FOOD STAMPS, TEMPORARY ASSISTANCE FOR NEEDY FAMILIES AND FOOD HARDSHIPS IN THREE AMERICAN CITIES

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Abstract:
We examine how participation in the Food Stamp and Temporary Assistance for Needy Families Programs is associated with self-reported household food hardships, using data from a longitudinal survey of low-income families living in Boston, Chicago and San Antonio. In addition to the measures of hardships and program participation, the survey includes measures of income, wealth, social resources, disability, physical health and family structure, measures that help us to account for selection between recipient and non-recipient households. For our multivariate analyses, we estimate multiple indicator multiple cause models that are modified to incorporate discrete outcome variables and to account for longitudinal data. Estimates from these models reveal that participation in the Food Stamp Program is associated with fewer food hardships, while participation in the Temporary Assistance for Needy Families program has no detectable association with hardships.

Article:

1. Introduction

The Food Stamp Program in the United States is intended to help low-income households obtain a more nutritious diet than they otherwise could afford.1 In fiscal year 2005, the program served 25.7 million people per month and distributed $US28.6bn in assistance. From 2000 to 2005, participation in the program rose 50%, and costs rose 82%. With the continuing decline in the Temporary Assistance for Needy Families (TANF) Program, food stamps have come to represent an especially important strand of the social safety net.

Participation in the Food Stamp Program should lead to better food outcomes for households, including a lower incidence of hunger and other problems. Indeed, the United States Department of Agriculture (USDA) has an overarching goal of reducing the incidence of very low food security among low-income families from its current rate of approximately 13% to a rate below 7.4% through the Food Stamp Program and other nutrition assistance programs (Nord, 2007). Self-reported food hardships are some of the indicators of program efficacy under the Government Performance and Results Act of 1993.

Most empirical research on the relationship between the Food Stamp Program and self-reported food hardships points in a different direction, namely that the receipt of food assistance is associated with more hardships rather than fewer. These results are rarely taken as causal. Researchers recognize that food stamp recipients are a select group who would likely face greater hardships than non-recipients even in the absence of a nutrition program. Despite this recognition, researchers have generally been unable to account for the special characteristics of assistance recipients, leading to counterintuitive findings.

In this article, we examine how food stamp and TANF receipt are associated with household food hardships using longitudinal data from the Three-City Study, a survey of low-income families living in Boston, Chicago and San Antonio. The Three-City Study has several features that make it valuable for this analysis. First, it contains a rich set of measures that have typically been absent from other studies. In addition to the measures of hardships and program participation, the survey includes measures of income, wealth, social resources, disability, physical health and family structure. These measures help us to account for selection between recipient and non-recipient households based on observable characteristics. Second, the survey responses have been matched to administrative program records describing assistance receipt. Therefore, we have highly accurate data regarding who was and was not participating in each of the programs. Third, the longitudinal design of the survey means that hardship responses and program participation can be compared over time, allowing us to control for selection based on permanent unobserved characteristics of the households.

For our multivariate analyses of food hardships, we estimate longitudinal multiple indicator multiple cause (MIMIC) models. The Three-City Study asked families about several different hardships. The MIMIC approach models the responses as indicators of a single, underlying index of hardships. Simultaneously modeling the outcomes this way leads to more efficient estimation. We modify the standard MIMIC approach to incorporate discrete outcome variables and to account for longitudinal data.

Descriptive analyses of our data reproduce the findings of previous studies that program receipt is associated with more food hardships for families. Estimates from our multivariate model, however, yield the theoretically expected result that food stamp receipt is associated with fewer hardships. We do not find a statistically significant association between TANF participation and food hardships. Our findings are robust to the use of survey reports and administrative indicators of program participation. They are also robust to the use of longitudinal controls for omitted variables.

2. Background

Conceptually, we expect the receipt of food stamp benefits to reduce food hardships, other things held constant. Food stamps add to a household's resources and in particular to its ability to purchase food. In their comprehensive review of the empirical literature, Fox et al. (2004) cite numerous studies that have found positive associations between food stamp receipt and food expenditures and other studies that have found positive associations between food stamp receipt and household dietary intakes. Based on this research, the positive association between food stamps and food consumption seems well-established.

Empirical research examining the relationship between food stamp receipt and self-reported food hardships, such as the food insecurity and food insufficiency scales, has been more equivocal. The unconditional associations between food stamp participation and food hardships are often found to be strongly positive. For example, the latest national food insecurity report (Nord et al., 2007) estimates that among households with incomes below 130% of the poverty line (households that meet the gross income test for the Food Stamp Program), 49% of food stamp recipient households reported being food insecure, while only 25% of non-recipient households reported this condition. Nord et al. report similar associations for the National School Lunch and Women, Infants, and Children nutrition programs.

As Wilde (2007) and others point out, selection issues might be contributing to the findings of positive associations. Households that participate in food assistance programs are likely to differ in both observable and unobservable ways from households that do not participate. Specifically, households with fewer resources of their own, greater food needs and stronger preferences for food consumption (including a higher sensitivity to food hardships) are more likely to participate in the Food Stamp Program and assistance programs generally than other households. Analyses that fail to account for these differences could be confounding the underlying resource, need and preference conditions with participation behaviour, leading to biased estimates of the association between participation and reported food hardships.

Several multivariate analyses have attempted to control for observable differences between participating and non-participating households yet have still found positive associations (see e.g. Cohen et al., 1999; Jensen, 2002; Gibson-Davis and Foster, 2006). Studies that have used methods to account for unobservable differences and other selection issues have reached different conclusions. Gundersen and Oliveira (2001) use state political variables as instruments for food stamp participation and find no association with food hardships. Borjas (2004) considers the natural policy experiment that occurred when food stamp eligibility for immigrants was restricted by the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1993; he finds that the losses in eligibility led to sizeable increases in food insecurity for this group. In contrast, Wilde and Nord (2005) use longitudinal (fixed effect) controls for unobserved heterogeneity in a panel constructed from Current Population Survey (CPS) households and find that food stamp participation is positively associated with food insecurity.2

Another shortcoming in the previous studies might be the measures of program use themselves. Nearly all of the studies have relied on binary participation measures, such as the indicator from the Food Security Supplement of the CPS of whether a household received food stamp benefits anytime in the past year. The amount of benefits and the intensity of use, measures that we consider, might each be better indicators of what a household gains from the program. The measures of participation in surveys might also be subject to either intentional or unintentional misreporting (Bollinger and David, 1997), which could further confound the empirical associations with food hardships.

Our investigation follows the general strategy of Wilde and Nord (2005) and estimates longitudinal multivariate models that can account for confounding effects from time-invariant omitted variables, using a modification of the standard fixed effects model. As with their study, we also specify a statistical model that relates multiple outcome indicators to a single underlying index. In addition, we consider amounts of benefits and months of benefit receipt as measures of food stamp use. We also look at administrative records of program participation rather than relying entirely on self-reports.

The data for our empirical analyses come from the Three-City Study, a longitudinal survey of 2458 children and their caregivers who were initially living in low-income neighborhoods in Boston, Chicago and San Antonio. At the time of the first interview in 1999, the families all had incomes below 200% of the poverty line. They also had at least one child either 0–4 or 10–14 years old whom the study designated as a ‘focal child’. Although the survey includes many food stamp and TANF recipients, it was not specifically restricted to these groups. Also, it was designed to include poor and near-poor families, so there are many families who could potentially become eligible for assistance if their economic circumstances were to shift. In sum, the study should contain many comparable recipient and non-recipient households.

After the initial interviews, follow-up interviews were conducted in 2000–2001 and 2005. Retention rates were high, with 88% of the original sample participating in the second round and 80% participating in the third round. In each wave, interviews were conducted with both the focal child and the child's caregiver. In cases where the child and caregiver separated, both were subsequently followed and interviewed. For this article, we rely on the information provided by the caregivers as they were in the best position to describe the households' food problems, economic circumstances and program participation.

In the most recent (third) wave of the survey, the caregivers who participated in face-to-face interviews were asked to give permission for the research team to gather administrative information about them. Caregivers who agreed to this provided names and social security numbers, which were then used to search for food stamp and TANF records. Of the 1980 caregivers who completed in-person interviews, 1448 gave permission to be included in the administrative part of the study, and of this smaller number, 1286 were successfully matched to case files in Illinois, Massachusetts or Texas.3

3.1. Dependent variables

Our empirical analyses examine responses to a series of food hardship questions as dependent, or outcome, variables. In each wave, caregivers were asked the following yes or no questions regarding themselves and the other adults in the household:4

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At any time in the past 12 months, did you or other adults in your household cut the size of your meals or skip meals because there wasn't enough money for food?

- At any time in the past 12 months, did you or any other adults in your household not eat for a whole day because there wasn't enough money for food?

- Sometimes people lose weight because they don't have enough to eat. In the past 12 months, did you lose weight because there wasn't enough food?

The caregivers were also asked questions regarding food hardships that the focal child might have experienced.

- At any time in the past 12 months, did you cut the size of [CHILD]'s meals because there wasn't enough money for food?

- At any time in the past 12 months, did [CHILD] skip a meal because there wasn't enough money for food?

- (If the child did skip a meal) did this happen only 1 or 2 months, some months but not every month, or almost every month

- At any time in the past 12 months, was [CHILD] hungry but you just couldn't afford more food?

The first three questions concerning household adults are taken directly from the 18-item food security scale, whereas the last four questions about focal children are adapted to gather information about a specific child.5 The food security questions selected for the Three-City Study capture deprivations, including the physical sensations of hunger, associated with household food shortages. Taken together, however, the items from the Three-City Study differ in two fundamental respects from the longer scale. First, they do not ask about possible anxiety associated with obtaining food, food not lasting, or changes in food choices, which are food insecurity items and tend to be less severe hardships. The items included in the Three-City module ask about conditions that are usually viewed as more severe hardships. Second, in keeping with the overall design of the Three-City Study, the hardship questions ask about the household's focal child, whereas the food insecurity questions ask about household children generally. In our empirical investigation, we conduct separate analyses in which we examine responses to the first three questions concerning just adults in the household and also examine responses to all of the questions concerning the adults and the focal child. Including or excluding the questions regarding the focal child has little practical effect on our findings.6

3.2. Explanatory variables

The explanatory variables in our analyses primarily describe resources and needs in the caregivers' households. These include several measures of economic resources. In each wave, caregivers were asked about the sources of income from all household members from the preceding month. We use the caregiver's responses to form measures of the household's monthly food stamp benefits, its monthly TANF income, the caregiver's monthly earnings, and an aggregate of all other household income. All of the dollar values are adjusted for inflation using the Consumer Price Index for Urban Consumers.7

In some alternative specifications, we replace the self-reported food stamp and TANF amounts with counts of the number of months out of the preceding 6 that the household spent participating in these programs as reported in the administrative records. The administrative data are not subject to reporting problems, as the survey data might be; however, they are only available for the subset of the sample that provided permission to obtain records and that could be matched into the state data systems. In the months covered by the survey, self-reports of program participation differ from the corresponding administrative reports for approximately 10% of the matched caregivers. Despite this, our subsequent empirical findings turn out to be robust to the use of self-reported and system-reported program data.

We also include measures of the caregiver's work status. All of our models include indicators for whether the caregiver worked full time during the preceding month. Our models with administrative data replace the monthly earnings indicator with a count of the number of months out of the past 6 that the caregiver reported working.8

Our analyses incorporate several measures of long-term economic resources, in the form of net wealth. These measures include binary indicators for home ownership, vehicle ownership, maintenance of financial accounts and outstanding loans. The first three indicators describe potential assets, whereas the last indicator describes potential liabilities or perhaps access to borrowing. The wealth measures are directly useful as measures of resources but also indirectly valuable as possible controls for assistance program eligibility, which depends on assets. Previous studies, including Borjas (2004), Gibson-Davis and Foster (2006), Gundersen and Oliveira (2001), Jensen (2002) and Wilde and Nord (2005), have typically lacked measures for wealth.

In addition to economic resources, we also include controls for resources in the form of help from social networks. Our models use four binary measures that indicate whether the caregiver reports having enough people who will listen, provide child care, help with small favors and loan money. We also control for the caregiver's own human capital resources and capabilities, using measures for his or her general health status, disability status and educational attainment.

Our models also include other demographic and geographic controls. There are measures for the caregiver's age, race/ethnicity, nativity and marital status. There are also measures of the number of adults in the household, the number of minors, the focal child's age and the city of residence. Finally, there are indicators for the wave of the interview.

3.3. Analysis samples

We restrict our analyses to caregivers who responded to all three waves of the Three-City Study and who continued to live with focal children. This reduces the sample to 1589 caregivers. We further exclude 29 caregivers who did not provide usable responses to one or more questions that were used to form the explanatory variables, leaving a final ‘survey’ analysis sample of 1560 caregivers with 4680 person-year observations. The analyses involving the matched survey and administrative data cover a smaller set of 991 caregivers, with 2973 person-year observations. All of our statistical analyses use weights that adjust for the survey's sampling design, initial response patterns and longitudinal attrition. Means of the variables for the two samples are reported in Appendix I.

4. Hardship and Program Trends

Table 1 lists the proportions of caregivers in our longitudinal sample reporting food hardships in each wave along with program and economic characteristics of the caregivers in each wave. The estimates indicate that reported hardships fell from the first wave in 1999 to the second in 2000–2001. The number of caregivers reporting that an adult in the household cut the size of a meal or skipped a meal during the preceding 12 months fell by a quarter from 12 to 9% across the first two waves. The proportion reporting that an adult lost weight or that the focal child skipped a meal also fell.

Table 1. Means of food hardships and economic resources

	Wave 1	Wave 2	Wave 3
Food hardships			
Adult cut size or skipped meals?	0.12	0.09	0.10
Adult did not eat for a whole day?	0.04	0.04	0.04
Adult lost weight?	0.03	0.02	0.03

Notes: Authors' calculations from Three-City Study. Estimates use sample weights. TANF, Temporary Assistance for Needy Families.

Table 1. Means of food hardships and economic resources

	Wave 1	Wave 2	Wave 3
Cut size of focal child's meals?	0.02	0.02	0.02
Focal child skipped a meal?	0.02	0.00	0.02
Focal child hungry?	0.02	0.02	0.02
Program income and earnings			
Any food stamp benefits?	0.43	0.39	0.44
Amount of monthly food stamp benefits (/$US100)	1.31	1.17	1.60
Any TANF benefits?	0.29	0.21	0.12
Amount of monthly TANF benefits (/$US100)	1.11	0.69	0.44
Any caregiver earnings?	0.51	0.60	0.59
Amount of caregiver's monthly earnings (/$US100)	5.49	7.42	8.15
Other household income (/$US100)	7.10	9.83	10.40

Notes: Authors' calculations from Three-City Study. Estimates use sample weights. TANF, Temporary Assistance for Needy Families.

From the second to the third waves, the proportion of caregivers reporting food hardships rebounded, leading to numbers that were very similar to those from 1999. The proportion of caregivers reporting reductions in adult meals was lower in 2005 than in 1999; however, the incidence of every other hardship was the same. The increase in reported food hardships from 2000–2001 in our low-income longitudinal sample is consistent with the trends in food insecurity in the wider population of low-income families that Nord (2007) found. Estimates from Table 1 also indicate that the proportion of households in our sample receiving food stamp benefits fell from Wave 1 to Wave 2 and then rebounded from Wave 2 to Wave 3. The average monthly amount of food stamp benefits received by sample households also fell then rose. These patterns of receipt are consistent with national trends, and the positive time-series association between food hardships and food stamp receipt is consistent with previous descriptive evidence.

Other estimates from Table 1 reveal that TANF receipt and monthly benefit amounts fell across the study period. The proportion of caregivers with earnings rose from the first wave to the second but remained essentially constant thereafter. The amount of caregiver earnings rose across the three waves, especially from the first wave to the second. Other income in the caregivers' households also increased over the study period. In Table 2, we estimate the proportions of caregivers with different Food Stamp and TANF Program histories reporting food hardships. The top panel in Table 2 lists estimates first for caregivers who did not participate in food stamps in any of the waves, then for caregivers who participated in some of the waves, and finally for caregivers who participated in all three waves. As with the descriptive analyses in other studies, households with histories of food stamp participation reported more hardships than households with no such participation. The relationship, however, between hardships and the frequency of participation was nonlinear. For several types of hardships, households with three waves of participation reported fewer problems than those with just one or two waves of participation. This pattern is consistent with Nord's (2007) finding of recent food stamp leavers being less food secure than current recipients.

Table 2. Means of food hardships for different program participation histories

	Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?

Table 2. Means of food hardships for different program participation histories

		Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?
Notes: Authors' calculations from Three-City Study. Estimates use sample weights.							
Food stamp participation							
No waves	Wave 1	0.09	0.03	0.01	0.01	0.03	0.01
	Wave 2	0.08	0.04	0.00	0.03	0.00	0.01
	Wave 3	0.08	0.02	0.02	0.01	0.01	0.01
Some waves	Wave 1	0.15	0.05	0.05	0.04	0.01	0.03
	Wave 2	0.11	0.05	0.04	0.03	0.01	0.02
	Wave 3	0.10	0.05	0.05	0.03	0.04	0.02
All three waves	Wave 1	0.13	0.03	0.03	0.04	0.01	0.03
	Wave 2	0.08	0.03	0.03	0.02	0.00	0.03
	Wave 3	0.11	0.08	0.04	0.01	0.02	0.02
Temporary Assistance for Needy Families Program participation							
No waves	Wave 1	0.11	0.03	0.03	0.02	0.03	0.02
	Wave 2	0.08	0.04	0.02	0.03	0.00	0.02
	Wave 3	0.07	0.02	0.02	0.02	0.01	0.01
Some waves	Wave 1	0.13	0.05	0.03	0.03	0.01	0.03
	Wave 2	0.10	0.04	0.02	0.02	0.00	0.02
	Wave 3	0.12	0.08	0.06	0.02	0.03	0.02
All three waves	Wave 1	0.18	0.04	0.05	0.04	0.02	0.05
	Wave 2	0.12	0.04	0.04	0.05	0.02	0.04

Table 2. Means of food hardships for different program participation histories

	Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?
Wave 3	0.24	0.12	0.04	0.03	0.05	0.05

Notes: Authors' calculations from Three-City Study. Estimates use sample weights.

The bottom panel of the table repeats this conditional analysis but does so in terms of TANF participation. In general, greater dependence on the TANF Program is associated with worse food outcomes. Frogner et al. (2007) report that caregivers in the Three-City Study who were dependent on TANF for all three waves of the survey were especially disadvantaged, with low rates of marriage, low levels of health, and high rates of disability and depression. All of these characteristics could contribute to more hardships.

5. Multivariate Model

There are many observed and unobserved characteristics that could be associated with food stamp and TANF participation on the one hand and food hardships on the other. For our remaining empirical analyses, we use multivariate statistical methods to better uncover the direct associations. In particular, we adapt the MIMIC framework to consider discrete outcome measures and to mitigate biases from time-invariant omitted variables.

5.1. Multiple indicator, multiple cause framework

The MIMIC framework was initially developed by Jöreskog and Goldberger (1975). The central idea behind this approach is that the multiple outcomes that can be observed (i.e. the reports of different food hardships) all derive from a single, underlying latent variable. Let $h^*(t)$ represent a continuous index of food hardship or deprivation for a household at time t with the property that higher values of the index correspond to greater levels of hardship. We do not observe $h^*(t)$ directly. Suppose, however, that we have j continuous indicators, $y_j^*(t)$, that are related to $h^*(t)$ such that each of them depends on the index but also on some random measurement error, $v_j(t)$.

If we stack the indicators $y_j^*(t)$ into a $j \times 1$ matrix, $Y^*(t)$, stack the random errors $v_j(t)$ into a $j \times 1$ matrix, $V(t)$, and define and stack a set of coefficients, λ_j, into a $j \times 1$ matrix, Λ, we can write the relationship between the indicators and the underlying latent index as:

$$Y^*(t) = \Lambda h^*(t) + V(t). \quad (1)$$

Equation 1 describes a factor-analytic relationship, in which the hardship index, $h^*(t)$, is the underlying common factor and the coefficients in Λ are the factor loadings. The specification brings with it all of the advantages and disadvantages of a factor analysis. On the one hand, the specification represents a sensible and data-driven approach for summarizing the information from the different indicators in terms of a common variable. The loadings, which are estimated as part of the MIMIC procedure, effectively weight the different indicators in forming the factor and maximize the amount of common information that is extracted. This should be preferable to the usual summary alternatives, such as summing the indicators or taking the maximum value of the indicators. On the other hand, there is an interpretive ambiguity because the underlying factor is not observed but rather is constructed as part of the statistical procedure. Although we interpret the factor as an index of hardship, it is formally just a measure of the common component of the indicators, $y_j^*(t)$.

5.2. Modification for categorical indicators

We have expressed the model in terms of a set of continuous indicators of food hardships (the $y_j^*(t)$ variables); however, the actual indicators are discrete variables. We could make a somewhat ad hoc transformation of the measures (re-expressing the relationships among the measures in terms of polychoric correlations) and then analyze them as if they were continuous. Instead, we follow Wilde and Nord (2005) and Ribar et al. (2006) and actually model them.

We assume that the continuous indicators, yj*(t), are related to the binary responses as follows:

$$y_j(t) = 0 \quad \text{if} \quad y_j^*(t) \leq \delta_j$$
$$y_j(t) = 1 \quad \text{if} \quad y_j^*(t) > \delta_j. \quad (2)$$

The specification of the relationship between the latent continuous indicator and the observed categorical response is the same used in standard probit and logit models.9 The thresholds, or δj terms, are estimated as part of the multivariate model and can take on different values for each type of hardship, which implicitly adjusts for differences in their frequencies and severities (higher values of the threshold mean that it is less likely that the associated condition will be met, which in turn indicates that the condition is less frequent; higher thresholds also mean that the index has to be larger for the condition to be met, which indicates greater severity).

Specifications (1) and (2) together constitute a measurement model and describe how the multiple discrete indicators are related to the underlying index, h*(t). In estimating the measurement model, we assume that the loadings, λj, and response thresholds, δ0j, are constant across panels and, therefore, that the measurement relationships are stable over time. We also assume that the random measurement error components (vj(t) terms) of the unobserved continuous indicators are independently distributed across outcomes and time and that each of these components follows a stan dard normal distribution.10

5.3. Behavioural model

The MIMIC approach combines a measurement model with a behavioural model that describes how other explanatory variables are associated with the common underlying index, h*(t). We specify the hardship indicator as a linear function of observed time-varying measures X(t), time-invariant measures, Z, and an unobserved variable ε(t) such that

$$h^*(t) = \boldsymbol{B}_X' \boldsymbol{X}(\boldsymbol{t}) + B_Z' \boldsymbol{Z} + \varepsilon(t), \quad (3)$$

where BX and BZ are matrices of coefficients. In the MIMIC framework, the measurement specifications (1) and (2), the ‘multiple indicator’ part of the model, and the behavioural specification (3), the ‘multiple cause’ part, are estimated together. Conditional on the validity of the specification's restrictions, the MIMIC approach is more efficient than an alternative strategy of estimating separate models for each of the food hardships. It is also more efficient than a two-stage strategy of first conducting a factor analysis of the different hardships and then using the resulting factor as the dependent variable in a regression model.

5.4. Modification for longitudinal data

There may be serial correlation in the unobserved determinants of food hardships and potential biases from the sources of this correlation. Assume that the error term in equation 3 can be decomposed into a permanent component, μ, and a transitory component e(t), such that ε(t) = μ + e(t). The permanent component generates serial correlation in the errors for each household. Just as in a least squares regression, this can lead to incorrect standard errors and inefficient estimation. It can also lead to biased estimates if μ is correlated with the explanatory variables in X(t) and Z (Godwin, 1988). As we mentioned in the background section, μ may include hard-to-measure characteristics like household needs and permanent resources that could be associated with program participation and other observed characteristics in the X(t) vector.

In a linear regression, we could condition out μ and obtain unbiased estimates of the coefficients in BX by differencing the outcome and explanatory measures across the three waves. Unfortunately, this is not generally possible in nonlinear models like the categorical MIMIC specification. Instead, we apply Chamberlain's (1982) quasi-fixed-effects procedure, which specifies the time-invariant component to be a function of the explanatory variables for all periods and a random error. For our three-period model, the specification is:

$$\mu = \Gamma_1' X(1) + \Gamma_2' X(2) + \Gamma_3' X(3) + u, \quad (4)$$

where Γ1, Γ2 and Γ3 are vectors of coefficients and u is a random error. The random effect, u, allows for correlation over time in the unobserved determinants of hardship. Through the X(1), X(2) and X(3) terms, the specification also allows for correlations with the time-varying observed measures in equation 3, addressing the source of bias in the estimates of BX. In a linear model, Chamberlain's method is equivalent to other fixed effects procedures; in nonlinear models, it provides an approximate correction.

The final model for adult food hardships is a system of nine probit specifications: three specifications representing each of the hardships, measured across three waves. The individual probit models have a number of cross-equation restrictions on their parameters. When we combine specifications (1), (3) and (4), the estimating equations for the latent severity of each hardship j in the three waves can be written as:

$$\begin{aligned} y_j^*(1) &= \lambda_j [\boldsymbol{B}_X + \boldsymbol{\Gamma}_1] \boldsymbol{X}(1) + \lambda_j \boldsymbol{\Gamma}_2' \boldsymbol{X}(2) + \lambda_j \boldsymbol{\Gamma}_3' \boldsymbol{X}(3) \\ &\quad + \lambda_j \boldsymbol{B}_Z' \boldsymbol{Z} + \lambda_j u + \lambda_j e(1) + v_j(1) \\ y_j^*(2) &= \lambda_j \boldsymbol{\Gamma}_1' \boldsymbol{X}(1) + \lambda_j [\boldsymbol{B}_X + \boldsymbol{\Gamma}_2]' \boldsymbol{X}(2) + \lambda_j \boldsymbol{\Gamma}_3' \boldsymbol{X}(3) \\ &\quad + \lambda_j \boldsymbol{B}_Z' \boldsymbol{Z} + \lambda_j u + \lambda_j e(2) + v_j(2) \\ y_j^*(3) &= \lambda_j \boldsymbol{\Gamma}_1' \boldsymbol{X}(1) + \lambda_j \boldsymbol{\Gamma}_2' \boldsymbol{X}(2) + \lambda_j [\boldsymbol{B}_X + \boldsymbol{\Gamma}_3]' \boldsymbol{X}(3) \\ &\quad + \lambda_j \boldsymbol{B}_Z' \boldsymbol{Z} + \lambda_j u + \lambda_j e(3) + v_j(3). \end{aligned} \quad (5)$$

Besides the restrictions on the parameters, the expressions reveal that there are two error terms that are common across the estimating equations: u, which appears in all 9 equations for a household, and e(t), which appears in the 3 equations for a given wave for a household. We assume that these errors are distributed independently of each other and of the response-specific errors, vj(t), and that they are normally distributed with means of zero and variances of σu2 and σe2, respectively.11 We obtain maximum likelihood estimates of the parameters in the system using the aML software package (http://www.applied-ml.com).

The model for combined adult and focal child hardships extends specification (5) to include 3 additional equations per wave: two probit specifications and an ordered probit specification. This model has 18 equations altogether.

6. Multivariate Estimation Results

6.1. Adult hardships

Estimation results from alternative specifications of the longitudinal MIMIC model for the three food hardship measures for adults are reported in Table 3. The first two columns of Table 3 list coefficient estimates and standard errors from models that were run using the sample based completely on survey responses. The first column contains results from a restricted, random-effects version of the model (a specification that restricts Γ1 = Γ2 = Γ3 = 0), while the second column lists results from a quasi-fixed-effects version (a specification without restrictions on the Γj terms). The final two columns in Table 3 list results from random-effects and quasi-fixed-effects MIMIC models that were estimated using the survey responses that could be matched to administrative data. For brevity, estimates of the Γj coefficients are not reported; detailed results are available upon request.

Table 3. Selected coefficient estimates from multiple indicator multiple cause models models of adult food hardships

	Survey sample		Matched sample	
	Random effects	Quasi-fixed effects	Random effects	Quasi-fixed effects

Note: Coefficients are from longitudinal multiple indicator multiple cause models specifications estimated using data from the Three-City Study; estimates use sample weights. In addition to the parameters shown, the quasi-fixed-effect models include controls for Wave 1, 2,and 3 covariates. Details of the estimation procedure are described in the text. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively. TANF, Temporary Assistance for Needy Families.

Amount of monthly food stamp benefits (/$US100)	−0.1691*** (0.0429)	−0.2130*** (0.0596)		
Amount of monthly TANF benefits (/$US100)	0.0336 (0.0356)	0.0126 (0.0455)		
Amount of caregiver's monthly earnings (/$US100)	0.0111 (0.0121)	0.0073 (0.0171)		
Number of months out of past 6 caregiver received Food Stamp income			−0.2360*** (0.0616)	−0.2210*** (0.0746)
Number of months out of past 6 caregiver received TANF income			0.0723 (0.0529)	0.0025 (0.0639)
Number of months out of past 6 caregiver reported holding a primary job			−0.0249 (0.0445)	−0.0004 (0.0590)
Indicator if number of months holding a primary job is missing			0.4519 (0.4837)	0.3442 (0.5962)
Other household income (/$US100)	−0.0478*** (0.0118)	−0.0270* (0.0158)	−0.0368** (0.0151)	−0.0073 (0.0203)
Caregiver worked full time last month	−0.3945* (0.2090)	−0.1623 (0.2673)	−0.0029 (0.2571)	0.1903 (0.3004)
Household owns home	−0.6224*** (0.2287)	−0.5055 (0.3620)	−0.7149** (0.3350)	−0.5023 (0.5021)
Household owns vehicle	−0.1322 (0.1560)	0.0721 (0.2199)	−0.2203 (0.2268)	−0.0206 (0.2854)
Household has bank account or financial assets	−0.8868*** (0.1873)	−1.2815*** (0.2759)	−1.1451*** (0.2924)	−1.4953*** (0.3688)
Household has outstanding loans	0.5499*** (0.1686)	0.3629* (0.2167)	0.5604** (0.2363)	0.3768 (0.2939)
Caregiver has disability that prevents work or other activities	0.7195*** (0.2052)	0.7402** (0.3055)	0.5405** (0.2663)	0.4659 (0.3370)
Caregiver's general health status	0.3132*** (0.0738)	0.2717*** (0.1040)	0.3717*** (0.1033)	0.3677*** (0.1270)
Caregiver has enough people to listen to him/her	0.1645 (0.1791)	−0.0090 (0.2523)	0.4997* (0.2703)	0.2064 (0.3383)
Caregiver has enough people to	−0.7216***	−0.4306*	−1.0016***	−0.5072*

Table 3. Selected coefficient estimates from multiple indicator multiple cause models models of adult food hardships

	Survey sample		Matched sample	
	Random effects	Quasi-fixed effects	Random effects	Quasi-fixed effects
provide child care	(0.1982)	(0.2315)	(0.3014)	(0.3072)
Caregiver has enough people to provide small favors	−0.3487* (0.1890)	−0.1615 (0.2300)	−0.2749 (0.2580)	0.0186 (0.2948)
Caregiver has enough people to loan money h	−0.4768** (0.2035)	−0.4371* (0.2609)	−0.7867*** (0.2977)	−0.7947** (0.3650)
Number of adults in household	0.2224** (0.0985)	0.1201 (0.1239)	0.2736** (0.1352)	0.1862 (0.1640)
Number of minors in household	0.0620 (0.0536)	−0.1163 (0.0961)	−0.0322 (0.0699)	−0.1560 (0.1204)
Caregiver is married with spouse present	−0.4727** (0.2213)	−0.5886* (0.3326)	−0.8514** (0.3450)	−1.3445*** (0.4715)
Household has focal child age 6 years or older	0.3046 (0.2740)	0.5037 (0.3224)	0.4112 (0.3657)	0.4298 (0.3895)
Caregiver's age (at Wave 1)	0.0020 (0.0103)	0.0000 (0.0120)	0.0008 (0.0133)	−0.0152 (0.0150)
Focal child's age (at Wave 1)	0.0492* (0.0257)	0.0780 (0.0678)	0.0862** (0.0346)	0.0574 (0.0855)
Caregiver is non-Hispanic black	−0.0247 (0.3117)	0.0096 (0.3389)	−0.1066 (0.4136)	−0.0093 (0.3640)
Caregiver is Hispanic	−0.8130** (0.3453)	−0.7733** (0.3650)	−0.6694 (0.4524)	−0.5537 (0.3913)
Caregiver was born outside the USA	0.3553 (0.2294)	0.3301 (0.2657)	0.4158 (0.3525)	0.2293 (0.3301)
Caregiver has high school or general equivalency diploma (at Wave 2)	0.1584 (0.1877)	0.0683 (0.1954)	0.4495* (0.2584)	0.2926 (0.2337)
Caregiver has college degree (at Wave 2)	0.2364 (0.2229)	0.2408 (0.2523)	0.4682 (0.3100)	0.4804 (0.3011)
Household lives in Boston	−0.6744*** (0.2259)	−0.6799** (0.2955)	−0.7428** (0.3168)	−0.6267* (0.3375)
Household lives in Chicago	−0.7842*** (0.2487)	−0.7478*** (0.2840)	−1.0813*** (0.3583)	−0.6951** (0.3175)
Wave 1	0.1927 (0.2056)	0.4149* (0.2460)	0.2578 (0.2695)	0.5768* (0.3151)
Wave 2	−0.1389 (0.2035)	0.0281 (0.2345)	−0.2343 (0.2668)	−0.0251 (0.2837)
Error components				
σ_u	1.4293*** (0.1983)	1.2565*** (0.1957)	1.6262*** (0.2918)	1.0560*** (0.2099)
σ_e	1.8398*** (0.2687)	1.8209*** (0.2897)	2.0496*** (0.3961)	1.7915*** (0.3306)

Table 3. Selected coefficient estimates from multiple indicator multiple cause models models of adult food hardships

	Survey sample		Matched sample	
	Random effects	Quasi-fixed effects	Random effects	Quasi-fixed effects
Measurement model parameters				
$\delta 2$	1.3124*** (0.1082)	1.3310*** (0.1217)	1.4578*** (0.1413)	1.4999*** (0.1752)
$\delta 3$	1.5374*** (0.1025)	1.5178*** (0.1019)	1.6471*** (0.1303)	1.6238*** (0.1428)
$\lambda 2$	0.9590*** (0.2104)	0.9592*** (0.2282)	0.8360*** (0.2232)	0.9860*** (0.2789)
$\lambda 3$	0.7607*** (0.1489)	0.7185*** (0.1524)	0.6876*** (0.1698)	0.7493*** (0.1952)
Log likelihood	−2086.01	−2005.27	−1524.25	−1413.14
Number of caregivers	1560	1560	991	991

Note: Coefficients are from longitudinal multiple indicator multiple cause models specifications estimated using data from the Three-City Study; estimates use sample weights. In addition to the parameters shown, the quasi-fixed-effect models include controls for Wave 1, 2,and 3 covariates. Details of the estimation procedure are described in the text. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively. TANF, Temporary Assistance for Needy Families.

For both the survey-only and matched survey–administrative data samples, log likelihood tests decidedly reject the restrictions of the random effects specifications that all of the Γj coefficients equal zero. The test results substantiate our initial concerns that omitted variables could be a source of bias in the analysis of food hardships.

When we examine the coefficients in the table, we see that monthly food stamp benefits are significantly negatively associated with adult food hardships in both the random-effects and the quasi-fixed-effects specifications. However, the magnitude of the estimated coefficient is 25% larger (more negative) in the quasi-fixed-effects model than in the random-effects model. The negative coefficients are consistent with our initial expectation that food stamp benefits reduce food hardships, and the difference in the coefficients across the two specifications is consistent with omitted variables biasing the estimated association upwards. The significant negative associations are a departure from most of the previous research.

The coefficients in the next row of Table 3 describe associations between food hardships and changes in TANF benefits. For the discussion of these and the remaining coefficients, we will focus on results from the quasi-fixed-effects specification.12 The estimates indicate that TANF benefits and the caregiver's own earnings are not associated with adult food hardships. As we move further down the table, we see that other household income, a category that includes other household members' earnings and other program income, has a modest negative association with food hardships. Indeed, the association between a one dollar change in other income and adult food hardships is one-eighth the size of the association between a dollar change in food stamps and these same hardships.

The controls for wealth appear to be important. Households that open bank or financial accounts are less likely to report adult hardships, whereas households that take out loans are more likely to report hardships. There is also evidence that home ownership is protective against food hardships, although the coefficient is imprecisely estimated.

Deteriorations in health status, either in the form of disability or poorer reported health, are associated with worse food outcomes. Improvements in social resources, most especially increased access to child care and lending, are associated with fewer food hardships. Becoming married is also associated with a reduction in food hardships.

We also find evidence of ethnic, geographic and longitudinal differences in hardships. Hispanics are less likely than non-Hispanics to report adult food hardships. Residents of Boston and Chicago are less likely to report hardships than residents of San Antonio, and consistent with the descriptive results, reports of hardships were higher in the first wave of the survey than in later waves.

The estimates of the standard deviations for the error components of the hardship index (the estimates of σu and σe) reveal that permanent unobserved characteristics account for approximately one-third of the overall unobserved variance in the index (calculated as $\sigma u2/(\sigma u2 + \sigma e2)$). This indicates that there is considerable persistence in reported food hardships, even after numerous observed characteristics are taken into account. Estimates of the indicator-specific threshold parameters, $\delta 2$ and $\delta 3$, are increasing in value. This is consistent with the associated conditions (e.g. adults not eating for a day and losing weight) being less frequent and possibly more severe hardships than that of adults skipping or skimping on meals. Estimates of the indicator-specific loading parameters, $\lambda 2$ and $\lambda 3$, are each significantly positive, revealing that the underlying hardship index contributes to each of the reported conditions. The estimates also tell us that the reports of adults losing weight might be a slightly less reliable indicator of the underlying hardship index (have more associated measurement error) than the other two reported conditions.

The second two columns of Table 3 report results from models estimated using the portion of the sample that could be matched to administrative data. In place of the self-reported benefit amounts, these specifications use counts of the months out of the previous 6 that the program records indicated the household received food stamp or TANF assistance. The results for the administrative variables are strikingly similar to those for the self-reported data. The estimates again indicate that participation in the Food Stamp Program is associated with fewer food hardships for adults, whereas participation in the TANF Program has virtually no detectable association with food hardships.

Many of the other results from the survey-only specifications carry through to the matched survey and administrative data specifications. One noticeable difference in the results, however, is that other household income is no longer significantly associated with adult food hardships in the matched sample.13

6.2. Food hardships for adults and children

We re-estimated the longitudinal MIMIC models using an extended set of six food hardships: the three hardships for adults that we have already examined along with the three other hardships for focal children (note that for this analysis we have combined the questions regarding whether and how often the focal child skipped meals into a single categorical variable). Results from these models are reported in Table 4. As with the previous table, coefficients and standard errors from random-effects and quasi-fixed-effects versions of the models estimated using just the survey responses are listed first, and results from similar models estimated using survey data matched to administrative records are listed next.

Table 4. Selected coefficient estimates from multiple indicator multiple cause models of adult and focal child food hardships

	Survey sample	Matched sample

	Random effects	Quasi fixed effects	Random effects	Quasi fixed effects
Note: Coefficients are from longitudinal multiple indicator multiple cause models specifications estimated using data from the Three-City Study; estimates use sample weights. In addition to the parameters shown, the quasi-fixed-effect models include controls for Wave 1, 2 and 3 covariates. Details of the estimation procedure are described in the text. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively.				
Amount of monthly food stamp benefits (/$US100)	−0.1500*** (0.0410)	−0.1772*** (0.0588)		
Amount of monthly TANF benefits (/$US100)	0.0406 (0.0337)	0.0093 (0.0513)		
Amount of caregiver's monthly earnings (/$US100)	0.0162 (0.0127)	0.0116 (0.0184)		
Number of months out of past 6 Caregiver received Food Stamp income			−0.2279*** (0.0602)	−0.2248*** (0.0791)
Number of months out of past 6 Caregiver received TANF income			0.0868 (0.0560)	0.0121 (0.0717)
Number of months out of past 6 Caregiver reported holding a primary job			−0.0144 (0.0470)	−0.0109 (0.0676)
Indicator if number of months holding a primary job is missing			0.3881 (0.4875)	0.2006 (0.6569)
Other household income (/$US100)	−0.0562*** (0.0122)	−0.0429** (0.0176)	−0.0491*** (0.0163)	−0.0311 (0.0238)
Caregiver worked full time last month	−0.5012** (0.2126)	−0.2079 (0.2842)	−0.0831 (0.2533)	0.2082 (0.3291)
Household owns home	−0.6466*** (0.2313)	−0.5565 (0.3823)	−0.6803** (0.3308)	−0.5624 (0.5561)
Household owns vehicle	0.0079 (0.1622)	0.2983 (0.2382)	−0.0072 (0.2353)	0.3220 (0.3244)
Household has bank account or financial assets	−0.7857*** (0.1872)	−1.1479*** (0.2819)	−1.0781*** (0.2935)	−1.4961*** (0.4033)
Household has outstanding loans	0.6175*** (0.1733)	0.5046** (0.2444)	0.6298** (0.2484)	0.5155 (0.3430)
Caregiver has disability that prevents work or other activities	0.6228*** (0.1929)	0.5426* (0.3121)	0.4346 (0.2817)	0.2595 (0.3903)
Caregiver's general health status	0.3481*** (0.0776)	0.3043*** (0.1130)	0.4094*** (0.1053)	0.4334*** (0.1457)
Caregiver has enough people to listen to him/her	0.1473 (0.1873)	−0.0225 (0.2666)	0.4605 (0.2826)	0.1635 (0.3696)
Caregiver has enough people to provide child care	−0.6839*** (0.1971)	−0.3985 (0.2423)	−0.8850*** (0.2982)	−0.4612 (0.3359)

Table 4. Selected coefficient estimates from multiple indicator multiple cause models of adult and focal child food hardships

	Survey sample		Matched sample	
	Random effects	Quasi fixed effects	Random effects	Quasi fixed effects
Caregiver has enough people to provide small favors	−0.4519** (0.1967)	−0.3015 (0.2555)	−0.3891 (0.2665)	−0.1733 (0.3193)
Caregiver has enough people to loan money	−0.4753** (0.2110)	−0.4471 (0.2861)	−0.7755** (0.3045)	−0.8340** (0.4090)
Number of adults in household	0.2698*** (0.1006)	0.1276 (0.1315)	0.3447** (0.1365)	0.1812 (0.1744)
Number of minors in household	0.0453 (0.0559)	−0.1349 (0.1063)	−0.0208 (0.0720)	−0.1693 (0.1374)
Caregiver is married with spouse present	−0.6027** (0.2344)	−0.6463* (0.3692)	−0.9330*** (0.3489)	−1.2362** (0.5212)
Household has focal child age 6 years or older	0.4550 (0.2805)	0.5853* (0.3443)	0.6365* (0.3731)	0.6208 (0.4327)
Caregiver's age (at Wave 1)	0.0006 (0.0109)	−0.0028 (0.0133)	−0.0008 (0.0140)	−0.0195 (0.0171)
Focal child's age (at Wave 1)	0.0653** (0.0271)	0.0779 (0.0745)	0.1029*** (0.0361)	0.0470 (0.0981)
Caregiver is non-Hispanic black	−0.0693 (0.3263)	0.0095 (0.3848)	−0.1463 (0.4223)	−0.0582 (0.4108)
Caregiver is Hispanic	−0.7490** (0.3445)	−0.7297* (0.4013)	−0.7235 (0.4590)	−0.6840 (0.4473)
Caregiver was born outside the USA	0.3808 (0.2396)	0.4292 (0.2929)	0.5581 (0.3895)	0.4624 (0.3809)
Caregiver has high school or general equivalency diploma (at Wave 2)	0.1226 (0.1988)	0.0843 (0.2180)	0.3372 (0.2779)	0.2372 (0.2704)
Caregiver has college degree (at Wave 2)	0.1158 (0.2307)	0.1873 (0.2759)	0.3318 (0.3251)	0.4503 (0.3431)
Household lives in Boston	−0.7170*** (0.2332)	−0.8473*** (0.3262)	−0.7686** (0.3361)	−0.7860** (0.3842)
Household lives in Chicago	−0.6846*** (0.2482)	−0.7315** (0.3021)	−1.0771*** (0.3555)	−0.8149** (0.3620)
Wave 1	0.3329* (0.2012)	0.5100** (0.2507)	0.4599* (0.2667)	0.7005** (0.3353)
Wave 2	−0.0557 (0.2099)	0.0561 (0.2475)	−0.1004 (0.2707)	0.0296 (0.3079)
Error components				
σu	1.4929*** (0.1831)	1.4350*** (0.2022)	1.6808*** (0.2740)	1.2387*** (0.2449)
σe	1.9127*** (0.2417)	1.9872*** (0.2742)	2.1066*** (0.3725)	2.0271*** (0.3699)

Table 4. Selected coefficient estimates from multiple indicator multiple cause models of adult and focal child food hardships

	Survey sample		Matched sample	
	Random effects	Quasi fixed effects	Random effects	Quasi fixed effects
Measurement model parameters				
δ2	1.1889*** (0.0812)	1.2079*** (0.0856)	1.2970*** (0.1054)	1.3077*** (0.1127)
δ3	1.4853*** (0.0895)	1.4898*** (0.0911)	1.5574*** (0.1114)	1.5577*** (0.1193)
δ4	1.6895*** (0.0999)	1.6914*** (0.1054)	1.8256*** (0.1398)	1.8337*** (0.1537)
δ51	1.7853*** (0.1012)	1.7878*** (0.1154)	1.8944*** (0.1351)	1.8852*** (0.1745)
δ52	2.1305*** (0.1226)	2.1292*** (0.1467)	2.2985*** (0.1489)	2.2877*** (0.2028)
δ53	2.8748*** (0.2360)	2.8772*** (0.2801)	2.9832*** (0.2631)	2.9845*** (0.3494)
δ6	1.8416*** (0.1128)	1.8339*** (0.1230)	1.7760*** (0.1119)	1.7406*** (0.1253)
λ2	0.7027*** (0.1095)	0.6610*** (0.1113)	0.6241*** (0.1298)	0.6310*** (0.1447)
λ3	0.6567*** (0.1124)	0.6020*** (0.1117)	0.5835*** (0.1308)	0.5797*** (0.1400)
λ4	0.6648*** (0.1173)	0.6104*** (0.1187)	0.5774*** (0.1275)	0.5791*** (0.1436)
λ5	0.5208*** (0.0860)	0.4779*** (0.0875)	0.4901*** (0.1064)	0.4819*** (0.1155)
λ6	0.7180*** (0.1237)	0.6537*** (0.1199)	0.5719*** (0.1181)	0.5431*** (0.1191)
Log likelihood	−2962.92	−2887.97	−2191.03	−2086.28
Number of caregivers	1560	1560	991	991

Note: Coefficients are from longitudinal multiple indicator multiple cause models specifications estimated using data from the Three-City Study; estimates use sample weights. In addition to the parameters shown, the quasi-fixed-effect models include controls for Wave 1, 2 and 3 covariates. Details of the estimation procedure are described in the text. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively.

The estimates are not especially sensitive to the inclusion of the hardship measures for focal children. In the quasi-fixed-effects MIMIC model estimated using the survey data, the coefficients for food stamp benefits and other household income are once again significantly negative, with the association for food stamps being several times larger than the association for other income. As with Table 3, caregiver earnings and TANF benefits are not strongly associated with food hardships.

Results for the other explanatory variables are also robust to the respecification. Most of the statistically significant coefficients from the second column of Table 3 are reproduced in Table 4. Two coefficients for help from social networks lose their significance but keep their same signs and approximate magnitudes.
The estimates of the threshold parameters indicate that reports of focal-child hardships are rarer and more extreme measures of household food deprivation. This is consistent with households attempting to protect children from deprivations. Estimates from the factor loading parameters indicate that the latent hardship index in the MIMIC model is strongly, positively associated with all of the outcome measures, including the focal-child measures.

The last column in Table 4 reports results from models that were estimated using survey data matched to administrative program records. As with the specifications for adult hardships, the specifications that also include focal-child hardships are robust to the use of administrative data. In particular, the estimates continue to indicate that food stamp participation has a negative association with food hardships, while TANF participation has little, if any, association.

6.3. Marginal effects of food stamp participation

Although the coefficients from Tables 3 and 4 show the directions of the associations between the explanatory variables and food hardships, it is difficult to get a sense of the magnitudes of the relationships. The coefficients are essentially probit coefficients; thus, there is a nonlinear relationship with the outcome measures. Interpretation of the coefficients is further complicated by the different sizes of the factor loadings, which mediate the relationship between the latent hardship index and the outcomes.

We are especially interested in the size of the associations between the food stamp variables and the different hardship measures. To estimate the magnitudes of these associations, we used the coefficient estimates from Tables 3 and 4 and the available data to predict probabilities of reporting each hardship for each caregiver in our sample, assuming different levels of food stamp receipt. In particular, we first predict probabilities of experiencing hardships, assuming no food stamp receipt, and then predict probabilities assigning a level of food stamp receipt. We averaged the predicted probabilities under each of these scenarios and report the differences for each hardship outcome in Table 5.

Table 5. Predicted changes in food stamp receipt and food hardships

	Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?
Survey sample: Change in monthly food stamp benefits from $US0 to $US300 per month.						
Caregiver food hardships						
Change from just the time-varying measure	−0.039 [−0.177]	−0.019 [−0.215]	−0.014 [−0.212]			
Change including the permanent control	−0.036 [−0.163]	−0.018 [−0.204]	−0.013 [−0.196]			

Notes: Table reports the differences between the average predicted food hardship responses for households receiving and not receiving food stamps using model coefficients from Tables 3 and 4 and weighted data from the Three-City Study. Figures in brackets are the implied elasticities from these changes.

Table 5. Predicted changes in food stamp receipt and food hardships

	Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?
Caregiver and focal child food hardships						
Change from just the time-varying measure	−0.030 [−0.136]	−0.014 [−0.159]	−0.010 [−0.151]	−0.009 [−0.204]	−0.006 [−0.136]	−0.008 [−0.121]
Change including the permanent control	−0.030 [−0.136]	−0.014 [−0.159]	−0.010 [−0.151]	−0.009 [−0.204]	−0.006 [−0.136]	−0.008 [−0.121]
Matched sample: Change in food stamp participation from 0 to 5 out of the past 6 months.						
Caregiver food hardships						
Change from just the time-varying measure	−0.079 [−0.337]	−0.040 [−0.443]	−0.030 [−0.554]			
Change including the permanent control	−0.073 [−0.311]	−0.036 [−0.399]	−0.028 [−0.517]			
Caregiver and focal child food hardships						
Change from just the time-varying measure	−0.072 [−0.307]	−0.033 [−0.366]	−0.026 [−0.480]	−0.020 [−0.369]	−0.016 [−0.443]	−0.021 [−0.388]
Change including the permanent control	−0.067 [−0.286]	−0.031 [−0.343]	−0.024 [−0.443]	−0.019 [−0.351]	−0.014 [−0.388]	−0.019 [−0.351]

Notes: Table reports the differences between the average predicted food hardship responses for households receiving and not receiving food stamps using model coefficients from Tables 3 and 4 and weighted data from the Three-City Study. Figures in brackets are the implied elasticities from these changes.

The top panel of Table 5 lists results based on the survey data in which we compare hardships assuming $US300 in monthly food stamp benefits and no monthly benefits. The $US300 figure is approximately the average among participating households in our sample. The first row in Table 5 reports results from an analysis in which we just changed the time-varying food stamp measure (the X(t) variable from eqn 3) but left the ‘permanent’ variables (the corresponding X(1), X(2) or X(3) variables from eqn 4) alone. This corresponds to estimating the marginal effect of the relevant BX coefficient, that is, the effect of a temporary change in food stamp receipt, holding everything including the fixed effect (μ) constant.

The estimates indicate that moving all of the caregivers from non-receipt to $US300 in food stamp benefits would reduce the incidence of adults cutting back on meals by 3.9%, the incidence of adults going without food for a day by 1.9%, and the incidence of adults losing weight by 1.4%. These correspond to elasticities of 17.8, 21.5 and 21.2%, respectively.

The estimates in the second row incorporate changes to both the time-varying food stamp variable and to the fixed effect. Therefore, these simulations incorporate permanent wealth and income effects, among other things. The estimated changes in food hardships are slightly smaller when accounting for these additional effects. The next two rows repeat the analysis, predicting changes in adult and focal child hardships using the coefficient estimates from Table 4. The predicted changes in food hardships are muted further when focal child outcomes are also considered.

The bottom panel of Table 5 uses the subset of data that could be matched to administrative records and considers differences in food hardships that are associated with changes in participation. Specifically, we first predict hardships assuming that households did not participate at all in the Food Stamp Program and then predict hardships assuming that they participated for 5 out of the past 6 preceding months (again, approximately the average for households with any participation). These simulations lead to much larger reductions in food hardships than the simulations based on monthly benefit amounts. When we examine the survey sample and just consider adult hardships, participating in the Food Stamp Program for 5 months (v no partication) reduces the incidence of adults skipping or skimping on meals by 7.3%, the incidence of adults going a day without food by 3.6%, and the incidence of adults losing weight by 2.8%. The implied elasticities are 31.1, 39.9 and 51.7%, respectively.

6.4. Sensitivity analyses

Our multivariate results depart markedly from the descriptive evidence and from most previous empirical studies by indicating that food stamp program use is strongly negatively associated with food hardships. An immediate question arises regarding which parts of our specification and methodology lead to the change in results. To examine this, we estimated alternative versions of the random-effects MIMIC model of adult hardships, introducing different explanatory variables. Coefficient estimates of food stamp variables from these alternative specifications are reported in Table 6.

Table 6. Food stamp coefficients from alternative specifications of the random-effects multiple indicator multiple cause model for adult hardships

Food stamp receipt measure: model specification	Coefficient
Note: Coefficients are from longitudinal multiple indicator multiple cause specifications estimated using data from the Three-City Study; estimates use sample weights. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively.	
Binary indicator of food stamp benefit receipt (based on amount measure): no other controls	0.1856 (0.1410)
Amount of monthly food stamp benefits: no other controls	−0.0062 (0.0357)
Amount of monthly food stamp benefits: demographic controls	−0.0356 (0.0392)
Amount of monthly food stamp benefits: demographic, employment and source of income controls	−0.0981** (0.0432)
Amount of monthly food stamp benefits: demographic, employment, source of income and physical ability controls	−0.1163*** (0.0421)
Amount of monthly food stamp benefits: demographic, employment, source of income and social network controls	−0.1204*** (0.0435)
Amount of monthly food stamp benefits: demographic, employment, source of income and financial controls	−0.1390*** (0.0449)
Amount of monthly food stamp benefits: all Table 3 controls	−0.1691***

Table 6. Food stamp coefficients from alternative specifications of the random-effects multiple indicator multiple cause model for adult hardships

Food stamp receipt measure: model specification	Coefficient
	(0.0429)
Amount of monthly food stamp benefits: all Table 3 controls, excludes Wave 1	−0.2219*** (0.0639)
Amount of monthly food stamp benefits: all Table 3 controls, excludes Wave 2	−0.1006*** (0.0354)
Amount of monthly food stamp benefits: all Table 3 controls, excludes Wave 3	−0.1757** (0.0858)

1. Note: Coefficients are estimated using data from the Three-City Study; estimates use sample weights. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively.

The coefficient in the first row of Table 6 comes from a random-effects MIMIC model that includes a binary indicator based on the survey data of whether the household received any food stamp benefits in the month prior to the interview and no other explanatory variables. This is similar to the contrasts that were drawn in the descriptive analyses (and similar to the way that program use was specified in previous studies). The estimated association between participation and reported hardships is positive, as it was in the descriptive analysis.

The second row in Table 6 lists results from a nearly identical specification that uses the monthly food stamp benefit amount variable in place of the binary any-receipt measure but again includes no other explanatory variables. The estimated association is effectively zero, indicating that the benefit amount measure leads to a more negative association than the binary indicator. In the third row we see that the addition of demographic controls leads to an even more negative estimate, although the association is still statistically insignificant. The fourth row in Table 6 lists results from a specification that adds controls for the other sources of income (TANF, earnings and other household income) to the demographic controls. The coefficient on food stamp benefits becomes more negative and statistically significant, although it remains approximately half the size of the estimate from Table 3. The next three rows report estimates from specifications that also add the other explanatory variables from Table 3, including the health and disability variables (row 5), the social network variables (row 6) and the asset and liability variables (row 7). Each of these specifications produces stronger negative estimates of the association between food stamp benefits and hardships. In all, the specifications from the first seven rows of Table 6 indicate that the use of a benefit measure and the inclusion of economic and other controls lead to more negative estimates.

The last three rows from Table 6 list estimates from specifications of the ‘full’ random-effects model that each exclude one of the waves of data. These specifications help us determine whether the negative association between food stamp amounts and food hardships are an artifact of a particular wave of data. Although there are differences in the magnitudes of the estimates (the Wave 1 data appear to contribute the weakest association, while the Wave 2 data contribute the strongest), all three coefficients from these specifications are significantly negative.

To test whether the MIMIC approach fundamentally altered our findings, we estimated random-effects and fixed-effects regression models in which the dependent variables were counts of the hardships reported. The regression models (not shown) also produced negative and statistically significant estimates of the association between food stamps and hardships. As with the MIMIC specifications, the regression results were robust to the use of adult and focal child hardship measures and to the inclusion of administrative measures of program use.

Finally, we estimated random-effect probit models of each of the individual hardship indicators. Results from specifications that include monthly food stamp benefits as the indicator of program use are reported in Table 7. The estimated coefficients for food stamp use were significantly negative for all three adult hardships. For the focal child hardships involving reduced and skipped meals, the estimates were also negative, although statistically insignificant. The results indicate that the single index restriction of the MIMIC model does not seriously alter the findings for the food stamp measure.

Table 7. Estimates from random effect probit models of food hardship responses

	Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?
Amount of monthly food stamp Benefits (/$US100)	−0.0936*** (0.0196)	−0.0701** (0.0296)	−0.0547** (0.0255)	−0.0529 (0.0636)	−0.0580 (0.0720)	0.0056 (0.0424)
Amount of monthly TANF benefits (/$US100)	0.0365** (0.0177)	−0.0169 (0.0209)	−0.0402 (0.0354)	0.0606** (0.0276)	−0.0373 (0.0725)	0.0292 (0.0226)
Amount of caregiver's monthly earnings (/$US100)	0.0090 (0.0060)	−0.0081 (0.0101)	0.0049 (0.0120)	−0.0062 (0.0173)	0.0180 (0.0208)	0.0102 (0.0200)
Other household income (/$US100)	−0.0234*** (0.0052)	−0.0241*** (0.0090)	−0.0152 (0.0121)	−0.0245 (0.0159)	−0.0471** (0.0200)	−0.0186 (0.0160)
Caregiver worked full time last month	−0.1463 (0.1015)	−0.2151 (0.1622)	−0.3293* (0.1905)	−0.0817 (0.2315)	−0.5418* (0.3062)	−0.4406* (0.2597)
Household owns home	−0.3005*** (0.1148)	−0.2463 (0.1988)	−0.4105** (0.2004)	−0.3903 (0.3181)	0.1683 (0.3411)	−0.3323 (0.2827)
Household owns vehicle	−0.0547 (0.0836)	−0.1223 (0.1236)	−0.0505 (0.1374)	0.1247 (0.2100)	0.2972 (0.2945)	0.3828* (0.2051)
Household has bank account or Financial assets	−0.4660*** (0.0876)	−0.4188*** (0.1405)	−0.2097 (0.1335)	−0.1577 (0.2088)	0.1254 (0.2275)	−0.1990 (0.1948)
Household has outstanding loans	0.2795*** (0.0782)	0.2102* (0.1208)	0.1208 (0.1464)	0.3021 (0.1966)	0.3319 (0.2756)	0.3223* (0.1690)
Caregiver has disability that prevents work or other activities	0.3244*** (0.0976)	0.3294** (0.1314)	0.3920*** (0.1429)	0.4937** (0.2176)	0.2925 (0.3129)	0.1473 (0.2136)
Caregiver's general health status	0.1502*** (0.0347)	0.2174*** (0.0534)	0.2247*** (0.0606)	0.1860* (0.0953)	0.2571** (0.1023)	0.2232*** (0.0826)
Caregiver has enough people to	0.1573* (0.0952)	−0.0853 (0.1418)	−0.1271 (0.1474)	−0.3443 (0.2132)	0.4421* (0.2655)	−0.3799 (0.2356)

Note: Coefficients are estimated using data from the Three-City Study; estimates use sample weights. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively.

Table 7. Estimates from random effect probit models of food hardship responses

	Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?
listen to him/her						
Caregiver has enough people to provide child care	−0.4064*** (0.0882)	−0.2657* (0.1525)	−0.2032 (0.1494)	−0.0409 (0.2557)	−0.3439 (0.2615)	−0.1843 (0.2141)
Caregiver has enough people to provide small favors	−0.1630* (0.0924)	−0.1002 (0.1543)	−0.2641 (0.1698)	−0.3581 (0.2682)	−0.8514*** (0.3069)	−0.1043 (0.2558)
Caregiver has enough people to loan money	−0.1776* (0.1018)	−0.2610 (0.1756)	−0.4677** (0.2125)	−0.3091 (0.3456)	0.0496 (0.3878)	−0.1836 (0.3694)
Number of adults in household	0.1025** (0.0472)	0.0923 (0.0785)	0.0537 (0.0838)	0.2064* (0.1146)	0.2354 (0.1562)	0.1178 (0.1296)
Number of minors in household	0.0469* (0.0279)	0.0044 (0.0412)	−0.0196 (0.0463)	−0.0307 (0.0686)	0.0042 (0.0797)	−0.0018 (0.0679)
Caregiver is married with spouse present	−0.2489** (0.1084)	−0.1220 (0.1841)	−0.2670 (0.1756)	−0.6308 (0.4091)	−0.6171* (0.3450)	−0.5890** (0.2979)
Household has focal child age 6 years or older	0.2067 (0.1383)	−0.1210 (0.2261)	−0.0773 (0.2555)	0.4548 (0.3682)	−0.0115 (0.4436)	0.6198* (0.3507)
Caregiver's age (at Wave 1)	0.0039 (0.0055)	0.0015 (0.0071)	−0.0178* (0.0102)	0.0009 (0.0144)	−0.0092 (0.0200)	−0.0094 (0.0144)
Focal child's age (at Wave 1)	0.0196 (0.0131)	0.0321 (0.0199)	0.0433** (0.0212)	0.0719* (0.0396)	0.1137*** (0.0434)	0.0619* (0.0340)
Caregiver is non-Hispanic black	−0.0772 (0.1681)	0.2273 (0.2283)	0.2066 (0.2597)	0.6642 (0.4844)	0.9476* (0.4965)	0.1003 (0.4190)
Caregiver is Hispanic	−0.4017** (0.1724)	−0.1795 (0.2386)	−0.0970 (0.2653)	0.3877 (0.4886)	0.7378 (0.5016)	−0.2428 (0.4635)
Caregiver was born outside the USA	0.2687** (0.1159)	−0.1761 (0.1789)	−0.0892 (0.1767)	0.3132 (0.3105)	−0.0149 (0.3423)	−0.0410 (0.2940)
Caregiver has high school or general equivalency diploma (at Wave 2)	0.0885 (0.0971)	0.2725* (0.1632)	0.1723 (0.1516)	0.1934 (0.2470)	0.0576 (0.2226)	0.1241 (0.2265)
Caregiver has college degree (at Wave 2)	0.0970 (0.1157)	0.4082** (0.1859)	0.1098 (0.1879)	0.0865 (0.2862)	−0.1154 (0.3125)	0.2694 (0.2685)
Household lives in	−0.3827***	−0.1625	−0.2749	−0.7508**	−0.2371	−0.0696

Table 7. Estimates from random effect probit models of food hardship responses

	Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?
Boston	(0.1134)	(0.1806)	(0.1974)	(0.3690)	(0.3533)	(0.2667)
Household lives in Chicago	−0.3991*** (0.1238)	−0.4183** (0.1909)	−0.3265* (0.1910)	−0.6194* (0.3244)	0.0343 (0.3139)	−0.0851 (0.2931)
Wave 1	0.2061** (0.1043)	−0.1575 (0.1610)	−0.0558 (0.1756)	0.3241 (0.2420)	−0.1093 (0.2796)	0.3135 (0.2284)
Wave 2	0.0043 (0.1039)	−0.0386 (0.1674)	−0.2335 (0.1681)	0.4050* (0.2170)	−0.7369** (0.3343)	0.3583 (0.2358)
Intercept	−1.8225*** (0.3059)	−2.4497*** (0.4362)	−1.8025*** (0.4660)	−4.6273*** (0.9248)	−4.8874*** (0.8429)	−4.1366*** (0.7128)
σu	0.7385*** (0.0719)	0.8192*** (0.1310)	0.6447*** (0.1569)	1.0091*** (0.2395)	0.7421*** (0.2684)	0.8432*** (0.1727)
Log likelihood	−1311.31	−659.82	−496.73	−387.51	−280.67	−363.54

Table 7. *Estimates from random effect probit models of food hardship responses*

Adult cut size or skipped meals?	Adult did not eat for a whole day?	Adult lost weight?	Cut size of focal child's meals?	Focal child skipped a meal?	Focal child hungry?

1. Note: Coefficients are estimated using data from the Three-City Study; estimates use sample weights. Asymptotic standard errors appear in parenthesis. ***, ** and * represent statistical significance at the 1, 5 and 10% level, respectively.

7. Conclusion

This article examines longitudinal data on families' food hardships from three American cities. Consistent with previous research, descriptive analyses indicate that participation in the Food Stamp and TANF Programs is associated with a higher incidence of hardships. A problem with such raw associations is that they are confounded by other characteristics that might have led recipient households to report more hardships even in the absence of assistance programs. When we re-examine the data using multivariate models that account for some of these observed characteristics, we find the expected negative relationship between food stamp participation and food hardships and little association between TANF participation and food hardships.

Our results stand in sharp contrast to empirical findings from many other multivariate studies. One explanation for these differences is that our analysis data from the Three-City Study contain measures for other sources of income, wealth, social resources, disability and health status that often have not been available to other researchers. We find evidence that these characteristics contribute to families' food outcomes. Wealth and social resources are negatively associated with food hardships; each provides a form of insurance against short-term income shocks. Disability and poor health are positively associated with hardships. Caregivers with such limitations might be less effective in producing food outcomes with a given set of money resources. In sensitivity analyses, we also find that adding these variables to our models leads to more negative estimates of the association between program use and food hardships.

Another methodological innovation in our study is its use of self-reported amounts of benefits and administratively-reported participation histories as measures of program use. These measures capture aspects of the intensity of participation that may be missed by previous yes/no binary variables. The administrative data bring with them the additional benefit of being highly accurate. However, our findings are not affected in a major way by using administrative data on participation instead of self-reported participation, a result not found in some other studies with these data examining different issues (e.g. Fomby, 2008; Goerge et al., 2008). Nevertheless, the similarity of our results when using administrative data strengthens our conclusions by demonstrating that the findings based on survey reports are not a result of response error.

Our study differs from previous work in several other ways, although these departures are less consequential to our final conclusions. Unlike the studies by Borjas (2004) and Wilde and Nord (2005), we focus on a relatively disadvantaged population: families with children living in poor neighborhoods who initially had incomes below 200% of the poverty line. However, most other studies have been restricted to low-income populations and have still found counterintuitive positive associations between food stamp use and food hardships. Another difference with previous work is that the food hardships in the Three-City Study are more severe than some of the hardships that enter the USDA food security measure. Also, the data in our analysis is longitudinal, which allows us to address concerns regarding omitted variables. The longitudinal controls lead to stronger negative findings in some of the models but do not substantively alter our conclusions.

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Footnotes

1
The Food Stamp Program was renamed the Supplemental Nutrition Assistance Program on 1 October 2008. Throughout this article, we refer to the Food Stamp Program, the name of the program during the period of the study.
2
Wilde (2007) comprehensively and critically reviews the empirical literature on the Food Stamp Program and food hardships.
3
Robert Goerge at the Chapin Hall Center at the University of Chicago supplied the records for Illinois; Daniel Shroeder from the Ray Marshall Center at the University of Texas supplied the records for Texas; and Jesse Valente from the Massachusetts Department of Transitional Assistance provided the records for that state.
4
Caregivers were also asked 'In the past 12 months, were you ever hungry but didn't eat because you couldn't afford enough food?' However, the responses to this question are dropped from our multivariate analyses because we could not get them to fit with our MIMIC model.
5
The use of only a subset of the full set of food insecurity questions was adopted in the construction of the first-wave survey instrument when there were severe constraints on the survey minutes available. The researchers did not adopt the shorter six-item food security scale that was available (Blumberg et al., 1999), because the six-item omitted questions regarding children's hardships.
6
Wilde and Nord (2005) restrict their analysis to the 10 food security questions that only concern adults. Other studies use the food security scale, which is based on 10 questions in households with only adults and 18 questions in households with children.
7
In a study of food insecurity, Rose et al. (1998) separate the effect of participation in the Food Stamp Program per se from the effect of benefits by entering separate variables for them. This is based on the presumption that the participation effect itself might be biased by self-selection and that the effect of benefits can be estimated only for participants. We will test this separation in future work.
8
Presently, we only have administrative data on work status (unemployment insurance earnings records) for one state.
9
Responses to the two questions regarding whether and how often the focal child skipped meals are treated differently. They are combined into a four-category index (did not skip meals, skipped meals in 1 or 2 months, skipped meals in some but not all months, or skipped meals almost every month) and modeled as an ordered probit.
10

Recall that in a probit model one parameter must be normalized; this is usually done in terms of the error variance. Because of the normalization, each j (factor) parameter in our model actually represents a ratio of the true factor loading and the measurement error standard deviation. Therfore, a higher value of j could arise from a stronger factor loading, a smaller degree of measurement error, or some combination of the two.

11

A few other normalizations are required for identification, including a restriction on one of the factor loadings ($\lambda 1$ is normalized to 1) and a restriction on one of the thresholds ($\delta 1$ is normalized to 0).

12

Because the quasi-fixed-effects specifications account for (net out) the time-invariant components of food hardships and the explanatory variables, the coefficients (BX) on the time varying explanatory variables are best interpreted as estimated associations between changes in the explanatory variables and changes in hardships.

13

As a sensitivity test, we re-estimated the specification using the self-reported benefit amounts with the smaller matched sample and found no appreciable differences in the results.

APPENDIX I

Means of analysis variables

	Survey sample	Matched sample
1. Notes: Authors' calculations from Three-City Study. Estimates use sample weights. TANF, Temporary Assistance for Needy Families.		
Outcome measures: food hardships		
Adult cut size or skipped meals because not enough money for food (0, 1)	0.10	0.13
Adult did not eat for a whole day because not enough money for food (0, 1)	0.04	0.05
Adult lost weight because not enough food (0, 1)	0.03	0.03
Cut size of focal child's meals because not enough money for food (0, 1)	0.02	0.03
Number of times focal child skipped a meal because not enough money for food (0 to 3)	0.03	0.04
Focal child hungry but could not afford more food (0, 1)	0.02	0.03
Time-varying explanatory measures		
Amount of monthly food stamp benefits (/$US100)	1.36	1.61
Amount of monthly TANF benefits (/$US100)	0.75	0.86
Amount of caregiver's monthly earnings (/$US100)	7.02	6.68
Number of months out of past 6 caregiver received Food Stamp income (0 to 6)		2.77
Number of months out of past 6 caregiver received TANF income (0 to 6)		1.29
Number of months out of past 6 caregiver reported holding a primary job (0 to 6)		2.95
Indicator if number of months holding a primary job is missing		0.04
Other household income (/$US100)	9.11	8.56
Caregiver worked full time last month (0, 1)	0.34	0.33
Household owns home (0, 1)	0.25	0.21
Household owns vehicle (0, 1)	0.56	0.52
Household has bank account or financial assets (0, 1)	0.43	0.39

	Survey sample	Matched sample
Household has outstanding loans (0, 1)	0.54	0.55
Caregiver has disability that prevents work or other activities (0, 1)	0.18	0.20
Caregiver's general health status (0, 5)	2.71	2.75
Caregiver has enough people to listen to him/her (0, 1)	0.54	0.54
Caregiver has enough people to provide child care (0, 1)	0.51	0.50
Caregiver has enough people to provide small favors (0, 1)	0.48	0.46
Caregiver has enough people to loan money (0, 1)	0.39	0.37
Number of adults in household	1.97	1.93
Number of minors in household	2.53	2.57
Caregiver is married with spouse present (0, 1)	0.33	0.29
Household has focal child age 6 years or older (0, 1)	0.65	0.64
Time-invariant explanatory measures		
Caregiver's age (at Wave 1)	32.66	31.99
Focal child's age (at Wave 1)	6.63	6.45
Caregiver is non-Hispanic black (0, 1)	0.40	0.42
Caregiver is Hispanic (0, 1)	0.53	0.50
Caregiver was born outside the USA (0, 1)	0.21	0.16
Caregiver has high school or general equivalency diploma (at Wave 2) (0, 1)	0.40	0.42
Caregiver has college degree (at Wave 2) (0, 1)	0.23	0.20
Household lives in Boston (0, 1)	0.33	0.27
Household lives in Chicago (0, 1)	0.34	0.35
Number of observations	4680	2973