



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

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

Travis A. Smith, Pourya Valizadeh

April 25, 2023

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 use this exogenous program rule for identification and find diet quality declines nearly 20%, on average, for those who have yet to transition into kindergarten. Decreases are mainly driven by reduced consumption of healthier WIC-targeted foods. A quantile regression discontinuity approach reveals children prone to lower-quality diets experience the largest decreases in diet quality, reaching nearly 30%, while those prone to higher-quality diets experience no aging-out-of-WIC effects. There are no effects on calorie consumption, regardless of school attendance, indicating caregivers maintain diet quantity for children at the expense of diet quality. Policy implications include allowing children to stay on WIC until they enter kindergarten. We calculate back-of-the-envelope program costs over the next five years for such a “kindergarten-roll-off” WIC policy under current rules and newly proposed rules to realign WIC packages with the Dietary Guidelines for Americans. Under current rules, costs would average \$112 million over the next five years (2024-2028), or about 2% of total program costs. Under proposed rule changes, kindergarten-roll-off costs would average \$144 million per year, or 2.25% of total program costs.

Keywords: child nutrition, food assistance, fuzzy quantile regression discontinuity design, school food programs

JEL Classification: I18, H51, H53

Running Head: Aging out of WIC and Child Nutrition

Author Information: Travis A. Smith is an associate professor in the Department of Agricultural and Applied Economics at the University of Georgia. Pourya Valizadeh is a Research Assistant Professor in the Department of Agricultural Economics at Texas A&M University.

Correspondence: Travis A. Smith. Department of Agricultural and Applied Economics, The University of Georgia, 313C Conner Hall, 147 Sedar St., Athens, GA, 30602, GA, USA. Email: tasmith@uga.edu

Acknowledgement and Disclaimer: Lead authorship is shared equally among the authors. We would like to thank Marianne Bitler, Chelsea Crain, David Frisvold for their helpful comments, as well as seminar participants at the University of Minnesota and the 2018 American Society of Health Economists annual meeting. The authors also gratefully acknowledge useful comments from two anonymous reviewers and the editor, Jill McCluskey. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Healthy eating in early childhood is important: it promotes proper growth and development ([Marshall, Burrows, and Collins 2014](#)), prevents a variety of adverse health outcomes, such as childhood obesity and dental caries ([Epstein et al. 2001, 2008](#); [Nunn et al. 2009](#)), and leads to better cognitive performance ([Glewwe and King 2001](#); [Frisvold 2015](#)). Importantly, skills related to nutrition are learned early on in life and tend to persist into adulthood ([Birch 1999](#); [Benton 2004](#); [Dovey et al. 2008](#)). Because children from low-income households are particularly susceptible to nutritional deficiencies (see, e.g., [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 nearly 6.2 million individuals with nearly \$5 billion in benefits in fiscal year 2021 ([FNS-USDA, 2022a](#)). WIC currently provides benefits in the form of vouchers for specific foods (e.g., milk, juice, whole grains, eggs, cereal, and legumes, along with a cash-value voucher for produce) and nutrition services (e.g., nutrition education). The goal of WIC is to improve the health and nutritional well-being of 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; in 2018, about 45 percent of all infants received WIC benefits, as did roughly 24 percent of all pregnant and postpartum women, and 22 percent of all children up to age 5 ([FNS-USDA, 2018](#)).

This study focuses on the diet quality and quantity of child beneficiaries, who make up half of all WIC participants ([Kline et al. 2022](#)). According to federal WIC eligibility criteria, children remain eligible up to the age of 5 years, and WIC eligibility ends in the month following their fifth birthday. We use this exogenous program rule as our main source of identification using regression discontinuity.

The arbitrariness of the 5-year age limit has long been recognized by WIC administrators. For example, a report by the Government Accounting Office (GAO, 1985) states, “Most WIC officials suggested that the Congress established the limit at age 5 to provide a bridge between participation in WIC and entry into other feeding programs that begin when children enter the educational system.” Yet, children do not enter school immedi-

ately following their fifth birthday. Indeed, children begin school, in many cases, after turning 5, depending on their state’s cutoff date.¹ In March 2021, a bill was proposed in the House ([H.R.2011 - 117th Congress 2021](#)) and Senate ([S.853 - 117th Congress 2021](#)) which would allow the U.S. Department of Agriculture to grant waivers to states seeking to extend eligibility up to a child’s sixth birthday or when the child enters kindergarten, whichever comes first.²

The arbitrary cutoff of 5 years potentially creates a gap in federal food assistance for child beneficiaries, placing a strain on household resources. Thus, we focus on aging-out-of-WIC effects for children who are in school versus those who are not. At least two possible mechanisms are at play. First, is a substitution effect: previous research has demonstrated federally-subsidized school meals, as opposed to home-produced meals, significantly improve low-income children’s diets, especially the most nutritionally disadvantaged ([Smith 2017](#); [Valizadeh and Ng 2020](#); [Smith, Mojduszka, and Chen 2021](#)). Second, is an income effect: attending public kindergarten potentially frees up household resources related to childcare. For example, parents of children who age out of WIC while in school may have more resources to purchase healthier WIC foods after aging out. Along the same lines, parental employment increases when the youngest child begins kindergarten ([Gelbach 2002](#)).³

A small literature examines the effects of aging out of WIC, mostly using regression discontinuity. Using the Early Childhood Longitudinal Study, Birth Cohort (ECLS-B), [Arteaga, Heflin, and Gable \(2016\)](#) find household food insecurity increases when children age out of WIC. Similarly, [Cho \(2022\)](#) develops a partial identification method to address self-selection into WIC and finds aging out of WIC increases child food insecurity. [Si and Leonard \(2020\)](#) show that losing access to WIC significantly increases the probability of food bank utilization. Similarly, [Frisvold, Leslie, and Price \(2020\)](#) find the boost in whole-grain purchases while on WIC fades away within 6 months after children age out of WIC. Our study is closest to [Bitler et al. \(2022\)](#), who examine the impact of losing WIC on a range of laboratory (e.g., hemoglobin, hematocrit, and anemia) and nutritional outcomes, including adults’ diets. [Bitler et al. \(2022\)](#) find minimal effects on child outcomes; rather, adult women in the household reduce caloric intake and have higher reports of food

insecurity.

We extend this literature by estimating the effects of aging out of WIC on the quality and quantity of children’s diets while addressing the role of school attendance. While the aforementioned 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 heterogeneous population due to, for example, parental and environmental factors. We contribute to the literature by estimating both the average and distributional effects of aging out of WIC on measures of dietary quality and dietary quantity of children.

Using twenty years of food intake data from the National Health and Nutrition Examination Survey (NHANES), we construct our research design in two ways to better understand the interplay between WIC and school attendance. First, we restrict our main sample to those surveyed during the school year. Second, we examine the aging-out-of-WIC effects for those who are in school versus those who are not. This design is effectively a “difference-in-discontinuity” approach, which is valid under standard continuity and orthogonality conditions (see [Grembi, Nannicini, and Troiano 2016](#)).⁴

If we ignore school attendance, we find insignificant aging-out effects on both dietary quality and quantity (i.e., caloric intake). However, when we split the sample by those who have transitioned into school and those who have not, we find aging out of WIC while not in school reduces diet quality by about 20% (roughly 10 HEI points). No effects are found for children who age out of WIC while in school.

We apply a fuzzy regression discontinuity design to quantile regression and find effects are more pronounced in the lower tail of the diet quality distribution, with decreases reaching nearly 30% at low quantiles. While these results may appear large, they are local treatment effects (i.e., for the set of compliers at the cutoff of 61 months) and are best interpreted as short-term effects.⁵

We further find three-quarters of the average decrease in diet quality is from reduced intakes of healthier, WIC-targeted foods (e.g., fruits, vegetables, whole grains, and dairy), and the remainder is from increased consumption of less-healthy components (e.g., saturated fats).

In terms of the quantity of food consumed, we find no aging-out-of-WIC effects on calorie intake, regardless of school attendance. This indicates children maintain similar quantities of food consumption when aging out of WIC but substitute towards a lower quality diet, provided they have yet to transition into school.

We discuss the policy implications of our findings, such as allowing children to stay on WIC until they enter kindergarten, as most recently proposed in the U.S. Congress ([H.R.2011 - 117th Congress 2021](#); [S.853 - 117th Congress 2021](#)). We calculate back-of-the-envelope program costs over the next five years for such a “kindergarten-roll-off” WIC policy under current rules and newly proposed rules that would realign WIC packages with the Dietary Guidelines for Americans.⁶ Under current rules, kindergarten-roll-off costs would amount to \$99.4 million in 2024, or about 1.9% of total program costs, reaching \$119.8 in 2028, or 2% of total costs. Under proposed rule changes ([Federal Register 2022](#)), kindergarten-roll-off costs would be \$128.1 million in 2024 (2.1% of total program costs) and \$155.6 million in 2028 (2.3% of total costs).

Background: WIC Eligibility and Benefits

WIC eligibility is limited to four groups of individuals: pregnant women, postpartum women, infants up to the age of 1 year, and children up to 5 years old. In the fiscal year 2020, roughly one-quarter of WIC participants were women (22.8%), another one-quarter were infants (24.0%), and over half (53.2%) were children ([Kline et al. 2022](#)). In addition, WIC is a means-tested program: individuals must either live in a household with family income below 185% of the Federal Poverty Guidelines (FPG) or be adjunctively eligible through participation in another assistance program such as Medicaid, Temporary Assistance to Needy Families (TANF), or Supplemental Nutrition Assistance Program (SNAP).⁷ After the initial income certification, re-certification occurs every six months to one year.

The following final eligibility criteria are important in understanding how the program delivers benefits: individuals must be nutritionally at-risk due to either a medical condition or an inadequate diet, as determined by a health professional (e.g., a physician, nutritionist,

dietitian, or nurse). In practice, almost all income-eligible applicants are deemed at risk due to an inadequate diet pattern, even if other risk criteria are not identified (Bitler, Currie, and Scholz 2003).⁸ Nevertheless, the “nutritionally at-risk” eligibility criteria places 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. Nutrition 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 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 billion in total program costs in the fiscal year 2021, the aforementioned nutrition services amounted to \$2 billion, or about 40% (FNS-USDA, 2022a). The remaining \$3 billion came in the form of food package redemptions (i.e., only redeemed items incur a cost). Food packages are provided on a monthly basis in the form of vouchers that can be redeemed for specific foods.⁹ Currently, the food package for children includes 100% juice, low-fat/skim milk, breakfast cereal, eggs, fruits and vegetables, whole grains, and legumes and/or peanut butter (FNS-USDA, 2022b).¹⁰ Each food item is available for redemption for one month, and benefits do not carry over. In 2019, the average monthly redemption cost of the child food package was about \$41 (FNS-USDA, 2022a). To put this number in perspective, the average per-person benefit level for SNAP was \$130 per month in the same year (FNS-USDA, 2022c).

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.¹¹

Empirical Approach

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 one if child i is *off* WIC and zero otherwise. The primary difficulty in estimating the causal effects of D_i on nutritional outcomes 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 our nutritional outcomes (Y_i), leading to biased and inconsistent estimates.

Regression Discontinuity Design

Our identification strategy is a regression discontinuity design (RDD), exploiting the fact that WIC participation is a discontinuous function of a child’s age.¹² In particular, program rules stipulate that children are no longer 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). Because RDD is a local treatment effect estimator, consistent for compliers at the cutoff, it identifies the short-term effects of aging out of WIC on child nutrition.

A primary identifying assumption of RDD – referred to as the *local continuity* assumption – 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 one 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 the child’s age). However, since D_i involves self-selection into WIC prior to aging out, $Pr(D_i)$ is not a deterministic function of age, and the Sharp RDD will not yield consistent estimates. In particular, negative selection into the WIC program, as suggested by [Bitler and Currie \(2005\)](#), will lead to downward biased estimates.

We use a “Fuzzy” RDD, which still assumes $Pr(D_i)$ changes discontinuously at $Age_i = 61$, but this change must not be deterministic with regard to age. The fuzzy design considers the change in $Pr(D_i)$ at the cutoff T_i ,

$$(1) \quad D_i = \alpha_0 + \alpha_1 T_i + \alpha_2 (Age_i - 61) + \alpha_3 T_i \times (Age_i - 61) + v_i,$$

as estimated by α_1 , relative to being off WIC (D_i) in the vicinity of T_i ,

$$(2) \quad \log Y_i = \beta_0 + \beta_1 D_i + \beta_2 (Age_i - 61) + \beta_3 T_i \times (Age_i - 61) + u_i,$$

as estimated by β_1 . Since we are examining the ratio of these two changes (i.e., β_1/α_1), which is a Wald-type estimator, we can use instrumental variable (IV) estimation with equation (1) as the first stage and (2) as the second stage (Hahn, Todd, and Van der Klaauw 2001).¹³

A local linear estimator with a uniform kernel is shown to be the optimal order and kernel as determined by a data-driven procedure proposed by Pei et al. (2022), which is based on minimizing the asymptotic mean squared error (MSE) of the RDD point estimate (see the online supplementary appendix Table A2).¹⁴ The estimated optimal bandwidth choice, based on the MSE-optimal bandwidths method in Calonico, Cattaneo, and Titiunik (2014), is roughly 12 months on either side of the cutoff.¹⁵ Finally, in calculating aging-out-of-WIC semi-elasticities from β_1 in equation (2), we apply a small-sample bias correction suggested in Kennedy et al. (1981). The corresponding standard errors for the bias-corrected semi-elasticities are calculated following Jan van Garderen and Shah (2002).

A Fuzzy Quantile Regression Discontinuity Design

We are also interested in how aging out of WIC affects children prone to poorer nutrition separately from those prone to better nutrition. Specifically, a child’s parental and/or environmental characteristics may vary in unobservable ways that interact with the transition out of WIC. For example, parents with a relatively high preference for investing in child health, as compared to consuming adult goods, may choose to maintain a WIC-type diet for their child (c.f. Havnes and Mogstad 2015). This sort of unobserved heterogeneity can be modeled in a distributional analysis via quantile regressions.

We use a linear-in-parameters quantile regression corresponding to equation (2):

$$(3) \quad \log Y_i = \beta_0(u_i) + \beta_1(u_i)D_i + \beta_2(u_i)(Age_i - 61) + \beta_3(u_i)T_i \times (Age_i - 61),$$

where u_i is a non-separable error term also called a “rank” variable. The rank variable u_i is interpreted as unobserved “proneness” for the outcome (Doksum 1974). For example, children with relatively higher values of rank/unobserved proneness (e.g., more favorable parental and/or environmental characteristics) are placed at higher quantiles of the conditional outcome distribution. This portion of the distribution may be affected differently when losing WIC packages as compared to the lower portion of the distribution.

As in the mean case, u_i will in general correlate with the treatment status and the outcome, necessitating a Fuzzy design. We use the “Method of Moments-Quantile Regression” (MM-QR) estimator developed in Machado and Santos Silva (2019), which allows for endogenous regressors, to estimate the Fuzzy quantile RDD specification in equation (3). Briefly, MM-QR obtains conditional quantile estimates by simultaneously estimating the local and scale functions via conditional expectations. The information provided by these conditional moments is equivalent to the information provided by regression quantiles (see Machado and Santos Silva 2019, for details).¹⁶

An additional key identifying assumption in a quantile RDD is *rank similarity* (see Chernozhukov and Hansen 2005). This framework states that conditional ranks of children around the cutoff do not systematically change between treatment status. Intuitively, this implies children who are highly prone to more favorable nutritional outcomes remain highly prone in either treatment state.¹⁷ Thus, the entire distribution can change location and scale due to losing WIC, but changes in rankings cannot be systematically related to losing WIC.

We believe the rank similarity assumption holds in the present context, given that WIC provides very specific and relatively healthy food baskets. It is hard to imagine a counterfactual situation where children prone to low-quality diets become systematically ranked above their counterparts when losing WIC. Put simply, the rank similarity assumption states: whatever is driving the conditional ranking of children prior to aging out of WIC will persist into the untreated state, and those rankings are assumed to remain stable once

we instrument for WIC and control for age.

Data

Our regression discontinuity design necessitates a sample of children with ages around the policy cutoff of 5 years (60 months). Therefore, to ensure sufficient representation, we use ten waves of data from the continuous cycles of the public-use National Health and Nutrition Examination Survey (NHANES), covering 1999–2018. Each NHANES cycle is an independently drawn, nationally representative sample covering a two-year period.

Our nutritional outcomes are based on in-person 24-hour dietary recalls collected during NHANES’s standardized medical exam.¹⁸ For children under the age of six, dietary interviews are ascertained by the person most knowledgeable about the child’s food intake (e.g., a parent or other caregiver). All interviews use computer-assisted, automated multi-pass data collection methods to reduce misreporting of foods (Moshfegh et al. 2008; Foster and Bradley 2018).

NHANES provides demographic characteristics and self-reported participation in food assistance programs. We define current WIC participants as those who report receiving WIC benefits at the time of the interview.¹⁹ While the public-use version of NHANES does not provide birth dates, we do know the child’s age in months at the time dietary intake was collected. In our main analysis below, we focus on four- and five-year-old children (i.e., aged 48-71 months). This corresponds to the estimated optimal bandwidth of 12 months on either side of the cutoff. The comparison group is WIC-eligible non-participants, defined as those who live in households with family income less than 200% of the FPG.²⁰

Nutritional Outcomes: Diet Quantity and Quality

Diet quantity is measured by the amount of calories consumed.²¹ 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 DGA forms the basis for a host of federal nutrition policies such as dietary standards for Federal food assistance programs, public nutrition information

campaigns, and nutrition labeling of foods. The original HEI was created in 1995 and has since been revised several times to reflect key changes in the DGA. In this paper, we use the HEI-2015 that reflects the different food groups and key recommendations in the 2015-2020 DGA for ages two years and older (see [Krebs-Smith et al. 2018](#); [Reedy et al. 2018](#)).

The HEI-2015 is a continuous, scalar measure calculated as the sum of 13 components based on the *per-calorie* consumption of various foods and nutrients. There are nine *adequacy* components (total fruits, whole fruits, 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 four *moderation* components (refined grains, sodium, added sugars, and saturated fats) for which higher scores reflect lower intakes. Each component assigns a score ranging from 0 to 5 (total fruits, whole fruits, total vegetables, greens and beans, total protein foods, seafood and plant proteins), 0 to 10 (whole grains, dairy, fatty acids, and all moderation components). The total HEI-2015 is scored from 0 to 100. The online supplementary appendix Table A3 provides exact details of the scoring procedure according to [Krebs-Smith et al. \(2018\)](#).

Because WIC promotes the consumption of healthier foods while reducing the consumption of less-healthy foods, we also utilize the two main sub-categories of the HEI-2015: the adequacy score, which is out of 60 points, and the moderation score, which is out of 40 points. Adequacy foods should be consumed in greater quantities (e.g., fruits, vegetables, and whole grains) and moderation foods should be consumed in lower quantities (e.g., added sugars and fats). Thus, a higher moderation score corresponds to lower consumption of these foods/nutrients.

Identifying Current School Attendance

NHANES does not have a specific question pertaining to current school attendance for four- and five-year-old respondents. However, we can identify current school attendance using a subsample of children surveyed during the school year in conjunction with a question about typical school attendance.

The question states: “**During the school year**, does [child] attend a kindergarten,

grade school, junior or high school?” [emphasis ours]. As we show, when this question is fielded during the summer months, parents answer in the affirmative if their child *will be* attending in the upcoming school year. Although this is a valid answer to the question, it does not tell us if the child is in school when dietary intakes are collected.

We expect the aforementioned “typical” school attendance question to more closely align with “current” school attendance if asked during the school year, rather than during the summer months. Interviews are identified as occurring either November 1 to April 30 (i.e., the “Nov-Apr” sample) or May 1 to October 31 (i.e., the “May-Oct” sample). The Nov-Apr sample clearly occurs during the school year, while for the model state roughly half of the May-Oct sample occurs during the summer months (e.g., June-August) when children are not typically attending school.²²

With an eye towards validating this approach, we use a question from 1999-2010 NHANES asked of 6-to-19-year-olds:²³ “{Are you/Is Sample Person} **now**... (a) attending school, (b) On vacation from school (between grades), (c) Neither in school or on vacation from school (between grades), or (d) refused/don’t know” [emphasis ours]. We compare answers to this question with the “during the school year” question across the two six-month interview periods: Nov-Apr versus May-Oct. We group the “between grades” responses, (b) and (c), into a single category and cross-tabulated “In school now” and “In school during the year” by interview period. As we can see in the online supplementary appendix Table A4, in the Nov-Apr sample, 88.7% of 6-to-19-year-olds report they were currently in school, as compared to 56.3% in the May-Oct sample, which makes sense. Moreover, there is high agreement among the two questions during Nov-Apr: 97.3% of those who responded affirmatively to the “During the school year” question also responded they were currently in school. However, during the May-Oct interviews, there is much lower agreement: 61% of those who stated they attended school during the school year were currently in school.

A second issue arises with the May-Oct sample. We should expect a valid measure of current school attendance to transition smoothly around the age cutoff of 61 months. That is, given birth months are distributed uniformly throughout the year, we should not expect children to start school immediately following their fifth birthday. Indeed, the left column in Figure 1 shows a smooth transition in the school attendance question for the

Nov-Apr sample but a statistically significant increase in affirmation of nearly 30% at 61 months for the May-Oct sample.

One possibility for this jump in the summer/fall months (May-Oct) is a behavioral one: when parents are asked about school attendance “during the school year” in the May-Oct months, they might be thinking about the upcoming school year. Results from the left column in Figure 1 imply a child’s fifth birthday during the summer/fall months prompts a parent to respond affirmatively.

In summary, in understanding how school attendance interacts with aging out of WIC, our strongest research design will be to use the Nov-Apr sample. In the online supplementary appendix, we show results are null for the May-Oct sample, which is expected given we cannot accurately define school attendance (i.e., results are prone to measurement error and attenuation bias). In what follows, we focus on the Nov-Apr sample, and interested readers can find the corresponding tables/figures for the May-Oct sample in the online supplementary appendix.

Summary Statistics

Table 1 provides summary measures for our nutritional outcomes of interest for the full Nov-Apr sample, as well as by school attendance and, separately, by WIC participation. Outcomes vary by school attendance in expected ways: overall diet quality is higher, mainly driven by healthier adequacy foods, and calorie consumption is higher. WIC participants, on the other hand, have higher quality diets arising from both adequacy and moderation components, with lower (insignificant) calorie consumption. Such differences in outcomes by WIC/school status, however, are potentially confounded by age, as well as the interaction between school and WIC.

Table 2, Panel A provides summary statistics for regressors in equations (1) and (2). The full Nov-Apr sample includes 958 children aged 48-71 months old living in households with incomes below 200% of the federal poverty guidelines. Consistent with uniform sampling across age, the average child is 59 months old, with 42% being at least 61 months old. About 72% of children report being off WIC at the time of the interview, consistent with take-up rates from administrative records for four-year-old children (see [FNS-USDA](#),

2018). Finally, nearly half of the sample (or 491 children) report attending school.

Perhaps unsurprisingly, children who report attending school during the school year are older on average (62 vs. 56 months old), more likely to fall on the right side of the age cutoff (65% vs. 19%), and be off WIC (81% vs. 62%) than those not in school. Similarly, WIC participants are younger, must fall to the left of the age cutoff, and much less likely to attend school. Our sample shows 35% of WIC (four-year-old) participants attend school, which equates to roughly 10% of the total sample (i.e., 35% of 271 is 95).²⁴

Table 2 also includes summary statistics for selected (baseline) demographic variables. Although we do not include demographic variables in our regressions, as they are not needed in an RDD framework, it's instructive to see how/if they change with school attendance and WIC participation. In terms of school status, the only differences are with respect to race/ethnicity and one of the income categories. However, a joint F -test reveals demographics are statistically insignificant (p -value=0.139). Differences by WIC status are numerous, as expected, given the self-selection problem: WIC participants are less likely to be non-Hispanic white, have less-educated caregivers, and live in larger households. However, any concerns with regard to identification should be due to differences in baseline demographics at the policy cutoff, which we test in the next section.²⁵

Tests of Identifying Assumptions

Discontinuities 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. The right column in Figure 1 plots out average WIC participation rates over age in months, overlaid with a local linear regression. As one can see, in both Nov-Apr and May-Oct samples the probability of WIC participation among eligibles declines significantly at the cutoff point of 61 months.²⁶

Child's Characteristics Balance at Cutoff

The validity of RDD also requires that individuals are not able to precisely manipulate the assignment variable. In the present context, we want to know if parents are systematically

misreporting the age of their children (for instance, by reporting that their children are younger than they actually are if they believe responses to the survey are related to WIC receipt). As shown in the online supplementary appendix Figure A3, consistent with expectations, the [McCrary \(2008\)](#) density test fails to reject the null hypothesis of random sorting of children around the age cutoff of 61 months.

We also examine whether baseline demographics are locally balanced on either side of the cutoff point. To do so, we replace the dependent variable in equation (1) with each of the covariates listed in Table 2. For categorical variables (i.e., child’s race/ethnicity and reference person’s educational attainment), we conduct a test for the linear hypothesis of joint significance of discontinuity gaps in all categories (see [Lee and Lemieux 2010](#)). Results are presented in the online supplementary appendix Table A8, which indicates that in all samples discontinuity gaps in covariates are insignificant at 5 percent, suggesting observed characteristics of children transition smoothly around the threshold.

Discontinuities in Nutritional Outcomes

Figure 2 plots out average nutritional outcomes by age-in-months for the Nov-Apr sample. The discontinuity estimates presented in the figure panels represent estimates from a Sharp RDD design. Starting with the full Nov-Apr sample (column (1)), we observe a decline in the HEI-2015 score by 1.8 HEI points (3.6% of the sample mean), which is not statistically significant. Discontinuity plots for the adequacy and moderation sub-categories of the HEI suggest this reduction in overall diet quality is primarily driven by reduced intakes of adequacy foods. Moreover, graphical evidence across sub-samples by school attendance in columns (2) and (3) indicate the reduction in diet quality tends to be concentrated in the not-in-school sub-sample, where we see an average decline in HEI scores by 3.8 points (8% of the sample mean). Again, this reduction in the overall diet quality is largely due to a statistically significant decrease in the consumption of adequacy foods. Regarding caloric intake, Figure 2 indicates children do not change their calorie consumption as they age out of WIC.²⁷

Results

Average Effects of Aging out of WIC

Table 3 reports the average effects of aging out of WIC on our nutritional outcomes, overall and by school participation for the Nov-Apr sample. We focus on the bias-corrected (Kennedy et al. 1981) aging-out-of-WIC effect estimates in percentage terms. The second-stage Fuzzy RDD coefficient estimates from equation (2) are in the online supplementary appendix Table A9.

Regarding the impact on overall diet quality for the full sample, we see a negative but statistically insignificant effect of roughly 10%, or 5 HEI-2015 points. Similarly, the estimated aging-out-of-WIC effect for the in-school sample is small and statistically insignificant (6.4%). However, for the not-in-school sample, we estimate a statistically significant decrease of 19.6% in overall diet quality, or about 10 HEI-2015 points. Together, these latter two results provide evidence the transition out of WIC while in school plays an important role in maintaining the dietary quality of low-income children.

Turning attention to adequacy (healthy) versus moderation (less healthy) components of the HEI, we again observe statistically insignificant effects for the full sample and for the in-school sub-sample. However, for children who have yet to transition into kindergarten, we see a large and statistically significant decrease of 28.5% in the adequacy score (or 7.7 HEI points). The reduction in moderation components of 11.2%, although insignificant, equates to about 2.5 HEI points. In other words, the decline in the overall diet quality of children who have yet to enroll in school largely stems from reduced intakes of healthier WIC-targeted foods.

Finally, we see no significant average effects on calorie consumption (i.e., energy intake) across all samples. Taken together with the previous results, this implies parents maintain a smooth level of energy intake, but at the sacrifice of quality.²⁸

In terms of robustness, we note results are effectively the same with the addition of baseline covariates found in Table 2, panel B, with or without indicators for the survey wave (see the online supplementary appendix Table A11). Moreover, results do not change

if we use an indicator for consuming school meals, rather than school attendance (see the online supplementary appendix Table A12).

Distributional Effects of Aging out of WIC

Figure 3 shows the distributional aging-out-of-WIC effects on child nutritional outcomes for the Nov-Apr sample. The first column presents the results for the full sample. Columns (2) and (3) are for the in-school and not-in-school sub-samples, respectively. In each panel, the solid line represents fuzzy RDD point estimates, reflecting the percentage change in the level of the nutritional outcome of interest, from the 5th to the 95th quantiles. The shaded areas represent the 90% and 95% confidence intervals (CI). When interpreting the results, note the quantiles on the x -axis refer to the counterfactual distribution – the (conditional) quantiles of the outcome to the right of the cutoff (i.e., five-year-olds) as if they were to stay on WIC.

Beginning with the full sample, we see losing access to WIC packages leads to large and significant declines at lower quantiles of the HEI-2015 distribution, ranging from 21.5% at 5th quantile to 10.5% at 40th quantile. This portion of the distribution is more likely to be comprised of children prone to lower-quality diets. At the median, and at higher quantiles, we find no aging-out-of-WIC effects. In other words, the insignificant average effects seen in the previous section mask important declines at low quantiles, regardless of school attendance.

Results by school-enrollment show aging-out-of-WIC effects on overall diet quality are concentrated among children not in school, consistent with results from mean regressions. For the not-in-school-sample, we observe sharp declines in diet quality, ranging from 27.6% at 5th quantile to 16.4% at 55th quantile. Effects become statistically insignificant at higher quantiles of the HEI-2015 distribution. No significant effects on HEI are observed for those in school.

In terms of “healthy” versus “less healthy” foods, for the full sample, we find statistically significant impacts at lower quantiles of both sub-categories’ distributions. For adequacy foods, the significant effects range from 23.2% at 5th quantile to 12.5% at 45th quantile, whereas for the moderation foods, significant effects range from 30.2% at 5th

quantile to 10.9% at 30th quantile. Results by school enrollment show that the decline in adequacy scores is driven by reduced intakes of adequacy foods for children not yet in school, with the size of the significant effects varying from 36.8% at 5th quantile to 22.3% at 75th quantile. In contrast, the reduction in moderation score is due to higher consumption of less healthy foods by both groups of children.

Finally, we find no aging-out-of WIC effects across the calorie consumption distribution in any sample. Here again, this is consistent with the idea that parents tend to maintain calorie consumption for their children, but at the expense of healthier eating.²⁹

Policy Implications

As of the writing of this article, a recent bill proposed in the House ([H.R.2011 - 117th Congress 2021](#)) and Senate ([S.853 - 117th Congress 2021](#)) would allow states to seek a waiver to extend WIC eligibility up to a child's sixth birthday or when the child enters kindergarten, whichever comes first. Extending WIC eligibility beyond the age of five clearly has monetary costs. For children who turn five during the summer months, this would equate to an extension of relatively few months; for children born in early fall, the extension would approach an additional year. We calculate back-of-the-envelope program costs over the next five years for such a "kindergarten-roll-off" WIC policy under current WIC rules and under newly proposed rules, as described next.

On November 21, 2022, FNS-USDA proposed a rule change to WIC ([Federal Register 2022](#)) to realign food packages with the most recent version of the Dietary Guidelines for Americans and to reflect the suggested changes by the National Academies of Sciences, Engineering, and Medicine ([NASEM, 2017](#)). FNS-USDA asked NASEM for both cost-neutral recommendations and recommendations not constrained by costs. The proposed rule states, "...FNS is proposing revisions to the food packages that prioritize WIC participants' supplemental nutrition needs over maintaining cost neutrality." ([NASEM, 2017](#), p.71092).

For child food packages (ages 2-4), the proposed rule would increase the cash-value voucher (CVV) for produce from \$9 to \$25, add canned fish, and require all breakfast

cereals to be whole grain, while also reducing whole grain offerings from 32 to 24 ounces, milk from 16 to 14 quarts, and juice from 128 to 64 ounces. The proposed rule allows states more flexibility in tailoring food packages to accommodate personal and cultural food preferences, while also ensuring more equitable access to supplemental foods by requiring states and vendors to offer wider varieties of foods.

Table 4, panels A through C, collates participation and spending projections from the proposed rule change ([Federal Register 2022](#)). For example, the increase in CVV amounts to \$914 million in additional spending in 2024, while the remaining rule changes create budget savings of \$142 million. Panel D presents our cost estimates for extending WIC eligibility until kindergarten (see table 4 notes for details on this calculation).

Under current WIC rules, we estimate kindergarten-roll-off costs to be \$99.4 million in 2024, or about 1.9% of total program costs, reaching \$119.8 in 2028, or 2% of total costs (see panel D of table 4). Under proposed rule changes ([Federal Register 2022](#)), we estimate kindergarten-roll-off costs to be \$128.1 million in 2024 (2.1% of total program costs) and \$155.6 million in 2028 (2.3% of total costs). In sum, the kindergarten-roll-off policy appears to be monetarily modest and in line with FNS-USDA’s sentiment toward prioritizing nutritional needs over cost neutrality.

Discussion and Conclusions

This study investigates the impact of losing eligibility for the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) on the nutritional well-being of children under the age of 5. WIC has a wide reach over this target population, reaching nearly one-quarter of all children in the United States ([FNS-USDA, 2018](#)). Due to program stipulations, children lose WIC in the month following their fifth birthday. We use this program rule to identify aging-out-of-WIC effects.

We find when the average child loses WIC and has yet to transition into kindergarten, the overall quality of their diet declines by nearly 20%. This equates to 10 HEI points, or just under one standard deviation. We estimate roughly three-quarters of this decrease comes from reduced consumption of WIC-targeted, healthier foods (i.e., the HEI adequacy

components). Moreover, decreases in dietary quality are concentrated among children most vulnerable to very low-quality diets (i.e., low quantiles), where declines in diet quality reach nearly 30%. Finally, we find no evidence of reduced calorie consumption. Together, these findings imply that a smooth transition off the WIC program and into kindergarten effectively shields children from decreases in the quality of food they consume.

Although we are unable to explore the exact mechanisms behind our findings due to data limitations, two prominent ones exist. First, federally subsidized school meal programs (School Breakfast and National School Lunch Programs), which are offered at no cost or very low costs to WIC participants, are known to increase diet quality ([Smith 2017](#); [Valizadeh and Ng 2020](#); [Smith, Mojduszka, and Chen 2021](#)). In fact, if we use an indicator for consuming school meals, rather than simply attending school, our results are largely the same (see the online supplementary appendix Table A12). Second, when children enter (public) kindergarten, this frees up household resources that were previously devoted to childcare – if child nutrition is a normal good, entering kindergarten creates an income effect. Similarly, if parents choose to devote more time to the labor force, this will also increase resources. Unfortunately, we do not have information on childcare costs, nor on parental labor force participation.

Another limitation of our data is we do not know if children are participating in Head Start, pre-kindergarten, or Child and Adult Care Food Programs (CACFP). However, if these programs shield children from the negative effects of aging out of WIC as seen with kindergarten, then we would expect this to attenuate our results for the not-in-school sample. Therefore, our estimates are conservative in this regard.

Policy implications include allowing children to stay on WIC until they enter kindergarten, as recently proposed in the House ([H.R.2011 - 117th Congress 2021](#)) and Senate ([S.853 - 117th Congress 2021](#)). We calculate back-of-the-envelope program costs over the next five years for such a “kindergarten-roll-off” WIC policy under current rules and newly proposed rules to realign WIC packages with the Dietary Guidelines for Americans ([Federal Register 2022](#)). Under current rules, costs would average \$112 million over the next five year (2024-2028), or about 2% of total program costs. Under proposed rule changes ([Federal Register 2022](#)), kindergarten-roll-off costs would average \$144 million per year, or

2.25% of total program costs.

Notes

¹In most states, children must reach the age of 5 on or before a specific date to start kindergarten. For example, thirty-eight states and the District of Columbia currently use a date sometime in August or September (NCES, 2018). However, some children began school before they turned five. For example, up until 2010, California used a date of December 2, before switching to September 1. Previous research has found fewer than 2% of children enter school before they are legally eligible (Bedard and Dhuey 2006; Elder and Lubotsky 2009) indicating high compliance with school entry laws.

²Earlier companion bills (H.R.2660 - 114th Congress 2015; S.1796 - 114th Congress 2015) sought to increase the age limit to 6 years, with no reference to kindergarten. The current (and past) proposed bills also seek to extend certification periods for infants and postpartum women to two years instead of one year.

³We cannot tease out these mechanisms due to data limitations, specifically the income effects, and therefore our results speak to school attendance in general.

⁴That is, the probability of currently attending school is continuous at age 5, and WIC participation is orthogonal to school attendance.

⁵By comparison, Smith (2017) finds for a 33% shift in calories from home-prepared to school-prepared food (roughly one meal) among food insecure children, HEI scores increase by 3.3 to 6.4 points, or an 8-21% increase. Similarly, Smith, Mojduszka, and Chen (2021) find school meals boost low-income children's diet quality by 10-16%.

⁶On November 21, 2022, USDA proposed a host of changes to WIC packages, namely increasing the cash-value voucher while reducing maximum monthly allowances for milk and juice, among other changes (Federal Register 2022). We use the projected costs and participation numbers from USDA ((Federal Register 2022)) to calculate our cost estimates.

⁷Bitler et al. (2022) show that the SNAP and Medicaid participation vary smoothly through the age threshold of 60 months.

⁸Other types of nutritional risk for WIC eligibility (e.g., anemia, under/overweight, or drug abuse) are recognized by federal regulations (see Oliveira and Frazão 2015).

⁹As of November 2022, all states have fully transitioned to electronic benefit transfer (EBT) cards.

¹⁰See the online supplementary appendix Table A1 for details pertaining to amounts.

¹¹For instance, in the context of the 2009 WIC revisions, Frisvold, Leslie, and Price (2020) find that WIC habits are short-lived; that is, while WIC vouchers change purchasing behavior during eligibility, such effects fade away as eligibility ends (see also, Hinno Saar 2022).

¹²We refer the reader to [Angrist and Pischke \(2008\)](#), [Imbens and Lemieux \(2008\)](#), [Lee and Lemieux \(2010\)](#), and [Cattaneo and Escanciano \(2017\)](#) for details on RDD.

¹³It is possible to include a set of exogenous baseline covariates (e.g., individual characteristics and the survey year). This adjustment is generally motivated by the desire to increase precision or restore RDD identification if the local continuity assumption is invalid ([Calonico et al. 2019](#)). Below, we demonstrate covariate balance. Moreover, using our mean regression model in equations (1) and (2), augmented with various sets of covariates, we show in the Results section that the efficiency gain for including covariates is trivial (i.e., not large enough to change any conclusions) with virtually no change in point estimates of local treatment effects, as suggested by theory. However, pointing ahead to our quantile RDD in equation (3), including covariates, would change the interpretation of the conditional outcome distribution, thereby changing the interpretation of the coefficients ([Powell 2020](#)). It also introduces optimization complexities for estimating the quantile effects. For these reasons, we do not exclude covariates from our main analyses.

¹⁴This result is consistent with the recommendation by [Cattaneo and Titiunik \(2022\)](#), indicating that the order of the polynomial should always be low, to avoid overfitting and erratic behavior near the cutoff point. The default recommendation is $p = 1$ (local linear regression), but $p = 2$ (local quadratic regression) or $p = 3$ (local cubic regression) is also a reasonable choice in some empirical settings (see also, [Gelman and Imbens 2019](#)).

¹⁵We use one common MSE-optimal bandwidth selector on a larger sample of 24-to-96-month-olds (i.e., centered around 60 months). For our quantity and quality outcomes, the optimal bandwidths are 12.59 and 12.47 months, respectively.

¹⁶[Guiteras \(2008\)](#) suggests using the instrumental variable quantile regression (IVQR) developed in [Chernozhukov and Hansen \(2006\)](#) in the context of a Fuzzy quantile RDD. [Machado and Santos Silva \(2019\)](#) show that MM-QR performs similarly to IVQR but has the dual advantage of being less demanding in terms of computation and provides quantile estimates that do not cross ([He 1997](#)). We tried IVQR and experienced computational complexities at quantiles in the tails of the distribution, and that quantiles crossed. For these reasons, we use MM-QR.

¹⁷Rank similarity effectively allows for noisy variations in rank, called “slippages” by [Heckman, Smith, and Clements \(1997\)](#), across treatment states. The similarity assumption relaxes the rank invariance assumption, which states ranks must be exactly the same across treatment states. See [Chernozhukov, Hansen, and Wüthrich \(2017\)](#) for details.

¹⁸Beginning with the 2003-2004 NHANES, a second day of recall is conducted randomly 3–10 days after the medical exam in a follow-up telephone interview.

¹⁹[Bitler, Currie, and Scholz \(2003\)](#) and [Meyer, Mok, and Sullivan \(2015\)](#) have documented under-reporting of WIC in other nationally representative surveys: Current Population Survey (CPS), Panel Study of Income Dynamics (PSID), and Survey of Income and Program Participation (SIPP). The online supplementary appendix Figure A1 demonstrates WIC take-up rates (i.e., participation among eligibles)

for 4-year-olds, calculated based on 2006-2019 Current Population Survey, Annual Social and Economic Supplement (CPS-ASEC) data, derived from FNS-USDA (FNS-USDA, 2018), falls within the bounds of those found in the NHANES data used herein.

²⁰Recall, households with incomes above 185% of the FPG may be adjunctively eligible.

²¹We considered a measure of caloric needs by using the ratio of reported calories to the Institute of Medicine’s Estimate Energy Requirements (EER) (Gerritor, Juan, and Peter 2006). EER is a function of a child’s age, gender, height, weight, and physical activity level. We do not have a good measure of physical activity. Moreover, since EER is a function of age in years, it will necessarily jump at age five. Nevertheless, if these factors transition smoothly around the cutoff, then examining calories in levels will suffice.

²²Differences in school calendars will lead to variation in terms of when school is in session or not (e.g., early or later school start/end dates and holidays). In terms of year-round school, for the 2007-08 school year, 4.4% of school districts had year-round cycles (NCES, 2008). Taken together, these differences should only work to attenuate our results.”

²³Clearly, we cannot use this question for our research question because 6-to-19-year-olds are outside the policy cutoff. Moreover, the question is only asked in the first 10 years of NHANES data. It does serve, however, as a point of validity.

²⁴For ease of comparison, The online supplementary appendix Table A5 shows the cross-tabulation for being on WIC versus in school. According to the National Center for Education Statistics (NCES, 2019), 8.7% of four-year-old children attended kindergarten during 2000-2018. Some states (California, Connecticut, Hawaii, Michigan, and Washington D.C.) and certain districts in Massachusetts, New Jersey, New York, Ohio, Pennsylvania, and Vermont have allowed children to start school when they are less than five years old throughout our sample period (Bush and Zinth, 2011; NCES, 2018).

²⁵The online supplementary appendix Tables A6 and A7 report the corresponding summary statistics for the May-Oct sample.

²⁶The online supplementary appendix Figure A2 shows similar discontinuities in the probability of WIC participation across sub-samples by school participation status.

²⁷In the online supplementary appendix Figure A4 we conduct similar graphical analyses for the May-Oct sample. Overall, we do not observe a significant change at the cutoff for any of the nutritional outcomes.

²⁸The online supplementary appendix Table A10 reports results for the May-Oct sample, which are all insignificant.

²⁹For the May-Oct sample, consistent with results from mean regressions, we find no distributional effects of losing WIC benefits for any nutritional outcome (online supplementary appendix Figure A5).

References

- Alaimo, K., C.M. Olson, E.A. Frongillo Jr, and R.R. Briefel. 2001. “Food Insufficiency, Family Income, and Health in US Preschool and School-Aged Children.” *American Journal of Public Health* 91:781–786.
- Angrist, J.D., and J.S. Pischke. 2008. *Mostly Harmless Econometrics*. Princeton University Press.
- Arteaga, I., C. Heflin, and S. Gable. 2016. “The Impact of Aging Out of WIC on Food Security in Households with Children.” *Children and Youth Services Review* 69:82–96.
- Bedard, K., and E. Dhuey. 2006. “The Persistence of Early Childhood Maturity: International Evidence of Long-Run Age Effects.” *The Quarterly Journal of Economics* 121:1437–1472.
- Benton, D. 2004. “Role of Parents in the Determination of the Food Preferences of Children and the Development of Obesity.” *International Journal of Obesity* 28:858–869.
- Birch, L.L. 1999. “Development of Food Preferences.” *Annual Review of Nutrition* 19:41–62.
- Bitler, M., J. Currie, H.W. Hoynes, K.J. Ruffini, L. Schulkind, and B. Willage. 2022. “Mothers as Insurance: Family Spillovers in WIC.” NBER Working Paper No. 30112, National Bureau of Economic Research. Available at: <https://www.nber.org/papers/w30112>. Accessed: February 18, 2023.
- Bitler, M.P., and J. Currie. 2005. “Does WIC Work? The Effects of WIC on Pregnancy and Birth Outcomes.” *Journal of Policy Analysis and Management* 24:73–91.
- Bitler, M.P., J. Currie, and J.K. Scholz. 2003. “WIC Eligibility and Participation.” *Journal of Human Resources* 38:1139–1179.
- Bush, M., and K. Zinth. 2011. “Kindergarten Entrance Ages: A 35 Year Trend Analysis.” Education Commission of the States, Retrieved from: <https://www.ecs.org/clearinghouse/73/67/7367.pdf> [Accessed February 18, 2023].
- Calonico, S., M.D. Cattaneo, M.H. Farrell, and R. Titiunik. 2019. “Regression Discontinuity Designs Using Covariates.” *Review of Economics and Statistics* 101:442–451.
- Calonico, S., M.D. Cattaneo, and R. Titiunik. 2014. “Robust Nonparametric Confidence

- Intervals for Regression-Discontinuity Designs.” *Econometrica* 82:2295–2326.
- Cattaneo, M., and J.C. Escanciano. 2017. *Regression Discontinuity Designs: Theory and Applications*. Emerald Group Publishing.
- Cattaneo, M.D., and R. Titiunik. 2022. “Regression Discontinuity Designs.” *Annual Review of Economics* 14:821–851.
- Chernozhukov, V., and C. Hansen. 2006. “Instrumental Quantile Regression Inference for Structural and Treatment Effect Models.” *Journal of Econometrics* 132:491–525.
- . 2005. “An IV Model of Quantile Treatment Effects.” *Econometrica* 73:245–261.
- Chernozhukov, V., C. Hansen, and K. Wüthrich. 2017. *Instrumental Variable Quantile Regression*. Chapman and Hall/CRC.
- Cho, S.J. 2022. “The Effect of Aging out of Women, Infants, and Children on Food Insecurity.” *Health Economics* 31:664–685.
- Currie, J. 2005. “Health Disparities and Gaps in School Readiness.” *The Future of Children* 15:117–138.
- Doksum, K. 1974. “Empirical Probability Plots and Statistical Inference for Nonlinear Models in the Two-Sample Case.” *The Annals of Statistics* 2:267–277.
- Dovey, T.M., P.A. Staples, E.L. Gibson, and J.C. Halford. 2008. “Food Neophobia and ‘Picky/Fussy’ Eating in Children: A Review.” *Appetite* 50:181–193.
- Elder, T.E., and D.H. Lubotsky. 2009. “Kindergarten Entrance Age and Children’s Achievement Impacts of State Policies, Family Background, and Peers.” *Journal of Human Resources* 44:641–683.
- Epstein, L.H., C.C. Gordy, H.A. Raynor, M. Beddome, C.K. Kilanowski, and R. Paluch. 2001. “Increasing Fruit and Vegetable Intake and Decreasing Fat and Sugar Intake in Families at Risk for Childhood Obesity.” *Obesity Research* 9:171–178.
- Epstein, L.H., R.A. Paluch, M.D. Beecher, and J.N. Roemmich. 2008. “Increasing Healthy Eating vs. Reducing High Energy-dense Foods to Treat Pediatric Obesity.” *Obesity* 16:318–326.
- Federal Register. 2022. “Special Supplemental Nutrition Program for Women, Infants, and Children (WIC): Revisions in the WIC Food Packages.” Federal Register 87, No. 223 (21 November). Retrieved from: <https://www.govinfo.gov/content/pkg/>

[FR-2022-11-21/pdf/2022-24705.pdf](https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap) [Accessed April 20, 2023].

Food Nutrition Service, United States Department of Agriculture (FNS-USDA).

2022a. “SNAP Data Tables. Retrieved from: <https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap>. Accessed June 25, 2022.”

—. 2022b. “Special Supplemental Nutrition Program for Women, Infants, and Children, Participation and Costs, 1974–2021.” Retrieved from: <https://www.fns.usda.gov/pd/wic-program>. Accessed May 30, 2022..

—. 2018. “WIC Eligibility and Coverage Rates - 2018.” Retrieved from: <https://www.fns.usda.gov/wic/eligibility-and-coverage-rates-2018#6>. Accessed May 30, 2022.

—. 2022c. “WIC Food Packages - Maximum Monthly Allowances. Retrieved from: <https://www.fns.usda.gov/wic/wic-food-packages-maximum-monthly-allowances>. Accessed June 02, 2022.”

Foster, E., and J. Bradley. 2018. “Methodological Considerations and Future Insights for 24-hour Dietary Recall Assessment in Children.” *Nutrition Research* 51:1–11.

Frisvold, D., E. Leslie, and J.P. Price. 2020. “Do Targeted Vouchers Instill Habits? Evidence from Women, Infants, and Children.” *Contemporary Economic Policy* 38:67–80.

Frisvold, D.E. 2015. “Nutrition and Cognitive Achievement: An Evaluation of the School Breakfast Program.” *Journal of Public Economics* 124:91–104.

Gelbach, J.B. 2002. “Public Schooling for Young Children and Maternal Labor Supply.” *American Economic Review* 92:307–322.

Gelman, A., and G. Imbens. 2019. “Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs.” *Journal of Business & Economic Statistics* 37:447–456.

Gerrior, S., W. Juan, and B. Peter. 2006. “An Easy Approach to Calculating Estimated Energy Requirements.” *Preventing Chronic Disease* 3:1–4.

Glewwe, P., and E.M. King. 2001. “The Impact of Early Childhood Nutritional Status on Cognitive Development: Does the Timing of Malnutrition Matter?” *The World Bank Economic Review* 15:81–113.

Grembi, V., T. Nannicini, and U. Troiano. 2016. “Do Fiscal Rules Matter?” *American Economic Journal: Applied Economics* 8:1–30.

- Guiteras, R. 2008. "Estimating Quantile Treatment Effects in A Regression Discontinuity Design." Unpublished Manuscript. Retrieved from: <https://www.semanticscholar.org/paper/Estimating-Quantile-Treatment-Eects-in-a-Regression-Guiteras/585b87cdaf1ef8981e73bf600e3371c10ad70c69#related-papers>. Accessed: April 20, 2020.
- Hahn, J., P. Todd, and W. Van der Klaauw. 2001. "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design." *Econometrica* 69:201–209.
- Havnes, T., and M. Mogstad. 2015. "Is Universal Child Care Leveling the Playing Field?" *Journal of Public Economics* 127:100–114, The Nordic Model.
- He, X. 1997. "Quantile Curves without Crossing." *The American Statistician* 51:186–192.
- Heckman, J.J., J. Smith, and N. Clements. 1997. "Making the Most Out of Programme Evaluations and Social Experiments: Accounting for Heterogeneity in Programme Impacts." *The Review of Economic Studies* 64:487–535.
- Hinnosaar, M. 2022. "The Persistence of Healthy Behaviors in Food Purchasing." *Marketing Science* 0:null.
- H.R.2011 - 117th Congress. 2021. "The Wise Investment in Children (WIC) Act of 2021." Retrieved from: <https://www.congress.gov/bill/117th-congress/house-bill/2011>. Accessed July 1, 2022.
- H.R.2660 - 114th Congress. 2015. "The Wise Investment in our Children (WIC) Act of 2015. Retrieved from: <https://www.congress.gov/bill/114th-congress/house-bill/2660>. Accessed October 25, 2022."
- Imbens, G.W., and T. Lemieux. 2008. "Regression Discontinuity Designs: A Guide to Practice." *Journal of Econometrics* 142:615–635.
- Jan van Garderen, K., and C. Shah. 2002. "Exact Interpretation of Dummy Variables in Semilogarithmic Equations." *The Econometrics Journal* 5:149–159.
- Kennedy, P.E., et al. 1981. "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations [The Interpretation of Dummy Variables in Semilogarithmic Equations]." *American Economic Review* 71:801–801.
- Kline, N., P. Zvavitch, K. Wroblewska, M. Worden, B. Mwombela, B. Thorn, and D. Cassar-Uhl. 2022. "WIC Participant and Program Characteristics

- 2020.” Working paper, Food Nutrition Service, United States Department of Agriculture (FNS-USDA). Retrieved from: <https://www.fns.usda.gov/wic/participant-program-characteristics-2020>. Accessed: February 15, 2023.
- Krebs-Smith, S.M., T.E. Pannucci, A.F. Subar, S.I. Kirkpatrick, J.L. Lerman, J.A. Tooze, M.M. Wilson, and J. Reedy. 2018. “Update of the Healthy Eating Index: HEI-2015.” *Journal of the Academy of Nutrition and Dietetics* 118:1591–1602.
- Lee, D.S., and T. Lemieux. 2010. “Regression Discontinuity Designs in Economics.” *Journal of Economic Literature* 48:281–355.
- Machado, J.A., and J. Santos Silva. 2019. “Quantiles via Moments.” *Journal of Econometrics* 213:145–173, Annals: In Honor of Roger Koenker.
- Marshall, S., T. Burrows, and C.E. Collins. 2014. “Systematic Review of Diet Quality Indices and Their Associations with Health-Related Outcomes in Children and Adolescents.” *Journal of Human Nutrition and Dietetics* 27:577–598.
- McCrary, J. 2008. “Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test.” *Journal of Econometrics* 142:698–714.
- Meyer, B.D., W.K. Mok, and J.X. Sullivan. 2015. “Household Surveys in Crisis.” *Journal of Economic Perspectives* 29(4):199–226.
- Moshfegh, A.J., D.G. Rhodes, D.J. Baer, T. Murayi, J.C. Clemens, W.V. Rumpler, D.R. Paul, R.S. Sebastian, K.J. Kuczynski, L.A. Ingwersen, et al. 2008. “The US Department of Agriculture Automated Multiple-Pass Method Reduces Bias in the Collection of Energy Intakes.” *The American Journal of Clinical Nutrition* 88:324–332.
- National Academies of Sciences, E., and M. (NASEM). 2017. *Review of WIC Food Packages: Improving Balance and Choice. Final Report*. National Academies Press, Washington, DC.
- National Center for Education Statistics (NCES). 2018a. “Enrollment of 3-, 4-, and 5-Year-Old Children in Preprimary Programs, by Age of Child, Level of Program, Control of Program, and Attendance Status: Selected Years, 1970 through 2018. Retrieved from: https://nces.ed.gov/programs/digest/d19/tables/dt19_202.10.asp. Accessed February 15, 2023.”
- . 2018b. “Total Number of Schools, Percentage of Schools that Have All Students At-

- tending A Year-Round Calendar Cycle, and Average Number of Days in the Cycle, by Selected School Characteristics: 2007–08. Retrieved from: https://nces.ed.gov/surveys/sass/tables/sass0708_1023181_s1n.asp. Accessed February 15, 2023.”
- . 2018c. “Types of State and District Requirements for Kindergarten Entrance and Attendance, Waivers and Exemptions for Kindergarten Entrance, by State: 2018. Retrieved from: https://nces.ed.gov/programs/statereform/tab5_3.asp. Accessed May 30, 2022.”
- Nunn, M., N. Braunstein, E.K. Kaye, T. Dietrich, R. Garcia, and M. Henshaw. 2009. “Healthy Eating Index Is a Predictor of Early Childhood Caries.” *Journal of Dental Research* 88:361–366.
- Oliveira, V., and E. Frazão. 2015. “The WIC Program: Background, Trends, and Economic Issues, 2015 Edition.” Economic Information Bulletin No. 197543, United States Department of Agriculture, Economic Research Service, Jan.
- Pei, Z., D.S. Lee, D. Card, and A. Weber. 2022. “Local Polynomial Order in Regression Discontinuity Designs.” *Journal of Business & Economic Statistics* 40:1259–1267.
- Powell, D. 2020. “Quantile Treatment Effects in the Presence of Covariates.” *The Review of Economics and Statistics* 102:994–1005.
- Reedy, J., J.L. Lerman, S.M. Krebs-Smith, S.I. Kirkpatrick, T.E. Pannucci, M.M. Wilson, A.F. Subar, L.L. Kahle, and J.A. Tooze. 2018. “Evaluation of the Healthy Eating Index-2015.” *Journal of the Academy of Nutrition and Dietetics* 118:1622–1633.
- S.1796 - 114th Congress. 2015. “The Wise Investment in our Children (WIC) Act of 2015. Retrieved from: <https://www.congress.gov/bill/114th-congress/senate-bill/1796>. Accessed October 25, 2022.”
- S.853 - 117th Congress. 2021. “The Wise Investment in Children (WIC) Act of 2021. Retrieved from: <https://www.congress.gov/bill/117th-congress/senate-bill/853>. Accessed July 1, 2022.”
- Si, X., and T. Leonard. 2020. “Aging Out of Women Infants and Children: An Investigation of the Compensation Effect of Private Nutrition Assistance Programs.” *Economic Inquiry* 58:446–461.
- Smith, T.A. 2017. “Do School Food Programs Improve Child Dietary Quality?” *American*

Journal of Agricultural Economics 99:339–356.

Smith, T.A., E.M. Mojduszka, and S. Chen. 2021. “Did the New School Meal Standards Improve the Overall Quality of Children’s Diets?” *Applied Economic Perspectives and Policy* 43:1366–1384.

Valizadeh, P., and S.W. Ng. 2020. “The New School Food Standards and Nutrition of School Children: Direct and Indirect Effect Analysis.” *Economics & Human Biology* 39:100918.

Figures

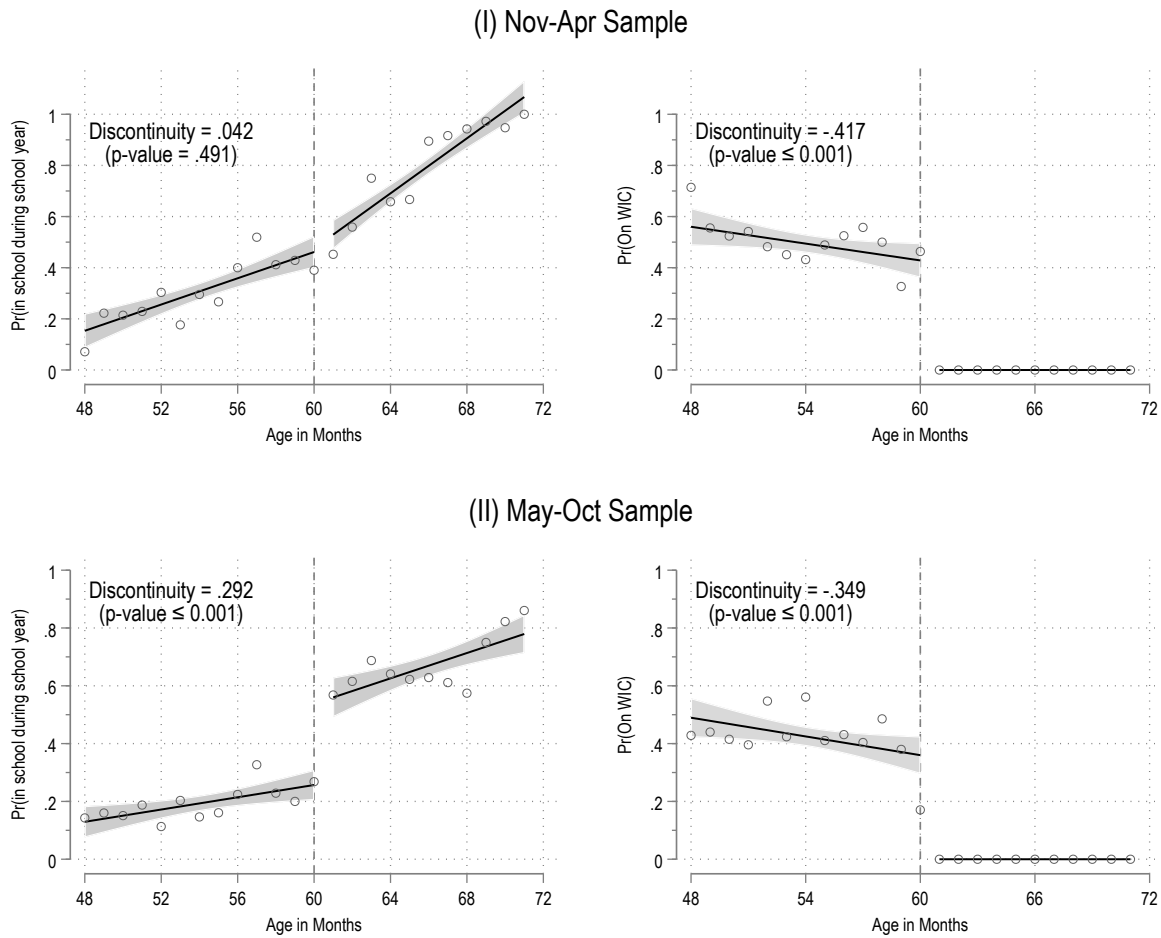


Figure 1. Discontinuities in the probabilities of WIC participation and school attendance during the school year by age in months

Notes: The probability of school attendance during the school year is based on the affirmative response to the NHANES question: “During the school year, does [child] attend a kindergarten, grade school, junior or high school?” asked of children 4 years and older. The left column shows the probability of school attendance is not continuous around age 5 for the May-Oct sample. The right column shows, in both Nov-Apr and May-Oct samples, the probability of WIC participation among eligibles declines at age 61 months.

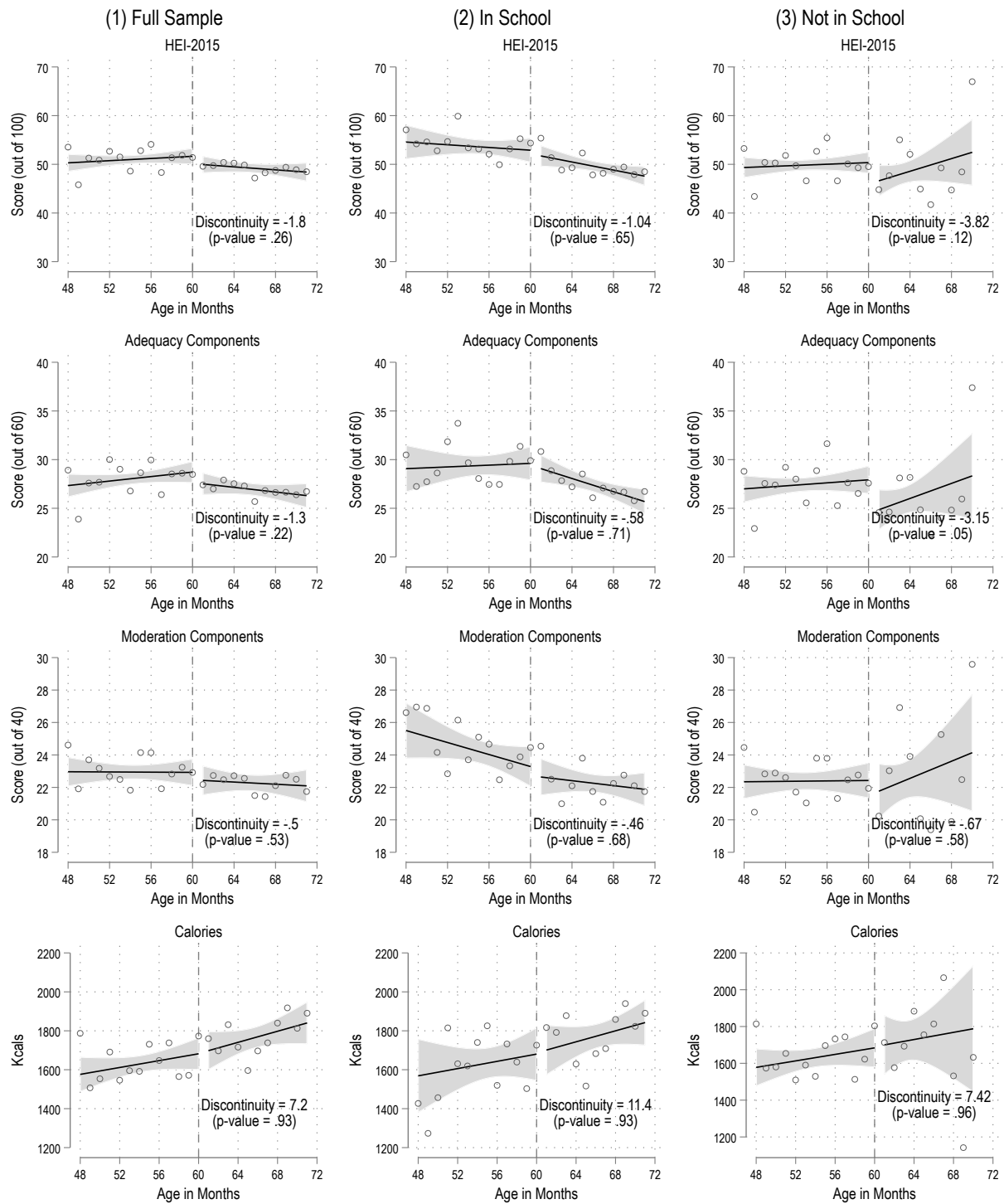


Figure 2. Discontinuities in nutritional outcomes by age in months, Nov-Apr sample

Notes: “In School” and “Not in School” refer to school attendance during the school year based on the question “During the school year, does [child] attend a kindergarten, grade school, junior or high school?”. The discontinuity estimates presented in each panel represent local linear estimates from a Sharp RDD design with a uniform kernel and no additional covariates.

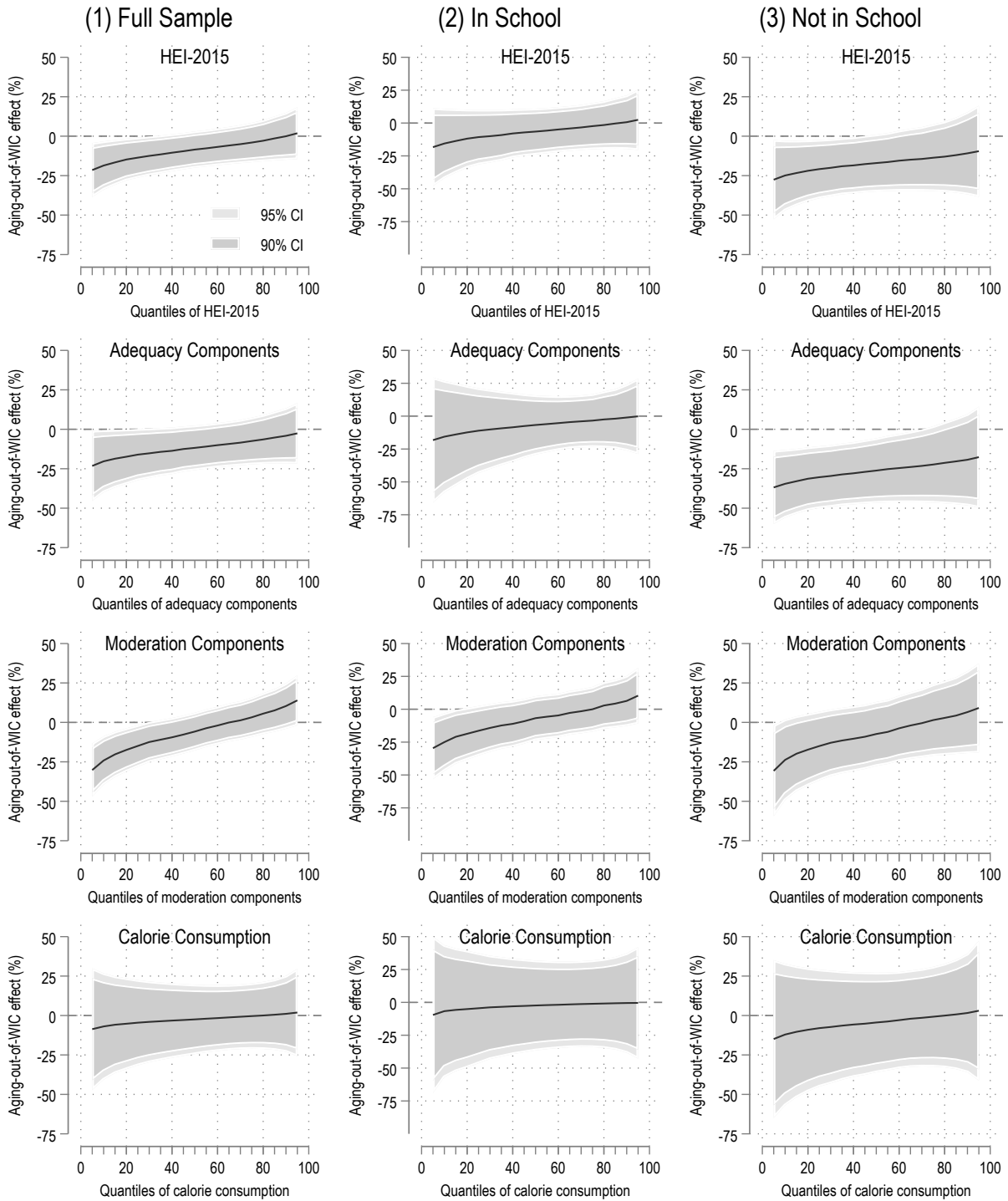


Figure 3. Distributional effects of aging out of WIC on nutritional outcomes, Nov-Apr sample

Notes: “In School” and “Not in School” refer to school attendance during the school year based on the question “During the school year, does [child] attend a kindergarten, grade school, junior or high school?”. Bias-corrected aging-out-of-WIC effect estimates in percentage terms are calculated following [Kennedy et al. \(1981\)](#). All quantile treatment effect estimates are accompanied by 90% and 95% confidence intervals, represented by shaded areas.

Tables

Table 1. Summary Statistics for Outcomes: Diet Quality and Quantity, Nov-Apr Sample

	Full Sample	School=1	School=0	WIC=1	WIC=0
HEI-2015 (out of 100)	50.25 (12.02) [19.81,82.47]	50.95 (11.49) [22.35,80.12]	49.52* (12.52) [19.81,82.47]	52.44 (12.28) [23.14,82.47]	49.39*** (11.81) [19.81,82.34]
Adequacy score (out of 60)	27.59 (7.92) [5.10,53.26]	28.03 (7.64) [5.10,49.30]	27.13* (8.19) [7.46,53.26]	28.98 (8.04) [10.54,53.26]	27.00*** (7.81) [5.10,50.90]
Moderation score (out of 40)	22.66 (6.10) [5.81,40.00]	22.92 (5.88) [5.81,40.00]	22.39 (6.32) [7.64,37.72]	23.45 (6.21) [7.64,40.00]	22.35** (6.03) [5.81,39.38]
Energy (kcal)	1688.09 (635.03) [298,4672]	1726.59 (656.07) [298,4672]	1647.61* (610.20) [507,4093]	1642.44 (643.71) [298,3728]	1706.10 (634.71) [410,4672]
Observations	958	491	467	271	687

Notes: “School” refers to typical school attendance during the school year based on the question “During the school year, does [child] attend a kindergarten, grade school, junior or high school?”. Standard errors are in parentheses. Minimum and maximum values are in square and curly brackets. Statistical differences by school status, and separately by WIC status, are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Summary Statistics: Regressors and Demographics, Nov-Apr Sample

Variables	Full Sample	School=1	School=0	WIC=1	WIC=0
<i>Panel A: Regressors</i>					
Age in months at exam	59.12 (0.21)	62.40 (0.28)	55.67*** (0.23)	54.04 (0.21)	61.13** (0.24)
T=1[Age \geq 61]	0.42 (0.02)	0.65 (0.02)	0.19** (0.02)	0.00 (.)	0.59*** (0.02)
D=1[Child is off WIC]	0.72 (0.01)	0.81 (0.02)	0.62*** (0.02)	0.00 (.)	1.00*** (.)
Child attends school	0.51 (0.02)	1.00 (.)	0.00*** (.)	0.35 (0.03)	0.58*** (0.02)
<i>Panel B: Demographics</i>					
Child Female	0.53 (0.02)	0.51 (0.02)	0.54 (0.02)	0.56 (0.03)	0.52 (0.02)
Child NH White	0.16 (0.01)	0.14 (0.02)	0.19** (0.02)	0.09 (0.02)	0.19*** (0.01)
Child NH Black	0.26 (0.01)	0.26 (0.02)	0.27 (0.02)	0.23 (0.03)	0.28 (0.02)
Child Hispanic	0.50 (0.02)	0.55 (0.02)	0.46*** (0.02)	0.60 (0.03)	0.47*** (0.02)
Child other race/ethnicity	0.07 (0.01)	0.06 (0.01)	0.09* (0.01)	0.08 (0.02)	0.07 (0.01)
Reference No HS diploma	0.40 (0.02)	0.42 (0.02)	0.39 (0.02)	0.47 (0.03)	0.38*** (0.02)
Reference HS diploma	0.24 (0.01)	0.24 (0.02)	0.25 (0.02)	0.24 (0.03)	0.25 (0.02)
Reference at least some college	0.21 (0.01)	0.21 (0.02)	0.21 (0.02)	0.15 (0.02)	0.24*** (0.02)
Reference Female	0.59 (0.02)	0.59 (0.02)	0.60 (0.02)	0.59 (0.03)	0.59 (0.02)
Household Size	4.93 (0.05)	4.93 (0.06)	4.92 (0.07)	5.20 (0.09)	4.82*** (0.05)
Percent Poverty \leq 50%	0.21 (0.01)	0.22 (0.02)	0.21 (0.02)	0.20 (0.02)	0.22 (0.02)
Percent Poverty (50%, 100%]	0.34 (0.02)	0.34 (0.02)	0.33 (0.02)	0.32 (0.03)	0.34 (0.02)
Percent Poverty (100%, 130%]	0.17 (0.01)	0.17 (0.02)	0.18 (0.02)	0.17 (0.02)	0.18 (0.01)
Percent Poverty (130%, 185%]	0.17 (0.01)	0.19 (0.02)	0.16 (0.02)	0.11 (0.02)	0.20*** (0.02)
Percent Poverty $>$ 185%	0.07 (0.01)	0.05 (0.01)	0.09** (0.01)	0.10 (0.02)	0.06* (0.01)
Percent Poverty (missing)	0.03 (0.01)	0.03 (0.01)	0.03 (0.01)	0.11 (0.02)	0.00*** (.)
Observations	958	491	467	271	687

Notes: “School” refers to typical school attendance during the school year based on the question “During the school year, does [child] attend a kindergarten, grade school, junior or high school?”. Standard errors are in parentheses. Statistical differences by school status, and separately by WIC status, are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Joint tests of statistical differences of demographics by school and WIC status yield p -values of 0.139 and < 0.001 , respectively.

Table 3. Average Effects of Aging out of WIC on Nutritional Outcomes for the Nov-Apr sample, in Percentage Terms

Outcome	Full Sample	In School	Not in School
HEI-2015	-10.00 (7.13)	-6.44 (10.26)	-19.62* (10.67)
Adequacy Components	-12.72 (8.41)	-6.35 (12.47)	-28.47** (11.61)
Moderation Components	-9.24 (8.13)	-9.77 (11.02)	-11.19 (13.23)
Calories	-2.18 (11.57)	-1.82 (17.54)	-4.78 (17.04)
Observations	958	491	467

Notes: “In School” and “Not in School” refer to school attendance during the school year based on the question “During the school year, does [child] attend a kindergarten, grade school, junior or high school?”. Bias-corrected aging-out-of-WIC effect estimates in percentage terms are calculated following [Kennedy et al. \(1981\)](#). Robust standard errors for the bias-corrected semi-elasticities are calculated following [Jan van Garderen and Shah \(2002\)](#) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Cost Estimates of Extending WIC Eligibility among Four-Year-Olds until Kindergarten Entry

	Fiscal Year					
	2024	2025	2026	2027	2028	2024-2028
<i>Panel A: Projected WIC Participation</i>						
Two-year Olds	1,060,900	1,112,072	1,165,712	1,165,712	1,165,712	-
Three-year Olds	945,169	990,758	1,038,547	1,038,547	1,038,547	-
Four-year Olds	579,446	607,395	636,692	636,692	636,692	-
Total (2-4 Years)	2,585,515	2,710,225	2,840,951	2,840,951	2,840,951	-
<i>Panel B: Projected Monthly Cost per Capita (\$):</i>						
Current Rules	31.19	32.46	33.03	33.62	34.21	
Proposed Rule	40.21	41.42	41.94	43.19	44.44	
<i>Panel C: Projected Federal WIC Expenditures (\$ Millions)</i>						
Cost of Current Food Packages	3,069.20	3,211.70	3,362.90	3,426.10	3,490.70	16,560.60
Cost of cash-value voucher (CVV) Increase	913.80	949.80	975.20	1,029.20	1,075.50	4,943.50
Incremental Cost of Proposed Rule (not CVV)	-142.30	-158.80	-169.30	-173.30	-177.30	-821.00
Total Nutrition services & Administrative Costs	2,157.60	2,224.50	2,293.40	2,364.50	2,437.80	11,477.80
Total Costs under Proposed Rule	5,998.30	6,227.20	6,462.20	6,646.50	6,826.70	32,160.90
<i>Panel D: Cost Estimates of Extending WIC Eligibility</i>						
Current rules (\$ Millions)	99.39	108.43	115.66	117.73	119.81	561.02
Current rules (% of Total Costs)	1.90	1.99	2.04	2.03	2.02	2.00
Proposed Rule (\$ Millions)	128.14	138.37	146.87	151.24	155.63	720.25
Proposed Rule (% of Total Costs)	2.14	2.22	2.27	2.28	2.28	2.24

Notes: Details of proposed rule changes are found in [Federal Register \(2022\)](#). Projected total WIC participation among two-to-four-year-old children in Panel A is found in Table 5 of [Federal Register \(2022\)](#). Projections of WIC participation by age (Panel A) are calculated using a 6-year-average (2014-2019) of historical shares of 2-, 3-, and 4-year olds among all 2-4-year-olds from ([FNS-USDA, 2018](#)). Projected monthly costs (Panel B) are calculated by summing annual costs for current rules (baseline) and proposed rule from tables A-1 through A-12 in [Federal Register \(2022\)](#) for food package IV-B (children 2-4 years) and converting to monthly per capita cots. Projected federal WIC Expenditures in Panel C is extracted from Table 3 in [Federal Register \(2022\)](#). Projected costs of extending WIC eligibility until Kindergarten entry (Panel D) are calculated by assuming uniform births across months of the year such that eleven-twelfths of four-year-old children remain on WIC for one additional month, five-sixths for two additional months, and so on.