



Local food prices, SNAP purchasing power, and child health[☆]

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ABSTRACT

The Supplemental Nutrition Assistance Program (SNAP, formerly food stamps) is one of the most important elements of the social safety net. Unlike most other safety net programs, SNAP varies little across states and over time, which creates challenges for quasi-experimental evaluation. Notably, SNAP benefits are fixed across 48 states; but local food prices vary, leading to geographic variation in the *real* value – or purchasing power – of SNAP benefits. In this study, we provide the first estimates that leverage variation in SNAP purchasing power across markets to examine effects of SNAP on child health. We link panel data on regional food prices to National Health Interview Survey data and use a fixed effects framework to estimate the relationship between local purchasing power of SNAP and children's health and health care utilization. We find that lower SNAP purchasing power leads to lower utilization of preventive health care and more days of school missed due to illness. We estimate no effect on parent-reported health status.

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1. Introduction

The Supplemental Nutrition Assistance Program (SNAP, formerly the Food Stamp program) is the nation's most important food assistance program and one of the largest safety net programs in the United States. SNAP plays a crucial role in reducing poverty for children in the U.S., with only the EITC (combined with the Child Tax Credit) raising more children above poverty (Fox, 2017; National Academy of Sciences, 2019). Eligibility for the program is universal in that it depends only on a family's income and assets, and due to the relatively small phase-out rate, the program impacts both working and nonworking families (Bauer et al., 2018). In fiscal

year 2018, SNAP provided \$61 billion in food benefits to 40 million individuals in 20 million households.

SNAP's primary goals are to improve food security among low-income households, reduce hunger, and increase access to a healthful diet.¹ While many prior studies have estimated the impact of SNAP on food security, in this study, we examine the impacts of SNAP on child health, advancing a new identification strategy. Estimating the causal relationship between SNAP and child and family wellbeing is difficult because SNAP benefits and eligibility rules are legislated at the federal level and do not vary across states, leaving few opportunities for quasi-experimental analysis. Furthermore, because SNAP serves people when they need the program, it is difficult to disentangle the (presumably positive) impact of SNAP from the (presumably negative) impact of the circumstances that made a family become eligible for SNAP or decide to enroll in the program (see Bitler, 2015 for recent evidence on this issue).

The existing evidence on the causal effects of SNAP on child health and food insecurity takes several approaches.² One set of studies uses variation in state SNAP application and administra-

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¹ See, for example, the most recently amended authorizing legislation, the Food and Nutrition Act of 2008, available at <https://fns-prod.azureedge.net/sites/default/files/snap/Food-And-Nutrition-Act-2008.pdf>.

² We limit the discussion here to the literature focused on SNAP and child outcomes. See reviews by Currie (2003); Bartfeld et al. (2015); Hoynes and Schanzenbach (2016) and Bitler and Seifoddini (2019) for a more comprehensive review on the benefits and costs of SNAP.

tive procedures (e.g., allowing online applications, whether there is a finger printing requirement, asset requirements, recertification intervals) to instrument for SNAP participation and finds reductions in food insecurity (Yen et al., 2008; Mykerezi and Mills, 2010; Shaefer and Gutierrez, 2013; Ratcliffe et al., 2011) and reductions in child BMI (Schmeiser, 2012).³ A second set of quasi-experimental studies analyzes the rollout of the food stamp program across counties in the 1960s and 1970s and finds that the program leads to improvements in birth outcomes (Currie and Moretti, 2008; Almond et al., 2011). A third approach uses variation in immigrant eligibility for SNAP generated by welfare reform legislation in the 1990s. For U.S.-born children of immigrants, the evidence indicates that SNAP improves infant health, and access to SNAP prior to age 5 positively affects health at ages 6–16 (East, 2019). Finally, the USDA Summer Electronic Benefits Transfer for Children (SEBTC) demonstration documents that higher SNAP benefits in the summer months (to offset the loss of school meal programs) leads to a reduction in food insecurity (Collins et al., 2016).⁴ Taken together, this literature provides consistent evidence of beneficial effects of SNAP on food insecurity but more limited evidence on SNAP's causal impacts on child health, particularly beyond BMI (see also reviews by Bitler, 2015; Bitler and Seifoddini, 2019; Hoynes and Schanzenbach, 2016; Gregory et al., 2015; Gundersen and Ziliak, 2015).

Our study contributes to this literature by examining the effects of SNAP on a broad set of child health outcomes and by advancing a new research design. We consider the impacts of SNAP on health care utilization, preventive health care visits, days missed from school, obesity, mental health, and self-reported health status. We leverage plausibly exogenous geographic variation in the purchasing power of SNAP benefits to identify the effects of variation in SNAP generosity on health. Importantly, the SNAP benefit formula is fixed across 48 states (benefits are higher in Alaska and Hawaii) even though the price of food varies greatly across the country (Todd et al., 2010, 2011).⁵ Across the continental U.S., maximum benefits vary only with family size; in 2018 a family of three was eligible for a maximum benefit of \$504/month regardless of the local cost of living. Though SNAP benefits are implicitly adjusted for variation in the cost of living through allowed deductions (e.g., for housing and child care) in the calculation of net income, the limited available evidence indicates these adjustments are not sufficient to equalize *real* benefits, particularly in high cost areas (Breen et al., 2011). Gundersen et al. (2011) and the Institute of Medicine (2013) propose this as an area for future research.

Higher SNAP purchasing power may impact children's health through three possible channels. A *direct* (nutrition) effect occurs if higher SNAP purchasing power leads to increases in the quality or quantity of food. By freeing up resources more generally, higher SNAP purchasing power may also impact health *indirectly*, facilitating households to increase consumption of other inputs into the health production function, like health care. Finally, if additional SNAP purchasing power leads to reductions in stress and “bandwidth poverty” (Bertrand et al., 2004; Mullainathan and Shafir,

2013), it may result in better compliance with activities such as getting children to school and to the doctor for annual exams.

Linking nationally representative data from the 1999 to 2010 National Health Interview Surveys (NHIS) to information on regional food prices from the Quarterly Food-at-Home Price Database (QFAHPD), we study the effect of variation in SNAP purchasing power on children's health care utilization and health. Our measure of SNAP purchasing power compares the maximum SNAP benefit to the regional cost of the Thrifty Food Plan (TFP), a nutrition plan constructed by the USDA to represent a nutritious diet at minimal cost and the basis for maximum legislated SNAP benefits (i.e., maximum benefits are set to the national average TFP cost). The QFAHPD includes information on food prices that allows us to construct an estimated TFP price for each of 30 designated “market group” geographic areas across the U.S. We relate child health care utilization and health outcomes to SNAP purchasing power (i.e., the ratio of the national SNAP maximum benefit to the market group-level TFP price faced by a household) in a fixed effects framework that controls for a number of individual-level and region characteristics (including non-food prices in the area) and state policy variables. Identification comes from differences across the 30 market groups in trends in the price of the TFP.

Our study contributes to the growing body of evidence on the SNAP program and its effects in a few key ways. First, we provide new evidence on the relationship between SNAP benefit generosity and the health and wellbeing of children. Our findings consistently indicate that children in market groups with lower purchasing power of SNAP utilize less preventive/ambulatory health care. We find that a 10 percent increase in SNAP purchasing power raises the likelihood a child has an annual checkup by 6.3 percentage points (8.1 percent) and the likelihood of *any* doctor's visit by 3.1 percentage points (3.4 percent). While lower SNAP purchasing power does not result in contemporaneous declines in parent reported health status, we document evidence of detrimental impacts on some health indicators, like the number of school days missed due to illness, as well as on children's food security. Summary indices corroborate the existence of effects on health care utilization, but not health outcomes generally. We confirm that these estimated effects are not driven by relationships between geographic variation in food prices and SNAP participation or health insurance coverage, nor are they present in placebo samples of children of college educated mothers and non-citizen children, both of which have low rates of SNAP participation.

A second contribution is methodological, in that our approach highlights a new identification strategy for estimating effects of proposed changes in SNAP generosity on other outcomes of interest. To our knowledge, ours is the first study to utilize variation in the real value of SNAP as a source of identification.⁶ Future research could leverage geographic variation in SNAP purchasing power to examine SNAP's impacts on nutrition, food consumption and other spending patterns, birth outcomes, and adult health.⁷

We interpret our estimates as reflecting the impacts of variation in SNAP purchasing power, rather than simply the effects of variation in local food prices.⁸ Variation in real SNAP generosity may

³ Ziliak (2015) and Ganong and Liebman (2018) provide direct evidence on the effects of state policies.

⁴ Other nonexperimental approaches have been utilized in the literature. Some studies use a household fixed effects estimator to examine impacts on food insecurity (DePolt et al., 2009; Wilde and Nord, 2005) and child BMI (Gibson, 2004); these provide more mixed evidence for beneficial effects of SNAP (though transitions into and out of SNAP may be correlated with other factors that affect food insecurity). Another well-known set of studies uses partial identification bounding methods and examines impacts of SNAP on food insecurity (Gundersen and Kreider, 2008; Kreider et al., 2012; Gundersen et al., 2017) and child health (Kreider et al., 2012).

⁵ Studying data from the Quarterly Food at Home Price Database (QFAHPD), Todd et al. (2011) find that regional food prices vary from 70 to 90 percent of the national average at the low end to 120–140 percent at the high end.

⁶ In related work, Gregory and Coleman-Jensen (2013) study the direct relationship between local food prices and food insecurity for a sample of SNAP households. The authors find that SNAP participants in high-priced areas are 15–20 percent more likely to be food insecure than those in low-priced areas.

⁷ Bronchetti et al. (2017) link National Household Food Acquisition and Purchase Survey (FoodAPS) data on SNAP recipients' diets to local data on the cost of the TFP to study the effects of variation in SNAP purchasing power on nutrition among the SNAP population.

⁸ Throughout, our models include market area and time fixed effects and controls for local housing costs (HUD fair market rent), other non-food prices, and local labor market conditions.

affect households differently than variation in prices to the extent that local earnings adjust to account for higher local prices (Roback, 1982; Albouy, 2008; Moretti, 2013), while SNAP benefits do not. Indeed, we demonstrate that SNAP purchasing power does not have statistically significant impacts on our key health outcomes or food insecurity within samples that are mostly ineligible for SNAP or have very low SNAP utilization (e.g., non-citizen children, children in families with a college educated mother). Perhaps most importantly, we find no statistically significant effects of SNAP purchasing power on measures of household income or poverty, and our child health results are robust to including controls for regional prices of other goods (such as housing, energy, transportation, etc.), suggesting that we are not simply capturing the broader effects of living in differing labor or housing markets.

More broadly, our findings point to sizable, beneficial impacts of SNAP (and of increasing the generosity of SNAP benefits) for children's health care utilization, food security, and some measures of their health, benefits which should be weighed carefully against the cost savings of any proposed cuts to the SNAP program. These results also shed light on the expected impact of adjusting benefit levels to account for geographic variation in food prices across market groups. Such adjustments would likely reduce disparities in preventive/ambulatory care, school absenteeism, and food insecurity among low-income children, but may not lead to contemporaneous changes in other health outcomes. Our research design does not allow us to make conclusions about beneficial effects of SNAP that may accrue over the longer run.

The paper proceeds as follows. The next section describes our multiple sources of data on regional food prices, child health, food security, and SNAP participation, and Section 3 lays out our empirical approach. Section 4 presents our main results regarding the impact of SNAP purchasing power on children's health care utilization and health, Section 5 explores mechanisms and several robustness checks, and Section 6 concludes.

2. Data

In this study, we combine three sets of data to estimate the effect of SNAP on children's health. Below we describe the data on the price of the TFP, the National Health Interview Survey (NHIS), and the state and county control variables. Additionally, we supplement our main analysis with administrative data on SNAP caseloads and household-level data on food insecurity from the December Current Population Survey (CPS).

2.1. Regional cost of the Thrifty Food Plan (TFP)

The Thrifty Food Plan (TFP) is a food plan constructed by the USDA, specifying foods and amounts that represent a nutritious diet at a minimal cost. The TFP is used as the basis for legislated maximum SNAP benefit levels. In 2016, the U.S. average weekly TFP cost was \$146.90 for a family of four with two adults and two children (ages 6–8 and 9–11).⁹

To assign food prices to our sample of households in the NHIS, we construct data on the regional price of the TFP using the Quarterly Food-at-Home Price Database (QFAHPD) (Todd et al., 2010) for the years from 1999 through 2010. The QFAHPD, created by the USDA's Economic Research Service, uses Nielsen scanner data to compute quarterly estimates of the price of 52 food categories (e.g. three categories of fruit: fresh or frozen fruit, canned fruit, fruit juices; nine categories of vegetables, etc.) for 35 regional market

groups. The 35 market groups covered in the QFAHPD are exhaustive of the U.S.; each market group consists of a set of counties, and each county is located in a single market group. 26 of these market groups are constructed around metropolitan areas and the remaining counties are in nonmetropolitan areas, one for each of the nine Census divisions. Appendix Fig. 1 shows the market groups.¹⁰ We map the 52 QFAHPD food categories to the 29 TFP food categories to create a single price estimate for the TFP for each market group and year during the full 1999–2010 period covered by the QFAHPD, following the methods in Gregory and Coleman-Jensen (2013).^{11,12}

To map the QFAHPD food group prices to the TFP food group prices in the market basket, we use an expenditure-weighted average of the prices for the QFAHPD foods, where the weights are the expenditure shares for the QFAHPD foods within each TFP category (most TFP food categories consist of multiple QFAHPD food groups). We construct *national* expenditure shares by averaging the shares across all market groups. To avoid confounding regional variation in food prices with regional variation in consumption of different food categories, we apply these *national* expenditure shares to each market group's prices when constructing the market group-level cost of the TFP.^{13,14} We use the 2006 specification of the TFP, which features food categories that are relatively closely aligned with the food categories in the QFAHPD data (Carlson et al., 2007).

We assign each household in the NHIS to a market group-level TFP price based on the county of residence and the year of interview. When estimating the relationship between the real value of SNAP benefits and health, we measure the purchasing power of SNAP using the ratio of the maximum SNAP benefit to the TFP price faced by the household. Our main regression models use the natural log of this ratio as the key independent variable for ease of interpretation; however, results are qualitatively very similar when the level of the ratio is employed instead.¹⁵

Fig. 1 illustrates the variation across regions and over time in the real value of SNAP, equal to the maximum SNAP benefit for a

¹⁰ In 1999–2001, the QFAHPD identified only four nonmetropolitan areas - one for each of the 4 census regions (east, central, south and west). In 2002 and later, the nonmetropolitan areas were expanded to include one for each of the 9 census divisions: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific. For comparability, we use the four nonmetropolitan areas (30 market areas) throughout.

¹¹ We come very close to reproducing their estimates. As in this earlier work, we can cleanly link the QFAHPD categories to 23 of the 29 TFP categories without duplication or overlap of QFAHPD prices. The remaining six TFP categories contain foods that are accounted for in other parts of the QFAHPD TFP basket. For details on the construction of the TFP itself, see Carlson et al. (2007).

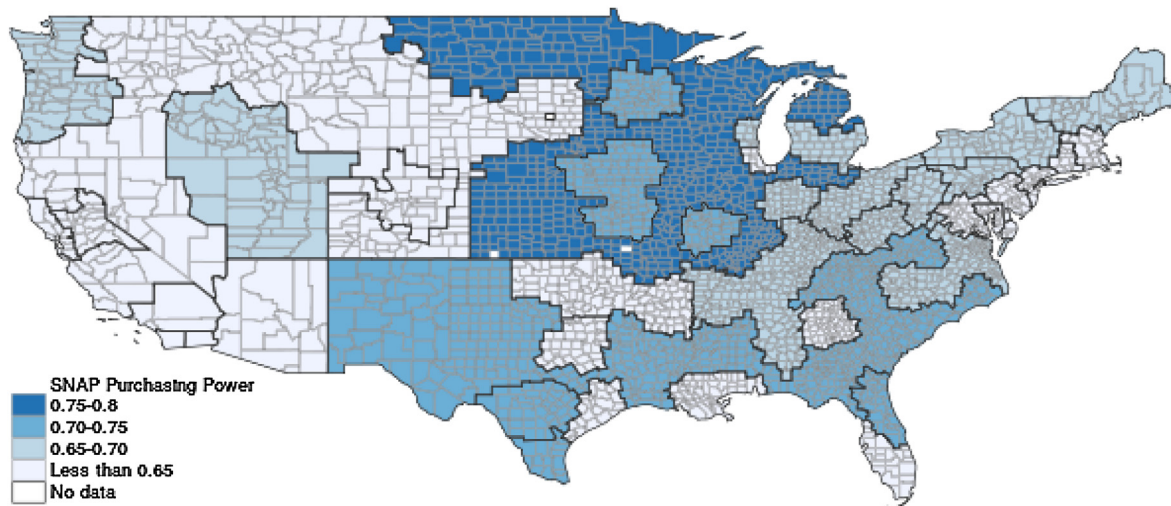
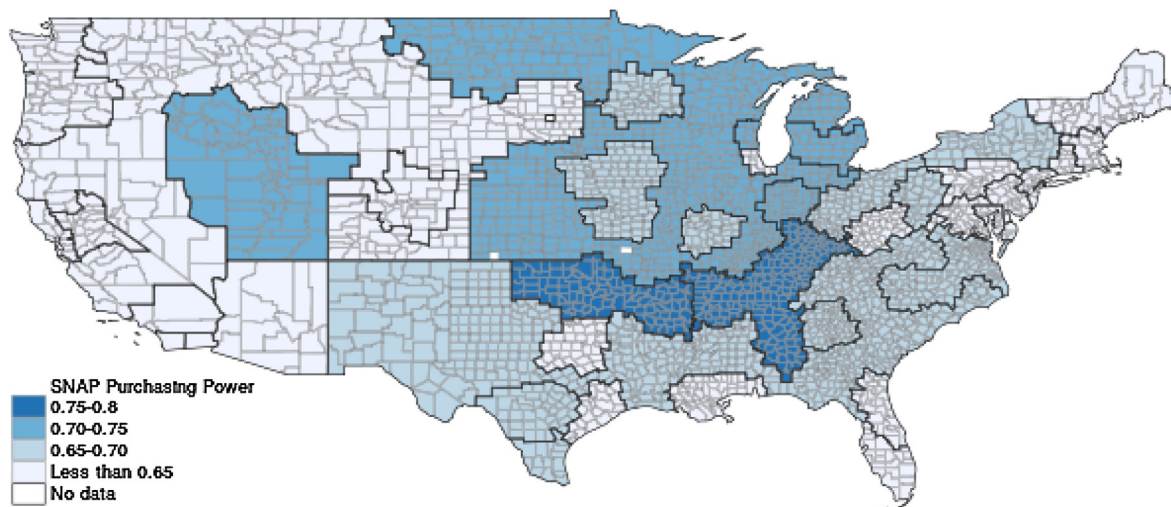
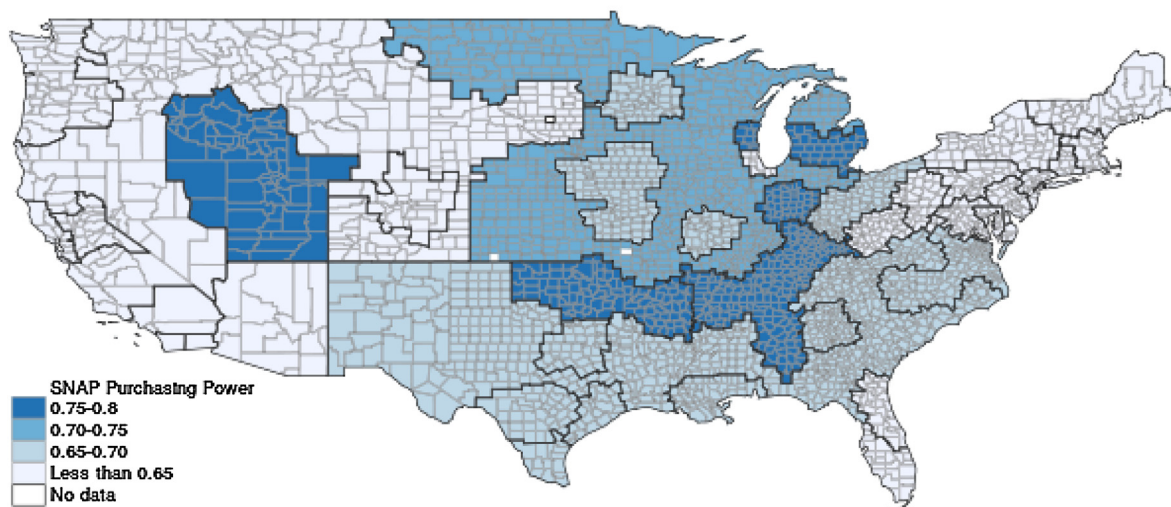
¹² There are two versions of the QFAHPD: QFAHPD-1, which provides price data on 52 food groups for 1999–2006, and QFAHPD-2, which includes prices for 54 food groups for 2004–2010. We bridge the two series by estimating the average ratio of QFAHPD-1 to QFAHPD-2 for years 2004 through 2006 for each market group. We then divide the price data for 1999–2003 (i.e. the years with information on only 52 food groups) by this ratio to put everything in consistent units.

¹³ We have also constructed measures of TFP cost using total national expenditure shares (as opposed to averaging the weights across market groups) and obtain very similar estimates of the TFP and effect sizes.

¹⁴ An example (borrowed from Gregory and Coleman-Jensen (2013)) is illustrative. The TFP food category “whole fruit” consists of two QFAHPD food groups: “fresh/frozen fruit” and “canned fruit.” In Hartford (market group 1) in the first quarter of 2002, expenditures on fresh/frozen fruit were \$35.7 million, and expenditures on canned fruit were \$5.8 million. This yields expenditure weights for whole fruit (in Hartford in quarter 1 2002) of 0.86 and 0.13, respectively. We then average these expenditure shares across *all market groups* to generate the national expenditure shares (for each item and period). In 2002, these national expenditure weights are 0.84 and 0.16 for fresh fruit and canned fruit, respectively. We apply these shares to the first-quarter 2002 prices of fresh/frozen and canned fruit in the Hartford market group (\$0.218 and \$0.244 per 100 grams, respectively) to compute a price for whole fruit in Hartford for the first quarter of 2002 ($0.84 \times \$0.218 + 0.16 \times \$0.244 = \$0.222$ per 100 grams).

¹⁵ These results are available upon request.

⁹ See <https://www.cnpp.usda.gov/sites/default/files/CostofFoodNov2016.pdf>. (Accessed 1/28/17)

Panel A: 1999*Panel B: 2008**Panel C: 2010***Fig. 1.** Purchasing Power of SNAP by Market Group.

Notes: Maps plot SNAPMAX/TFP for each of the 30 market groups identified consistently in the Quarterly Food at Home Price Database (QFAHPD).

family of 4 divided by the regional cost of the TFP.¹⁶ Panel A displays the value of this ratio in 1999, Panel B shows its value in 2008, and Panel C shows its value in 2010. In each case, a darker shading represents a higher SNAP/TFP ratio, or greater SNAP purchasing power. In lower-cost areas the SNAP benefit covers up to 80 percent of the cost of the TFP, while in higher cost areas (e.g., the west and northeast) this ratio falls to less than 65 percent. Note that since the statutory TFP is constructed using a national average, some areas are, by definition, likely to have SNAP benefits that exceed the cost of the TFP. However, our purchasing power measure (maximum SNAP benefit/price of TFP) is less than 1 for all market groups. One reason for this is that the regional TFP prices from the QFAHPD are based on average prices paid for each food category by all consumers, whereas the statutory TFP price is based on prices paid by low-income persons. If low-income households are shopping at different stores, or buying on sale or buying cheaper (e.g., store) brands, then the TFP price we estimate using the QFAHPD will consistently be too high.

Our identification strategy relies not on the exact level of the TFP price (or SNAP purchasing power), but on differences across markets in trends in SNAP purchasing power. Using the QFAHPD we can compare prices paid by all households (which we use to construct the regional cost of the TFP) to the prices paid by low income households (who would more closely track prices paid by SNAP households). Fig. 3 demonstrates a strong, positive correlation between the market area price paid by low-income households and the market area all-household price for a variety of food categories, suggesting that the all-households price tracks well the low-income household price.¹⁷ In Appendix Fig. 2, we compare our estimated TFP price to a lowest-cost TFP price measure, by market area, which we construct using only the lowest-cost QFAHPD food category within each TFP category (similar to how the statutory TFP price is calculated). Reassuringly, we find a strong correlation (0.98) between our index and this lowest-cost alternate measure across market areas.

Fig. 1 also demonstrates noticeable changes in SNAP purchasing power within regions over the 1999–2010 period. The changes in 2010 reflect, in part, the effect of the stimulus package (ARRA), which raised the maximum SNAP benefit by 13.6 percent in the second half of 2009 and throughout 2010 (Hoyne and Schanzbach, 2016). Fig. 2a and b present trends in the TFP price and SNAP purchasing power, respectively, for each of the market group areas. Fig. 2a shows that the TFP price varies considerably across areas – prices are higher in places such as San Francisco and Metro New York but with different trend paths.¹⁸ The same is true for SNAP purchasing power, though the effect of the increase in benefits due to the ARRA is common to all areas. In robustness checks presented below, we examine the sensitivity to dropping the ARRA years and obtain qualitatively similar findings (see Appendix Tables 10 and 11).

¹⁶ An interactive version of this figure is available online at <http://garretchristensen.shinyapps.io/Food.Price.Maps>.

¹⁷ The low-income sample is from households below 185 percent of the federal poverty line in Nielsen HomeScan data. See Appendix C of Todd et al. (2010) for details. The plotted data come from Tables C1–C5. Todd et al. conclude “When the markets are ranked by the price index in each food group, we consistently see the most expensive markets as determined by the full sample also appearing as the most expensive markets in the low-income sample, and the same pattern holds for the least expensive markets as well.”

¹⁸ Prices may vary across areas due to differences in costs of labor or rent. DellaVigna and Gentzkow (2019) find evidence of uniform pricing across the U.S. at large food chains. Stroebel and Vavra (2019) find that prices across stores vary with housing prices, suggesting more evidence of local variation. They show that the differences across areas are not due to changes in store or product quality. Less is known about geographic price variation across smaller stores.

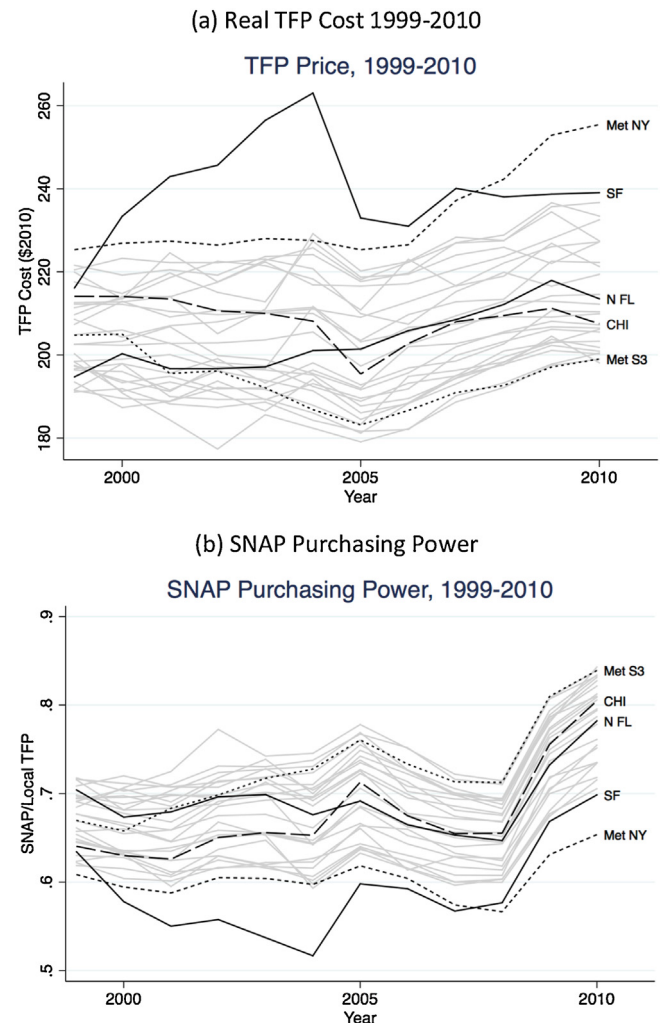


Fig. 2. Variation across Market Group Areas, 1999–2010.

Notes: Figure shows (a) the TFP in constant 2010 dollars and (b) the ratio of maximum SNAP benefits to market group TFP. Highlighted regions are those with the largest increase over the period (North Florida; New York; San Francisco) and the largest decrease (Chicago; Metro South; Little Rock; Metro Oklahoma).

Given that food stamp recipients are not limited to purchasing the TFP basket, why do we use it? Ultimately, we are looking for a standardized index across places and over time that allows us to trace out variation in food prices that are relevant for the low-income population. Our investigations (Fig. 3, Appendix Fig. 2) indicate that the different price series are very highly correlated across place. In the end, we view the TFP as appealing because it is the index used by USDA in setting benefits. Furthermore, by using the price of a set basket we remove the influence of any (endogenous) changes in food choices that recipients make in the face of higher prices.

2.2. National health interview survey (NHIS) data on SNAP children

We use restricted-access micro data from the National Health Interview Survey (NHIS) for the years 1999–2010 to examine effects on child health and health care utilization.¹⁹ The NHIS surveys

¹⁹ State and county identifiers are masked in the public use NHIS data. Researchers interested in accessing the restricted geocode data should contact Peter Meyer at rdca@cdc.gov.

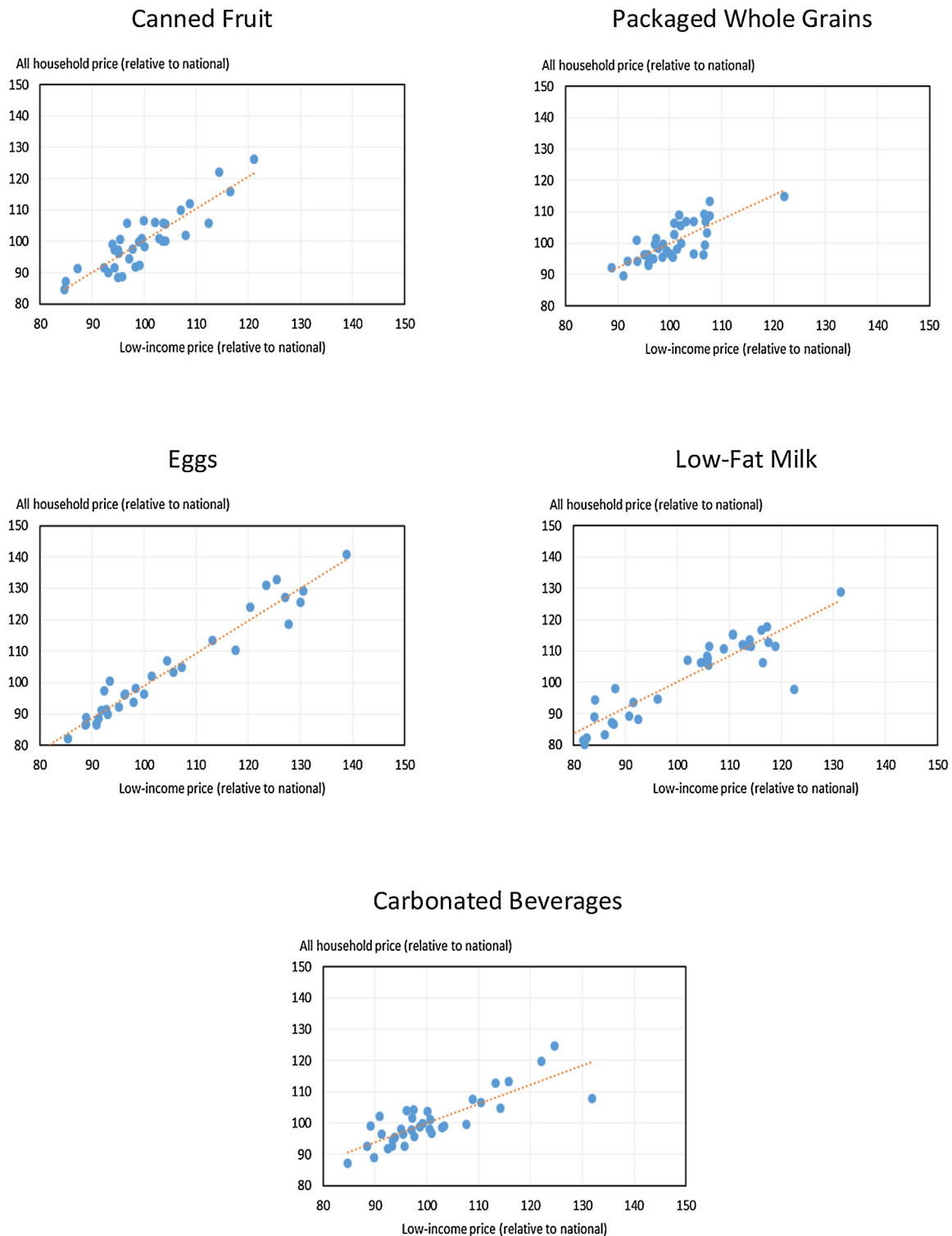


Fig. 3. Comparison of Prices Across Market Groups. Full Sample vs. Low-income Sample.
Source: Authors' tabulations of data reported in [Todd et al. \(2010\)](#).

approximately 35,000 households per year. With restricted-use access to this data we can observe the county of residence for each household in the survey. This allows us to link respondents to regional area food prices and access detailed information on children's health and the characteristics of their parents and households for a large and representative national sample. From each household with children, the survey selects one child at random (the "sample child") and collects more extensive and detailed infor-

mation on this child's health and health care utilization. Several of the outcomes we study are only available in these Sample Child files, while others (e.g., parent-reported health status) are available for all NHIS respondents in the Person-level file.

Our primary sample includes children ages 17 and under who are citizens of the United States. We impose the citizenship restriction because the post-welfare reform era witnessed dramatic changes to rules regarding non-citizens' eligibility for many social

safety net programs, including SNAP.²⁰ (We analyze non-citizen children as a placebo group below.) We conduct our main analyses on the sample of children in households who report having received SNAP benefits in at least one of the past 12 months. For the years from 1999 through 2010, there are 44,627 such children; 18,299 of them are also interviewed as Sample Children. While the advantage of limiting our analysis to the SNAP recipients is clear (this is the group most affected by SNAP), non-random selection into SNAP participation would call into question a causal interpretation of our estimates. In Section 4.1, we analyze the impact of SNAP purchasing power on SNAP participation at the county level; our estimates of the relationship between the real value of SNAP benefits and the per-capita SNAP caseload are not statistically significant.²¹

Because our sample is based on self-reports of SNAP receipt, one might be concerned about bias in our estimates caused by underreporting of SNAP participation. Meyer et al. (2018) document significant rates of SNAP underreporting in the CPS, with less underreporting in the American Community Survey (ACS) and Survey of Income and Program Participation (SIPP). Unfortunately, the literature provides no comparable evidence for the NHIS. The evidence in Meyer and Mittag (2019) indicates that the underreporting of SNAP in the CPS is most severe among households with a disabled member and single mother-headed households. If the same is true for the NHIS, children in our SNAP recipient sample may be less disadvantaged (and less responsive to a marginal increase in SNAP purchasing power) than those omitted due to underreporting. It is reassuring that in Section 5 we estimate similar effects for an alternative treatment sample with a high likelihood of being on SNAP – children living with low-educated, unmarried parent(s).

Families with limited resources may respond to lower SNAP purchasing power by reducing consumption of other goods that impact health, like ambulatory or preventive health care. Additionally, lower SNAP purchasing power could lead to increases in stress and bandwidth poverty, resulting in lower compliance with preventive care. Our primary measures of health care utilization are indicators for whether the child has had a check-up in the past 12 months and whether the child has had any doctor's visit in the past 12 months. According to guidelines from the American Academy of Pediatrics (AAP), children should have 6–7 preventive visits before age 1, 3 visits per year as 1-year olds, 2 visits as 2-year olds, and at least one visit per year for ages 3 through 17. We also analyze the relationship between SNAP purchasing power and whether (the parent reports that) a child has delayed or forgone care due to cost in the past 12 months. Finally, we study whether the child has visited the emergency room (ER) in the past year, but we note that the predicted relationship between SNAP purchasing power and ER use is ambiguous. Lower SNAP purchasing power may worsen health, which could lead to an increase in ER utilization. On the other hand, a decrease in SNAP purchasing power may result in reduced ER use if patients face out-of-pocket costs associated with ER care.

We also analyze the effects of SNAP purchasing power on several direct measures of child health that might respond to reduced nutrition, or to reduced consumption of other inputs in the health production function (e.g., health care). We study school attendance

as a key measure of contemporaneous health. In particular, we estimate the relationship between SNAP purchasing power and the number of school days missed due to illness in the past 12 months (for the sub-sample of school aged children), and an indicator for whether the child missed 5 or more days of school due to illness. Lower SNAP purchasing power should lead to more school days missed, given that worse health would lead to more absences. Additionally, lower SNAP purchasing power may lead to increases in maternal stress that impact the ability to comply with desirable activities, like getting the children to school (Bertrand et al., 2004; Mullainathan and Shafir, 2013). On the other hand, these SNAP-recipient children are likely eligible for school meal programs, and the availability of meals at school may lead children with low SNAP purchasing power to be less likely to miss school because doing so would mean missing the school meals. If so, this should work against our finding that an increase in SNAP purchasing power reduces school absences. Related literature has found school absences to be responsive to SNAP (e.g., East, 2019).

We also study whether the child was hospitalized over the past 12 months, as well as a measure of the child's overall health status. Parental respondents report the child's health status on a 5-point scale (excellent, very good, good, fair, and poor); we use this measure to construct an indicator for whether the child is in excellent or very good health. In addition, we estimate the relationship between SNAP purchasing power and two health outcomes that may be affected by reduced nutrition or food insecurity: an indicator for obesity based on height and weight data (for the subsample of children ages 12–17), and whether the child has emotional problems (defined for the universe of children ages 4 and older). Obesity and emotional health may be less sensitive to contemporaneous changes in SNAP purchasing power given that they are more cumulative in nature.

In addition, we test both of these groups of outcomes (preventive health care utilization, health outcomes) using summary index methods as in Kling et al. (2007).²²

Table 1 displays summary statistics for SNAP recipient children and for the entire population of children. As expected, SNAP children are likely to be poor, live in single-parent households (only a third live with both parents), and are disproportionately likely to be black or Hispanic. Because such a high fraction (72 percent) of SNAP children receive Medicaid, the rate of uninsurance among this sample is low, at about 7 percent. Health care utilization and health outcomes are somewhat similar for SNAP citizen children compared to the general population of children in the U.S. Nearly one-quarter of SNAP children went without a check-up in the past year, but 90 percent had at least some sort of doctor's visit during that time, and more than 5 percent report having delayed or gone without care due to its cost. However, ER utilization is high, at over 30 percent, compared to 21 percent among the entire population. In terms of health itself, SNAP children have similar health status, but miss more school days (5, on average, but one-third of SNAP children missed 5 or more in the past year), and more commonly have emotional problems (46 percent of SNAP children 4 or older compared to 27 percent in the general population).

²⁰ In particular federal welfare reform passed in 1996 imposed waiting periods or otherwise restricted access for many immigrant groups (see Bitler and Hoynes, 2013 for a description of these changes). Subsequent legislation restored or lessened some of the restrictions. As of October 1, 2003, "qualified" non-citizen children (e.g., legal permanent residents, asylees, and refugees) are eligible for SNAP without the 5-year waiting period that imposed on other groups (even if their parents are not eligible). Non-citizen children as a group have very low SNAP participation rates.

²¹ We also document no statistically significant relationship between SNAP purchasing power and the likelihood of SNAP participation at the individual level, among Sample Children in the NHIS or the December Current Population Survey which we use to examine impacts on food insecurity (see Appendix Table 3).

²² We create summary indices by subtracting the mean and dividing by the standard deviation of each variable, then averaging across variables within items in the index (with the variables that reflect undesirable outcomes, like delaying health care or having an ER visit, first multiplied by -1 .) Typically, the mean and standard deviation of a control group are used, but lacking that, we use the full sample. Note that the sample in these regressions is limited to those with full data from all included measures. For the health outcomes index this implies school age children only. Anderson (2008) explains similar indices clearly, and Hoynes et al. (2016) use the technique when evaluating long-run impacts of SNAP.

Table 1
Summary Statistics for Children in NHIS.

<i>Child/Household Characteristics</i>	SNAP Citizen Children	All Children	<i>Health Care Utilization</i>	SNAP Sample Children	All Sample Children
TFP price	203 (14.36)	205 (14.18)	Any check-up (12 m)	0.77 (0.42)	0.74 (0.44)
Max SNAP benefit	143 (11.57)	141 (10.17)	Any doctor's visit (12 m)	0.90 (0.30)	0.88 (0.32)
Income to poverty ratio	0.90 (0.74)	3.06 (2.24)	Any ER visit (12 m)	0.32 (0.47)	0.21 (0.41)
Child's age	7.50 (5.09)	8.54 (5.19)	Delay/forgo care (12 m)	0.06 (0.23)	0.05 (0.22)
Child is male	0.51 (0.50)	0.51 (0.50)	<i>Health Outcomes</i>		
Child is black	0.34 (0.47)	0.16 (0.36)	Health status exc. or v. good	0.71 (0.45)	0.70 (0.46)
Child is Hispanic	0.26 (0.44)	0.19 (0.40)	Hospitalized overnight (12 m)	0.09 (0.28)	0.08 (0.26)
Mother is present	0.94 (0.24)	0.95 (0.23)	School days missed, illness (12 m)	4.96 (9.36)	3.53 (6.43)
Father is present	0.39 (0.49)	0.75 (0.43)	5+ school days missed (12 m)	0.33 (0.47)	0.25 (0.43)
Both parents	0.36 (0.48)	0.71 (0.45)	Obese	0.20 (0.40)	0.13 (0.34)
Child receives Medicaid	0.72 (0.45)	0.21 (0.41)	Emotional problem	0.46 (0.76)	0.27 (0.59)
Child has no health insurance	0.07 (0.25)	0.10 (0.30)			
Number of observations	44,627	296,779	Number of observations	18,299	139,268

Notes: Table contains estimates of means of US citizen children in household receiving SNAP, weighted to account for complex survey design. Standard errors in parentheses. Left panel are children from the person-file dataset (i.e. all children in household, separately for SNAP and all households) while right panel shows only children from sample child file (i.e. one child per household.).

2.3. State and county control variables

We include several variables to control for regional policies and prices that might affect child health and be correlated with local food prices. First, we control for local labor market conditions with the county unemployment rate (and in some robustness tests we also control for log employment and average earnings by 1-digit sector using the Quarterly Census of Employment and Wages). Second, we include a summary index of state-level SNAP policies developed by [Canong and Liebman \(2018\)](#), which incorporates measures for simplified reporting, recertification lengths, interview format (e.g. in person or not), call centers, online applications, Supplemental Security Income Combined Application Project, vehicle exemptions for asset requirement, and broad-based categorical eligibility. Third, we control for other state policies including the minimum wage, state EITC, TANF maximum benefit guarantee amounts, and Medicaid/State Children's Health Insurance Program (CHIP) income eligibility limits. Finally, we control for prices of other goods by including HUD's fair market rent (measured by county as the "40th percentile of gross rents for typical, non-substandard rental units occupied by recent movers in a local housing market"²³) and regional Consumer Price Indices (CPIs) for non-food, non-housing categories (apparel, commodities, education, medical, recreation, services, transportation and other goods and services). These regional CPI prices are available for 26 metro areas; for the remaining areas, the CPI is calculated within each of the four census regions and for four county population sizes (<50,000, 50,000–1.5 million, >1.5 million).

²³ More specifically, HUD estimates FMRs for 530 metropolitan areas and 2,045 nonmetropolitan county FMR areas.

2.4. Supplemental data on SNAP caseloads and food insecurity

We investigate the relationship between SNAP purchasing power and SNAP participation in Section 4.1, using administrative data on county-level SNAP caseloads from the U.S. Department of Agriculture (USDA), for the years from 1999 through 2010. We match each county-year observation to that year's TFP price for the market group to which the county belongs.

To further probe mechanisms whereby variation in regional food prices may impact child health, we supplement our main analysis by studying the relationship between SNAP purchasing power and food insecurity.²⁴ For this analysis we use data from the December Current Population Survey Food Security Supplement (CPS-FSS) for the years from 2001–2010.^{25,26} We identify a sample of 37,277 citizen children, ages 0–17, who live in households that report receiving SNAP, and link them to market group TFP prices according to location of residence.

Substate geographic information is incomplete in the CPS, but we are still able to use the available information to assign more than 85 percent of households to market groups. First, for states where combined statistical areas (CSAs) or core-based statistical

²⁴ Food insecurity is a household-level measure of well-being, defined as being unable to obtain, or uncertain of obtaining, an adequate quantity and quality of food due to money or resources. Very low food security is defined as food insecurity that includes disrupted or restricted dietary patterns. Prior to 2006, very low food security was labeled "food insecurity with hunger". Throughout, we use the phrases "very low food security" and "very food insecure" interchangeably.

²⁵ While our NHIS analysis spans from 1999 to 2010, the December CPS food security supplement was not collected in 1999 and 2000 but has been consistently used for studying food insecurity since 2001. Prior to 2001, the food security supplement was collected in varying months (April, August, or September, depending on the year).

²⁶ As our indicator of food insecurity, we use a pre-coded CPS variable (hrfs12m1) that combines information from a series of 18 questions on access to food. We treat respondents as food insecure if they are indicated as facing food insecurity with hunger or without hunger.

Table 2
Effect of SNAP Purchasing Power on Per-Capita SNAP Caseload.

Dependent Variable = SNAP Caseload / County Population	(1)	(2)	(3)	(4)	(5)
log(SNAPMAX/TFP)	0.091** (0.036)	0.024 (0.089)	0.003 (0.088)	−0.004 (0.079)	0.010 (0.085)
Mean of dep. var.	0.111	0.111	0.111	0.111	0.111
Effect of a 10% increase in SNAP purchasing power	0.009	0.002	0.000	0.000	0.001
As a % of mean of dep. var.	7.8%	2.1%	0.3%	−0.3%	0.9%
N	37,277	37,277	37,277	37,177	37,177
R ²	0.299	0.497	0.514	0.539	0.544
Fixed effect for year, market group	Yes	Yes	Yes	Yes	Yes
County UR	No	Yes	Yes	Yes	Yes
State SNAP and other policy controls	No	No	Yes	Yes	Yes
Regional price controls	No	No	No	Yes	Yes
Linear time trend	No	No	No	No	Yes

Notes: Data consists of county by year panel for 1999–2010. Results are weighted using county population. Standard errors in parentheses are corrected for clustering at the market group level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include fixed effects for market group and year. Columns (2)–(5) add controls for the county unemployment rate; an index of state SNAP policies (Ganong and Liebman, 2018), the state minimum wage, EITC, and Medicaid/SCHIP income eligibility limits, and TANF generosity; controls for HUD's fair market rent and regional CPIs for non-food, non-housing categories (apparel, commodities, education, medical, recreation, services, transportation and other goods and services); and a market group-specific linear time trend.

areas (CBSAs) that are within a single market group, we assign all respondents residing in that jurisdiction to the relevant market group. Second, respondents living in counties that are identified in the CPS are matched to their county's market group. 71.2 percent of December CPS respondents are matched to a market group in one of these two ways. Third, we take the CPS respondents living in non-metropolitan areas and assign these households to the rural market group ("other northeast," "other central," etc.) for states where there is only one "other" market group. An additional 14.2 percent of respondents are matched through this step, leading to an overall match rate of 85.4 percent. Excluded from our analyses are respondents residing in non-metropolitan areas in states with multiple market groups. In terms of external validity, therefore, our CPS food insecurity analyses cannot speak fully to the impact of variation in SNAP purchasing power on children in rural areas.

3. Empirical methods

We estimate the causal impact of variation in the real value of SNAP benefits on measures of child health and health care utilization for children in households who report receiving SNAP benefits during the past 12 months. Throughout, our regressions take the following form:

$$y_{irt} = \alpha + \beta \ln \left(\frac{\text{SNAPMAX}_t}{\text{TFP}_{rt}} \right) + X_{irt}\theta + Z_{rt}\gamma + \delta_t + \lambda_r + \varepsilon_{irt} \quad (1)$$

where y_{irt} is the health outcome of individual i who resides in region r (market group) in time t . The key independent variable is the natural log of the ratio of maximum SNAP benefits for a family of four (which vary by year, but are constant across regions) to the TFP price in region r in year t . The vector X_{irt} contains a set of controls for the child's characteristics, including his/her age (and its square), race, Hispanic ethnicity, family size, indicators for the presence of the mother (and/or father) in the household, and interactions between indicators for the mother's (father's) presence and the mother's (father's) education, marital status, age, and citizenship. The unemployment and state policy variables described in Section 2.3 are included in Z_{rt} , as are the county HUD fair market rent and a set of regional CPIs in non-food, non-housing consumption categories. All models also include a full set of fixed effects for the year (δ_t) and market group (λ_r). In all models, the standard errors are corrected for clustering at the market group level.

One important question is how much variation in the cost of food remains after controlling for the prices of other goods. Appendix Table 1 shows an R^2 of 0.82 when regressing our main food price measure on other price indexes, and R^2 of 0.97 after adding fixed

effects. Appendix Fig. 3 plots the residuals, which exhibit a fair amount of idiosyncratic variation. What causes these residuals (and leads to our plausibly exogenous variation) is by definition difficult to explain but could be related to local wages and demand conditions, which grocery/outlet chains are in a market, or local supply shocks.²⁷

Identification in this model comes from variation in trends in the price of the Thrifty Food Plan across market groups. As we discussed in Section 2.1 (see Fig. 1), there is substantial variation across geographic areas in the purchasing power of SNAP benefits, but this variation is netted out in our estimation by market group fixed effects. More importantly for our identification strategy, these regional differences change over time (see Fig. 2a and b), with some areas experiencing larger increases in SNAP purchasing power from 1999 to 2010, and others experiencing smaller increases (e.g., purchasing power in some southern metropolitan areas increased nearly 17 percent, but only about 4.5 percent in urban New York).²⁸

4. Results

4.1. SNAP participation

We begin by analyzing the effects of SNAP purchasing power on the SNAP caseload. If variation in the real value of SNAP leads to changes in SNAP participation, then selection may bias our estimates of the effect of SNAP purchasing power on child health.

Using data from USDA, we construct a county panel for annual SNAP caseloads covering 1999–2010. We estimate Eq. (1) where the dependent variable is SNAP caseloads divided by county population. Table 2 displays the results of five different specifications of the model. Each includes year and market group fixed effects, as well as the natural log of the ratio of maximum SNAP benefits to the market group TFP price. In the second column we add a control for the county unemployment rate, which is a determinant of SNAP caseloads (Bitler and Hoynes, 2016) and possibly correlated

²⁷ It is similarly difficult to fully explain regional prices for other commodities such as gasoline in California. See for example Borenstein et al. (2004) and Borenstein (2015).

²⁸ SNAP benefits in 2010 and 6 months of 2009 include increased benefits provided through the American Recovery and Reinvestment Act (ARRA). ARRA benefits amounted to \$62, or about a 13.6 percent increase above the base 2009 levels. Over the period prior to the ARRA, changes in SNAP purchasing power ranged from a decrease of 5.8 percent in San Francisco to 4.3 percent increase in metropolitan areas in Arkansas and Oklahoma.

Table 3

Effects of Variation in SNAP Purchasing Power on Children's Health Care Utilization. Sample: SNAP Recipient U.S. Citizen Children in the NHIS, 1999–2010.

	Children in Sample Child File			All Children
	(1) Had a checkup past 12 m	(2) Doctor's visit past 12 m	(3) Any ER visit past 12 m	(4) Delay or forgo care past 12 m
log(SNAPMAX/TFP)	0.656*** (0.225)	0.323** (0.147)	−0.178 (0.215)	−0.089 (0.092)
Mean of dep. var.	0.770	0.901	0.315	0.051
Effect of 10% increase in SNAP purchasing power	0.063	0.031	−0.017	−0.009
As a % of mean of dep. var.	8.1%	3.4%	−5.4%	−16.6%
N	18,169	18,108	18,217	44,626
R ²	0.077	0.038	0.046	0.022

Notes: Results from weighted OLS regressions. Standard errors in parentheses are corrected for clustering at the market group level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include controls for the child's age (and its square), whether the child is black or Hispanic, the child's family size, indicators for the presence of the mother (and/or father) in the household, and interactions between indicators for the mother's (father's) presence and the mother's (father's) education, marital status, age, and citizenship. All regressions also include controls for local economic and policy variables: the county unemployment rate, an index of state SNAP policies (Ganong and Liebman, 2018), the state minimum wage, EITC, Medicaid/CHIP income eligibility limits, TANF generosity, as well as controls for HUD's fair market rent, and regional CPIs for non-food, non-housing categories (apparel, commodities, education, medical, recreation, services, transportation and other goods and services). Finally, all models include year and market group fixed effects. Outcomes in columns 1–3 are observed only for children in the Sample Child files.

with regional prices. In column 3 we add controls for state policy variables, including for SNAP, EITC, minimum wages, TANF generosity, and Medicaid. In column 4 we add controls for regional prices, including the county HUD fair market rent and regional CPIs for goods other than food. In column 5, we extend the specification by including a market group linear time trend.

When only year and market group fixed effects are included, the estimated coefficient on SNAP purchasing power is positive and statistically significant, consistent with the SNAP caseload per capita rising when the purchasing power of SNAP increases. However, once we add the county unemployment rate, in column (2), the coefficient drops substantially in magnitude and is no longer statistically different from zero. The addition of the state policy controls (column 3) and the regional prices (column 4) does not change the coefficient meaningfully. Adding market group-specific linear time trends (column 5) leads to little change in the estimated coefficient on SNAP purchasing power.

In Appendix Table 2, we show that these results are robust to the addition of further controls for local economic conditions, including aggregate and sector-specific employment and wages from the QCEW. Appendix Table 3 presents the results of analogous regressions at the individual level, wherein we estimate the relationship between SNAP purchasing power and the likelihood of SNAP participation among children ages 0–17 in the Sample Child Files of the NHIS (1999–2010) and the December CPS (2001–2010). Similar to the per capita caseload analysis (Table 2), the individual-level results also document no evidence of a statistically significant relationship between SNAP purchasing power and SNAP participation. Taking all of this evidence together, we conclude that there is no statistically significant relationship between the real value of SNAP and SNAP participation, and thus we interpret our main results free of concerns about selection.

4.2. SNAP purchasing power and health care utilization

The primary goal of our study is to analyze the impacts of variation in the purchasing power of SNAP benefits on outcomes related to child health. We begin by examining evidence for measures of health care utilization, recognizing that families facing higher food prices may respond to lower real value of their SNAP benefits by reducing out-of-pocket spending on other goods, including health care.

We present the results of this analysis in Table 3. Our primary measure of health care utilization is an indicator for whether the child has had a check-up in the past 12 months (column 1), which is observed only for children in the Sample Child file. We also exam-

ine indicators for whether the child has had any doctor's visit in the past 12 months (column 2), and whether a child has visited an ER in the past 12 months (column 3). Whether a child has delayed or forgone care is reported in the Person file of the NHIS so is observed for all NHIS children under age 18; we report this estimate in column 4. The model includes fixed effects for market group, year, individual controls, and regional controls for unemployment rate, non-food prices, and state safety net policies (similar to column 4 of Table 2).²⁹ The key independent variable, representing SNAP purchasing power, is $\ln(\text{SNAPMAX}/\text{TFP})$.

Among SNAP-recipient children, we find that increased purchasing power of SNAP raises the likelihood a child has had a checkup in the past 12 months. A ten percent increase in the ratio (SNAPMAX/TFP) leads to a 6.3 percentage point (or 8.1 percent) increase in the likelihood of a checkup. We also estimate a smaller but statistically significant impact of increased SNAP purchasing power on the probability a child has had any doctor's visit over the past 12 months. A ten percent increase in the purchasing power of SNAP raises the likelihood of any doctor's visit by 3.1 percentage points, or 3.4 percent.

The estimated effects of SNAP purchasing power on whether children have visited the ER in the past 12 months, or on whether they are reported to have delayed or forgone care due to cost (Table 3, columns 3 and 4) are statistically insignificant. Taken at face value, however, the coefficients are negative, consistent with a protective effect of SNAP.

4.3. SNAP purchasing power and health outcomes

Table 4 presents evidence on the extent to which variation in SNAP purchasing power affects child health outcomes. The regression specifications include the same set of controls as in Table 3. Note that several of the outcomes are defined only for sub-samples of children, leading to different numbers of observations across the columns of Table 4. Specifically, obesity is measured only for children ages 12 through 17,³⁰ emotional problems are identified for

²⁹ Individual-level controls include the child's age (and its square), whether the child is black or Hispanic, the child's family size, indicators for the presence of the mother (and/or father) in the household, and interactions between indicators for the mother's (father's) presence and the mother's (father's) education, marital status, age, and citizenship.

³⁰ The indicator for obesity is based on BMI calculations, which are affected by some outlying height and weight measurements. We trim the top and bottom of the BMI distribution to exclude the top and bottom percentile. In addition, height and weight information was only collected for children ages 12 and older in years 2008 through 2010. We therefore limit the sample to children ages 12–17.

Table 4

Effects of Variation in SNAP Purchasing Power on Children's Health Outcomes. Sample: SNAP Recipient U.S. Citizen Children in the NHIS, 1999–2010.

	Children in Sample Child File				All NHIS Children 0-17	
	(1) School days missed due to illness	(2) 5 or more school days missed	(3) Obese	(4) Emotional problem	(5) Health status excellent or very good	(6) Hospitalized overnight past 12 m
log(SNAPMAX/TFP)	–11.43** (5.374)	–0.148 (0.272)	–0.24 (0.374)	0.055 (0.468)	–0.121 (0.199)	0.020 (0.065)
Mean of dep. var.	4.955	0.332	0.199	0.464	0.700	0.075
Effect of 10% increase in SNAP purch. power	–1.090	–0.014	–0.023	0.005	–0.012	0.002
As a % of mean of dep. var.	–22.0%	–4.2%	–11.5%	1.1%	–1.6%	2.6%
N	11,420	11,420	4,471	10,779	44,627	44,620
R ²	0.033	0.041	0.035	0.055	0.032	0.150

Notes: Results from weighted OLS regressions. Standard errors in parentheses are corrected for clustering at the market group level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include the same controls as in Table 3. Outcomes in columns 1–4 are observed only for children in the Sample Child files. Missed school days is defined only for children ages 5 and older who attend school; information on obesity is consistently available for children ages 12–17, trimmed to exclude the top and bottom percentile of the BMI distribution; and emotional problem is defined for the universe of children ages 4 and older.

children ages 4 and older, and the number of school days missed is recorded only for children age 5 and older who are in school. Parent-reported health status and hospitalization in the past 12 months are reported for all children, but the other health outcomes are only provided for children in the Sample Child file.

We document a strong negative and robust relationship between the real value of SNAP and the number of school days children missed due to illness. For SNAP recipient children, a ten percent increase in SNAP purchasing power is associated with a decrease in missed school days of just over 1 day (or a 22 percent decrease relative to the mean of approximately 5 days missed). However, we estimate no statistically significant relationship between SNAP purchasing power and an indicator for the child's (parent-reported) health status being excellent or very good, nor the likelihood of having been hospitalized in the past year.³¹

The evidence in Table 4 indicates no statistically significant relationship between SNAP purchasing power and obesity or the propensity to have emotional problems, but the results are imprecisely estimated, and the wide confidence intervals prevent us from ruling out sizeable positive or negative effects. We also note that these are longer term health problems that often develop over time and should be less likely to respond contemporaneously to variation in SNAP purchasing power. It is possible that these outcomes would be likely to respond only after a longer, cumulative period of food insecurity, poor nutrition, or reduced health care.

4.4. Summary index tests

To address concerns of multiple hypothesis testing, we conduct a collective test of these health care utilization and health outcomes by constructing summary index estimates as in Kling et al. (2007). We normalize and combine the outcomes into a health care utilization index and a health index, changing signs when necessary so that all positive outcomes reflect more desirable health care utilization or health outcomes. The index for health care utilization includes the variables for whether the child had a checkup, any doctor visits, delayed seeking health care, and any ER visit. Specifically, the index is the sum of the standardized versions of these variables, with the indicators for delaying health care or having an ER visit both multiplied by –1 to reflect that increases in these outcomes are undesirable. The summary index for health outcomes adds the standardized versions of the indicators for excellent or very good health status, any hospitalizations, and emotional prob-

Table 5

Summary Index Estimates. Sample: SNAP Recipient U.S. Citizen Children in the NHIS, 1999–2010.

	(1) Index for health care utilization	(2) Index for health outcomes
log(SNAPMAX/TFP)	0.919*** (0.298)	0.311 (0.354)
Mean of dep. var.	–0.003	0.032
Effect of 10% increase in SNAP purchasing power	0.088	0.030
N	18,023	9,514
R ²	0.043	0.036

Notes: Table features coefficients from mean effects estimates for health care utilization variable (checkups, any doctor visits, delay seeking health care, and any ER visit) or for health outcome variables (school days missed, emotional problem, health status, and any hospitalization). Obesity is not included in the health outcomes index because it is only defined for children ages 12 and older. In constructing the index, an outcome variable enters positively if a higher value of the outcome is desirable (e.g., checkups, any doctor visits, and health status) and negatively if the variable reflects an undesirable outcome (e.g., delay or forgo seeking care, any ER visit, school days missed, emotional problem, and any hospitalization). Variables are standard normalized and averaged, so coefficient represents standard deviation units. All observations are from the Sample Child file and from the sub-sample for whom we observe all relevant outcomes.

lems, and the number of school days missed, with the latter three multiplied by –1.³²

Results are shown in Table 5. We find that a 10% increase in SNAP purchasing power leads to a statistically significant 0.09 standard deviation increase in health care utilization. The estimated effect of SNAP purchasing power on children's health is positive but smaller in magnitude and not statistically significant.

Broadly, we interpret our results (in Tables 3 and 5) as indicating that children in households facing lower SNAP purchasing power receive less preventive and ambulatory care. Our findings for health outcomes (Tables 4 and 5) suggest that variation in the real value of SNAP may lead to changes in school attendance but has no overall impact on children's contemporaneous health. To gauge the magnitudes of our main results, it is helpful to consider that a 10 percent increase in SNAP purchasing power amounts to an additional \$15–\$40 per SNAP recipient per month, or an additional \$800–\$2200 per year for SNAP households.³³ In light of this

³¹ We also estimated impacts on fair/poor health though this is very low incidence even in our disadvantaged sample (4.8 percent of children). As with excellent/very good health, the coefficient is wrong signed.

³² Note that obesity is not included in the construction of the health outcomes summary index because it is only defined for the much smaller sample of children ages 12–17.

³³ We calculate the per-recipient, per-month increase by noting that the average SNAP purchasing power ratio in our sample is 0.7 (because the average per-person SNAP maximum is \$143, and the average TFP price is \$203). To increase that ratio

increase in resources, we view an 8 percent increase in the likelihood of getting the child to his/her recommended annual checkup and a 1-day reduction in school absences as plausible.³⁴

5. Mechanisms and robustness checks

5.1. Mechanisms

We outlined three possible mechanisms for effects of SNAP purchasing power on child health care utilization and health, including: direct (nutrition) effects, indirect (other goods) effects, and stress/bandwidth effects.

One test for the direct channel is to examine impacts of SNAP purchasing power on food insecurity. Children in families facing higher SNAP purchasing power may be able to consume more (or higher quality) food, which may then lead to a reduction in food insecurity. Because the NHIS did not provide information on food security or nutritional intake in the years of data we analyze, we turn to data from the December food security supplement to the CPS to estimate the impact of SNAP purchasing power on food insecurity among SNAP-recipient children.

We display these results in Table 6.³⁵ We find that a higher real value of SNAP benefits is associated with an improvement in children's food security: A 10 percent increase in SNAP purchasing power reduces the likelihood a child is food insecure by 6.4 percentage points (a 21.3 percent decrease relative to the mean). These results are qualitatively quite similar to those in Gregory and Coleman-Jensen (2013), which used fewer years of the same data and a different estimation strategy. They are also robust to the inclusion of additional controls for local economic conditions like employment and wages (see Appendix Table 4). The estimate for very food insecure (column 2) is not statistically significant, but the standard error is large. This degree of food insecurity is a rare outcome even for SNAP children (only 4 percent of the children in our sample are very food insecure, while almost 30 percent are food insecure). In particular, a household that is very food insecure is not only uncertain of obtaining an adequate quantity and quality of food due to money or resources, but has also experienced restricted or disrupted food intake because of a lack of resources. It is perhaps not surprising, then, that this more extreme outcome does not display a statistically significant relationship to SNAP purchasing power. Nonetheless, because the estimates are imprecise, we are unable to rule out large positive or negative impacts.

Overall, these results are suggestive that the direct effect may be part of the mechanism for our findings. In addition, they confirm a well-studied and robust finding that higher SNAP generosity leads to a reduction in food insecurity (see review of the evidence in Hoynes and Schanzenbach, 2016). This is important as it provides validation for our research design.³⁶

by 10 percent would require an increase in SNAP benefits of approximately \$15 or a decrease in the TFP cost of approximately \$40. We calculate the annual increase for households by multiplying by 12 and then by the average family size for SNAP households in our sample (4.7).

³⁴ There are few comparable estimates in the literature. East (2019) finds that \$1,000 of additional food stamps received in early childhood (*in utero* to age 4) leads to a reduction in 0.5 school days missed at ages 6–16.

³⁵ The regression specifications include the same set of controls as in Tables 3 and 4 except that we do not control for local CPI for nonfood nor the HUD fair market rent data, which are measured at the county level, because we cannot identify counties in the CPS.

³⁶ Of the 16 questions that form the definition of food insecurity, the point estimate is negative for 13 – consistent with higher SNAP purchasing power lowering food insecurity. The most robust statistically significant finding is for the question, “The children were not eating enough because we couldn’t afford enough food.” Was that often, sometimes, or never true for you over the past 12 months?” Note that while there are a total of 18 questions used to assess food security in the CPS, we omit two

Table 6

Effects of SNAP Purchasing Power on Food Insecurity Sample: SNAP Recipient U.S. Citizen Children in the December CPS, 2001–2010.

	(1) Child is food insecure	(2) Child is very food insecure
log(SNAPMAX/TFP)	−0.670* (0.330)	0.086 (0.107)
Mean of dep. var.	0.301	0.034
Effect of 10% increase in SNAP purchasing power	−0.064	0.008
As a % of mean of dep. var.	−21.3%	23.5%
N	29,324	29,324
R ²	0.033	0.021

Notes: Results from weighted OLS regressions. Standard errors in parentheses are corrected for clustering at the market group level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Because narrow geographic information is only available for the largest metropolitan areas in the CPS, we use the following algorithm to assign households to market groups. First, for states, combined statistical areas (CSAs), and core-based statistical areas (CBSAs) that are within a single market group, we assign all respondents residing in that jurisdiction to the relevant market group. We then match all respondents with valid county-level information to their county's market group. 71.2 percent of CPS respondents are matched to a market group this way. Next, we take the CPS respondents living in non-metropolitan areas and assign these households to the rural market group (“other northeast,” “other central,” etc.) for states where there is only one “other” market group. An additional 14.2 percent of respondents are matched through this step, leading to an overall match rate of 85.4 percent. Excluded from our analyses are respondents residing in non-metropolitan areas in states with multiple market groups. All regressions include controls for the child's age (and its square), whether the child is black or Hispanic, the child's family size, indicators for the presence of the mother (and/or father) in the household, and interactions between indicators for the mother's (father's) presence and the mother's (father's) education, marital status, age, and citizenship. All regressions also include controls for local economic and policy variables: the state unemployment rate, an index of state SNAP policies (Ganong and Liebman, 2018), the state minimum wage, EITC, and Medicaid/CHIP income eligibility limits, and TANF generosity. Finally, all models include year and market group fixed effects.

Table 7

Effects of SNAP Purchasing Power on Health Insurance Coverage. Sample: SNAP Recipient U.S. Citizen Children in the NHIS, 1999–2010.

	(1) Child has no health insurance
log(SNAPMAX/TFP)	−0.071 (0.136)
Mean of dep. var.	0.067
Effect of 10% increase in SNAP purchasing power	−0.007
As a % of mean of dep. var.	−10.1%
N	44,540
R ²	0.033

Notes: Results from weighted OLS regressions. Standard errors in parentheses are corrected for clustering at the market group level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include controls for the child's age (and its square), whether the child is black or Hispanic, the child's family size, indicators for the presence of the mother (and/or father) in the household, and interactions between indicators for the mother's (father's) presence and the mother's (father's) education, marital status, age, and citizenship. All regressions also include controls for local economic and policy variables: the county unemployment rate, an index of state SNAP policies (Ganong and Liebman, 2018), the state minimum wage, EITC, and Medicaid/CHIP income eligibility limits, TANF generosity, as well as controls for HUD's fair market rent, and regional CPIs for non-food, non-housing categories (apparel, commodities, education, medical, recreation, services, transportation and other) goods and services. Finally, all models include year and market group fixed effects.

In Table 7 we investigate whether the impacts of SNAP on health care utilization and health could be explained by a relationship between SNAP purchasing power and health insurance coverage.

questions that are conditional on preceding questions and ask only “How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?”

Such a relationship would be unexpected for this sample, given that SNAP recipient children are all likely to be income-eligible for Medicaid or CHIP. Returning to our sample of NHIS children, we estimate Eq. (1), where the dependent variable is now an indicator for whether the child is uninsured. While the standard errors suggest wide confidence intervals, it is somewhat reassuring that we do not estimate a statistically significant relationship between SNAP purchasing power and the likelihood a child has no health insurance. Additionally, the estimates in Appendix Table 5 suggest no statistically significant relationship between SNAP purchasing power and children's participation in other food and nutrition programs.

Two of our most robust findings – that higher SNAP purchasing power leads to reductions in school absences and increases in compliance with well child checkups – are consistent with the stress and bandwidth channel. We are limited in our ability to test more directly for this channel, though the NHIS does include mental health variables for the sample adult. These include questions related to how often the respondent felt sad, worthless, nervous, hopeless, etc. We analyzed the relationship between SNAP purchasing power and these variables for sample adults who were mothers of the children in our sample and found small and statistically insignificant estimates, though the signs of the coefficients are consistent with protective effects of SNAP purchasing power on these measures of mental health (see Appendix Table 6).

5.2. SNAP purchasing power versus local prices

A natural check of our main results is to estimate our models for health care utilization and health outcomes on a placebo sample of children that should not be affected by SNAP. We present results for two groups: non-citizen children and children living with mothers who have a college education or higher, both of which have low rates of SNAP participation.³⁷ If our main results reflect impacts of SNAP on children's health, rather than simply impacts of local food prices, we would expect SNAP purchasing power to have no significant impact on these placebo samples.

The results for the health care utilization index and health outcomes index in these two placebo samples are presented in Table 8. Column 1 presents estimates for the college educated sample, and Column 2 presents estimates for non-citizen children. SNAP participation rates are low among these samples, at 2 percent for children living with college educated mothers, and 14 percent for non-citizen children.³⁸ Confirming our expectations, we find small statistically insignificant coefficients on the indices for both non-citizen children and children with college educated mothers. Appendix Table 7 (panels A and B) provides the full set of outcomes for our placebo samples. The estimates are small and statistically insignificant; in fact only one of the 20 coefficients is (marginally) statistically significant (for the presence of an emotional problem in the non-citizen children sample). In Appendix Table 8, our estimates indicate no evidence of a statistically significant impact of

SNAP purchasing power on child food insecurity in these placebo samples.

We also explore the sensitivity of our findings to whether we control for non-food regional CPI price controls (such as housing, energy, transportation, et cetera). As shown in Appendix Table 9, our main results in Tables 3 and 4 are qualitatively unchanged if we drop the regional price controls, suggesting that we are not simply capturing the broader effects of living in a more or less expensive market.³⁹ More generally, there is no evidence that SNAP purchasing power is associated with household income and poverty, suggesting that we are not capturing the effects of local labor market conditions.⁴⁰

5.3. Robustness checks

As shown in Fig. 2b, our measure of SNAP purchasing power exhibits a large increase across all geographic areas following the ARRA temporary benefit increase. In Appendix Tables 10 and 11 we test the sensitivity of these results to excluding the years of ARRA expansions (2009 and 2010). The results show that limiting the data to the pre-ARRA period generates qualitatively similar findings to our main estimates (Tables 3 and 4), although they are somewhat less precisely estimated. The pre-ARRA period estimates show a beneficial effect of SNAP purchasing power on healthcare utilization among SNAP children (Appendix Table 10) and health care outcomes (Appendix Table 11). We also test for equality of coefficients between the full sample and pre-ARRA sample. Those results, provided in the bottom row of Appendix Tables 10 and 11, indicate that we cannot reject equality for 12 of the 13 sets of coefficients (the p-value on the test of equality for “had a checkup in the past 12 m” is 0.053, but the estimate remains positive and statistically significant when we drop the ARRA years).⁴¹ We conclude that the main results in Tables 3 and 4 are not being driven by the ARRA expansions.

Table 9 displays the results of a series of additional robustness checks to our main findings regarding the impacts of SNAP purchasing power on health care utilization and health. In panel A, we re-estimate the models including a lead term that uses the market group TFP price in period $t + 1$. This lead specification provides a test for the validity of our fixed effects design. If the estimated coefficient on future SNAP purchasing power is statistically significant (while controlling for current purchasing power), we might be concerned that we are capturing the effects of some other trend in the regions. That is, we estimate:

$$y_{irt} = \alpha + \beta_1 \ln \left(\frac{\text{SNAPMAX}_t}{\text{TFP}_{rt}} \right) + \beta_2 \ln \left(\frac{\text{SNAPMAX}_{t+1}}{\text{TFP}_{r,t+1}} \right) + X_{irt}\theta + Z_{rt}\gamma + \delta_t + \lambda_r + \varepsilon_{irt} \quad (2)$$

Only in one of the ten specifications is the lead of SNAP purchasing power statistically significant. Importantly, our results for the contemporaneous effect of SNAP purchasing power are largely unchanged: The magnitudes of the estimated coefficients for “had

³⁷ An alternative placebo group could be based on family income (since SNAP eligibility requires income below 130 percent of poverty). This is potentially problematic, however, as the NHIS exhibits high levels of income non-response (weighted item nonresponse rates to an exact amount question on annual total family income were around 30 percent during our study period; see Pleis et al., 2007). As with our main sample, the placebo sample of children with college-educated mothers is limited to children ages 0 through 17 who are citizens of the U.S.

³⁸ As discussed above, some noncitizen are eligible for SNAP. Additionally, mixed status households are common, consisting of some family members that are citizens and some that are not. SNAP is a household benefit so an ineligible child could live in a household with some eligible family members and thus “participate” in SNAP (that is, be in a household with SNAP benefits).

³⁹ In results not shown here, we estimated models where we dropped the non-food regional CPI price controls and the state SNAP and other policy controls, and find very similar results.

⁴⁰ In particular, we use the 1999–2010 Annual Social and Economic Supplement to the CPS and estimate the relationship between SNAP purchasing power and official poverty, after tax and transfer income poverty (excluding SNAP from the resource measure), and log after tax and transfer income. We find small and statistically insignificant estimates for all of these outcomes. Results are available on request.

⁴¹ A related check is to include 2009 and 2010 but use a simulated benefit measure that suppresses the ARRA SNAP adjustment. We find results that are very similar to our main estimates (available upon request).

Table 8
Summary Index Estimates, Placebo and Alternative Treatment Groups.

A. Health Care Utilization			
SAMPLE	Placebo Samples		Alternative Treatment Group
	(1) Children of College Educated Mothers	(2) Noncitizen Children	(3) Citizen Children of Low-Education Unmarried
log(SNAPMAX/TFP)	0.213 (0.271)	−0.189 (0.442)	0.793*** (0.264)
Mean of dep. var.	−0.008	0.013	−0.002
Effect of 10% increase in SNAP purchasing power	0.020	−0.018	0.076
N	28,538	5,402	17,651
R ²	0.05	0.13	0.05
B. Health Outcomes			
SAMPLE	Placebo Samples		Alternative Treatment Group
	(1) Children of College Educated Mothers	(2) Noncitizen Children	(3) Citizen Children of Low-Education Unmarried
log(SNAPMAX/TFP)	−0.016 (0.207)	−0.027 (0.436)	0.650 (0.457)
Mean of dep. var.	−0.047	0.020	0.033
Effect of 10% increase in SNAP purchasing power	−0.001	−0.003	0.062
N	15,863	3,941	9,869
R ²	0.03	0.05	0.03
Mean SNAP participation rate	0.02	0.14	0.48

Notes: Table features coefficients from mean effects estimates for health care utilization variable (checkups, any doctor visits, delay seeking health care, and any ER visit) or for health outcome variables (school days missed, emotional problem, health status, and any hospitalization). Note that obesity is not included in the health outcomes index because it is only defined for children ages 12 and older. In constructing the index, an outcome variable enters positively if a higher value of the outcome is desirable (e.g., checkups, any doctor visits, and health status) and negatively if the variable reflects an undesirable outcome (e.g., delay or forgo seeking care, any ER visit, school days missed, emotional problem, and any hospitalization). Variables are standard normalized and averaged, so coefficient represents standard deviation units. All observations are from the Sample Child file and from the sub-sample for whom we observe all relevant outcomes. The sample varies by column.

checkup” and “school days missed” are quite similar to those in Tables 3 and 4. One exception is that the estimated impact of current-period SNAP purchasing power on whether a child had any doctor’s visit in the past 12 months is a third as large and is no longer statistically significant.

The second panel of Table 9 contains results from a model that includes a set of market group linear time trends. This approach places serious demands on the data in that identification now must come from departures in market groups’ TFP prices from their trends (assumed to be linear). The main estimates for health care utilization (had checkup, had any doctor’s visit) are qualitatively similar to those in Table 3, but they are smaller in magnitude and no longer statistically significant. The estimated impact of SNAP purchasing power on missed school days, however, remains nearly identical in magnitude and significance to that in Table 4.

Finally, to address concerns about endogenous selection into our sample of SNAP recipients or bias from underreporting of SNAP receipt, we estimate the impacts of variation in SNAP purchasing power for an alternative high intent-to-treat sample. In particular, we identify a sample of children living with unmarried parent(s) with less than a college education. In this alternative treatment group, 48 percent of NHIS children live in households participating in SNAP. Even though this is a high intent to treat group, based on the SNAP participation rate as well as other characteristics it is more advantaged, on average, than our main treatment group (SNAP children). Therefore, we expect somewhat lower effects of SNAP purchasing power in this sample.

The results for health care utilization and health outcomes are presented in panel C of Appendix Table 7, and the index models are shown in column 3 of Table 8. The estimated impacts on the likelihood of a checkup and on the number of missed school days are quite similar in magnitude to those for our main sample (although the p-value on the coefficient for missed school days rises to 0.141). The estimated relationship between SNAP purchas-

ing power and having had any doctor’s visit is smaller and no longer statistically significant. Interestingly, we document a negative effect of increased SNAP purchasing power on ER utilization for this somewhat higher-income sample: a 10 percent increase in the ratio (SNAPMAX/TFP) reduces the likelihood of an ER visit by 4.8 percentage points.⁴² Using tests of equality across our main and alternative treatment sample, we cannot reject equality for all but one outcome (doctor’s visit, $p = 0.094$).

The results for food insecurity, however, are somewhat different for this alternative treatment group. As shown in Column 3 of Appendix Table 8, the estimated effect of SNAP purchasing power on child food insecurity is negative (as expected) but statistically insignificant. Given that this alternative treatment group has a lower rate of food insecurity, 0.19 compared to 0.30 in the main sample of SNAP recipient children, it is perhaps not surprising that the estimated relationship between SNAP generosity and food insecurity is more muted for this sample.

6. Discussion and conclusion

In this paper we provide some of the first direct evidence on how variation in the purchasing power of SNAP benefits affects children’s health care utilization and health outcomes. We find evidence consistent with families adjusting to lower SNAP purchasing power by reducing utilization of preventive/ambulatory medical care. In particular, we document that a 10 percent increase in SNAP purchasing power increases the likelihood a child had a check-up in the past year by 8.1 percent and increases the likeli-

⁴² We also tested models with additional family control variables including income, parental health status, and an indicator for insurance coverage. As these may change endogenously with SNAP purchasing power, we omit them from our main specifications. The results are generally similar, however; see Appendix Tables 12 and 13.

Table 9

Effects of SNAP Purchasing Power on Health Care Utilization and Health: Robustness Checks. Sample: SNAP-Recipient U.S. Citizen Children, 1999–2010.

	A. Health Care Utilization				B. Health Outcomes					
	Children in Sample Child File		All Children		Children in Sample Child File		All Children			
A. Include lead term using future TFP price	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)	(6)
	Had checkup	Doctor's visit	Any ER visit	Delay or forgo care	School days missed	5+ school days missed	Obese	Emotional problem	Health status exc or v good	Hosp. overnight
log(SNAPMAX/TFP _t)	0.517* (0.278)	0.111 (0.161)	0.011 (0.308)	0.040 (0.089)	−13.48** (5.90)	−0.161 (0.327)	−0.273 (0.535)	0.003 (0.774)	−0.065 (0.305)	0.043 (0.060)
log(SNAPMAX/TFP _{t+1})	0.194 (0.247)	0.260 (0.192)	−0.386 (0.238)	−0.185* (0.097)	−4.756 (4.020)	−0.303 (0.295)	0.072 (0.473)	0.266 (0.792)	−0.155 (0.316)	−0.076 (0.089)
Mean of dep. var.	0.764	0.900	0.312	0.054	4.981	0.333	0.201	0.459	0.697	0.075
Effect of 10% increase in SNAP PP	0.049	0.011	0.001	0.004	−1.284	−0.015	−0.026	0.000	−0.006	0.004
As a % of mean of dep. var.	6.5%	1.2%	0.3%	7.1%	−25.8%	−4.6%	−13.0%	0.1%	−0.9%	5.5%
N	15,874	15,821	15,916	39,070	9,971	9,971	3,897	9,164	39,070	39,063
R ²	0.082	0.039	0.049	0.023	0.036	0.043	0.039	0.058	0.032	0.153
B. Include market group-level linear time trends	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)	(6)
	Had checkup	Doctor's visit	Any ER visit	Delay or forgo care	School days missed	5+ school days missed	Obese	Emotional problem	Health status exc or v good	Hosp. overnight
log(SNAPMAX/TFP _t)	0.268 (0.272)	0.148 (0.196)	0.073 (0.315)	−0.032 (0.116)	−12.53* (6.82)	−0.018 (0.289)	−0.351 (0.433)	−0.098 (0.671)	−0.228 (0.248)	0.078 (0.064)
Mean of dep. var.	0.770	0.901	0.315	0.051	4.955	0.332	0.199	0.464	0.700	0.075
Effect of 10% increase in SNAP PP	0.026	0.014	0.007	−0.003	−1.194	−0.002	−0.034	−0.009	−0.022	0.007
As a % of mean of dep. var.	3.3%	1.6%	2.2%	−5.9%	−24.1%	−0.5%	−16.8%	−2.0%	−3.1%	9.9%
N	18,169	18,108	18,217	44,626	11,420	11,420	4,471	10,779	44,627	44,620
R ²	0.081	0.042	0.048	0.025	0.038	0.044	0.043	0.058	0.033	0.151

Notes: Results from weighted OLS regressions. Standard errors in parentheses are corrected for clustering at the market group level; *** p < 0.01, ** p < 0.05, * p < 0.1. All regressions include controls for the child's age (and its square), whether the child is black or Hispanic, the child's family size, indicators for the presence of the mother (and/or father) in the household, and interactions between indicators for the mother's (father's) presence and the mother's (father's) education, marital status, age, and citizenship. Insurance coverage not included as control in columns 1 and 5. All regressions also include controls for local economic and policy variables: the county unemployment rate, an index of state SNAP policies (Ganong and Liebman, 2018), the state minimum wage, EITC, TANF generosity, and Medicaid/CHIP income eligibility limits, as well as controls for HUD's fair market rent, and regional CPIs for non-food, non-housing categories (apparel, commodities, education, medical, recreation, services, transportation and other). Finally, all models include year and market group fixed effects. Outcomes in Panel A, columns 1–3, and outcomes on Panel B, columns 1–4 are observed only for children in the Sample Child files.

hood that children had any doctor's visit in the past 12 months by 3.4 percent.

In terms of beneficial health effects of increased SNAP purchasing power, we document a lower likelihood of food insecurity and a reduction in the number of school days missed due to illness (22 percent fewer, relative to a baseline mean of 5 missed days, when SNAP purchasing power is increased by 10 percent). This decrease in school absences could reflect a direct effect of improved nutrition or, perhaps more likely, a result of increased preventive health care (e.g., receiving vaccinations, maintaining treatment plans to prevent asthma flares or manage seasonal allergies). It may also reflect a reduction in maternal stress, though we are unable to identify the exact channel.

We do not find much evidence that variation in SNAP purchasing power impacts health status, the likelihood of a hospitalization, or other measures of physical (e.g., obesity) and mental health (e.g., child has emotional problems). However, some of these health measures are more chronic and cumulative in nature (e.g., obesity, emotional problems) and therefore may not be expected to respond contemporaneously to marginal variation in SNAP purchasing power. And while caregiver-reported health status could respond more quickly to more minor or subtle changes in the child's health, it could also be the case that the types of health improvements that occur due to increased SNAP purchasing power are simply not of the size or type to alter a parent's impression of her child's overall health.

We also note that our measure of variation in the price of food is constructed using 30 market groups that perhaps mask variation in urban and rural customers who are in fact paying different prices, thus masking why certain SNAP recipients are able to buy relatively inexpensive food and stay relatively healthy. In related work, Bronchetti and Christensen (2019) use food prices measured at a much finer geographic level from the National Household Food Acquisition and Purchase Survey (FoodAPS) and demonstrate that whether SNAP benefits are sufficient to buy the TFP depends largely on whether recipients are able to identify and travel to the lowest-cost store in their area. Relating health and other outcomes to SNAP purchasing power using finer geographic variation may be a fruitful research area in the future.

Finally, our results speak to whether adjusting benefit levels to account for geographic variation in food prices across market groups would help improve child health and wellbeing. We conclude that such adjustment would reduce disparities in child healthcare utilization and school absenteeism in low-income households, but may not lead to significant changes in contemporaneous health status.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.jhealeco.2019.102231>.

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