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Moving Policies Toward Racial and Ethnic Equality: The Case of the Supplemental Nutrition Assistance Program

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Abstract

We analyze the role played by the Supplemental Nutrition Assistance Program (SNAP) in alleviating or exacerbating inequality across racial and ethnic groups in food expenditures and in the resources needed to meet basic food needs (the "food resource gap"). To do this, we propose a simple framework that decomposes differences across groups in SNAP benefit transfer levels into three components: eligibility, participation, and generosity. This decomposition is then linked to differences in food expenditures and the food resource gap. Our results reveal that among the three components, differences in eligibility contribute the most to SNAP benefits differentials for Black and Hispanic households relative to White households. Given that SNAP is often a target of policy changes, we employ the framework to provide counterfactual analyses of how selected SNAP policy changes can impact group differences in benefits and, ultimately, disparities in food expenditures and the food resource gap. The proposed framework can be applied to analyze other safety net programs.

JEL No.: D12, D63, I38, J15

Keywords: decomposition, inequality, race and ethnicity, supplemental nutrition assistance program

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1. Introduction

Racial and ethnic disparities have been long-standing and extensive in the United States.[1] Historically, policymakers have not explicitly addressed potential policy impacts on the racial and ethnic disparities in outcomes, but policymakers increasingly express interest in ameliorating these inequities.[2] Safety net programs such as the Supplemental Nutrition Assistance Program (SNAP) play an important role in providing people living with disadvantages with a minimal level of well-being and basic needs. Despite numerous studies addressing how these programs alleviate overall hardship, few have discussed how they affect differences in exposure to adversity by race, ethnicity, and other demographic characteristics.[3]

In this paper, we analyze the role that SNAP can play in *differentially* mitigating exposure to food insecurity across racial and ethnic groups. SNAP is one of the largest public assistance programs in the U.S. and a central tool for the government to alleviate the consequences of poverty. Based on income and family structure, SNAP does not target specific racial and ethnic groups. As a result, SNAP benefits reach a broad range of disadvantaged households; yet, minority households report food

[1] About one in five Black and Hispanic households live below the poverty level compared to one in ten White households (US Census, 2020). Figures from the U.S. Bureau of Labor Statistics routinely report that the unemployment rate is chronically higher for Black and Hispanic individuals (e.g., 7.1 percent and 4.9 percent in December 2021) relative to White individuals (3.2 percent). Perennially, Black- and Hispanic-headed households have substantially higher rates of food insecurity (21.7 percent and 17.2 percent in 2020) than White-headed households (7.1 percent) (Coleman-Jensen et al., 2021). These demographic groups also differ in terms of their sensitivity to the shocks such as economic downturns, recessions, and other crises such as pandemics (e.g., Fairlie, 2022).

[2] Notably, in 2021, the Biden Administration directed all federal agencies to "…recognize and work to redress inequities in their policies and programs that serve as barriers to equal opportunity" to take "…a systematic approach to embedding fairness in decision-making processes" (The White House, 2021). Observers have also weighed in. For instance, Perry and Hamilton (2021) propose that changes in policies be scored for racial equity just as they are scored based on their budgetary impact. See also Briggs and McGahey (2022) who report on how impact assessment at different levels of government has increasingly incorporated an equity perspective.

[3] Bitler et al. (2017) argue that the safety net is doing less for people who are most disadvantaged in protecting against negative economic shocks, likely from their more limited access to the safety net.

insecurity at a rate more than twice that of White households (Coleman-Jensen et al., 2021). In our analysis, we focus on how SNAP impacts differences in two outcomes that directly relate to a household's exposure to food insecurity: food expenditures and the dollars needed to meet basic food needs (the "food resource gap").

We propose a decomposition framework to understand how SNAP—a program that is blind to group membership such as race and ethnicity—can have differential effects across groups on policy-relevant outcomes.[4] First, we decompose differences in SNAP benefits across racial and ethnic groups into three components: (1) the proportion of households that are eligible for SNAP (eligibility component), (2) the propensity to participate in SNAP (participation component), and (3) the amount of SNAP benefits that participating households receive (generosity component). Second, we show how the decomposition of SNAP benefits can be linked to differences in outcomes (e.g., food expenditures) through a factor of proportionality given by the marginal propensity to spend on food (MPSF) from SNAP benefits.[5] Lastly, we relate food expenditures to the food resource gap.

In our empirical exercise, we use data from the Current Population Survey (CPS) and its Food Security Supplement (FSS) between 2003 and 2016.[6] Our main findings are as follows: First, based on the target population in the FSS (households below 185 percent of the poverty line or short of money for food), Black and Hispanic households receive higher SNAP benefits relative to White households, on average. These unconditional SNAP monthly benefits are $67, $64, and $29 among Black, Hispanic, and White households. These differences are not surprising given that Black and Hispanic households

[4] Our framework builds on the Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973). It is also related to a recent proposal by Goldsmith-Pinkham et al. (2022) to measure changes in disparity gaps caused by a policy.
[5] As we show later, the relative importance of differences in eligibility, participation, and generosity obtained in our decomposition remains the same regardless of whether we are looking at SNAP benefits or food expenditures.
[6] We discuss data limitations in Section 3.3.

face more disadvantages than their White counterparts. Second, we find that differences in the eligibility component explain most of the overall unconditional differences in SNAP benefits between Black and White households ($38) and between Hispanic and White households ($35). The eligibility component accounts for 73 percent of this difference for Black households, and the same component accounts for 80 percent of this difference for Hispanic households.

Third, the participation component works in opposite directions for Black and Hispanic households, consistent with their observed participation rates. For Black households, the participation component increases the difference in SNAP benefits relative to White households by 21 percent, less than one-third relative to the importance of the eligibility component. For Hispanic households, the participation component decreases the difference in SNAP benefits relative to White households by 16 percent. Fourth, the generosity component increases the SNAP benefit levels of Black and Hispanic households relative to White households. This component is more relevant for Hispanic households, raising relative SNAP benefits by 36 percent, than for Black households, for whom this component increases relative SNAP benefits only by 6 percent. Fifth, SNAP reduces the observed differences in the food resource gaps between Black-White and Hispanic-White households by 25 percent and 18 percent, respectively.

We also conduct counterfactual decompositions under six different hypothetical policy scenarios that involve large (benchmark) and small (marginal) changes in the design of the program. The large counterfactuals shut down completely one component at a time. Among these, we find that a uniform benefit level of $638 per month (the average amount for a family of four in 2022) for all participating households (i.e., shutting down the generosity component) would increase the level of food expenditures of Black households more relative to White households, and thus reduce the difference in the food resource gaps by an additional 44 percent compared to the current program. A universal eligibility policy would increase the levels of food expenditures of minority households and White households by approximately the same amount, leaving differences in food expenditures roughly unchanged. An automatic enrollment policy that makes every eligible household receive the benefit would increase the level of food expenditures of Hispanics households more relative to White households, and thus lower the difference in the food resource gaps by an additional 14 percent compared to the current program.

The three small counterfactuals represent a 20 percent change in each component in turn. Among these three counterfactuals, we find that an across-the-board 20 percent increase in SNAP benefits (generosity component) generates the greatest reduction in racial and ethnic inequality of the food resource gap relative to a similar change to the eligibility or participation components. However, the magnitude of this change in SNAP benefit levels would not substantially reduce the inequality in food resource gaps across racial and ethnic groups.[7] The other two small counterfactuals—20 percent changes in eligibility and participation—do not result in meaningful modifications in the relative food expenditures or food resource gaps across racial and ethnic groups.

Our results are useful to current policy debates about the reforming and funding of SNAP and can help policymakers target the program more effectively to alleviate inequality, in addition to overall outcomes of interest. For instance, our results indicate that reducing the relative food resource gap between Hispanic and White households is more difficult than between Black and White households, partly because of differences across the group's marginal propensity to spend on food (MPSF) from of SNAP benefits, among other factors.

[7] Even though these policy scenarios do not substantially change the inequality in food resource gaps, they do increase the food expenditures of each of the three groups under consideration.

2. Inequality in Food Insecurity and SNAP

A food insecure household has difficulty providing enough food for its members because of a lack of resources (Coleman-Jensen et al., 2021).[8] Food insecurity, which affects over 35 million people annually, has become one of the main indicators of economic well-being in the U.S. (Coleman-Jensen et al., 2021; Gundersen, 2021).

SNAP is the main policy lever to ameliorate food insecurity. In 2017, SNAP provided benefits to 20.8 million households at the cost of $68 billion, substantially larger than any other food and nutrition assistance program (US Department of Agriculture, 2019). Despite the prominence and evidence of effectiveness of SNAP (e.g., Bartfield et al., 2015), food insecurity varies considerably among households with different demographic and socioeconomic characteristics (Coleman-Jensen et al., 2021). In particular, Black- and Hispanic-headed households perennially have higher food insecurity rates than White-headed households, as shown in Figure 1, and food insecurity is likely a contributing factor to the disadvantaged status of these groups.[9] Yet, few studies have analyzed the differential exposure to food insecurity across racial and ethnic groups (the exceptions include Berning, Bonanno, and Cleary 2022; Flores-Lagunes et al., 2018; Gundersen, 2008; and Nam et al., 2015).

SNAP provides monthly benefits to eligible households to purchase food items at SNAP-authorized retailers. A typical household must meet three financial criteria to be eligible: (1) gross

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[8] The measure of food insecurity captures household access to food, which may be different from actual nutrition intake.

[9] Previous literature finds that exposure to food insecurity early in life has the potential to heighten and preserve economic inequality (e.g., Currie, 2009; Ratcliffe, 2015). Food insecurity affects health outcomes such as obesity, diabetes, anemia, overall health, etc. (Baum, 2011; Ding et al., 2014; Kalichman et al., 2014; Nicholas, 2011; Shaefer and Gutierrez, 2013; Yen, 2010). These health outcomes are in turn related to long-term cognitive and non-cognitive skills of children that affect human capital investments (e.g., Alaimo et al., 2001; Currie, 2009) and ultimately adult human capital and economic self-sufficiency (e.g., Bailey et al., 2020; Currie, 2009; Ratcliffe, 2015).

monthly income does not exceed 130 percent of the poverty line; (2) net monthly income (gross income minus allowable deductions) is at or below the poverty line; [10] (3) countable assets are no more than $2,250.[11] Households with a disabled or an elderly member (aged 60 or above) have less stringent criteria.[12] Besides these criteria, households can be categorically eligible for SNAP if all members are eligible for or receive benefits from Supplemental Security Income (SSI), Temporary Assistance for Needy Families (TANF), or General Assistance programs. In contrast, able-bodied adults without dependents (ABAWDs) between ages 18 and 50 face work requirements (Cuffey et al., 2021; Han, 2022). The monthly SNAP benefit amount is equal to the maximum SNAP allotment, varied by household size, less 30 percent of a household's net monthly income, and the benefit amount is subject to a minimum amount.[13] In 2017, the average benefit level was about $254 per household per month (US Department of Agriculture, 2019). To receive SNAP benefits, program applicants must provide the required documentation and participate in an interview, and recipients are required to recertify every 6 to 24 months after initial eligibility. According to the structure of SNAP, states can shape the program's rules, such as easing reporting requirements and waiving asset or work requirements. Previous research has shown that statewide administrative changes may have contributed to changes in SNAP receipt (e.g., Gray, 2019; Han, 2016; Kabbani and Wilde, 2003; Ribar et al., 2008).[14]

[10] Allowable deductions include a 20 percent deduction from gross income, a standard deduction, a deduction for households incurring expenses in the care of their children and/or disabled dependents, a medical deduction for expenses, and a shelter deduction for costs above 50 percent of a household's net income, computed before the shelter deduction and capped except for elderly or disabled households.
[11] By October 2022, at least 41 states have eliminated the asset test under broad-based categorical eligibility (US Department of Agriculture, 2022).
[12] The gross income threshold is 165 percent of the poverty line and the asset limit is $3,250 for households with a disabled or an elderly member.
[13] The U.S. Department of Agriculture adjusts the income eligibility standards, the deductions, and the maximum allotments at the beginning of each fiscal year, which takes effect from October 1st of the previous year to September 30th of the current year. The changes are based on changes in the cost of living.
[14] In our analysis, we consider these policy variations using information from the SNAP Policy Database to estimate participation, which is available up to 2016 and maintained by the U.S. Department of Agriculture's

Policymakers frequently target SNAP with proposals to change its rules. For instance, during 2019, the U.S. Department of Agriculture (USDA) proposed the termination of the Broad-Based Categorical Eligibility (BBCE), whereby certain households can access SNAP through a simplified application process (Schanzenbach, 2019). States with a BBCE allow households to bypass a "gross income test" and an "asset test." Other examples of past proposals include a more generous indexation of SNAP benefits (e.g., Ziliak, 2016), a proportional increase in SNAP benefits relative to the household's food insecurity (Gundersen et al., 2018), and the provision of additional SNAP benefits to cover transportation costs (Chojnacki et al., 2021). Thus, it is important to evaluate the impact of proposed changes to SNAP rules on the inequality in food insecurity across racial and ethnic groups.

3. Data

We use the Current Population Survey (CPS) and its Food Security Supplement (FSS) between 2003 and 2016. These data are nationally representative of the U.S. population and include sufficient information on household characteristics that allow us to conduct our analysis. The unit of observation is the household. We focus on households below 185 percent of the poverty line or that report being short of money for food because the CPS enumerators target these households for the FSS. Naturally, these households are more economically disadvantaged and more food-insecure than the general population. We focus on groups of households defined based on whether the respondent of the

Economic Research Service. We include dummy variables indicating if a state had a simplified reporting system, an online application, and/or requires fingerprinting, whether the broad-based categorical eligibility (BBCE) rules were in place, and the median certification period.

household in the CPS belongs to one of three racial and ethnic groups: non-Hispanic White, non-Hispanic Black,[15] and Hispanic.[16]

3.1 Imputed SNAP Eligibility and Benefits

We impute SNAP eligibility and benefits for each observation since program eligibility is not available in the data. Program parameters of eligibility standards and benefit calculation every year are collected from the USDA. To obtain adequate information on income, we read in the Outgoing Rotation Group (ORG) files in January-March each year and match the December CPS-FSS data to the appropriate ORG, similar to Schmidt et al. (2016).[17] Overall, a total of 157,533 respondents within our study's scope have complete information on earnings, family income, and food expenditures after matching the FSS to the ORG.[18]

We impute SNAP eligibility as follows. We calculate monthly income to pass through the gross and net monthly income tests, accounting for family structure and specific eligibility standards for disabled and elderly (age 60 and older) respondents. We also use family income variables to screen out ineligible households. We then rule out immigrants who have lived in the U.S. for less than five years as they are not eligible for SNAP. Lastly, we assume households to be eligible for SNAP if they reported receiving SNAP benefits.[19]

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[15] We pool all Black categories (such as White-Black and Black-American Indian) into the "Black" category.
[16] Because some households could have members of several races and ethnicities, our household categories may involve grouping multi-racial/ethnic individuals.
[17] For respondents in the December CPS, the ORG is split into December-March CPS surveys. We use CPS identifiers to match households across survey months of January-March. The match may fail because of identifier errors (due to migration, mortality, non-response, and recording errors), inconsistencies in respondents' basic demographic attributes (race, age, or gender), or incomplete information on the key variables.
[18] More detailed description of our imputation process and sample attrition can be found in Online Appendix A.
[19] Among our imputed ineligible households, about 6 percent of them are shown participating in SNAP, which could be due to misreporting or the lack of information to identify eligibility.

We calculate SNAP benefits for participating households according to the SNAP benefit formula using survey information on the respondent's income and household size. Our analysis uses imputed benefits since several issues exist with self-reported benefits in the CPS (e.g., Almada et al., 2016; Meyer and Mittag, 2019). First, the self-reported values have a rounding problem, with clear spikes in the density at benefit amounts divisible by 100 (see Online Appendix Figure A3). Second, the SNAP benefits are top-coded in the CPS (the top code is $450 before 2011 and $700 in 2011 and after). Third, the continuous measure of benefits is only available until 2014, which has been substituted with a categorical measure since 2015. Fourth, many participants refused, did not know, or did not report their SNAP benefit amounts in the data.

3.2 Food Expenditures and the Food Resource Gap

Exposure to food insecurity directly relates to food expenditures and the food resource gap (the amount needed to meet basic food needs in the household), which we use as the main outcomes in our analysis. We measure food expenditures by the total amount the household spent on food last week, available in the CPS-FSS.[20] We use food expenditures to provide an explicit link to SNAP benefits in the form of the marginal propensity to spend on food from SNAP benefits (MPSF), as outlined in Section 4.2. The food resource gap allows us to assess perceived food assistance shortcomings and evaluate the differences in the amount needed to meet basic food needs between groups. This variable uses information from three survey questions in the CPS-FSS: (1) relative amount of money needed to meet needs (more, same, or less); (2) how much additional money needed to meet weekly basic household food needs; and (3) how much less money could be spent and still meet basic

[20] We drop 1.58 percent of the sample (2,532 out of 160,065) due to missing food expenditure information (see Online Appendix Table A1).

household food needs. Combining these three questions, we create a variable that measures the amount deviating from a reference level of food spending to be food secure.[21] While these self-reported amounts are subject to personal interpretation and potential mismeasurement, they are often used to explore the food resource gap associated with SNAP (e.g., Gundersen et al., 2018; Gundersen and Ribar, 2011; Zheng et al., 2021).

3.3 Data Limitations

Use of the CPS data presents several limitations. First, the CPS does not track all the information needed to identify eligible households. For instance, we lack information on households' assets, Supplemental Security Income (SSI) and Temporary Assistance to Needy Families (TANF) receipt, the presence of a disabled or elderly member in the household other than the respondent, expenses related to shelter, childcare, and health care to calculate deductions for net income.[22] As a result, we are not able to address policy changes regarding these items. Second, a fraction of the sample in the December CPS cannot be matched with the Outgoing Rotation Group (ORG) (Schmidt et al., 2016), and the observations for the January-March data might be different from the December data, which could reduce the reliability of the imputation. Third, SNAP participation in the survey data could be significantly under-reported (e.g., Gundersen and Kreider, 2008; Meyer and Mittag, 2019; Meyer et al., 2022; Nguimkeu et al., 2019). Our estimated participation rates, calculated as the ratio of participating households to estimated eligible households, seem fairly reasonable compared to previous studies using survey data (e.g., Gundersen et al., 2018) but lower than those documented in the USDA

[21] The continuous measures of total food expenditures and relative amount needed are only available until 2014 and replaced with categorical measures from 2015; therefore, the mean values of each category are used in these two years. Starting in 2011, food expenditures and the relative amount needed are also top-coded.

[22] Similar to Schmidt et al. (2016), we set all income other than self-reported family income and expenses to zero.

reports (e.g., Cunnyngham, 2018; Gray and Cunnyngham, 2016; Wolkwitz, 2008).[23] Another concern is that reporting errors may differ by race and ethnicity and that some of the findings may reflect reporting differences. Fourth, we cannot account for detailed linkages between changes in reporting rules and SNAP benefits (e.g., some states allow households to keep their level of benefits throughout a certification period if their income rises but stays below the gross eligibility threshold), which could play out differently across groups.

In spite of the limitations, our imputed benefits capture important policy changes, such as the 2009 American Recovery and Reinvestment Act (ARRA), which considerably increased maximum monthly benefits for participating households. Furthermore, we compared our imputed benefits (conditional on participation) to the SNAP Quality Control dataset. This comparison shows that our imputed benefits closely track the differences across groups.[24] Thus, the data and imputation, with limitations, serve our purposes.

4. The Decomposition Framework

4.1 Decomposition of SNAP Benefits

We consider a population with two non-overlapping subgroups indexed by $g \in \{0,1\}$; for example, 0 denotes the White population, and 1 denotes the Black population. For any household in group g, we observe whether the household is eligible for the program, an event that we denote by l.

[23] However, the participation rates could vary substantially across studies due to different data, methodology, and analysis samples. The estimates in these reports reflect the overall population, which is different from our sample of households under 185 percent of the poverty line.
[24] We thank a Reviewer for suggesting this exercise. The comparison is presented in Online Appendix B.

Among eligible households, we observe whether they take up the program, an event that we denote by t. The observed value of program benefits is denoted by z.

Using the factorization formula, the mean benefit level for group g can be written as $\mathbb{E}_g[z] = \mathbb{P}_g[l]\,\mathbb{P}_g[t|l]\,\mathbb{E}_g[z|l,t]$.[25] This equation holds for both groups, so one can take the difference between them. The overall difference in program benefit levels between groups ($\Delta = \mathbb{E}_1[z] - \mathbb{E}_0[z]$) can then be decomposed into:

$$\Delta = \Delta_l + \Delta_t + \Delta_z, \tag{1}$$

where $\Delta_l = \Delta\mathbb{P}[l]\,\mathbb{P}_1[t|l]\,\mathbb{E}_1[z|l,t]$, $\Delta_t = \mathbb{P}_0[l]\,\Delta\,\mathbb{P}[t|l]\,\mathbb{E}_1[z|l,t]$, and $\Delta_z =$ $\mathbb{P}_0[l]\,\mathbb{P}_0[t|l]\Delta\,\mathbb{E}[z|l,t]$. The first term is the eligibility component (Δ_l) which is attributed to the group difference in the proportions of households that are eligible for the program. The second term is the participation component (Δ_t) which reflects the group difference in program participation rates. The third term is the generosity component (Δ_z) which reflects the group difference in the average benefit levels.

Each of these three components (Δ_l , Δ_t, and Δ_z) can be thought as capturing the effect of a counterfactual experiment conducted in group 1 that changes the component's distribution to group 0's distribution while holding everything else constant.[26] For example, Δ_l answers the counterfactual

[25] It is also useful to write this equation in logs: $\log(\mathbb{E}_g[\mathrm{z}]) = l_g + t_g + z_g$, where $l_g = \log(\mathbb{P}_g[l])$, $t_g = \log(\mathbb{P}_g[t|l])$, and $z_g = \log(\mathbb{E}_g[z|l,t])$. It follows taking differences between groups that the decomposition of log differences will be order invariant and independent of the choice of the reference group.

[26] For example, suppose that eligibility for group 1 is larger than eligibility for group 0. One can think of a counterfactual experiment that lowers eligibility for group 1 households while keeping unchanged the differences in participation or generosity levels, by dropping at random and independently of participation and generosity levels some group 1 households from the pool of eligible households. This counterfactual experiment (although unusual) would lead to the same differences in participation and generosity as before, but with no differences in eligibility. We discuss more realistic policy scenarios later in Section 5.4 and Online Appendix D.

question of how the average benefit level would change if group 1 were to have the same eligibility rate as group 0 while the likelihood of participating in the program and the average level of transfers they are entitled to remain fixed. Similarly, Δ_t answers the counterfactual question of how the average benefit level would change if, on top of having the same eligibility rate as group 0, group 1 were to have the same likelihood of participating in the program as group 0. Finally, the term Δ_z answers the counterfactual question of how the average benefit level would change if, on top of having the same eligibility and participation rates as group 0, we were to entitle group 1 to the same benefit level on average as group 0. These three policy components (differences in eligibility rate, participation rate, and generosity), by construction, add up to the overall difference between groups. In this sense, this decomposition exercise is completely atheoretical and illustrative of how different components – eligibility, participation, and generosity – shape the observed differences in benefit levels across demographic groups.

4.2 Linkage to Differences in Food Expenditures

The exercise above helps understand the forces that lead to differences in the mean benefit levels between groups. However, the differences in mean benefits are important only to the extent that these differences can trace the differences in policy-relevant outcomes, such as food expenditures and the food resource gap. By estimating a simple model relating SNAP benefits to food expenditures, we can link the previous decomposition to these outcomes.[27] To fix ideas, we assume a linear relationship amongst food expenditures, SNAP benefits, and household characteristics:

[27] More generally, any credible available estimate of the relationship between program benefits and policy-relevant outcomes from the extant literature can be employed instead.

$$y_{ig} = \beta_g z_{ig} + \boldsymbol{\theta}_{\boldsymbol{g}} \boldsymbol{x}_{ig} + \varepsilon_{ig}, \quad (2)$$

where y_{ig}, z_{ig}, and x_{ig} denote food expenditures, SNAP benefit amounts, and household characteristics of household i in group g. β_g denotes the marginal propensity to spend on food (MPSF) from SNAP benefits, which is allowed to vary by group, and ε_{ig} is a mean-zero error term.[28] Taking the difference in expected food expenditure levels between groups, we get:

$$\Delta\mathbb{E}[y] = \beta_1 \Delta\mathbb{E}[z] + \Delta\beta\mathbb{E}[z_0] + \boldsymbol{\theta}_1 \Delta\mathbb{E}[\boldsymbol{x}] + \Delta\boldsymbol{\theta}\mathbb{E}[\boldsymbol{x}_0]. \quad (3)$$

This equation is the standard Oaxaca-Blinder decomposition. Note that group differences in SNAP benefits from the decomposition will affect differences in food expenditures through a factor of proportionality given by the MPSF from SNAP benefits. Thus, the relative importance of differences in eligibility, participation, and generosity from our decomposition will remain the same regardless of whether we look at SNAP benefits or food expenditures.[29] In other words, the term $\beta_1 \Delta\mathbb{E}[z]$ can be written as $\beta_1(\Delta_l + \Delta_t + \Delta_z)$, which shows that the mechanical decomposition of group differences in SNAP benefits connects directly into group differences in food expenditures through a proportionality constant given by the MPSF from SNAP benefits for the group of interest.

In Equation 3, $\Delta\beta\mathbb{E}[z_0]$ captures the differences in food expenditures between groups that is attributed to differences in the MPSF from SNAP benefits between groups. This term will be equal to

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[28] In reporting food expenditures, we acknowledge that not all food purchased is consumed or consumed by the household alone. For example, the US Department of Agriculture (2021) calculates a food waste factor in Thrifty Food Plan, and food waste research finds evidence that consumers dispose of some portion of product without consumption (Wilson, et al. 2017). Some researchers report a marginal propensity to spend on food, which is equivalent to the marginal propensity to consume food (e.g., Beatty and Tuttle, 2015). Others equate expenditure to consumption (e.g., Hoynes and Schanzenbach, 2009; Hastings and Shapiro, 2018).

[29] If we allow the MPSF to be heterogeneous within groups, then a covariance term between the MPSF and SNAP benefits shows up in Equation 3. This term is zero if (1) $Cov(\beta, z)$ is zero for both groups, which must happen if SNAP benefits are constant in the population; if (2) these covariances are the same regardless of group membership; or (3) β_i and z_i are independent.

zero when the MPSF is the same between groups.[30] The next terms in Equation 3 are $\boldsymbol{\theta}_1 \Delta \mathbb{E}[\boldsymbol{x}]$ and $\Delta \boldsymbol{\theta} \mathbb{E}[\boldsymbol{x}_0]$. The first component, $\boldsymbol{\theta}_1 \Delta \mathbb{E}[\boldsymbol{x}]$, captures the difference in food expenditures that corresponds to the differences in observable pre-determined characteristics between groups (known in the decomposition literature as the "explained part" of these covariates). The second component, $\Delta \boldsymbol{\theta} \mathbb{E}[\boldsymbol{x}_0]$, captures the difference in food expenditures that corresponds to the heterogeneity in the effects of these observable characteristics between groups (known as the "unexplained part").

4.3 The Use of the Decomposition Framework for Counterfactual Analysis

The previous sections show the decomposition of group differences in SNAP benefits into differences in eligibility, participation, and generosity; and how the decomposition can be linked to food expenditures. Once linked to food expenditures, the decomposition can also be linked to group differences in the food resource gap. Analyzing SNAP using this decomposition is useful insofar as it provides policymakers a deeper understanding about the relative contribution of these three policy components to disparities between minority and White households. Perhaps more importantly, the proposed decomposition framework can be employed to evaluate how changes in the current SNAP rules can ultimately influence the differences in benefits received from SNAP, food expenditures, and the food resource gap.[31] Thus, it can provide useful information in the evaluation of proposed changes to SNAP along the important dimension of racial and ethnic disparities in outcomes.

[30] An interesting interpretation of this term is how much SNAP induces differences in expenditures in *all other goods*-such as shelter, durable goods, and leisure-between groups. In other words, it is a dollar measure of how much SNAP subsidizes the consumption of goods other than food and how that differs by group.
[31] Researchers and policymakers are often interested in evaluating potential changes to current policies. For instance, see the interesting evaluation of a proposal to consider turning SNAP into a universal basic income policy for food in Gundersen (2021), which entails expanding the program along the three components we consider. Gundersen (2021), however, does not consider the potential impacts on inequality across racial and ethnic groups. Our proposed framework could be useful for this purpose.

As with any counterfactual exercise, however, one must keep in mind that the underlying assumptions of the exercise will likely be more plausible for marginal changes in the program relative to large changes that may elicit behavioral responses that are not being modelled (e.g., King and Zeng, 2006). For example, if one were to consider a dramatic increase in benefits, this change could prompt a non-negligible behavioral response in participation or in labor supply, both of which are not currently explicitly modelled. In contrast, if a marginal change to the program is under consideration, counterfactual exercises using our proposed method are more likely to be accurate. Thus, in Section 5.4, we first provide a set of counterfactual exercises that represent large changes to SNAP to illustrate the inner workings of the framework. Then, we turn to a second set of counterfactual exercises that consider marginal, more realistic changes to the program.

5. Results

5.1 Descriptive Statistics

Table 1 shows how monthly SNAP benefits and key aspects of the three SNAP components differ by group for households under 185 percent of the poverty line.[32] The unconditional mean benefits are larger for Black and Hispanic households ($67 and $64, respectively), compared to White households ($29), which reflects the higher relative disadvantage of minority households in the population under analysis. Correspondingly, Black and Hispanic households are more likely to be eligible for SNAP. The proportions of eligible households are 25 percent for White households, 43 percent for Black households, and 44 percent for Hispanic households. Among the eligible households, Black households have the highest participation rate (61 percent), followed by White households (49

[32] Online Appendix Table C1 shows the descriptive statistics for all the variables employed in the analysis.

percent) and Hispanic households (42 percent). Conditional on participation, Hispanic households receive the highest SNAP benefits on average ($344 per month), and Black households receive an average benefit level of $257 per month, higher than the amount that White households receive ($238 per month). This is explained by the different characteristics of the households in each group.

Table 2 displays unconditional group differences in food-related outcomes for households under 185 percent of the poverty line. For food expenditures, Black households spend $76 less on food per month compared to White households, whereas Hispanic households spend about $17 more than White households. Both Black ($93) and Hispanic ($59) households report needing on average more money per month to meet basic food needs than White households, which is the food resource gap. In spite of a positive difference in food expenditures, Hispanic households report a higher food resource gap relative to White households. These unconditional averages mask the hardship that households with different characteristics—particularly of different household size—endure. Figure 2 shows that, when broken up by household size, White households consistently spend more on food per week relative to minority households.[33] Figure 3 shows the food resource gap by household size, where it can be seen that the differences in gaps between minority households and White households persist over different household sizes.

Consistent with Flores-Lagunes et al. (2018), we observe in the bottom panel of Table 2 that Black and Hispanic households have higher—by about 10 percentage points—food insecurity incidence than White households within this population. When looking at the Rasch score differences (a measure of food insecurity severity experienced), Black households observe higher severity relative to White

[33] The only exception to this statement is among single-person households, where Hispanic households spend more on food relative to White households.

households, whereas the mean differences in severity between Hispanic and White households are essentially non-existent, which is in line with their results.

5.2 Decomposition of Differences in SNAP Benefits

Table 3 presents the results of our decomposition by race and ethnicity. Row by row, we report estimates of the overall difference (Δ) in SNAP benefits and the contributions from the eligibility (Δ_l), participation (Δ_t), and generosity (Δ_z) components. Compared with White households, Black households receive $38 more from SNAP per month, which is the net of the eligibility component ($28), the participation component ($8), and the generosity component ($2). Hispanic households receive $35 more SNAP benefits than White households, which is the net of the eligibility component ($28), the participation component (-$6), and the generosity component ($13).

Our results show that the eligibility component of SNAP contributes the most to SNAP benefits for Black (73 percent) and Hispanic (80 percent) households relative to White households. This finding is consistent with the notion that, as a group, Black and Hispanic households are more disadvantaged—thus more likely to be eligible for SNAP—relative to White households. The participation component increases the relative amount of benefits that Black households (by 21 percent) receive but lowers SNAP benefits of Hispanic households (by 16 percent) relative to that of White households. These results are consistent with each group's take up behavior observed in Table 1. The generosity component increases the relative amount of benefit levels that Black (by 6 percent) and Hispanic (by 36 percent) households receive, but this component is larger for Hispanic households. Overall, these results highlight differences between these two minority groups in the pathways that SNAP may reduce food insecurity.

5.3 Decomposition of Differences in Food Expenditures and Food Resource Gaps

We link SNAP benefits with food expenditures to provide insights from the decomposition of an outcome that directly relates to a household's exposure to food insecurity. Several credible studies in the literature estimate the relationship between SNAP benefits and food expenditures (e.g., Beatty and Tuttle, 2015; Bruich, 2014; Hastings and Shapiro, 2018; Hoynes and Schanzenbach, 2009).[34] Following, among others, Fraker et al. (1995) and Hoynes and Schanzenbach (2009), we estimate the MPSF from SNAP benefits for each racial and ethnic group under analysis using a linear model:

$$y_{ig} = \beta_g z_{ig} + \boldsymbol{\theta}_g \boldsymbol{x}_{ig} + \delta_s + \mu_t + \varepsilon_{ig}, \tag{4}$$

where y_{ig} denotes food expenditures for household i in group g; z_{ig} denotes SNAP benefits; $\boldsymbol{x}_{ig}$ is a vector of covariates accounting for household characteristics in the data (including family size, number of children, age and gender makeup, immigration status, marital status, urban status, education, whether the respondent is the household head, employment status, earnings, and family income); δ_s are state fixed effects; μ_t are year fixed effects; ε_{ig} is an error term. Estimates of β_g provide estimates of the MPSF from SNAP benefits by group.[35]

[34] Hoynes and Schanzenbach (2009) found that the MPSF from food stamps is 0.16 for all non-elderly and 0.30 for female-headed households. Bruich (2014) suggested that the MPSF from food stamps is 0.3. Beatty and Tuttle (2015) found that the increase in SNAP benefits led to a MPSF from SNAP of 0.48. Hastings and Shapiro (2018) estimate an MPSF from SNAP benefits is 0.5 to 0.6. Any estimate of the MPSF deemed credible can be used to establish the linkage of SNAP benefits to differences in food expenditures when implementing this approach.

[35] We note that these estimates may not be causal due to possible self-selection into the program (e.g., Gundersen et al., 2011; Hoynes and Schanzenbach, 2009; Ratcliffe et al., 2011; Schmidt et al., 2016). In addition, the SNAP benefit is a function of income, making it difficult to identify the MPSF with cross-sectional variation. We attempted the use of instrumental variables (IVs) based on the variation in state policies and rules regarding SNAP, similar to the approach in Ratcliffe et al. (2011) and Flores-Lagunes et al. (2018) on the effect of SNAP on food insecurity. However, these IVs are weak in this context, so we refrained from using this strategy.

Our estimated MPSF from SNAP benefits shows that a dollar of SNAP benefits increases food expenditures by 0.4 in the sample (see Online Appendix Table C2). The MPSF from SNAP benefits is the highest among Black households (0.6), followed by White households (0.4) and then Hispanic households (0.3).[36] In what follows, we use these MPSF estimates to decompose overall differences in food expenditures.

Table 4 combines the estimates of the MPSF from SNAP benefits with the decomposition results in Section 5.2. The top panel shows that differences in SNAP benefits are attributable to $23 more per month in food expenditures for Black households relative to White households from the eligibility component ($17), the participation component ($5), and the generosity component ($1). For Hispanic households, differences in SNAP benefits are attributable to $10 more per month in food expenditures relative to White households from the eligibility component ($8), the participation component (-$2), and the generosity component ($4). Hence, differences in the proportion of households that are eligible for SNAP can explain a considerable part of the overall differences in food expenditures. The generosity of SNAP is also associated with higher food expenditures for minority households relative to White households, but by a smaller amount. Lastly, the participation component increases food expenditures of Black households but marginally decreases food expenditures for Hispanic households, both relative to White households.

Since we have estimated parameters of Oaxaca-Blinder decomposition (see Equation 3), we can discuss the role of differences in the MPSF from SNAP benefits across groups and the role of other covariates. In the bottom panel of Table 4, labeled as "unexplained part," we find that differences in the MPSF from SNAP benefits account for a small difference in food expenditures between Black and

[36] We estimate the model with and without covariates related to income (employment, earnings, and family income). As shown in Appendix Table C2, the results are similar whether we control for income variables or not.

White households (about $6), as well as between Hispanic and White households (about -$3).[37] Turning to the role of other covariates besides SNAP, we find that the combined explanatory power of differences in other observable characteristics account for a considerable -$33 difference in food expenditure averages between Black and White households, whereas they account for a -$19 difference in food expenditures between Hispanic and White households. The so-called unexplained part associated with these covariates (which refers to differences in their marginal effects on food expenditures) accounts for a -$77 difference in food expenditures between Black and White households, and a -$211 difference in food expenditures between Hispanic and White households. The sign of the decomposition components related to the observed covariates implies that they work towards decreasing food expenditures of minority households relative to White households. The magnitude of the role of the explained and unexplained parts of the covariates suggest that it will be difficult for a single policy lever such as SNAP to close the gap in food insecurity across groups.

Is the current amount of SNAP benefits enough to close the relative food resource gaps across groups? We use the information on the reported amount needed to meet basic food needs as a measure of the food resource gap to assess perceived food assistance shortcomings.[38] From Table 2, Black households reported needing $93 more per month, and Hispanic households reported needing $59 more per month, relative to White households. Our results imply that the current average SNAP benefits reduce the food expenditure gaps between minority and White households by 25 percent and 18 percent of the corresponding relative food resource gaps for Black and Hispanic households.

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[37] These values resulting from differences in the MPSF have an intuitive interpretation as the differences across groups of expenditures on *anything besides food* (e.g., shelter, durable goods, savings, and leisure) that can be attributed to the receipt of SNAP benefits.

[38] Note that closing this perceived food resource gap does not imply that all groups would become food secure. It does, however, equalize the perceived food resource gaps across groups.

5.4 Hypothesized Policy Scenarios

We start by considering three illustrative hypothesized policy scenarios that vary SNAP policy rules to shed light on the differential effects on SNAP benefits, food expenditures, and food resource gaps. In Online Appendices D and E, we lay out the details of the procedures we used to obtain these counterfactual decompositions and the specific conditions required for the validity of these exercises.[39] The first scenario is "universal eligibility," which allows the entire sample (households under 185 percent of the poverty line) to become eligible for SNAP, shutting down the eligibility component. The second scenario, "automatic enrollment," involves the automatic enrollment in SNAP of all eligible households, shutting down the participation component. The third scenario, "constant transfer," provides every participating household the same SNAP benefit amount ($638 per month),[40] shutting down the generosity component.

By shutting down completely one component, these provide three benchmark policy scenarios. However, since each one of these scenarios represent large modifications to SNAP rules, the accuracy of this counterfactual exercise may be impacted by potential behavioral responses to these modifications (e.g., potential impacts on participation rates or labor supply responses; see Online Appendix D). This caveat follows the discussion in Section 4.3. Still, the illustrative nature of the

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[39] In short, for these counterfactual exercises to be valid, we need to be able to correctly predict participation behavior under the hypothesized policy scenarios. For certain policies that involve participation, such as automatic enrollment, this is straightforward to do. For policies that enlarge the set of eligible households, however, we must be able to correctly predict participation behavior of the households that are currently ineligible. In contrast, note that eligibility and generosity are easier objects to evaluate since they are deterministic functions of observed covariates. For a detailed discussion on these issues, see Online Appendix D.

[40] The constant amount is approximately the size of the estimated average monthly benefit for a family of four in 2022: https://www.cbpp.org/research/food-assistance/a-quick-guide-to-snap-eligibility-and-benefits (accessed July 23, 2022).

exercise appears valuable, as the results will reflect the first-order impact on racial and ethnic gaps from such hypothetical policies. Keeping this in mind, we describe broad insights from these benchmark policies here, and derive more lessons from the next policy scenarios that represent marginal changes to the current program.

Columns 2-4 in Table 5 (Black - White) and Table 6 (Hispanic - White) present the results of these three benchmark policy scenarios. Among them, constant transfer (Column 4) increases SNAP benefits for Black households relative to White households the most. Automatic enrollment (Column 3) increases SNAP benefits for Hispanic households relative to White households the most, likely since the negative participation component for Hispanics is shut down. Compared to the baseline decomposition results in Column 1 of each table, universal eligibility would lower or have slight changes in SNAP benefits for Black and Hispanic households relative to White households. Since differences in SNAP benefit levels are linked to differences in food expenditures through the MPSF, the constant transfer counterfactual policy increases relative food expenditures and lowers the relative food resource gap between Black and White households (by an additional 44 percent). Similarly, the automatic enrollment policy increases relative food expenditures the most, lowering the food resource gap between Hispanic and White households, by an additional 24 percent.[41]

We now turn to a set of three more realistic counterfactual exercises that consider smaller policy changes relative to the current SNAP rules, to learn about how these policies impact group inequality and provide additional insights about our decomposition. As argued in Section 4.3, marginal changes to existing rules are more likely to satisfy the *ceteris paribus* assumption implicit in the

[41] For the counterfactual policy scenarios, we calculate the additional percentage reduction in the food resource gap by taking the difference in the difference in food expenditures that results from a particular policy scenario and divide it by the food resource gap. In this way, the entire effect of the policy scenario on food expenditures is considered.

evaluation of counterfactual policies. We implement a marginal change in eligibility by increasing the gross and net income limits to qualify for SNAP by 20 percent, a marginal change in participation rates by increasing SNAP participation rates by 20 percent, and a marginal change in generosity by increasing the SNAP benefit levels for eligible households by 20 percent. These policy scenarios could be linked to recent policy proposals.[42]

Columns 5-7 in Table 5 (Black - White) and Table 6 (Hispanic - White) present the results of these three marginal changes to the program. Among them, the marginal increase in SNAP benefit levels (Column 7 in each table) leads to the largest difference in SNAP benefits for both Black and Hispanic households relative to White households. Compared to the baseline results, this policy results in an increase in relative benefits of Black households to White households by $8 ($46 - $38). When decomposing the counterfactual food expenditures under this policy, we find that the eligibility component increases from $17 to $20, that the participation component increases from $5 to $6, and that the generosity component increases slightly from $1.4 to $1.7. For Hispanic households, this policy results in an increase in relative benefits by $7 ($42 - $35). By applying the group-specific MPSF, we estimate that the part of the Hispanic-White difference in food expenditures that is explained by SNAP would grow from $10.6 to $12.7, due to an increase in the eligibility component (from $8.5 to $10.2) and the generosity component (from $3.9 to $4.6), with the participation component being almost unchanged (around -$2).

In summary, a 20 percent increase in SNAP benefits would increase the average level of food expenditures of minority households relative to that of White households. This policy would lead to

[42] In principle, a similar analysis can be applied to specific proposals such as the termination of the BBCE analyzed in Schanzenbach (2019), the more generous indexation of SNAP benefits in Ziliak (2016), or a proportional increase in SNAP benefits relative to the household's food insecurity in Gundersen et al. (2018).

reductions in inequality in food resource gaps across groups (beyond those achieved by the current program) of 6 percent and 3 percent for Black and Hispanic households relative to White households.

Note also that, under this scenario, the relative importance of differences in eligibility, participation, and generosity are the same as in our baseline results. This result is expected because an increase in SNAP benefits should simply re-scale the levels of each one of the components, leaving their relative importance intact.[43] In contrast to the policy that marginally increases SNAP benefit levels, the relative importance of the components changes when we consider marginal increases in eligibility standards or in participation. This outcome happens because differences in the distribution of covariates across groups lead to (i) differences in the proportion of households that are marginally ineligible across groups, (ii) differences in the propensity to participate among marginally ineligible households across groups, and (iii) differences in the benefit levels that these marginal households would receive. Each of these different channels—with the first one being relevant only for the policy changing eligibility—has the potential to change the outcomes in a way that affects inequality across groups.

Our results show that a marginal increase in the income eligibility limits increases the average levels of benefits for both Black and White households (Column 5 in Table 5). However, the increase is greater for White households than for Black households, resulting in a reduction in relative SNAP benefits. When decomposing the counterfactual food expenditures, we find that the eligibility component decreases the differences in food expenditures from $17 in the baseline to $12 under these new eligibility standards. The participation component would also change, but by a smaller amount in the opposite direction, going from $5 to $6. The generosity component decreases the differences

[43] The reason the relative importance of the components is not preserved in the decomposition results in Column 4 in Tables 5 and 6 is that in the policy scenario of Column 4 the change is not proportional.

slightly, from $1.4 to $0.6. For Hispanic households, the relative benefits to White households remain almost unchanged (from $35 to $36), so do the part of the Hispanic-White difference in food expenditures that SNAP explains (Column 5 in Table 6). The eligibility component is also similar to the baseline result, whereas the participation component decreases from -$2 to -$5, and the generosity component increases from $4 to $7.

When considering a marginal increase in participation rates, we find that the average level of SNAP benefits increases from $67 to $77 for Black households and from $29 to $32 for White households, leading to an increase in relative benefits from $38 to $45 (Column 6 in Table 5). Decomposition of the difference in counterfactual food expenditures shows that all three components increase. The overall difference in food expenditures explained by SNAP increases from $23 to $27.[44] For Hispanic households, we find that their average level of SNAP benefits increases from $64 to $72, whereas the average level of SNAP benefits among White households increases from $29 to $32, implying an increase in relative benefits by $5 (Column 6 in Table 6). By decomposing the difference in counterfactual food expenditures, we estimate that the eligibility and generosity components increase slightly, whereas the participation component is virtually unchanged.

In summary, the two marginal counterfactual policy scenarios related to eligibility and participation would induce small changes in the relative levels of food expenditures between minority

[44] Given that the estimated MPSF from SNAP benefits differs across groups, these counterfactual policies also lead to differences in the unexplained part of SNAP (bottom panel in Tables 5 and 6). This part would be zero if the MPSF is equal across groups, and it will remain at its baseline (current) value only if the policy does not alter the average amount of SNAP benefits that households taking up the program receive. The results in Table 5 show that the unexplained part of SNAP increases from $6 to $14 under the scenario with a marginal increase in eligibility, to $7 under the scenario with a marginal increase in the generosity, and remains almost unchanged under the scenario with a marginal increase in participation. These values have an intuitive interpretation as the differences across groups of expenditures on *anything besides food* (e.g., shelter, durable goods, savings, and leisure) that can be attributed to SNAP.

and White households. As such, while alleviating hardship overall, these alternative policies would not substantially influence the inequality in food resource gaps.

More generally, our results illustrate that different counterfactual policies, while they impact the level of SNAP benefits and food expenditures in the same direction for each group, can also preserve or increase the inequality in food resource gaps across groups. Interestingly, among the three hypothetical policy scenarios representing marginal changes, the scenario with a marginal increase in SNAP benefits would lead to the largest reduction in inequality of food resource gaps between minority and White households. These insights provide information for policymakers to understand better how changes in the program rules, beyond their effects on overall outcomes, may alter the picture of inequality across different populations.

6. Conclusion

This paper analyzes the pathways through which SNAP can impact the existing heterogeneity in program benefits, food expenditures, and the food resource gap (the dollar amount needed to meet basic food needs) for different racial and ethnic groups. The latter two variables are directly related to food insecurity, and thus provide information as to the role of SNAP in ameliorating or exacerbating the long-standing inequality in the rates of food insecurity across these groups. To do this, we propose a simple framework that sequentially decomposes differences in SNAP benefits across groups into three components: eligibility, participation, and generosity, and links the results to differences in food expenditures and food resource gaps through the MPSF from SNAP benefits.

Our results suggest that differences in eligibility alone can explain a substantial part of the differences in current SNAP benefits, food expenditures, and the food resource gap for both Black-

White and Hispanic-White household differentials. Generosity of SNAP is associated with a smaller increase in relative benefits for minority households, while participation modestly increases the relative benefits for Black households but lowers the relative benefits for Hispanic households, compared to White households. Overall, SNAP increases the level of food expenditures of minority households more than that of White households, which reduces the differences in the food resource gaps by 25 percent between Black and White households, and by 18 percent between Hispanic and White households.

We consider three hypothetical policy scenarios that completely shut down each of the three components in turn. Since these illustrative scenarios represent substantial changes from the current program, the results of our decomposition need to be interpreted with care. Among these hypothesized policies, automatic enrollment appears as more effective in alleviating inequality in food resource gaps between Hispanic and White households, and a uniform benefit level of $638 per month is more effective in alleviating inequality between Black and White households. Subsequently, we consider three marginal changes to each of the components, which appear as more realistic policy changes and require less extrapolation of the decomposition framework. From these three hypothetical marginal changes, we find that a 20 percent increase in SNAP benefits would result in the highest amount of SNAP benefits and food expenditures for minority households relative to White households. However, these increases appear insufficient to alleviate the inequality in outcomes, as food expenditures increase by 8 percent for Black households and 9 percent for Hispanic Households relative to White households, while the food resource gap relative to White households decreases by 6 percent for Black households and 3 percent for Hispanic households. This illustrative counterfactual analysis, while just carving out the contours of the problem, provides useful insights into the impact of alternative SNAP changes in inequality across racial and ethnic groups, by taking into consideration the pathways through which each considered policy works.

Researchers can apply the decomposition framework in this paper to a broad range of government programs to learn about the impacts of policies (and their reforms) on the inequality in variables of interest across groups. One example is health care reform that expands health insurance coverage and increases provisions to uninsured and underinsured populations. Our framework can help understand how these provisions narrow existing health care disparities across racial and ethnic groups and, by parsing out the key policy components, the analysis can help policymakers design more effective policies.

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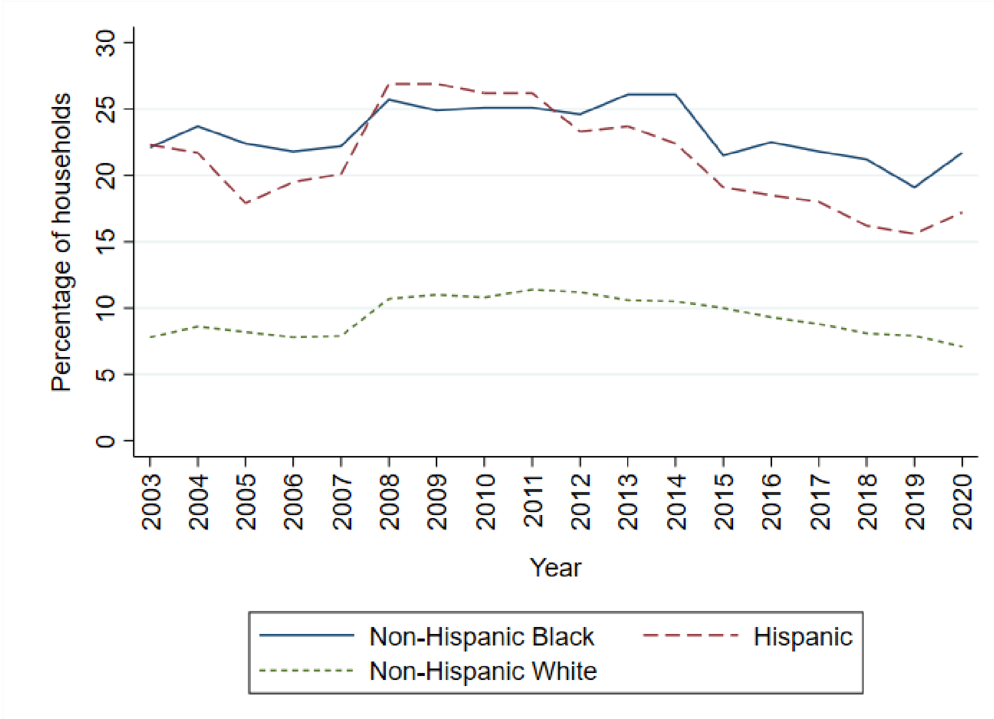
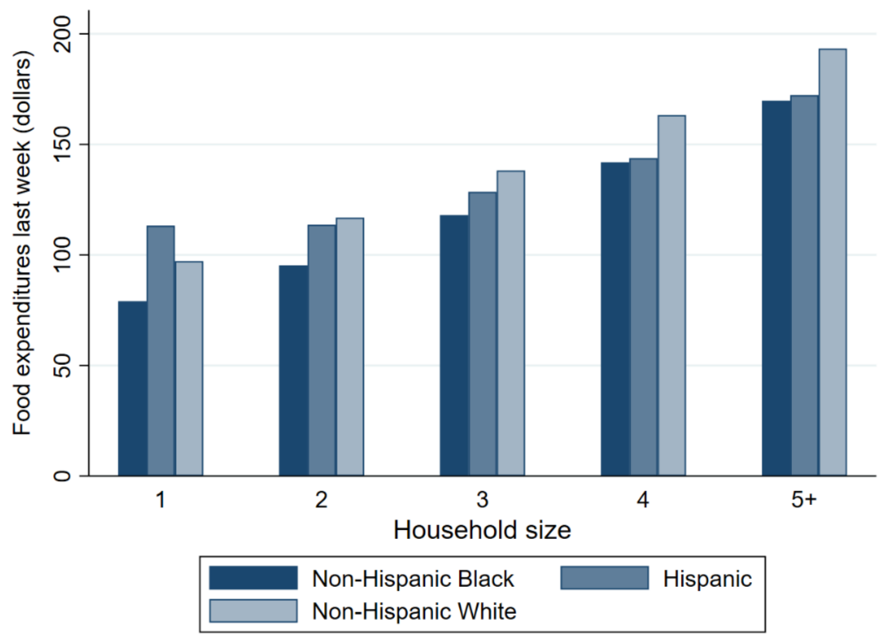
Figure 1: Food Insecurity by Race and Ethnicity, 2003-2020



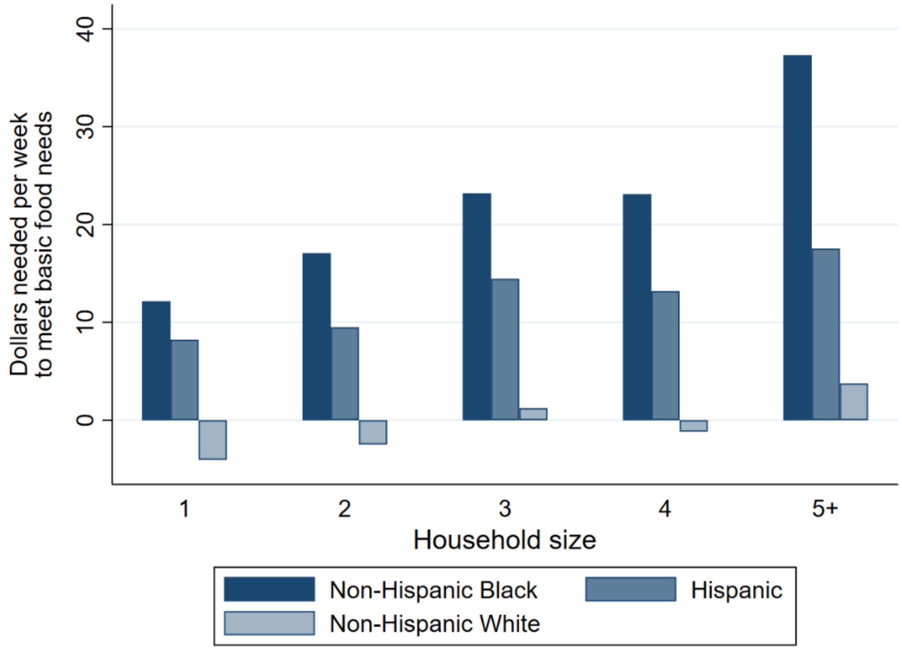
Source: U.S. Department of Agriculture, Economic Research Service.

Figure 2: Food Expenditures by Household Size, Race, and Ethnicity



Note: Data from the 2003-2016 CPS Food Security Supplement (FSS). We measure food expenditures by the total amount the household spent on food last week. The sample is composed of households below 185 percent of the poverty line or that report being short of money for food (the target population of the FSS).

Figure 3: Food Resource Gap by Household Size, Race, and Ethnicity



Note: Data from the 2003-2016 CPS Food Security Supplement (FSS). We measure the food resource gap by the amount deviating from a reference level of food spending to be food secure, based on three survey questions: (1) relative amount of money needed to meet needs (more, same, or less); (2) how much additional money needed to meet weekly basic household food needs; and (3) how much less money could be spent and still meet basic household food needs. The sample is composed of households below 185 percent of the poverty line or that report being short of money for food (the target population of the FSS).

Table 1: Summary Statistics of SNAP Benefits and SNAP Components by Race and Ethnicity

	White	Black	Hispanic	Difference: Black - White	Difference: Hispanic - White
	(1)	(2)	(3)	(4)	(5)
Unconditional monthly SNAP benefits	28.98 [113.60]	67.28 [170.60]	64.35 [176.34]	38.30 [0.91]	35.37 [0.84]
SNAP components					
Eligibility	0.25 [0.43]	0.43 [0.49]	0.44 [0.50]	0.18 [0.003]	0.19 [0.003]
Conditional on eligibility					
Participation	0.49 [0.50]	0.61 [0.49]	0.42 [0.49]	0.12 [0.01]	-0.07 [0.01]
Conditional on participation					
Benefits	237.90 [237.16]	256.81 [249.83]	343.75 [264.72]	18.91 [3.89]	105.85 [3.94]
Observations	98,145	18,866	28,207		

Note: This table reports means, standard deviations (Columns 1-3, in brackets), and standard errors (Columns 4-5, in brackets) for the analysis samples in 2003-2016 CPS, weighted by the CPS Food Security Supplement (FSS) weights. We focus on households below 185 percent of the poverty line or that report being short of money for food (the target population of the FSS) and with complete information on food expenditures.

Table 2: Summary Statistics of Food-related Outcomes by Race and Ethnicity

	White	Black	Hispanic	Difference: Black - White	Difference: Hispanic - White
	(1)	(2)	(3)	(4)	(5)
Total expenditures on food	553.51 [405.34]	477.03 [410.52]	570.75 [424.39]	-76.48 [2.88]	17.24 [2.56]
Relative amount needed to meet basic food needs (food resource gap)	-3.91 [180.32]	88.93 [225.40]	54.66 [211.74]	92.85 [1.40]	58.57 [1.21]
Food insecurity exposure					
Binary indicator	0.27 [0.44]	0.39 [0.49]	0.35 [0.48]	0.12 [0.003]	0.09 [0.003]
Rasch score	4.25 [2.39]	4.54 [2.43]	4.28 [2.30]	0.29 [0.02]	0.025 [0.02]

Note: This table reports means, standard deviations (Columns 1-3, in brackets), and standard errors (Columns 4-5, in brackets) for the analysis samples in 2003-2016 CPS, weighted by the CPS Food Security Supplement (FSS) weights. We focus on households below 185 percent of the poverty line or that report being short of money for food (the target population of the FSS) with complete information on food expenditures. To match with the frequency of SNAP benefit distribution, we multiply the reported amount of weekly food expenditures and food resource gap by four to obtain the monthly values of these variables.

Table 3: Decomposition of Differences in SNAP Benefits

	Black - White		Hispanic - White	
	Estimates	Relative Importance of the component	Estimates	Relative Importance of the component
	(1)	(2)	(3)	(4)
Overall difference in SNAP benefits (Δ)	38.30 [1.54]		35.37 [1.26]	
Eligibility (Δ_l)	28.06 [0.92]	73% [0.01]	28.22 [0.72]	80% [0.01]
Participation (Δ_t)	7.94 [0.48]	21% [0.01]	-5.74 [0.55]	-16% [0.02]
Generosity (Δ_z)	2.30 [0.59]	6% [0.01]	12.89 [0.62]	36% [0.01]

Notes: This table reports decomposition of group differences in SNAP benefits, using non-Hispanic White households as the reference group. Bootstrapped standard errors (in brackets) are obtained with 1,000 bootstrap replications. Relative importance of the component is calculated as: Δ_k/Δ , for $k = l, t, z$.

Table 4: Decomposition of Differences in Food Expenditures

	Black - White	Hispanic - White
	(1)	(2)
Difference in food expenditures	-76.48 [3.36]	17.24 [2.87]
Mean of group 1 (Black; Hispanic)	477.03	570.75
Mean of group 0 (White)	553.51	553.51
Decomposition of the difference in food expenditures		
Explained part	-10.10 [4.55]	-7.91 [5.09]
SNAP	22.98 [0.93]	10.61 [0.38]
Eligibility	16.83 [0.55]	8.47 [0.22]
Participation	4.77 [0.29]	-1.72 [0.17]
Generosity	1.38 [0.35]	3.87 [0.18]
Other covariates	-33.08 [4.46]	-18.52 [5.08]
Unexplained part	-66.38 [5.27]	25.15 [5.64]
SNAP	5.80 [0.07]	-2.90 [0.04]
Other covariates	-77.12 [25.60]	-211.46 [45.86]
Constants	4.95 [25.54]	239.51 [46.38]

Notes: This table reports group differences in food expenditures and the results of two-fold Oaxaca-Blinder decomposition with constrained linear regressions using the estimated marginal propensity to spend on food (MPSF) from SNAP benefits (see Appendix Table C2). Standard errors are in brackets. Other covariates include age, gender, immigration status, marital status, household head indicator, number of children, family size, urban status, education, family income, and state.

Table 5: Counterfactual Policy Experiments: Black - White Households

	Baseline	Counterfactual Policy Experiments					
		Universal eligibility	Automatic enrollment	Constant transfer: $638/m	Increase income eligibility limits by 20%	Increase participation rates by 20%	Increase benefit levels by 20%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Counterfactual SNAP benefits							
Difference	38.30	29.71	50.26	89.44	31.75	45.01	45.96
Mean of Black	67.28	100.04	109.21	167.16	99.40	76.81	80.74
Mean of White	28.98	70.33	58.95	77.72	67.65	31.79	34.78
Counterfactual food expenditures							
Difference	-76.48	-73.36	-63.31	-36.05	-72.67	-71.89	-70.72
Mean of Black	477.03	496.68	502.18	536.95	496.30	482.75	485.11
Mean of White	553.51	570.05	565.50	573.00	568.98	554.63	555.83
Counterfactual decomposition of difference in food expenditures							
Explained Part	-10.10	-15.26	-2.93	20.58	-14.03	-6.07	-5.50
SNAP	22.98	17.82	30.15	53.66	19.05	27.01	27.58
Eligibility	16.83	0	27.32	41.82	12.20	19.22	20.20
Participation	4.77	2.57	0	11.84	6.24	6.09	5.72
Generosity	1.38	15.25	2.83	0	0.61	1.70	1.66
Other covariates	-33.08	-33.08	-33.08	-33.08	-33.08	-33.08	-33.08
Unexplained part	-66.38	-58.11	-60.38	-56.63	-58.64	-65.82	-65.22
SNAP	5.80	14.07	11.79	15.54	13.53	6.36	6.96
Other covariates	-77.12	-77.12	-77.12	-77.12	-77.12	-77.12	-77.12
Constants	4.95	4.95	4.95	4.95	4.95	4.95	4.95

Notes: This table displays the decomposition of differences in SNAP benefits and food expenditures between Black and White households. Column (1) is the baseline decomposition as shown in Tables 3 and 4. Columns (2)-(7) show the following hypothesized changes to SNAP policy rules: (2) makes the entire sample eligible for SNAP; (3) makes all eligible households automatically enroll in SNAP; (4) provides all participants the same amount of SNAP benefits (set to be $638 per month); (5) increases gross and net income limits to qualify for SNAP by 20 percent; (6) increases participation rates by 20 percent; (7) increases benefit levels for eligible households by 20 percent. Standard errors of the estimates are shown in Appendix Table C3. Details of the procedures to obtain these counterfactual decompositions can be found in Appendix E.

Table 6: Counterfactual Policy Experiments: Hispanic - White Households

	Baseline	Counterfactual Policy Experiments					
		Universal eligibility	Automatic enrollment	Constant transfer: \$638/m	Increase income eligibility limits by 20%	Increase participation rates by 20%	Increase benefit levels by 20%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Counterfactual SNAP benefits							
Difference	35.37	36.40	92.38	41.72	36.47	40.09	42.45
Mean of Hispanic	64.35	106.74	151.33	119.43	104.12	71.89	77.22
Mean of White	28.98	70.33	58.95	77.72	67.65	31.79	34.78
Counterfactual food expenditures							
Difference	17.24	13.41	31.34	14.27	13.70	18.37	18.78
Mean of Hispanic	570.75	583.46	596.84	587.27	582.68	573.01	574.61
Mean of White	553.51	570.05	565.50	573.00	568.98	554.63	555.83
Counterfactual decomposition of difference in food expenditures							
Explained Part	-7.91	-7.60	9.20	-6.00	-7.58	-6.49	-5.79
SNAP	10.61	10.92	27.72	12.51	10.94	12.03	12.73
Eligibility	8.47	0	19.91	15.71	8.51	9.46	10.16
Participation	-1.72	-10.95	0	-3.20	-4.80	-1.71	-2.07
Generosity	3.87	21.88	7.81	0	7.23	4.29	4.64
Other covariates	-18.52	-18.52	-18.52	-18.52	-18.52	-18.52	-18.52
Unexplained part	25.15	21.01	22.15	20.27	21.28	24.86	24.57
SNAP	-2.90	-7.03	-5.89	-7.77	-6.76	-3.18	-3.48
Other covariates	-211.46	-211.46	-211.46	-211.46	-211.46	-211.46	-211.46
Constants	239.51	239.51	239.51	239.51	239.51	239.51	239.51

Notes: This table displays the decomposition of differences in SNAP benefits and food expenditures between Hispanic and White households. Column (1) is the baseline decomposition as shown in Tables 3 and 4. Columns (2)-(7) show the following hypothesized changes to SNAP policy rules: (2) makes the entire sample eligible for SNAP; (3) makes all eligible households automatically enroll in SNAP; (4) provides all participants the same amount of SNAP benefits (set to be \$638 per month); (5) increases gross and net income limits to qualify for SNAP by 20 percent; (6) increases participation rates by 20 percent; (7) increases benefit levels for eligible households by 20 percent. Standard errors of the estimates are shown in Appendix Table C4. Details of the procedures to obtain these counterfactual decompositions can be found in Appendix E.

ONLINE APPENDIX

Appendix A. Data Management and Imputation Procedures

We use the Current Population Survey (CPS) and its Food Security Supplement (FSS) between 2003 and 2016. We focus on households below 185 percent of the poverty line or short of money for food, which is the target population of the FSS. To obtain household eligibility for SNAP, we need household information on earned income and family composition. Since the December CPS lacks adequate information on earnings, we read in the Outgoing Rotation Group (ORG) files for January-March each year and match the December data to the appropriate ORG.[45] The match may fail because of identifier errors (due to migration, mortality, non-response, and recording errors), inconsistencies in respondents' basic demographic attributes (race, age, or gender), or incomplete information on the key variables. Table A1 summarizes the retention patterns for our sample. A total of 161,167 respondents within the scope of our study had earnings information after matching the FSS to the ORG. We lost a negligible 1,102 from missing information on family income, and 2,532 from missing information on food expenditures, which leaves 157,533 observations successfully matched with complete earnings, family income, and food expenditure information.

We impute SNAP eligibility and benefits for each observation because program eligibility is not available in the data. Households must meet three financial criteria to be eligible for SNAP: a gross income test, a net income test, and an asset test. Typically, households are eligible if (1) their gross monthly incomes are at or below l30 percent of the poverty line (or 165 percent of the poverty line for households with an elderly or disabled member);[46] (2) their net monthly incomes are at or below the

[45] For respondents in the December CPS, the ORG is split into December-March CPS surveys. We use CPS identifiers to match households across survey months of January-March.

[46] Note that the poverty line is nonlinearly related to household size and composition. The USDA adjusts the income eligibility standards, the deductions, and the maximum allotments at the beginning of each fiscal year,

poverty line;[47] (3) their countable assets are no more than $2,250 (or $3,250 for households with an elderly or disabled member).[48] Households are categorically eligible for SNAP if all members receive Supplemental Security Income (SSI), Temporary Assistance for Needy Families (TANF), or General Assistance (GA). If eligible, the monthly SNAP benefit amount is the maximum SNAP allotment, based on household size, less 30 percent of a household's net monthly income.[49] Households must be recertified every 6 to 24 months after initial eligibility. We collect program parameters of eligibility standards and benefit calculation from the USDA.

Based on the above eligibility criteria, there are five steps to generate imputed household eligibility using the merged CPS data. First, by multiplying weekly earnings by four, we calculate the respondent's monthly income, which is the period to determine SNAP eligibility, to pass through the gross and net monthly income tests. Second, the categorical family income variable is useful to screen out certainly ineligible households further. Third, we employ different income eligibility standards for disabled adults and the elderly (age 60 or older). Fourth, we rule out immigrants who have lived in the United States for less than five years as they are ineligible for SNAP. Fifth, households are eligible if they reported participating in SNAP.[50] Note that the December CPS-FSS does not track all the information needed to identify eligible households. For instance, we lack information on households'

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which takes effect from October 1st of the previous year to September 30th of the current year. These parameters are the same for all states in the continental U.S. but different for Alaska and Hawaii.

[47] Net income is calculated as gross income minus allowable deductions, which include a 20 percent deduction from gross income, a standard deduction, a deduction for households incurring expenses in the care of their children and/or disabled dependents, a medical deduction for expenses, and a shelter deduction for costs above 50 percent of a household's net income (computed before the shelter deduction and capped except for elderly or disabled households).

[48] Historical asset limit is $2,000. Most states now elect to waive this asset test.

[49] The income eligibility standards and deductions are adjusted based on the inflation rate for the CPI, and the monthly maximum allotments are adjusted based on the "food-at-home" series of the CPI. The benefit amount is subject to a minimum amount, which also varies across household size.

[50] Among our imputed ineligible households, about 6 percent are shown participating in SNAP. This could be due to misreporting or the lack of information to identify eligibility.

assets, expenses related to medical and shelter deductions, SSI and TANF receipt, and whether there is a disabled or elderly member in the household other than the respondent. We assume that all types of income other than self-reported earnings and family income are zero.

Compared to the estimates from the USDA reports (e.g., Wolkwitz, 2008; Gray and Cunnyngham, 2016),[51] our estimated participation rates are lower (Figure A1) but have similar trends.[52] In Figure A2, we show that Black households constantly have the highest participation rates, followed by White households and then Hispanic households, which is in line with Coleman-Jensen et al. (2021). We also show a countercyclical pattern of the program, with increases in participation rates notably during the Great Recession. The reduction in participation rates after 2013 is consistent with the evidence that, in November 2013, all SNAP benefits fell when temporary increases in the American Recovery and Reinvestment Act (ARRA) expired. In addition, the participation rates are much lower for eligible elderly adults (age 60 or older) than their counterparts in our data, consistent with documented evidence.[53]

It is worth noting that the estimates in the USDA reports reflect the overall population, which is different from our sample of households under 185 percent of the poverty line. Overall, the participation rates could vary substantially across studies due to different data, methodology, and analysis samples.

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[51] The USDA reports collect administrative data from the SNAP Quality Control data to get information on SNAP participation, along with the data from the CPS Annual Social and Economic Supplement to generate SNAP eligibility (e.g., Gray and Cunnyngham, 2016).

[52] Previous studies have pointed out that respondents tend to underreport SNAP participation in survey data (Gundersen and Kreider, 2008; Gray and Cunnyngham, 2016).

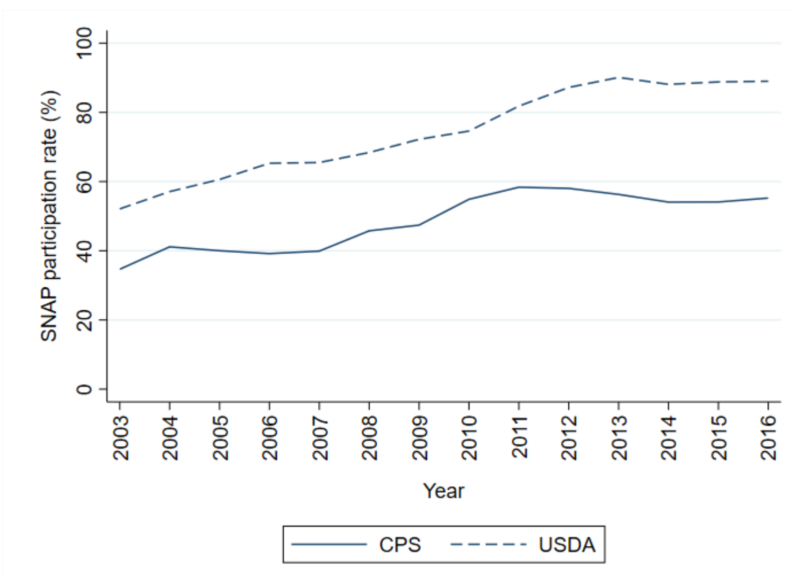
[53] See, for example, "SNAP Participation Lags Among Eligible Seniors in Every State, Putting Them at Greater Risk of Hunger," Food Research & Action Center (2019). https://frac.org/news/snap-participation-lags-among-eligible-seniors-in-every-state-putting-them-at-greater-risk-of-hunger.

Figure A3 shows the imputed and self-reported benefits among SNAP participants. The self-reported values seem to have a rounding problem since spikes in the density at benefit amounts divisible by 100 appear. Furthermore, SNAP benefits are top-coded in the CPS (the top code is $450 before 2011 and $700 in 2011 and after). Because of this and other issues discussed in Section 3.1, we use the imputed benefits instead of the self-reported benefits in our analysis.

Table A1: Sample Attrition

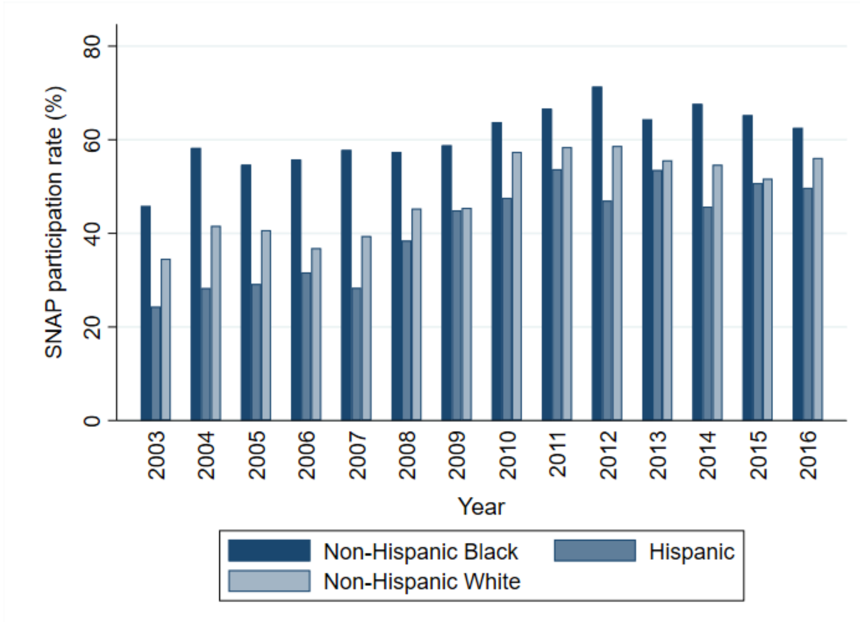
Reason for exclusion	Sample Size
No excluded cases	339,713
Missing earnings data	161,167
Missing family income data	160,065
Missing food expenditures	157,533

Figure A1: SNAP Participation Rates in the CPS versus USDA Data, 2003-2016



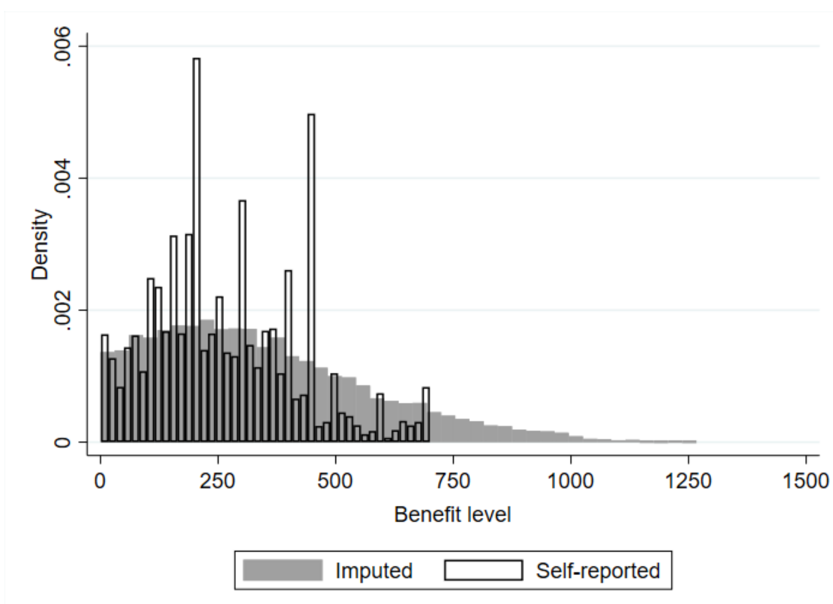
Notes: The dashed line shows the mean participation rates using 2003-2016 CPS, weighted by the CPS Food Security Supplement (FSS) weights. The sample consists of households below 185 percent of the poverty line or that report being short of money for food. The dashed line plots the participation rates reported by the USDA.

Figure A2: SNAP Participation Rates by Race and Ethnicity, 2003-2016



Notes: Authors' calculation using 2003-2016 CPS, weighted by the CPS Food Security Supplement (FSS) weights. The sample consists of households below 185 percent of the poverty line or that report being short of money for food (the target population of the FSS).

Figure A3: Imputed and Self-reported SNAP Benefits



Note: Figure shows the imputed and self-reported SNAP benefits among SNAP participants using data from 2003-2016 CPS. We plot the imputed benefit levels between $1 and $1,500 (there are 22 observations with a value above $1,500).

Appendix B. Comparison between CPS and SNAP Quality Control Data

We assess the accuracy of our imputation in Appendix A using the SNAP Quality Control (QC) data over the same analysis period (2003-2016). The data contain detailed economic and demographic information on a random sample of SNAP participating households.

First, we verify that the benefit amounts in the QC data are generally parallel to those imputed in our paper. The key variables in the QC data involved in this exercise are final calculated SNAP benefit and race/ethnicity of person 1 in the SNAP unit.[54] Please note that we are only able to compare *the benefit levels conditional on participation* because the QC data are based on a sample of SNAP participants. Table B1 compares the means of the imputed values in the paper (Row A) to those in the QC data (Row B) across racial and ethnic groups. Importantly, results from both datasets show that conditioning on participation, Hispanic households receive the highest SNAP benefits on average, followed by Black and White households. Moreover, the differences in the average benefit amounts between Black and White households are very similar between both datasets. If anything, Hispanic households have a higher average benefit level based on our imputed values. This suggests that our results may overestimate the average SNAP benefit level that Hispanic households receive and therefore overestimate how SNAP alleviates the Hispanic-White inequality in food resource gaps.

Second, we assess whether the data limitations might potentially invalidate our decomposition approach. Specifically, one concern is that our imputed benefit amounts are based on a set of observed covariates in the CPS data and that we lack the information on other determinants such as households' assets, SSI and TANF receipt, the presence of a disabled or elderly member in the household other than

[54] Vigil, Alma, Sarah Lauffer, Kelsey Farson Gray, Chrystine Tadler, and Brad Miller. "Technical Documentation for the Fiscal Year 2016 Supplemental Nutrition Assistance Program Quality Control Database and the QC Minimodel." Washington, DC: Mathematica Policy Research, October 2017.

the respondent, expenses related to shelter, child care, and health care to calculate deductions for net income (Section 3.3). To address this, we extract from the QC data the closest possible covariates to the ones used in the paper, which are: reported number of people in the household, monthly income of the respondent, whether the respondent is age 60+, disabled,[55] or an immigrant who have lived in the U.S. for less than five years.[56] We then estimate the predicted values with a linear regression model based only on these covariates and compare them to the actual values. This allows us to evaluate how well our imputation performs. As shown in Table B1, the predictions of the benefit amounts by group (Row C) are very similar to the actual amounts (Row B), suggesting that our imputation could be a valid approach to obtain the average levels of SNAP benefits by group used in our decomposition analysis.

[55] Person-level disabled indicators on the 2003-2006 QC datafiles were dropped; therefore, we use unit-level disabled indicators for these years.
[56] The closet possible variable in the QC data is the citizenship indicator.

Table B1: Comparison between CPS and SNAP Quality Control Data

	Mean SNAP benefits conditional on participation				
Data sources	Non-Hispanic White	Non-Hispanic Black	Hispanic	Difference: Black - White	Difference: Hispanic - White
A. CPS data (imputed values)					
	236.85	254.62	342.10	17.77	105.25
B. SNAP Quality Control data (actual values)					
	231.80	250.51	277.05	18.71	45.25
C. SNAP Quality Control data (predicted values based on observed covariates)					
	231.92	250.64	283.45	18.72	51.53

Notes: Row A reports the imputed mean benefits using the CPS data. Row B reports the final calculated SNAP benefits in the QC data. Row C reports the predicted benefits using the QC data with similar observed covariates to those used in the paper. The CPS and QC files' sampling weights are used to estimate these mean values.

Appendix C. Supplemental Tables

Table C1: Descriptive Statistics of Socioeconomic Characteristics by Race and Ethnicity

Variables	White	Black	Hispanic	Difference: Black - White	Difference: Hispanic - White
	(1)	(2)	(3)	(4)	(5)
Age	37.87	37.24	35.39	-0.64*** (0.10)	-2.49*** (0.08)
Male	0.49	0.40	0.55	-0.08*** (0.003)	0.07*** (0.003)
Immigrant	0.04	0.12	0.57	0.07*** (0.002)	0.52*** (0.002)
Married	0.47	0.31	0.49	-0.16*** (0.003)	0.02*** (0.003)
Family size	2.96	3.08	3.82	0.12*** (0.01)	0.86*** (0.01)
Number of children	0.91	1.04	1.25	0.13*** (0.01)	0.34*** (0.01)
Monthly earnings	2393.22	2044.60	1913.07	-348.62*** (12.62)	-480.15*** (10.73)
Unemployed	0.03	0.05	0.04	0.02*** (0.001)	0.01*** (0.001)
Household head	0.52	0.59	0.46	0.07*** (0.003)	-0.06*** (0.003)
Metropolitan area	0.77	0.88	0.92	0.11*** (0.003)	0.15*** (0.002)
Education					
12 grades or less	0.11	0.14	0.39	0.03*** (0.002)	0.28*** (0.002)
High school degree	0.35	0.37	0.32	0.03*** (0.003)	-0.03*** (0.003)
Some college or Associate's degree	0.33	0.34	0.21	0.01** (0.003)	-0.12*** (0.003)
Bachelor's degree	0.15	0.10	0.06	-0.05*** (0.002)	-0.09*** (0.002)
Master's degree or above	0.05	0.04	0.02	-0.02*** (0.002)	-0.04*** (0.001)
Family income					
< $10,000	0.07	0.14	0.09	0.06*** (0.002)	0.02*** (0.002)
$10,000 - $19,999	0.14	0.20	0.20	0.06*** (0.003)	0.06*** (0.002)
$20,000 - $29,999	0.18	0.21	0.23	0.03*** (0.003)	0.05*** (0.002)
$30,000 - $39,999	0.15	0.15	0.19	-0.002 (0.003)	0.03*** (0.002)
$40,000 - $49,999	0.10	0.08	0.10	-0.02*** (0.002)	-0.004** (0.002)
$50,000 - $59,999	0.09	0.06	0.06	-0.03*** (0.002)	-0.02*** (0.002)
$60,000 - $74,999	0.09	0.06	0.05	-0.03*** (0.002)	-0.04*** (0.002)
$75,000 - $99,999	0.08	0.04	0.04	-0.04*** (0.002)	-0.04*** (0.002)
$100,000 - $149,999	0.05	0.03	0.02	-0.02*** (0.001)	-0.03*** (0.001)
>= $150,000	0.02	0.01	0.01	-0.01*** (0.001)	-0.01*** (0.001)

Census region					
New England	0.05	0.02	0.02	-0.03*** (0.001)	-0.03*** (0.001)
Middle Atlantic	0.12	0.12	0.10	0.0003 (0.002)	-0.02*** (0.002)
East North Central	0.19	0.14	0.06	-0.05*** (0.003)	-0.12*** (0.002)
West North Central	0.10	0.04	0.02	-0.06*** (0.002)	-0.08*** (0.002)
South Atlantic	0.17	0.35	0.14	0.18*** (0.003)	-0.03*** (0.002)
East South Central	0.08	0.10	0.01	0.02*** (0.002)	-0.06*** (0.001)
West South Central	0.10	0.16	0.22	0.05*** (0.002)	0.12*** (0.002)
Mountain	0.08	0.02	0.11	-0.06*** (0.002)	0.03*** (0.002)
Pacific	0.11	0.06	0.30	-0.05*** (0.002)	0.19*** (0.002)
Observations	101,359	19,682	29,245		

Notes: This table reports means and standard errors (Columns 5-6, in parentheses) for the analysis samples using 2003-2016 CPS, weighted by the CPS Food Security Supplement (FSS) weights. We focus on households below 185 percent of the poverty line or that report being short of money for food (the target population of the FSS). *** P-value ≤ 0.01; ** P-value ≤ 0.05; * P-value ≤ 0.1.

Table C2: Estimated Marginal Propensity to Spend on Food (MPSF) from SNAP Benefits

	All		White		Black		Hispanic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expenditures on food at home last week (SNAP-eligible spending)								
SNAP benefits	0.412	0.424	0.361	0.378	0.625	0.619	0.296	0.316
	(0.025)	(0.025)	(0.032)	(0.032)	(0.056)	(0.056)	(0.052)	(0.052)
Observations	16,283	16,283	8,341	8,341	3,285	3,285	3,594	3,594
R^2	0.145	0.153	0.164	0.179	0.191	0.200	0.131	0.146
Demographics	Y	Y	Y	Y	Y	Y	Y	Y
Income variables	N	Y	N	Y	N	Y	N	Y
State and year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Each column reports results from a separate regression of food expenditures on SNAP benefits among the set of SNAP adopters. We use data from the 2003-2014 CPS Food Security Supplement (FSS) because the outcome variable, total amount spent on food intended for preparation and consumption at home last week (SNAP-eligible food purchases), is only available up to 2014. This outcome variable collects information on food expenditures at grocery stores, supermarkets, convenience stores, and specialty stores, making it a close match to allowable food purchases with SNAP benefits. It is top coded at $500 weekly. The sample consists of households below 185 percent of the poverty line or that report being short of money for food (the target population of the FSS). Demographic variables include age, gender, marital status, family size, number of children, household head indicator, immigrant status, urban status, education. Income variables include weekly earnings, unemployment, and family income. Columns (1), (3), (5), (7) are from regressions without controlling for income variables, whereas Columns (2), (4), (6), (8) are those with income variables. Robust standard errors are in parentheses. Estimates are weighted using the CPS FSS weights.

Table C3: Counterfactual Policy Experiments: Black - White Households

	Baseline	Counterfactual Policy Experiments					
		Universal eligibility	Automatic enrollment	Constant transfer: $638/m	Increase income eligibility limits by 20%	Increase participatio n rates by 20%	Increase benefit levels by 20%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Counterfactual SNAP benefits							
Difference	38.30 [1.54]	29.71 [1.72]	50.26 [1.82]	89.44 [2.51]	31.75 [1.75]	45.01 [1.55]	45.96 [1.85]
Mean of Black	67.28	100.04	109.21	167.16	99.40	76.81	80.74
Mean of White	28.98	70.33	58.95	77.72	67.65	31.79	34.78
Counterfactual food expenditures							
Difference	-76.48 [3.36]	-73.36 [3.43]	-63.31 [3.39]	-36.05 [3.45]	-72.67 [3.43]	-71.89 [3.36]	-70.72 [3.40]
Mean of Black	477.03	496.68	502.18	536.95	496.30	482.75	485.11
Mean of White	553.51	570.05	565.50	573.00	568.98	554.63	555.83
Counterfactual decomposition of difference in food expenditures							
Explained Part	-10.10 [4.55]	-15.26 [4.61]	-2.93 [4.57]	20.58 [4.62]	-14.03 [4.61]	-6.07 [4.55]	-5.50 [4.58]
SNAP	22.98 [0.93]	17.82 [1.03]	30.15 [1.09]	53.66 [1.51]	19.05 [1.05]	27.01 [0.93]	27.58 [1.11]
Eligibility	16.83 [0.55]	0	27.32 [0.78]	41.82 [1.15]	12.20 [0.44]	19.22 [0.59]	20.20 [0.66]
Participation	4.77 [0.29]	2.57 [0.37]	0	11.84 [0.69]	6.24 [0.40]	6.09 [0.27]	5.72 [0.35]
Generosity	1.38 [0.35]	15.25 [0.94]	2.83 [0.51]	0	0.61 [0.60]	1.70 [0.34]	1.66 [0.42]
Other covariates	-33.08 [4.46]	-33.08 [4.46]	-33.08 [4.46]	-33.08 [4.46]	-33.08 [4.46]	-33.08 [4.46]	-33.08 [4.46]
Unexplained part	-66.38 [5.27]	-58.11 [5.27]	-60.38 [5.27]	-56.63 [5.27]	-58.64 [5.27]	-65.82 [5.27]	-65.22 [5.27]
SNAP	5.80 [0.07]	14.07 [0.10]	11.79 [0.10]	15.54 [0.13]	13.53 [0.10]	6.36 [0.07]	6.96 [0.09]
Other covariates	-77.12 [25.60]	-77.12 [25.60]	-77.12 [25.60]	- 7.12 [25.60]	-77.12 [25.60]	-77.12 [25.60]	-77.12 [25.60]
Constants	4.95 [25.54]	4.95 [25.54]	4.95 [25.54]	4.95 [25.54]	4.95 [25.54]	4.95 [25.54]	4.95 [25.54]

Notes: This table displays the decomposition of differences in SNAP benefits and food expenditures between Black and White households, with standard errors in brackets. Column (1) is the baseline decomposition as shown in Tables 3 and 4. Columns (2)-(7) show the following hypothesized changes to SNAP policy rules: (2) makes the entire sample eligible for SNAP; (3) makes all eligible households automatically enroll in SNAP; (4) provides all participants the same amount of SNAP benefits (set to be $638 per month); (5) increases gross and net income limits to qualify for SNAP by 20 percent; (6) increases participation rates by 20 percent; (7) increases benefit levels for eligible households by 20 percent. Details of the procedures to obtain these counterfactual decompositions can be found in Appendix E.

Table C4: Counterfactual Policy Experiments: Hispanic - White Households

	Baseline	Counterfactual Policy Experiments					
		Universal eligibility	Automatic enrollment	Constant transfer: $638/m	Increase income eligibility limits by 20%	Increase participatio n rates by 20%	Increase benefit levels by 20%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Counterfactual SNAP benefits							
Difference	35.37 [1.26]	36.40 [1.52]	92.38 [1.68]	41.72 [1.86]	36.47 [1.54]	40.09 [1.25]	42.45 [1.51]
Mean of Hispanic	64.35	106.74	151.33	119.43	104.12	71.89	77.22
Mean of White	28.98	70.33	58.95	77.72	67.65	31.79	34.78
Counterfactual food expenditures							
Difference	17.24 [2.87]	13.41 [2.91]	31.34 [2.88]	14.27 [2.87]	13.70 [2.91]	18.37 [2.87]	18.78 [2.88]
Mean of Hispanic	570.75	583.46	596.84	587.27	582.68	573.01	574.61
Mean of White	553.51	570.05	565.50	573.00	568.98	554.63	555.83
Counterfactual decomposition of difference in food expenditures							
Explained Part	-7.91 [5.09]	-7.60 [5.11]	9.20 [5.10]	-6.00 [5.09]	-7.58 [5.11]	-6.49 [5.09]	-5.79 [5.10]
SNAP	10.61 [0.38]	10.92 [0.46]	27.72 [0.50]	12.51 [0.56]	10.94 [0.46]	12.03 [0.38]	12.73 [0.45]
Eligibility	8.47 [0.22]	0	19.91 [0.40]	15.71 [0.35]	8.51 [0.19]	9.46 [0.23]	10.16 [0.26]
Participation	-1.72 [0.17]	-10.95 [0.28]	0	-3.20 [0.30]	-4.80 [0.23]	-1.71 [0.15]	-2.07 [0.20]
Generosity	3.87 [0.18]	21.88 [0.52]	7.81 [0.23]	0	7.23 [0.30]	4.29 [0.17]	4.64 [0.22]
Other covariates	-18.52 [5.08]	-18.52 [5.08]	-18.52 [5.08]	-18.52 [5.08]	-18.52 [5.08]	-18.52 [5.08]	-18.52 [5.08]
Unexplained part	25.15 [5.64]	21.01 [5.64]	22.15 [5.64]	20.27 [5.64]	21.28 [5.64]	24.86 [5.64]	24.57 [5.64]
SNAP	-2.90 [0.04]	-7.03 [0.05]	-5.89 [0.05]	-7.77 [0.07]	-6.76 [0.05]	-3.18 [0.04]	-3.48 [0.04]
Other covariates	-211.46 [45.86]	-211.46 [45.86]	-211.46 [45.86]	-211.46 [45.86]	-211.46 [45.86]	-211.46 [45.86]	-211.46 [45.86]
Constants	239.51 [46.38]	239.51 [46.38]	239.51 [46.38]	239.51 [46.38]	239.51 [46.38]	239.51 [46.38]	239.51 [46.38]

Notes: This table displays the decomposition of differences in SNAP benefits and food expenditures between Hispanic and White households, with standard errors in brackets. Column (1) is the baseline decomposition as shown in Tables 3 and 4. Columns (2)-(7) show the following hypothesized changes to SNAP policy rules: (2) makes the entire sample eligible for SNAP; (3) makes all eligible households automatically enroll in SNAP; (4) provides all participants the same amount of SNAP benefits (set to be $638 per month); (5) increases gross and net income limits to qualify for SNAP by 20 percent; (6) increases participation rates by 20 percent; (7) increases benefit levels for eligible households by 20 percent. Details of the procedures to obtain these counterfactual decompositions can be found in Appendix E.

Appendix D. Counterfactual Decompositions

In this appendix, we discuss in greater detail how we obtain the counterfactual values of SNAP benefits under hypothetical policy scenarios. As it will become clear, the strength of the assumptions required for our counterfactual SNAP benefit estimates across groups to be valid depend in subtle ways on the nature of the policy under consideration.

To begin, recall that for any household, the value of SNAP benefit can be written as a product of three terms:

$$z = lt\mathscr{z},$$

where z is the SNAP benefit level that the household receives, l (eligibility) is a binary variable that takes the value of one when the household is eligible for SNAP, t (participation) is a binary variable that takes the value of one when the household decides to enroll, and $\mathscr{z}$ (generosity) is a variable that denotes the level of SNAP benefits that the household qualifies for. This equation clearly demonstrates that households that are not eligible for SNAP, as well as households that are eligible but choose not to enroll in the program, will have an observed value of SNAP benefits of zero; households that are eligible and enroll in the program will have an observed value that is precisely the benefit level that they qualify to receive.

If we observe all of the determinants of eligibility and generosity, both l and $\mathscr{z}$ are deterministic, non-random functions of covariates observed in the data. In this case, the only probabilistic relationship that needs to be modelled is the participation equation. As shown below, this will have implications for the kind of counterfactuals that are identified with weaker assumptions.

For a household with a given set of covariates $\boldsymbol{X}$, eligibility as a function of covariates is *known* to be either one—when the household is eligible for SNAP—or zero—when the household is not eligible for SNAP. Similarly, for households that are eligible, the level of benefits they qualify for are also a known function of their observable characteristics. Thus, the only non-trivial object to be computed is the participation *probabilities* for those that are eligible and qualify for a certain value of benefits. Let this probability be given as a function of covariates by:

$$\mathbb{P}_g[t|l, \boldsymbol{x}, z\,] = \boldsymbol{F}\big(\boldsymbol{\theta}_g \boldsymbol{x} + \delta_g z\big)$$

for some known link function $\boldsymbol{F}$—typical cases are the logistic function or the normal distribution cumulative function. As shown below, the fact that participation must be estimated, whereas eligibility and generosity do not lead to subtle differences in the credibility of otherwise similar counterfactual policies. Whenever a policy leads participation behavior to be irrelevant—such as automatic enrollment—knowledge of the participation function is not necessary. However, in other scenarios—such as policies that loosen eligibility requirements or increase generosity—a model for participation probabilities, if correctly specified, allows us to impute counterfactual participation for those who would either not qualify for the program before the policy or qualify for a different benefit amount before. It is useful to note that there is a clear distinction between interpolation and extrapolation: It is inherently easier to impute average levels of SNAP benefits across groups in counterfactual policy scenarios that tighten eligibility requirements than in those that relax requirements. This is because the participation behavior of every eligible household under counterfactual scenarios with more stringent requirements has *already been observed* in the data. In contrast, the participation behavior of some households must be *predicted* under counterfactual scenarios that enlarges the set of eligible households—those whose participation decision was censored in the observed data because they were ineligible.

Using Rubin's potential outcome notation, a counterfactual SNAP policy is defined by a counterfactual level of SNAP benefits $z(c)$ that is given by the counterfactual values of eligibility $l(c)$, participation $t(c)$, and generosity $z(c)$ that would prevail under the policy in consideration. That is,

$$z(c) = l(c)t(c)z(c).$$

It is typically the case that a policy would target one of the three terms above that determine SNAP benefits. For example, a universal eligibility policy would set the counterfactual value of eligibility $l(c)$ equal to one for everyone in the data. Similarly, an automatic enrollment policy would set the counterfactual participation component $t(c)$ equal to one for everyone.[57] Note that, to obtain the counterfactual levels of SNAP benefits, we still must be able to construct the counterfactual values of the remaining terms. Thus, the credibility of this exercise depends on how hard it is to compute these terms, and how sensitive the counterfactual levels of SNAP benefits are to the way we construct them. As it turns out, for several policies we might be interested in, the construction of the remaining counterfactual terms is a trivial exercise because the remaining terms are determinist functions of the observed values of covariates in the data, or because the policy is such that knowing the value of the remaining terms turns out to be unnecessary.

Automatic Enrollment

Automatic enrollment is defined as a policy that sets $t(c) = 1$ for every eligible household. That is, once the household is eligible for SNAP, they will automatically get the benefit that they qualify for. Given that the policy by design keeps eligibility standards and generosity levels unchanged, all the

[57] We could also say that it would induce the counterfactual participation term to be one for everyone that is eligible for the program.

terms in the counterfactual levels of SNAP benefits are immediately obtained. This is because under automatic enrollment we have $l(c) = l$ and $z(c) = z$, the counterfactual level of SNAP benefits $z(c)$ now becomes

$$z(c) = l(c)t(c)z(c) = lz.$$

That is, the counterfactual levels of SNAP benefits under automatic enrollment can be obtained by taking eligibility and generosity levels observed in the data and replacing the participation observed in the data with a value of one for every households. Note that under automatic enrollment, we can bypass the need for modeling the participation behavior of households since the policy renders this behavior irrelevant. The average levels of SNAP benefits across groups under this scenario can then be readily computed by averaging the counterfactual levels of SNAP obtained for each household using the procedure described above.

Tightening Eligibility Standards

A policy that tightens eligibility standards is another policy for which computation of counterfactual SNAP benefits is straightforward because we do not need to know or have a correctly specified model for counterfactual participation behavior to evaluate the counterfactual values of SNAP benefits.

More stringent eligibility rules will set a counterfactual level of $l(c)$ to zero for some households, based on the values of their covariates. In that instance, it is not required to know these households' participation behavior since the structure of SNAP benefits make the counterfactual values independent of their participation behavior when eligibility is *tightened*. For households unaffected by the changes in eligibility standards—that is, those that remain eligible—their participation behavior is directly observed so there is no need to model their behavior. For those that become ineligible under the new eligibility requirements, we have that:

$$z(c) = l(c)t(c)z(c) = 0t(c)z(c) = 0.$$

Once $l(c)$ is set to zero, whether or not we are able to accurately access participation probabilities in the counterfactual policy scenario does not matter. Thus, under a policy that tightens eligibility, a predictive model for participation behavior is not required as the status of being ineligible for the program renders participation irrelevant under the counterfactual scenario. The average levels of SNAP benefits across groups can then be readily computed by averaging the counterfactual levels of SNAP benefits obtained for each household using the procedure described above.

Loosening Eligibility Standards

In contrast, a policy that loosens eligibility standards and thus enlarges the set of eligible households is harder to evaluate. This is because it requires a model to predict the participation behavior of newly eligible households.

A policy that loosens eligibility standards, such as universal eligibility, will set a counterfactual value of eligibility to be one for a set of households that do not currently qualify for the program in the data. In this case, we have the following counterfactual values for these households:

$$z(c) = 1t(c)z(c) = t(c)z(c).$$

Note that we still need to obtain the benefit levels they qualify for. Given that SNAP benefits are a known function of observable covariates, this part of the task is relatively straightforward. We can use the observed (imputed) SNAP benefits for these households, and as a result, the counterfactual levels of SNAP benefits become:

$$z(c) = 1t(c)z(c) = t(c)z.$$

We still need to ask whether these (now eligible) households will take up the program. The policies we looked at before bypassed the need to think about the participation behavior because they either specify the participation values, leaving only deterministic variables to be evaluated, or because they render the participation behavior to be irrelevant (for example, under tightened eligibility rules, once eligibility is zero, SNAP benefits do not depend on participation anymore).

If the eligibility censoring is conditionally at random, we can use parameters of the participation equation estimated for eligible households to predict the take up behavior of those that are, in the observed data, still not eligible for the program. Naturally, the quality and credibility of our counterfactual estimates will depend on the appropriateness of this assumption. Under this assumption, we have:

$$\mathbb{P}_g[t|\boldsymbol{x}, l, z] = \boldsymbol{F}\big(\boldsymbol{\theta}_g \boldsymbol{x} + \delta_g z\big) = \mathbb{P}_g[t(c)|\boldsymbol{x}, l(c), z].$$

The equation above links the participation behavior among the set of households currently eligible for the program, which is observed in the data, to the participation behavior of households that are yet eligible. If this assumption is valid, we can generate participation by using predicted values from the participation model to obtain counterfactual participation probabilities under a policy that enlarges the set of eligible households. The average levels of SNAP benefits of a group can be computed by averaging the counterfactual levels of SNAP benefits with weights proportional to the counterfactual participation probabilities of households.

Changes in Generosity

A policy that changes the generosity level would generate counterfactual SNAP benefits as follows:

$$z(c) = l(c)t(c)z(c).$$

The counterfactual values of $z(c)$ under such a policy are readily available from the description (design) of the policy. Given that this policy does not change eligibility, the value of the eligibility term $l(c)$ will coincide with the eligibility observed in the data. Thus, the counterfactual levels of SNAP benefits under this policy can be written as:

$$z(c) = lt(c)z(c).$$

Note that under this policy the value of $z(c)$ is known for every household. Therefore, the only term we need to impute to obtain the counterfactual levels of SNAP benefits is participation, $t(c)$. *If participation is insensitive to generosity*, we have:

$$z(c) = lt(c)z(c) = \; ltz(c).$$

In this case, we can obtain the counterfactual levels of SNAP benefits for all households by imputing the new benefit levels that they qualify for among those that are currently eligible and currently enroll in the program.

This assumption of insensitivity to generosity is obviously not appropriate for large changes to the program, but it can be a reasonable approximation of the actual behavior of agents under marginal changes to the program. We can decompose the changes in the average benefit levels that households will qualify for into the mechanical terms that are obtained by the formula above with a behavioral component that comes from changes in participation that is induced by changes in the program's generosity.

Is it possible to account for changes in participation due to changes in generosity? The answer is yes. To do that, one only needs to add the generosity term to the participation model. Under standard assumptions that allow us to identify the parameters of the model, we can use the counterfactual levels of participation under the counterfactual levels of generosity (instead of the observed levels of participation under the counterfactual levels of generosity). Once again, for small changes to the program generosity levels, this distinction should not be very important.[58]

In the case that participation is sensitive to generosity, we can compute counterfactual participation probabilities using the participation model. That is, counterfactual participation probabilities are given by:

$$\mathbb{P}_g[t(c)|\boldsymbol{x}, l, z(c)].$$

We can then obtain the average levels of SNAP benefits of a group by averaging the counterfactual levels of SNAP benefits with weights proportional to the counterfactual participation probabilities of households.

Encouraging Participation

A policy that encourages marginal households to take up the program does not alter eligibility standards or generosity levels but increases participation rates by encouraging households to enroll in the program. Under such policy, we have:

$$z(c) = l(c)t(c)z(c) = lt(c)z.$$

[58] It is useful to contrast the need of thinking about responsiveness of participation to generosity with the absence of such need for eligibility. The reason we can readily obtain counterfactual eligibility levels but we cannot do so for participation is because we have a deterministic rule for eligibility, which allows us to perform counterfactuals without the need for behavioral assumptions; whereas we have non-deterministic, behavioral model for participation, which forces us to consider assumptions about participation and how people respond to the program's generosity.

As shown, both eligibility and benefits that households will qualify for will be identical to those observed in the data. However, counterfactual participation probabilities will be higher due to the policy change.

This type of policy that nudges households to take up the program (e.g., application assistance, reminder letters) would naturally target households that are at the margin of indifference between taking up the program and not doing so. This can be incorporated into our framework by marginally increasing the predicted probability of participation and then computing the weighted average of benefit levels across groups.

Appendix E. Algorithm

This appendix explains the empirical procedures we use to obtain the terms of the decomposition of both the observed differences and the counterfactual differences under hypothetical policy scenarios.

A. Imputation of SNAP eligibility, benefits, and group differences

1. Impute SNAP eligibility for each observation i.

   To be eligible, one needs to have

$$monthly\ income_i < gross\ income\ limit$$

$$\text{and } (monthly\ income_i \times 0.8 - standard\ deduction) < net\ income\ limit$$

   where $gross\ income\ limit, net\ income\ limit$, and $standard\ deduction$ vary by year, household size, whether the household has an elderly (age 60+) or a disabled member, employment, state, and immigration status.

2. Impute SNAP benefits for observations that are eligible for SNAP:

   $z_i = \max(0, maximum\ benefit - 0.3 \times (0.8 \times monthly\ income_i - standard\ deduction))$,

   where $maximum\ benefit$ and $standard\ deduction$ vary by year and household size. z_i has a minimum value of zero, so for z_i less than zero will be replaced by zero.

3. Compute the mean take-home benefit level (the product of probability of participation and z_i) by group and then take the difference between group 1 (Black/Hispanic households) and group 0 (White households).

B. Decomposition of SNAP benefits and food expenditures

1. Compute the sample analogs of the eligibility (Δ_l), participation (Δ_t), and generosity (Δ_z) components, which are $\Delta\mathbb{P}[l]\ \mathbb{P}_1[t|l]\ \mathbb{E}_1[z|l,t]$, $\mathbb{P}_0[l]\ \Delta\ \mathbb{P}[t|l]\ \mathbb{E}_1[z|l,t]$, and $\mathbb{P}_0[l]\ \mathbb{P}_0[t|l]\Delta\ \mathbb{E}[z|l,t]$, respectively (see Section 4.1 for the model).
2. To obtain the decomposition of food expenditures, multiply the difference in SNAP benefits and the three components obtained above by the estimated marginal propensity to spend on food (MPSF) from SNAP benefits of group 1.[59]

C. Counterfactual policy experiments

Scenario 1: Universal eligibility

(1) Set eligibility equal to one for all observations.[60]

(2) For observations that were already eligible, set the counterfactual benefit levels equal to the observed benefit levels. For observations that now become eligible, generate the predicted probabilities of participation using parameter estimates from the participation probability model that we estimated among those that are currently eligible.[61]

[59] The MPSF can come from credible studies in the literature or can be estimated by group using Equation 4 in Section 5.3. The roles of other covariates and the MPSF can be estimated with Oaxaca-Blinder decomposition.
[60] Note that our sample consists of households below 185 percent of the poverty line, which could be considered as disadvantaged households at a broader range.
[61] This yields counterfactual participation probability estimates for those we cannot observe their participation probabilities due to ineligibility. We use a logit model to impute counterfactual participation probabilities. The covariates in the model include state program rules (dummy variables indicating if a state had a simplified reporting system, an online application, and/or requires fingerprinting, whether the broad-based categorical eligibility (BBCE) rules were in place, and the median certification period), age, age squared, gender, marital status, family size, number of children, household head indicator, immigrant status, urban status, education, earnings, unemployment, family income (categorical), region fixed effects, and year fixed effects. The information on state policy rules is obtained from the SNAP Policy Database, maintained by the USDA's Economic Research Services and available up to 2016.

(3) Average, for each group, the benefit levels with weights proportional to the participation probabilities imputed in step (2). This yields the counterfactual average levels of SNAP benefits by group under universal eligibility.

Scenario 2: Automatic enrollment

(1) Set participation equal to one for all eligible households.

(2) Average, for each group, the benefit levels among all eligible households (note that here weights proportional to the probability of participation become irrelevant). This yields the counterfactual average levels of SNAP benefits by group under automatic enrollment.

Scenario 3: Constant transfer

(1) Set counterfactual SNAP benefits equal to a fixed amount—in our empirical exercise, we set this value to be $638 per month—for all participating households.

(2) Under the assumption that participation probabilities do not depend on the program's generosity, we can just compute the averages, for each group, of the benefit levels among all currently participating households. This yields the counterfactual average levels of SNAP benefits by group under a constant transfer.[62]

Scenario 4: Marginal changes in eligibility

(1) Set counterfactual eligibility under policies that strengthening or loosening eligibility rules - in our empirical exercise, we do so by increasing the $gross\ income\ limit$ and $net\ income\ limit$ to qualify for SNAP by 20 percent.

[62] If participation depends on generosity, one needs to impute counterfactual participation probabilities among eligible households. These probabilities come from estimated parameters of the participation probability model. Then, to obtain counterfactual average amount of SNAP benefits, compute averages, for each group, of SNAP amounts with weights proportional to counterfactual participation probabilities among eligible households.

(2) For observations that were already eligible, set the counterfactual SNAP benefits to be equal to the observed SNAP amounts. For observations that now become eligible, generate the predicted probabilities of participation using parameter estimates from the participation probability model that we estimated among those that are currently eligible.

(3) Average, for each group, the benefit levels with weights proportional to participation probabilities imputed in step (2). This yields the counterfactual average levels of SNAP benefits by group under a policy with marginal changes in eligibility.

Scenario 5: Marginal changes in participation

(1) Set counterfactual participation under policies that encourage or discourage marginal household to participate—in our empirical exercise, we do so by increasing participation rates by group by 20 percent.

(2) Average, for each group, the benefit levels with weights proportional to participation probabilities imputed in step (1). This yields the counterfactual average levels of SNAP benefits by group under a policy with marginal changes in participation.

Scenario 6: Marginal changes in generosity

(1) Set counterfactual SNAP benefits under policies that change benefits amounts - in our empirical exercise, we do so by increasing the benefit levels for all eligible households by 20 percent.

(2) Under the assumption that participation does not depend on the program's generosity, we can just compute the averages, for each group, of the benefit levels among all currently participating households. This yields the counterfactual average levels of SNAP benefits by group under a policy with marginal changes in generosity.[63]

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[63] As discussed in Appendix D, if participation depends on generosity, one needs to impute counterfactual participation probabilities among eligible households. These probabilities come from estimated parameters of the

participation probability model. Then, to obtain counterfactual average amount of SNAP benefits, compute averages, for each group, of SNAP amounts with weights proportional to counterfactual participation probabilities among eligible households.