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The Lifecycle Transmission of Food Security

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Abstract: Using data from the Panel Study of Income Dynamics, we provide the first evidence on the causal transmission of food security from childhood to young adulthood. A causal assessment is complicated by unobserved factors that jointly influence food security status as a child and subsequently as a young adult. Using nonparametric partial identification methods, we find that growing up in a food secure household increases the chances of being food secure as a young adult by between 5.7 and 10.5 percentage points, or at least 7.9%. Among nonwhites, we bound this effect to lie within the narrow range of 5.9 and 6.7 percentage points, or at least 8.6%.

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1. Introduction

Food security, or having reliable access to adequate food necessary to sustain an active and healthy life, has become a leading metric of well-being in the United States. In 2023, more than 47 million Americans resided in households facing food insecurity (Rabbitt et al., 2024). Of these, 14 million were children. Beyond the inability to procure enough food, food insecurity is correlated with numerous adverse health outcomes, higher healthcare expenditures (Berkowitz et al., 2018), and lower educational attainment (Heflin et al., 2022).[1] These adverse socioeconomic and health consequences may have long-term effects such that growing up in a food insecure household increases the likelihood of being food insecure as a young adult.

This study provides the first evidence on the causal transmission of food security from childhood to adulthood. Our key contribution is to account for the endogenous selection problem that arises when unobserved factors such as parents' attitudes towards public assistance, work and family, cognitive ability, education, addictions, neighborhood, and emotional well-being may influence both whether a child is in a food secure household and subsequent food security status as a young adult. Given the presence of unknown counterfactuals (e.g., what would have happened to a child growing up in a food insecure household had the household instead been food secure), the data alone can never reveal the degree to which food insecurity is causally transmitted.

Most studies of the determinants of food insecurity and its consequences have concentrated over very short time horizons, generally within a year or less (see, e.g., Gundersen and Ziliak (2015, 2018)). The literature following respondents over extended time horizons has been sparse. The closest precedents to our analysis are the studies by Millimet and Roy (2015) and McDonough and Millimet (2024). The former study provides a partial identification analysis of the causal impact of being food secure as a young child on future health (rather than food security) as an older child. The

[1] Adverse outcomes include cardiovascular disease (Nikolaus et al., 2022), aggression and anxiety (Hatsu et al., 2022), diabetes (Reid et al., 2022), behavioral problems (King, 2018), chronic pain (Tham et al., 2023), depression (Berkowitz et al., 2022), suicide ideation (Brown et al., 2022), and worse oral health (Giannoni & Grignon, 2022).

latter study analyzes intra- and inter-lifecycle patterns of food security using data from the PSID accounting for the possibility that households may misreport food security. Because McDonough and Millimet (2024) do not address the possible endogeneity of food security, they do not draw causal conclusions.[2,3]

Using longitudinal data from the Panel Study of Income Dynamics (PSID), we build on this literature by first documenting lifecycle associations and then assessing potential causal lifecycle impacts. In particular, we examine how the food security status of young adults between the ages of 17 and 30 in 2015 was affected by their food security status in 1999, when they were younger than 15 years old.[4] We focus on children who lived in households with incomes not exceeding 200% of the poverty line in 1999, along with presenting parallel sets of results for households across the income spectrum.[5]

Our goal is to infer the average effect of being food insecure in at least one year as a child on food insecurity as an adult. Providing direct evidence about the lifecycle transmission of food insecurity is critical for policymakers and program administrators in the formulation of sound policy. If food insecurity is not transmitted across the lifecycle, then the benefits associated with alleviating food insecurity – e.g., through increasing resources to households or keeping food prices low – may be vital to affected households, yet relatively transitory in nature. In contrast, if food insecurity is transmitted across the lifecycle, then these efforts should be interpreted more comprehensively as impacting households over much longer time horizons.

Food insecurity during childhood might causally affect food insecurity in adulthood through a variety of mechanisms. For example, the negative health consequences associated with food

[2] Other related work includes, for example, Corman et al. (2022), Heflin et al. (2022), Insolera (2022), Tiehen et al. (2020), and Hamersma and Kim (2025).
[3] Our analysis assumes food security is accurately reported. If there are measurement errors, McDonough and Millimet's (2024) results suggest our approach will provide informative bounds on the causal effect as long as the degree of misreporting is not severe – especially under their maintained assumption that respondents may overstate but rarely understate their food security.
[4] This time horizon is similar to the one used in McDonough and Millimet (2024).
[5] Much of the empirical literature on food security has focused on poor and near poor households (Gundersen and Ziliak, 2018).

insecurity in childhood could lead to worse work labor markets outcomes and lower income as an adult. This lower income could then lead to a higher likelihood of food insecurity. Parallel to much of the literature examining intergenerational transmission of socioeconomic outcomes (e.g., Pepper's (2000) analysis of the intergenerational transmission of government assistance receipt), we cannot identify mechanisms through which food security as a child is transmitted to adulthood. Nevertheless, our methods place informative lower and upper bounds on the average causal effects under plausible monotonicity assumptions.

After describing the PSID data in Section 2, our analysis proceeds in two parts. First, we begin with a descriptive analysis exploring the lifecycle association in food security. We find that food security rates are positively correlated across the lifecycle. In our low-income sample, young adults who were in a food secure household in 1999 were 16.1 percentage points more likely than their food insecure counterparts to be food secure as young adults. This difference rises to 20 percentage points for the full sample. These associations are reinforced in standard linear and instrumental variable regressions.

In light of the ambiguities created by the selection problem, in Section 3 we evaluate the average treatment effect (ATE) of being in a food secure household as a child in 1999 through the use of the nonparametric partial identification framework introduced in Manski (1990) and Pepper (2000), along with subsequent methodological advances in related applied research (e.g., Manski and Pepper, 2000; Kreider et al., 2012; Gundersen et al., 2017). This framework is especially well suited for studying lifecycle effects (see Pepper, 2000) where it is difficult to find credible exogenous instrumental variables and, as now widely recognized, the strong homogeneity restrictions in the linear simultaneous equations model seem unlikely to hold in practice. Our partial identification methods place lower and upper bounds on the ATE that allow for selection based on unobserved attributes.

Using this partial identification framework, we apply three different types of assumptions. First, we consider the identifying power of 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. Next, we consider a *Monotone Instrumental Variable* (MIV) assumption (Manski and Pepper, 2000) that the latent probability of food security varies monotonically with certain observed covariates (e.g., household income) or a stronger *Instrumental Variable* (IV) assumption that the latent probability is mean independent of certain covariates (e.g., state-specific Supplemental Nutrition Assistance Program (SNAP) rules such as fingerprinting requirements). Finally, we consider a *Monotone Treatment Response* (MTR) assumption (Manski, 1997) that being in a food secure household for at least one year as a child would not reduce the chances of being food secure as an adult, at least on average.

We present empirical results in Section 4. 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, very little can be inferred about the lifecycle effects. The data alone cannot identify whether being in a food secure household for at least one year increases or decreases likelihood of being food secure as an adult. Under stronger but plausible assumptions, however, we estimate narrower bounds on the ATE that imply substantial lifecycle effects; being in a food secure household for at least one year increases the chances of being food secure as a young adult at least 7.9%. Section 5 concludes.

2. Data and Descriptive Analysis

We use lifecycle data from the PSID. In 1968, this longitudinal survey began interviewing a national sample of about 4,800 households that overrepresented low-income households and nonwhite households. [6] Since then, 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. In 1999, the PSID began asking questions about food insecurity and did so in 2001 and 2003 as well.

[6] Throughout this analysis, the estimates are weighted to account for the survey design.

The questions were removed in the 2005 wave but reinstated in the 2015 PSID. This provides a unique opportunity to study lifecycle relationships in food security. We do so by comparing data on the food security status of young adults in 2015 with their previous food security status in 1999.[7] Our full 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 as a child in 1999 and then later as a young adult in 2015. Food security is defined over a 12-month period based on a set of 18 questions used to ascertain official food insecurity rates in the U.S. (Rabbitt et al., 2024). 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).[8] Based on official USDA definitions, we use these 18 questions to construct a comparison of children in food secure households (two or fewer affirmative responses) with children in food insecure households (three or more affirmative responses).

For our primary sample of 2,249 young adults who grew up in households with income not exceeding 200% of the poverty line, Table 1 displays weighted means and standard deviations of the variables used in this study. For each respondent, we observe gender, race, age, SNAP participation status, and household income as a child relative to the poverty line (adjusted for family size and composition). As described in the next section, we treat the ratio of household income to the poverty line as a child as an MIV. Specifically, we assume that the latent probability of being food secure as

[7] One concern with using these longitudinal data is that attrition may be endogenous; poor health and socio-economic outcomes caused by childhood exposure to food insecurity may lead to nonrandom attrition. In this analysis, we maintain the assumption that attrition is exogenous, or unrelated, to food security status in 1999 and 2015. Fitzgerald et al. (1994) suggest that attrition in the PSID does not affect the estimated relationships in intergenerational welfare participation studies.
[8] For the full set of questions, see, e.g., Rabbitt et al. (2023).

an adult is weakly increasing with household income when the respondent was young. We also consider two common state-level IVs: in 1999, (i) whether SNAP applicants are subject to fingerprinting in all, some, or no parts of the state and (ii) whether noncitizens are eligible for SNAP benefits. Such IVs capturing state-specific SNAP policies are commonly used in the food assistance literature (e.g., Gregory and Deb, 2015; Ratcliffe et al., 2011; Yen et al., 2008). In the parts of our analysis that employ IVs, we assume that fingerprinting and citizenship eligible rules in 1999 affect food security though their influence on applications for SNAP benefits when the respondent is young but have no direct effect on subsequent food security when older.[9] Because the mean independence assumption is much stronger than the income monotonicity assumption, our preferred results do not rely on the state-level IVs.

Table 1 shows that young adults who lived in a food secure household in 1999 have substantially higher food security rates as adults than their counterparts who were food insecure in 1999. In particular, the 2015 food security rate is 78.9% for respondents who resided in food secure households in 1999, 16.1 points higher than the food security rate of 62.7% among those who were in a food insecure household in 1999.[10] Respondents who were in a food secure households also have notably higher income levels on average than those who were food insecure for at least one year. Throughout our analysis, online appendix tables provide parallel results for the sample of young adults who grew up in households of all income levels (N = 4,993). In the full sample, the food security rate is 20.2 points higher for respondents who lived in a food secure household in 1999.

To further explore these lifecycle associations, in Table 2 we present coefficient estimates from a series of linear probability regression models of the 2015 food security rate. The first column

[9] We also considered other SNAP eligibility rules as IVs, such as whether a vehicle was exempt from the assets test and the average recertification period, but these potential IVs did not have significant identifying power in our application.

[10] Allowing for misclassified food security status in up to 20% of their sample, McDonough and Millimet (2024) find under their strongest assumptions that the intergenerational probability of an adult child's household being food secure in 2017 conditional on the parents' household being food secure in 1999 is at least 77%, and conditional on being very low food secure in 1999 is at most 73%. As one form of potential misclassification, it is possible that some of the lifecycle association could be driven by cultural differences in the approach to answering survey questions.

replicates the results displayed in Table 1 by reporting estimates from a simple bivariate regression of food security in 2015 on food security in 1999. Consistent with Table 1, the coefficient on being food secure as a child in Model 1 is 0.161, reflecting that the rate of food security as a young adult is 16.1 points higher for those who grew up in food secure households than those who grew up in food insecure households.

This difference falls slightly to 14.7 points in Model 4 when the full set of covariates is included in the regression. In this model, we allow food security as a child to interact with race. In our sample of low-income households, the estimated interaction is slightly negative but statistically insignificant. For the full sample (online appendix Table A2), we find that nonwhite children who were food secure in 1999 are 3.6% less likely to be food secure 15 years later than their white counterparts who also were food secure in 1999, a result that is strongly statistically significant. For the full sample, we also include an interaction with an indicator for income above twice the poverty threshold. Children were in food secure households with income higher than twice the poverty line are 5.7% more likely to be food secure as young adults than those growing up in lower income households, a statistically significant finding.

3. Research Methods

Despite the substantial positive lifecycle associations in food insecurity, the effect of growing up in a food insecure household remains uncertain. Assessing the degree of lifecycle transmission of food insecurity is complicated by the selection problem; unobserved factors (e.g., parents' attitudes towards welfare, work and family, addictions, and emotional well-being) 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 paper is to uncover what can be learned from the data when combined with various assumptions to address the selection process.

Our interest is in learning the average treatment effect of being in a food secure household as opposed to a food insecure household in 1999, defined as

$$ATE(X) = P[FS_{15}(1) = 1 \mid X] - P[FS_{15}(0) = 1 \mid X] \quad (1)$$

where FS_{15} is an indicator of food security as an adult in 2015, $FS_{15}(1)$ and $FS_{15}(0)$ represent the (latent) 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.[11] This ATE is positive if, on average, being in a food secure household in 1999 increases the probability of being food secure 16 years later. For our main analysis, we condition on the subpopulation of respondents who grew up in households with income no more than twice the poverty line. We also present separate sets of results that condition on whether the respondent is white or nonwhite. 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 $FS_{15}(1)$ is counterfactual for all adults who were in a food insecure household in 1999and $FS_{15}(0)$ is counterfactual for all adults who were in a food secure household in 1999. To address this selection problem, we build on Pepper (2000) and more 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. For example, as noted above, unobserved factors such as parents' cognitive ability, education, addictions, and emotional well-being may influence both whether a child

[11] In a usual regression framework, the inclusion of additional observed covariates is motivated as a means of controlling for other factors that may influence food security outcomes; omitting relevant explanatory variables could lead to biased estimates. Omitted variable bias does not arise in our framework, however, because there are no regression disturbance orthogonality conditions to be met. Conditioning on covariates in Equation (1) serves only to define population groups of interest, and our problem is well-defined regardless of how the groups are specified (Pepper, 2000).

resides in a food secure household and subsequent food security status as a young adult. Let $FS_{99} = 1$ indicate that the respondent was in a food secure household in 1999, with $FS_{99} = 0$ otherwise. Then the MTS assumption is formalized as follows:

$$P[FS_{15}(t)=1 \mid FS_{99}=1] \geq P[FS_{15}(t)=1 \mid FS_{99}=0] \text{ for } t=1,0. \quad (2)$$

That is, young adults who were food secure as a child have a higher latent likelihood of being food secure as an adult than those who were food insecure.

Second, the *Monotone Instrumental Variable* (MIV) assumption (Manski and Pepper, 2000) formalizes the notion that the latent probability of food security, $P[FS_{15}(t)=1]$, varies monotonically with certain observed covariates. Let v be an observed monotone instrumental variable such that

$$u_1 \leq u \leq u_2 \Rightarrow P[FS_{15}(t)=1 \mid v=u_1] \leq P[FS_{15}(t)=1 \mid v=u] \leq P[FS_{15}(t)=1 \mid v=u_2]. \quad (3)$$

There is a positive association between income and food security. For example, in 2023, households with incomes under 185% of the poverty line had a food insecurity rate of 33.5% while those with incomes above this line had a food insecurity rate of 7.5% (Rabbitt et al., 2024). Thus, following Kreider et al. (2012), we treat the ratio of a household's income to the poverty threshold in 1999 as an MIV; we assume that, on average, the latent probability of being food secure as an adult weakly rises with family income relative to the poverty line as a child.

As discussed earlier, we also separately consider the identifying power of two standard IVs commonly employed in the food assistance literature based on SNAP state eligibility rules. In these cases, we assume that a SNAP benefit rule in 1999 is associated with household food security as a child but mean-independent of the potential outcome as an adult. Formally,

$$P[FS_{15}(t)=1] = P[FS_{15}(t)=1 \mid v=u] \quad (4)$$

for all values of the instrument. In particular, the IV assumption is that a SNAP fingerprinting or citizenship requirement in 1999 affects the likelihood of being food secure when the respondents where children but is otherwise unrelated to their food security as adults. Without additional assumptions, these conditional probabilities in Equations (3) and (4) are not identified but can be bounded.[12] See Manski and Pepper (2000), Pepper (2000), and Kreider et al. (2012). Because the IV mean-independence assumption is much stronger than the MIV monotonicity assumption, our preferred results rely only on the MIV assumption.

Finally, the *Monotone Treatment Response* (MTR) assumption (Manski, 1997; Pepper, 2000) formalizes the idea that, on average, being food secure as a child would not harm the chances of being food secure as an adult:

$$P[FS_{15}(1)=1\,|\,Z] \;\geq P[FS_{15}(0)=1\,|\,Z]. \tag{5}$$

It is difficult to imagine that being food insecure as a child would improve the chances of being food secure as an adult. As noted above, food insecurity is known to cause adverse socioeconomic and health outcomes (see footnote 1 and Heflin et al., 2022) which arguably lead to longer run adverse outcomes including food insecurity. Moreover, being in a food insecure household may perpetuate long-term food insecurity if information and stigma costs have been reduced. While the MTR assumption precludes a strictly negative ATE in Equation (1) by construction, it allows for the possibility that alleviating food insecurity as a child would have strong beneficial effects on adult food security, mild beneficial effects, or perhaps no effects at all on average. Additionally, the MTR assumption does not preclude the possibility that being food insecure as a child could lead to better food security outcomes for some respondents. It only rules out such a pattern on average. The usefulness of the MTR assumption does not lie in weakly identifying the sign of the ATE by construction, but rather in helping us isolate the magnitude of the ATE when combined with other assumptions.

[12] As discussed in Manski and Pepper (2000), the plug-in 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.

4. Empirical Results

Before examining the full set of results, we show how the bounds are constructed. Starting with the basic moments, Table 3 displays the partial identification bounds on the response probabilities as well as the ATEs under the various nonparametric assumptions. The bounds are estimated by replacing population probabilities with the corresponding sample probabilities. To focus attention on the identification problem arising from the unobservability of counterfactual outcomes, we display only the estimates of the bounds in Table 3 and not corresponding confidence intervals. These estimates account for identification uncertainty and abstract away from the additional layer of uncertainty associated with sampling variability. In Table 4, we present results that account for both identification uncertainty and sampling variability and, in some cases, separately by race.

As shown in Table 3, 68.1% of respondents were in a food secure household in 1999. In 2015, food security rates were 78.9% for respondents who were in a food secure household and 62.7% for those who were in food insecure households (see also Table 1).

Using these moments and the law of total probability, it follows that the food security rate would lie within [0.537, 0.856] if all respondents were in food secure households and within [0.200, 0.881] if all were in food insecure households. That the data alone imply relatively narrow bounds on the response probability if all children were to have been food secure, $P[FS_{15}(1)=1]$, reflects the fact that over two-thirds of respondents were in food secure households. In contrast, since only about a third of respondents were in food insecure households, the bounds on $P[FS_{15}(0)=1]$ if all children were to have been food insecure are relatively wide; the data do not reveal much information about this potential outcome.

Using these bounds on the treatment response probabilities, we then generate bounds on the ATE. Abstracting from sampling variability, the data alone reveal that the lifecycle effect lies within the range [–0.344, 0.656] (using 0.537 – 0.881 and 0.856 – 0.200). As formalized in Manski (1990), these worst-case bounds have a width of 1 and always include 0, so they can never identify the sign of the ATE.[13]

To address uncertainty reflected in the worst-case bounds, researchers commonly impose some form of the exogenous selection assumption (recall Table 2). If one assumes selection is exogenous, then the ATE is point identified and estimated to equal 0.161, the difference in conditional probabilities $P(FS_{15}=1 \mid FS_{99}=1) - P(FS_{15}=1 \mid FS_{99}=0)$; being 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 being 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 3, we assess what can be identified under the MTS, MIV, IV, and MTR assumptions described above. Under the MTS assumption alone, the upper bound on the ATE falls from 0.656 to 0.161. When the MTS assumption is additionally combined with the income MIV assumption, the bounds on the ATE shrink to [-0.297, 0.105]. The lower bound naturally rises to zero under the MTR assumption (not shown). Combined with the data, these three monotonicity restrictions establish that being in a food secure household weakly increases the food security rate by no more than 10.5 percentage points.

Finally, when combining the MTS-MTR assumption with the income MIV assumption, the estimated bounds $[0.0567, 0.105]$ imply that being in a food secure household in 1999 increases the probably of being food secure 16 years later by at least 5.7 percentage points and at most 10.5

[13] 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. In fact, the ATE point estimate from a linear IV regression model (not shown) using either the fingerprint or noncitizen IV lies outside of the worst-case bounds. Specifically, the ATE point estimate of -0.437 using the fingerprint IV and -0.406 using the noncitizen IV for the main sample are notably outside the [–0.344, 0.656] worst-case ATE bounds in Table 3. That these point estimates lie substantially outside of the worst-case bounds suggests that this linear IV model is invalid. Corresponding IV estimates for the full sample are even further outside the worst-case bounds. Estimates from these linear IV models are available from the authors upon request.

percentage points.[14] This estimated bound implies that alleviating food insecurity as a child would improve the chances of being food secure as an adult by at least $0.0567 / 0.716$, or 7.9%.[15]

Table 4 summarizes the estimated ATE bounds across a range of assumptions, along with Imbens-Manski (2004) confidence intervals that cover the true value of the ATE with 95% probability. Results are presented for the primary sample of relatively low-income respondents, as well as separately by race. Table A4 in the online appendix provides parallel sets of results for the full sample across the income spectrum.

Combining the MTS, MTR, and MIV income assumptions in Table 4, the estimated bounds $[0.0567, 0.105]$ restrict the ATE to be strictly positive even after accounting for sampling variability. After conditioning the analysis by race, we are barely able to sign the ATE for the subpopulation of whites, finding a lower bound of just one-tenth of a percentage point – a result not statistically significantly different than zero – but an upper bound of 13.6 percentage points. Thus, we cannot rule out the possibility that there are no lifecycle effects or that the effects are substantial. In part, the statistically insignificant finding reflects the relatively small number of respondents who are white (N = 698). For nonwhites (N=1,546), however, we estimate the ATE to lie within the narrow range of 5.9 and 6.7 percentage points. Since the estimated upper bound on $P[FS_{15}(0)=1]$ for nonwhites is 0.689, our estimates imply that alleviating food insecurity as a child would improve the chances of being food secure as an adult by at least $0.0594 / 0.689$, or 8.6%. We estimate somewhat wider bounds using the standard IVs.

For the nonwhite population, we also estimate narrow bounds for the lifecycle effect across the full income spectrum (Table A4). In this case, the ATE is estimated to lie within 2.0 and 4.4 percentage points, significantly different from zero after accounting for sampling variability. In this

[14] Results for the fingerprint and noncitizen IVs are similar, providing somewhat less identifying power on the lower bound while somewhat further restricting the upper bound.

[15] For a randomly chosen respondent, the percentage change improvement in the chances of being food secure as an adult when food insecurity is alleviated as a child is given by $\{P[FS_{15}(1)=1]-P[FS_{15}(0)=1]\} / P[FS_{15}(0)=1]$, or $ATE / P[FS_{15}(0)=1]$, which is at least as large as $ATE^{LB} / P[FS_{15}(0)=1]^{UB}$. The estimated upper bound on $P[FS_{15}(0)=1]$ is 0.716. Thus, the percentage change is at least 0.079 = 0.0567/0.716.

case, we can also identify the ATE as at least slightly positive (a lower bound of 0.8 percentage points) and statistically significant for the white population using the fingerprint IV, but not with our preferred income MIV.

While there is uncertainty about the exact lifecycle effect, the estimates found under the MTS-MTR-(M)IV assumptions suggest a positive lifecycle transmission of food security. We find that being in a food secure household as a child increases the probably of being food secure as a young adult.

5. Conclusion

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

Like in Pepper's (2000) analysis of the intergenerational transmission of government assistance receipt, we do not identify mechanisms through which food security as a child is transmitted to adulthood. Nevertheless, our methods place informative bounds on average causal effects under plausible monotonicity assumptions. Under our weakest assumptions, there is very little that can be inferred about the lifecycle effects. The data cannot identify whether growing up food secure increases or decreases likelihood of being food secure as an adult. By combining a monotone instrumental variable with monotone treatment selection and monotone treatment response assumptions, however, we estimate strong positive impacts. Among respondents who grew up in low-income households, we find that growing up in a food secure household increases the probability of being food secure as a young adult between 5.7 and 10.5 percentage points, or at least 7.9%. For nonwhites, we are able to precisely bound the effect to lie between 5.9 and 6.7 percentage points, or at least 8.6%.

As noted in the introduction, previous work has examined various aspects of the transmission of child food insecurity to subsequent adult food insecurity using the PSID. Corman et al. (2022) considered the impact of being exposed to welfare reform in childhood on adult food insecurity. They find that children born after (rather than before) the introduction of welfare reform has lower probabilities of food insecurity as adults. Heflin et al. (2022) examined the relationship between food insecurity as a child and educational attainment as an adult. They find that children exposed to food insecurity have lower levels of educational attainment than children not exposed to food insecurity. Tiehen et al. (2020) compared the food insecurity rates in the CPS with those of the PSID in the two time frames considered in this paper. They found that the trends are similar between the two data sets albeit the rates of food insecurity are slightly lower in the PSID, especially in the earlier time periods.

Each of these studies provides important insights into how to understand past food insecurity effects current outcomes and, conversely, the impacts of past outcomes on food insecurity. A fourth paper, Hamersma and Kim (2025), has a primary emphasis on the mediating effect of education on the relationship between food insecurity as a child and as an adult. Their work does, though, have an estimate, net of other factors, of the association between food insecurity as a child and as an adult. They find that children in food insecure households (i.e., in their usage, low food secure or very low food secure households) have a 9.3 percentage point higher probability of food insecurity in adulthood. Their sample is for the full population while our main estimates are for households with incomes less than 200% of the poverty line. In one of our alternative specifications (Appendix Table A3) we use all incomes, the range for our estimate after imposing MTS, MTR, and the income MIV is 2.5 to 3.8 percentage points which doesn't include their estimate. However, their estimated coefficient derived from an OLS estimate, 0.093, is within the 95% confidence interval of our estimate of 0.130 in our fully specified OLS estimates for all income levels (Appendix Table A2).

The paper posing the central question of our paper is McDonough and Millimet (2024). They do not seek to address endogeneity and, instead, are concerned with measurement error. The result comparable to ours that they emphasize in the introduction is that the conditional probably of being food secure as an adult in 2017 after being food secure as a child in 1999 is at least 88% under the assumption of a misclassification rate of 20%. Like Hamersma and Kim, their primary analytical sample is for the full population. As seen in Appendix Table A1, the food security rate in 1999 was 85.3%. We estimate that the resulting probability of being food secure in 2015 would be between 87.8% and 89.1%, a range which includes the estimate of McDonough and Millimet (2024).

A vast literature has documented factors that influence child food insecurity. Lower incomes, residing in a single-parent household, residing in a household with someone with a disability, living in chaotic situations, having a parent with poor financial management skills, and many other factors are associated with childhood food insecurity (see, e.g., Gundersen and Ziliak, 2018). One approach known to help vulnerable households overcome these challenges is the provision of resources to obtain food. The largest food assistance program, SNAP, has been shown in multiple studies to improve food security outcomes, including for children (see Smith and Gregory, 2023, for a review). The National School Lunch Program, designed specifically for school age children, has also been shown to be effective in combatting food insecurity (see Gundersen et al., 2012).

Policies designed to alleviate food security have been justified largely based on short-term benefits. Our findings suggest that such policies are likely to also have impacts persisting many years into the future. When considering the effects of various policies on the wellbeing of children, the longer-term benefits associated with improved chances of being food secure as an adult should be factored into any thorough cost-benefit calculation.

As an example, consider what happened from 2021 to 2022. In 2021, there were 63.2 million food secure children but in 2022 there were 59.2 million, a fall of 4 million children. The results of this paper for the full population indicates that there will then be between 100,000 and 150,000 fewer food secure adults in 2037.

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Table 1. Weighted Means and Standard Deviations, Main Sample[a]

	Full Sample	Food Secure in 1999	Food Insecure in 1999
Food Secure in 2015	0.737 (0.440)	0.789 (0.408)	0.627 (0.484)
Food Secure in 1999[†]	0.681 (0.466)		
Nonwhite	0.442 (0.497)	0.427 (0.495)	0.475 (0.500)
Female	0.492 (0.500)	0.482 (0.500)	0.512 (0.500)
Age in 2015	23.5 (3.73)	23.5 (3.72)	23.3 (3.73)
SNAP participant[†]	0.329 (0.470)	0.287 (0.452)	0.420 (0.494)
Income-to-poverty ratio, MIV[†]	1.10 (0.541)	1.17 (0.540)	0.955 (0.510)
Fingerprint IV: statewide[†]	0.228 (0.419)	0.165 (0.371)	0.359 (0.480)
Fingerprint IV: select areas[†]	0.188 (0.390)	0.198 (0.398)	0.166 (0.373)
Fingerprint IV: none[†]	0.586 (0.493)	0.637 (0.481)	0.475 (0.500)
Noncitizen IV[†]	0.273 (0.445)	0.219 (0.414)	0.386 (0.487)
N	2,244	1,646	598

[a] Grew up in a household with income no more than twice the poverty line

[†] Measured in 1999 when the respondent was a child

Table 2. Linear Regression of 2015 Food Security on 1999 Food Security (Weighted), Main Sample[†]

	Model 1	Model 2	Model 3	Model 4
Constant	0.627 (0.0162)[‡]	0.170 (0.388)	0.239 (0.387)	0.238 (0.388)
Food Secure in 1999	0.161 (0.0197)	0.160 (0.0197)	0.145 (0.0200)	0.147 (0.0272)
Female		-0.0325 (0.0183)	-0.028 (0.0183)	-0.0289 (0.0183)
Nonwhite		0.0128 (0.0185)	0.0271 (0.0187)	0.0285 (0.0324)
Age in 2015		0.0354 (0.0338)	0.0303 (0.0337)	0.0302 (0.0337)
Age in 2015 squared		-0.000644 (0.000721)	-0.000533 (0.000719)	-0.000533 (0.000719)
SNAP participant in 1999			-0.0824 (0.0214)	-0.0822 (0.0215)
Income-to-poverty ratio in 1999			0.0178 (0.0187)	0.0178 (0.0187)
Food secure in 1999*Nonwhite				-0.002232 (0.0396)
R^2	0.03	0.03	0.04	0.04
N = 2,244				

[†] Grew up in a household with income no more than twice the poverty line

[‡] Standard errors in parentheses

Table 3. Summary Analysis, Main Sample (N = 2,244)[a]

Observed Moments:

Food security rate in 2015:	$P(FS_{15}=1)=0.737$
Food security rate in 1999:	$P(FS_{99}=1)=0.681$
Food security rate in 2015 among those food secure in 1999:	$P(FS_{15}=1 \mid FS_{99}=1)$
	$=P[FS_{15}(1)=1 \mid FS_{99}=1]=0.789$
Food security rate in 2015 among those food insecure in 1999:	$P(FS_{15}=1 \mid S_{99}=0)$
	$=P[FS_{15}(0)=1 \mid FS_{99}=0]=0.627$

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

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

$$0.537=0.789*0.681+0*(1-0.681)\ \leq P[FS_{15}(1)=1]\leq\ 0.789*0.681+1*(1-0.681)=0.856$$

$$0.200=0.627*(1-0.681)+0*0.681\ \leq P[FS_{15}(0)=1]\leq\ 0.627*(1-0.681)+1*0.681=0.881$$

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

$$0.537=0.789*0.681+0*(1-0.681)\ \leq P[FS_{15}(1)=1]\leq\ 0.789*0.681+0.789*(1-0.681)=0.789$$

$$0.627=0.627*(1-0.681)+0.627*0.681\ \leq P[FS_{15}(0)=1]\leq\ 0.627*(1-0.681)+1*0.681=0.881$$

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

Worst-Case:	–0.344 = 0.537 – 0.881 $\leq ATE \leq$ 0.856 – 0.200 = 0.656
MTS:	–0.344 = 0.537 – 0.881 $\leq ATE \leq$ 0.789 – 0.627 = 0.161
MTS + Income MIV:	–0.297 $\leq ATE \leq$ 0.105
MTS + Income MIV + MTR:	0.0567 $\leq ATE \leq$ 0.105
MTS + Fingerprint MIV:	–0.300 $\leq ATE \leq$ 0.0831
MTS + Fingerprint MIV + MTR:	0.0311 $\leq ATE \leq$ 0.0831
MTS + Noncitizen IV:	–0.295 $\leq ATE \leq$ 0.0865
MTS + Noncitizen IV + MTR:	0.0338 $\leq ATE \leq$ 0.0865

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[a] Grew up in a household with income no more than twice the poverty line

Table 4. Estimated Bounds on the Lifecycle Transmission of Food Security,

Main Sample (N = 2,244)[a]

		All (N = 2,224)		White (N = 698)		Nonwhite (N = 1,546)	
		LB	UB	LB	UB	LB	UB
Exogenous	p.e.[b]	[0.161,	0.161]	[0.171,	0.171]	[0.151,	0.151]
	CI[c]	[0.106,	0.220]	[0.098	0.250]	[0.070	0.231]
Worst Case	p.e.	[-0.344,	0.656]	[-0.335,	0.665]	[-0.356,	0.644]
	CI	[-0.364	0.676]	[-0.363	0.693]	[-0.384	0.672]
MTS	p.e.	[-0.344,	0.161]	[-0.335,	0.171]	[-0.356,	0.151]
	CI	[-0.364	0.207]	[-0.363	0.233]	[-0.384	0.213]
MTR	p.e.	[0.000,	0.656]	[0.000,	0.665]	[0.000,	0.644]
	CI	[0.000	0.676]	[0.000	0.693]	[0.000	0.672]
MTS + MTR	p.e.	[0.000,	0.161]	[0.000,	0.171]	[0.000,	0.151]
	CI	[0.000	0.207]	[0.000	0.233]	[0.000	0.213]
MTS+ MTR	p.e.	[0.0567,	0.105]	[0.0010,	0.136]	[0.0594,	0.0670]
+ Income MIV	CI	[0.0157	0.133]	[0.000	0.195]	[0.0118	0.120]
MTS+ MTR	p.e.	[0.0311,	0.0831]	[0.0642,	0.120]	[0.0253,	0.0752]
+ Fingerprint IV	CI	[0.0033	0.161]	[0.000	0.163]	[0.0050	0.130]
MTS+ MTR	p.e.	[0.0338,	0.0865]	[0.0695,	0.0934]	[0.000,	0.0723]
+ Noncitizen IV	CI	[0.0005	0.164]	[0.000	0.181]	[0.000	0.150]

Notes:

[a]Household income as a child at most twice the poverty line

[b]Point estimates of the lower and upper bounds

[c]Imbens-Manski confidence intervals

Online Appendix Tables

Appendix Table A1. Weighted Means and Standard Deviations, All Income Levels

	Full Sample	Food Secure in 1999	Food Insecure in 1999
Food Secure in 2015	0.832 (0.374)	0.862 (0.345)	0.660 (0.474)
Food Secure in 1999†	0.853 (0.353)		
Nonwhite	0.260 (0.439)	0.232 (.422)	0.428 (0.495)
Female	0.490 (0.354)	0.490 (0.500)	0.494 (0.500)
Age in 2015	23.6 (3.75)	23.6 (3.74)	23.56 (3.81)
SNAP participant†	0.138 (0.344)	0.101 (0.302)	0.350 (0.477)
Income-to-poverty ratio, MIV†	3.68 (4.82)	4.08 (5.11)	1.40 (1.05)
Fingerprint IV: statewide†	0.166 (0.373)	0.141 (0.349)	0.312 (0.463)
Fingerprint IV: select areas†	0.153 (.360)	0.154 (.361)	0.147 (0.354)
Fingerprint IV: none†	0.681 (0.466)	0.705 (.456)	0.541 (0.499)
Noncitizen IV†	0.229 (0.421)	0.211 (0.408)	0.338 (0.473)
N	4,993	4,217	776

†Measured in 1999 when the respondent was a child

Appendix Table A2. Linear Regression of 2015 Food Security on 1999 Food Security (Weighted), All Income Levels

N = 4,993	Model 1	Model 2	Model 3	Model 4
Constant	0.660 (0.0136)†	0.588 (0.221)	0.629 (0.219)	0.622 (0.219)
Food Secure in 1999	0.202 (0.015)	0.192 (0.0148)	0.153 (0.0152)	0.130 (0.0214)
Female		-0.0170 (0.0104)	-0.0163 (0.0103)	-0.0167 (0.0103)
Nonwhite		-0.0484 (0.0120)	-0.0199 (0.0112)	0.00396 (0.0271)
Age in 2015		0.00657 (0.0192)	0.00601 (0.0190)	-0.00535 (0.0190)
Age in 2015 squared		0.0000932 (0.000408)	0.0000973 (0.000404)	-0.0000819 (0.000404)
SNAP participant in 1999			-0.129 (0.0159)	-0.111 (0.0165)
Income-to-poverty ratio in 1999			0.00466 (0.00111)	0.00460 (0.001)
Food secure in 1999*Nonwhite				-0.0316 (0.00117)
Food secure in 1999*Income-to-poverty ratio in 1999 exceeds 2				0.0574 (0.0140)
R^2	0.04	0.04	0.06	0.06
N = 4,993				

† Standard errors in parentheses

Appendix Table A3. Summary Analysis, All Income Levels, N = 4,993

Observed Moments:

Food security rate in 2015:	$P(FS_{15}=1)=0.832$
Food security rate in 1999:	$P(FS_{99}=1)=0.853$
Food security rate in 2015 among those food secure in 1999:	$P(FS_{15}=1 \mid FS_{99}=1)$ $=P[FS_{15}(1)=1 \mid FS_{99}=1]=0.862$
Food security rate in 2015 among those food insecure in 1999:	$P(FS_{15}=1 \mid S_{99}=0)$ $=P[FS_{15}(0)=1 \mid FS_{99}=0]=0.660$

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

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

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

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

II. MTS: $P[FS_{15}(j)=1 \mid FS_{99}=1] \ge P[FS_{15}\left(j\right)=1 \mid FS_{99}=0]$

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

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

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

Worst-Case:	–0.215 = 0.736 – 0.950 $\le ATE \le$ 0.882 – 0.097 = 0.785
MTS:	–0.215 = 0.736 – 0.950 $\le ATE \le$ 0.862 – 0.660 = 0.202
MTS + Income MIV:	–0.196 $\le ATE \le$ 0.0376
MTS + Income MIV + MTR:	0.0249 $\le ATE \le$ 0.0376
MTS + Fingerprint MIV:	–0.177 $\le ATE \le$ 0.132
MTS + Fingerprint MIV + MTR:	0.0104 $\le ATE \le$ 0.132
MTS + Noncitizen IV:	–0.195 $\le ATE \le$ 0.131
MTS + Noncitizen IV + MTR:	0.0287 $\le ATE \le$ 0.131

Appendix Table A4. Estimated Bounds on the Lifecycle Transmission of Food Security, All Income Levels, N = 4,993

		All (N = 2,224)		White (N = 698)		Nonwhite (N = 1,546)	
		LB	UB	LB	UB	LB	UB
Exogenous	p.e.[a]	[0.202,	0.202]	[0.214,	0.214]	[0.158,	0.158]
	CI[b]	[0.158,	0.245]	[0.153	0.276]	[0.0889	0.227]
Worst Case	p.e.	[-0.215,	0.785]	[-0.185,	0.815]	[-0.298,	0.702]
	CI	[-0.224	0.795]	[-0.197	0.826]	[-0.318	0.723]
MTS	p.e.	[-0.215,	0.202]	[-0.185,	0.214]	[-0.298,	0.158]
	CI	[-0.224	0.236]	[-0.197	0.262]	[-0.318	0.212]
MTR	p.e.	[0.000,	0.785]	[0.000,	0.815]	[0.000,	0.702]
	CI	[0.000	0.795]	[0.000	0.826]	[0.000	0.723]
MTS + MTR	p.e.	[0.000,	0.202]	[0.000,	0.214]	[0.000,	0.158]
	CI	[0.000	0.236]	[0.000	0.262]	[0.000	0.212]
MTS+ MTR + Income MIV	p.e.	[0.0249,	0.0376]	[0.000,	0.0325]	[0.0204,	0.0438]
	CI	[0.000	0.101]	[0.000	0.106]	[0.0069	0.0796]
MTS+ MTR + Fingerprint IV	p.e.	[0.0104,	0.132]	[0.0079,	0.0756]	[0.0275,	0.181]
	CI	[0.000	0.204]	[0.0058	0.136]	[0.000	0.211]
MTS+ MTR + Noncitizen IV	p.e.	[0.0287,	0.131]	[0.0049	0.0636]	[0.0523,	0.152]
	CI	[0.000	0.203]	[0.000	0.157]	[0.0130	0.229]

Notes:

[a]Point estimates of the lower and upper bounds

[b]Imbens-Manski confidence intervals