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Does Early Food Insecurity Impede the Educational Access Needed to Become Food Secure?

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Abstract

Education is considered one of the great equalizers of economic opportunity. However, pre-existing differences in educational access may generate differences in educational investment, which may perpetuate the economic inequalities that education is supposed to mitigate. In this paper, we examine the role of reduced educational investment as a mechanism for the intergenerational transmission of food insecurity. Specifically, we examine how food insecurity during childhood may reduce educational investments, which, in turn, may increase food insecurity during adulthood. Identifying the mechanism(s) for the intergenerational transmission of food insecurity is essential for designing effective policies to address food insecurity and improve national nutrition and health. Furthermore, understanding the extent to which improvements in food security create positive spillovers in future educational attainment and food security will provide a clearer assessment of the value of programs designed to improve food security. We use longitudinal data from the Panel Study of Income Dynamics to examine education as a potential mechanism (mediator) in the intergenerational transmission of food insecurity. We follow a sample of children almost two decades as they transition from childhood to adulthood. We use an estimator developed by Flores and Flores-Lagunes (2009) to estimate the share of the intergenerational transmission of food insecurity that can be attributed to compromised educational investments. In our preliminary analysis, we find only a small amount of evidence for reduced educational investment as a mechanism for the intergenerational transmission of food insecurity. However, the estimates vary widely across specifications such that large effects are not ruled out.

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I. Introduction

Education is considered one of the great equalizers of economic opportunity. However, the extent to which education can “level the playing field” depends on the quality (and equality) of individuals’ access to educational opportunities. Pre-existing inequality in educational access may lead to differences in educational investments, which perpetuates the economic inequalities that education is supposed to mitigate.

This paper examines the role of educational investment as a mechanism for the intergenerational transmission of food insecurity. Specifically, we examine how food insecurity during childhood may reduce post-secondary educational investments, which, in turn, may increase food insecurity during adulthood. Recent work on families with teenagers (Hamersma and Kim, 2016) suggests that teenage employment may contribute to increased food security of children in a household. Teenagers who choose work over educational engagement during high school may not be poised to make the educational investments needed to achieve food security as adults.

We are not aware of any research to date on the intergenerational transmission of food insecurity or its mechanisms. A handful of small-sample studies describe food insecurity as a common problem for college students: food insecurity is more prevalent among urban and minority students (Maroto, 2013), students living away from their families (Chaparro et al., 2009), and students receiving food assistance (Gaines et al., 2012). Food insecurity is also related to lower academic performance (Patton-López et al., 2014). These findings are consistent with elementary and secondary education research that calls food insecurity a “risk to the growth, health, cognitive, and behavioral potential of America’s poor and near-poor children" (Cook and Frank, 2008). More recently, Goldrick-Rab et al. (2017) gather data from more than 33,000 students from 70 community colleges in 24 states. They find that two-thirds of college students surveyed reported some degree of food insecurity (30-day measure), including one-third reporting very low food security.

Blagg et al. (2017) use nationally-representative data from the October and December supplements of the Current Population Survey to estimate food insecurity (12-month measure) among households that include college students. During the period 2011-2015, they estimate rates of food insecurity among households that contain four-year college students (11 percent), two-year college students (17 percent), and vocational education students (14 percent).

Our paper builds upon these studies in several important ways. First, we use nationally-representative longitudinal data from the Panel Study of Income Dynamics (PSID) instead of localized samples of college students. Second, by not relying on a sample of only college students, we can assess how differences in food security may affect pre-college outcomes, e.g., high school graduation or college matriculation. Third, instead of estimating contemporaneous correlations between food security and education, we will utilize the PSID's longitudinal dimension to investigate how differences in food security during childhood may cause differences in post-secondary education and, in turn, food security during adulthood. This will deepen our understanding of the intergenerational transmission of food insecurity by estimating the extent to which potential compromises in education may perpetuate disadvantage. In this sense, our work will contribute more broadly to the literature on the intergenerational transmission of poverty and welfare receipt (e.g., Pepper, 2000; Bird, 2007;

Dahl et al., 2014; Hartley et al., 2016) and the role of higher education as a mechanism for intergenerational mobility (e.g., Corak, 2013).

Identifying the mechanism(s) for the intergenerational transmission of food insecurity is an essential step for designing effective policies to address food insecurity and improve national nutrition and health. Furthermore, understanding the extent to which improvements in food security create positive spillovers in future educational attainment and food security will provide a clearer assessment of the value of food assistance programs (or other programs designed to improve food security). Since adult food insecurity is linked to mental and physical health problems and higher health expenditures (Tarasuk et al., 2015), investment in food assistance programs could improve health and well-being in both the short-run and long-run.

II. Conceptual Design

A. Basic framework

Our research question is simple: Is lower educational attainment a mechanism for the intergenerational transmission of food insecurity? In other words, does food insecurity during childhood compromise another outcome (i.e., education) that could alleviate food insecurity in adulthood?

Our conceptual model begins with the notion of three major time periods during the life-cycle: childhood, young adulthood, and adulthood. Children experience a particular level of household food insecurity; young adults make educational investments; and adults experience a level of household food insecurity, which depends on both current and past factors, including the educational investment determined during young adulthood. This simple model allows us to frame food insecurity during childhood as intergenerationally transmitted in at least two ways: directly (in the usual sense of intergenerational persistence) and indirectly (through reduced schooling, which generates its own negative effect on food security during adulthood).

As a starting point for discussion, we begin with a simple (naïve) model of food insecurity:

$$FI_{iA} = \alpha + \beta FI_{iC} + \gamma Z_{iC} + \delta E_{iY} + \theta X_{iA} + \varepsilon_{iA} \tag{1}$$

Food insecurity during adulthood (FI_{iA}) is modeled as a function of food insecurity during childhood (FI_{iC}) and other observable childhood factors (Z_{iC}), young adult educational investments (E_{iY}), and current observable (X_{iA}) and unobservable (ε_{iA}) factors. This model treats childhood food insecurity and education as distinct factors predicting adult food insecurity; we expect food insecurity during childhood to have a positive coefficient ($\beta > 0$) and education to have a negative coefficient ($\delta < 0$). Our goal is to determine whether the apparent effect of food insecurity during childhood, β, may not fully capture the intergenerational transmission of food security, namely, the extent to which education itself may be negatively affected by food insecurity during childhood. Therefore, along with the usual concerns about endogeneity that arise in an intergenerational transmission context (i.e., separating state dependence from unobserved heterogeneity), OLS estimation of (1) will not separately identify the direct and indirect (via education) effects of food insecurity during childhood on food insecurity in adulthood.

B. *Mediation analysis framework*

Recent work by Flores and Flores-Lagunes (2009, 2010, and 2013, henceforth FFL) develops estimation strategies that separately identify the "direct" and "indirect" causal effects of a treatment variable on an outcome variable.[2] This estimation strategy decomposes the total average treatment effect (ATE) into a "mechanism average treatment effect" (MATE)—the indirect effect of the treatment variable via a mechanism variable—and a "net average treatment effect" (NATE)—the direct effect of the treatment variable net of the mechanism variable.[3]

We use the FFL approach to establish how much of the intergenerational transmission of food insecurity can be attributed to compromised educational investments. The direct effect (i.e., the NATE) is what we typically understand as intergenerational transmission, while the indirect effect of interest to us (i.e., the MATE) is the potentially compromised schooling decisions of someone who experienced food insecurity during childhood, which may itself increase the probability of food insecurity in adulthood. Thus, schooling is the mechanism of interest for this study.

We follow the method developed by FFL (2009). Consider a potential outcomes framework. Let Y_i be the outcome of interest—a measure of food insecurity during adulthood. The treatment, $T_i \in \{0,1\}$, is a binary measure of food insecurity during childhood for the same person. Finally, the mechanism of interest, M_i, is an indicator for the individual's educational attainment (which is established during the time between the childhood and adulthood measures of food insecurity). FFL use the example of modeling the effect of smoking (T_i) on

[2] VanderWeele (2015) provides an excellent overview of methods for so-called mediation (or mechanism) analysis.
[3] FFL develop both point and partial (bounds) identification results for their decomposition estimator, which depend on the strength of the identification assumptions.

birthweight (Y_i) when part of the effect of smoking is a reduction in gestational age (M_i) that, in turn, may reduce birthweight.

The usual model of potential outcomes suggests that Y_i may vary with the value of T_i—i.e., the potential outcome under treatment T_i is $Y_i(T_i)$. This difference in potential outcomes, $Y_i(1) - Y_i(0)$, is traditionally interpreted as the treatment effect. The FFL model adds another layer, noting that a mechanism may exist that (a) directly affects the outcome and (b) itself depends upon the treatment. Importantly, this mechanism occurs after treatment but before the outcome. While condition (a) on its own may justify including M_i as a covariate, condition (b) means this will not be enough to separately identify how the treatment's effects may operate partly through M_i. Thus, we define $M_i(T_i)$ as the potential mechanism value (post-treatment value) under treatment T_i. This mechanism can, in turn, affect the outcome Y_i, such that the composite potential outcome under treatment T_i and post-treatment value $M_i(T_i)$ is expressed as $Y_i\big(T_i, M_i(T_i)\big)$.

The key to disentangling the indirect effect (i.e., MATE) and direct effect (i.e., NATE) of treatment on the outcome is to first estimate the ATE overall and then use estimated counterfactuals to identify the role of the mechanism. The MATE is the part of the ATE that operates through the mechanism, while the NATE is the residual part of the ATE (hence, it is "net of mechanism"). The usual definition of the average treatment effect applies, i.e.,

$$ATE = E\big[Y\big(1, M(1)\big) - Y\big(0, M(0)\big)\big] \tag{2}$$

There are several ways to estimate the ATE with the treatment and comparison groups, given the usual unconfoundedness assumption. We can directly compare the means of the treatment and comparison groups, or we can compare some adjusted means to account for selection (i.e., in practice, we must argue we have sufficient covariates to justify the "selection on observables" assumption).

We can decompose (2) to illustrate the role of the mechanism:

$$ATE = E\big[Y\big(1, M(1)\big) - Y\big(1, M(0)\big)\big] + E\big[Y\big(1, M(0)\big) - Y\big(0, M(0)\big)\big] \tag{3}$$

The first bracketed term of (3) compares the outcomes of a treated person whose mechanism is affected by that treatment to the (hypothetical) outcome of a treated person who does not experience any mechanism effect. The second bracketed term of (3) compares the (hypothetical) outcome of a treated person who does not experience any mechanism effect to the outcome of an untreated person. The goal of our estimation is to identify the first bracketed term by establishing an appropriate counterfactual.

FFL (2009) suggest two methods for estimating this counterfactual. First, one could possibly identify a subgroup of the sample that has an essentially fixed mechanism value, i.e. $M(1) = M(0)$ for this group. Unfortunately, we are not aware of any subgroup whose educational attainment cannot be affected by childhood traits like food insecurity. Second, FFL establish a set of unconfoundedness assumptions that point-identify the MATE.[4] The key is to identify principal strata, or subgroups of the data, in which we can assume that the *potential* value of the mechanism is the same, i.e., they share the same pair of potential values $(M(0), M(1))$ and their treatment status (0 or 1) determines which potential value they exhibit. If we are willing to assume we have sufficient covariates such that we are making apples-to-

[4] Under certain weaker assumptions, they are partially identified. We hope to explore this in the next draft.

apples comparisons within principal strata, we can estimate the mechanism effect in the following way:

1) Regress the outcome Y_i on explanatory covariates X_i and the mechanism M_i for the treatment group only.
2) Use the estimated parameters to produce alternative predicted values of Y_i for the treated group, substituting the actual mechanism values with the average mechanism value for the *untreated*. The mean of these predicted values is the mean we would expect in the treatment group, given (a) the treatment group's X_i and (b) the relationship between (X_i, M_i) and Y_i, if the treatment group had $M_i(0)$ instead of $M_i(1)$. Let A_1 denote this mean.
3) Run the same regression again for the untreated group.
4) Use the estimated parameters from this regression to create predicted values for the untreated group. Let A_0 denote the mean of these predicted values.
5) Calculate the difference between A_1 and A_0. Note that both A_1 and A_0 represent average outcomes when the mechanism value is $M(0)$—either artificially (in the case of A_1) or actually (in the case of A_0), but A_1 is in the presence of treatment and A_0 is in its absence. Thus, the difference between A_1 and A_0 is the NATE.
6) Calculate the MATE by subtracting the NATE from an estimate of the ATE; i.e., $MATE = ATE - NATE$.
7) Calculate the ratio of NATE (or MATE) to an estimate of ATE to determine the relative size of the direct (or indirect) effect.
8) Calculate standard errors for all estimates using the bootstrap.

This process generates a single estimate of the NATE, but the value of the MATE will vary depending upon the estimation process for the ATE. We follow FFL (2009) in estimating multiple versions of the ATE using a variety of propensity score weights and specifications, and then calculate MATE for each. Note that since the ATE is calculated independently of the NATE, there is no guarantee that the NATE ends up being smaller than the ATE, even though theoretically it ought to be smaller than ATE (or equal to ATE, if there is no mechanism effect). We revisit this issue in the discussion of our results.

III. Data

This paper utilizes data from the Panel Study of Income Dynamics (PSID), a longitudinal dataset that was launched in 1968 with over 18,000 individuals in over 5,000 families in the United States. This nationally-representative sample was followed over time, and their children (treated as having the "PSID gene") were added to the sample—and at times given supplemental surveys—even as they aged and left their households of origin and formed new households of their own. Over the course of the continuing study, over 70,000 variables have been collected from over 70,000 individuals (McGonagle, et al., 2012). The 50-year panel is the world's longest-running household panel survey.

The PSID data are ideally suited to address our research question since they provide the ability to construct a long panel that combines childhood data (Child Development Supplement, CDS), young adult data (Transition to Adulthood Supplement, TAS), and core PSID data into adulthood. The empirical key to our research design is new information gathered on food security of adults in 2015. Children in the first CDS that asked about food insecurity (1997) have transitioned into adulthood by the time we observe their outcomes in the most recent survey in 2015. While there is a gap in PSID food security data between 2004 and 2014, the TAS contains sufficient information to establish the educational investments being made by young adults who were (and were not) food insecure as children; food security information can be again observed for these individuals as they reach adulthood.

Our main sample for analysis consists of children ages 3-12 who were included in the 1997 CDS. We draw measures of observable childhood variables from the CDS, including food security status (12-month measure), age, gender, and marital status of the child's household head, the child's age and race/ethnicity, whether the child was born in the United States, the number of children in the household, and whether the household received food stamps in the previous year. As these birth-year cohorts age, we observe their education investments between childhood and young adulthood using data from the TAS. We also draw measures of observable adulthood variables from the TAS and core survey data, including food security status, age, gender, and marital status of household head (in 2015), number of children, whether there were positive earnings, and whether the household received food stamps in the previous year. Finally, we supplement the PSID sample with state-level data from the University of Kentucky Center for Poverty Research National Welfare Data (UKCPR, 2017), including the unemployment rate, gross state product per capita, and number of SNAP recipients per capita in 2015. The final sample contains 1,674 observations.

Summary statistics for this sample are provided in Table 1. In 1997, approximately 20 percent of households with children reported some degree of food insecurity. By 2015, the same cohort of children (now adults) reported a food insecurity rate of 28 percent, including more than doubling the proportion of households reporting very low food security (3 percent in 1997 to 7 percent in 2015).

We explore the food security transitions between 1997 and 2015 in Table 2. Table 2 reports the probability of transitioning to some food security status in 2015, conditional on the food security status in 1997. For example, among the approximately 80 percent of children whose households reported being food secure in 1997, by 2015, approximately 77 percent of those children reported being food secure, 12 percent marginally food secure, 6 percent low food secure, and 5 percent very low food secure.

Table 2 demonstrates two notable details. First, higher levels of food security during childhood (i.e., in 1997) correspond to higher probabilities of greater food security later in adulthood. This is shown in the first column of the table: the conditional probability of transitioning to food secure in 2015 monotonically increases with food security in 1997 (i.e., 37 percent among very low food secure to 77 percent among food secure). Second, food insecurity is not a strictly absorbing state. In fact, for every food security status in 1997, the plurality of children transition to food secure by 2015. The variation in persistence—and the lack of complete persistence—of food security status suggests that there may exist factors that influence intergenerational transmission of food insecurity. In the next section, we explore the possible role of education as one such factor.

IV. Results

A. Naïve OLS Estimation

Table 3 reports the results of naïve OLS estimation of equation (1). Panel A uses a relatively broad measure of food insecurity; i.e., whether a child's household reports experiencing any level of food insecurity—marginal food security, low food security, or very low food security. If taken at face value, the results suggest that both childhood food insecurity and educational investment (i.e., graduating high school by the age of 24) have large and statistically significant effects on the likelihood that a child will become food insecure as an adult. Furthermore, if taken at face value, the effect of graduating from high school mitigates—and nearly compensates for—the impact food insecurity as a child on food insecurity as an adult. Panels B and C replicate similar analyses using relatively narrower measures of food insecurity with qualitatively similar results. The magnitudes of the estimated impacts of childhood food insecurity on adulthood food security decrease with more severe levels of food insecurity. This is consistent with the transition probabilities in Table 2 that showed that overall persistence of food insecurity decreases with the severity of food insecurity.

However, as previously noted, OLS estimation of equation (1) will lead to potentially biased estimates because childhood food security may endogenously affect a child's educational investments made during young adulthood. Therefore, in the next subsection, we conduct mediation/mechanism analysis to explore how much of the intergenerational transmission of food insecurity can be attributed to compromised educational investments from childhood food insecurity.

B. Mediation analysis

Before estimating the NATE and MATE, we conduct a standard mediation analysis, as popularized by Baron and Kenny (1986). Table 4 provides the estimates for the total, direct, and indirect effects of food insecurity during childhood on food insecurity during adulthood, as well as an estimate of the proportion of the total effect mediated by education. We estimate these effects using three different definitions of food insecurity: any food insecurity, low or very low food security, and very low food security only.

The first column of Table 4 conducts the mediation analysis for the broadest definition of food insecurity. The estimates of the total effect and direct effect are approximately equal, which implies that the indirect effect—the intergenerational effect that is mediated by education—is approximately zero. We cannot reject the null hypothesis that the indirect effect is zero at any conventional levels. The implied proportion of the total effect mediated by education is approximately two percent, which is not statistically significant. The second column conducts a similar analysis using low or very low food security and generates numerically similar estimates; we cannot reject the hypothesis of a zero indirect effect. Finally, the third column considers only very low food security and finds no statistically significant evidence of any kind of effect, direct or indirect.

Table 5 displays the primary baseline estimates of the ATE of food insecurity during childhood on food insecurity during adulthood and the MATE corresponding to not completing high school by age 24.[5] In this case, the ATE is calculated as the difference in means between treatment and comparison groups; we test the robustness of the results to more sophisticated

[5] Note that this is the only educational attainment measure used in the analysis so far, but this is just a launching point for analysis that examine college matriculation, persistence, and completion.

methods in the next subsection. Under each ATE estimate is the NATE estimate, which indicates the estimated portion of the ATE that does *not* operate through the mechanism of education. This is followed by the MATE estimate (which is the difference between the estimated ATE and NATE) and the mechanism's share of the total ATE.

The first thing we note about the findings is that the estimated relationship between food insecurity in childhood and adulthood (i.e., the ATE) is smaller for narrower definitions of food insecurity. This is consistent with the transition table (Table 2) that illustrated the lack of persistence of the most severe forms of food insecurity. While knowing someone had *any* form of food insecurity during childhood indicates a 24.2 percentage point higher probability of being food insecure during adulthood, the estimated relationship for *very low* food security is about half that size, at only 13.4 percentage points.

In the broadest category of "any food insecurity," the estimated mechanism share of the ATE is approximately 8 percent; i.e., approximately 8 percent of intergenerational correlation can be explained by the negative effect food insecurity during childhood has on schooling, which in turn increases food insecurity during adulthood. The mechanism share estimate is statistically significantly different from zero at the 5 percent level. For the more severe measures of food insecurity, the mechanism estimates are much less precise. In the case of very low food security, we cannot rule out zero nor can we rule out quite large effects.

One strong assumption made in Table 5 was that the ATE could be effectively measured by comparing the treatment and comparison group mean outcomes. While this assumption could be justified in an experimental setting, our setting suggests the need to use other controls for handling selection into treatment. We follow FFL (2009) in using a variety of propensity-score-based ATE estimators. The first alternative estimator uses inverse propensity scores weights in a simple regression of the outcome on the treatment. Two additional alternatives include the propensity score directly into the model, either as a simple level or up to a cubic function. Table 6 displays the results from four ATE estimators (the original estimator reported in Table 5, plus these three alternatives) and their corresponding MATE estimates.

Since each ATE estimator relies on a distinct functional form from the decomposition that produces the NATE (which we estimate only in the single way described in the text), there is no guarantee that the NATE estimate will, in fact, be smaller than the ATE estimate, even though it should be in theory. In particular, if the true MATE is small, then sampling error could produce a zero or even negative estimated mechanism effect. Indeed, we find that the last two alternatives tend to produce negative estimates for some outcome measures, though none are statistically significant at the 5 percent level.

The use of alternative ATE estimators produces results that vary quite substantially from the baseline estimates. In fact, only the baseline ATE estimate generates a statistically significant estimated MATE, and it does so only for the "any food insecurity" measure. The other estimates vary widely and are imprecisely estimated. We do not, therefore, suggest that we have strong evidence of education as a key mechanism in transmitting food insecurity across generations. However, the imprecision of our estimates does not preclude the possibility that education plays a role.

V. Conclusion

The persistence of economic inequality across generations is of growing concern in the United States. This study investigates the possibility that inequality in food security could be perpetuated by compromised educational attainment for children growing up in food insecure households. Estimating the role of lower education as a mechanism for the intergenerational transmission of food insecurity cannot be done simply by including education to a model of food security in adulthood, as the value of the education variable itself could be influenced by treatment. Using a decomposition method developed by Flores and Flores-Lagunes (2009), we are able to disentangle the direct intergenerational transmission of food insecurity from the indirect effect of childhood food insecurity on educational attainment. In our analysis thus far, we find only a small amount of evidence for the education mechanism, though estimates vary widely across specifications such that large effects are not ruled out.

There are many more steps we will take in completing this project. First, we recognize that we have only used a single, very coarse measure of schooling in our initial estimates. The measure "any high school degree by age 24" is weak in the sense that only 12 percent of people fail to attain a high school degree by age 24, and this may not be the margin where the indirect effect of childhood food insecurity is most relevant. We plan to estimate the model using other binary variables reaching higher into the education distribution (ex. attended any college) as well as a continuous measure of schooling. Second, we are still developing our ATE models and need to determine which we think is the most appropriate for this context given the many options in the literature. Alongside this decision, we need to consider whether NATE can or should be estimated in more than one way, or be linked more tightly to the ATE estimate such that any decomposition will reliably generate two positive elements (as it should in theory).

Finally, we realize that even with the rich PSID data, the selection on observables assumption is strong. We plan to consider a version of this method that is designed for partial identification under weaker assumptions. We are confident that these improvements and extensions of the work will contribute to a deeper understanding of the role that education might play as a mechanism in intergenerational transmission of food insecurity.

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VII. Tables

Table 1: Descriptive Statistics (weighted)

	Mean	Std. Dev	Min	Max
Food security, 1997				
Marginal/Low/Very Low FS indicator	0.196	0.398	0	1
Low/Very Low FS indicator	0.110	0.313	0	1
Very Low FS indicator	0.028	0.164	0	1
Food security, 2015				
Marginal/Low/Very Low FS indicator	0.282	0.450	0	1
Low/Very Low FS indicator	0.155	0.362	0	1
Very Low FS indicator	0.073	0.260	0	1
Education				
Graduated HS by age 24	0.883	0.322	0	1
Childhood variables				
Household head age in 1997 (in yrs)	37.9	7.9	19	92
Household head female	0.212	0.409	0	1
Marital status = Married	0.738	0.440	0	1
Marital status = Never married	0.102	0.303	0	1
Marital status = Widowed	0.015	0.123	0	1
Marital status = Divorce/Sep/Annul	0.145	0.352	0	1
Number of children = 1	0.144	0.351	0	1
Number of children = 2	0.508	0.500	0	1
Number of children = 3	0.250	0.433	0	1
Number of children = 4+	0.099	0.298	0	1
Child age (in months)	95.3	33.8	36	155.9
Born in USA	0.971	0.167	0	1
Race = White	0.657	0.475	0	1
Race = Black	0.183	0.387	0	1
Race = Hispanic	0.097	0.296	0	1
Race = Other	0.064	0.244	0	1
Received food stamps last year	0.169	0.375	0	1

Table 1 (continued)	Mean	Std. Dev	Min	Max
Adulthood variables				
Household head age in 2015 (in yrs)	37.9	14.6	20	88
Household head = female	0.298	0.457	0	1
Marital status = Married	0.410	0.492	0	1
Marital status = Never married	0.454	0.498	0	1
Marital status = Widowed	0.021	0.143	0	1
Marital status = Divorce/Sep/Annul	0.115	0.319	0	1
Number of children = 0	0.710	0.454	0	1
Number of children = 1	0.166	0.372	0	1
Number of children = 2	0.085	0.279	0	1
Number of children = 3	0.026	0.160	0	1
Number of children = 4+	0.013	0.113	0	1
Received food stamps last year	0.138	0.345	0	1
Earnings > 0	0.889	0.314	0	1
State-level variables, 2015				
Unemployment rate	5.30	0.76	2.8	6.9
Gross state product (millions) per capita	0.055	0.012	0.036	0.182
# of SNAP recipients per capita	0.143	0.029	0.056	0.217

Notes: The data are from the PSID (Core, CDS, and TAS). The sample contains 1,674 observations of children aged 3-12 in the 1997 CDS. The reported statistics are weighted using the PSID-provided 2015 core weights.

Table 2: Food Security Transitions

	FS in 2015				
FS in 1997	Food Secure	Marginal FS	Low FS	Very Low FS	TOTAL
Food Secure	910 [77.5]	182 [11.7]	116 [6.0]	76 [4.8]	1,284 [100.0]
Marginal FS	83 [55.5]	29 [14.2]	23 [11.8]	26 [18.5]	161 [100.0]
Low FS	77 [44.4]	41 [23.0]	33 [15.1]	21 [17.6]	172 [100.0]
Very Low FS	22 [37.5]	5 [4.9]	18 [42.5]	12 [15.1]	57 [100.0]
TOTAL	1,092 [71.8]	257 [12.7]	190 [8.2]	135 [7.3]	1,674 [100.0]

Notes: The data are from the PSID (Core, CDS, and TAS). The sample contains 1,674 observations of children aged 3-12 in the 1997 CDS. Each cell entry reports the frequency count of observations that transitioned from a food security status in 1997 to a food security status in 2015. Row percentages (weighted) are reported in brackets.

Table 3: Estimated intergenerational correlations of food security (OLS)

	(1)	(2)	(3)	(4)
Panel A: Marginal/Low/Very Low FS (2015)				
Marginal/Low/Very Low FS (1997)	0.292***	0.272***	0.181***	0.128***
	(0.040)	(0.041)	(0.040)	(0.030)
Graduated HS by age 24		-0.230***	-0.133**	-0.081*
		(0.052)	(0.049)	(0.036)
Panel B: Low/Very Low FS (2015)				
Low/Very Low FS (1997)	0.262***	0.258***	0.206***	0.123***
	(0.051)	(0.051)	(0.049)	(0.034)
Graduated HS by age 24		-0.146**	-0.075	-0.076*
		(0.046)	(0.045)	(0.035)
Panel C: Very Low FS (2015)				
Very Low FS (1997)	0.080	0.077	0.037	0.100
	(0.062)	(0.060)	(0.065)	(0.054)
Graduated HS by age 24		-0.134**	-0.100*	-0.087**
		(0.041)	(0.039)	(0.027)
Additional controls	No	No	Yes	Yes
State fixed effects	No	No	No	Yes

Notes: N = 1,674. Each column reports OLS estimates of equation (1) with heteroskedasticity-robust standard errors reported in parentheses. Regressions in columns (3) and (4) include childhood (in 1997) controls (i.e., age, gender, and marital status of the child's household head, the child's age and race/ethnicity, whether the child was born in the United States, the number of children in the household, whether the household received food stamps in the previous year) and adulthood (in 2015) controls (i.e., age, gender, and marital status of household head, number of children, whether there were positive earnings, and whether the household received food stamps in the previous year) and state-level measures of economic climate (unemployment rate, gross state product per capita, and number of SNAP recipients per capita). Full estimation results are available upon request.
*** significant at the 0.1 percent level, ** significant at the one percent level, * significant at the five percent level.

Table 4: Estimates of Mediation Effects

	Measure of Food Security in 2015		
Estimate	Any Food Insecurity	Low or Very Low Food Security	Very Low Food Security
Total Effect	0.184***	0.189***	0.010
	(0.038)	(0.046)	(0.065)
Direct Effect	0.180***	0.191***	0.019
	(0.038)	(0.046)	(0.064)
Indirect Effect	0.004	-0.003	-0.009
	(0.004)	(0.003)	(0.007)
Proportion Mediated	0.020	-0.014	-0.992
	(0.022)	(0.017)	(6.884)

Notes: N = 1,674. Estimation method follows Baron and Kenny (1986). Heteroskedasticity-robust standard errors reported in parentheses.
*** significant at the 0.1 percent level, ** significant at the one percent level, * significant at the five percent level.

Table 5: Estimates of Mechanism Effects

	Measure of Food Security in 2015		
Estimate	Any Food Insecurity	Low or Very Low Food Security	Very Low Food Security
ATE	0.242***	0.198***	0.134**
	(0.027)	(0.032)	(0.053)
NATE	0.223***	0.188***	0.117
	(0.027)	(0.032)	(0.124)
MATE	0.018*	0.010	0.017
	(0.008)	(0.008)	(0.110)
Mechanism share	0.077*	0.052	0.129
	(0.035)	(0.044)	(0.800)

Notes: N = 1,673. Standard errors are obtained through 200 bootstrap replications.
*** significant at the 0.1 percent level, ** significant at the one percent level, * significant at the five percent level.

Table 6: Alternative Estimates of Mechanism Effects

Estimate:	Any Food Insecurity				Low or Very Low Food Security				Very Low Food Security			
	1	2	3	4	1	2	3	4	1	2	3	4
ATE	0.242***	0.225***	0.197***	0.194***	0.198***	0.196***	0.181***	0.180***	0.134**	0.144**	0.139*	0.138*
	(0.027)	(0.028)	(0.029)	(0.030)	(0.032)	(0.032)	(0.034)	(0.034)	(0.053)	(0.059)	(0.062)	(0.062)
NATE	0.223***	0.223***	0.223***	0.223***	0.188***	0.188***	0.188***	0.188***	0.117	0.117	0.117	0.117
	(0.027)	(0.027)	(0.027)	(0.027)	(0.032)	(0.032)	(0.032)	(0.032)	(0.124)	(0.124)	(0.124)	(0.124)
MATE	0.018*	0.002	-0.026	-0.029	0.01	0.008	-0.007	-0.008	0.017	0.027	0.021	0.02
	(0.008)	(0.011)	(0.015)	(0.016)	(0.008)	(0.016)	(0.021)	(0.022)	(0.110)	(0.116)	(0.118)	(0.118)
Mech share	0.077*	0.007	-0.139	-0.156	0.052	0.038	-0.051	-0.061	0.129	0.186	0.154	0.148
	(0.035)	(0.052)	(0.088)	(0.093)	(0.044)	(0.083)	(0.133)	(0.139)	(0.800)	(0.594)	(0.747)	(0.758)

Notes: N = 1,673. Standard errors are obtained through 200 bootstrap replications.
*** significant at the 0.1 percent level, ** significant at the one percent level, * significant at the five percent level.