Aging out of WIC and Child Nutrition: Evidence from a Regression Discontinuity Design

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Abstract

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) is the third largest food assistance program in the United States. Child participants lose WIC in the month following their fifth birthday. We exploit this exogenous program rule and find much larger decreases in diet quality for those who have yet to transition into federally-subsidized school meal programs. Decreases are mainly driven by lower consumption of healthier WIC-targeted foods, particularly among children who are prone to lower-quality diets. We find no effects on food insecurity reports within the household.

Key Words: WIC, Diet Quality, Food Security, Regression discontinuity design, Instrumental variable quantile regression

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1 Introduction

Healthy eating in childhood is important: it promotes proper growth and development, prevents a variety of adverse health outcomes (e.g., childhood obesity and dental caries) (Epstein et al., 2001, 2008; Nunn et al., 2009), and leads to better cognitive performance (e.g., Glewwe et al., 2001; Frisvold, 2015). Moreover, dietary habits are learned early and persist into adulthood (Benton, 2004; Birch, 1999; Dovey et al., 2008). Subsequently, the consumption of a lower quality diet in the long term is associated with four of the top ten major causes of death in the United States (Jemal et al., 2008): cardiovascular disease (Nicklas et al., 2012), type 2 diabetes, stroke (Chiuve et al., 2012), and several types of cancer (Bosire et al., 2013; Nicklas et al., 2012; Reedy et al., 2008; Shahril et al., 2013). Because low-income children are particularly susceptible to nutritional deficiencies, (see, for example, Alaimo et al., 2001; Currie, 2005), a variety of federal food assistance programs in the United States (U.S.) target such children.

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) is the third largest federal food assistance program in the U.S., providing over 7 million individuals with nearly $5.6 billion in benefits in 2017 (FNS-USDA, 2018a). The goal of WIC is to improve the health and nutritional well-being of a particular subset of the U.S. population: low-income pregnant and postpartum women, infants, and children up to the age of 5 years old. WIC's reach across this U.S. subpopulation as a whole is fairly wide: over half of all infants receive WIC benefits, as do roughly thirty percent of all pregnant and postpartum women, and thirty percent of all children up to age 5 (FNS-USDA, 2018a).

This study focuses on the child beneficiaries of WIC, who make up half of all WIC participants (FNS-USDA, 2018a), and we examine WIC's impact on nutritional outcomes. According to federal WIC eligibility criteria, children remain eligible for WIC up to the age of 5 years, and WIC eligibility ends in the month following their fifth birthday. We use this program rule as our source of identification and ask, how does aging out of WIC affect child nutrition? In particular, we estimate the aging-out effect on several measures of diet quality and quantity, as well as spillover effects to other household members via a food security questionnaire.

A body of literature evaluates the extent to which WIC accomplishes its goal in improving the health and nutritional well-being of participants (for reviews of this literature see, Currie, 2003, and Colman et al., 2012). There are, however, some limitations and gaps. First, despite the fact that children (aged 1 to 4 years) comprise over half of all WIC participants, much of the literature has focused on birth- and pregnancy-related outcomes (e.g., Bitler and Currie, 2005; Joyce et al., 2005; Figlio et al., 2009; Brodsky et al., 2009; Yunzal-Butler et al., 2010; Hoynes et al., 2011; Kreider et al., 2018) and breastfeeding practices (e.g., Chatterji et al., 2002; Bitler and Currie, 2005; Jiang et al., 2010). Second, the current literature focuses on estimating the *average* effects of WIC participation. While average effects provide useful information for many policy applications, it may limit what we can learn about the heterogeneity in the effects of WIC. Conceptually, losing access to a relatively homogeneous benefit package may have differing effects within a heterogenous population due to, for example, parental and environmental factors. Finally, most studies have employed research designs that do not fully account for self-selection into WIC. We address each of these issues in this study.

A major hurdle in examining the program effects of WIC is a credible identification strategy. Existing studies have used a variety of non-experimental approaches to account for non-random selection into WIC. Some restrict their samples to narrowly defined WIC participants and non-participants and employ regression analyses to control for a detailed set of personal characteristics (e.g., Bitler and Currie, 2005; Joyce et al., 2005). This approach will mitigate some selection biases, but not all.[1] A separate set of studies have used maternal fixed-effects

[1]Bitler and Currie (2005) limit their analysis to women who had Medicaid-funded deliveries. Joyce et al. (2005), on the other hand, restricted their sample to women on Medicaid who had initiated prenatal care during the first four months of pregnancy. Both studies acknowledge the aforementioned limitations, while advancing the literature on the nature of selection bias. Specifically, Bitler and Currie (2005)

on samples of siblings to control for unobserved family characteristics (Kowaleski-Jones and Duncan, 2002; Chatterji et al., 2002; Foster et al., 2010). As noted previously (Bitler and Currie, 2005; Hoynes et al., 2011), this approach could again lead to underestimation of program effects due to spillovers between participating and non-participating siblings, and/or changes in family conditions between births. A final set of studies have used geographic variation in eligibility and benefit rules across states as instrumental variables for WIC participation (e.g., Brien and Swann, 2001; Chatterji et al., 2002). While WIC is administered at the state level, there is little geographic variation in eligibility and benefit levels. Thus, these instruments have limited power in predicting WIC participation, once again leading to downward biases.[2]

In this study, we exploit an exogenous WIC program rule for identification: children remain eligible for WIC up to the age of 5 years and in the month following their fifth birthday (i.e., at the age of 61 months) WIC eligibility ends. This strategy is known as a regression discontinuity design (RDD), which has been used to study the impact of WIC on food insecurity (Arteaga et al., 2016) and the effects of the School Breakfast Program on cognitive achievement (Frisvold, 2015). Our study differs from the Arteaga et al. (2016) approach in that we examine a more diverse set of outcomes in addition to food security, estimate distributional impacts, and use a so-called "fuzzy" RDD to account for the self-selection nature into WIC. We also go to great lengths to examine how school meal programs may bridge the gap between going off WIC and starting school, which we discuss next.

An important identifying assumption in RDD is that observed and unobserved determinants of the outcome vary continuously around the exogenous policy cutoff. In the present context, we must therefore assume there are no other policies or structural changes occurring at an age of 61 months that could influence our nutritional outcomes. If this assumption

suggest participants negatively self-select into WIC which would lead to estimates that are downward biased.

[2]For example, Bitler and Currie (2005) report F-stats of roughly 3-4 in their first-stage regressions, which is well below the convention value of 10, indicating weak identification.

holds, our estimates can be interpreted as an aging-out-of-WIC effect. However, we recognize that most children start kindergarten some time after turning 5 years old. Importantly, it has been shown that low-income children experience an increase in dietary quality when participating in school meal programs, and such increases are especially large for the most nutritionally-disadvantaged children (Smith, 2017).

In order to better understand the interplay between WIC and school meal programs, we being by estimating "naive" aging-out effects using a full sample of children who are and are not consuming meals from school. Here, we find no significant effects, which either suggests there truly is no aging-out-of-WIC effect or the consumption of school meals corrupts our sample estimates. We therefore refine our sample, somewhat in the spirt of Bitler and Currie (2005) and Joyce at al. (2005), in the following incremental way: (1) we exclude those who report consuming any school meals; (2) we then further exclude any child in elementary school (regardless of their consumption of school meals); and (3) we further refine the sample to "late school starters"–those who are born and turn 5 between November and April and will therefore most likely start school the following year. This final refinement leverages the "randomness" of survey timing with respect to a child's age and restricts the sample to the group of children who are less likely to smoothly transition out of WIC and into school.[3]

Our overall finding is that school meals do seem to pick up some of the otherwise decreases in the quality of children's diets when they age out of WIC. Specifically, when we use the full sample of children, we estimate a negative but insignificant aging-out affect of about 5% on our measure of overall dietary quality, the Healthy Eating Index (HEI). Once we begin to exclude children who consume school meals, or are not in school at all, we find much larger and significant decreases in dietary quality: roughly a 20% decrease in the average quality of diets (or about 10-11 HEI points, which equates to roughly one standard deviation). A

[3]In most states, children must reach the age of 5 on or before a specific date to start kindergarten. Thirty-four states and the District of Columbia use a date sometime in August or September (NCES, 2018). As discussed below, our data only tell us if the survey occurred in November-April or May-October. Thus, we use the November-April subsample to define those who are potentially late school starters.

majority of this decrease in overall diet quality is from reduced intakes of healthier, WIC-targeted foods (e.g., fruits, vegetables, whole grains and dairy), although we do see increased consumption of less-healthy components (e.g., saturated fats). Effects are more pronounced in the lower tail of the diet quality distribution with decreases reaching upwards of 25-35%. While these results may appear large, they are local effects (i.e., for the set of compliers at the cutoff of 61 months) and not overall WIC program effects at any age.

In terms of the quantity of food consumed, we find no aging-out effects on calorie intake or food security reports. This indicates that children maintain similar quantities of calorie consumption when aging out of WIC but substitute towards a diet that is lower in overall quality. We discuss the policy implications of our findings, such as allowing children to stay on WIC until they enter kindergarten. We calculate a back-of-the-envelope program cost increase for such a policy at $196 million ($126 million for food packages and $70 million for nutrition services), or about 3.5% of the current $5.6 billion program cost.

The remainder of this paper proceeds as follows. Section 2 provides more details about the WIC program, and section 3 discusses our identification strategy. Section 4 describes our data, as well as measurements of dietary quality and food insecurity. Section 6 presents the main results. In section 7, we provide concluding remarks and derive policy implications.

2 Background: WIC Eligibility and Benefits

WIC eligibility is limited to three broad groups of individuals: pregnant and postpartum women, infants up to the age of 1 year, and children up to 5 years old. For the fiscal year 2017, roughly one-quarter of WIC participants were women (23.9%), another one-quarter were infants (24.6%), and just over half (51.6%) were children (FNS-USDA, 2018b). In addition, WIC is a means-tested program: individuals must either live in a household with family income below 185% of the Federal Poverty Level (FPL), or be adjunctively eligible through participation in another welfare program such as Medicaid, Temporary Assistance to Needy Families (TANF), or Supplemental Nutrition Assistance Program (SNAP). After the initial income certification, re-certification occurs every six months to one year.

The following final eligibility criteria is particularly important in understanding how the program delivers benefits: individuals must be nutritionally at-risk due to either a medically-based condition or an inadequate diet, as determined by a health professional (e.g., a physician, nutritionist, dietician, or nurse). In practice, almost all eligible applicants are certified to be at risk due to an inadequate diet pattern, even if other risk criteria are not identified (Bitler et al., 2003).[4] Nevertheless, the underlying reason for the "nutritionally at-risk" eligibility criteria is to place WIC participants, and/or their caregivers in the case of children, in contact with a health professional not only at the initial income certification but also during re-certification periods.

The reoccurring face-to-face meetings with a health professional is one mode by which WIC delivers its benefits. Nutritional services not only include nutrition education and the promotion of breastfeeding and immunization, but also referrals for preventative and coordinating services such as health care, smoking cessation, and/or other family care services. For example, the health professional may administer a depression screener questionnaire to determine if the mother is experiencing symptoms of postpartum depression.

Of the $5.6 billion in program costs in fiscal year 2017, the aforementioned nutritional services amounted to $2 billion, or about 35% (FNS-USDA, 2018c). The other $3.6 billion came in the form of food packages. Food packages are typically provided on a monthly basis in the form of vouchers that can be redeemed for specific foods.[5] Currently, the food package for children includes 100% juice, low-fat/skim milk, breakfast cereal, eggs, fresh fruits and vegetables, whole grains, and legumes and/or peanut butter (FNS-USDA, 2018d) (see, table A1 in the appendix for details). Food packages can be tailored by the health professional

[4] Other types of nutritional risk for WIC eligibility are recognized by federal regulations (see, Oliveira and Frazão, 2015), such as anemia, under/overweight, or drug abuse.

[5] In some states, benefits are issued through electronic benefit transfer (EBT) cards, and all states are required to migrate to EBT systems by 2020.

during the certification and re-certification periods (e.g., substituting low-fat or skim milk for yogurt, cheese or non-dairy products). In 2010, the average monthly cost of the child food package was about $37 (Vericker et al., 2013). To put this number in perspective, the average per-person benefit level for SNAP was $134 per month in the same year (FNS-USDA, 2018e)

In summary, food packages in conjunction with nutritional services are the main tools by which WIC affects child nutrition. Clearly, when children age out of WIC, they lose access to the food packages, but the information provided to WIC families via nutritional services may persist. Whether or not children are able to maintain healthful eating is clearly an empirical question, one that we attempt to investigate below.

3 Identification Strategy

Recall the research question: How does aging out of WIC affect child nutrition? This implies our main policy variable of interest D_i will take on a value of 1 if child i is off WIC and 0 otherwise. The primary difficulty in estimating the causal effect of D_i on some nutritional outcome Y_i is the nonrandom selection into the WIC program. That is, unobservable characteristics u_i of the child (e.g., parental preferences or environmental conditions) are most likely correlated with both selection into WIC (D_i) and the outcome (Y_i), which would yield biased and inconsistent estimates.

We use an identification strategy referred to as a regression discontinuity design (RDD).[6] RDD is a quasi-experimental estimator of treatment effects that exploits an exogenous change in the probability of treatment status based on a single covariate, called the assignment variable. In the present context, we exploit the fact that WIC participation is a discontinuous function of a child's age. In particular, program rules stipulate that children are no longer

[6] We refer the reader to Angrist and Pischke (2008), Imbens and Lemieux (2008) and Lee and Lemieux (2010) for details on RDD, and we discuss the intuition of the approach here.

eligible for WIC beginning with the month following their fifth birthday (i.e., the month in which they turn 60 months old is the last month they receive benefits).

The primary identifying assumption of RDD is that both observable and unobservable characteristics of children vary continuously with respect to the assignment variable (i.e., the child's age) in the vicinity of the policy cutoff (i.e., 61 months of age). Thus, we define the policy cutoff by the indicator $T_i = \mathbf{1}[Age_i \geq 61]$ where Age is defined in months and $\mathbf{1}[c]$ is the indicator function that equals 1 if c is true, and zero otherwise.

A "Sharp" RDD assumes the probability of being off WIC, $Pr(D_i)$, is wholly determined by T_i (i.e., $Pr(D_i)$ is a deterministic function of age). In this case, one could uncover causal *average* effects of aging out of WIC by the following mean regression

$$Y_i = \alpha_0 + \alpha_1 T_i + \alpha_2 \widetilde{Age_i} + \alpha_3 T_i \times \widetilde{Age_i} + e_i \tag{1}$$

where $\widetilde{Age_i} = (Age_i - 61)$. Note, we can also include a set of covariates X in the regression, such as a time period fixed effects and individual characteristics. If we believe the effect to be nonlinear around the age cutoff, we can consider flexible forms of $\widetilde{Age_i}$, such as higher-order polynomials or a fully nonparametric approach. However, including too many higher-order polynomials can lead to noisy estimates of the treatment effect (Gelman and Imbens, 2017). Under the proper specification, α_1 would yield an average treatment effect for aging out of WIC.

However, since D_i involves self-selection into WIC prior to aging out, $Pr(D_i)$ is not a deterministic function of age in months and the Sharp RDD will not yield consistent estimates. In particular, negative selection into the program, as suggested by Bitler and Currie (2005), will lead to downward biased estimates. To this end, we consider the "Fuzzy" RDD, which still assumes $Pr(D_i)$ changes discontinuously at $Age_i = 61$, but the change doesn't have to be deterministic with regards to age. That is, instead of examining the change in the conditional expectation at the cutoff T_i (i.e., estimating α_1), we need to consider the change in the $Pr(D_i)$ at the cutoff T_i,

$$D_i = \delta_0 + \delta_1 T_i + \delta_2 \widetilde{Age_i} + \delta_3 T_i \times \widetilde{Age_i} + v_i, \tag{2}$$

as estimated by δ_1, relative to being off WIC (D_i) at any age,

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 \widetilde{Age_i} + \beta_3 T_i \times \widetilde{Age_i} + u_i, \tag{3}$$

as estimated by β_1. Since we are examining the ratio of these two changes (i.e., β_1/δ_1), which is a Wald-type estimator, we can use the instrumental variable (IV) estimation with equation (2) as the first stage and (3) as the second stage (see, Imbens and Lemieux (2008) for details). As before, we can consider higher-order polynomials of $\widetilde{Age_i}$ (or nonparametrics), as well as including covariates X. Importantly, this estimator is a local effect, consistent for compliers at the cutoff. This is exactly what we want to know: how does aging out of WIC affect child nutrition?

To estimate the *distributional* effects of aging out of WIC, we use a linear-in-parameter quantile regression model corresponding to equation (3):

$$Y_i = \beta_0(u_i) + \beta_1(u_i) D_i + \beta_2(u_i) \widetilde{Age_i} + \beta_3(u_i) T_i \times \widetilde{Age_i}, \tag{4}$$

where u_i is a non-separable error term also called "rank" variable and is interpreted as unobserved "proneness" for the outcome variable (Doksum, 1974). This rank variable determines the relative position of children with the same observables (e.g., age in months) throughout the distribution of outcome such that children with relatively higher values of rank (e.g., better nutrition) are placed at higher quantiles of the outcome distribution.

Similar to our mean regression model, we can consider including higher-order polynomials of $\widetilde{Age_i}$ in equation (4). We, however, do no condition on characteristics of children and their households in the model. In general, conditioning on covariates in a quantile regression model makes some parts of the unobserved proneness (e.g., u_i in equation (4)) to become observed. This can change ranks of individuals across the outcome distribution. Consequently, the interpretation of coefficient estimates is changed and they would be interpreted as the effect of treatment on the *conditional* distribution of outcome (see, Powell, 2016).

Yet, we are interested in the impact of aging out of WIC on the *unconditional*[7] outcome distribution as it gives the desirable interpretation for the policy question at hand—how does aging out of WIC affect children prone to poor nutrition separately from those prone to good nutrition? Since the key identification assumption behind a RDD analysis is that observable and unobservable determinants of outcome do not vary discontinuously around the cutoff point, then conditioning on covariates is not required for identification.[8] Therefore, to maintain the ranking structure and obtain unconditional quantile treatment effects, our covariate vector X includes only time fixed effects.

Besides, we should note that u_i in general depends on the treatment status. That is, if we consider all children with the same age, the median child when all these children are exposed to treatment need not to be the median child when the treatment is withheld form all of them (see, Guiteras, 2008). The key identifying assumption, however, behind our quantile RDD analysis is that ranks of children with the same age do not change systematically between treated and untreated states. This assumption is referred to as *rank similarity* (see, Chernozhukov and Hansen, 2005; Guiteras, 2008).[9]

[7] The term "unconditional" used here refers to "mean unconditional on the covariates" but the resulting distribution is still conditional on the treatment variable (see, Powell and Goldman, 2016).

[8] In practice, however, it is common to include covariates in regression models to reduce sampling variability in the RDD estimator (Lee and Lemieux, 2010).

[9] To conceptualize the rank similarity condition, suppose there are two children, A and B, with the same age in months, and that child A has a higher proneness for a better nutrition than child B. We assume the child A will be ranked higher than the child B in the counterfactual treatment states where they both get WIC, or both do not get WIC. The rank similarity assumption requires that if both children lose WIC, the child A cannot experience detrimental effects so great that she would be ranked below B when aging out of WIC. We should note that A or B can experience different effects (in magnitude) from aging out of WIC, but these differences cannot be so large that they "switch" in ranking.

To estimate equation (4), we use the instrumental variable quantile regression (IVQR) estimator developed in Chernozhukov and Hansen (2006), performed via a grid search optimization procedure.[10] The IVQR estimate of $\beta_1(\tau)$ would then yield the quantile treatment effect for aging out of WIC on the τ^{th} quantile, $\tau \in (0, 1)$, of the outcome distribution.

Before we discuss the details of our data, it is important to point out a potential threat to one of our main identifying assumptions that the characteristics of children transition smoothly at the cutoff of 61 months of age. This program cutoff was presumably chosen because a vast majority of children are expected to begin kindergarten at this age.[11] Indeed, according to the U.S. Census Bureau (2015), in 2014, 6.5% of 4-year-old children attended kindergarten, whereas 75.4% of 5 year olds were enrolled in elementary school. Thus, in some respect, low-income children should transition off WIC and onto federally subsidized school meal programs (i.e., the National School Lunch and School Breakfast Programs). Also note, most children participating in WIC would be eligible for either free or reduced-price meals, which have means-tested thresholds of 130% and 185% FPL, respectively.

Clearly, not all children start elementary school in the month following their fifth birthday. We will show there is a marked uptick in not only attending school at our cutoff of 61 months, but also reports of consuming meals at school. Because previous research has shown that school meal programs increase the overall quality of low-income children's diet, especially those prone for very-low quality diets (Smith, 2017), participation in such programs may confound our aging-out-of-WIC estimates. Therefore, our approach will be to utilize this information to our advantage. First, we use a "full sample" that includes all age-relevant and income-eligible children, including those in and out of school and possibly consuming school meals. We will then refine our sample, first to those who are not consuming school meals, then to those who have yet to attend school, and finally to those who are not in school and

[10] Inferences are conducted using the analytical estimated variance-covariance matrices following the formulae given in Section 4.3 of Chernozhukov and Hansen (2008).

[11] According to the National Center for Education Statistics (NCES, 2018), half of the states used a date of August 31 or September 1 in 2014. Most other states use some date between July 31 and October 15.

are surveyed between November 1 and April 31 (i.e., late-school starters). By comparing results across these samples, the goal is to better understand the effects of transitioning out of WIC and possibly onto school meal programs.

4 Data

We use eight waves of data from the continuous cycles of the 1999-2014 National Health and Nutrition Examination Survey (NHANES). Each NHANES cycle is an independently drawn, nationally representative sample occurring over a 12-month period, beginning November 1 of the odd year and ending October 31 of the even year. While we do not know the month of the survey for each individual, we do know if the survey occurred over the first six months (i.e., November 1 - April 30) or the second six months (i.e., May 1 - October 31).

The survey provides rich dietary intake information as well as detailed demographic characteristics. Specifically, in-person proxy interviews (e.g., from mom, dad, or other caregiver) elicit 24-hour dietary recalls for children using computer-assisted, automated data collection. We pool data over this 15-year time span to ensure sufficient representation of WIC children, and we will control for the survey wave in our analysis. While the data do not provide us with birth dates, we do know the child's age in months at the time of the interview.

We focus on children aged 24-72 months, because our measure of diet quality is only valid for those who are 2 years and older (more discussion below).[12] We further restrict our sample to all WIC participants defined as those who are reported as receiving WIC benefits at the time of the interview and WIC-eligible non-participants defined as those who live in households with family income less than 200% of the FPL.[13]

In order to better understand the role of school meals (or school attendance, in general), we

[12]Dietary intake data are collected during NHANES physical examinations. Thus, we utilize child's age at the time of physical exams.

[13]Although households must have income less than 185% of the FPL in order to be eligible for WIC, households with higher incomes may be eligible due to adjunctive eligibility. Further, income recertification occurs every six months, and we want to allow for variation in income over time.

use a series of questions that are only asked of children 4 years and older. The first question is "During the school year, does [child] attend a kindergarten, grade school, junior or high school?" We use this question to define the no-school sample. If the child does attend school, then the survey elicits the number of times per week the child usually consumes a complete school breakfast and/or complete school lunch. We define the no-school-meal sample as those who usually consume neither a school breakfast nor school lunch during the school week.

Table 1 provides summary statistics for child characteristics as we refine our samples. The main comparison will be estimates from the full sample (column 1) versus the no-school-meal sample (column 2). Some of the demographics change with the definition of the sample, while others do not. Nevertheless, the main identifying assumption is that covariates transition smoothly around the cutoff within the sample. Thus, within each sample, our identification strategy holds. However, in comparing results across samples, we must take into consideration these differences in demographics when interpreting the results.

4.1 Measurement of Diet Quality and Quantity

Diet quantity is simply measured by the amount of calories consumed.[14] We quantify dietary quality using the Healthy Eating Index (HEI), which is a measure of compliance to the federal government's official recommendations for healthy eating: the Dietary Guidelines for Americans (DGA). The HEI has been evaluated as a valid and reliable measure of diet quality (Guenther et al., 2008, 2014) and is widely used in studies of WIC and other nutrition assistance programs (see, e.g., Basiotis et al., 1998; Hiza et al., 2013; Tester et al., 2016; Gu and Tucker, 2017; Smith, 2017). The original HEI was created in 1995 to measure compliance to the 1990 DGA and has since been revised several times to reflect key changes in the DGA.

[14]In robustness checks, we also use the ratio of reported calories to the Institute of Medicine's Estimate Energy Requirements (EER) (Gerrior et al., 2006). The EER is a function of a child's age, gender, height, weight and physical activity level. We do not have a good measure of the latter and assume a constant sedentary lifestyle. Nevertheless, if these variables transition smoothly around the cut off, then examining calories in levels should suffice.

In this paper, we use the HEI-2010, corresponding to the 2010 DGA, as a measure of child's overall dietary quality.

The HEI-2010 is a continuous, scalar measure calculated as the sum of 12 components based on the per-calorie consumption of various food and nutrients. There are nine *adequacy* components (total fruit, whole fruit, total vegetables, greens and beans, whole grains, dairy, total protein foods, seafood and plant proteins, and fatty acids) for which higher scores indicate higher intakes, and three *moderation* components (refined grains, sodium, and empty calories) for which higher scores reflect lower intakes. Each component assigns a score ranging from 0 to 5 (total fruit, whole fruit, total vegetables, greens and beans, total protein foods, seafood and plant proteins), 0 to 10 (whole grains, dairy, fatty acids, refined grains, sodium), and 0 to 20 for empty calories (calories from solid fats, alcoholic beverages, and added sugars). The total HEI-2010 is scored from 0 to 100. Table 2 provides exact details of the scoring procedure (Guenther et al., 2013).

We also utilize the two main sub-categories of the HEI-2010: the adequacy score, which is out of 60 points, and the moderation score, which is out of 40 points. Adequacy foods are those foods one should eat more of (e.g., fruits, vegetables and whole grains) and moderation foods are those one should eat less of (e.g., added sugars and fats). We do so to better understand whether any effects of losing WIC benefits are due to changes in intakes of adequacy foods or moderation foods.[15] We also examine changes in children's intakes of added sugar and saturated fat as a percent of total energy intake because WIC food packages are partially designed to have minimal added sugars and fats.[16]

Table 3 provides means across samples for our main outcomes of dietary quality and quantity. Here, we see fairly consistent summary measures across samples, which is in contrast to the demographics we saw earlier. The main difference is in calorie consumption,

[15] Keep in mind that a higher score on moderation components corresponds to lower intakes of these foods.

[16] Indeed, previous research suggests that WIC is associated with improved diets among children as measured by the intakes of added sugars and fats (see, Colman et al., 2012), although these effects are not causal.

but this is no doubt correlated with the fact that the more refined samples are more likely to exclude older children. One of the main takeaways is that children have substantial room for improving their diet quality, with scores hovering around 56 out of a possible 100. The main deficiency is in the adequacy components, although the average moderation score is roughly 75% of the possible 40 points.

4.2 Measurement of Food Insecurity

Food insecurity is defined as a lack of access to the kinds and amounts of food necessary for each member of a household to lead an active, healthy lifestyle. Official food insecurity rates in the U.S. for households with children are calculated using a series of 18 questions posed in the Core Food Security Module (CSFM)—10 questions refer to adults and 8 questions to children. Each question elicits a response to progressively more severe states of food hardship, and the CSFM has been validated as a reliable measure of latent food insecurity through psychometric studies (e.g. Hamilton et al., 1997; National Research Council, 2006). We use responses to these questions to measure food insecurity not only among children, but also the household in general to test for any spillover effects.

Following official definitions, we classify a household with children as "food insecure" if the respondent responds affirmatively to three or more questions and "very low food secure" if the respondent responds affirmatively to eight or more questions. Similarly, we categorize an adult (child) in the household as "food insecure" if the respondent responds affirmatively to three (two) or more questions and "very low food secure" if the respondent responds affirmatively to six (five) or more questions. Rates for each measurement are reported in table 4. The sample is slightly smaller due to non-response. Overall, the rates appear to be fairly consistent across each sample.

5 Tests of Identifying Assumptions

5.1 Covariate Balance at Cutoff

A fundamental assumption behind RDD generating local random assignment is that individuals are not able to precisely manipulate the assignment variable. Although this assumption cannot be tested directly (because only one observation on the assignment variable is observed per individual), an intuitive test of this assumption can be conducted by investigating whether there is a discontinuity in aggregate distribution of the assignment variable at the cutoff point (see, Lee and Lemieux, 2010). McCrary (2008) proposes a simple procedure for testing whether the density of the assignment variable shows discontinuities around the cutoff.

Figure 1 displays the results of the McCrary test for our analysis samples. Visual inspection of the graph as well as the estimates of the discontinuities suggest that the difference between the frequency to the right and to the left of the threshold is not statistically significant. Therefore, we fail to reject the null hypothesis that the discontinuity in the density of the child's age at the cutoff is zero, indicating that parents are not systematically misreporting the age of their children (for instance, by arguing that their children are younger than they actually are if they believe responses to the survey are related to WIC receipt).

An alternative way to testing the validity of RDD is to examine whether observable characteristics of individuals are locally balanced on either side of the cutoff point. To investigate this issue we conduct a formal discontinuity estimation, replacing the dependent variable in equation (1) with each of the baseline covariates in X. However, instead of estimating each equation individually, we run a Seemingly Unrelated Regression (SUR) model where each equation represents a different covariate and test for the joint significance of discontinuity gaps in all equations (see, Lee and Lemieux, 2010).

The results of discontinuity tests for our four samples are presented in table 5. As one can see, in all samples discontinuity gaps in covariates are jointly statistically insignificant, suggesting that observed characteristics of children vary smoothly around the threshold. Moreover, to account for the possibilities of nonlinear effects around the cutoff, we repeat our discontinuity test using other specifications including the second- and third-order polynomials of $\widetilde{Age_i}$ and conduct a graphical analysis. The formal test results are reported in appendix tables A2 and A3. Graphical evidence for the full and no-school-meals samples are shown in appendix figures A1 and A2.[17]

Overall, additional test results confirm the findings of table 5. Although we observe some significant discontinuities in smaller samples, in particular the late-schoolers sample (likely due to smaller number of observations), they are not problematic as we condition on these variables in our regression model. However, as we discussed earlier, our full sample includes children attending elementary school. In figure 2 we see that there is a significant discontinuity in the probability of school attendance and subsequently, enrolling into school meal programs. Given that participation in school meal programs is itself a choice variable, we cannot include that in our model as a covariate. Thus, the aging out of WIC effect estimates from the full sample are likely to be confounded by the effects of school meal programs. We examine this possibility by estimating the aging out of WIC effects using our three refined samples.

5.2 Discontinuity in WIC Participation

A valid RDD recovers the causal effects of aging out of WIC by exploiting the fact that WIC participation is a discontinuous function of a child's age. In some sense, this strategy may be regarded as a difference-in-differences approach, while accounting for self-selection into WIC. Figure 3 displays the share of age-eligible children participating in WIC by child's age. As one can see, in all samples the probability of WIC participation drops significantly at the

[17] Figures for other samples are available from the authors upon request.

cutoff point of 61 months. Given that child's observable and unobservable characteristics vary continuously in the vicinity of the cutoff point, we can identify the effects of aging out of WIC by comparing child's outcomes just below and just above the threshold.

5.3 Discontinuity in Outcomes

Figure 4 plots the average HEI-2010 scores by the child's age. In panel A (full sample), we see that the mean HEI-2010 varies almost continuously around the age cutoff. Again, this could be in part due to the effect of school meal programs. In our refined samples the mean HEI-2010 shows a (insignificant) drop at the cutoff. These simple comparisons of the mean outcome on either side of the cutoff point (i.e., sharp RDD), however, due to the imperfect compliance of age-eligible children to WIC participation, underestimate the true effects of aging out of WIC on the outcome. Our Fuzzy RDD approach deals with this non-compliance problem by utilizing the exogenous assignment to WIC participation by the child's age as an instrumental variable for our treatment variable.

6 Results

6.1 Average Effects

We first present the results for the average effects of aging out of WIC on child's nutrition. Table 6 reports the effects on HEI-2010 for the full sample from different models; the first two columns present the estimates from a model linear in $\widetilde{Age_i}$, whereas the third and fourth columns show estimates from models including the second and third-order polynomials of $\widetilde{Age_i}$, respectively. Panel A reports the FRDD estimates, panel B the SRDD estimates, and panel C the first-stage results. For brevity, we only report estimation results for the key parameter, β_1.

The first-stage results and associated F-Statistics confirm that our instrumental variable (i.e., the cutoff indicator, T), strongly predicts WIC enrollment. The reported Bayesian information criterion (BIC) suggest that models with first- and second-order polynomials of $\widetilde{Age_i}$ and covariates provide a slightly better fit to the data in the full sample.[18] Overall, Fuzzy RDD estimates from our preferred specifications indicate that on average children experience no significant decrease in their overall diet quality as they age out of WIC. As discussed earlier, this could be because losing access to WIC food packages truly has no adverse effect on diet quality of children or it could be because the estimates using the full sample are confounded by the effects of school meal programs.

Table 7 shows the results from the no-school-meals sample. BIC estimates suggest that the model linear in $\widetilde{Age_i}$ with covariates is the preferred specification in the no-school-meal sample.[19] From the results we see that after excluding children who consume school meals from the sample, aging out of WIC leads to fairly large decrease of about 10 HEI-2010 (20% of the average diet quality) points in diet quality.[20] Moreover, in appendix tables A4 and A5 we see that by further refining our sample and excluding all children in elementary school and late-school starters we find even larger effects on diet quality of about 12 and 17 HEI-points, respectively, highlighting the role of school meal programs even more. Thus, we can conclude that insignificant results from the full sample are downward-biased by the beneficial effects of school meal programs on dietary quality of children.

In interpreting the magnitude of coefficient estimates, we should note that they are local effects of aging out of WIC and are consistent for compliers in the proximity of the cutoff point and not overall population of children on WIC. Besides, because participation into

[18]Kass and Raftery (1995) view improvements in BIC of less than 2 as negligible, while differences greater than 10 are often regarded as constituting strong evidence. In other words, only reductions in the BIC of more than ten should indicate a clear improvement in the model.

[19]We should, however, note that including covariates in the model does not have much impact on the magnitude of coefficient estimates. This is expected because covariates vary smoothly around the cutoff point.

[20]The magnitude of this effect was larger (about 14 HEI-2010 points decrease) in the period following the 2009 implementation of WIC food package revisions. This finding is intuitive given that 2009 revisions shifted WIC food packages towards even healthier foods (see, Oliveira and Frazão, 2015 for more details)

WIC, similar to other nutrition assistance programs (e.g., SNAP), is underreported (Kreider et al., 2016) our fuzzy RDD estimates are an upper bound of the true effects of aging out of WIC.

Table 8 present the estimation results for sub-categories of diet quality and also diet quantity (via kilocalorie consumption) for the full sample. We present results from a model linear in $\widetilde{Age_i}$ as in general it provides a better fit.[21] Again, we find no significant effects on either sub-categories of diet quality or calorie consumption in the full sample. In table 9 which shows the results from the no-school-meals sample, we see a significant effect of about 6.6 HEI-2010 points on the adequacy component. No significant impact, however, is found on the moderation score. This finding suggest that the decrease in overall diet quality is primarily driven by a decrease in the intakes of adequacy foods, although the sum of the two sub-components correspond to the overall effects. In appendix table A6 we observe similar results for the no-schoolers sample, whereas in appendix table A7 we find marginally significant decreases in the moderation score and percentage of energy intake from added sugars as well as a significant increase in the percentage of energy intake from saturated fat for the late-schoolers sample.

Finally, tables 10 and 11 summarize the estimation results for rates of food insecurity and very low food security in the full sample and no-school-meal sample, respectively.[22] As one can see, aging out of WIC has no significant impact on the prevalence of food insecurity or very low food security for either households as a whole or their adult and child members. Similarly, no significant effect is observed in appendix table A8 for the no-schoolers sample. In appendix table A9, however, we find a significant increase in the probability of household-level food insecurity.

[21]Estimation results from models with higher-order polynomials of $\widetilde{Age_i}$ are available from the authors upon request.

[22]Fuzzy RDD results are obtained as marginal effects from a bivariate Probit estimation of equations (2) and (3) (see, Nichols, 2011 for more details), whereas Sharp RDD estimates are marginal effects from a Probit model.

6.2 Distributional Effects

In this subsection, we present the distributional effects of aging out of WIC on dietary quality and quantity. Figure 5 shows the quantile treatment effects on the HEI-2010 distribution. Panels A and B present the results for the full sample from models with the first and second-order polynomials of $\widetilde{Age}$, respectively. Likewise, panels C and D for the no-school-meals sample. In each panel, the solid line represents the fuzzy IVQR point estimates, the horizontal dashed line represents the average fuzzy RDD estimate, and the shaded area represents the 90% confidence interval (CI). The quantiles on the x-axis refer to the counterfactual or untreated diet quality distribution, which gives the estimated quantile treatment effects a *ceteris paribus* interpretation. Intuitively, these are the (conditional) quantiles of diet quality just to the left of the age cutoff. The IVQR estimation was performed over the parameter space $\Re = [-25, 10]$ using β_1 equally spaced with a step size of 0.1 for quantiles 5 to 85 at 5-unit increments.[23]

In the figure, we see that our estimates are not sensitive to the order of polynomial of the assignment variable. Similar to the mean effects, we find almost no significant effects across the distribution of HEI-2010 in the full sample. In the no-school-meal sample, however, we observe large significant effects at lower quantiles of the HEI-2010 distribution (i.e., lower-quality diets). As we move toward the the higher quantiles (i.e., higher-quality diets) magnitudes of the effects shrink slightly and become statistically insignificant.

Figure 6 displays the estimated distributional effects on sub-categories of dietary quality as well as diet quantity. The left column (panels A to E) show the results for the full sample and the right column (panels F to J) for the no-school-meal sample. The IVQR estimation for these diet quality sub-categories were conducted over the parameter space $\Re = [-10, 5]$ with a step size of 0.1 for β_1 for quantiles 5 to 85 at 5-unit increments. For calorie consumption $\Re = [-100, 300]$ and a step size of 5 was used.

[23]The IVQR estimates for higher-quality diet quantiles (e.g., 90 and 95) are highly imprecisely estimated, and thus are not reported.

Starting from adequacy and moderation components, we find almost no significant effect in the full sample. In the no-school-meal sample, however, we find larger effects on lower quantiles. Similar effects are observed for other sub-categories of diet quality in both samples. We see some marginally significant decreases in the percentage of energy intake from added sugar within the bottom quartile of the distribution. With respect to percentage of energy intake from saturated fat, however, we find positive effects above the median. Lastly, we also see similar effects across the distribution of calorie consumption in both samples with effects from the no-school-meals sample being estimated imprecisely.

7 Conclusions and Discussion

This study investigates the effect of aging out of the WIC program on the nutritional well-being of children aged 2-4 years. Specifically, using nationally representative data from the NHANES, we examine how losing WIC benefits at the age of 61 months affects child's dietary quality and quantity. Although there has been considerable amount of research examining the effects of WIC participation on birth outcomes and breastfeeding, fewer studies have investigated the effects of WIC on child's nutrition. More importantly, existing studies have struggled to fully address the issue of non-random participation into WIC, and therefore may not be able to make causal inferences about the effects of WIC on health and diet related outcomes. Further, current studies have mostly focused on estimating the average effects of WIC and full distributional effects of WIC participation are almost unknown.

To address the selection-bias problem, we use a fuzzy regression discontinuity deign. Using a sample of children who are not on school meal programs, we find that aging out of WIC has a fairly sizable adverse effect (about 20%) on the HEI-2010 as a measure of child's overall diet quality, which is a local effect for children around the age of five and not all children at any age. Given that children who stay on WIC until their eligibility ends are more likely to be more disadvantaged than the average WIC participant, then losing WIC benefits could have potentially larger effect on their diet quality.

Furthermore, our results for several subcategories of diet quality indicate that the estimated decrease in child's overall diet quality is mainly driven by adequacy foods and smaller impact is observed on moderation food. We find no significant increase in the percentage of total energy intake from added sugar and from saturated fat. Given that foods provided by WIC are all adequacy foods, observing larger effects on adequacy score due to losing food package is reasonable. Although WIC food packages target the moderation score for instance by imposing restrictions on the amounts of added sugar or saturated fat, smaller effect on moderation could be due to other unobserved factors. For example, after losing WIC benefits parents could still provide foods with lower added sugar or saturated fat content.

With respect to food insecurity rates, unlike Arteaga et al. (2016) we find that aging out of WIC has no significant effects on the prevalence of food insecurity or very low food security. One explanation is that Arteaga et al. (2016) examine the effects of aging out of WIC on a 30-day proxy for food insecurity, whereas in this study we use 12-month food insecurity measures. Given the subjective nature of the food-insecurity, it is more likely that households report as food insecure in the month following losing benefits from WIC.

Moreover, our distributional results show that losing WIC benefits has larger negative effects on lower quantiles of the HEI-2010 and its major sub-categories. These results indicate that the impacts of becoming age-ineligible for WIC are more detrimental for children falling in the lowest portion of diet quality distribution. This is a policy-relevant finding because WIC appears to have the largest benefits for children prone to the lowest quality diets.

Using a larger sample including children who report receiving food from school meal programs, we find that aging out of WIC has no significant effect on either measures of child's dietary quality. This finding suggests that school meal programs might pick up some of the otherwise decreases in diet quality due to becoming age-ineligible for WIC. Thus, one solution to avoid detrimental effects of losing WIC benefits on diet quality and fill the gap in the patchwork of federal food and nutrition assistance programs could be extending the WIC eligibility until school-entry. In other words, instead of ending eligibility for all children at the age of 61-months, eligibility could end upon enrolling in school meal programs. Using the estimated child food packages cost of about $37 per month (Vericker et al., 2013) with an enrollment of 620,000 4 year olds (CITE), and assuming uniform births across months, this could increase the program costs for food packages by $126 million. Nutrition services could cost an additional $70 million, if we assume these costs are proportional to the current breakdown. Thus, this back-of-the-envelope calculation suggests a total increase of about $196 million, or 3.5% of the current $5.6 billion.

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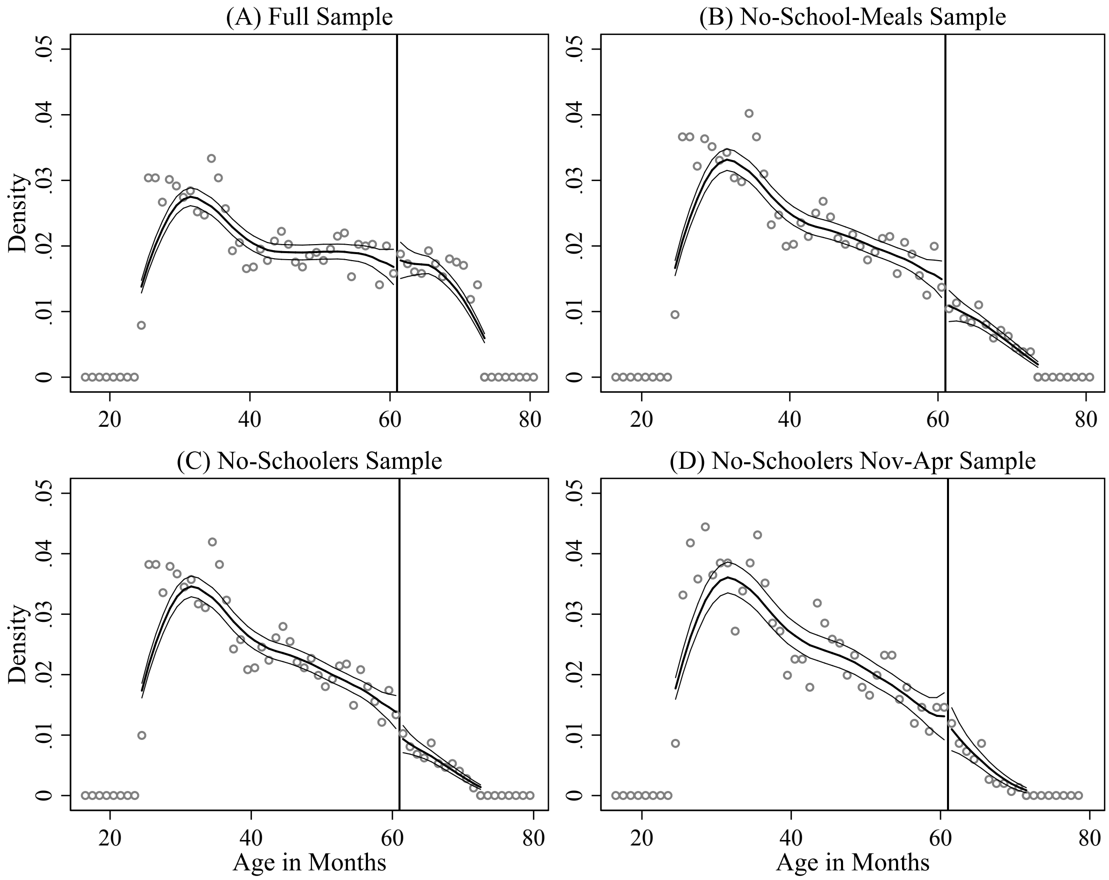

Figure 1: McCrary Test for manipulation of the assignment variable

Note: Discontinuity estimates in panels A (0.19, S.E. = 0.22), B (-0.29, S.E. = 0.26), C (-0.23, S.E. = 0.27), and D (-0.19, S.E. = 0.36) are calculated using defaults bandwidths.

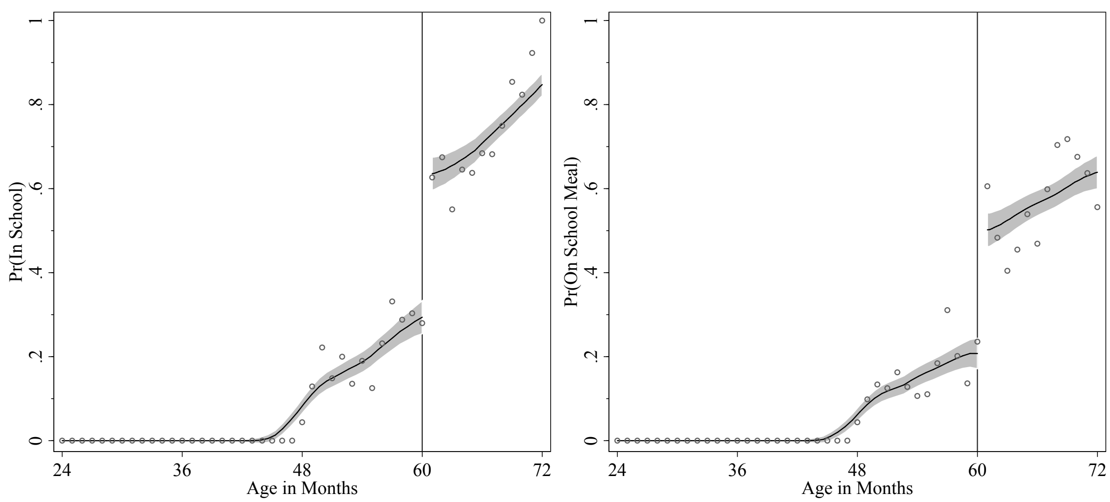

Figure 2: Discontinuities in school and school meal program participation by child's age in months

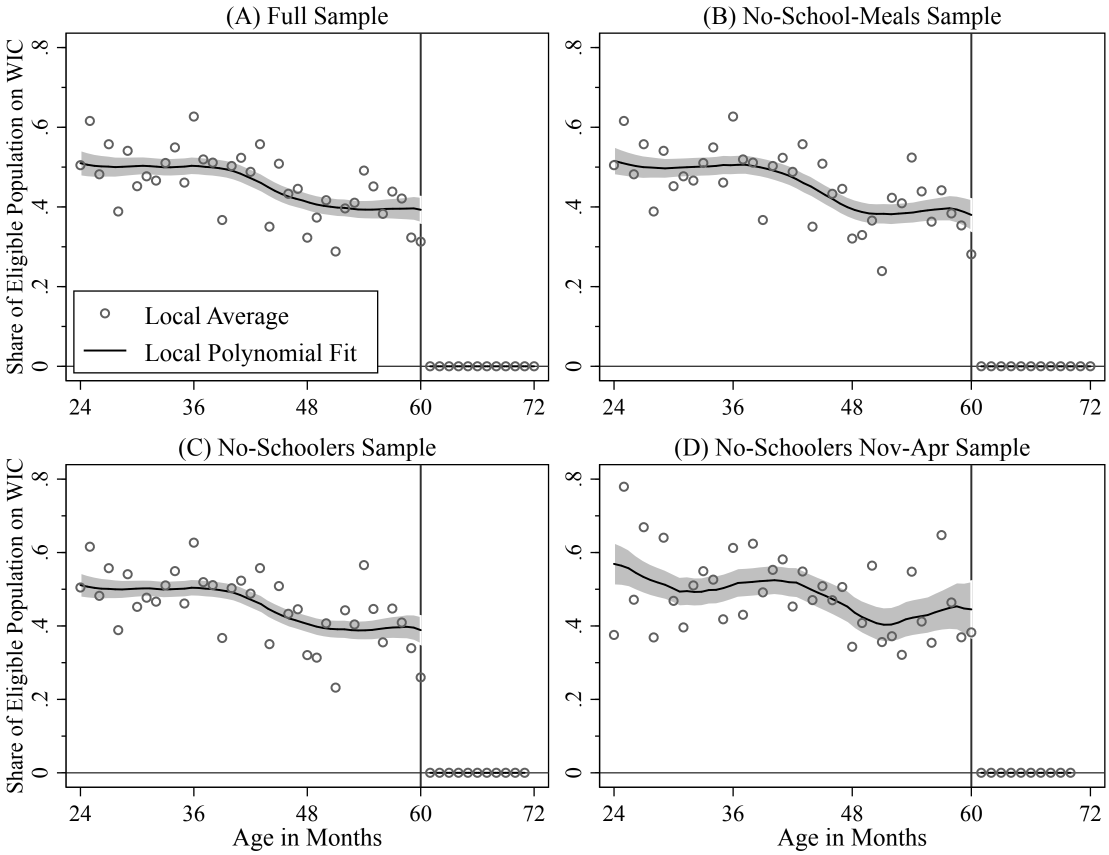

Figure 3: Discontinuity in WIC participation by child's age in months

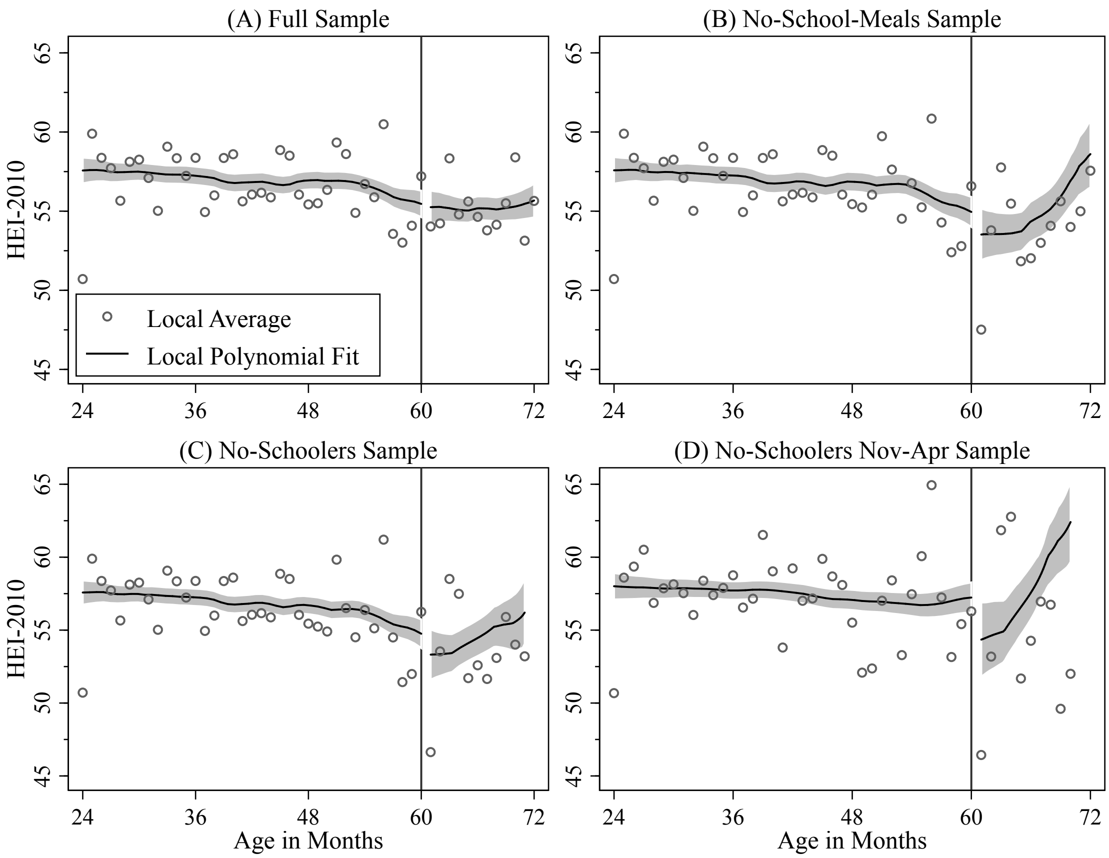

Figure 4: Discontinuity in HEI-2010 by child's age in months

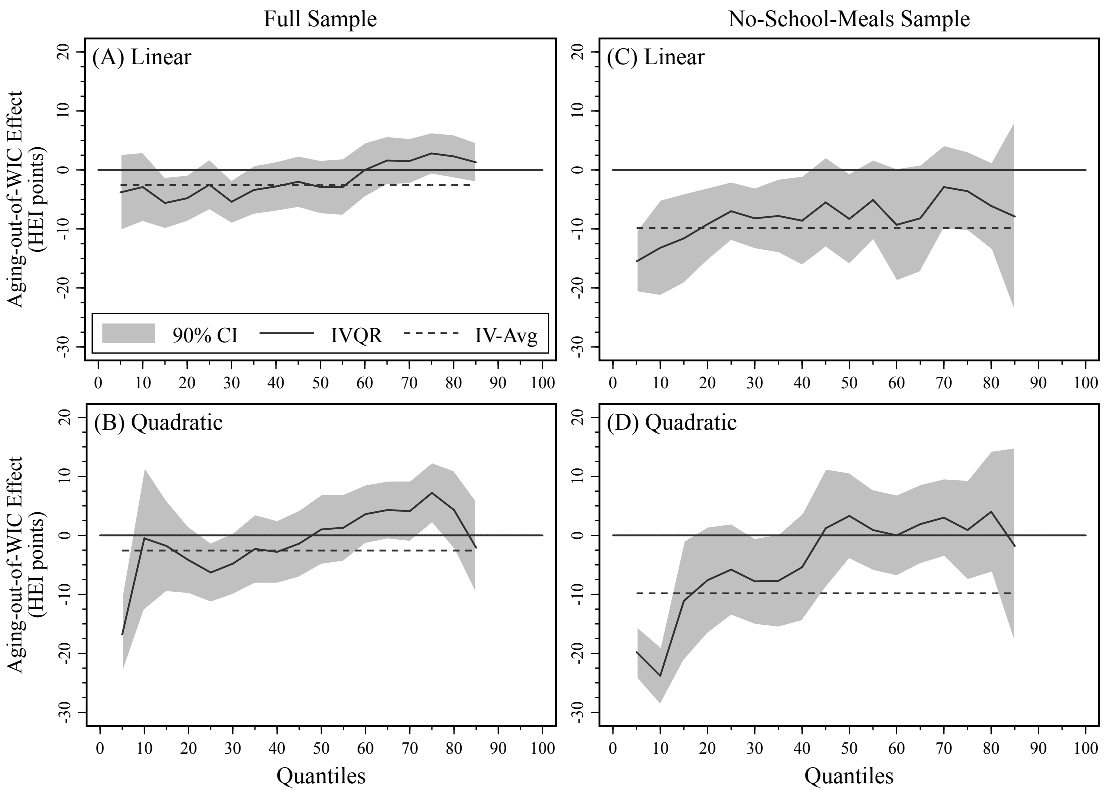

Figure 5: Distributional effects of aging out of WIC on HEI-2010

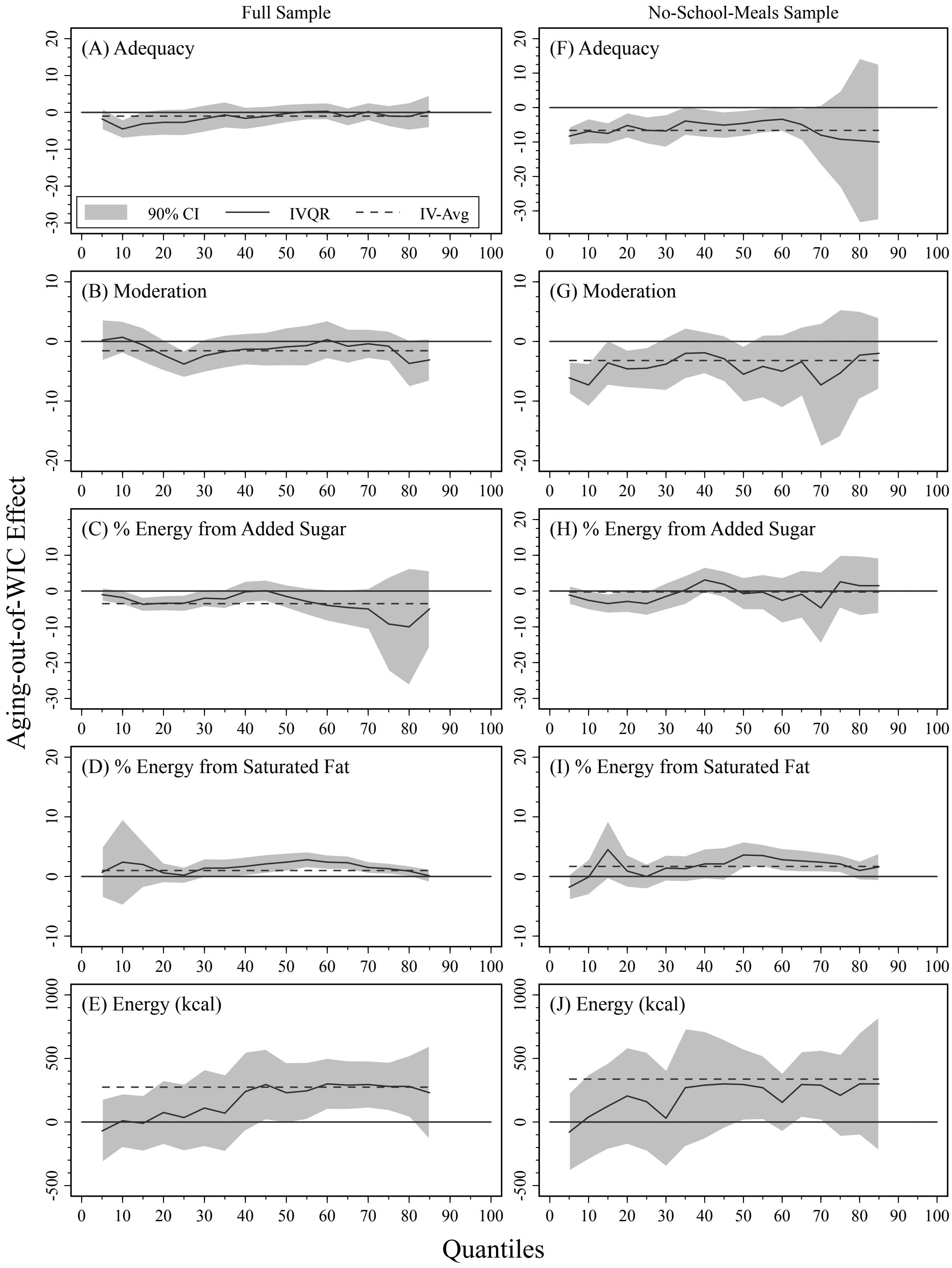

Figure 6: Distributional effects of aging out of WIC on sub-categories of child's dietary quality and diet quantity

Table 1: Summary Statistics for Demographics

Variable	Full	No School Meals	No School	Nov-Apr
Sample selection:				
Consume school meals	0.17	–	–	–
	(0.01)	–	–	–
Attends elementary school	0.22	0.06	–	–
	(0.01)	(0.01)	–	–
Surveyed in Nov-Apr	0.45	0.43	0.43	–
	(0.03)	(0.03)	(0.03)	–
Main Regressors:				
$T = 1[\text{Age} \geq 61 \text{ months}]$	0.22	0.11***	0.08***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
$D = 1[\text{Off WIC}]$	0.65	0.60***	0.58***	0.54***
	(0.01)	(0.01)	(0.02)	(0.02)
Age in months	47.32	43.98***	42.70***	41.83***
	(0.27)	(0.33)	(0.28)	(0.38)
Covariates:				
Child Female	0.50	0.49**	0.49	0.47
	(0.01)	(0.01)	(0.01)	(0.02)
Child NH White	0.42	0.45***	0.44***	0.33***
	(0.03)	(0.03)	(0.03)	(0.03)
Child NH Black	0.20	0.18***	0.19	0.22
	(0.02)	(0.02)	(0.02)	(0.02)
Child Hispanic	0.31	0.29***	0.29***	0.38***
	(0.02)	(0.02)	(0.02)	(0.03)
Child other race/ethnicity	0.08	0.08	0.08	0.07
	(0.01)	(0.01)	(0.01)	(0.01)
Reference No HS diploma	0.35	0.34***	0.34*	0.37
	(0.01)	(0.02)	(0.02)	(0.02)
Reference HS diploma	0.27	0.27	0.27	0.26
	(0.01)	(0.01)	(0.01)	(0.02)
Reference at least some college	0.38	0.40***	0.39*	0.38
	(0.01)	(0.02)	(0.02)	(0.02)
Reference Female	0.55	0.54***	0.55	0.53
	(0.01)	(0.01)	(0.01)	(0.02)
Household Size	4.67	4.66	4.66	4.71
	(0.04)	(0.04)	(0.04)	(0.06)
Income-Poverty Ratio	1.04	1.06***	1.06***	1.05
	(0.02)	(0.02)	(0.02)	(0.02)
No. of Observations	4049	3358	3219	1508
Obs. left of cut ($T = 0$)	3246	3057	3015	1431
Obs. right of cut ($T = 1$)	803	301	204	77

Notes: Standard errors are in parentheses and are clustered at the PSU-strata level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ indicates those who are dropped from the full sample are significantly different from those who remain in the sample.

Table 2: Healthy Eating Index 2010 Components and Scoring Standards

Component	Score Range	Standard for Max Score	Standard for Min Score
Adequacy:			
Total Fruit	[0,5]	$\geq$ 0.8 cup equivalent/1,000 kcal	No Fruit
Whole Fruit	[0,5]	$\geq$ 0.4 cup equivalent/1,000 kcal	No Whole Fruit
Total Vegetables	[0,5]	$\geq$ 1.1 cup equivalent/1,000 kcall	No Vegetables
Greens and Beans	[0,5]	$\geq$ 0.2 cup equivalent/1,000 kcal	No Dark/Green Vegetable or Beans and Peas
Whole Grains	[0,10]	$\geq$ 1.5 oz equivalent/1,000 kcal	No Whole Grains
Dairy	[0,10]	$\geq$ 1.3 cup equivalent/1,000 kcal	No Dairy
Total Protein Foods	[0,5]	$\geq$ 2.5 oz equivalent/1,000 kcal	No Protein Foods
Seafood and Plant Proteins	[0,5]	$\geq$ 0.8 oz equivalent/1,000 kcal	No Seafood or Plant Proteins
Fatty Acids	[0,10]	(PUFAs + MUFAs)/SFAs* $>$ 2.5	(PUFAs + MUFAs)/SFAs $\leq$ 1.2
Moderation:			
Refined Grains	[0,10]	$\leq$ 1.8 oz equivalent/1,000 kcal	$\geq$ 4.3 oz equivalent/1,000 kcal
Sodium	[0,10]	$\leq$ 1.1 g equivalent/1,000 kcal	$\geq$ 2.0 g equivalent/1,000 kcal
Empty Calories	[0,20]	$\leq$ 19% of energy	$\geq$ 50% of energy

*PUFAs: polyunsaturated fatty acids. MUFAs: monounsaturated fatty acids. SFAs: saturated fatty acids.
Source: Recreated from Guenther et al. (2013)

Table 3: Summary Statistics for Outcomes

Outcome	Full	No School Meals	No School	Nov-Apr
HEI-2010	56.53	56.62	56.62	57.47
	(0.33)	(0.35)	(0.35)	(0.49)
Adequacy Score	26.49	26.48	26.42	27.01
	(0.21)	(0.22)	(0.23)	(0.32)
Moderation Score	30.04	30.14	30.20	30.46
	(0.19)	(0.20)	(0.19)	(0.27)
% Energy from Added Sugar	13.90	13.75	13.73	13.87
	(0.21)	(0.23)	(0.24)	(0.33)
% Energy from Saturated Fat	11.76	11.83	11.81	11.47
	(0.11)	(0.13)	(0.13)	(0.14)
Energy (kcal)	1611.88	1584.50	1584.47	1567.80
No. of Observations	4049	3358	3219	1508

Notes: Standard errors are in parentheses and are clustered at the PSU-strata level.

Table 4: Rates of Food Insecurity and Very Low Food Security

	Full	No School Meals	No School	Nov-Apr
Panel A: Rates of Food Insecurity				
Household	0.29	0.29	0.29	0.30
	(0.01)	(0.01)	(0.01)	(0.02)
Adult	0.26	0.26	0.26	0.27
	(0.01)	(0.01)	(0.01)	(0.02)
Child	0.15	0.14	0.15	0.15
	(0.01)	(0.01)	(0.01)	(0.01)
Panel B: Rates of Very Low Food Security				
Household	0.08	0.08	0.08	0.07
	(0.01)	(0.01)	(0.01)	(0.01)
Adult	0.09	0.09	0.09	0.07
	(0.01)	(0.01)	(0.01)	(0.01)
Child	0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)
No. of Observations	4029	3343	3204	1503

Notes: Standard errors are in parentheses and are clustered at the PSU-strata level.

Table 5: Discontinuities in Baseline Covariates

	Full	No School Meals	No School	Nov-Apr
Child Female	-0.02	-0.09	-0.11	-0.14
	(0.06)	(0.09)	(0.10)	(0.14)
Child NH White	0.05	0.04	0.04	0.11
	(0.06)	(0.07)	(0.08)	(0.12)
Child NH Black	-0.03	-0.03	-0.03	-0.09
	(0.03)	(0.04)	(0.04)	(0.06)
Child Hispanic	0.01	-0.01	-0.01	-0.05
	(0.04)	(0.05)	(0.06)	(0.09)
Reference HS diploma	-0.02	-0.06	-0.03	0.07
	(0.05)	(0.06)	(0.08)	(0.10)
Reference at least some college	-0.07	-0.07	-0.03	-0.06
	(0.05)	(0.08)	(0.08)	(0.13)
Reference Female	0.04	0.11	0.10	0.01
	(0.05)	(0.07)	(0.08)	(0.12)
Household Size	-0.03	0.26	0.36	0.37
	(0.15)	(0.21)	(0.22)	(0.33)
Income-Poverty Ratio	-0.13**	-0.17**	-0.21**	-0.22
	(0.06)	(0.08)	(0.10)	(0.14)
Joint Test p-values[a]	0.18	0.23	0.43	0.33
No. of Observations	4049	3358	3219	1508

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights.
[a] p-values for tests of linear restrictions that all discontinuities are jointly zero.

Table 6: Average effects of Aging Out of WIC on HEI-2010, Full Sample

	Order of Polynomial of $\tilde{Age}$			
	1^{st}	1^{st}	2^{nd}	3^{rd}
Panel A: Fuzzy RDD				
Off WIC (D)	-3.38	-2.58	-1.79	-2.92
	(3.32)	(3.16)	(4.83)	(5.80)
Panel B: Sharp RDD				
Age $\geq$ 61 months (T)	-1.22	-0.93	-0.61	-1.08
	(1.19)	(1.14)	(1.65)	(2.15)
Panel C: First-stage Estimates				
Age $\geq$ 61 months (T)	0.36***	0.36***	0.34***	0.37***
	(0.03)	(0.03)	(0.03)	(0.05)
Covariates	No	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
First-stage F-Statistic	106.57	71.09	64.31	61.98
BIC	30572.35	30524.48	30523.91	30565.76
No. of Observations	4049	4049	4049	4049

* *Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights.

Table 7: Average Effects of Aging Out of WIC on HEI-2010, No-School-Meal Sample

	Order of Polynomial of $\tilde{Age}$			
	1st	1st	2nd	3rd
Panel A: Fuzzy RDD				
Off WIC (D)	-11.29**	-9.82**	-10.45	-11.97
	(5.18)	(4.92)	(7.46)	(9.09)
Panel B: Sharp RDD				
Age $\geq$ 61 months (T)	-3.90**	-3.46**	-3.38	-4.37
	(1.78)	(1.73)	(2.46)	(3.29)
Panel C: First-stage Estimates				
Age $\geq$ 61 months (T)	0.35***	0.35***	0.32***	0.36***
	(0.03)	(0.03)	(0.04)	(0.05)
Covariates	No	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
First-stage F-Statistic	104.98	63.68	57.61	55.43
BIC	25961.43	25791.02	25872.34	26058.99
No. of Observations	3358	3358	3358	3358

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights.

Table 8: Average Effects of Aging Out of WIC on Sub-categories of Child's Dietary Quality, Full Sample

	Dependent Variable				
	Adequacy Score	Moderation Score	%Energy from Added Sugar	%Energy from Saturated Fat	Energy (kcal)
Panel A: Fuzzy RDD					
Off WIC (D)	-1.01	-1.56	-3.52	1.00	274.50
	(1.95)	(1.91)	(2.23)	(1.16)	(172.41)
Panel B: Sharp RDD					
Age $\geq$ 61 months (T)	-0.37	-0.56	-1.27	0.36	99.30
	(0.71)	(0.69)	(0.81)	(0.42)	(62.02)
Covariates	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
No. of Observations	4049	4049	4049	4049	4049

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from the linear model are reported.

Table 9: Average Effects of Aging Out of WIC on Sub-categories of Child's Dietary Quality, No-School-Meals Sample

	Dependent Variable				
	Adequacy Score	Moderation Score	%Energy from Added Sugar	%Energy from Saturated Fat	Energy (kcal)
Panel A: Fuzzy RDD					
Off WIC (D)	-6.62**	-3.20	-0.25	1.68	337.53
	(2.70)	(3.07)	(3.06)	(1.87)	(284.94)
Panel B: Sharp RDD					
Age $\geq$ 61 months (T)	-2.34**	-1.13	-0.09	0.59	119.02
	(0.95)	(1.08)	(1.08)	(0.66)	(100.60)
Covariates	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
No. of Observations	3358	3358	3358	3358	3358

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from linear model are reported.

Table 10: Average Effects of Aging Out of WIC on Rates of Food Insecurity, Full Sample

	Food Insecurity			Very Low Food Security		
	Household	Adult	Child	Household	Adult	Child
Panel A: Fuzzy RDD						
Off WIC (D)	5.78	7.34	-7.06	0.78	7.56	-1.02
	(7.54)	(7.60)	(6.91)	(5.30)	(5.52)	(1.10)
Panel B: Sharp RDD						
Age $\geq$ 61 months (T)	1.36	3.50	-1.92	1.12	4.99	-1.08
	(3.99)	(4.04)	(3.14)	(2.37)	(2.74)	(0.79)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4029	4029	4029	4029	4029	4029

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from the linear model are reported.

Table 11: Average Effects of Aging Out of WIC on Rates of Food Insecurity, No-School-Meals Sample

	Food Insecurity			Very Low Food Security		
	Household	Adult	Child	Household	Adult	Child
Panel A: Fuzzy RDD						
Off WIC (D)	9.82	13.83	-7.06	-5.02	8.34	-0.20
	(11.09)	(11.24)	(6.91)	(7.31)	(8.77)	(0.86)
Panel B: Sharp RDD						
Age $\geq$ 61 months (T)	3.34	5.91	-2.58	-0.48	6.27	-0.46
	(5.61)	(5.59)	(3.97)	(2.95)	(3.64)	(0.97)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3343	3343	3343	3343	3343	3343

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from the linear model are reported.

8 Appendix

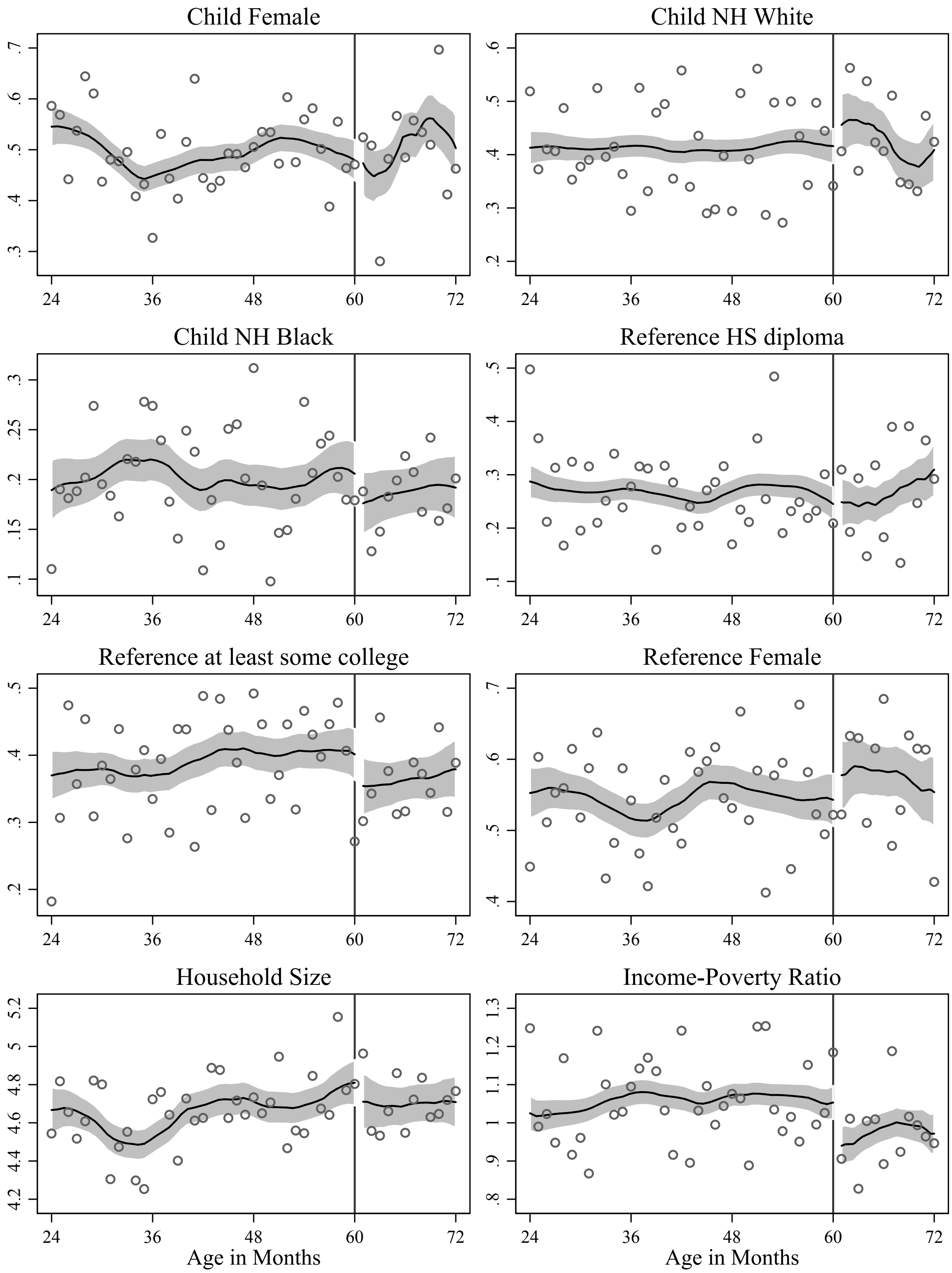

Figure A1: Discontinuity in baseline covariates, full Sample

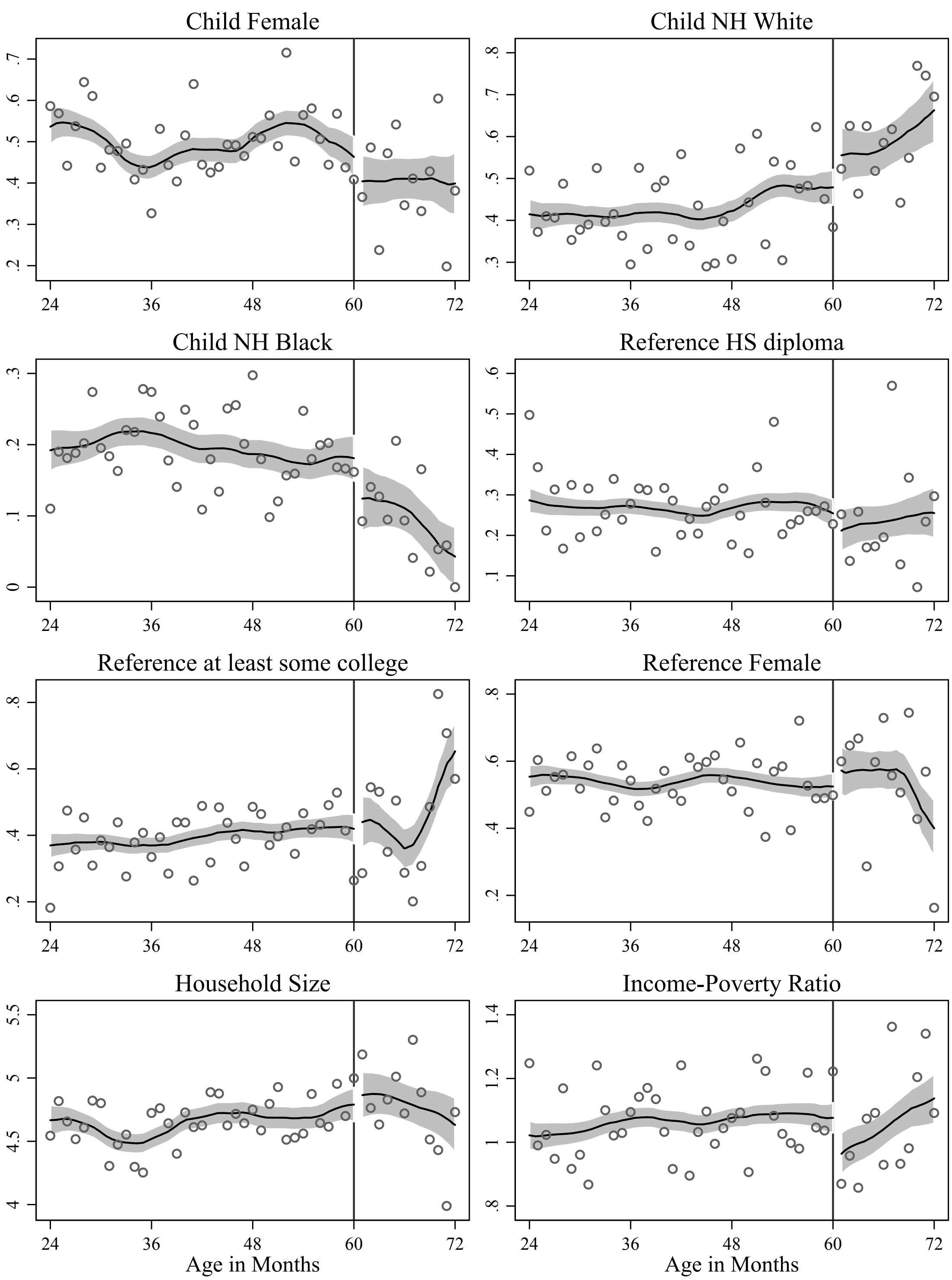

Figure A2: Discontinuity in baseline covariates, no-school-meals Sample

Table A1: Maximum monthly allowances for 12-59 month olds

Foods	Amount	Notes
Juice (100%)	128 fl oz	Can sub. single strength juice for concentrate
Milk (reduced fat or skim)	16 qt	Can sub. yogurt, cheese, soy beverage, and tofu
Cereal	36 oz	$\geq \frac{1}{2}$ of approved cereal must be whole grain
Eggs	1 dozen	
Produce	$8	fresh or processed w/o added sugar, fat, oil, or salt
Whole wheat bread	2 lb.	Can sub. whole grains, brown rice, bulgur, oatmeal, soft corn or whole wheat pasta or tortillas
Legumes (dry)	1 lb	
OR Legumes (canned)	64 oz	
OR Peanut butter	18 oz	

Table A2: Discontinuities in Baseline Covariates, Second-order Polynomial of $\widetilde{Age}$

	Full	No School Meals	No School	Nov-Apr
Child Female	-0.09	-0.17	-0.23**	-0.20
	(0.08)	(0.11)	(0.12)	(0.17)
Child NH White	0.05	0.06	0.07	0.32**
	(0.08)	(0.10)	(0.10)	(0.13)
Child NH Black	-0.04	-0.05	-0.05	-0.17**
	(0.05)	(0.05)	(0.05)	(0.07)
Child Hispanic	0.03	0.03	0.01	-0.17
	(0.06)	(0.07)	(0.07)	(0.11)
Reference HS diploma	-0.01	-0.09	-0.04	0.03
	(0.07)	(0.09)	(0.10)	(0.16)
Reference at least some college	-0.06	0.04	-0.01	0.04
	(0.07)	(0.10)	(0.10)	(0.17)
Reference Female	-0.01	0.01	0.08	-0.09
	(0.06)	(0.09)	(0.10)	(0.14)
Household Size	-0.07	0.07	0.01	-0.47
	(0.19)	(0.28)	(0.31)	(0.47)
Income-Poverty Ratio	-0.15*	-0.21**	-0.24**	0.01
	(0.08)	(0.10)	(0.12)	(0.15)
Joint Test p-values[a]	0.20	0.20	0.08	0.03
No. of Observations	4049	3358	3219	1508

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights.
[a] p-values for tests of linear restrictions that all discontinuities are jointly zero.

Table A3: Discontinuities in Baseline Covariates, Third-order Polynomial of $\widetilde{Age}$

	Full	No School Meals	No School	Nov-Apr
Child Female	0.07	-0.04	-0.09	-0.15
	(0.09)	(0.12)	(0.12)	(0.19)
Child NH White	0.01	0.06	0.06	0.24
	(0.09)	(0.11)	(0.12)	(0.16)
Child NH Black	-0.07	-0.10	-0.11	-0.19**
	(0.06)	(0.06)	(0.07)	(0.09)
Child Hispanic	0.07	0.06	0.06	-0.13
	(0.07)	(0.09)	(0.09)	(0.13)
Reference HS diploma	0.06	-0.03	0.04	0.15
	(0.08)	(0.11)	(0.11)	(0.19)
Reference at least some college	-0.05	0.03	-0.11	-0.24
	(0.09)	(0.12)	(0.12)	(0.18)
Reference Female	0.04	0.16	0.13	-0.15
	(0.08)	(0.11)	(0.12)	(0.17)
Household Size	0.13	0.26	0.52	-0.20
	(0.25)	(0.37)	(0.39)	(0.60)
Income-Poverty Ratio	-0.15	-0.24**	-0.24**	-0.18
	(0.09)	(0.11)	(0.12)	(0.17)
Joint Test p-values[a]	0.44	0.24	0.18	0.00
No. of Observations	4049	3358	3219	1508

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights.

[a] p-values for tests of linear restrictions that all discontinuities are jointly zero.

Table A4: Average Effects of Aging Out of WIC on HEI-2010, No-Schoolers Sample

	Order of Polynomial of $\widetilde{Age}$			
	1^{st}	1^{st}	2^{nd}	3^{rd}
Panel A: Fuzzy RDD				
Off WIC (D)	-13.15**	-12.15**	-9.89	-17.98*
	(6.24)	(5.88)	(9.32)	(10.03)
Panel B: Sharp RDD				
Age $\geq$ 61 months (T)	-4.55**	-4.28**	-3.20	-6.66*
	(2.20)	(2.12)	(3.05)	(3.60)
Panel C: First-stage Estimates				
Age $\geq$ 61 months (T)	0.35***	0.35***	0.32***	0.37***
	(0.03)	(0.03)	(0.04)	(0.05)
Covariates	No	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
First-stage F-Statistic	103.50	56.82	53.58	50.86
BIC	25094.17	24959.99	24726.04	25752.59
No. of Observations	3219	3219	3219	3219

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights.

Table A5: Average Effects of Aging Out of WIC on HEI-2010, No-Schoolers November-April Sample

	Order of Polynomial of $\widetilde{Age}$			
	1^{st}	1^{st}	2^{nd}	3^{rd}
Panel A: Fuzzy RDD				
Off WIC (D)	-16.90**	-17.66**	-20.96	-38.24**
	(8.19)	(8.41)	(14.82)	(19.29)
Panel B: Sharp RDD				
Age $\geq$ 61 months (T)	-6.56**	-6.35**	-5.94	-11.25**
	(3.28)	(3.13)	(4.54)	(4.99)
Panel C: First-stage Estimates				
Age $\geq$ 61 months (T)	0.39***	0.36***	0.28***	0.29***
	(0.05)	(0.06)	(0.08)	(0.10)
Covariates	No	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
First-stage F-Statistic	60.96	23.30	24.23	22.61
BIC	11941.59	12010.16	12249.97	13414.67
No. of Observations	1508	1508	1508	1508

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights.

Table A6: Average Effects of Aging Out of WIC on Sub-categories of Child's Dietary Quality, No-Schoolers Sample

	Dependent Variable				
	Adequacy Score	Moderation Score	%Energy from Added Sugar	%Energy from Saturated Fat	Energy (kcal)
Panel A: Fuzzy RDD					
Off WIC (D)	-8.04**	-4.11	-1.25	2.88	367.78
	(3.74)	(3.25)	(3.50)	(1.91)	(283.54)
Panel B: Sharp RDD					
Age $\geq$ 61 months (T)	-2.83**	-1.45	-0.44	1.02	129.67
	(1.37)	(1.15)	(1.24)	(0.68)	(99.27)
Covariates	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
No. of Observations	3219	3219	3219	3219	3219

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from the linear model are reported.

Table A7: Average Effects of Aging Out of WIC on Sub-categories of Child's Dietary Quality, No-Schoolers November-April Sample

	Dependent Variable				
	Adequacy Score	Moderation Score	%Energy from Added Sugar	%Energy from Saturated Fat	Energy (kcal)
Panel A: Fuzzy RDD					
Off WIC (D)	-9.01	-8.65*	-9.64*	5.35**	141.03
	(5.50)	(4.67)	(5.84)	(2.65)	(305.55)
Panel B: Sharp RDD					
Age $\geq$ 61 months (T)	-3.24	-3.11*	-3.46*	1.92**	50.68
	(2.10)	(1.64)	(2.02)	(0.90)	(112.25)
Covariates	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
No. of Observations	1508	1508	1508	1508	1508

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from the linear model are reported.

Table A8: Average Effects of Aging Out of WIC on Rates of Food Insecurity, No-Schoolers Sample

	Food Insecurity			Very Low Food Security		
	Household	Adult	Child	Household	Adult	Child
Panel A: Fuzzy RDD						
Off WIC (D)	-6.47	-5.06	-12.26	-9.57	-5.27	0.04
	(12.33)	(13.72)	(6.67)	(6.65)	(10.20)	(0.81)
Panel B: Sharp RDD						
Age $\geq$ 61 months (T)	-0.62	1.81	-1.55	-2.74	1.74	-0.13
	(6.56)	(6.48)	(4.68)	(3.30)	(3.54)	(1.04)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3204	3204	3204	3204	3204	3204

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from the linear model are reported.

Table A9: Average Effects of Aging Out of WIC on Rates of Food Insecurity, No-Schoolers November-April Sample

	Food Insecurity			Very Low Food Security		
	Household	Adult	Child	Household	Adult	Child
Panel A: Fuzzy RDD						
Off WIC (D)	42.22***	24.60	10.84	15.10	17.10	7.04
	(9.02)	(22.84)	(18.73)	(12.13)	(13.26)	(7.24)
Panel B: Sharp RDD						
Age $\geq$ 61 months (T)	9.74	12.15	4.41	4.11	6.50	1.46
	(9.73)	(10.32)	(8.01)	(3.68)	(3.47)	(1.33)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1503	1503	1503	1503	1503	1503

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are clustered at the PSU-strata level. All calculations use survey weights. Coefficient estimates from the linear model are reported.