UKCPR
University of Kentucky Center for Poverty Research

Discussion Paper Series
DP 2019-07

ISSN: 1936-9379

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May 2019

Preferred citation

Gundersen, C., Kreider, B., and Pepper, J. (2019, May). The intergenerational transmission of food security: A nonparametric bounds analysis. *University of Kentucky Center for Poverty Research Discussion Paper Series, DP2019-07*. Retrieved [Date] from http://ukcpr.org/research.

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The Intergenerational Transmission of Food Security:
A Nonparametric Bounds Analysis

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September 2018

Abstract: Using partial identification methods and data from the PSID, we analyze the causal transmission of food security across generations. Food security rates are positively correlated across generations; food security rates in 2015 are 20 points higher for respondents who grew up in households that were secure in 1999 than those growing up in food insecure households. Despite these strong associations, the intergenerational effect of growing up in a food secure household remains uncertain. . Assessing the degree of intergenerational transmission of food security is complicated by unobserved factors (e.g., human capital, health issues) that jointly influence whether a child resides in a food secure household and, subsequently, whether likely to be food secure as a young adult. Identifying causal transmission across generations requires addressing this important selection problem. In light of the ambiguities created by the selection problem, a number of alternative assumptions and estimates are presented. While under the weakest assumptions very little can be inferred, results derived under strong but plausible assumptions provide evidence that growing up in a food insecure household increases the probability of being food secure as a young adult.

Acknowledgements: This project was supported with a grant from the University of Kentucky Center for Poverty Research through funding by the U.S. Department of Agriculture, Food and Nutrition Service, cooperative agreement #58-5000-3-0066. The opinions and conclusions expressed herein are solely those of the author(s) and should not be construed as representing the opinions or policies of UKCPR or any agency of the Federal Government.

Executive Summary

While there has been extensive research on the causes and consequences of food insecurity (see, e.g., Gundersen, Kreider and Pepper, 2011), the literature has not formally studied its long-term intergenerational impacts. Recently, after an 11-year hiatus, the Panel Study of Income Dynamics (PSID) began asking respondents about food security. Using these new data from the PSID, we address this research lacuna by first documenting the intergenerational associations and then examining the intergenerational effects of growing up in a food secure household on the probability of being food secure as a young adult. In particular, we examine how the food security status of respondents between the ages of 17 and 30 in 2015 are affected by growing up in a food secure household in 1999, when the respondents were younger than 15 years old.

The answers to these questions are critical for policymakers and program administrators in the formulation of sound policy. If food security is not be transmitted across generations, then the benefits associated with food security (e.g., through SNAP participation) may be vital to the well-being of affected households, yet relatively transitory in nature. In contrast, if food security is transmitted across generations, then benefits should be interpreted more comprehensively as impacting households over much longer time horizons. This research also provides evidence useful for the USDA to meet its Strategic Goal 5, *Improve the Nation's Nutrition and Health.* In particular, this project addresses a key outcome noted therein: "The reduction and prevention of hunger by improved access to federal nutrition-assistance programs" https://www.ocfo.usda.gov/usdasp/pdf/sp05-07.pdf.

After describing the data from the PSID, our paper proceeds in two parts. First, we begin with a descriptive analysis exploring the intergenerational association in food security. Using descriptive statistics and linear probability regression models, we find that food security rates are positively correlated across generations; food security rates in 2015 are 20 points higher for respondents who grew up in households that were secure in 1999 than those growing up in food insecure households. Moreover, using basic linear probability models, we find the 1999 food security rate has a small positive interaction with income and a negative interaction with an African-American indicator variable. That is, African-American and poorer children in food secure households are somewhat less likely to be food secure as young adults.

Despite these strong and interesting associations, the causal intergenerational effect of growing up in a food secure household remains uncertain. Assessing the degree of intergenerational transmission of food security is complicated by unobserved factors (e.g., human capital, health issues) that jointly influence whether a child resides in a food secure household and, subsequently, whether likely to be food secure as a young adult. Identifying causal transmission across generations requires addressing this important selection problem.

Given the presence of unknown counterfactuals, the data alone can never reveal the degree to which food security is causally transmitted. In light of the ambiguities created by the selection problem, a key contribution of our project is to uncover what can be learned from the data when combined with various parametric and nonparametric assumptions.

We begin by estimating a standard linear instrumental variable regression model. In particular, state variation in program rules for the Supplemental Nutrition Assistance Program (SNAP), which are correlated with whether a household is food secure in 1999, are assumed to be mean independent of the latent indictors of food security in 2015. We use two such instrumental variables: whether the state SNAP rules require certain applicants to be fingerprinted and whether noncitizens are eligible to receive benefits. The resulting estimates are imprecise and vary across the instruments, with some suggesting a negative effect and others a positive effect.

Combining these traditional instruments with the linear model identifies the effect of growing up in a food secure household. Yet, we caution against drawing strong conclusions on the intergenerational effects based on these findings alone. The linear response model imposes a strong homogeneity restriction on the response function that seems unlikely to hold in practice. As is now widely recognized, the classical linear response model assumption is difficult to justify when considering factors such as food security that are thought to have heterogeneous effects.

In light of concerns about the credibility of the linear IV model, we further address the selection problem using a nonparametric partial identification framework introduced in Pepper (2000) and subsequent methodological advances in related applied research (e.g., Manski and Pepper, 2000; Kreider et al. 2012; Gundersen et al. 2017). Pepper (2000) used data from the PSID to examine the intergenerational transmission of participation in the Aid to Families with Dependent Children (AFDC, now TANF). These econometric methods translate easily to the proposed project given the conceptual similarity of the selection problem.

By layering successively stronger sets of assumptions, these partial identification methods allow us to make transparent how the strength of the conclusions are tied to the strength of the assumptions the researcher is willing to make. Under the weakest assumptions, there is very little that can be inferred about the intergeneration effects. The data alone cannot identify whether growing up in a food secure increases or decreases likelihood of being food secure as an adult. Under stronger but plausible assumptions, however, we estimate narrow bounds that imply a nonnegative intergenerational effect that may be negligible but may also be substantial; growing up in a food secure household increases the probability of being food secure as an adult. In particular, under our strongest nonparametric assumptions, we find that growing up in a food secure household in 1999 increases the likelihood of being food insecure in 2015 by as much as 18 points. In many cases, however, the estimated bounds include zero and are not statistically significant.

1. Introduction

Food security has become a leading measure of well-being in the United States. In response, an extensive literature on the determinants and consequences of food security has emerged.[1] However, due to a lack of data across time, this literature has not yet formally studied food security across generations. Using recently collected longitudinal data from the Panel Study of Income Dynamics (PSID), we fill this gap by first documenting intergenerational associations and then by studying potential causal intergenerational impacts. In particular, we examine how the food security status of young adults between the ages of 17 and 30 in 2015 are affected by growing up in a food secure household in 1999, when respondents were younger than 15 years old.

The answers to these questions are critical for policymakers and program administrators in the formulation of sound policy. If food insecurity is not transmitted across generations, then the benefits associated with alleviating food insecurity (e.g., through Supplemental Nutrition Assistance Program (SNAP) participation[2]) may be vital to affected households, yet relatively transitory in nature. In contrast, if food insecurity is transmitted across generations, then the benefits should be interpreted more comprehensively as impacting households over much longer time horizons. This research also provides evidence useful for the USDA to meet its Strategic Goal 5, *Improve the Nation's Nutrition and Health.* In particular, this project addresses a key outcome noted therein: "The reduction and prevention of hunger by improved access to federal nutrition-assistance programs" https://www.ocfo.usda.gov/usdasp/pdf/sp05-07.pdf.

[1] For reviews of the former see, e.g., Gundersen et al. (2011) and Gundersen and Ziliak (2014) and for reviews of the latter see Gundersen and Ziliak (2015).
[2] For more on the role of SNAP in improving food security see, e.g., Gundersen et al. (2017), Swann (2018), and references therein.

After describing the data from the PSID in Section 2, our analysis proceeds in two parts. First, we begin with a descriptive analysis exploring the intergenerational association in food security. Using descriptive statistics and linear probability regression models, we find that food security rates are positively correlated across generations; food security rates in 2015 are twenty points higher for respondents who grew up in households that were secure in 1999 than those growing up in food insecure households. Moreover, using basic linear probability models, we find the 1999 food security rate has a small positive interaction with income and a negative interaction in with variable reflecting whether a child is African-American. That is, African-American and poorer children in food secure households are less likely to be food secure as young adults.

Despite these substantial intergenerational associations, the effects of growing up in a food insecure household are uncertain. Assessing the degree of intergenerational transmission of food insecurity is complicated by unobserved factors (e.g., human capital, health issues) that jointly influence whether a child is food insecure and, subsequently, whether likely to be food insecure as an adult. Given the presence of unknown counterfactuals, the data alone can never reveal the degree to which food insecurity is causally transmitted.

In light of the ambiguities created by this selection problem, in Section 4 we uncover what can be learned from the data when combined with various parametric and nonparametric assumptions. We begin by estimating a standard linear instrumental variable regression model. In particular, state variation in 1999 program rules for SNAP, which are correlated with whether a household is food secure in 1999, are assumed to be mean independent of the latent indictors of food security in 2015. We use two instrumental variables: whether the state SNAP rules require applicants to be fingerprinted and whether noncitizens are eligible to receive benefits. The resulting estimates are imprecise and vary across the instruments, with some suggesting a negative effect and others a positive effect.

Combining these traditional instruments with the linear model identifies the effect of growing up in a food insecure household. Yet, we caution against drawing strong conclusions on the intergenerational effects based on these findings alone. As is now widely recognized, the linear response model imposes a strong homogeneity restriction on the response function that seems unlikely to hold in practice. The classical linear response model assumption is difficult to justify when considering factors such as food security that are thought to have heterogeneous effects.

In light of concerns about the credibility of the linear IV model, we further address the selection problem using a nonparametric partial identification framework introduced in Pepper (2000) and subsequent methodological advances in related applied research (e.g., Manski and Pepper, 2000; Kreider et al. 2012; Gundersen et al. 2017). In particular, we consider three different types of assumptions:

i. A *Monotone Treatment Selection* (MTS) assumption (Manski and Pepper, 2000) that unobserved factors associated with being food secure as an adult are positively associated with food security status as a child;

ii. A *Monotone Treatment Response* (MTR) assumption that, on average, growing up in a food secure household would not reduce the chances of being food secure as an adult; and

iii. *Monotone Instrumental Variable* (MIV) and *Instrumental Variable* assumptions (Manski and Pepper, 2000) that the latent probability of food security either varies monotonically with certain observed covariates (e.g., household income) or is mean independent of certain covariates (e.g., state SNAP rules).

By layering successively stronger sets of assumptions, these partial identification methods allow us to make transparent how the strength of the conclusions are tied to the strength of the assumptions the researcher is willing to make. Under the weakest assumptions, there is very little that can be inferred about the intergeneration effects. The data alone cannot identify whether growing up in a food secure increases or decreases likelihood of being food secure as an adult. Under stronger but plausible assumptions, however, we estimate narrow bounds that imply a non-negative intergenerational effect that may be negligible but may also be substantial; growing up in a food secure household increases the probability of being food secure as an adult. In particular, under our strongest nonparametric assumptions, we find that growing up in a food secure household in 1999 increases the likelihood of being food secure in 2015, as a young adult, by as much as 18 points. In general, however, the estimated bounds include zero and are not statistically significant.

In Section 5, we draw conclusions. Overall, the results are mixed. The intergenerational associations are strong, suggesting a substantial and statistically significant positive correlation across generations. However, the causal effects of growing up in a food secure household are less certain. The estimates from the linear IV models are highly sensitive to the instrument and are statistically insignificant. Under the strongest partial identification assumptions, we find the intergenerational effects may substantial but, in general, we cannot reject the zero null hypothesis.

2. Data and Descriptive Analysis

We use intergenerational data from the PSID. In 1968, this longitudinal survey began interviewing a national sample of nearly 4,800 households that overrepresented low income households and non-white households. Each year since, the heads of these families and any other families formed by members or descendants of the original 1968 sample (i.e., split-off families) have been surveyed. After an 11-year hiatus, the PSID began collecting information on food security. This provides a unique opportunity to study intergenerational relationships in food security. In particular, our analysis compares data on the food security status of young adults in 2015 with their food security status in 1999.[3] Our sample includes 4993 "PSID" young adults between the ages for 17 and 30 in 2015.

Our two central variables of interest measure the food security status of the respondent's household when she is a child in 1999 and then later when she is a young adult in 2015. Food security is defined over a 12-month-period using a series of 18 questions. Each question is designed to capture some aspect of food insecurity and, for some questions, the frequency with which it manifests itself. Examples include: "I worried whether our food would run out before we got money to buy more" (the least severe outcome); "Did you or the other adults in your household ever cut the size of your meals or skip meals because there wasn't enough money for food?" and "Did a child in the household ever not eat for a full day because you couldn't afford enough food?" (the most severe outcome). We use these 18 questions to construct a comparison

[3] Although these data are well suited for examining the intergenerational transmission of food security, there exists substantial sample attrition in the PSID. In this analysis, we maintain the assumption that attrition is exogenous, or unrelated, to food security status in 1999 and 2015. There is some empirical support for this assumption. Specifically, Fitzgerald, Gottschalk, and Moffitt (1994) suggest that attrition in the PSID does not affect the estimated relationships in intergenerational welfare participation studies. If, however, unobserved factors jointly affect both attrition and intergenerational food security, then these data will provide inconsistent estimates of the population relationships of interest.

of children in food secure households (two or fewer affirmative responses) with children in food-insecure households (three or more affirmative responses).

Table 1 displays the means and standard deviations of the variables used in this study by the respondents' food security status in 1999. The estimates in this table and elsewhere in the analysis are weighted to account for the survey design. For each respondent, we observe information on respondent's gender (female), race (black), age, 1999 household income relative to the poverty line, and the household's SNAP participation status in 1999. We also observe two instrumental variables characterizing the 1999 state SNAP rules, one indicating whether the state requires applicants to be fingerprinted and one indicating whether noncitizens are eligible for benefits. In Section 3, we will use these variables as instruments to learn the intergenerational effect of growing up in a food secure household.

Most importantly, we see that young adults who grew up in food secure households in 1999 have substantially higher food security rates in 2015 than those growing up in food insecure households. In particular, 2015 food security rate is 86.2% for respondents who resided in food secure households in 1999, nearly 20 points higher than the food security rate of 66.0% among those who grew up in food insecure households. Likewise, respondents residing in food secure households having notably higher income levels than those in food insecure households.

To explore further these intergenerational associations, in Table 2 we present the coefficient estimates from a series of linear probability regression models of the 2015 food security rate. The first column replicates the results displayed in Table 1 by reporting estimates from a simple bivariate regression of the food security in 2015 on food security in 1999. As seen in Table 1, the 2015 food security rate of young adults is 0.202 points higher for those who grew up in food secure households than those who grew up in food insecure households. When the full set of covariates are included in the regression, the difference falls to 0.156 (see column 3). In column 4, we present estimates that allow for food security in 1999 to interact with race and income. These results imply a positive interaction with income. Children growing up in food secure households with income over two times the poverty line are 5.5% more likely to be food secure in 2015 than those growing up in relatively low income households. The estimates also suggest a negative interaction with the black indicator variable. That is, black children in food secure households are 10.1% less likely to be food secure as young adults as non-black food secure children.

3. Research Methods

Despite the substantial positive intergenerational associations in food insecurity, the effects of growing up in a food insecure household are uncertain. Assessing the degree of intergenerational transmission of food insecurity is complicated by the selection problem; unobserved factors (e.g., human capital, health issues) might jointly influence whether a child is food insecure and, subsequently, whether likely to be food insecure as an adult.

In light of the ambiguities created by the selection problem, a key contribution of our project is to uncover what can be learned from the data when combined with various parametric and nonparametric assumptions about the selection process.

Our interest is in learning the average treatment effect (ATE) of growing up in a household that is food secure as opposed to a food insecure, defined as

$$ATE(X) = P[Y(1) = 1 \mid X] - P[Y(0) = 1 \mid X] \tag{1}$$

where Y is an indicator of food security as an adult, $Y(1)$ and $Y(0)$ represent the potential outcome if the adult were to have been food secure or insecure as a child, respectively, and X represents conditioning on subpopulations of interest. This ATE is positive if, on average, growing up in a food secure household increases the probability of being food secure as an adult. In what follows, we suppress conditioning on X for ease of notation.

The mean response function in Equation (1) is not identified by the data alone since $Y(1)$ is counterfactual for all adults who grew up in food insecure households and $Y(0)$ is counterfactual for all adults who grew up in food secure households. To address this selection problem, we build on Pepper (2000) and other recent work by Kreider et al. (2012) and Gundersen et al. (2017) by applying a range of middle ground assumptions that restrict relationships between food security as a child, food security as an adult, and observed covariates. In particular, we consider the identifying power of three common monotonicity assumptions.

First, a Monotone Treatment Selection (MTS) assumption (Manski and Pepper, 2000) places structure on the selection mechanism through which adults become food secure. Given what we know about the transmission of other well-being measures (e.g., income, poverty, health), unobserved factors associated with being food secure as an adult are likely to be positively associated with food security status as a child. Let z indicate if the respondent grew up in a food secure household. Then the MTS assumption is formalized as follows:

$$P[Y(t)=1 \mid Z=1] \geq P[Y(t)=1 \mid Z=0] \text{ for } t=1,0. \tag{2}$$

That is, young adults who grew up in food secure environments as a child have a higher latent prevalence of being food secure as an adult than those who grew up in food insecure households.

Second, the Monotone Instrumental Variable (MIV) assumption (Manski and Pepper, 2000) formalizes the notion that the latent probability of food security, $P[Y(t)=1]$, varies monotonically with certain observed covariates. Let v be the observed monotone instrumental variable such that

$$u_1 \leq u \leq u_2 \Rightarrow P[Y(t)=1 \mid v=u_1] \leq P[Y(t)=1 \mid v=u] \leq P[Y(t)=1 \mid v=u_2]. \tag{3}$$

Following Kreider et al. (2012), we assume that the ratio of a households income to the poverty threshold in 1999 is an MIV; the latent food security rate for adults weakly increases with family's income to the poverty-line ratio.

A stronger but related assumption is that SNAP benefit rules for the county/state of residence when the respondent was a child in 1999 is a standard instrumental variable, v, that is associated with food security as a child but mean independent of the potential outcome as an adult. Formally,

$$P[Y(t)=1] = P[Y(t)=1 \mid v=u] \tag{4}$$

for all values of the instrument. Using information on the 1999 state SNAP rules, we apply two instrumental variables: one that indicates whether state SNAP rules require applicants to be fingerprinted in any part of the state and one that indicates whether noncitizens are eligible to receive benefits. These instruments are related to the 1999 food security rates, but they assumed to be otherwise mean independent of the latent food security rates in 2015.

Without additional assumptions, these conditional probabilities in (3) and (4) are not identified but can be bounded. See Manski and Pepper (2000), Pepper (2000), and Kreider et al. (2012). Yet, when the IV assumption is combined with the linear response model, the ATE is point identified. In addition to presenting partial identification results under the IV and MIV assumptions, we also provide results found using a more conventional linear IV model that is point identified.

Finally, as in Pepper (2000), we will also consider the identifying power of a Monotone Treatment Response (MTR) assumption:

$$P[Y(1)=1 \mid Z] \geq P[Y(0)=1 \mid Z]. \tag{5}$$

That is, growing up in a food secure household would not reduce the probability of being food secure as an adult.

4. Results and Discussion

We begin by presenting results from the conventional linear IV model, where state SNAP rules in 1999 as used as instruments. The results from linear IV model are presented in Table 3. The results are mostly statistically insignificant and highly variable, with some estimates suggesting a negative effect and others a positive effect. In particular, the estimated ATE ranges from −0.323 when using the indicator for whether noncitizens are eligible for benefits as an instrument to 0.088 when using the indicator for whether the state requires applicants to be fingerprinted as an instrument. With one exception, all of the estimates are statistically insignificant.

Combining these traditional instruments with the linear model identifies the effect of growing up in a food secure household. Not only are the estimates highly variable across the different instruments, but the linear response model imposes the strong homogeneity restriction on the response function that seems unlikely to hold in practice. As is now widely recognized, the classical linear response model assumption is difficult to justify when considering factors such as food security that are thought to have heterogeneous effects. In fact, when evaluating the partial identification results below, we find evidence that the linear model can be rejected in this application.

Next, we turn to the partial identification estimates. Before examining a full set of results, it is useful to see how the bounds are constructed. To do this, Table 4 display the basic moments along with the partial identification bounds on the response probabilities and the average effect of growing up in a food secure household on the probability of being food secure as a young adult. The bounds are estimated by replacing population probabilities with the corresponding sample probabilities.[4] To focus attention on the identification problem arising from the unobservability of counterfactual outcomes, we display only point estimates of the bounds in Table 4. These estimates account for identification uncertainty and abstract away from the additional layer of uncertainty associated with sampling variability. In Table 5, we present selected results that account for both identification uncertainty and sampling variability.

In total, 85.3 percent of respondents report growing up in a food secure household in 1999, with the remaining 14.7 percent in food insecure households. Reported food security rates in 2015 are 86.2 percent for respondents who grew up in food secure household and 66.0 percent for those who grew up in insecure households (see Table 1).

Given these moments, it follows that the food security rate would lie within [0.736, 0.882] if all respondents grew up in food secure households, and within [0.097, 0.950] if all grew up in food insecure households. That the data alone imply narrow bounds on the response probability if all households were to be food secure reflects the fact that over eighty percent of respondents actually grew up in food secure households. In contrasts, since only 14.7% of respondents grew up in food insecure households, the bounds if all households were to be food insecure are relatively wide; the data do not reveal much information about this potential outcome.

Using the bounds on the treatment response probabilities, we can then generate bounds on the ATE. Abstracting from sampling variability, the data alone reveal that the intergenerational effect lies within the range [-0.215, 0.785] (using 0.736-0.950 and 0.882-

[4] To estimate the MIV bounds, we first divide the sample into ten income-to-poverty ratio groups. To find the MIV bounds, we take the appropriate weighted average of the plug-in estimators of lower and upper bounds across the groups. As discussed in Manski and Pepper (2000), this MIV and IV estimator is consistent but biased in finite samples. We employ Kreider and Pepper's (2007) modified estimator that accounts for the finite sample bias using a nonparametric bootstrap correction method.

0.097). As formalized in Manski (1990), these worst-case bounds have a width of 1 and do not identify the sign of the ATE.[5]

Although these worst-case bounds are wide and cannot sign the ATE, they provide a natural starting point for the analysis by revealing what the data alone reveal. A model should be rejected if the resulting estimates lie significantly outside of the no-assumptions bounds, while estimates lying within these bounds cannot be rejected without additional information or assumptions. In fact, notice that the estimates from linear bivariate regression model where the noncitizen indicator is used as an instrumental variable lies outside of the worst-case bounds. In particular, the point estimate of -0.323 is notably less than the lower bound estimate of -0.215. Although the difference is not statistically significant, the fact that this point estimate lies substantially outside of the worst-case bounds suggests that this linear IV model may be invalid.

To address uncertainty reflected in the worst case bounds, researchers commonly impose some form of the exogenous selection assumption (see Table 2). If one assumes selection is exogenous, then the ATE is point identified and estimated to equal 0.202; growing up in a food secure household increases the probability of being food secure as a young adult. The problem, however, is that the exogenous selection assumption is untenable. Unobserved factors associated with growing up in a food secure household in 1999 are almost certainly related to unobserved factors associated with food security in 2015.

Rather than focusing on these two polar extremes (no assumptions vs. exogenous selection), it is useful to apply middle ground assumptions. Continuing with Table 4, we assess what can be identified under the MTS, (M)IV, and MTR assumptions described above. Under the MTS assumption alone, the upper bound on the ATE falls to 0.202. When the MTS

[5] While these worst-case assumption bounds leave much uncertainty about the ATE, note that the data alone (if accurately measured) have already eliminated half the uncertainty compared with the pre-data knowledge that the ATE can lie anywhere within $[-1, 1]$.

assumption is additionally combined with the income MIV assumption, the bounds on the ATE shrink to [-0.215, 0.075]. When further combined with the MTR assumption, the lower bound increases to zero. Thus, given these three monotonicity restrictions, we learn that growing up in a food secure household weakly increases food security rates by no more than 0.073 percentage points. Finally, when combining the MTS-MTR assumption with an IV assumption that state laws on whether noncitizens can receive benefits are mean independent of the response probabilities, the bounds of [0.028, 0.131] are strictly positively. Thus, under this model, the estimates imply that growing up in a food secure household increases the probably of being food secure as a young adult by at least 0.028 and as much as 0.131.

Table 5 displays a more complete set of estimated bounds and confidence intervals on the ATE under range of different assumptions. Results are presented for the full sample as well as the subsample of respondents who grew up in household with income less than two-times the poverty line. We present Imbens-Manski (2004) confidence intervals that cover the true value of the ATE with 90% probability.

When combining the MTS, MTR and (M)IV assumptions, the estimated bounds are generally positive although the 90% confidence intervals often include zero. For the full sample, the estimated bounds under the income MIV assumption are [0.000, 0.075], implying that the true intergenerational effect is nonnegative and cannot exceed 7.5%. The estimated bounds under the IV assumptions are strictly positive, with the lower bounds ranging from 1.2% when using the fingerprint instrument, to 2.8% when using the noncitizen instrument, to 11.8% when using both instruments. Notice that in this last model, the lower bound exceeds the upper bound of 0.075. Since the confidence intervals do not overlap, we do not take this as evidence that joint MTS-MTR-IV model is invalid. Rather, is seems that this model nearly point identifies the ATE to be around 0.10. For the lower income subsample, the bounds are strictly positive under the

MTS-MTR-MIV assumption and under the model whether the noncitizen indicator is an instrument. For the other IV models, the bounds include zero.

While there is much uncertainty about the exact intergenerational effect, the estimates found under the MTS-MTR-(M)IV assumptions suggests a positive intergenerational effect. Growing up in a food secure household increases the probably of being food secure as a young adult by at least a couple of points and perhaps much more. Of course, this finding should be interpreted with some caution. As seen in Table 5, the results are sensitive to the underlying assumptions and all three assumptions are needed to sign the ATE. Moreover, even when combining the assumptions, many of the confidence intervals include zero.

5. Conclusion

As the first study to formally analyze the causal transmission of food security across generations, this paper contributes to the food insecurity, food assistance, health, nutrition, and broader poverty literatures. Our approach, which formalizes the basic intergenerational identification problem associated with unknown counterfactuals, provides researchers with a statistical framework for thinking about food security over time. In particular, by successively layering stronger nonparametric and parametric identifying assumptions into the model, the approach makes transparent how assumptions on the selection processes shape inferences. The partial identification approach is especially well-suited for this application where it is difficult to justify the assumption of a homogenous treatment effect across observationally-similar households.

Under the weakest assumptions, there is very little that can be inferred about the intergenerational effects. The data cannot identify whether growing up in a food secure increases or decreases likelihood of being food secure as an adult. Under stronger but plausible assumptions, however, we estimate narrow bounds on average treatment effects which suggest a positive intergenerational effect; growing up in a food secure household increases the probability of being food secure as an adult.

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Table 1: Weighted Means and Standard Deviations by 1999 Food Security Status

	Full Sample	Food Secure in 1999	Food Insecure in 1999
Food Secure 2015	0.832 (0.374)	0.862 (0.345)	0.660 (0.474)
Female	0.490 (0.354)	0.490 (0.500)	0.494 (0.500)
Black	0.152 (0.359)	0.144 (0.352)	0.194 (0.396)
Age 2015	23.61 (3.75)	23.64 (3.74)	23.46 (3.81)
Income to poverty ratio 1999	3.68 (4.82)	4.08 (5.11)	1.40 (1.05)
SNAP Participant 1999	0.138 (0.344)	0.101 (0.302)	0.350 (0.477)
Finger\\print_IV	0.319 (0.466)	0.295 (0.456)	0.459 (0.499)
Noncitizens Eligible_IV	0.229 (0.421)	0.211 (0.408)	0.338 (0.473)
N	4993	4217	776

Note: Standard deviations are in parenthesis. The weighted probability of food security in 1999 is 0.853 (0.353). The fingerprint IV is an indicator for whether the 1999 state SNAP rules required fingerprinting of applicants in any part of the state. The noncitizen IV is an indicator for whether the 1999 state SNAP rules allowed noncitizen to receive benefits.

Table 2: Linear Regression of 2015 Food Security on 1999 Food Security:
Coefficient Estimates and Standard Errors (weighted)

Full Sample, N = 4993

	Model 1	Model 2	Model 3	Model 4
FS_1999	0.202	0.198	0.156	0.145
	(0.015)	(0.015)	(0.015)	(0.019)
Female		-0.017	-0.016	-0.017
		(0.010)	(0.010)	(0.010)
Black		-0.065	-0.025	0.064
		(0.014)	(0.015)	(0.034)
Age		-0.002	-0.001	-0.001
		(0.004)	(0.004)	(0.004)
Age*Age		0.0001	0.0000	0.000
		(0.0003)	(0.0003)	(0.004)
SNAP_99			-0.126	-0.108
			(0.016)	(0.017)
IPR_99			0.005	0.003
			(0.001)	(0.001)
FS*Black				-0.101
				(0.038)
FS*IPR2				0.055
				(0.014)
R2	0.037	0.041	0.059	0.062

NOTE: Standard errors are in parentheses. FS*Black and FS*IPR2 are variables interacting the FS_1999 variable (food secure in 1999) with the black and IPR2 variables, respectively, where the IP2 variable indicates whether the 1999 income to poverty ratio exceeds 2.

Table 3: Linear Instrumental Variable Regression of 2015 Food Security on 1999 Food Security: Coefficient Estimates and Standard Errors (weighted)

Full Sample, N = 4993

	Fingerprint	Fingerprint	Noncitizen	Noncitizen	Fingerprint & Noncitizen	Fingerprint & Noncitizen
FS_1999	0.058 (0.119)	0.088 (0.115)	**-0.323** (0.154)	-0.223 (0.139)	-0.079 (0.112)	-0.034 (0.106)
Female		-0.017 (0.010)		-0.018 (0.011)		-0.017 (0.011)
Black		-0.071 (0.016)		-0.086 (0.017)		-0.076 (0.016)
Age		-0.002 (0.004)		-0.001 (0.004)		-0.002 (0.004)
Age*Age		0.0001 (0.0003)		0.00004 (0.0003)		0.0001 (0.0003)
First Stage	-0.094 (0.011)	-0.097 (0.011)	-0.090 (0.012)	-0.097 (0.012)	-0.072 (0.012) -0.052 (0.013)	-0.073 (0.012) -0.059 (0.013)

Note: The fingerprint IV is an indicator for whether the 1999 state SNAP rules required fingerprinting of applicants in any part of the state. The noncitizen IV is an indicator for whether the 1999 state SNAP rules allowed noncitizen to receive benefits.

Table 4: Summary Analysis

Observed Moments:

Food security rate in 1999: $P(FS_{99} = 1) = 0.853$

Food security rate in 2015: $P(FS_{15} = 1) = 0.832$

Food security rate in 2015 among those food secure in 1999: $P[FS_{15}(1) = 1 | FS_{99} = 1] = 0.862$

Food security rate in 2015 among those food insecure in 1999: $P[FS_{15}(0) = 1 | FS_{99} = 0] = 0.660$

Treatment Response Probabilities: $P[FS_{15}(j) = 1], j = 1,0$

I. Worst-Case: $P[FS_{15}(j) = 1 | FS_{99} \neq j] \in [1,0]$

$0.736 = 0.862*0.853 + 0*(1-0.853) \leq P[FS_{15}(1) = 1] \leq 0.862*0.853 + 1*(1-0.853) = 0.882$

$0.097 = 0.660*(1-0.853) + 0*0.853 \leq P[FS_{15}(0) = 1] \leq 0.660*(1-0.853) + 1*0.853 = 0.950$

II. MTS: $P[FS_{15}(j) = 1 | FS_{99} = 1] \geq P[FS_{15}(j) = 1 | FS_{99} = 0]$

$0.736 = 0.862*0.853 + 0*(1-0.853) \leq P[FS_{15}(1) = 1] \leq 0.862*0.853 + 0.862*(1-0.853) = 0.862$

$0.660 = 0.660*(1-0.853) + 0.660*0.853 \leq P[FS_{15}(0) = 1] \leq 0.660*(1-0.853) + 1*0.853 = 0.950$

ATE: $P[FI(1)=1] - P[FI(0)=1]$[1]

I. Worst-Case: $-0.215 = 0.736 - 0.950 \leq ATE \leq 0.882 - 0.097 = 0.785$

II. MTS: $-0.215 = 0.736 - 0.950 \leq ATE \leq 0.862 - 0.660 = 0.202$

MTS + MIV: $-0.215 \leq ATE \leq 0.075$

MTS + MIV + MTR: $0.000 \leq ATE \leq 0.075$

MTS + IV: $-0.195 \leq ATE \leq 0.131$

MTS + IV + MTR: $0.028 \leq ATE \leq 0.131$

Note:

1. The MIV is the income to poverty ratio. The IV is an indicator for whether the 1999 state SNAP policy allowed income eligible noncitizens to receive benefits.

Table 5: Estimated Bounds and Standard Errors[a] on the ATE Under Different Assumptions

	Full Sample	Low Income Sample[b]
No Assumptions	[-0.215, 0.785]	[-0.344, 0.656]
	(-0.228, 0.798)	(-0.370, 0.681)
MTS	[-0.215, 0.202]	[-0.344, 0.161]
	(-0228, 0.248)	(-0.370, 0.218)
MTR	[0.000, 0.785]	[0.000, 0.656]
	(0.000, 0.798)	(0.000, 0.681)
MTS+ MTR + (M)IV		
Income MIV[c]	[0.000, 0.075]	[0.030, 0.103]
	(0.000, 0.119)	(0. 009, 0.117)
Fingerprint IV[d]	[0.012, 0.181]	[0.000, 0.154]
	(0.000, 0.223)	(0.000, 0.185)
Noncitizen IV[e]	[0.028, 0.131]	[0.035, 0.087]
	(0.000, 0.212)	(0.000, 0.181)
Fingerprint & Noncitizen IV	[0.118, 0.075]	[0.000, 0.054]
	(0.001, 0.224)	(0.000, 0.176)

Note:

a. 90% Imbens-Manski confidence intervals (CI) using 1,000 pseudosamples are in parentheses.
b. The low income sample is restricted to respondents whose1999 income to poverty ratio is less than 2.
c. The income MIV is a measure of the 1999 income to poverty ratio.
d. The fingerprint IV is an indicator for whether the 1999 state SNAP rules required fingerprinting of applicants in any part of the state.
e. The noncitizen IV is an indicator for whether the 1999 state SNAP rules allowed noncitizen to receive benefits.