocks; the public health literature allows for an understanding of health services in order to apply the exogeneity criteria to identify health shocks within EMR data; and our food bank partner provided the rational for collecting many of the coping outcome measures that were examined. Research results generated from the present work demonstrate how the non-profit and academic research sectors can work together to generate policy-relevant, actionable results facilitated by novel data linkages.

### 4.3 Limitations

Our study has a number of limitations, many of which are reflective of potential short-comings from our linked data sources. Crossroads data collection is opportunistic, which generated a non-random sample and non-random timing of data collection. This limits the external validity of our results. We also employed a rather non-traditional characterization of head of household based upon the definition used by Crossroads. Low-SES households have very diverse household structures rendering any universal definition of head of household problematic. Our results should be interpreted in light of how head of household has been defined within this study—the adult household member who typically acquires food for the household. Finally, we were not able to exhaustively examine all coping strategies. In particular we did not observe changes in social service utilization along the intensive margin because Crossroads limits the amount of food and services received at each visit. Additionally, we did not have data on food security of the households in our study or measures of direct cash transfers the household may have received from family or friends.

Also, use of EMR data to identify health shocks has some advantages and disadvantages. Use of EMR data to ascertain health shocks is an advantage over the majority of the health shocks literature to date, which has largely defined health shocks using self-reported survey data. In contrast to survey data which suffer from recall and mono-method biases, EMR data provide an objective source of health data wherein health events are date- and time-stamped. However, the exogeneity of health shocks cannot be assumed based upon review of ICD9 codes of emergency room visits. Some included codes may represent conditions that are related to underlying client behaviors, such as a tendancy to engage in more risky behavior. This possibility may create confounding and challenge the causal interpretation of our results. Additionally, EMR data are limited to only a single healthcare system. However, it is the primary integrated safety-net health system in the region, so exclusive utilization of this system by our sample is expected to be very high. Nevertheless, some health shocks may not be observed if patients choose to visit a healthcare provider outside of the Parkland system or choose not to seek healthcare.

### 4.4 Data Sustainability and Future Directions

The data linkages leveraged by this study are part of a larger effort to establish a longitudinal data resource for diverse users: the Hunger Center Longitudinal Database (HCL Database). De-identified Crossroads data are archived annually to build the HCL Database. This endeavor is self-sustaining due to a collaboration between CARE, Crossroads and the regional food bank. CARE guides the scientific rigor and validity of Crossroads data collection through new question development, data collection process monitoring, and evaluation of existing data. Crossroads facilitates fidelity in data collection procedures, ensures client representation and advocates for innovative use of the data to benefit clients. The regional food bank maintains data sharing policies and makes data available to the research and nonprofit community. To date, 2 years of data have been archived in the HCL Database.

The HCL Database was designed to create, house, and share administrative data that is scientifically valid and amenable to linkage with other data sources. Because none of the data collection used in this study is tied to a funding stream (i.e. research grant, etc.), we anticipate data collection to continue indefinitely. We have facilitated the appropriate memorandums of understanding to support data storage and administration of sharing agreements among the local non-profit community.

Our study highlights several important areas for further research using multi-sector data linkages, such as the linkage highlighted herein. First, the impact of health shocks on very low-SES households needs to be further examined in light of both 1) a broader array of coping strategies (e.g., food security, more refined financial information) and a more granular examination of the type, severity, and time horizon of health shocks (e.g., trauma, disability). Second, our study highlights the role of residential mobility in household's coping behaviors. This warrants further study and will inform our understanding of how, when, and why neighborhood social and built environments impact low-income households.

### 4.5 Conclusions

Health shocks impact low-income households in ways that result in changes in household structure, mobility, and utilization of social services. Interestingly, for the low-income sample examined, employment is less likely to be affected, perhaps because employment is already fragile for these households even prior to a potential health shock. Due to limited representation of the very low-SES population in most research datasets, novel data linkages are necessary to understand how health and social policies impact this vulnerable population. Our results represent the first steps towards informing how safety-net systems across diverse sectors (i.e. health, housing, and food) might provide enhanced benefit to low-SES families through greater integration. Our highlighted multi-sector data linkage, as part of the HCL Database, offers promise for future transdispiclinary researchers interested in the very low-SES population.

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## Table 1

**Summary statistics, full analysis sample and multiple-adult sample**

| | **Full Sample** | | **Multiple-Adult Sample** | |
|---|---|---|---|---|
| | **N=3235** | | **N=1151** | |
| Continuous Variable | Mean | (S.D) | Mean | (S.D) |
| Crossroads Visit Rat | 0.85 | (0.26) | 0.78 | (0.28) |
| Study Window (days) | 501.07 | (178.10) | 517.49 | (175.85) |
| Household Size | 2.53 | (1.99) | 4.19 | (1.93) |
| Employed Adults | 0.26 | (0.49) | 0.55 | (0.62) |
| Head's Age | 47.43 | (17.74) | 43.03 | (13.99) |
| Health Visits | 25.92 | (40.02) | 22.93 | (35.16) |
| Discrete Variables | Percent (%) | | Percent (%) | |
| Outcomes | | | | |
| Health Shock to Head | 20.2 | | - | |
| Health Shock to Head | - | | 16.9 | |
| Health Shock to Nonhead | - | | 12.2 | |
| Household measures | | | | |
| Children present | 37.3 | | 63.9 | |
| Male Head | 24.2 | | 15.8 | |
| Married Head | 31.7 | | 65.9 | |
| Gained an Employed Adult | 3.7 | | 3.9 | |
| Moved | 8.2 | | 9.6 | |
| Moved > 1 Mile | 5.7 | | 6.9 | |
| Head's Race/Ethnicity | | | | |
| Nonhispanic White | 12.9 | | 9.2 | |
| Hispanic | 33.3 | | 61.1 | |
| Nonhispanic Black | 52.9 | | 28.9 | |
| Head's Educational Attainment | | | | |
| Completed High School (no college) | 37.9 | | 30.7 | |
| Some College (or more) | 13.6 | | 9.3 | |
| Head's Insurance Status | | | | |
| No Insurance | 51.8 | | 67.4 | |
| Medicaid | 17.4 | | 10.5 | |
| Medicare | 26.8 | | 16.0 | |
| Other Insurance | 3.9 | | 6.1 | |
| Change in Number of Adults in Household | | | | |
| Lost >1 adult | 0.7 | | 1.8 | |
| Lost 1 adult | 2.9 | | 8.1 | |
| No change | 83.3 | | 74.3 | |
| Gained 1 adult | 10.4 | | 12.9 | |

| | **Full Sample** | **Multiple-Adult Sample** |
|---|---|---|
| | **N=3235** | **N=1151** |
| Gained >1 adult | 2.2 | 3.0 |

**Table 2**

**OLS Estimation results for Crossroads visiting rate**

| | Full Sample | | Multiple-adult Subsample[1] | | | |
|---|---|---|---|---|---|---|
| | Household Shock | | Head Shock | | Non-head Shock | |
| Health Shock | -0.04 | *** | -0.02 | | 0.02 | |
| | -(0.01) | | -(0.02) | | -(0.02) | |
| Kids in Household | -0.03 | + | -0.03 | | -0.03 | |
| | -(0.02) | | -(0.03) | | -(0.03) | |
| Study Window | 0.00 | | 0.01 | | 0.01 | |
| | (0.00) | | -(0.01) | | -(0.01) | |
| Household Size | -0.01 | + | 0.00 | | 0.00 | |
| | (0.00) | | -(0.01) | | -(0.01) | |
| Employed Adults | 0.04 | *** | 0.03 | + | 0.03 | * |
| | -(0.01) | | -(0.01) | | -(0.01) | |
| Head's Age | 0.00 | *** | 0.00 | *** | 0.00 | *** |
| | (0.00) | | (0.00) | | (0.00) | |
| Hispanic | -0.14 | *** | -0.15 | *** | -0.15 | *** |
| | -(0.01) | | -(0.02) | | -(0.02) | |
| Male Head of Household | -0.02 | | 0.02 | | 0.02 | |
| | -(0.01) | | -(0.02) | | -(0.02) | |
| Completed High School | 0.02 | | 0.01 | | 0.01 | |
| | -(0.01) | | -(0.02) | | -(0.02) | |
| Some College | -0.01 | | -0.02 | | -0.02 | |
| | -(0.01) | | -(0.03) | | -(0.03) | |
| Married Head | -0.04 | ** | -0.01 | | -0.01 | |
| | -(0.01) | | -(0.02) | | -(0.02) | |
| Health Visits | 0.00 | | 0.00 | | 0.00 | |
| | (0.00) | | (0.00) | | (0.00) | |
| Medicaid | 0.00 | | 0.06 | * | 0.06 | * |

| | Full Sample | | Multiple-adult Subsample[1] | | | |
|---|---|---|---|---|---|---|
| | **Household Shock** | | **Head Shock** | | **Non-head Shock** | |
| | -(0.01) | | -(0.03) | | -(0.03) | |
| Medicare | 0.00 | | 0.01 | | 0.01 | |
| | -(0.01) | | -(0.03) | | -(0.03) | |
| Other Insurance | 0.00 | | -0.01 | | -0.01 | |
| | -(0.02) | | -(0.03) | | -(0.03) | |
| Constant | 0.85 | *** | 0.75 | *** | 0.75 | *** |
| | -(0.02) | | -(0.05) | | -(0.05) | |
| Observations | 3,235 | | 1,151 | | 1,151 | |
| R-squared | 0.17 | | 0.14 | | 0.14 | |

Standard errors in parentheses

*** p<0.001,

** p<0.01,

* p<0.05,

+ p<0.10

[1] The multiple-adult subsample is defined as all households having >1 adult member.

**Table 3**

**Estimated odds ratios for models examining change in household composition**

| | Full Sample | | | | Multiple-adult Subsample[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Household Shock | | | | Head Shock | | | | Non-head Shock | | | |
| | Change in Number of Adults in Household[2] | | Household Gained an Employed Adult[3] | | Change in Number of Adults in Household[2] | | Household Gained an Employed Adult[3] | | Change in Number of Adults in Household[2] | | Household Gained an Employed Adult[3] | |
| Health Shock | 1.63 | *** | 1.80 | * | 1.31 | | 1.15 | | 1.97 | *** | 2.05 | + |
| | -(0.20) | | -(0.43) | | -(0.24) | | -(0.48) | | -(0.40) | | -(0.85) | |
| Kids in Household | 4.56 | *** | 2.07 | + | 2.08 | ** | 2.10 | | 2.11 | *** | 2.13 | |
| | -(0.84) | | -(0.85) | | -(0.47) | | -(1.40) | | -(0.48) | | -(1.41) | |
| Study Window | 1.11 | * | 1.03 | | 1.07 | | 0.97 | | 1.07 | | 0.94 | |
| | -(0.06) | | -(0.11) | | -(0.07) | | -(0.16) | | -(0.07) | | -(0.16) | |
| Household Size | 0.77 | *** | 0.91 | | 0.90 | * | 1.12 | | 0.89 | * | 1.12 | |
| | -(0.04) | | -(0.07) | | -(0.05) | | -(0.11) | | -(0.05) | | -(0.11) | |
| Employed Adults | 0.53 | *** | 0.13 | *** | 0.80 | + | 0.22 | *** | 0.78 | + | 0.22 | *** |
| | -(0.06) | | -(0.03) | | -(0.10) | | -(0.07) | | -(0.10) | | -(0.07) | |
| Head's Age | 0.99 | | 0.95 | *** | 1.00 | | 0.98 | | 0.99 | | 0.98 | |
| | (0.00) | | -(0.01) | | -(0.01) | | -(0.02) | | -(0.01) | | -(0.02) | |
| Hispanic | 1.40 | * | 7.68 | *** | 1.11 | | 4.84 | * | 1.09 | | 4.81 | * |
| | -(0.21) | | -(2.90) | | -(0.23) | | -(3.07) | | -(0.22) | | -(3.04) | |
| Male Head of Household | 0.84 | | 0.31 | * | 0.99 | | 0.19 | | 0.98 | | 0.18 | + |
| | -(0.11) | | -(0.17) | | -(0.19) | | -(0.20) | | -(0.19) | | -(0.18) | |
| Completed High School | 0.86 | | 0.78 | | 0.89 | | 0.88 | | 0.88 | | 0.90 | |
| | -(0.10) | | -(0.20) | | -(0.14) | | -(0.38) | | -(0.14) | | -(0.39) | |
| Some College | 0.80 | | 0.81 | | 0.74 | | 1.85 | | 0.72 | | 1.83 | |
| | -(0.13) | | -(0.36) | | -(0.19) | | -(1.10) | | -(0.18) | | -(1.10) | |
| Married Head | 1.62 | *** | 2.73 | *** | 1.12 | | 1.20 | | 1.10 | | 1.17 | |
| | -(0.21) | | -(0.71) | | -(0.18) | | -(0.49) | | -(0.18) | | -(0.48) | |
| Health Visits | 1.00 | | 0.99 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | |
| | (0.00) | | -(0.01) | | (0.00) | | -(0.01) | | (0.00) | | -(0.01) | |

| | Full Sample | | Multiple-adult Subsample[1] | | | |
|---|---|---|---|---|---|---|
| | Household Shock | | Head Shock | | Non-head Shock | |
| | **Change in Number of Adults in Household[2]** | **Household Gained an Employed Adult[3]** | **Change in Number of Adults in Household[2]** | **Household Gained an Employed Adult[3]** | **Change in Number of Adults in Household[2]** | **Household Gained an Employed Adult[3]** |
| Medicaid | 0.82 | 0.74 | 0.82 | 0.38 | 0.82 | 0.38 |
| | -(0.12) | -(0.26) | -(0.19) | -(0.29) | -(0.19) | -(0.29) |
| Medicare | 0.88 | 0.79 | 0.82 | 0.92 | 0.83 | 0.93 |
| | -(0.13) | -(0.42) | -(0.19) | -(0.66) | -(0.19) | -(0.67) |
| Other Insurance | 1.10 | 0.74 | 1.02 | 0.57 | 1.07 | 0.61 |
| | -(0.26) | -(0.33) | -(0.29) | -(0.43) | -(0.31) | -(0.46) |
| Observations | 3,235 | 3,235 | 1,151 | 1,151 | 1,151 | 1,151 |

Standard errors in parentheses

*** $p<0.001$,

** $p<0.01$,

* $p<0.05$,

+ $p<0.10$

[1] The multiple-adult subsample is defined as all households having >1 adult member.

[2] Ordered logistic regression results reported as odds ratios.

[3] Logistic regression results reported as odds ratios.

## Table 4

### Estimated odds ratios for residential mobility

| | Full Sample | | | | Multiple-adult Subsample[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Household Shock | | | | Head Shock | | | | Non-head Shock | | | |
| | Moved | | Moved > 1 Mile | | Moved | | Moved > 1 Mile | | Moved | | Moved > 1 Mile | |
| Health Shock | 1.99 | *** | 2.22 | *** | 1.84 | * | 1.93 | * | 0.98 | | 1.20 | |
| | (0.29) | | (0.37) | | (0.46) | | (0.55) | | (0.31) | | (0.42) | |
| Kids in Household | 0.87 | | 0.71 | | 0.57 | | 0.46 | + | 0.57 | | 0.46 | + |
| | (0.21) | | (0.20) | | (0.21) | | (0.19) | | (0.21) | | (0.19) | |
| Study Window | 1.31 | *** | 1.16 | + | 1.20 | + | 1.08 | | 1.23 | + | 1.10 | |
| | (0.09) | | (0.09) | | (0.13) | | (0.13) | | (0.14) | | (0.14) | |
| Household Size | 1.11 | * | 1.18 | ** | 1.13 | + | 1.18 | * | 1.13 | + | 1.18 | * |
| | (0.06) | | (0.07) | | (0.08) | | (0.09) | | (0.08) | | (0.09) | |
| Employed Adults | 0.70 | * | 0.67 | * | 0.89 | | 0.93 | | 0.85 | | 0.89 | |
| | (0.10) | | (0.12) | | (0.17) | | (0.21) | | (0.16) | | (0.19) | |
| Head's Age | 0.96 | *** | 0.96 | *** | 0.95 | *** | 0.96 | ** | 0.95 | *** | 0.96 | *** |
| | (0.01) | | (0.01) | | (0.01) | | (0.01) | | (0.01) | | (0.01) | |
| Hispanic | 1.81 | ** | 1.27 | | 1.55 | | 1.47 | | 1.54 | | 1.45 | |
| | (0.36) | | (0.30) | | (0.52) | | (0.57) | | (0.51) | | (0.55) | |
| Male Head of Household | 1.10 | | 1.24 | | 0.73 | | 0.91 | | 0.74 | | 0.91 | |
| | (0.20) | | (0.26) | | (0.27) | | (0.36) | | (0.27) | | (0.35) | |
| Completed High School | 0.87 | | 0.99 | | 1.04 | | 1.17 | | 1.05 | | 1.17 | |
| | (0.14) | | (0.18) | | (0.26) | | (0.34) | | (0.26) | | (0.34) | |
| Some College | 1.25 | | 1.30 | | 1.31 | | 1.87 | | 1.26 | | 1.79 | |
| | (0.26) | | (0.32) | | (0.51) | | (0.77) | | (0.48) | | (0.73) | |
| Married | 0.75 | + | 1.00 | | 0.63 | + | 0.76 | | 0.61 | + | 0.72 | |
| | (0.13) | | (0.21) | | (0.16) | | (0.23) | | (0.16) | | (0.21) | |
| Health Visits | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | |
| | (0.00) | | (0.00) | | (0.00) | | (0.00) | | (0.00) | | (0.00) | |

| | Full Sample | | Multiple-adult Subsample[1] | | | |
|---|---|---|---|---|---|---|
| | Household Shock | | Head Shock | | Non-head Shock | |
| | Moved | Moved > 1 Mile | Moved | Moved > 1 Mile | Moved | Moved > 1 Mile |
| Medicaid | 1.24 | 1.14 | 0.75 | 0.57 | 0.77 | 0.58 |
| | (0.23) | (0.25) | (0.28) | (0.26) | (0.28) | (0.27) |
| Medicare | 1.47 + | 1.32 | 1.25 | 0.86 | 1.25 | 0.87 |
| | (0.32) | (0.34) | (0.51) | (0.41) | (0.50) | (0.42) |
| Other Insurance | 1.10 | 0.87 | 1.03 | 0.83 | 1.06 | 0.87 |
| | (0.34) | (0.34) | (0.42) | (0.41) | (0.43) | (0.43) |
| Constant | 0.40 * | 0.23 *** | 0.66 | 0.27 + | 0.81 | 0.34 |
| | (0.15) | (0.10) | (0.43) | (0.20) | (0.53) | (0.25) |
| Observations | 3,235 | 3,235 | 1,151 | 1,151 | 1,151 | 1,151 |

Standard errors in parentheses

*** p<0.001,

** p<0.01,

* p<0.05,

+ p<0.10

[1] The multiple-adult subsample is defined as all households having >1 adult member.