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Cash Transfers, Diet Quality, and Child Growth Among Refugee Children: Evidence from Turkey's ESSN Program

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Abstract

This study examines the impact of the world's largest humanitarian unconditional cash transfer program targeting refugees—the Emergency Social Safety Net (ESSN) program—on child nutrition and growth outcomes. Using the 2018 Turkey Demographic and Health Survey, which includes a representative sample of Syrian refugees, and employing a regression discontinuity design, we assess the program's effects on child growth—measured by height-for-age (HAZ), weight-for-age (WAZ), and weight-for-height (WHZ), including their extreme values—and on child-level nutrition, measured across five major food categories. We find that receiving cash transfers increases HAZ by 0.6 to 0.8 standard deviations. Additionally, the transfers reduce the incidence of both underweight and overweight status based on WAZ scores. WHZ scores and the incidence of overweight status based on WHZ also decline. Examining the program's impact on nutrition, we find a significant reduction in children's energy-dense, nutrient-poor food consumption, consistent with the decrease in overweight incidence. Overall, the ESSN program improves food consumption patterns among refugees, leading to better child growth outcomes.

JEL classification

F22, I14, I15, I38, O15, Q18

Keywords

refugees, cash transfers, anthropometrics, nutrition, program evaluation, Turkey

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1. Introduction

Forced displacement has emerged as a pressing global concern. By the end of 2020, the number of forcibly displaced persons worldwide reached 79.5 million—40 percent of whom were children (UNHCR, 2020a). These children often experience a long-term disruption in human capital accumulation due to early exposure to conflict, instability, and deprivation (Fiala, 2015). Despite growing attention to humanitarian responses, evidence on the effectiveness of large-scale social assistance programs in addressing the nutritional needs of refugee children remains limited, particularly outside of camp settings. This paper addresses this gap by studying the impact of the Emergency Social Safety Net (ESSN), the world's largest humanitarian cash transfer program for refugees, on the nutrition and growth outcomes of Syrian refugee children in Turkey. Hosting the largest refugee population globally—3.6 million Syrians as of 2020—Turkey provides a unique context to examine the effects of large-scale, unconditional assistance on refugee populations integrated into host communities.

Unconditional cash transfers (UCTs) are increasingly used as a policy tool to alleviate poverty and improve well-being in crisis settings. A substantial body of literature has evaluated the effects of UCTs on child nutrition and growth in general populations.[1] In their meta-analysis, Manley et al. (2020, 2022) report that the average effect of cash transfers on child height-for-age z-scores (HAZ) is positive and statistically significant, but there is no evidence of effects on weight-for-age (WAZ) or weight-for-height (WHZ) z-scores. Reviewing this literature in the context of low- and middle-income countries, Cooper et al. (2020) find that cash transfers tend to improve chronic nutritional outcomes more reliably than acute or composite measures like WHZ and WAZ. The estimated effects are generally small but statistically significant for HAZ, particularly in contexts with complementary health and nutrition services.

Although a large literature documents the effects of cash transfers on child nutrition and growth in general populations, it is not clear that these findings extend to refugee households. Refugee families differ from chronically poor households not only because of displacement-related

[1] See, for instance, Ahmed et al. (2024), Cunha (2014), Fenn (2015), Fernald and Hidrobo (2011), Gertler (2004), González & Trommlerová (2022), Hidrobo et al. (2014), Hoddinott and Skoufias (2004), Labrecque et al. (2018), Patwardhan (2023), Paxson and Schady (2010), Premand and Barry (2022), Raza et al. (2018) and Reader (2023).

shocks but also because many arrive with substantially different pre-migration dietary norms, food preferences, and nutritional expectations. Prior to the conflict, Syrian households typically enjoyed more diverse and balanced diets than those found in many low-income settings where cash-transfer programs are commonly evaluated. After displacement, however, refugees must adapt to a new food environment and relative price structure, often relying on cheaper, energy-dense substitutes for their previous diets. In this context, cash transfers may operate less by expanding calories and more by enabling households to partially restore elements of their prior diet quality, particularly protein-rich or higher-quality items that would otherwise be unaffordable.

Return intentions further differentiate refugees from other poor households. Many Syrian families in Turkey expect to return home, which can shift spending priorities away from diet quality toward savings, debt repayment, or assistance to relatives in Syria. Such intentions also reduce incentives to learn and adapt to Turkey's food environment or to invest in longer-term nutritional practices for children, even though health care and food markets are broadly accessible. As a result, cash transfers may stabilize consumption without necessarily improving dietary diversity to the same extent observed in settled populations. These distinct dietary baselines and adjustment patterns make it theoretically ambiguous whether the effects identified in non-refugee populations should generalize to refugees.

Implemented in 2016, the ESSN program provides monthly cash transfers to refugee families that meet specific demographic criteria, such as high dependency ratios or large numbers of children. In 2018, the average monthly ESSN transfer for a Syrian family of six was 720 TL—equivalent to 36% of the average family consumption and 55% of average male labor income among Syrian refugees in Turkey (Aygün et al., 2024). We evaluate the program using nationally representative data from the 2018 Turkey Demographic and Health Survey (TDHS), which provides a nationally representative sample of the Syrian refugee population in Turkey. Although this dataset is not specifically designed to evaluate the impact of the ESSN program—unlike the Comprehensive Vulnerability Monitoring Exercise (CVME) or the Post-Distribution Monitoring (PDM) conducted by the WFP (World Food Programme)—it offers several advantages. First, unlike the other surveys, it provides detailed information on child growth outcomes. Second, while the CVME and PDM include data on the Food Consumption Score (FCS)—which reflects the consumption of various food items—and the Reduced Coping Strategies Index (RCSI), these measures are collected at the household level. In contrast, the 2018 TDHS provides detailed nutrition information for each infant and child.

The TDHS also provides a detailed household roster and information on relationships to the household head, which enables us to identify families according to the ESSN program's definition of a family. This definition is critical to our identification strategy, which leverages one of the program's key eligibility criteria: families with a dependent-to-working-age adult ratio (dependency ratio) of 1.5 or higher qualify for the ESSN. We define two samples for our analysis: (i) the full sample of refugee households, and (ii) a restricted sample that excludes families who qualify for the program through criteria other than the dependency ratio. Using these samples, we implement a regression discontinuity–like design (RDD) with discrete support (Lee and Card, 2008) to compare families just below and just above the 1.5 threshold. Because the number of discrete values that the dependency ratio can take is relatively limited, we rely on parametric identification and therefore conduct several robustness checks to ensure the credibility of our estimates. Crossing the 1.5 cutoff increases the likelihood of receiving cash transfers by about 25 percentage points. To estimate the causal effect of program participation, we apply a fuzzy RDD framework and conduct a comprehensive assessment of the RDD assumptions. Our RDD methodology also extends previous work in this context by allowing for separate trends in the numbers of dependents and working-age adults—the two components of the running variable.

In terms of child growth outcomes, the results indicate that ESSN transfers have a positive impact on height-for-age (HAZ), suggesting improvements in long-term child development. Specifically, receiving transfers increases HAZ by 0.57 to 0.79 standard deviations across different samples. There is also a statistically significant reduction in weight-for-height (WHZ) and in the probability of being overweight (measured by both WAZ and WHZ scores), while underweight prevalence also decreases—underscoring the program's role in mitigating nutritional extremes.

Nutritional intake results support the growth findings. The most consistent and statistically robust effect is a large reduction in energy-dense, nutrient-poor (EDNP) food consumption following cash transfer receipt. This decline is evident across various samples and withstands corrections for multiple hypothesis testing. While the evidence for increased protein intake is weaker and less robust, particularly after adjusting for multiple comparisons, the direction of the effect aligns with the observed improvements in HAZ and reductions in underweight prevalence.

Taken together, these results suggest that the ESSN cash transfer program contributes to healthier dietary patterns and improved child growth among refugees. By reducing consumption of unhealthy foods and potentially enhancing protein intake, the program supports more balanced nutrition, leading to better physical development and a decrease in both undernutrition and overnutrition among children.

As an additional validation, we implement a second identification strategy that leverages the sharp reclassification of household members when a child turns age 18. Because individuals aged 18 or older are no longer counted as "children" in the ESSN formula, families experience a discrete change in both the dependency ratio and the four-children eligibility rule exactly at this age threshold. Using an RDD centered on this administrative cutoff, we obtain estimates that closely mirror the main results: HAZ is higher, while WHZ and the likelihood of being overweight are lower in refugee families with children below age 18 compared to those with a child who has turned 18. Although this alternative strategy relies on a narrower and more selective sample—and therefore has less power for nutrition outcomes—the consistency of the anthropometric effects across both designs reinforces the robustness of our main findings.

Across the literature, reviewed in the next section, few studies jointly examine child-level food intake and anthropometric outcomes using a robust identification strategy. Our study contributes by (i) evaluating a large-scale cash transfer to refugees, and (ii) using individual-level data on growth and nutrition in an urban**,** middle-income setting.

In contrast to many prior studies, we find that cash transfers lead to improved long-term growth (HAZ) and reduce both undernutrition (underweight) and overnutrition (overweight)—a dual burden often overlooked. In our context, ESSN transfers equaled 36% of family consumption, compared to 10–25% in most other studies. This might explain the strong effects. Also, most prior refugee studies focus on camp-based or conflict-displaced populations in low-income or rural settings. Our study evaluates urban-dwelling Syrian refugees in Turkey, an upper middle-income country with institutional capacity. Refugees have access to universal healthcare in our context. Postnatal care, mortality and vaccination rates are largely similar between Syrian refugee and native children once socioeconomic factors are controlled for, but refugee children lag natives and international peers in growth outcomes (Demirci et al., 2024). Our findings demonstrate that cash transfers—without conditions or complementary services such as other supporting intervention about behavioral change communication (see, e.g., Ahmed et al., 2024; Premand and Barry, 2022)—can improve child growth when targeted effectively to vulnerable refugee populations that reside in urban areas and have access to basic health care services.

In addition, our results highlight that reducing the consumption of energy-dense, nutrient-poor (EDNP) foods is critical for improving child growth—an insight that is not well documented in the existing cash-transfer literature. This mechanism also connects to broader debates on the nutritional transition in low- and middle-income countries. Popkin (2001) and Popkin and Laar (2025) show that, as economies change, diets often shift toward inexpensive, processed foods, leading to the coexistence of stunting and overweight, particularly among poorer households. Although the drivers differ from those in rapidly urbanizing settings, Syrian refugees in Turkey—who live largely in poverty and face significant barriers to formal employment (Demirci and Kırdar, 2023)—may experience similar pressures that push diets toward EDNP foods. At the same time, many refugee families may retain healthier dietary preferences shaped by pre-conflict food environments but lack the resources to act on them, making diet quality highly income elastic. This framework helps explain our findings: cash transfers substantially reduce EDNP consumption, leading to marked improvements in child growth.

2. Related Literature

A large body of literature has evaluated the effects of cash transfer programs on child welfare outcomes, including nutrition and growth. However, there is limited evidence on the impact of large-scale, unconditional cash transfers on refugee children, particularly those residing outside of camps. Moreover, few studies have used child-level data on both anthropometrics and food consumption, which is a key contribution of our study.

2.1. Cash Transfers and Refugee Populations

Several recent studies examine the impact of cash-based assistance on refugee families, but very few assess child growth or individual-level nutrition. Among the closest to our context, Özler et al. (2021), Aygün et al. (2024), and Robson et al. (2024) evaluate Turkey's ESSN program. Özler et al. use PDM and Pre-Assistance Baseline (PAB) survey data and apply an inverse probability weighting approach to study outcomes such as food security (measured by household-level indicators like the Food Consumption Score and the Reduced Coping Strategies Index), poverty, schooling, and migration intentions. They find that the program caused a moderate increase in the diversity and frequency of food consumption among eligible households. However, the datasets they use do not allow them to assess child-level growth or food intake. Similarly, Aygün et al. (2024) apply an RDD using the ESSN eligibility rule but focus on schooling and child labor outcomes, using CVME data. Robson et al. (2024) find that the ESSN significantly reduces the incidence and intensity of multidimensional poverty, particularly in the dimensions of food security and health. However, like the previous evaluations, their analysis relies on composite indices and household-level data, leaving a gap in understanding the program's impact on individual child growth and specific nutritional intake.

In Lebanon, Altındağ and O'Connell (2020) and Moussa et al. (2021) study cash transfers to Syrian refugees, evaluating food coping behaviors, education, and employment. While Altındağ and O'Connell assess food-related outcomes, they focus on coping mechanisms and food expenditures rather than direct measures of nutrition or child growth. They find that the program led to immediate improvements in food security, child well-being, and a reduction in negative livelihood coping strategies. Moussa et al. do not study nutrition outcomes; however, they show that cash transfers reduce morbidity. Similarly, De Hoop et al. (2019) evaluated the 'Min Ila' cash transfer program for Syrian refugees in Lebanon, finding significant positive impacts on food security and school attendance. However, like the other studies in the region, their focus remained on household-level welfare or education rather than the specific anthropometric outcomes we examine here. As such, these studies provide limited insights into the child-level health effects of cash transfers.

Two studies—Grijalva-Eternod et al. (2018) and MacPherson and Sterck (2021)—evaluate nutritional impacts of humanitarian cash assistance for internally displaced people (IDP) in Somalia and for refugees in Kenya, respectively. Grijalva-Eternod et al. find no impact on anthropometric outcomes (HAZ, WHZ, stunting), despite observing improvements in household-level food security and dietary diversity. MacPherson and Sterck find gains in dietary diversity and caloric intake among refugees, but these are measured at the household level, and no child growth outcomes are reported. These null or partial results highlight the difficulty of translating improved household food access into measurable child health gains. Taken together, these refugee-focused studies do not examine the child-level growth and nutrition outcomes together that are central to our analysis.

2.2. Cash Transfers and Child Growth in Other Humanitarian Settings

Other studies evaluate how cash transfers affect child anthropometric outcomes in conflict-affected or food-insecure settings. In Pakistan, Fenn et al. (2017) find that cash-based interventions reduce stunting and wasting, although they do not directly examine dietary changes. Similarly, Kurdi et al. (2019) document positive impacts of a conditional cash transfer program in Yemen on HAZ and WHZ, but only when accompanied by behavioral change communication (BCC); cash alone did not improve growth. Schwab et al. (2013) present findings from a randomized evaluation of emergency cash and food assistance in Yemen. Although they find significant improvements in food security outcomes, they report no improvements in child anthropometric outcomes, attributing this to chronic conditions and external constraints. Likewise, Ecker et al. (2019, 2020) examine cash transfers during the civil war in Yemen, finding that while transfers helped mitigate acute malnutrition (wasting), they were insufficient to prevent chronic stunting due to the severity of the conflict and market disruptions. In contrast, our study finds significant improvements in HAZ and reductions in the prevalence of overweight and underweight from cash alone, suggesting a more direct link between transfers and child growth—possibly due to the larger transfer size and a more favorable institutional environment.

Other studies find mixed or null effects. Gilligan et al. (2016) report reduced anemia and increased starch intake in Uganda, but no changes in stunting or underweight prevalence. Quattrochi et al. (2020), in the Democratic Republic of Congo, find no impact of cash vouchers on WHZ, mid-upper arm circumference (MUAC), or other health indicators. Several studies focus on Niger, which experiences recurrent seasonal food crises and high rates of acute malnutrition. Sibson et al. (2018) report no effect of cash transfers on child growth, despite improvements in food security and dietary diversity. Using household-level data, Hoddinott et al. (2018) similarly find that while cash transfers improved food quantity and caloric intake, they had limited impact on dietary quality or diversity. Langendorf et al. (2014) report that cash transfers helped households access more food, but this did not necessarily translate into higher-quality diets for young children.

They also document a reduction in the incidence of wasting; however, the impact was inferior to that of food-based interventions—particularly those including both household- and child-focused components.

These findings underscore the challenge of achieving improvements in physical development outcomes through cash transfers alone—particularly in high-disease or extremely resource-constrained environments. In this context, it is important to note that our setting is a non-conflict area with well-established health services and no extreme levels of hunger, poverty, or disease. In addition, a key driver of our substantial linear growth estimates is likely the continuous, long-term nature of the ESSN, which contrasts with the temporary assistance often evaluated in the literature. For instance, studies in Lebanon find that benefits dissipate quickly: Altındağ and O'Connell (2020) show welfare gains fade within six months of discontinuation, while Moussa et al. (2021) find that reductions in acute child illness disappear once payments stop. Similarly, the six-month emergency transfers studied by Kurdi (2021) in Yemen were likely too short to generate broad growth impacts. Unlike these transitory interventions, the ESSN's ongoing support provides the stability required for the cumulative biological recovery necessary for catch-up growth.

3. Background

3.1 Syrian Refugees in Turkey

Since the Syrian conflict began in 2011, over 5.5 million people have fled the country. By mid-December 2020, Turkey—Syria's largest neighbor and closest to the conflict—had taken in 3.6 million refugees (65% of the total), nearly half of them children (UNHCR, 2020b). Only 1.6% of Syrian refugees in Turkey live in camps; the rest reside in urban areas within host communities. Despite occasional border closures and tighter controls post-2015, Turkey largely maintained an open-door policy, resulting in a steady rise in refugee numbers between 2013 and 2017.

Demographically, Syrian refugees differ significantly from the Turkish population. They live in larger households (average of 6 vs. 3.5 for Turkish citizens), are younger, less educated, and poorer (HUIPS 2019a, 2019b). According to the Pre-Assistance Baseline (PAB) survey, 28.6% of Syrians outside camps were food insecure, and 93% lived below the national poverty line (WFP, 2016).

Regarding refugees' labor market integration, Demirci and Kirdar (2023) outline the following key features using the nationally representative refugee sample of the 2018 TDHS. Syrian refugee men in Turkey exhibit similar rates of paid employment (61.8%) compared to native men (68.9%), with their employment rate peaking within the first year of arrival and remaining stable thereafter. In contrast, refugee women have a much lower employment rate (6%) compared to native women (22.2%) and show little improvement over time, remaining largely outside the labor force regardless of their length of stay. Refugees are more likely to be wage workers and less likely to be self-employed or employers, likely reflecting financial constraints. They are also more likely to work part-time and are heavily concentrated on informal employment, with a particularly large gap in formal job access. Overall, while refugee men integrate into the labor market relatively quickly—albeit through low-quality, informal jobs—refugee women remain largely excluded, and substantial barriers to decent work persist across the refugee population.

3.2 Child Growth and Nutrition among Syrian Refugees in Turkey

Demirci et al. (2024) investigate disparities in early childhood growth and nutrition between Syrian refugee and native children in Turkey also using the 2018 TDHS. While infant and child mortality rates are similar across groups, refugee infants born in Turkey exhibit significantly lower birthweight and height-for-age (HAZ) scores than natives. After accounting for a rich set of birth and socioeconomic characteristics, the birthweight gap narrows but remains at 121 grams (0.17 SD), and the HAZ gap persists at 0.23 SD. These disadvantages are concentrated at the lower end of the distribution, with refugee infants significantly more likely to experience low birthweight, underweight status, and stunting. By contrast, the gap in weight-for-age (WAZ) disappears after controlling for covariates, suggesting no direct refugee effect on overall weight, while weight-for-height (WHZ) is actually higher for refugee children, possibly reflecting dietary shifts post-birth as well as lower HAZ.

Demirci et al. (2024) also identify gaps in the utilization of health services, alongside notable behavioral and nutritional differences between refugees and natives. Refugee mothers receive fewer prenatal health checks and are less likely to have at least four prenatal visits, but postnatal care and vaccination rates are largely similar once socioeconomic factors are controlled for. In contrast, refugee children are less likely to be breastfed for six months and to consume protein-rich foods during infancy and toddlerhood, pointing to nutritional deficiencies that may contribute to growth delays. These findings suggest that, despite equal access to public health services, early-life growth deficits among refugee children stem from a combination of pre-migration adversity, limited prenatal care utilization, and dietary inadequacies in the postnatal period.

3.3 The ESSN Program

The ESSN program, which provides unconditional cash transfers, was launched in Turkey in November 2016 and had reached 1.8 million refugees as of February 2021.[2] To be eligible for ESSN assistance, refugees must first be registered by the Directorate General of Migration Management (DGMM) and have a residential address registered at local Population Directorates. Households are considered eligible for the ESSN program if they meet at least one of the following six demographic criteria: i) Families with a dependency ratio of 1.5 or higher (i.e., at least three dependents for every two able-bodied adults aged 18–59); ii) Families with four or more children; iii) Women living alone; iv) Families headed by an elderly person; v) Single-parent family; vi) Families with at least one member with a documented disability of 40% or more. These criteria were selected as proxy indicators of a household's inability to meet basic needs, as they are believed to correlate well with poverty and vulnerability among households—especially important for a program that requires simple and transparent inclusion rules (TRC, 2020; Cuevas et al., 2019). Refugees can apply for cash assistance via TRC (Turkish Red Crescent) Service Centers or Social Assistance and Solidarity Foundation offices.

In 2018, households receiving ESSN support received 120 TL per household member per month. For an average Syrian family of six, this amounted to 720 TL per month (approximately 105 USD). In addition, the program provided quarterly top-up payments ranging from 100 to 600 TL, depending on household size, to help cover large expenses such as rent.[3] Households with members requiring special care also received a special payment of 600 TL per month. Transfer

[2] By the end of 2020, total aid disbursed under the ESSN program reached €1.1 billion, with monthly payments averaging around €24 million.

[3] In our sample, 85.3 percent of the children live in households that pay rent.

payments were loaded onto bank cards provided to beneficiaries, who could either withdraw the cash from ATMs or use the card for purchases.

Compared to refugees' monthly labor income, the ESSN cash transfer amounts were relatively high. Excluding special payments, monthly ESSN payments for a six-person family (720 TL) were equivalent to 55% of the average monthly labor income of Syrian men in Turkey, as estimated by the International Labour Organization (ILO), and 36% of the average monthly consumption value of refugee households in the CVME dataset of the WFP (Aygün et al., 2024).

4. Data

We use the 2018 round of Turkey Demographic and Health Survey (TDHS), which elicits child anthropometric outcomes for a representative sample of Syrian refugees and natives in Turkey. For each child born in the preceding five years, the survey provides the current height, weight, and weight for height. We use the age adjusted standardized versions of these variables based on the corresponding WHO averages. Thus, our variables are in terms of z-scores; and, following the literature, we refer them as HAZ (for the standardized height), WAZ (weight), and WHZ (weight for height) throughout this study.

In our empirical analysis, we estimate the effect of receiving cash transfer via the ESSN program on HAZ, WAZ, and WHZ. Based on these measures, we also generate and analyze new variables indicating whether these anthropometric outcomes fall below or exceed certain thresholds, such as its one or two standard deviations. The THDS data also reports what children ate among the list of detailed items in the last 24 hours preceding the survey for the children aged 36 months or younger. We group these food items into major categories (milks, proteins, carbohydrates, vegetables, EDNP foods)[4] and analyze the effect of cash transfer on the total number of items consumed in each category as a potential mechanism.

[4] Milks include 1) breast milk, 2) other milk, and 3) baby formula; proteins include 1) yogurt, 2) cheese, 3) egg, 4) meat, 5) chicken, and 6) fish; carbohydrates include 1) bread, 2) other cereals (e.g., rice, pasta, noddle), and 3) soup; vegetables include 1) fresh fruits or vegetables, 2) fresh juices, and 3) legumes; and EDNP foods include 1) canned food (e.g., biscuits, pastries, chocolate), 2) instant drinks (e.g., canned juices, spirits), and 3) gravy from other meals.

Of the six eligibility conditions for the ESSN program, the survey provides information on whether a household meets each of the first five, with the exception of the final condition related to disability. The survey also records whether the household received the ESSN cash transfer. This information is collected at the individual level for each household member. We consider a child to be a beneficiary if at least one parent is receiving the aid.

Refugee families must be registered in the Turkish Presidency Migration Management (TPMM) to be able to benefit from the ESSN program. The TPMM provides the cash transfers to eligible families—where a family is defined as a unit consisting of its head and spouse, their parents, their unmarried children, and other unmarried members of the family. Therefore, we first exclude respondents in the sample who are not officially registered by the TPMM or not usual residents of the household, both of which are available in the dataset. A caveat of the TDHS data is that the family records of the TPMM are not observed; instead, all people living in the same address are recorded as the same household. Hence, we first define the core family members of household heads according to the family definition of the TPMM.

For each household, the survey identifies household head, and the relationship to the head is coded for each member in the sample. We define families as units consisting of its head and spouse, their unmarried kids, their parents, and all other unmarried members of the household except for those whose married parents are identified in the survey.[5] Once we make these restrictions, we reach the core family unit—as defined by the TPMM—within each household in the TDHS. After we form families in accordance with the TPMM definition, we can define variables for family composition, as well as for the dependency ratio and other family structures earning ESSN eligibility (such as having at least four children in the family).

The above approach defines families—according to the TPMM definition of ESSN eligibility—within the households in the TDHS. Using this group of families, we define two

[5] First, we examine married individuals in the household. In accordance with the family definition of TPMM, we exclude any *married* son/daughter, son/daughter in law, grandchild, sibling, sibling's partner, siblings' child, father's sibling, mother's sibling, step child, cousin, sibling-in-law, sibling-in-law's partner, sibling-in-law's children, other relatives, and "not related" people. However, we keep married parent, parent-in-law, grandparent, grandparent-in-law, second wife, husband's second wife. Second, we examine children in the household because it is critical to know who the parents are. We exclude children whose parents are married members of the household other than the household head (essentially children of the married individuals we dropped in the first stage).

samples: (i) full sample, which we call sample A, and (ii) a subsample excluding families who are eligible for the ESSN program via criteria other than the dependency ratio, which we call sample B. The number of families is 778 in sample A and 433 in sample B.

Our child-level analysis of anthropometric measures makes the same set of restrictions on children. We take children (i) who are registered with TPMM, (ii) who are usual residents of the household, and (iii) who are family members of the household heads according to the TPMM family definition. In addition, we restrict the child sample to observations for whom all three anthropometric measures are observed to enhance the comparability across estimates. This results in 1,204 observations in sample A and 662 observations in sample B. Finally, in our main analysis, we restrict the values of the running variable—dependency ratio—to be between 0 and 3, taking a bandwidth of 1.5 on each side of the cutoff. Consequently, the number of observations in sample A reduces to 1,111 while the sample size of sample B remains the same. (We also check the robustness of our findings using alternative bandwidths.)

TDHS also provides a rich set of variables used as control variables in our study. Specifically, we control two sets of variables: 1) basic biological characteristics (baby's sex, mother's height and body mass index), 2) household and environmental characteristics (the interaction of the region and type of current residence (urban, rural, and camp), household head's education, the interaction of the household head's sex and age, mother tongue, arrival year, province and type of birth region).

Table 1 presents descriptive statistics for the dependent variables, using the main sample where the dependency ratio is restricted to the [0, 3] interval. The table shows that Syrian refugee children in Turkey lag behind their international peers in height-for-age (HAZ) but not significantly in weight-for-age (WAZ). The mean HAZ is −0.8, while the mean WAZ is only −0.05. As a result, the mean weight-for-height (WHZ) is relatively high, at approximately 0.6, and the incidence of overweight based on WHZ is notable at 9%. Table 1 also indicates that, on average, children consume just under one of the three items across the categories of milk, EDNP food, and vegetables; 1.3 out of six protein items; and 1.45 out of three carbohydrate items. There is clear room for improvement in all categories: the share of children consuming one or fewer items from each food group is 80% for milk, 67% for protein, 57% for carbohydrates, and 84% for vegetables. In contrast, 59% of children consume at least one type of EDNP food. Appendix Table A1 reports descriptive statistics for the control variables. The share of children whose families receive ESSN transfers is 56% in Sample A and 40% in Sample B.

5. Identification Method and Estimation

Our empirical strategy builds on the eligibility criterion based on the dependency ratio (as in Aygün et al., 2024). We estimate the effect of receiving a cash transfer using the following fuzzy regression discontinuity design (RDD),

$$E_i = \alpha_0 + \alpha_1 T_i + F(d_i) + X_i \tau + u_i \, , \qquad (1)$$

$$y_i = \beta_0 + \beta_1 \hat{E}_i + G(d_i) + X_i \varphi + e_i \, , \qquad (2)$$

where the first equation illustrates the first stage, and β_1 in the second equation shows the effect of interest on y_i, the anthropometric outcome of child i. E_i is a binary indicator for whether the family of child *i* receives the cash transfer, and its predicted value, $\hat{E}_i$, based on Equation (1) serves as an input for Equation (2). T_i shows the treatment variable such that it takes the value of one if the dependency ratio for the family of child i is 1.5 or above. $F(.)$ and $G(.)$ denote the trends in outcome variable as a function of d_i, that is the dependency ratio for the family of child i. Lastly, X_i denotes the control variables, as defined in the Data Section, and u_i and e_i are error terms.

A critical aspect of our setting is the discrete nature of the running variable. This discreteness makes local identification around a narrow neighborhood of the cutoff challenging, necessitating the choice of a functional form to model the relationship between the outcome variable and the running variable. Lee and Card (2008) demonstrate that in an RDD with a discrete running variable, inference can be conducted by treating the difference between the expected value of the outcome variable and the predicted value from a specified functional form as a specification error. Because this approach introduces a common variance component across observations corresponding to a given value of the dependency ratio, Lee and Card (2008) recommend using clustered standard errors for inference. Hence, we cluster the standard errors at the level of dependency ratio. Since we have a relatively small number of clusters (21 in sample A and 14 in sample B), we also calculate wild-cluster bootstrapped p-values.

We take the [0,3] bandwidth in our primary analysis because this is the largest equally spaced interval around the cutoff. At the same time, we check the robustness of our findings to alternative intervals. A crucial decision in our parametric identification strategy is the specification regarding the trends. In our primary specification, we take split linear trends on each side of the cutoff within a bandwidth of [0,3]. This choice results from the method developed by Pei et al. (2022) to guide the choice of polynomial order, which relies on comparing asymptotic mean squared errors across different polynomial orders. Our results indicate that linear polynomials yield the best performance for the vast majority of variable and sample combinations, leading us to adopt linear polynomials in our main analysis (Appendix Table A2). Our preference for lower-order polynomials aligns with the recommendation of Gelman and Imbens (2019). Nonetheless, we check the robustness of our findings to the use of alternative specifications.

We conduct several key robustness checks regarding the bandwidth and the trend specifications. First, we keep the split linear time trends but take several alternative bandwidths around the cutoff. Essentially, we begin with the full dataset and progressively narrow the bandwidth around the cutoff. Specifically, we take the [0,6] interval (corresponding to a bandwidth of 1.5 on the left and 4.5 on the right of the cutoff), the [0,4.5] interval (bandwidth of 1.5 on the left and 3 on the right of the cutoff), and finally the baseline [0,3] interval. As noted earlier, the discrete nature of our running variable constrains our ability to further zoom in around the cutoff to directly compare observations just below and just above the threshold. In fact, the first stage F-statistics fall below the recommended levels in the literature when we zoom in further than [0,3] interval.

We also utilize various other specifications for the time trend. First, we use a single linear polynomial throughout the bandwidth, rather than splitting it on either side of the cutoff. Second, we use a single quadratic polynomial in the running variable. We take the approach of using a single polynomial because there is no obvious reason to expect a break in how the outcome variable changes with the dependency ratio at the specific value of 1.5. On one hand, split trends are more flexible; on the other hand, one needs to be cautious with split trends when the number of discrete values of the running variable is small, as is the case in our sample B.

Our running variable is peculiar in that it is a composite variable, depending on both the number of dependents and the number of prime-age adults. When the running variable is the dependency ratio, we force the effects of these two components to be equal, which does not necessarily have to be true. Therefore, in a third specification, we use separate linear polynomials for the number of dependents and the number of prime-age adults. Finally, in the fourth specification, we use linear polynomials in the logarithmic values of the numbers of dependents and prime-age adults to account for the potentially diminishing effects of these variables on the outcome variables.

5.1 Plausibility of the Identification Strategy

A potential threat to our identification strategy would be families manipulating their composition to qualify for the program. However, this is highly improbable given Turkey's institutional safeguards. Refugees applying for the ESSN program must first register with the Provincial Directorate of Migration Management (PDMM) upon arrival, where their background documents are verified, statements are taken if needed, and eligibility for Temporary Protection Status is assessed. If approved, they receive a Temporary Protection Identification Card linked to their family. They must then register their residence with the Directorate of Civil Registry, after which they can apply for ESSN using their family ID number.

All applications are recorded in the Integrated Social Assistance System (ISAS), which centrally manages Turkey's social assistance programs. ISAS's strict verification process minimizes errors from false declarations or subjective staff decisions. Eligible applicants receive an SMS to collect their ATM cards but remain subject to unannounced home visits within a year to confirm the accuracy of their application. If discrepancies are found, assistance is revoked. In addition, ISAS reassesses eligibility monthly, discontinuing aid if family conditions change, such as a child turning 18 or an adult obtaining a work permit. Previously ineligible families may also qualify due to these periodic checks. Overall, the stringent registration process, continuous monitoring, and home visits make eligibility manipulation highly unlikely.

Another potential concern in our identification strategy is that if family structures exhibited little variation, our method would compare fundamentally different family types across the eligibility cutoff. For instance, if all households consisted of two parents, we would primarily compare two-parent families with three children (to the right of the cutoff) to those with two children (to the left of the cutoff). However, our setting features substantial variation in refugee family composition, particularly in the number of prime adults and dependents.

Table 2 presents these variations in matrix form for the sample of families with a dependency ratio in the [0,3] range, highlighting treated families (dependency ratio ≥ 1.5). Crucially, for families with 1 to 4 prime adults, observations exist on both sides of the cutoff. For example, in the [1,2] range around the cutoff, left-side families include (1,1), (2,2), (3,3), (3,4), (4,4), (5,5), and (5,6) combinations of prime adults and dependents, while right-side families include (1,2), (2,3), (2,4), (3,5), (3,6), (4,6), (4,7), and (4,8). This diversity mitigates concerns about systematic family structure differences influencing our identification strategy.

5.2 Checks of the Identification Assumption

The primary identification assumption is that the outcome variables exhibit continuity in relation to the running variable at the cutoff point. In the literature, three standard tests are used to evaluate the validity of this assumption: (i) no treatment effects on pretreatment covariates, (ii) smoothness of the score density near the cutoff, and (iii) no treatment effects at artificial cutoff points.

First, we analyze the impact of the treatment on pretreatment covariates at the cutoff point. If there is no sorting around the cutoff, there should be no discontinuity observed at the cutoff for the pretreatment covariates. Table 3 shows evidence of a jump that is statistically significant at least at the 10 percent level for 3 covariates out of 31 with sample A and for 3 covariates out of 26 with sample B—which are expected given the statistical significance level. Given the discrete nature of our running variable, concerns may arise about a possible discontinuity at the cutoff for the family-structure covariates. However, for none of the family-structure variables (including the numbers of children, elderly, adults, male adults, and total family members) is there evidence of a discontinuity at the cutoff, although some of the estimated coefficients are sizeable with sample A. As discussed earlier, the large variation in family structure enhances the continuity of these covariates across the cutoff.

Second, maintaining continuity of the score density around the cutoff necessitates that families do not manipulate the running variable to qualify for the program. As discussed earlier, manipulation of the family structure is nearly impossible in our institutional context (except for changes in fertility behavior of parents or marriage behavior of teenage family members). If manipulation were present, we would anticipate a higher concentration of observations just to the right of the cutoff. To investigate this, Appendix Figure A1 offers a histogram of the dependency-ratio variable. As expected, there are peaks at every half value of the dependency ratio (e.g., 0.5, 1.0, 1.5). However, the peak at 1.5 is not more prominent than the other peaks.

Finally, we examine the potential effect of the policy at artificial cutoff values. To do this, we create two subsamples: one limited to the left-hand side of the actual cutoff and the other to the right-hand side. Within each subsample, we set alternative cutoff points while ensuring sufficient sample sizes on both sides. For the left-side sample, we use cutoffs at dependency ratios of 0.75 and 1, while for the right-side sample, we use 2, 2.25, 2.5, and 3. Since we split the sample into two when examining the potential policy effect at artificial cutoffs, the number of clusters in the regressions is even smaller, making it more important to focus on bootstrapped p-values. The estimation results presented in Appendix Table A3 show that the bootstrap p-value is 0.08 in one case and 0.018 in another out of 54 artificial cutoff values. Thus, we observe no policy effect beyond statistical expectations at these artificial cutoffs.

6. Results

6.1 Child Growth Outcomes

Figure 1 illustrates the relationship between beneficiary status and the dependency ratio. We present the fraction of beneficiaries by dependency ratio for Sample A in Panel (A) and for Sample B in Panel (B). To ensure equal intervals on each side of the cutoff, we restrict the bandwidth for the dependency ratio to the [0,3] interval. The advantage of Sample B is that it provides a stronger first stage (a larger jump in ESSN take-up at the RDD cutoff). In contrast, the larger Sample A covers a wider range of dependency-ratio values and therefore yields a greater number of clusters in the estimation.

To construct the plots, we use the *rdplot* software (Calonico et al., 2015, 2017), which groups data into bins and plots the average outcome within each bin. We address the uneven distribution of the running variable by dividing it into three equal-width bins on each side of the cutoff in sample (A), and into three equal-width bins on the left and two on the right of the cutoff in sample (B). For each bin, we plot the mean of the outcome variable, along with 90 percent heteroskedasticity-robust confidence intervals shown as error bars. To illustrate the trends on either side of the threshold, we fit linear local polynomial regressions separately using the underlying individual-level data. Both plots indicate a significant jump at the cutoff value of the dependency ratio: the percentage of families receiving benefits increases from approximately 50 percent to 70 percent in Panel (A) and from about 40 percent to 70 percent in Panel (B).[6]

We examine the relationship between key child growth outcomes and the dependency ratio in Figure 2 (Sample A) and Figure 3 (Sample B). In both figures, height-for-age shows a slight upward shift at the cutoff, although the confidence intervals overlap. In contrast, weight-for-age exhibits a clearer drop at the cutoff, with an even larger decline for weight-for-height. It is important to note that the confidence intervals in the smaller sample (B) are noticeably wider. The underweight and overweight indicators also suggest decreases at the cutoff, with the drop in overweight based on WHZ particularly pronounced. However, the wide confidence intervals indicate that these patterns should be interpreted with caution.

Table 4 presents the reduced-form RDD estimation results, showing how beneficiary status and child growth outcomes change at the cutoff, accounting for the split linear time trends on each side of the cutoff and the control variables. The probability of receiving ESSN cash transfers increases by 23.1 percentage points in Sample A and by 27.4 percentage points in Sample B. This increase is larger for Sample B, as expected, since this sample excludes families that qualify via other criteria. Both samples provide statistical evidence of an increase in HAZ and a decline in WHZ at the cutoff. Additionally, both samples indicate a reduction in the probability of being

[6] The plot for Sample B in Figure 1 indicates a significant share of families receiving ESSN cash transfers on the left-hand side of the cutoff, even though Sample B excludes families eligible for the ESSN through criteria other than the dependency ratio. There are several reasons for this. First, we cannot account for disability status using the TDHS, even though it is one of the ESSN eligibility criteria. As a result, we underestimate the ESSN receipt rate. Second, because we lack access to family registry data as defined by the TDGMM, we construct families according to the ESSN definition using the detailed household roster, which includes each member's relationship to the household head. This introduces additional measurement error. In contrast, the CVME data, collected by the WFP, do not suffer from these two limitations. However, when constructing the RDD graph excluding other qualifiers (as in Sample B) using the CVME data, we still observe a sizable group to the left of the cutoff receiving transfers, though the share is smaller than in Figure 1. Specifically, the linear fit on the left-hand side of the cutoff reaches 0.2 in the CVME data, compared to 0.4 in the TDHS data for Sample B in Figure 1. This indicates that measurement error persists even when the family definition aligns with TDGMM criteria and disability status is accounted for.

underweight or overweight, based on the weight-for-age score, as well as a decrease in the probability of being overweight based on the weight-for-height score. Finally, while Sample A also shows evidence of a decline in WAZ, this finding does not hold for Sample B. Overall, these patterns align with those observed in Figures 2 and 3.

Table 5 presents the 2SLS estimates, demonstrating the impact of receiving ESSN cash transfers on child growth outcomes. For both samples, the estimates provide statistical evidence—supported by bootstrapped p-values—of a positive impact of the cash transfers on children's HAZ scores. The z-score of height increases by 0.57 standard deviations in Sample A and 0.79 standard deviations in Sample B. However, we find no evidence of an impact of cash transfers on extreme values of the HAZ scores (i.e., being stunted or very tall).

Our estimated impact on linear growth (0.6–0.8 SD) is notably larger than those found in other recent humanitarian evaluations. In Yemen, Kurdi (2021) finds a 0.31 SD increase in HAZ for the poorest children receiving cash combined with nutritional training. The stronger effects observed in the ESSN context likely reflect the advantages of a middle-income host setting: unlike in active conflict zones where disease environments and broken supply chains dampen the effectiveness of cash, refugees in Turkey can leverage functional markets and health systems to convert income gains directly into improved child health. Additionally, as reported in Table 1, the mean level of HAZ is considerably lower than WAZ or WHZ, leaving substantial room for catch-up growth in height.

The evidence regarding the impact of cash transfers on WAZ scores is more mixed. While the estimates for Sample A indicate statistical evidence that WAZ decreases with cash transfers, no such evidence is found for Sample B. Moreover, the difference in statistical evidence between the two samples is not simply due to low precision in the smaller Sample B; the estimated negative coefficient for Sample B is much smaller in absolute magnitude. In contrast, both samples provide robust statistical evidence—statistically significant at least at the 5 percent level**,** even with bootstrapped p-values—of an impact on extreme values of WAZ. Notably, cash transfers reduce the incidence of both extremes: underweight and overweight. The probability of being underweight decreases by 9.9 percentage points in Sample A and 13.3 percentage points in Sample B. Similarly, the probability of being overweight declines by 16.7 percentage points in Sample A and 12.1

percentage points in Sample B.[7] The substantially larger reduction in overweight prevalence compared to underweight prevalence in Sample A is consistent with the observed decline in the mean WAZ score for this sample.

Table 5 also provides statistical evidence of a decline in the WHZ score following cash transfers, which aligns with the observed increase in HAZ and the negative coefficients for WAZ. Quantitatively, the receipt of cash transfers reduces WHZ by 1.83 standard deviations in Sample A and 1.12 standard deviations in Sample B. Moreover, the receipt of ESSN cash transfers decreases the probability of being overweight in terms of the WHZ score. This finding is consistent with both the decline in overweight prevalence based on the WAZ score and the increase in the mean HAZ score. Specifically, the probability of being overweight in terms of the WHZ score decreases by 24.8 percentage points in Sample A and 18.8 percentage points in Sample B (for the set of compliers at the cutoff point).

6.2 Child Food Consumption

To understand the observed changes in child growth outcomes, we also examine the impact of the ESSN program on child food consumption. In particular, we focus on macronutrient intakes, including protein, carbohydrates, milk or baby formula, vegetables, and EDNP food. Figures 4 and 5 provide the RDD graphs for these five food groups for samples A and B, respectively. The most obvious change at the cutoff in Figure 4 is the drop for EDNP food. Moreover, the confidence intervals around the cutoff are relatively tight. While we also observe a sizable drop in milks and jumps in proteins and carbohydrates, the confidence intervals around the cutoff are quite large. The patterns for sample B in Figure 5 are overall similar.

Table 6 provides the reduced-form RDD estimates for food consumption. The probability of ESSN receipt increases by about 20 percentage points for both samples A and B. (The samples for nutrition outcomes are smaller as these outcomes are available for only 6- to 35-month-old children.).[8] Since we test hypotheses across multiple food categories, we also calculate Romano

[7] Although the magnitudes of these effects are large compared to the mean levels of these extreme events given in Table 1, these estimates are for the group of compliers and they are at the cutoff level.

[8] Food consumption for babies younger than 6 months is not analyzed (despite availability of its data) since exclusive breastfeeding is suggested for this period.

and Wolf's (2005a, b) p-values, which are robust to multiple hypothesis testing. The estimates indicate a statistically significant drop in EDNP food consumption at the cutoff for both samples, even after accounting for multiple hypothesis testing. The sign of the coefficient estimates for the consumption of milks, proteins, and carbohydrates are consistent with the patterns in Figures 4 and 5. However, the fall in milks and the rises in carbohydrates are statistically insignificant. Although the increase in proteins is statistically significant with sample B, this is not robust to multiple hypothesis testing.

Table 7 presents the 2SLS estimates of the impact of ESSN cash transfers on children's consumption of these five food categories. The key finding is that receiving the cash transfer reduces children's consumption of EDNP food. This effect is highly statistically significant in both samples, with similar coefficient magnitudes across them. Quantitatively, the results imply that cash transfers reduce the number of different EDNP items consumed by about 1.6 units, which corresponds roughly to two standard deviations. This finding aligns with the observed decline in WHZ scores and the probability of being overweight (both in terms of WAZ and WHZ scores).

Table 7 also provides suggestive evidence of a positive impact of ESSN transfers on children's protein intake. While the positive effect in sample A is statistically insignificant, the impact in sample B is larger and more precisely estimated. After correcting for multiple hypothesis testing, however, the statistical significance of protein intake in sample B drops to the 25 percent level, whereas the significance of EDNP food consumption remains at the 5 percent level in sample A and at the 10 percent level in sample B.

Consistent with Kurdi (2021), who finds that households in Yemen used cash transfers to purchase nutrient-rich animal proteins rather than simply increasing staple calorie consumption, we also find suggestive evidence of an increase in protein intake among ESSN beneficiaries. However, distinct from the survival context of Yemen, the improvement in our setting is further characterized by a robust reduction in cheap EDNP foods. This indicates that in a middle-income host country like Turkey, cash transfers enable families not only to access better nutrition but also to actively substitute away from unhealthy, filling staples toward a more balanced diet.

The suggestive increase in protein intake is consistent with the rise in HAZ scores reported in Table 5. Moreover, it aligns with the decline in the incidence of underweight children. Overall, the findings on ESSN's impact on nutrition strongly align with its effects on child growth. The program promotes better nutrition by increasing protein intake and reducing EDNP food consumption. Consequently, children's HAZ scores rise, WHZ scores fall, and both underweight and overweight incidences decrease—representing improvements in child growth.

6.3 Robustness Checks

6.3.1 Alternative Bandwidths

First, using our baseline trend specification (split linear trends on each side of the cutoff), we assess the robustness of our findings to alternative bandwidth choices using Sample A. This check is only feasible for Sample A, as Sample B does not include any observations of the running variable outside the [0,3] interval. Table 8 presents the results for child growth outcomes, while Table 9 reports the results for nutrition outcomes. We use four different bandwidths in both tables: (i) the full sample in Panel A, (ii) [0,6] in Panel B, (iii) [0,4.5] in Panel C, and (iv) [0,3] (baseline) in Panel D. The number of clusters is 33 in Panel A, 31 in Panel B, 27 in Panel C, and 21 in Panel D of Table 8, and 30 in Panel A, 29 in Panel B, 25 in Panel C, and 20 in Panel D of Table 9. We also experimented with bandwidths narrower than the baseline; however, the first-stage F-statistics for child growth outcomes fall to 5.8 for the [0.5,2.5] bandwidth and 5.43 for the [1,2] bandwidth. Therefore, we do not use these narrower bandwidths.

The findings related to child growth outcomes in Table 8 are highly robust, both in terms of statistical significance and coefficient magnitudes. Similarly, our key finding—that cash transfers reduce the consumption of EDNP food—is robust across specifications in Table 9. The effect remains statistically significant at the 5 percent level even after accounting for multiple hypothesis testing, except when using the full bandwidth, where statistical significance drops to the 10 percent level after the correction.

Table 9 also shows a positive impact of cash transfers on carbohydrate consumption when using cluster-robust standard errors and bandwidths wider than the baseline [0,3]. However, this evidence becomes marginally statistically insignificant when standard errors are adjusted for the small number of clusters with the [0,4.5] and [0,6] bandwidths, and only marginally statistically significant at the 10 percent level with the full sample. Nonetheless, these results all become statistically insignificant (with p-values above 0.2) after correcting for multiple hypothesis testing.

Hence, the only robust statistical evidence pertains to the reduction in EDNP food consumption due to cash transfers.

6.3.2 Alternative Specifications

Tables 10 and 11 display the estimates resulting from the use of alternative specifications for time trends in child growth and nutrition outcomes, respectively. The common feature of these four specifications are that they use a single polynomial throughout the full bandwidth range, instead of split polynomials on each side of the cutoff. Particularly, in both tables, panel (I)s use single linear trends, panel (II)s use single quadratic trends, panel (III)s use separate linear trends for the number of dependents and the number of prime-age adults, and panel (IV)s use separate linear trends for the logarithmic forms of the numbers of dependents and prime-age adults. In each panel, the estimates are provided separately for Sample A and Sample B.

The findings on the WHZ score are highly robust across the four specifications and two samples. Based on the bootstrapped p-values, statistical significance is at least at the 5 percent level in all but one case, which is marginally insignificant at the 10 percent level. Similarly, the reduction in the incidence of being overweight based on the WHZ score is statistically significant in all samples, at least at the 5 percent level, based on the bootstrapped p-values. Statistical evidence of a drop in the incidence of being overweight based on the WAZ score also exists for all but one specification and sample combination (Panel I-Sample B). Overall, the results regarding reductions in WHZ and in the incidence of being overweight are highly robust. Quantitatively, the estimated effects in Table 10 under alternative specifications are generally smaller than those in Table 5 but still sizeable. For instance, the reduction in WHZ ranges between 0.5 and 1.2 standard deviations for Sample A, and between 0.7 and 0.9 standard deviations for Sample B.

As in the main results shown in Table 5, the reduction in the mean WAZ score resulting from the cash transfers is more pronounced in the larger Sample A, and the statistical evidence is fairly consistent across the various results in Table 10. Quantitatively, the reduction ranges from about 0.34 to 0.6 standard deviations. For Sample B, statistical evidence of a negative impact of the cash transfers on WAZ also emerges with the more flexible specifications in Panels (III) and (IV), where we allow the effects of the number of dependents and the number of prime-age adults to vary. The magnitude of the reduction ranges from about 0.3 to 0.4 standard deviations.

The statistical evidence on the incidence of being underweight decreasing with cash transfers, as shown in Table 5, is less robust across the alternative specifications in Table 10. Although the coefficients are all negative and sometimes sizeable, statistical significance exists only for the specification with quadratic single polynomials in Panel II with Sample A, and for the specification with separate terms for the components of the dependency ratio in Panel III with Sample B. Nonetheless, the precision in Panel IV is notable for both samples. Overall, the evidence regarding the impact on being underweight is only partially supportive.

Finally, the increase in HAZ resulting from the ESSN program is supported by the evidence for Sample B in Table 10. For all specifications, the statistical evidence is significant at least at the 1 percent level based on the bootstrapped standard errors. In contrast, the results for Sample A provide statistical evidence only for Specification II, which uses a quadratic single polynomial. At the same time, the weaker statistical evidence for Sample A compared to Sample B is consistent with the results in Table 5.

Table 11 presents the results for alternative specifications and two samples for the nutrition outcomes. The finding regarding the reduction in EDNP food consumption with cash transfers is pretty robust. Even after correcting for multiple hypothesis testing, the statistical evidence remains for six of the eight estimates; and, the statistical evidence is marginally insignificant for the remaining two estimates (both of which are for the smaller sample B). Quantitatively, the results indicate a 0.8–1.2 reduction in the number of EDNP food items with the receipt of cash transfers, which is larger than one standard deviation drop in the number of EDNP food items.

The cluster-robust standard errors yield statistical evidence of a positive effect of cash transfer on protein consumption for three out of the four estimates with sample B. However, this evidence vanishes once we adjust for few clusters and multiple-hypothesis testing. Essentially, the only robust evidence regarding the impact of cash transfers on nutrition is that EDNP food consumption decreases.

6.4 Alternative Identification Strategy

To identify the causal effect of the ESSN program on child growth outcomes, here we exploit the institutional rule that individuals are classified as children—and thus counted as dependents—only until they reach age 18. When a child turns 18, the family experiences a discrete shift in the variables used to determine ESSN eligibility: the number of dependents falls, the number of prime-aged adults increases, and the count of "children" relevant for the alternative four-children eligibility rule decreases. Consequently, the probability that a family becomes eligible for the program changes sharply at the exact moment a child turns 18 due to discontinuities in two eligibility criteria: (i) having at least four children and (ii) having a dependency ratio of 1.5 or higher. Later in this subsection, we verify that these discontinuities arise mechanically from program rules and cannot be manipulated by households.

We use this institutional feature to implement a fuzzy regression discontinuity design, where having a child above age 18 serves as an instrument for ESSN eligibility. A family may have more than one child close to age 18, which raises the question of how to determine on which side of the cutoff the household should be placed. To address this, we focus on all family members whose ages fall within a chosen window around 18 and compute the average age within that window. This family-level average age serves as our running variable and determines whether the family is classified as just below or just above the cutoff. Within a narrow window around age 18, households just below the cutoff are expected to be nearly identical to those just above it, except that the latter experience a sudden decline in their likelihood of qualifying for the program. By comparing child growth outcomes across this threshold, while allowing for smooth age trends on either side, we recover the local causal effect of ESSN participation for households whose eligibility status is altered by the age-18 reclassification.

The analysis builds on the sample used in the main specification (Sample A) by restricting it further to families with at least one child around the chosen window around age 18. Because the choice of the age window is inherently arbitrary, we assess robustness by repeating the analysis using several alternative bandwidths around age 18, including {15–20}, {14–21}, {13–22}, and {12–23}. The number of discrete values of the running variable for these bandwidths is 14, 27, 38, and 44, respectively. As in the main analysis, we use wild-cluster bootstrapping due to the relatively small number of clusters.

In the RDD estimation, we use split linear trends on each side of the cutoff and nearly the same set of control variables as in the main analysis. In particular, we use biological characteristics, household-level demographic and environmental indicators, and indicators for the other ESSN eligibility criteria. An exception is the indicator for having four or more children, which we exclude. Because the four-children rule changes mechanically when a child crosses the age-18 threshold, this variable is not predetermined; rather, it lies on the causal pathway through which the cutoff affects ESSN eligibility. Conditioning on it would block part of the treatment variation generated by the discontinuity and undermine the identification strategy. For the same reason, we also exclude the household head's age (whose interaction terms with the household head's sex enter the main specification), as households with older children are mechanically older. All other control variables remain the same.

6.4.1 Checks of the Identification Assumption

A potential concern for the age-18 identification strategy is that families might manipulate the age composition of their household—for example, by encouraging children to move out and re-register their residence once they turn 18—in order to retain ESSN eligibility. Such behavior would introduce a discontinuity at the threshold in the likelihood that a family has a child of a given age, violating the continuity assumption underlying the RDD. To assess this, we examine the fraction of families with at least one member at each age between 12 and 23, corresponding to the widest window used in our analysis. Appendix Figure A2 shows no evidence of a discontinuity at age 18: the probability of having an age-18 household member aligns smoothly with the surrounding ages. The higher frequencies observed at the younger ages (12–14) are mechanical, stemming from the fact that our sample is restricted to families with at least one child under age five. Overall, the absence of any break at age 18 supports the validity of the identification strategy and indicates that families do not manipulate household composition around the cutoff.

Next, we examine whether all pretreatment covariates evolve smoothly around the cutoff. Appendix Table A4 presents the results for the four samples defined by the age bandwidth around 18. The percentage of covariates showing evidence of imbalance at least at the 10 percent level ranges from 14 percent in samples (A) and (B) to 21 percent in sample (D). Although these figures are somewhat higher than expected, they remain within an acceptable range.

Finally, we examine the potential effect of the policy at artificial cutoff values. To do so, we use counterfactual age cutoffs below 18 and restrict the sample to age ranges entirely below 18. Since our main analysis uses 3- to 6-year bandwidths around the actual cutoff, we apply the same 3- to 6-year intervals around each counterfactual cutoff. For example, with a 3-year interval, the age range is 12–17 when the cutoff is 15, and 7–12 when the cutoff is 10. With a 5-year interval, the range is 8–17 around a cutoff of 13 and 3–12 around a cutoff of 8. Following this procedure, we obtain six counterfactual cutoffs for each of the four bandwidths, yielding 24 placebo regressions of treatment status on ESSN receipt. Appendix Table A5 shows that only 2 of the 24 placebo estimates are statistically significant at the 10 percent level, which is well within what would be expected by chance.

6.4.2 Results

Appendix Figure A3 presents the RDD graph for ESSN beneficiary status using the {13–22} age bracket, which yields the strongest first stage (as shown later in Table 12). In Figure A3, nearly 60 percent of families to the left of the age-18 cutoff receive ESSN benefits, compared to roughly 30 percent to the immediate right, indicating a substantial discontinuity at the threshold. Appendix Figure A4 displays the corresponding RDD graphs for anthropometric outcomes. The fitted line for HAZ is visibly higher to the left of the cutoff, whereas the fitted lines for WHZ and the indicator for being overweight are noticeably lower on that side. Finally, Appendix Figure A5 shows the RDD graphs for food-consumption outcomes, which reveal no clear evidence of discontinuities at the cutoff for any of these variables.

Table 12 presents the results for the child anthropometric outcomes. Column (2), where the dependent variable is ESSN receipt, reports estimates from a sharp RDD, while the remaining columns present fuzzy RDD estimates for the corresponding outcomes. Results are shown for four alternative bandwidths around age 18—{15–20}, {14–21}, {13–22}, and {12–23}—and are highly consistent across all panels. The first-stage results are stronger in panels (B) and (C), with F-statistics well above recommended thresholds, whereas those in panels (A) and (D) fall just below 10. All four panels exhibit a discontinuous change in the probability of receiving ESSN cash transfers at the cutoff, with a higher probability of receiving transfers on the left-hand side of the age-18 threshold than on the right-hand side. While the bootstrapped p-value is marginally insignificant in the smallest sample (panel A), the remaining estimates are highly statistically significant.

Based on the bootstrapped p-values in Table 12, we find evidence of a positive impact of receiving ESSN cash transfer on HAZ and negative impacts on WHZ and the probability of being overweight. The positive effect on HAZ is statistically significant in all samples except panel (A), whereas the negative effects on WHZ and overweight status are statistically significant (at least at the 5 percent level) across all four samples. These findings are consistent with the main results in Table 5. In addition, there is suggestive evidence of a negative impact on underweight status. This effect is statistically significant in panel (A) and marginally insignificant in panels (B) and (D) at the 10 percent level. This suggestive evidence is also consistent with the more conclusive finding regarding underweight status in Table 5.

We report the results for food consumption outcomes in Appendix Table A6, as all estimated effects are statistically insignificant, largely due to the smaller sample size, with the number of observations ranging from 198 in the narrowest bandwidth to 403 in the widest. The food consumption sample is more limited than the anthropometric sample because food-related questions are asked only for children aged 6 to 35 months, whereas anthropometric measures are available for all children under age five. Appendix Table A6 presents estimates using the same four bandwidths as in Table 12. Only panels (B) and (C) show statistically significant evidence—at the 10 percent level—of a discontinuous jump in ESSN receipt at the cutoff. The coefficients for the food consumption outcomes are not only statistically insignificant but also vary substantially in magnitude across the four samples.

Overall, the evidence from the alternative identification strategy corroborates our main findings. The anthropometric results—covering HAZ, WHZ, and overweight status—are highly consistent with those obtained from the dependency-ratio RDD, both in sign and statistical significance. By contrast, the food-consumption results are less consistent. This divergence is expected for two reasons. First, the age-18 threshold simultaneously shifts two ESSN eligibility criteria—the dependency ratio and the four-children rule—whereas our main design isolates changes driven almost exclusively by the dependency-ratio cutoff. Second, the alternative design relies on a more selective and substantially smaller sample: only families with both a young child (under age five) and another child near the age-18 cutoff are included, reducing power particularly for the nutrition outcomes, which are already measured for a narrower age group. Despite these differences, the close alignment of the anthropometric estimates across both designs strengthens confidence in the robustness of our main conclusions.

7. Conclusion

Attention to the health and well-being of refugee children is crucial in the design and implementation of social support programs. Whether, in the long run, these children remain in the country of refuge or return to their home country, their ability to succeed will be enhanced if they receive adequate education, health care, and nutrition during this critical stage of their lives. However, the achievement of these outcomes, given limited resources, depends largely on decisions made within the household. An increase in cash transfers may improve child health, but there are myriad ways such funds may be spent in a resource-constrained household, and it is possible that these resources could have limited or even adverse effects on child health.

In this paper, we have taken advantage of a kink in the policy role associated with the world's largest refugee program to measure the effects of a cash transfer on child body size and diet. Our results suggest that the additional resources do have a number of salutary effects. Height growth improves and obesity declines. Overall diet quality improves with increases in protein and decreases in foods that provide cheap calories and taste but are not nutritious. It seems that at least some component of the marginal dollar is being targeted toward better nutrition.

One interesting question is whether these robust improvements reflect the unique features of the ESSN and its target population. While the broader literature on cash transfers and child health yields mixed results, our findings suggest that program duration, transfer magnitude, host-country conditions, and beneficiary background are critical. Unlike short-term humanitarian interventions where benefits often dissipate quickly, the continuous nature of the ESSN likely provided the sustained support necessary for children to achieve biological catch-up growth. Moreover, the sizable value of the transfers appears sufficient to deeply relax binding budget constraints, allowing households to move beyond subsistence spending. In the middle-income setting of Turkey—characterized by functioning markets but high availability of cheap, unhealthy foods—this purchasing power enabled families to restore pre-displacement consumption habits. Rather than needing to 'learn' nutrition, refugees simply required the financial means to actively substitute away from cheap, energy-dense staples back to the balanced, nutrient-rich diet characteristic of their home environment.

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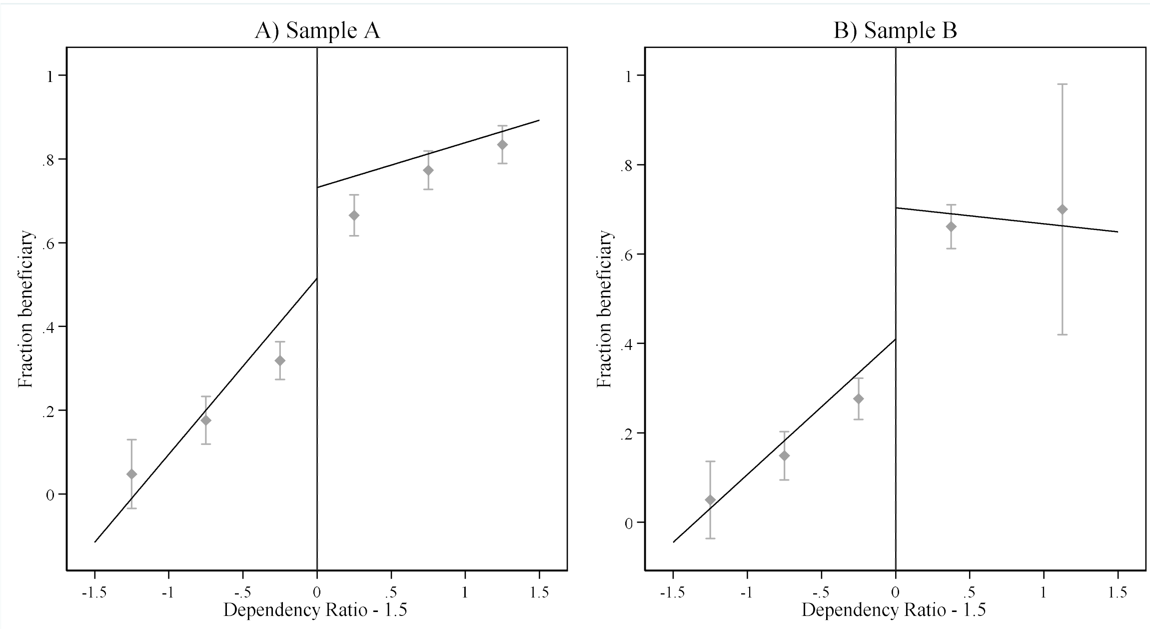
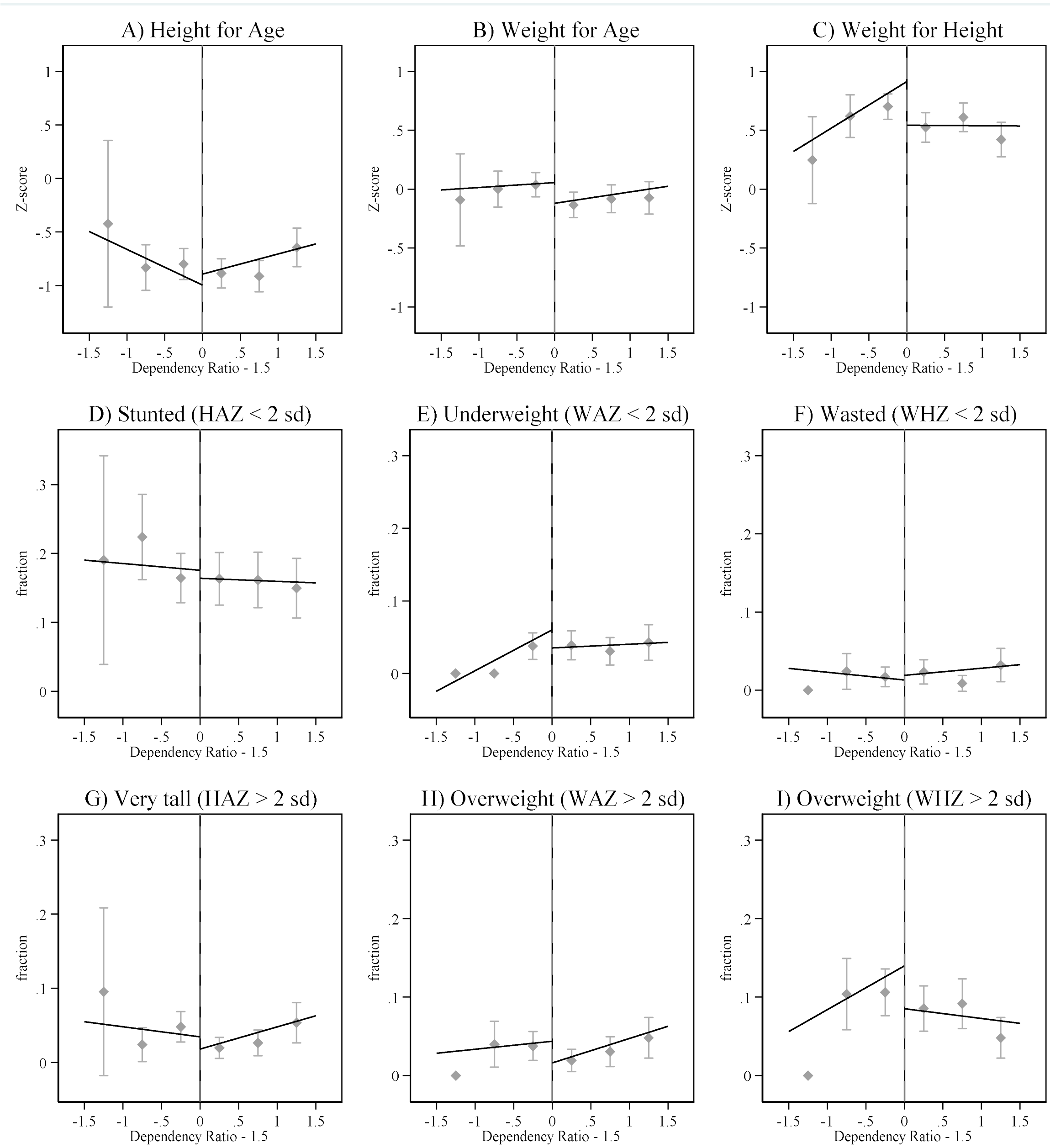
Tables and Figures

Figure 1: RDD Graph for ESSN Beneficiary Status



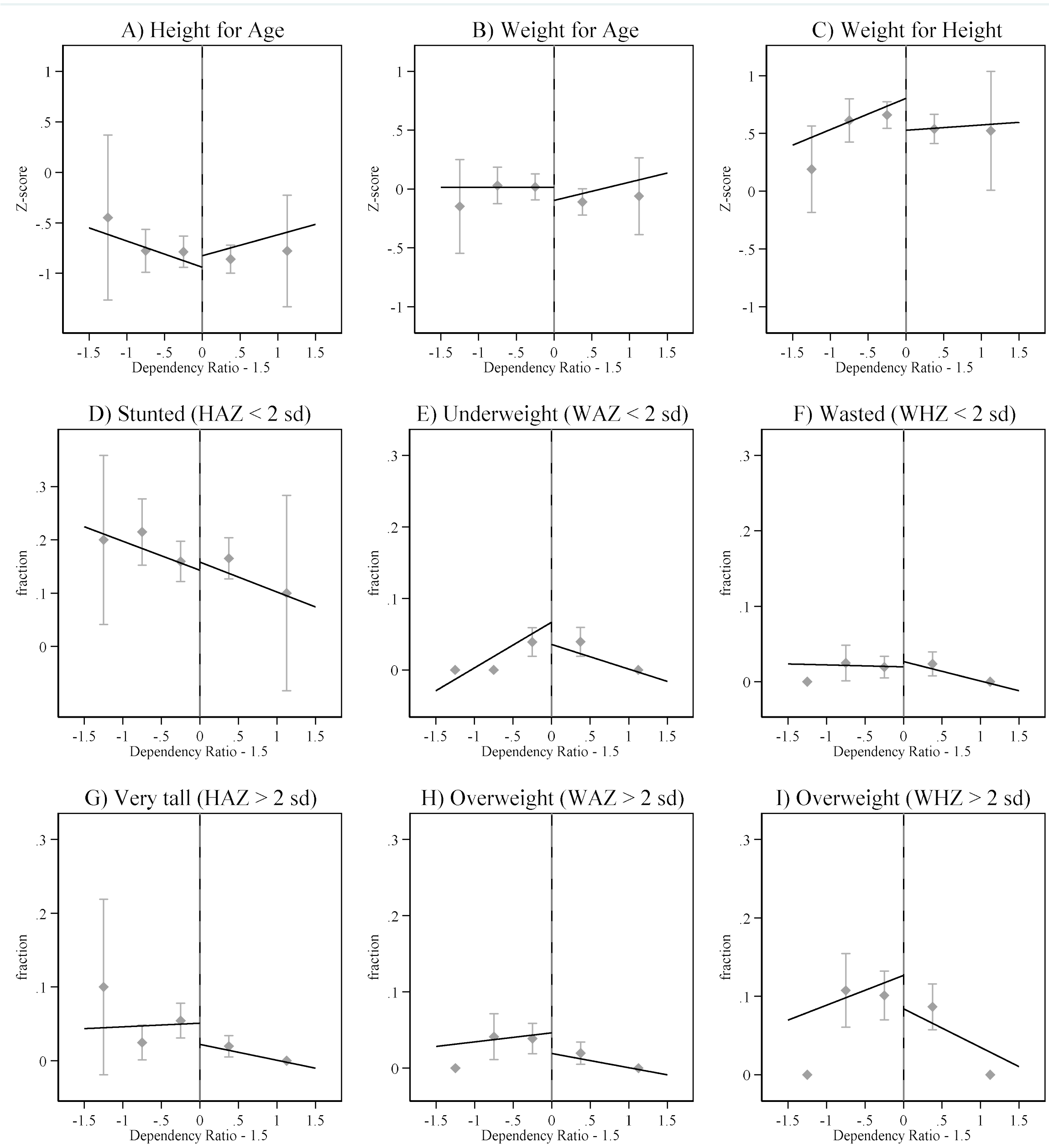
Notes: Sample B excludes families who are eligible for the ESSN program via criteria other than the dependency ratio. Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). To account for the uneven distribution of the running variable, it is partitioned into three equal bins on each side of the cutoff in sample A, and into three equal bins on the left and two equal bins on the right of the cutoff in sample B. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends.

Figure 2: RDD Graphs for Anthropometric Outcomes of Refugee Children, Sample A



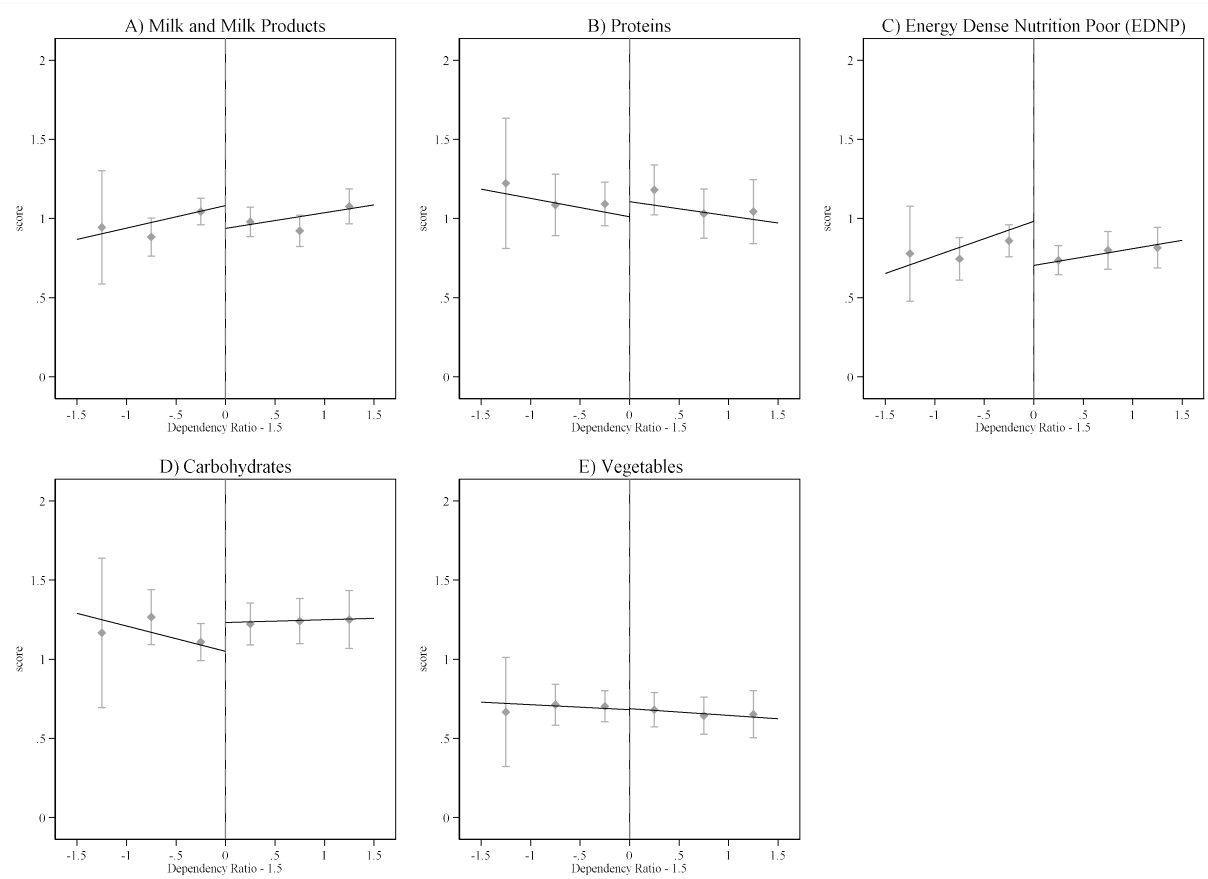
Notes: Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). To account for the uneven distribution of the running variable, it is partitioned into three equal bins on each side of the cutoff. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends.

Figure 3: RDD Graphs for Anthropometric Outcomes of Refugee Children, Sample B



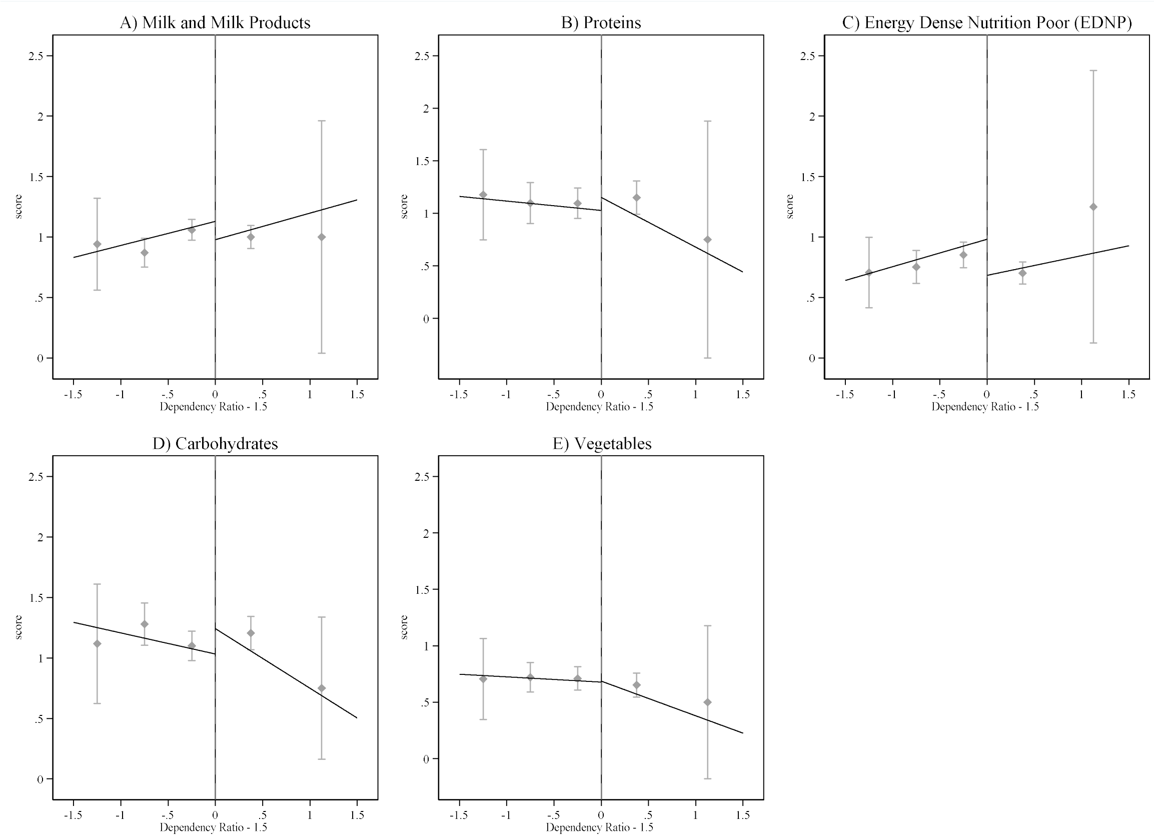
Notes: Sample B excludes families who are eligible for the ESSN program via criteria other than the dependency ratio. Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). To account for the uneven distribution of the running variable, it is partitioned into three equal bins on the left and two equal bins on the right of the cutoff. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends.

Figure 4: RDD Graphs for Nutrition Outcomes of Refugee Children, Sample A



Notes: Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). The dependent variable is the number of distinct food items in each category. To account for the uneven distribution of the running variable, it is partitioned into three equal bins on each side of the cutoff. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends.

Figure 5: RDD Graphs for Nutrition Outcomes of Refugee Children, Sample B



Notes: Sample B excludes families who are eligible for the ESSN program via criteria other than the dependency ratio. Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). The dependent variable is the number of distinct food items in each category. To account for the uneven distribution of the running variable, it is partitioned into three equal bins on the left and two equal bins on the right of the cutoff. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends

Table 1: Descriptive Statistics

	Sample A				Sample B			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
I) Anthropometric Outcomes								
Height for Age (HAZ)	-0.81	1.43	-5.64	5.56	-0.80	1.44	-5.34	5.1
Stunted (HAZ < 2sd)	0.17	0.37	0	1	0.17	0.38	0	1
Very Tall (HAZ > 2sd)	0.04	0.19	0	1	0.04	0.19	0	1
Weight for Age (WAZ)	-0.05	1.07	-4.38	3.68	-0.04	1.06	-4.38	3.68
Underweight (WAZ < 2sd)	0.03	0.18	0	1	0.03	0.17	0	1
Overweight (WAZ > 2sd)	0.03	0.18	0	1	0.03	0.17	0	1
Weight for Height	0.58	1.16	-4.88	4.58	0.59	1.17	-4.13	4.29
Wasted (WHZ < 2sd)	0.02	0.14	0	1	0.02	0.14	0	1
Overweight (WHZ > 2sd)	0.09	0.28	0	1	0.09	0.29	0	1
II) Food Outcomes								
Milk Count	0.93	0.70	0	3	0.94	0.70	0	3
Protein Count	1.31	1.11	0	5	1.33	1.12	0	4
Energy-Dense Nutrition-Poor Food Count	0.96	0.75	0	3	0.93	0.75	0	3
Carbohydrates Count	1.45	0.91	0	3	1.41	0.91	0	3
Vegetables Count	0.82	0.81	0	3	0.83	0.79	0	3

Notes: The data come from the 2018 Turkey Demographic and Health Survey (THDS). Both samples include refugee babies born to refugee families in the five years preceding the survey, where families are constructed from TDHS households according to the family definition used in ESSN eligibility. Sample B excludes families who are eligible for the ESSN program via criteria other than the dependency ratio. Food outcomes in panel (II) are available only for children who are 6- to 35-month-old. The sample size is 1,111 for sample A in panel (I), 545 for sample A in panel (II), 662 for sample B in panel (I), and 351 for sample B in panel (II).

Table 2: Family Composition in the Sample

A) Number of Children in Each Cell

# prime adults	# dependents										%
	0	1	2	3	4	5	6	7	8	9	
1	1	2	**6**	**10**							1.7
2	7	75	212	**243**	**179**	**111**	**65**				80.3
3		10	17	34	31	**12**	**20**	**13**		**1**	12.4
4		2	13	11	5		**1**	**1**	**7**	**4**	4.0
5		1		3	1	6	2				1.2
6				2							0.2
7						3					0.3

B) Dependency Ratio for Each Cell

# prime adults	# dependents										%
	0	1	2	3	4	5	6	7	8	9	
1	0	1.00	**2.00**	**3.00**							1.7
2	0	0.50	1.00	**1.50**	**2.00**	**2.50**	**3.00**				80.3
3		0.33	0.67	1.00	1.33	**1.67**	**2.00**	**2.33**		**3.00**	12.4
4		0.25	0.50	0.75	1.00		**1.50**	**1.75**	**2.00**	**2.25**	4.0
5		0.20		0.60	0.80	1.00	1.20				1.2
6				0.50							0.2
7						0.71					0.3

Notes: Prime adults include individuals aged 18 to 59. The dependents are the rest of the household members. The cells are given in bold when the dependency ratio is 1.5 or higher.

Table 3: Covariate Balance

(1)	(2)	(3)	(4)	(5)
	Sample A		Sample B	
	RD Effect	p-value	RD Effect	p-value
Family Structure				
Number of Family Members	-0.712	0.493	-0.185	0.718
Number of Dependents	-0.448	0.467	-0.222	0.381
Number of Children	-0.411	0.442	-0.140	0.393
Number of Elderly	-0.037	0.748	-0.082	0.743
Number of Adults aged 18-59	-0.263	0.598	0.037	0.941
Number of Male Adults aged 18-59	-0.065	0.787	0.087	0.781
Number of Male Members aged 15-59	-0.111	0.692	0.101	0.745
Family Structure regarding ESSN Qualification				
At least four children	-0.067	0.887	--	--
Female headed household	0.014	0.529	--	--
Single parent	-0.005	0.404	--	--
Elderly parent	0.000	--	--	--
Biological Characteristics				
Female child	0.177	0.018	0.089	0.310
Mother height	-7.138	0.509	-18.465	0.104
Mother BMI	0.013	0.965	0.096	0.746
Type of Residence				
Lives in a camp	0.019	0.669	-0.073	0.115
Year of arrival	0.334	0.047	0.183	0.154
Household Head Education				
Incomplete Primary	-0.010	0.861	-0.014	0.730
Complete Primary	0.019	0.960	-0.038	0.535
Incomplete secondary	-0.008	0.734	0.016	0.418
Complete secondary	-0.059	0.136	0.000	0.983
Incomplete high school	0.016	0.252	0.010	0.522
Complete high school or higher	0.003	0.901	-0.014	0.794
Age of Household Head				
25-34	-0.024	0.814	-0.023	0.821
35-44	0.028	0.670	-0.014	0.947
45-64	-0.050	0.381	-0.009	0.419
65+	0.000	0.972	--	--
Mother Tongue				
Kurdish	-0.009	0.780	0.047	0.021
Arabic	0.084	0.002	0.053	0.395
Other	-0.024	0.347	-0.034	0.022
Birth Place Type				
District Center	-0.001	0.988	-0.028	0.691
Sub-district/village	-0.020	0.384	-0.038	0.061

Notes: The data come from the 2018 Turkey Demographic and Health Survey. A bandwidth of 1.5 is taken on either side of the cutoff; in other words, the dependency ratio ranges between 0 and 3. The sample size is 1,111 in sample A and 662 in sample B. The dependent variables are given in column (1). All regressions include a control for the treatment dummy and split linear polynomials around the cutoff in the running variable. Clustering is done at the level of dependency ratio; wild cluster bootstrapped p-values are given. Statistically significant: *** 1 percent level; ** 5 percent level, * 10 percent level.

Table 4: Reduced-Form RDD Estimates for Child Anthropometric Outcomes

	ESSN	HAZ	Stunted (HAZ<2 sd)	Tall (HAZ>2 sd)	WAZ	Underweight (WAZ<2 sd)	Overweight (WAZ>2 sd)	WHZ	Wasted (WHZ<2 sd)	Overweight (WHZ>2 sd)
Panel A: Full sample										
Dependency-Ratio Criterion	0.231***	0.132**	-0.004	-0.016	-0.216***	-0.023**	-0.039***	-0.424***	0.005	-0.057***
	[0.062]	[0.061]	[0.042]	[0.014]	[0.057]	[0.009]	[0.011]	[0.086]	[0.007]	[0.017]
Bootstrapped p-value	0.088	0.070	0.947	0.401	0.042	0.182	0.055	0.000	0.572	0.049
Panel B: Sample excluding households who are eligible via other criteria										
Dependency-Ratio Criterion	0.274***	0.215***	0.017	-0.016	-0.098	-0.037***	-0.033***	-0.308**	0.004	-0.052**
	[0.038]	[0.069]	[0.037]	[0.018]	[0.084]	[0.009]	[0.008]	[0.114]	[0.008]	[0.023]
Bootstrapped p-value	0.087	0.092	0.678	0.458	0.435	0.066	0.025	0.213	0.708	0.175

Notes: The data come from the 2018 round of the Turkey Demographic and Health Survey. Both samples include refugee babies born in the five years preceding the survey. Sample B excludes children from households that are eligible for the ESSN program due to a condition other than the dependency ratio. Each estimate is derived from a separate regression based on a regression discontinuity design and indicates the reduced-form effect of crossing the dependency-ratio cutoff on the outcome stated in the corresponding column. Each regression controls for the child's sex, the mother's height and body mass index, and dummies for the interaction of region and current residence type, the household head's education, the interaction of the household head's sex and age, mother tongue, year of arrival, birth province, and type of birth region. Regressions in Panel A also include dummies for the other four ESSN eligibility criteria. Household-level sampling weights are used. Standard errors are clustered by the dependency ratio. The reported p-value corresponds to the wild cluster bootstrapped test. The number of observations is 1,111 in Panel A and 662 in Panel B. The number of clusters is 21 in Panel A and 14 in Panel B. Statistical significance is denoted as follows: * 10% level, ** 5% level, *** 1% level.

Table 5: The Effect of ESSN Cash Transfers on Child Anthropometric Outcomes

	HAZ	Stunted (HAZ<2 sd)	Tall (HAZ>2 sd)	WAZ	Underweight (WAZ<2 sd)	Overweight (WAZ>2 sd)	WHZ	Wasted (WHZ<2 sd)	Overweight (WHZ>2 sd)
Panel A: Full sample									
ESSN	0.571*	-0.018	-0.070	-0.933**	-0.099**	-0.167***	-1.831***	0.021	-0.248**
	[0.297]	[0.173]	[0.054]	[0.370]	[0.049]	[0.057]	[0.693]	[0.028]	[0.105]
Bootstrapped p-value	0.031	0.923	0.298	0.006	0.040	0.008	0.009	0.492	0.032
Panel B: Sample excluding households who are eligible via other criteria									
ESSN	0.785***	0.062	-0.057	-0.359	-0.133***	-0.121***	-1.122***	0.014	-0.188***
	[0.164]	[0.126]	[0.062]	[0.286]	[0.044]	[0.026]	[0.381]	[0.026]	[0.072]
Bootstrapped p-value	0.000	0.671	0.428	0.355	0.037	0.001	0.077	0.671	0.093

Notes: The data come from the 2018 round of the Turkey Demographic and Health Survey. Both samples include refugee babies born in the five years preceding the survey. Sample B excludes children from households that are eligible for the ESSN program due to a condition other than the dependency ratio. Each estimate comes from a separate regression based on a fuzzy regression discontinuity design and shows the effect of receiving a cash transfer on the outcome stated in the corresponding column. Each regression controls for the child's sex, mother's height and body mass index, and dummies for the interaction of region and current residence type, household head's education, the interaction of the household head's sex and age, mother tongue, year of arrival, birth province, and type of birth region. Regressions in Panel A also include dummies for the other four ESSN eligibility criteria. Sampling weights at the household level are used. Standard errors are clustered by the dependency ratio. The reported p-value corresponds to the wild cluster bootstrapped test. The number of observations is 1,111 in Panel A and 662 in Panel B. The number of clusters is 21 in Panel A and 14 in Panel B. The first-stage F-statistics are 14.94 and 53.31 in Panels A and B, respectively. Statistical significance is denoted as follows: * 10% level, ** 5% level, *** 1% level.

Table 6: Reduced-Form RDD Estimates for Food Consumption Outcomes

	ESSN	Milk and Milk Products	Proteins	Energy Dense Nutrition Poor	Carbohydrates	Vegetables
Panel A: Full sample						
Dependency-Ratio Criterion	0.204***	-0.099	0.102	-0.333***	0.153	0.058
	[0.043]	[0.122]	[0.142]	[0.049]	[0.120]	[0.065]
Bootstrapped p-value	0.054	0.624	0.508	0.020	0.447	0.305
Romano-Wolf p-value	--	0.822	0.822	0.010	0.772	0.822
Panel B: Sample excluding households who are eligible via other criteria						
Dependency-Ratio Criterion	0.206***	-0.089	0.245*	-0.332***	0.175	0.031
	[0.049]	[0.112]	[0.132]	[0.073]	[0.160]	[0.066]
Bootstrapped p-value	0.036	0.672	0.035	0.178	0.525	0.580
Romano-Wolf p-value	--	0.842	0.624	0.069	0.842	0.842

Notes: The data come from the 2018 round of the Turkey Demographic and Health Survey. Both samples include refugee babies born in the five years preceding the survey who are 6 to 35 months old at the time of the interview. Sample B excludes children from households that qualify for the ESSN program due to a condition other than the dependency ratio. Each estimate is derived from a separate regression based on a regression discontinuity design and indicates the reduced-form effect of crossing the dependency-ratio cutoff on the outcome stated in the corresponding column. Each regression controls for the child's sex, the mother's height and body mass index, and dummies for the interaction of region and type of current residence, the household head's education, the interaction of the household head's sex and age, mother tongue, year of arrival, birth province, and type of birth region. Household-level sampling weights are used. Regressions in Panel A also include dummies for the other four ESSN eligibility criteria. Standard errors are clustered by the dependency ratio. The reported p-value corresponds to the wild cluster bootstrapped test. The number of observations is 545 in Panel A and 351 in Panel B. The number of clusters is 20 in Panel A and 14 in Panel B. Statistical significance is denoted as follows: * 10% level, ** 5% level, *** 1% level.

Table 7: The Effect of ESSN Cash Transfers on Food Consumption Outcomes

	Milk and Milk Products	Proteins	Energy Dense Nutrition Poor	Carbohydrates	Vegetables
Panel A: Full sample					
ESSN	-0.486	0.497	-1.627***	0.748	0.282
	[0.509]	[0.609]	[0.336]	[0.508]	[0.312]
Bootstrapped p-value	0.493	0.469	0.000	0.236	0.333
Romano-Wolf p-value	0.753	0.753	0.020	0.634	0.753
Panel B: Sample excluding households who are eligible via other criteria					
ESSN	-0.435	1.188***	-1.613***	0.852	0.150
	[0.501]	[0.422]	[0.324]	[0.726]	[0.278]
Bootstrapped p-value	0.483	0.306	0.000	0.321	0.564
Romano-Wolf p-value	0.733	0.248	0.089	0.693	0.762

Notes: The data come from the 2018 round of the Turkey Demographic and Health Survey. Both samples include refugee babies born in the five years preceding the survey who are 6 to 35 months old at the time of the interview. Sample B excludes children from households that are eligible for the ESSN program due to a condition other than the dependency ratio. Each estimate comes from a separate regression based on a fuzzy regression discontinuity design and shows the effect of receiving a cash transfer on the outcome stated in the corresponding column. Each regression controls for the child's sex, mother's height and body mass index, and dummies for the interaction of region and current residence type, household head's education, the interaction of the household head's sex and age, mother tongue, year of arrival, birth province, and type of birth region. Regressions in Panel A also include dummies for the other four ESSN eligibility criteria. Sampling weights at the household level are used. Standard errors are clustered by the dependency ratio. The reported p-value corresponds to the wild cluster bootstrapped test. The number of observations is 545 in Panel A and 351 in Panel B. The number of clusters is 20 in Panel A and 14 in Panel B. The first-stage F-statistics are 22.36 and 17.93 in Panels A and B, respectively. Statistical significance is denoted as follows: * 10% level, ** 5% level, *** 1% level.

Table 8: Child Anthropometric Outcomes, 2SLS Estimates with Alternative Bandwidths, Sample A

	OLS	2SLS								
	ESSN	HAZ	Stunted (HAZ<2 sd)	Tall (HAZ>2 sd)	WAZ	Underweight (WAZ<2 sd)	Overweight (WAZ>2 sd)	WHZ	Wasted (WHZ<2 sd)	Overweight (WHZ>2 sd)
A) Full Data										
	0.228***	0.644**	0.038	-0.022	-0.852**	-0.099**	-0.123**	-1.755***	0.035	-0.270**
	[0.063]	[0.275]	[0.148]	[0.066]	[0.350]	[0.050]	[0.056]	[0.665]	[0.029]	[0.123]
Bootstrap p-value	0.116	0.004	0.815	0.770	0.010	0.030	0.056	0.003	0.288	0.040
B) Bandwidth [0,6]										
	0.221***	0.718**	0.016	-0.026	-0.836**	-0.086*	-0.130**	-1.800**	0.025	-0.291**
	[0.064]	[0.345]	[0.170]	[0.067]	[0.325]	[0.044]	[0.052]	[0.700]	[0.030]	[0.134]
Bootstrap p-value	0.092	0.016	0.923	0.748	0.006	0.064	0.049	0.008	0.455	0.023
C) Bandwidth [0,4.5]										
	0.224***	0.698**	-0.018	-0.042	-0.930***	-0.084*	-0.137***	-1.939**	0.031	-0.321**
	[0.063]	[0.350]	[0.178]	[0.061]	[0.358]	[0.043]	[0.052]	[0.759]	[0.032]	[0.149]
Bootstrap p-value	0.079	0.023	0.919	0.612	0.002	0.092	0.053	0.004	0.352	0.028
D) Bandwidth [0,3]										
	0.231***	0.571*	-0.018	-0.070	-0.933**	-0.099**	-0.167***	-1.831***	0.021	-0.248**
	[0.062]	[0.297]	[0.173]	[0.054]	[0.370]	[0.049]	[0.057]	[0.693]	[0.028]	[0.105]
Bootstrap p-value	0.088	0.031	0.923	0.298	0.006	0.040	0.008	0.009	0.492	0.032

Notes: The data and specification follow those in Table 4 for the ESSN variable and Table 5 for child growth outcomes. Standard errors are clustered by the dependency ratio. The reported p-value corresponds to the wild cluster bootstrapped test. The number of clusters is 33 in Panel A, 31 in Panel B, 27 in Panel C, and 21 in Panel D. The number of observations is 1,204 in Panel A, 1,198 in Panel B, 1,181 in Panel C, and 1,111 in Panel D. The F-statistics are 12.86 in Panel A, 11.81 in Panel B, 12.52 in Panel C, and 13.87 in Panel D. Statistical significance is denoted as follows: * 10% level, ** 5% level, *** 1% level.

Table 9: Food Consumption, 2SLS Estimates with Alternative Bandwidths, Sample A

	Milk and Milk Products	Proteins	Energy Dense Nutrition Poor	Carbohydrates	Vegetables
A) Full Data					
	-0.194	0.645	-1.408***	1.064**	0.346
	[0.617]	[0.545]	[0.333]	[0.468]	[0.378]
Bootstrap p-value	0.832	0.321	0.000	0.084	0.422
Romano-Wolf p-value	0.842	0.663	0.059	0.218	0.663
B) Bandwidth [0,6]					
	-0.399	0.746	-1.393***	0.919**	0.487
	[0.534]	[0.545]	[0.330]	[0.442]	[0.448]
Bootstrap p-value	0.601	0.290	0.000	0.109	0.370
Romano-Wolf p-value	0.574	0.555	0.010	0.248	0.574
C) Bandwidth [0,4.5]					
	-0.375	0.624	-1.330***	0.930**	0.488
	[0.539]	[0.558]	[0.340]	[0.466]	[0.433]
Bootstrap p-value	0.637	0.369	0.000	0.101	0.327
Romano-Wolf p-value	0.654	0.654	0.040	0.297	0.654
D) Bandwidth [0,3]					
	-0.486	0.497	-1.627***	0.748	0.282
	[0.509]	[0.609]	[0.336]	[0.508]	[0.312]
Bootstrap p-value	0.493	0.469	0.000	0.236	0.333
Romano-Wolf p-value	0.753	0.753	0.020	0.634	0.753

Notes: The data and specifications follow those in Table 7. Standard errors are clustered by the dependency ratio. The reported p-value corresponds to the wild cluster bootstrapped test. The number of clusters is 30 in Panel A, 29 in Panel B, 25 in Panel C, and 20 in Panel D. The number of observations is 586 in Panel A, 582 in Panel B, 578 in Panel C, and 545 in Panel D. The F-statistics are 22.61 in Panel A, 20.50 in Panel B, 19.22 in Panel C, and 22.26 in Panel D. Statistical significance is denoted as follows: * 10% level, ** 5% level, *** 1% level.

Table 10: Child Anthropometric Outcomes, 2SLS Estimates with Alternative Specifications

	HAZ	Stunted (HAZ<2 sd)	Tall (HAZ>2 sd)	WAZ	Underweight (WAZ<2 sd)	Overweight (WAZ>2 sd)	WHZ	Wasted (WHZ<2 sd)	Overweight (WHZ>2 sd)
I) Single (Not Split) Linear Polynomials in Dependency Ratio									
Panel A: Full sample									
ESSN	-0.013	-0.077	-0.073***	-0.421**	-0.009	-0.102***	-0.576**	-0.007	-0.079**
	[0.245]	[0.086]	[0.015]	[0.185]	[0.041]	[0.024]	[0.230]	[0.014]	[0.034]
Bootstrapped p-value	0.981	0.463	0.000	0.159	0.913	0.000	0.000	0.666	0.018
Panel B: Sample excluding households who are eligible via other criteria									
ESSN	0.761***	0.006	0.003	-0.199	-0.043	-0.057	-0.838**	0.046*	-0.139**
	[0.125]	[0.096]	[0.045]	[0.229]	[0.049]	[0.046]	[0.329]	[0.025]	[0.055]
Bootstrapped p-value	0.000	0.964	0.952	0.407	0.562	0.359	0.044	0.133	0.046
II) Single (Not Split) Quadratic Polynomials in Dependency Ratio									
Panel A: Full sample									
ESSN	0.479**	-0.078	-0.061	-0.593**	-0.075*	-0.137***	-1.235***	0.013	-0.171***
	[0.216]	[0.138]	[0.038]	[0.248]	[0.039]	[0.039]	[0.440]	[0.021]	[0.060]
Bootstrapped p-value	0.018	0.658	0.221	0.001	0.021	0.000	0.000	0.534	0.006
Panel B: Sample excluding households who are eligible via other criteria									
ESSN	0.757***	-0.003	0.020	-0.111	-0.015	-0.033*	-0.702**	0.056**	-0.116***
	[0.140]	[0.077]	[0.030]	[0.222]	[0.022]	[0.017]	[0.323]	[0.025]	[0.042]
Bootstrapped p-value	0.000	0.976	0.511	0.701	0.496	0.042	0.113	0.145	0.032
III) Linear Polynomials in Number of Dependents and Number of Prime Adults									
Panel A: Full sample									
ESSN	0.083	-0.042	-0.067***	-0.341**	-0.015	-0.082***	-0.533**	0.001	-0.094***
	[0.233]	[0.064]	[0.016]	[0.152]	[0.026]	[0.020]	[0.209]	[0.014]	[0.032]
Bootstrapped p-value	0.756	0.567	0.002	0.052	0.564	0.011	0.001	0.949	0.000
Panel B: Sample excluding households who are eligible via other criteria									
ESSN	0.367*	0.052	-0.054	-0.394**	-0.078***	-0.082***	-0.813***	0.015	-0.138**
	[0.187]	[0.099]	[0.039]	[0.161]	[0.022]	[0.027]	[0.289]	[0.021]	[0.058]
Bootstrapped p-value	0.006	0.639	0.215	0.064	0.036	0.031	0.027	0.510	0.083
IV) Linear Polynomials in Log Number of Dependents and Log Number of Prime Adults									
Panel A: Full sample									
ESSN	0.235	-0.061	-0.061**	-0.503***	-0.037	-0.118***	-0.889***	0.001	-0.138***
	[0.226]	[0.095]	[0.031]	[0.152]	[0.030]	[0.027]	[0.257]	[0.023]	[0.042]
Bootstrapped p-value	0.308	0.609	0.099	0.000	0.162	0.001	0.000	0.969	0.000
Panel B: Sample excluding households who are eligible via other criteria									
ESSN	0.481***	-0.029	-0.037	-0.294***	-0.048**	-0.082***	-0.761***	0.016	-0.139***
	[0.132]	[0.076]	[0.028]	[0.095]	[0.022]	[0.017]	[0.160]	[0.011]	[0.033]
Bootstrapped p-value	0.000	0.740	0.230	0.023	0.177	0.000	0.000	0.133	0.007

Notes: The data and the specifications are as in Table 5 except for the trend specifications, which are as given in panel headings. The p-value statistic displays the wild cluster bootstrapped p-value. The number of observations is 1,111 in all panel (A)s and 662 in panel (B)s. The F-statistic is 26.86 in panel I-A, 17.32 in panel II-A, 50.13 in panel III-A, and 40.00 in panel IV-A. The F-statistic is 90.58 in panel I-B, 89.08 in panel II-B, 248.7 in panel III-B, and 136.00 in panel IV-B. Statistical significance: *10% level, **5% level, ***1% level.

Table 11: Food Consumption, 2SLS Estimates with Alternative Specifications

	Milk and Milk Products	Proteins	Energy Dense Nutrition Poor	Carbohydrates	Vegetables
I) Single (Not Split) Linear Polynomials in Dependency Ratio					
Panel A: Full sample					
ESSN	-0.251	0.080	-0.813***	-0.104	-0.173
	[0.219]	[0.352]	[0.233]	[0.345]	[0.122]
Bootstrapped p-value	0.407	0.875	0.001	0.825	0.173
Romano-Wolf p-value	0.713	0.951	0.059	0.951	0.673
Panel B: Sample excluding households who are eligible via other criteria					
ESSN	-0.415	0.981***	-1.630***	0.824	0.088
	[0.428]	[0.353]	[0.319]	[0.651]	[0.285]
Bootstrapped p-value	0.425	0.183	0.000	0.296	0.724
Romano-Wolf p-value	0.723	0.248	0.099	0.683	0.861
II) Single (Not Split) Quadratic Polynomials in Dependency Ratio					
Panel A: Full sample					
ESSN	-0.419	0.520	-1.230***	0.382	0.069
	[0.344]	[0.453]	[0.216]	[0.349]	[0.199]
Bootstrapped p-value	0.394	0.350	0.000	0.361	0.730
Romano-Wolf p-value	0.762	0.762	0.010	0.762	0.772
Panel B: Sample excluding households who are eligible via other criteria					
ESSN	-0.459	0.517	-1.851***	0.850	-0.096
	[0.327]	[0.382]	[0.455]	[0.561]	[0.318]
Bootstrapped p-value	0.269	0.382	0.000	0.317	0.771
Romano-Wolf p-value	0.663	0.663	0.178	0.663	0.842
III) Linear Polynomials in Number of Dependents and Number of Prime Adults					
Panel A: Full sample					
ESSN	-0.029	0.204	-0.776***	0.083	-0.093
	[0.222]	[0.265]	[0.147]	[0.322]	[0.126]
Bootstrapped p-value	0.921	0.514	0.000	0.853	0.461
Romano-Wolf p-value	0.960	0.960	0.010	0.960	0.960
Panel B: Sample excluding households who are eligible via other criteria					
ESSN	-0.217	0.867**	-1.154***	0.680	0.017
	[0.390]	[0.365]	[0.257]	[0.539]	[0.290]
Bootstrapped p-value	0.653	0.289	0.000	0.324	0.956
Romano-Wolf p-value	0.881	0.337	0.109	0.753	0.960
IV) Linear Polynomials in Log Number of Dependents and Log Number of Prime Adults					
Panel A: Full sample					
ESSN	-0.192	0.349	-0.925***	0.253	0.012
	[0.263]	[0.330]	[0.154]	[0.372]	[0.170]
Bootstrapped p-value	0.572	0.333	0.000	0.613	0.948
Romano-Wolf p-value	0.881	0.812	0.010	0.881	0.980
Panel B: Sample excluding households who are eligible via other criteria					
ESSN	-0.083	0.672***	-0.930***	0.379	-0.020
	[0.286]	[0.251]	[0.158]	[0.392]	[0.194]
Bootstrapped p-value	0.807	0.358	0.000	0.426	0.932
Romano-Wolf p-value	0.990	0.416	0.050	0.911	0.990

Notes: The data and the specifications are as in Table 7 except for the trend specifications, which are as given in panel headings. The p-value statistic displays the wild cluster bootstrapped p-value, and Romano-Wolf p-values give the p-values corrected for multiple hypotheses testing. The number of observations is 545 in all panels (A)s and 662 in panel (B)s. The F-statistic is 20.11 in Panel I-A, 26.74 in Panel II-A, 36.30 in Panel III-A, and 50.94 in Panel IV-A. The F-statistic is 21.56 in panel I-B, 18.67 in panel II-B, 27.12 in panel III-B, and 33.84 in panel IV-B. Statistical significance: * 10% level, ** 5% level, *** 1% level.

Table 12: Child Anthropometric Outcomes, Alternative Identification Method

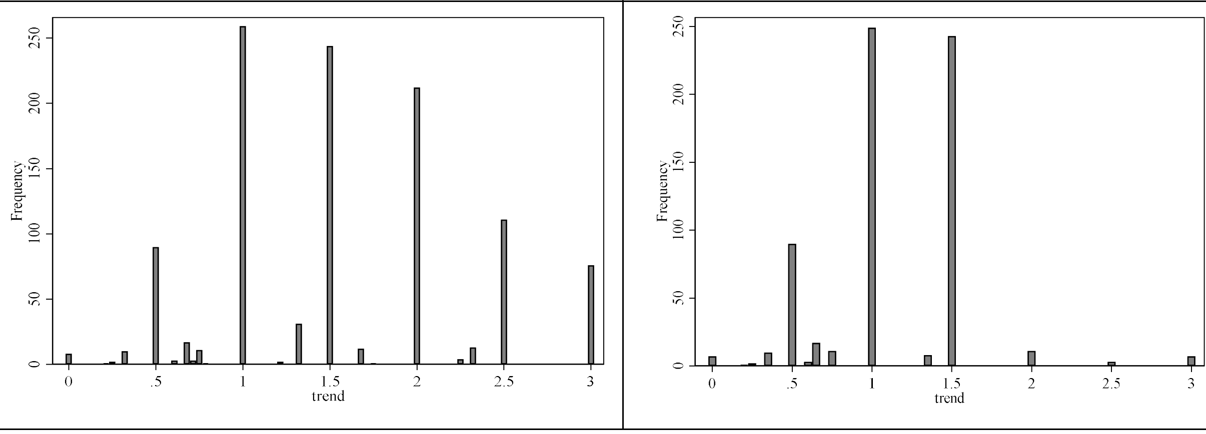
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	ESSN	HAZ	Stunted (HAZ<2 sd)	Tall (HAZ>2 sd)	WAZ	Underweight (WAZ<2 sd)	Overweight (WAZ>2 sd)	WHZ	Wasted (WHZ<2 sd)	Overweight (WHZ>2 sd)
A) Age Bandwidth: {15–20}										
Treatment	0.260**									
	[0.089]									
ESSN		1.026	-0.037	-0.156	-0.862*	-0.084	-0.032	-2.141***	-0.050	-0.423***
		[0.811]	[0.193]	[0.147]	[0.520]	[0.063]	[0.117]	[0.771]	[0.084]	[0.154]
Observations	307	307	307	307	307	307	307	307	307	307
Bootstrapped pvalue	0.134	0.312	0.872	0.384	0.135	0.095	0.810	0.004	0.548	0.025
Fstat		8.633	8.633	8.633	8.633	8.633	8.633	8.633	8.633	8.633
B) Age Bandwidth: {14–21}										
Treatment	0.386***									
	[0.088]									
ESSN		1.800**	-0.261*	0.077	0.181	-0.062	0.040	-1.199***	0.084*	-0.257**
		[0.738]	[0.152]	[0.104]	[0.464]	[0.039]	[0.089]	[0.409]	[0.048]	[0.120]
Observations	420	420	420	420	420	420	420	420	420	420
Bootstrapped pvalue	0.011	0.001	0.081	0.566	0.691	0.115	0.713	0.002	0.166	0.000
Fstat		19.410	19.410	19.410	19.410	19.410	19.410	19.410	19.410	19.410
C) Age Bandwidth: {13–22}										
Treatment	0.311***									
	[0.067]									
ESSN		1.822**	-0.180	-0.064	-0.010	0.002	-0.112	-1.486**	0.088	-0.418***
		[0.766]	[0.172]	[0.108]	[0.487]	[0.040]	[0.094]	[0.616]	[0.084]	[0.152]
Observations	541	541	541	541	541	541	541	541	541	541
Bootstrapped pvalue	0.000	0.053	0.337	0.572	0.986	0.970	0.264	0.003	0.428	0.003
Fstat		21.400	21.400	21.400	21.400	21.400	21.400	21.400	21.400	21.400
D) Age Bandwidth: {12–23}										
Treatment	0.228***									
	[0.073]									
ESSN		2.062**	-0.193	0.039	-0.240	-0.071	-0.093	-1.921**	0.011	-0.442*
		[0.972]	[0.252]	[0.123]	[0.623]	[0.050]	[0.126]	[0.886]	[0.092]	[0.240]
Observations	664	664	664	664	664	664	664	664	664	664
Bootstrapped pvalue	0.010	0.014	0.457	0.772	0.744	0.131	0.465	0.035	0.936	0.023
Fstat		9.710	9.710	9.710	9.710	9.710	9.710	9.710	9.710	9.710

Notes: The data come from the 2018 round of the Turkey Demographic and Health Survey and consist of refugee babies born within the five years preceding the survey. The running variable is the average age of children falling within the relevant age bracket in Panels (A)–(D), and treatment status is defined as one when this average age is below 18 and zero otherwise. Column (2), where the dependent variable is ESSN receipt, reports estimates from separate sharp regression discontinuity regressions. The remaining columns present estimates from fuzzy regression discontinuity regressions and reflect the causal effect of receiving an ESSN cash transfer on the corresponding outcome. All regressions control for split linear trends on either side of the cutoff, the child's sex, the mother's height and body mass index, and a set of household-level demographic and environmental characteristics: region-by-residence-type fixed effects, the household head's education and sex, mother tongue, year of arrival in Turkey, province of birth, and type of birth region. We also include dummy variables for the three ESSN eligibility criteria other than the dependency ratio and the four-children rule. Household-level sampling weights are applied, and standard errors are clustered by the average age used as the running variable. For inference, we report wild cluster bootstrap p-values. Statistical significance is indicated as follows: * 10 percent, ** 5 percent, *** 1 percent.

ONLINE APPENDIX

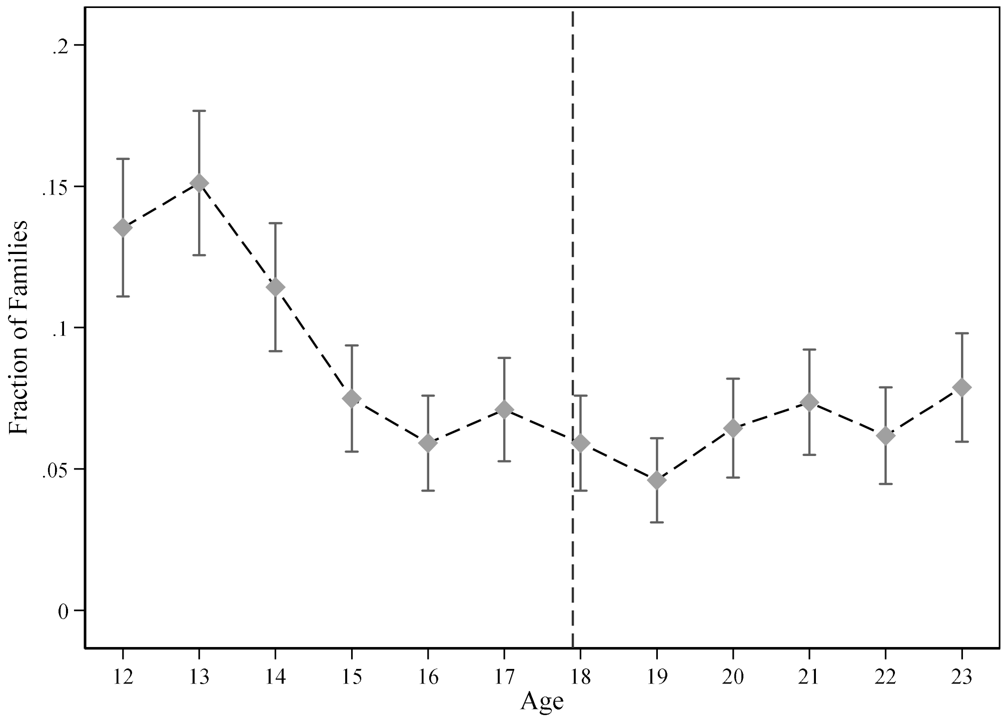
Figure A1: Histogram of the Running Variable

A) Sample A	B) Sample B



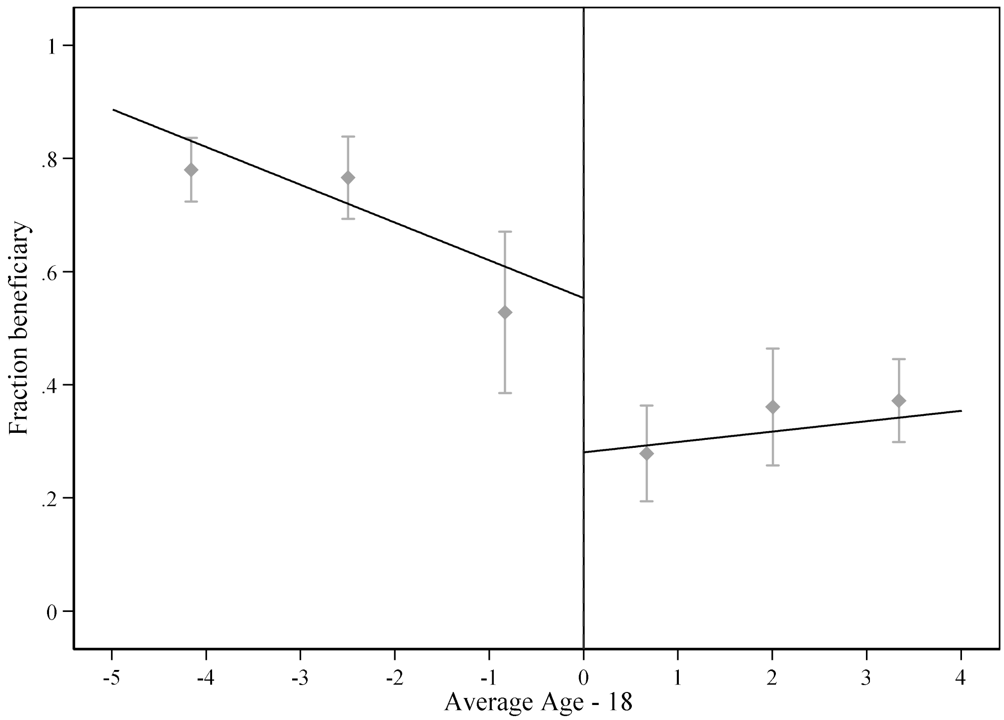
Notes: The running variable takes 21 discrete values in Sample A and 14 in Sample B.

Figure A2: Fraction Families with a Child of Age x



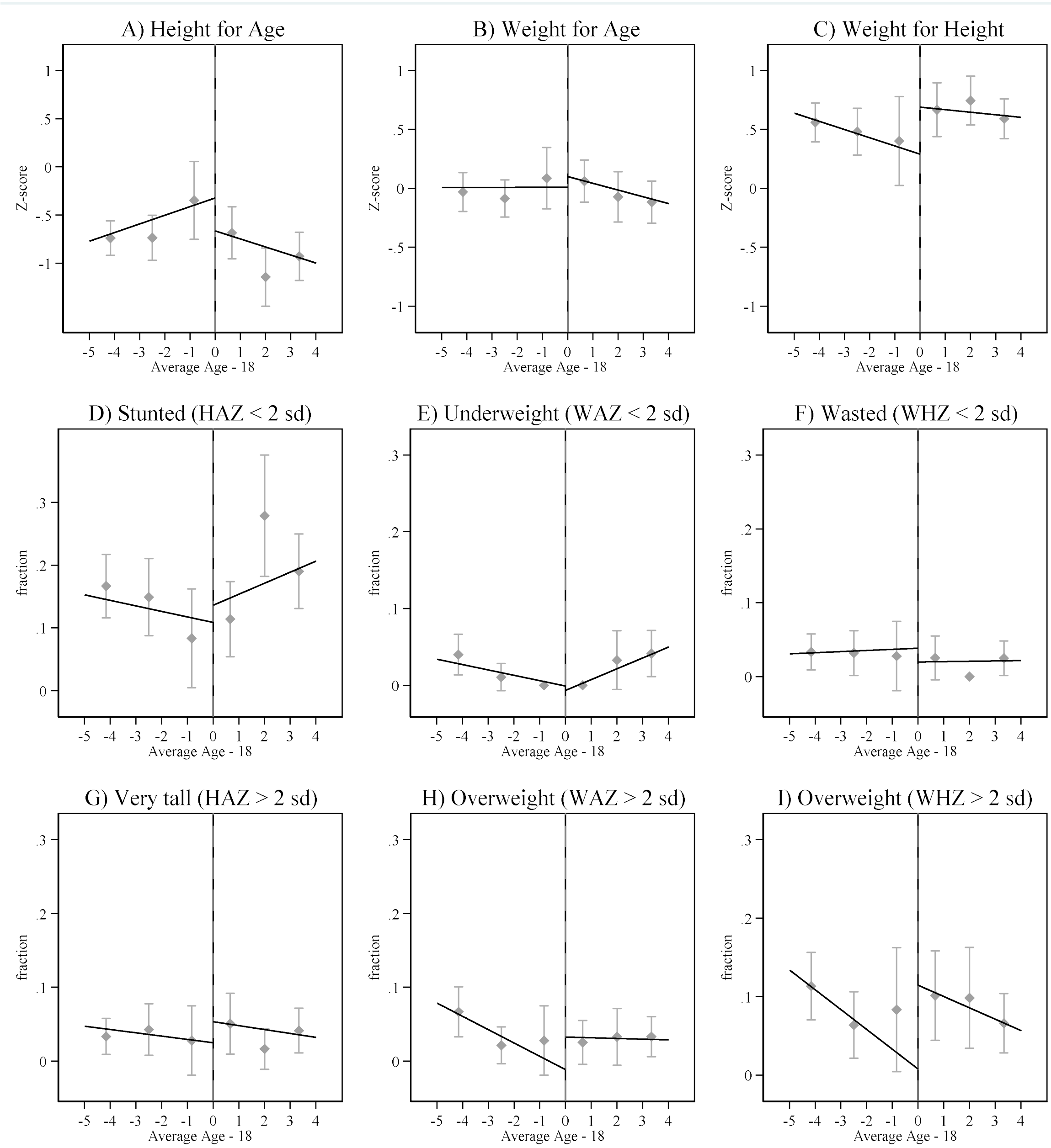
Notes: This figure plots the fraction of families with at least one household member of each age between 12 and 23.

Figure A3: RDD Graph for ESSN Beneficiary Status with Alternative Identification Strategy



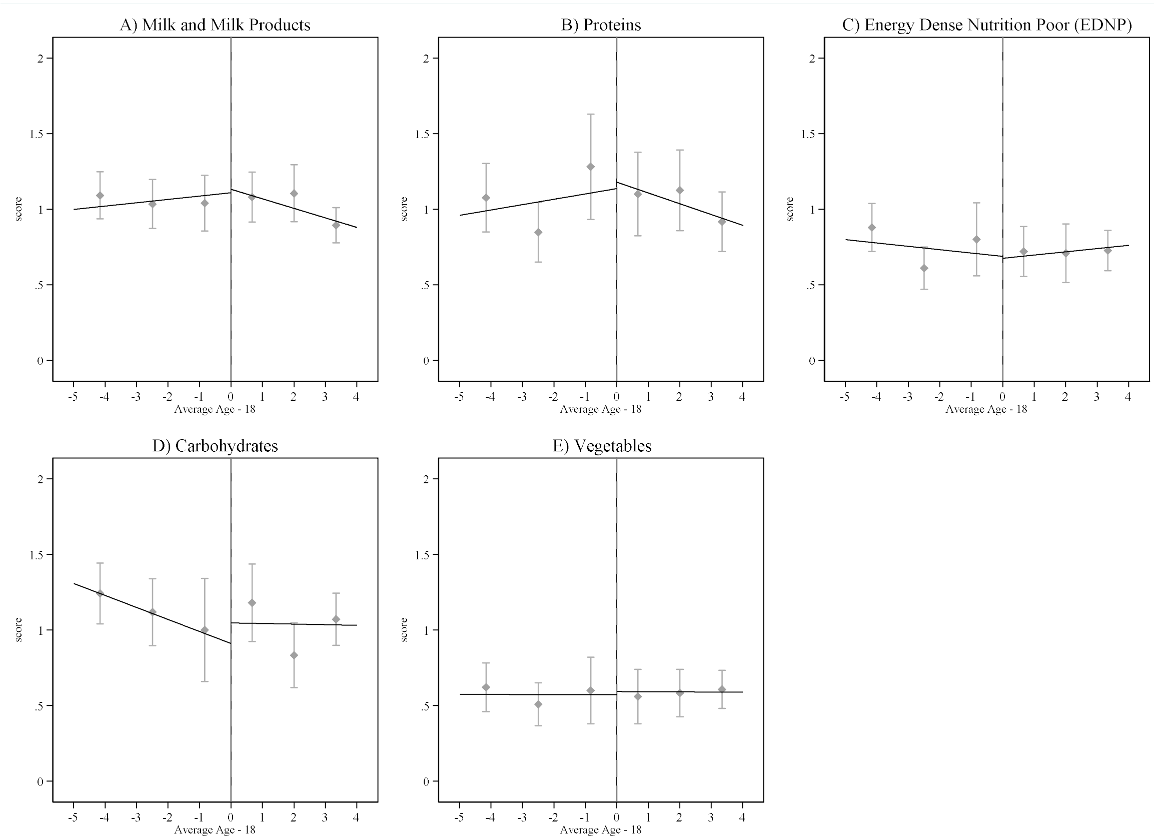
Notes: Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). To account for the uneven distribution of the running variable, it is partitioned into three equal bins on the left and two equal bins on the right of the cutoff. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends. In defining average age, we use the {13–22} age bandwidth and calculate the mean age of the children within this range for each family.

Figure A4: RDD Graphs for Anthropometric Outcomes of Refugee Children, Alternative Identification Strategy



Notes: Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). To account for the uneven distribution of the running variable, it is partitioned into three equal bins on the left and two equal bins on the right of the cutoff. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends. In defining average age, we use the {13–22} age bandwidth and calculate the mean age of the children within this range for each family.

Figure A5: RDD Graphs for Nutrition Outcomes of Refugee Children, Alternative Identification Strategy



Notes: Figures are constructed using the *rdplot* command from Calonico, Cattaneo, and Titiunik (2015, 2017). The dependent variable is the number of distinct food items in each category. To account for the uneven distribution of the running variable, it is partitioned into three equal bins on the left and two equal bins on the right of the cutoff. The mean of the outcome variable is plotted for each bin. Bin-specific 90 percent confidence intervals, robust to heteroskedasticity, are shown as error bars. Linear local polynomial regressions are fitted separately on each side of the cutoff using the original individual-level data to depict pre- and post-threshold trends. In defining average age, we use the {13–22} age bandwidth and calculate the mean age of the children within this range for each family.

Table A1: Descriptive Statistics for Control Variables

	Sample A				Sample B			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Child is Female	0.47	0.50	0	1	0.46	0.50	0	1
Mother Height (meters)	1.57	0.06	1.41	2.01	1.57	0.06	1.41	1.95
Mother BMI	27.32	5.62	15.10	54.25	26.42	5.28	15.10	48.46
Head is Female	0.03	0.17	0	1	0.03	0.16	0	1
Head's Age								
15-24	0.06	0.24	0	1	0.10	0.31	0	1
25-34	0.55	0.50	0	1	0.67	0.47	0	1
35-44	0.31	0.46	0	1	0.19	0.39	0	1
45-64	0.07	0.26	0	1	0.03	0.18	0	1
65+	0.00	0.03	0	1	--	--	--	--
Head's Education								
No education	0.11	0.31	0	1	0.11	0.32	0	1
Incomplete primary	0.06	0.23	0	1	0.06	0.24	0	1
Complete primary	0.33	0.47	0	1	0.32	0.47	0	1
Incomplete secondary	0.13	0.33	0	1	0.12	0.33	0	1
Complete secondary	0.19	0.39	0	1	0.18	0.38	0	1
Incomplete high school	0.02	0.14	0	1	0.02	0.14	0	1
High school or higher	0.16	0.37	0	1	0.18	0.39	0	1
Missing	0.01	0.10	0	1	0.01	0.10	0	1
Type of Place of Residence								
Urban	0.85	0.35	0	1	0.89	0.32	0	1
Camp	0.15	0.35	0	1	0.11	0.32	0	1
Mother Tongue								
Turkish	0.04	0.19	0	1	0.04	0.19	0	1
Kurdish	0.09	0.28	0	1	0.11	0.31	0	1
Arabic	0.86	0.35	0	1	0.83	0.38	0	1
Other	0.02	0.14	0	1	0.03	0.16	0	1
Birth Place Type								
Province Center	0.62	0.48	0	1	0.66	0.47	0	1
Distrcit Center	0.28	0.45	0	1	0.27	0.44	0	1
Subdistrict/Village	0.09	0.29	0	1	0.07	0.26	0	1
Missing	0.00	0.05	0	1	--	--	--	--
Year of Arrival								
2013	0.03	0.16	0	1	0.02	0.13	0	1
2014	0.13	0.33	0	1	0.11	0.31	0	1
2015	0.20	0.40	0	1	0.17	0.38	0	1
2016	0.22	0.42	0	1	0.23	0.42	0	1
2017	0.21	0.41	0	1	0.22	0.42	0	1
2018	0.21	0.41	0	1	0.24	0.43	0	1
Missing	0.01	0.09	0	1	0.01	0.10	0	1
Other ESSN Eligibility Criteria								
At least four children	0.40	0.49	0	1	--	--	--	--
Single Female Head	0.00	0.03	0	1	--	--	--	--
Single Parent with Children	0.01	0.08	0	1	--	--	--	--
Elderly Family Head	0.00	0.00	0	0	--	--	--	--

Notes: The data come from the 2018 Turkey Demographic and Health Survey (THDS). Both samples include refugee babies born in refugee families in the last five years preceding the survey, where families are constructed from the TDHS households according to the family definition used in ESSN eligibility. Sample B excludes families who are eligible for the ESSN program via criteria other than the dependency ratio. In addition to the above ones, the control variables also include dummies for the current region of residence and province of birth. The sample size 1,111 for sample A and 662 for sample B.

Table A2: Selection of the Order of the Polynomial

	HAZ	Stunted (HAZ<2 sd)	Tall (HAZ>2 sd)	WAZ	Underweight (WAZ<2 sd)	Overweight (WAZ>2 sd)	WHZ	Wasted (WHZ<2 sd)	Overweight (WHZ>2 sd)
Sample A									
p=1	0.0947	0.0025	0.0019	0.0206	0.0012	0.0013	0.0266	0.0012	0.0025
p=2	0.5380	0.0798	0.0087	0.0807	0.0034	0.0019	0.3303	0.0003	0.0119
p=3	0.4683	0.0426	0.0225	0.3477	0.0102	0.0051	0.2890	0.0019	0.0176
Sample B									
p=1	0.7587	0.0432	0.0229	0.0643	0.0057	0.0038	0.6612	0.0012	0.0212
p=2	0.3799	0.0670	0.0155	0.1834	0.0118	0.0025	0.1864	0.0012	0.0061

	Milks	Proteins	Junks	Carbs	Veggies
Sample A					
p=1	0.0158	0.2104	0.1980	0.0388	0.0251
p=2	0.8268	0.2755	0.1536	0.6488	0.1906
p=3	0.1744	0.3425	0.6500	0.7024	0.3638
Sample B					
p=1	0.0487	0.6282	0.0305	0.0875	0.0343
p=2	3.4320	0.3838	0.2215	2.3027	1.1385
p=3	0.7422	0.6769	2.2143	1.7708	0.6156

Notes: The data come from the 2018 round of the Turkey Demographic and Health Survey. The sample in panel (A) is defined as described in Table 5, and the sample in panel (B) is as in Table 7. The table uses the method developed by Pei et al. (2022), which provides guidance on the selection of the polynomial order. This method is based on the comparison of the asympotic mean squared errors with different polynomial orders. Above, p denotes the degree of the polynomial.

Table A3: Continuity-based Analysis for Alternative Cutoffs

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Sample: Left-Hand-Side of Actual Cutoff		Sample: Right-Hand-Side of Actual Cutoff			
	Location of the Alternative Cutoff relative to the Actual Cutoff in Months					
	-0.75	-0.5	+0.5	+0.75	+1	+1.5
Height for Age	0.279	0.110	-0.131	-0.009	0.083	-0.495*
	[0.239]	[0.195]	[0.176]	[0.223]	[0.279]	[0.278]
Bootstrapped p-value	0.447	0.503	0.584	0.976	0.843	0.322
Weight for Age	-0.058	0.019	-0.098	-0.037	0.316*	-0.163
	[0.175]	[0.192]	[0.134]	[0.246]	[0.159]	[0.198]
Bootstrapped p-value	0.815	0.914	0.579	0.913	0.374	0.584
Weight for Height	-0.272**	-0.236	-0.018	-0.018	0.413***	0.239
	[0.116]	[0.147]	[0.123]	[0.221]	[0.126]	[0.242]
Bootstrapped p-value	0.119	0.286	0.912	0.944	0.177	0.454
Stunted	-0.139**	-0.293**	0.079**	0.008	-0.024	0.063
	[0.063]	[0.108]	[0.029]	[0.039]	[0.057]	[0.042]
Bootstrapped p-value	0.139	0.582	0.289	0.887	0.757	0.320
Very Tall	0.008	-0.076	0.017	0.03	0.021	-0.044**
	[0.019]	[0.051]	[0.015]	[0.021]	[0.027]	[0.020]
Bootstrapped p-value	0.620	0.704	0.390	0.330	0.708	0.285
Underweight	0.024*	-0.003	-0.003	0.008	-0.046***	-0.034
	[0.013]	[0.019]	[0.010]	[0.012]	[0.012]	[0.024]
Bootstrapped p-value	0.140	0.942	0.754	0.459	0.080	0.259
Overweight (based on WAZ)	-0.014	0.039	0.009	0.019	0.024	-0.031**
	[0.033]	[0.027]	[0.020]	[0.031]	[0.022]	[0.014]
Bootstrapped p-value	0.778	0.355	0.794	0.788	0.629	0.018
Wasted	-0.005	0.061***	0.010	0.012	0.011	-0.012
	[0.030]	[0.011]	[0.010]	[0.011]	[0.009]	[0.013]
Bootstrapped p-value	0.830	0.156	0.352	0.353	0.435	0.361
Overweight (based on WHZ)	-0.029	0.107*	-0.006	0.003	0.087	0.117
	[0.038]	[0.054]	[0.028]	[0.040]	[0.052]	[0.087]
Bootstrapped p-value	0.513	0.287	0.871	0.957	0.224	0.490

Notes: The data come from the 2018 Turkey Demographic and Health Survey. The sample is restricted to the left of the actual cutoff in columns (2) and (3) and to the right of the actual cutoff in columns (4)–(7). Accordingly, the cutoff is at DR = 0.75 in column (2), DR = 1.0 in column (3), DR = 2.0 in column (4), DR = 2.25 in column (5), DR = 2.5 in column (6), and DR = 3.0 in column (7), where DR denotes the dependency ratio. These cutoffs are chosen to ensure a sufficient number of observations on each side of the threshold. Each estimate comes from a separate fuzzy regression discontinuity regression and shows the effect of receiving a cash transfer on the outcome stated in the corresponding column. All regressions control for split linear trends on either side of the cutoff, the child's sex, the mother's height and body mass index, and dummies for the interaction of region and current residence type, the household head's education, the interaction of the household head's sex and age, mother tongue, year of arrival, birth province, type of birth region, and the other four ESSN eligibility criteria. Household-level sampling weights are used. Standard errors are clustered by the dependency ratio. The reported p-value corresponds to the wild cluster bootstrap test. Statistical significance is denoted as follows: * 10% level, ** 5% level, *** 1% level.

Table A4: Covariate Balance for Alternative Identification Strategy

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	A) Age Bandwidth: {15–20}		B) Age Bandwidth: {14–21}		C) Age Bandwidth: {13–22}		D) Age Bandwidth: {12–23}	
	RD Effect	p-value	RD Effect	p-value	RD Effect	p-value	RD Effect	p-value
Family Structure Regarding ESSN Qualification								
Single parent	0.036	0.364	0.027	0.254	0.025	0.031	0.023	0.046
Biological Characteristics								
Female child	0.011	0.779	0.004	0.950	0.041	0.448	0.078	0.136
Mother height	2.441	0.862	-2.093	0.840	1.652	0.905	2.290	0.831
Nonmissing mother height information	0.000	0.513	0.000	0.289	0.000	0.786	0.000	0.842
Mother BMI	1.821	0.050	2.130	0.035	1.875	0.003	1.554	0.059
Nonmissing mother BMI information	0.000	0.546	0.000	0.324	0.000	0.812	0.000	0.840
Family Lives in a Camp	0.119	0.272	0.111	0.034	0.093	0.014	0.087	0.093
Household Head Education								
Incomplete Primary	-0.042	0.223	-0.057	0.179	-0.044	0.280	-0.032	0.407
Complete Primary	-0.019	0.845	-0.018	0.829	-0.029	0.651	-0.012	0.847
Incomplete secondary	-0.051	0.684	-0.012	0.895	-0.036	0.578	-0.027	0.498
Complete secondary	0.122	0.238	0.095	0.200	0.082	0.031	0.088	0.037
Incomplete high school	-0.008	0.572	0.003	0.774	0.009	0.404	0.006	0.616
Complete high school or higher	-0.020	0.252	0.009	0.716	-0.010	0.870	-0.020	0.520
Missing	0.012	0.811	0.004	0.877	-0.009	0.710	-0.007	0.692
Female Household Head	0.030	0.557	0.050	0.102	0.028	0.142	0.023	0.239
Year of Arrival	-0.249	0.087	-0.262	0.100	-0.424	0.074	-0.433	0.027
Mother Tongue								
Kurdish	-0.045	0.467	-0.035	0.347	-0.009	0.848	-0.023	0.461
Arabic	0.102	0.065	0.110	0.050	0.059	0.340	0.069	0.177
Other	-0.028	0.240	-0.029	0.128	-0.026	0.158	-0.022	0.292
Birth Place Type								
District Center	0.225	0.004	0.166	0.009	0.163	0.000	0.111	0.032
Sub-district/village	-0.028	0.482	-0.009	0.766	-0.042	0.131	-0.006	0.874
Region of Residence in Turkey								
Aegean	0.005	0.846	-0.023	0.591	-0.011	0.575	-0.013	0.580
East Marmara	-0.018	0.483	-0.017	0.358	-0.017	0.379	-0.019	0.356
West Anatolia	0.021	0.681	0.035	0.514	0.024	0.571	0.003	0.909
Mediterranean	0.135	0.161	0.046	0.414	0.057	0.336	0.063	0.213
Central Anatolia	0.005	0.837	-0.003	0.852	0.010	0.546	0.011	0.435
Central East Anatolia	-0.001	0.850	0.016	0.358	0.009	0.140	0.013	0.107
Southeast Anatolia	-0.039	0.525	0.042	0.553	0.005	0.908	0.013	0.869

Notes: The data come from the 2018 Turkey Demographic and Health Survey. The samples correspond to the definitions in panel headings (A) to (D). The sample size is 307 in panel (A), 420 in panel (B), 541 in panel (C), and 664 in panel (D). The dependent variables are listed in column (1). Among the family-structure variables related to ESSN qualification, the indicators for single female family head and elderly family head take the value of zero for all observations in these samples; hence, they are not given in this table. All regressions include a control for the treatment dummy and a split linear polynomial on either side of the cutoff for the running variable. Standard errors are clustered at the average-age level, and wild-cluster bootstrapped p-values are reported. Statistically significant at: *** 1 percent, ** 5 percent, * 10 percent.

Table A5: Continuity-based Analysis with Alternative Cutoffs for the Alternative Identification Strategy

Dependent Variable: ESSN Reciept						
Age Range	{7–12}	{8–13}	{9–14}	{10–15}	{11–16}	{12–17}
Age Cutoff	10	11	12	13	14	15
Treatment	0.046	0.004	0.095	0.038	-0.027	0.109
	[0.086]	[0.065]	[0.079]	[0.079]	[0.060]	[0.100]
Bootstrapped p-value	0.721	0.953	0.313	0.694	0.714	0.331
Observations	622	543	484	441	379	354
Age Range	{5–12}	{6–13}	{7–14}	{8–15}	{9–16}	{10–17}
Age Cutoff	9	10	11	12	13	14
Treatment	0.000	0.029	0.002	0.072	-0.060	0.034
	[0.072]	[0.091]	[0.050]	[0.061]	[0.054]	[0.057]
Bootstrapped p-value	0.998	0.797	0.953	0.387	0.304	0.566
Observations	755	700	641	571	503	468
Age Range	{3–12}	{4–13}	{5–14}	{6–15}	{7–16}	{8–17}
Age Cutoff	8	9	10	11	12	13
Treatment	0.198**	0.066	0.041	0.049	0.080	-0.025
	[0.076]	[0.093]	[0.074]	[0.067]	[0.100]	[0.087]
Bootstrapped p-value	0.067	0.649	0.665	0.519	0.695	0.807
Observations	995	901	768	717	655	595
Age Range	{1–12}	{2–13}	{3–14}	{4–15}	{5–16}	{6–17}
Age Cutoff	7	8	9	10	11	12
Treatment	0.117	0.124	0.252***	0.012	0.026	0.094
	[0.071]	[0.079]	[0.064]	[0.094]	[0.079]	[0.075]
Bootstrapped p-value	0.270	0.218	0.001	0.909	0.761	0.323
Observations	1,164	1,107	1,002	910	778	737

Notes: The data come from the 2018 round of the Turkey Demographic and Health Survey and consist of refugee babies born within the five years preceding the survey. The running variable is the average age of children falling within the relevant age range given in each panel. Treatment status is defined as one when this average age is below the age cutoff given in each panel and zero otherwise. The dependent variable is ESSN receipt. Each cell comes from a separate regression based on a sharp regression discontinuity design. All regressions control for the child's sex, the mother's height and body mass index, and a set of household-level demographic and environmental characteristics: region-by-residence-type fixed effects, the household head's education, the household head's sex, mother tongue, year of arrival in Turkey, province of birth, and the type of birth region. We also include dummy variables for the three ESSN eligibility criteria other than the dependency ratio and the four-children rule. Household-level sampling weights are applied, and standard errors are clustered by the average age used as the running variable. For inference, we report wild cluster–bootstrap p-values. Statistical significance is indicated as follows: * 10 percent, ** 5 percent, *** 1 percent.

Table A6: Food Consumption, Alternative Identification Strategy

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ESSN	Milk and Milk Products	Proteins	Energy Dense Nutrition Poor	Carbohydrates	Vegetables
A) Age Bandwidth: {15–20}						
Treatment	0.220					
	[0.127]					
ESSN		0.076	1.653	1.081	0.152	0.655
		[0.762]	[1.060]	[0.839]	[0.641]	[0.606]
Observations	198	198	198	198	198	198
Bootstrapped pvalue	0.206	0.933	0.100	0.144	0.874	0.560
Romano-Wolf p-value		0.891	0.337	0.475	0.891	0.535
Fstat		2.994	2.994	2.994	2.994	2.994
B) Age Bandwidth: {14–21}						
Treatment	0.442***					
	[0.145]					
ESSN		-0.594*	0.506	0.219	0.124	-0.020
		[0.340]	[0.578]	[0.419]	[0.289]	[0.293]
Observations	267	267	267	267	267	267
Bootstrapped pvalue	0.060	0.099	0.405	0.690	0.711	0.946
Romano-Wolf p-value		0.347	0.802	0.960	0.960	0.960
Fstat		9.235	9.235	9.235	9.235	9.235
C) Age Bandwidth: {13–22}						
Treatment	0.321***					
	[0.107]					
ESSN		-0.355	-0.454	-0.091	-0.613	-0.283
		[0.500]	[0.763]	[0.442]	[0.498]	[0.381]
Observations	332	332	332	332	332	332
Bootstrapped pvalue	0.026	0.619	0.619	0.840	0.245	0.496
Romano-Wolf p-value		0.881	0.881	0.881	0.515	0.881
Fstat		9.097	9.097	9.097	9.097	9.097
D) Age Bandwidth: {12–23}						
Treatment	0.156					
	[0.101]					
ESSN		-1.383	-1.365	0.522	-1.015	-0.062
		[0.874]	[1.682]	[0.925]	[0.961]	[0.820]
Observations	403	403	403	403	403	403
Bootstrapped pvalue	0.220	0.131	0.395	0.562	0.182	0.937
Romano-Wolf p-value		0.257	0.396	0.564	0.307	0.941
Fstat		2.366	2.366	2.366	2.366	2.366

Notes: a) The data come from the 2018 round of the Turkey Demographic and Health Survey and consist of refugee babies born within the five years preceding the survey who are between 6 and 35 months old at the time of interview. The running variable is the average age of children falling within the relevant age bracket in panels (A) through (D). Treatment status is defined as 1 when the average age is below 18 and 0 otherwise. Column (2), where the dependent variable is ESSN receipt, reports estimates from separate regressions based on a sharp regression discontinuity design. Each of the remaining columns presents estimates from separate fuzzy regression discontinuity regressions and reflects the causal effect of receiving an ESSN cash transfer on the corresponding outcome.
b) All regressions control for the child's sex, the mother's height and body mass index, and a set of household-level demographic and environmental characteristics: region-by-residence-type fixed effects, the household head's education, the household head's sex, mother tongue, year of arrival in Turkey, province of birth, and the type of birth region. We also include dummy variables for the three ESSN eligibility criteria other than the dependency ratio and the four-children rule. Household-level sampling weights are applied, and standard errors are clustered by the average age used as the running variable. For inference, we report wild cluster–bootstrap p-values. Statistical significance is indicated as follows: * 10 percent, ** 5 percent, *** 1 percent.