Thrifty Food Plan Price Index, SNAP Purchasing Power, and Participation*

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Abstract

This paper estimates the state-level spatial and temporal differences in the SNAP purchasing power by constructing panel price indices for the Thrifty Food Plan (TFP). We construct the TFP index using retail scanner data for the period 2006–2016. We find that the range of SNAP purchasing power for a household of four is between 5 and 9 percent across the states and that the regional disparities are persistent during the study period. Subsequently, we examine the extent to which the SNAP purchasing power affects program participation. Our results show that a ten percent increase in the real SNAP benefits leads to a 0.9 percentage point increase in the SNAP caseload per capita and an 8.1 percentage point increase in the SNAP caseload per eligible individual. We show that these effects would be overlooked if the TFP index is not corrected for the expenditure and outlet bias.

Keywords: SNAP purchasing power, food and nutrition policy, index number, panel price indices, SNAP participation.

JEL Codes: Q18, I38, C43, E31.

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1 Introduction

Decreasing food insecurity is a top public policy priority in the United States. The annual rate of food-insecure U.S. households has been above 10 percent for the last two decades.[1] The U.S. government implements several programs to address food insecurity. Among these, the Supplemental Nutrition Assistance Program (SNAP), formerly the Food Stamp Program, is the largest nutrition assistance program costing over $60 billion per year. In 2019, 38 million U.S. households, about 12 percent of the total population, were enrolled in the program. Participation in SNAP is associated with improved food security (Mykerezi and Mills 2010; Nord and Prell 2011; Schmidt et al. 2016), better health outcomes (Gregory and Deb 2015; East 2019), and increased economic self-sufficiency (Hoynes et al., 2016). An important feature of SNAP is that benefits are paid in cash and are fixed across the contiguous United States. Hence, due to the regional food price differences, the real value of SNAP benefits is not the same across states and over time. In this paper, we investigate the extent to which regional disparities in the SNAP purchasing power exist and whether such inequality is consequential to the program participation.

SNAP benefits are determined primarily by household size and income. For example, in the fiscal year 2019, a participant family of four with $1,000 of net monthly income was eligible for $342 anywhere in the contiguous United States.[2] The value of SNAP benefits is linked to the cost of the USDA's Thrifty Food Plan, TFP. The cost of the TFP is measured annually at the national level using the Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) for select food categories

[1] See https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=58378.

[2] The benefit amount equals the maximum benefit for a household of four in the fiscal year 2019 ($642) minus 30 percent of its net income (30 percent of $1000 is $300). We assume the household passes the asset test, which states that household assets must be less than $2250. For more details, see Center on Budget and Policy Priorities, "Policy Basics: The Supplemental Nutrition Assistance Program (SNAP)," June 2019, https://www.cbpp.org/research/food-assistance/policy-basics-the-supplemental-nutrition-assistance-program-snap.

(Carlson et al. 2007). However, food prices vary substantially across the country (Todd et al. 2011; Gregory and Coleman-Jensen 2013; Çakır et al. 2018). Consequently, the real SNAP benefits are unequal such that households who live in high-price regions cannot purchase the same amount of food as those who reside in the low-price regions.

Currently, there is no mechanism by which the regional SNAP purchasing power can be measured and adjusted periodically. This is because systematic information on regional food price differences is not available in the United States. In addition, to the extent that spatial differences in the SNAP purchasing power exist, the impact of the program on key outcomes such as household participation and food insecurity may not be measured accurately.[3] In this paper, we address each of these issues in turn. First, using state-of-the-art index number methods, we construct the TFP panel price index to document the changes in real SNAP benefits over time and across space. Our analysis explicitly addresses notable weighting biases that are overlooked in prior studies of the TFP price index. Next, we examine whether spatial differences in the SNAP purchasing power converge over time and investigate the relationship between the real value of SNAP benefits and program participation.

We use retail scanner data obtained from 48 contiguous states and the District of Columbia from 2006 to 2016 to construct the TFP panel price index.[4] Retail scanner data provide high-frequency store-level price and sales information on consumer food purchases and allow us to construct panel price indices at any geographic level and frequency. We construct state-level indices to coincide

[3] In our paper, the term "spatial" refers to comparisons across regions or states at a specific point in time.
[4] The contiguous United States consists of 48 adjoining states and the District of Columbia on the continent of North America (49 in total). The non-contiguous states (Alaska and Hawaii) and all other off-shore insular areas (American Samoa, U.S. Virgin Islands, Northern Mariana Islands, Guam, and Puerto Rico) are not included in this study.

with geographic boundaries along which policy implementation varies and examine the month-to-month differences.

To construct the TFP panel price index with store scanner data, we follow a similar approach to the one described by Çakır et al. (2018). Specifically, we use the GEKS method to construct the temporal index.[5,6] When using scanner data, the GEKS method has the advantage of both chained indices, which account for the introduction of new products and product attrition, and fixed base indices, which are free of the chain drift (Ivancic et al. 2011). We use the minimum spanning tree (MST) approach to construct the spatial index (Hill 1999). The MST approach accounts for the similarity in regional price structures and looks for a path through regions that minimizes the dissimilarity between each pairwise combination of regions. We then combine the temporal and spatial indices using the chronological graph (CG) method to construct panel price indices (Hill 2004).

SNAP recipients' food purchase patterns substantially differ from TFP recommendations. Also, SNAP households redeem a large portion of their SNAP benefits at mass merchandise outlets, different from the larger population. Hence, we construct the TFP price index by explicitly accounting for these behaviors and alleviate expenditure and outlet biases. We show that the difference between the contiguous states with the highest and lowest real SNAP benefits in our study period ranges between 5 and 9 percent. We also show that unless the TFP index is adjusted for the expenditure and outlet biases, the average range approximately doubles, suggesting that regional disparities in SNAP purchasing power found in previous studies could be overestimated.

[5] The GEKS method is named after Gini (1931), Elteto and Koves (1964), and Szulc (1964).
[6] In our paper, the term "temporal" refers to comparisons for a given region or state across different points in time.

We do not find evidence of price convergence between regions, indicating that the regional inequality in the SNAP purchasing power has been persistent over time. There are also differences in the temporal price changes. Specifically, we find that the official updates of the SNAP benefits each fiscal year are generally sufficient to offset the declines due to inflation. Nevertheless, there exist differences in the inflation rates between states. For example, we find that between 2006 and 2016, the TFP price in North Dakota increased by 25 percent, while the TFP price in California increased by 17 percent.

Finally, we examine the relationship between SNAP purchasing power and SNAP participation in a regression framework. Our results indicate that there exists a significant and positive relationship. In particular, we find a ten percent increase in SNAP purchasing power leads to a 0.9 percentage point increase in SNAP participation per capita. We conduct the same analysis using the ratio of SNAP participation to the state population below the poverty line as a SNAP participation measure. In this case, we find that a ten-percent increase in the SNAP purchasing power leads to an 8.1 percentage point increase in SNAP participation among eligible individuals. Our results suggest that in addition to unemployment rates and state-level SNAP policies that have been shown to impact SNAP participation (Ganong and Liebman 2018), the real value of SNAP benefits is another contributing factor. We also show that these results would be overlooked unless the TFP index was adjusted for the expenditure and outlet biases.

The paper proceeds as follows. Section 2 provides an overview of the SNAP and reviews previous literature. Section 3 describes the data, and Section 4 illustrates the methods we used to construct the price indices. In Section 5, we present the TFP price index. Section 6 reports SNAP benefits' real value and examines the relationship between SNAP purchasing power and participation. Section 7 concludes.

2 SNAP Overview and Previous Literature

SNAP Overview

SNAP provides participants with monthly benefits to purchase foods and beverages using an electronic benefit transfer card. However, not all foods and drinks are eligible for purchase using SNAP benefits. For example, purchases of hot foods, pre-prepared foods for immediate consumption, and alcoholic beverages cannot be made using SNAP benefits.

A household needs to meet three requirements to be eligible for SNAP. First, the household's gross monthly income needs to be less than 130 percent of the poverty line. Second, the household's income after deductions must be at or less than the poverty line. Third, household assets must be $2,250 or less.[7] A participating household receives SNAP benefits equal to the maximum benefit allotted based on the household's size minus 30 percent of the household's net income. The maximum value of SNAP benefits is determined by the cost of the USDA's TFP basket. The TFP basket comprises 29 food categories at different weights representing a national norm for a nutritious diet at a minimal cost.[8] The TFP basket includes four categories of grains, seven categories of fruit and vegetables, four categories of milk products, six categories of meat and beans, and eight categories of other foods (Table 1). The SNAP benefits are updated every fiscal

[7] These eligibility tests are for 48 contiguous states and the District of Columbia. Households with a member who is elderly or has a disability and households that are categorically eligible for SNAP have different income and asset requirements.

[8] Both volume and expenditure weights are provided in the TFP (Carlson et al., 2007).

year based on the Consumer Price Index (CPI) for each food category in the TFP (Carlson et al. 2007).[9]

In 2009, the American Recovery and Reinvestment Act (ARRA) increased SNAP benefits by 13.6 percent per month in response to the Great Recession of 2008. The ARRA specified that there would be no SNAP benefit adjustment for inflation during the benefit boost period until the real value of SNAP benefits dropped to pre-ARRA levels. Nevertheless, the ARRA benefit boost ended before achieving this target.[10] After October 2013, SNAP lowered the benefit and resulted in a 7 percent benefit cut on average (Keith-Jennings and Rosenbaum 2015). Nord and Prell (2011) show that the increase in the nominal value of SNAP benefits provided by ARRA increased food spending and reduced food insecurity among SNAP households. However, these improvements were partly offset as the SNAP benefits' real value declined due to inflation (Nord 2013).

Previous Literature on the TFP Price

Previous studies use various sources of data and methods to generate the TFP price index. Gregory and Coleman-Jensen (2013) and Bronchetti et al. (2019) use data from the Quarterly Food-at-Home Price Database (QFAHPD) to obtain TFP price index for designated market groups in the United States.[11] Both studies use expenditure-weighted average product prices to estimate the annual TFP basket price. Gregory and Coleman-Jensen (2013) use the TFP price to examine the

[9] Each SNAP fiscal year is from October in the past year through September this year (e.g., the allotments for 2012 are from October 1, 2011, through September 30, 2012). There was a change in SNAP benefits in 2009 due to the American Recovery and Reinvestment Act (ARRA) in responding to the Great Recession, thus in the table "2009-1" covers October 1, 2008, through March 31, 2009, and "2009-2" covers April 1, 2009, through September 30, 2009.
[10] See Dean and Rosenbaum (2013) for the details on the sunset of the ARRA benefit boost.
[11] QFAHPD is constructed using Nielsen Homescan data, which contains detailed information on household-level purchases. See https://www.ers.usda.gov/data-products/quarterly-food-at-home-price-database/documentation/ for a detailed overview of this data.

link between food prices and food insecurity. Bronchetti et al. (2019) use the TFP price to calculate the SNAP purchasing power for the years from 1999 to 2010 and estimate its relationship with health outcomes. They obtain the TFP price for 30 market groups using the expenditure-weighted average prices of foods in the QFAHPD.[12] Similarly, Feeding America for the Map the Meal Gap (Gundersen et al. 2018) uses Nielsen household and retail scanner datasets to construct the TFP basket price and estimate the relative pricing between the U.S. counties. This study uses expenditure weighted prices from a 4-week period in October to generate the annual TFP price. Another paper by Gundersen et al. (2016) uses retail scanner data to calculate weekly store-level TFP prices in 2012. Their approach is taking the median prices in each TFP food category to remove the potential effects of outliers on prices.

The existing literature on measuring the TFP price have several limitations. First, household scanner data used in the previous studies have a relatively small sample in each region. For instance, the San Francisco market group in QFAHPD data has fewer than 100 households in 1999, 2002, and 2003, and less than 400 households from 2004 to 2006.[13] The small sample of households limits constructing a representative regional TFP price index at high frequencies since the TFP basket includes a large number of food categories. In addition, the household scanner data may suffer from non-response bias as consumers may not always scan all of their purchases. We address these limitations by using a point-of-sale retail scanner dataset comprising richer purchase information than the household scanner data in any region.[14] The retail scanner data includes

[12] Market groups are geographic areas defined in the QFAHPD and each market group covers a set of counties.
[13] See Todd et al. (2010) for details on the number of households by market and year.
[14] Zhen et al. (2018) show that there exist significant differences between retail scanner data index and household scanner data based index.

weekly prices and quantities of all products sold at retail outlets. This feature allows us to make more accurate product-to-product price comparisons over time and across regions.

Second, prior methods used to construct the TFP price index are potentially subject to product heterogeneity and variety biases. The heterogeneity bias occurs when regional or temporal price comparisons are based on different varieties of a product. The variety bias arises if consumers do not have access to the same products in all regions. Our data and methods allow us to address the product heterogeneity bias to a great extent. Specifically, we resolve the product heterogeneity bias that arises from comparing aggregated goods by constructing our temporal and spatial indices based on matching products at the Universal Product Code (UPC). Also, our spatial index method allows us to mitigate the variety bias as we link regions with similar price structures, where the similarity is determined by product composition in baskets and the weights of each product.

Last, previous studies of the TFP index used TFP recommended weights for each food category and did not account for outlet heterogeneity. These aspects might limit the estimation of SNAP benefits' real value using the TFP index. Because the TFP food category weights are based on USDA recommendations for poor households to obtain sufficient nutrition and may not reflect SNAP households' actual food basket. In fact, in Section 5 we show that SNAP households do not follow the TFP recommendation closely. Also, SNAP households spend most of their benefits at specific retail outlets. Accounting for these aspects is essential for constructing the TFP price index and obtaining accurate estimates of the SNAP purchasing power.

3 Data

We use retail scanner data collected by the Nielsen Company (U.S.), LLC, to construct the TFP price index between 2006 and 2016.[15] The data includes information on retail prices and sales from more than 35,000 stores comprising more than 50 percent of the total sales volume of grocery and drug stores and 30 percent of the total sales volume of mass merchandisers in the United States.[16] We focus on mass merchandisers and grocery stores (listed as the "food" channel in the Nielsen data), as these have consistent reporting and represent more than 93 percent of all food sales in the TFP basket. Retail scanner data offers weekly information at the UPC or barcode level and provides new avenues to improve estimates of price changes using the index number methods. Specifically, the high frequency and the availability of both price and quantity information allow us to generate weighted price indices at detailed aggregation levels.

We create the TFP basket by selecting all observations in the scanner data that match the TFP food categories.[17] Table 1 presents the matching process and the sample data. Our sample consists of 640,679 UPCs from 414 product modules of the 40 matched categories.[18] We assign each of the 414 product modules to a TFP food type based on their description.[19] Then, we create the unit value price—the first level of aggregation used in the price index formulae—at the UPC level for each month and state.[20] We use monthly unit value prices since SNAP benefits are distributed monthly. Also, we use states, including the District of Columbia, as our geographic unit as they coincide with the administrative boundaries along which regional policies are implemented. Our

[15] The data are provided for research purposes by the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business.
[16] See http://research.chicagobooth.edu/nielsen/ for more information on the retail scanner data.
[17] We use "product category" to refer to the "product group" in the product hierarchy of the Nielsen data.
[18] Nielsen refers to a "product module" as a subset of "product group." For example, "Fresh Apple" is a product module under the product group "Fresh Produce."
[19] The detailed matching table for the 414 product modules and the 29 TFP categories is available upon request.
[20] Specifically, we take the expenditure weighted average of weekly store-level prices to generate monthly prices.

final sample consists of monthly prices and sales for each UPC between January 2006 and December 2016 in 48 states and the District of Columbia.

We collect data on SNAP participation and SNAP benefits from the USDA Food and Nutrition Service, FNS. Table 2 presents the maximum allotments for a household size of one, a household size of four, and the average monthly benefits of SNAP. We include the year 2017 since SNAP benefits are in effect from October to September (i.e., the allotments for 2017 are from October 1, 2016, through September 30, 2017). The average annual increase in maximum benefits for a household of four is about 5 percent from 2006 to 2009. Then there was a change in SNAP benefits in 2009 due to the ARRA that caused the nominal value of SNAP benefits to change twice in 2009, leading to a 14 percent increase in the max SNAP benefits for a household of four. Since the ARRA, a SNAP participant had received around $125, except between 2010 and 2013, when the benefits were around $133 per person. The USDA FNS provides the number of SNAP participants and households at the state level each month. We combine the participation data with state population and poverty rate from the Current Population Survey (CPS) to generate SNAP caseload per capita and SNAP caseload among eligible individuals, measured as a ratio of SNAP participation to the state population below the poverty line.

4 Price Index Methods

Temporal Index: The GEKS Method

The availability of price and quantity information in the retail scanner data makes it possible to construct superlative price indices, which account for the product-level substitution in consumer spending due to relative price changes.[21] Nevertheless, scanner data has two potential drawbacks: the high attrition and quality change of goods and the high volatility of prices and quantities because of sales and promotions. Chaining is often used to handle the issue of new and disappearing items. Chained indices compare the current period to the base period by taking the product of all chained links, which are the bilateral indices for two adjacent periods, between the two periods. However, chained indices might suffer from chain drift, which means that the indices do not return to unity even when prices return to those in the base period. The problem of chain drift exacerbates when using retail store scanner data due to the price oscillation or quantity shifts owing to the high prevalence of retail promotions (Feenstra and Shapiro 2003; de Haan and van der Grient 2011; Ivancic, Diewert, and Fox 2011).

To address the chain drift, we follow the method outlined by Ivancic, Diewert, and Fox (2011) that uses the multilateral index number method of Gini (1931), Elteto and Koves (1964), and Szulc (1964), i.e. GEKS. Studies have shown that the GEKS method performs well with scanner data as it addresses the high attrition rate and is free from the chain drift (e.g., de Haan and van der Grient 2011). The GEKS method is generated by taking the geometric mean of the ratios of all bilateral indices between the two periods that we are comparing, where each period (l = *1*, ..., T) in the sample is taken as the base. The GEKS index formula between periods j and k can be expressed as follows:

$$P_{GEKS}^{j,k} = \prod_{l=0}^{T} \left(P^{j,l} \times P^{l,k}\right)^{\frac{1}{T+1}}, \tag{1}$$

[21] See Çakır et al. (2018) and Zhen et al. (2018) for more information on superlative and bilateral indices.

where $P^{j,l}$ and $P^{l,k}$ are bilateral indices. Here we use the Törnqvist index, which has the formula:[22]

$$P_T^{0,t} = \prod_{i=1}^{N} \left(\frac{p_i^t}{p_i^0}\right)^{\frac{s_i^0+s_i^t}{2}}, \tag{2}$$

where p_i^t is the price of item *i* in period *t* and s_i^t is the expenditure share of item *i* in period *t.*

Spatial Index: The Minimum Spanning Tree Method

We use Hill's (1999) minimum spanning tree (MST) approach to construct the spatial price index. A desirable property of the MST method is that it accounts for price and consumption similarities between any two regions in the construction of the overall index. A spanning tree, by definition, is a connected, undirected graph with no cycles (loops). The no-cycles feature ensures the internal consistency (transitivity) of the price index. Any pair of vertices are connected to only one path of edges, and the MST approach chooses the spanning tree that connects all the vertices and has the minimum possible total edge weights.[23] In our spatial comparisons, each region represents a vertex, and each edge connects the two vertices. In the appendix to this manuscript, Appendix Figure B1 presents an example of the MST.

The MST approach starts with measuring the dissimilarity between the price structures of any two regions. These dissimilarity scores are the weights attached to each edge of the spanning tree. Following Çakır et al. (2018), we use a weighted log quadratic index suggested by Diewert (2009) to measure the relative price dissimilarity between the prices of regions *m* and *n*:

[22] The GEKS-Törnqvist index can also be referred to as CCD (Caves, Christensen, and Diewert, 1982) index.
[23] For a set of *M* vertices, we can have a maximum M^{M-2} number of spanning trees.

$$\Delta_{PLQ}(p^m, p^n, q^m, q^n) = \sum_{i=1}^{N}\left(\frac{1}{2}\right)(s_i^m + s_i^n)\left[\ln\left(\frac{p_i^n}{p_i^m P^{m,n}}\right)\right]^2, \quad (3)$$

where $s_i^n = \frac{p_i^n q_i^n}{p^n q^n}$ is the expenditure share of commodity i in region n, and any superlative price index formula can be used as $P^{m,n}$ to calculate the dissimilarity scores.[24] This index provides the relative price dissimilarity between any two regions with a lower bound of 0 if the prices in the two regions are proportional (i.e. if $p^m = \lambda p^n$ for $\lambda > 0$). The greater value of $\Delta_{PLQ}(p^m, p^n, q^m, q^n)$ represents that the relative prices for regions m and n are more dissimilar.

Once the relative price dissimilarity scores are attached, we use Kruskal's algorithm to find the path with the least sum of dissimilarity scores between all regions to obtain the MST (Hill 1999). We then link the bilateral comparisons along the path of the two regions. Specifically, if we have region *m* linked with region *n* through region *l,* then the spatial index between regions *m* and *n* can be calculated as:

$$P^{m,n} = P^{m,l} \times P^{l,n}, \quad (4)$$

where P denotes a superlative price index between two adjacent regions on the MST.

Panel Indices: The Chronological Graph Method

Last, we combine the temporal and spatial price indices using the "chronological graph" (CG) method to obtain the panel price index (Hill 2004).[25] The CG method has the properties of temporal fixity and temporal consistency. Temporal fixity means that adding new periods to the data does not affect the previous periods' price comparisons. Temporal consistency suggests that the

[24] Here we follow Diewert (2009) and use the Törnqvist index.
[25] We present an overview of steps required to compute our TFP price indices in Appendix Table A1.

temporal comparisons for each region do not depend on other regions in the panel. The CG method links the temporal price indices, which are chronological, with a reference multilateral spatial comparison (i.e. an MST in one of the periods). In the appendix, Figure B2 shows a schematic presentation of the CG method. The figure links temporal indices from period *t* to *t*+5 with a reference spatial index for regions A to D in period *t*+2.

In the CG method, the choice of the reference index could lead to different spatial comparison results. For example, changing the reference spatial index (e.g., from indices in period *t*+2 in Appendix Figure B2 to indices in period *t*) could result in different spatial disparities between regions in the panel index. This concern is due to the properties of the CG method, which is not able to maintain spatial consistency.[26] To address this issue, we take an approach similar to the GEKS method. Specifically, we use the geometric mean of all available periods as the base to link the spatial and temporal price indices to construct the panel price index. This approach maintains the same temporal changes while it also produces consistent spatial comparisons.

5 TFP Price Index

SNAP Expenditures vs. Recommended Expenditures

The TFP is designed to represent the minimal cost needed for a nutritious diet and provide guidance on the food spending behaviors of SNAP recipients. Thus, previous studies generally use the TFP recommended weights to estimate costs and calculate the SNAP purchasing power (Gregory and Coleman-Jensen 2013; Bronchetti et al. 2019; Christensen and Bronchetti 2020). However, SNAP

[26] Similar to temporal consistency, spatial consistency is satisfied if the comparison can be collapsed into a series of separate spatial comparisons for each period (Hill, 2004).

households' food expenditure patterns may differ from the TFP recommendation (Sanjeevi et al. 2018). Consequently, the TFP price index computed using the recommended weights may not accurately reflect food price changes that SNAP households face. We refer to this discrepancy as expenditure bias. To examine and address the expenditure bias, we obtain expenditure weights for each TFP food category in SNAP households' actual purchases using data from the Consumer Expenditure Surveys (CEX) Diary Survey.[27] The Diary Survey is a panel survey that provides detailed purchase information of U.S. consumers, including SNAP households.[28] Specifically, we obtain the average annual expenditure of each food category for SNAP households in the CEX Diary Survey from 2006 to 2016. Then, we match the CEX food categories with the food categories in the TFP and generate the expenditure weights for each TFP food category.[29]

Figure 1 displays the recommended TFP expenditure weights and the SNAP households' actual expenditure weights.[30] There are substantial differences for most of the food categories. There are 12 out of the 25 food categories for which the actual expenditures are higher than the TFP recommendation, in which soda (9 percent), frozen entrees (7 percent), and bacon, sausages, and other meat (4 percent) show the largest gaps. For the remaining food groups, actual expenditures are lower, with whole fruits (10 percent), milk (7 percent), dark-green vegetables (7 percent), and other vegetables (6 percent) showing the largest differences. Notably, SNAP households' largest

[27] The food expenditure weights obtained from Diary Survey are also used in the Bureau of Labor Statistics' Consumer Price Index.
[28] CEX Diary Survey explicitly asks participants: "Have any members of your CU received any Food Stamps, in the past month?" and "Have any members of your CU received any Food Stamps, during the past 12 months?" We obtain the expenditure weights from households who answered "Yes" in either of these questions. For details on the Diary Survey, see https://www.bls.gov/cex/pumd-getting-started-guide.htm#section4.
[29] To match the CEX categories with TFP categories, we aggregate the four categories in the "Grains" TFP food type, and thus we have 25 food categories. See Appendix Table A2 for the matching details.
[30] The recommended weights for food categories are based on the expenditure shares for a household of four (two adults and two children) in Carlson et al., (2007).

expenditures are on grains, soft drinks, red meat, frozen entrees, and milk, whereas vegetables, potato products, and soups have the lowest expenditure shares.

Figure 1 shows SNAP households are not following the TFP recommendations. Therefore, the TFP basket weights for food categories would not accurately reflect the overall changes in the TFP basket price for SNAP households. For example, TFP recommends zero percent of expenditure on soft drinks, which implies that the price changes in soft drinks do not affect the TFP cost. However, since SNAP households on average spend 9 percent of their food expenditure on soft drinks of which price changes would affect the real value of SNAP benefits. Thus, in constructing the TFP price index to estimate real SNAP benefits, one should use SNAP households' actual expenditure weights instead of the TFP recommended weights.

We construct the aggregate price index as:

$$P_{nt}^{TFP} = \sum_{c=1}^{25} P_{ntc} W_c \,, \tag{5}$$

where P_{ntc} is the price index value of product category c in region n in period t, and W_c is the expenditure weight of product category c. We obtain the category level panel price index, P_{ntc}, using the index number methods described in the previous section. Equation (5) addresses expenditure bias while accounting for the substitution bias within each food category.

Next, we examine the implications of the expenditure bias. To this end, we construct alternative TFP indices using the SNAP household expenditure weights, and the TFP recommended weights for 2006–2016. Figure 2 compares the range of the spatial TFP index values between the two approaches. The results show a clear difference between the spatial indices constructed using the alternative weights. In particular, the household expenditure weighted index displays lower spatial variation. The average range between the highest and lowest index values drops from 10.7 to 8.2, a 23 percent decrease. This change suggests that the spatial differences in SNAP expenditures are less than the cost of the TFP recommendation.

Adjusting for Outlet Bias

Outlet bias occurs when the sample of outlets is not representative of the outlets used by the target population (Hausman 2003; Hausman and Leibtag 2009; Greenlees and McClelland 2011). For example, to mitigate the potential outlet bias in CPI, BLS expanded its sample by adding observations from increasingly prevalent retailers such as mass merchandisers and club stores. Similarly, the TFP index may not accurately estimate price changes if SNAP households' expenditure distribution across retail outlets substantially differs from a representative households' expenditure distribution in the data.

In 2016, there were 260,115 authorized SNAP stores, and more than 84 percent of the stores were grocery or convenience outlets (USDA Food and Nutrition Services 2017).[31] The SNAP redemptions, however, were mainly at grocery and mass merchandise outlets. Figure 3 shows that the percentage of SNAP benefits redeemed and authorized store counts for grocery, mass merchandise, convenience, and other outlets between 2010 and 2016. The average authorized store percentage and redemption percentage for the grocery outlet are both around 44 percent. However, even though mass merchandisers represent about 8 percent of authorized stores, they account for

[31] SNAP benefits can be redeemed only at authorized stores. Retailers are required to apply and receive training in order to become authorized.

about 50 percent of all redeemed SNAP benefits. On the contrary, convenience stores represent about 40 percent of authorized stores, while they account for only 5 percent of redemptions. In general, the distribution of redemptions by outlet type is stable between 2010 and 2016.

In our data, grocery stores and mass merchandisers comprise more than 93 percent of the TFP food sales. Also, grocery store sales are about eight times more than mass merchandiser sales. Therefore, a TFP price index constructed using this data would mostly reflect the price changes for the grocery outlets, although SNAP households primarily shop from mass merchandisers. This discrepancy might create an outlet bias. To examine the extent to which the outlet bias exists, we construct and compare separate TFP price indices for grocery stores and mass merchandisers.

Figure 4 presents the range of the SNAP household expenditure weighted spatial indices using three alternative sample data: grocery stores and mass merchandisers combined, only grocery stores, and only mass merchandisers. The range values obtained from the grocery and mass merchandisers combined sample are close to those of only grocery stores sample. This is expected since about 90 percent of sales in the combined sample are from grocery stores. We observe that mass merchandisers have lower spatial price variability compared to grocery stores. The average range of the spatial index values from only mass merchandisers sample is 4.1 percentage points and is about 51 percent lower than the spatial index range for grocery stores.

Figures 3 and 4 suggest that the TFP price index can be subject to the outlet bias, which, in turn, may lead to inaccurate estimates of SNAP purchasing power. Therefore, we use SNAP households' expenditure shares by outlet type to adjust the TFP price index. Specifically, we first construct the

SNAP expenditure weighted TFP price index for each outlet and then aggregate them using their average redemption percentages as outlet weights.

Adjusted Spatial and Temporal Price Changes

Figure 5 illustrates the average spatial price variation at the state level before and after the SNAP expenditure and outlet weight adjustments. We use Utah's price level as the spatial comparison reference since it has the lowest index value.[32] In the figure, states are color-coded into five categories based on their index values ranging between "less than and equal to 102.2" and "above 106.3". The figure shows a notable reduction in the spatial price variation after the adjustments. For example, after the adjustment, no states remain in the category of the highest index value. Furthermore, all states in the second-highest category, except for the District of Columbia, appear in the lower categories after the adjustments. Overall, the average range of the spatial index values decreases by about 51 percent after the expenditure and outlet weight adjustments. The results indicate that explicitly accounting for SNAP households' purchase patterns substantially reduces differences in purchasing power of SNAP benefits across the contiguous states.

Figure 6 illustrates the temporal price movements for contiguous states from 2006 to 2016 and compares them with the official TFP cost.[33] The upper and lower panels of the figure present the temporal price changes before and after the expenditure and outlet weight adjustments, respectively. After the adjustments, the temporal price changes are lower and show less variability during the period. Notably, North Dakota has the highest price inflation in both cases, while

[32] The estimates of spatial price differences are invariant to the choice of the base state.
[33] The official TFP cost is published by the USDA and calculated using the BLS' CPI for food and beverages at the national level (Carlson et al. 2007).

California becomes one of the states with the lowest price inflation after the adjustments. In general, price trends are similar for all states and are analogous to the movements of the official TFP cost: an increasing trend from 2006 to 2008, a slight decrease in 2009, then increasing gradually until 2016.

The temporal price movements substantially differ across the states. For instance, between 2006 and 2016, the adjusted TFP price in North Dakota increased by about 25 percent, whereas prices in Florida, New York, and California increased by 22 percent, 19 percent, and 17 percent during the same period, respectively.[34] Overall, the range of the TFP price inflation among states is about 11 percent.

6 SNAP Purchasing Power and Participation

We estimate the SNAP purchasing power for each state from 2006 to 2016 using the TFP panel price index, which is constructed by linking the adjusted temporal and spatial indices via the CG method.[35] The SNAP purchasing power allows us to examine the extent to which updated SNAP benefits in each fiscal year are adequate to offset the price inflation and investigate the inequality of real SNAP benefits across states.

Figure 7 displays purchasing power of SNAP max benefits for a household of four in each state between 2006 and 2016. The vertical dashed lines in the figure indicate the time when the official

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[34] The high temporal price movement in North Dakota may be due to the oil boom that started in 2006, leading to a substantial growth job in population and per capita gross domestic product (U.S. Energy Information Administration 2013).

[35] Formally, the SNAP purchasing power is $SNAP\_Real_{it} = \frac{Benefit_t}{TFP_{it}}$, where $Benefit_t$ is the nominal SNAP benefit in period *t* and TFP_{it} is the TFP price index of state *i* in period *t*.

SNAP adjustments were made in each fiscal year.[36] The figure shows that SNAP purchasing power declined up to 7 percent in fiscal years 2007, 2008, and 2014, but the updates at the end of those fiscal years offset the declines. During the ARRA period (55 months) there were no adjustments and the average decline in the maximum real SNAP benefits across the states ranging from 3.5 to 7.7 percent with an average of 6 percent. In general, the average real value of SNAP benefits is about 7 percent higher in 2016 than in 2006, and the inflation rates vary across states.

Our results show that the inequality of real SNAP benefits across states is substantial. For instance, in 2006, a SNAP household of four can purchase about 6.5 percent more foods in Oklahoma than in California. Overall, the gap between the highest and the lowest real SNAP benefits among contiguous states is between 5 and 9 percent, which is about 27 to 58 dollars a month for a household of four.[37]

Convergence of Prices over Time

Next, we examine whether the differences in the SNAP purchasing power persist over time. Following the approach in Hill (2004), we calculate the standard deviation of the logarithm of price levels for $k=1,\dots,K$ states in each period t as:

$$\sigma_t = \sqrt{\frac{1}{K-1}\sum_{k=1}^{K}\left[\ln\left(\frac{P_{kt}}{P_{ot}}\right) - \overline{\ln\left(\frac{P_t}{P_{ot}}\right)}\right]^2}, \tag{6}$$

[36] During the ARRA period, from April 2009 to November 2013, the SNAP benefits remain unchanged. Also, there were no adjustments in fiscal years 2015 to 2017. Please see Table 2 for information on the SNAP allotments over time.

[37] The dollar amount depends on the maximum benefits of the period; therefore, the estimates do not match exactly with the percentage difference.

where P_o denotes the price level in the base state and $\overline{\ln\left(\frac{P_t}{P_{ot}}\right)} = \frac{1}{K}\sum_{k=1}^{K} \ln\left(\frac{P_{kt}}{P_{ot}}\right)$.[38] A decrease in σ_t indicates price levels are converging over time and an increase in σ_t signals that price levels are diverging.

Figure 8 presents the values of σ_t from 2006 to 2016. There is no clear evidence of convergence across the contiguous states over the period. There was a substantial decrease in σ_t from 2006 to 2008, suggesting that the price levels converged. After that, the value of σ_t fluctuated and did not show an obvious trend. Overall, the differences in TFP price levels have been fluctuating with a slight trend suggesting divergence in 2016. This finding implies that the TFP price levels between the states are likely to remain different. In other words, in the absence of regional adjustments, the inequality of the real SNAP benefits is likely to persist over time.

Impact of Real SNAP Benefits on SNAP Participation

SNAP has been an effective program, but it does not reach all households who need it. The number of people participating in SNAP rose during the recession but declined by more than 7 million people between 2013 and 2018 (Rosenbaum and Keith-Jennings 2019). This decline is mainly due to the economic recovery; however, the number of eligible people is still larger than the number of people participating in SNAP. Rosenbaum and Keith-Jennings (2019) show that the SNAP participation share was lower in 2018 than in 2013 for 45 states and the District of Columbia, and the timing and depth of the decline vary across states. Consequently, many public policies are

[38] The estimates of σ_t is invariant to the choice of base state (Hill, 2004).

directed to increase the SNAP participation rate, and increasingly more resources are devoted to research (Hoynes and Schanzenbach 2020).

Studies have shown that changes in unemployment (Bilter and Hoynes 2016) and state policy (Ganong and Liebman 2018) are the key determinants of SNAP participation. Also, incomplete information about eligibility and transaction costs are considered two of the main reasons for less than full participation in social programs (Currie 2006). Using a randomized field experiment, Finkelstein and Notowidigdo (2019) find that private costs of application can decrease SNAP participation. Similarly, the higher SNAP purchasing power would offset more costs of applying, such as time cost and transportation cost, and therefore could stimulate eligible individuals to apply and enroll in SNAP. In the following analysis, we contribute to this literature by examining the relationship between SNAP purchasing power and participation.

Following Bronchetti et al. (2019), our identification strategy relies on variations in temporal trends in real SNAP benefits across states. As shown above, the spatial differences in inflation rates are substantial. These spatial differences that lead to the plausibly exogenous variation could be attributed to local market conditions such as local wages, demand conditions, or local supply shocks.

We examine the effect of SNAP purchasing power on participation using the following model:

$$y_{it} = \alpha + \beta ln(SNAP\_Real_{it}) + \gamma_i + \theta_t + \boldsymbol{X}_{it}\lambda + \varepsilon_{it}. \tag{7}$$

where y_{it} is SNAP participation in state i at time t. We use two different measures of SNAP participation: SNAP caseload per capita and SNAP caseload per eligible individual. The key independent variable $ln(SNAP\_REAl)$ is the log of real SNAP benefits. The vector $\boldsymbol{X}_{it}$ includes determinants of SNAP participation found in previous studies, including the state unemployment rate and a SNAP policy index. The policy index variable is an omnibus adoption measure that takes the mean of eight SNAP policy indicators and is constructed by Ganong and Liebman (2018).[39] Last, γ_i and θ_t are state and time fixed effects, respectively.

Table 3 presents the results of equation (7) for the two SNAP participation measures: caseload per-capita SNAP participation (columns 1 and 2) and caseload per eligible SNAP participation (columns 3 and 4). Both models are estimated with and without control variables for the state-level unemployment and SNAP policy index.[40] In columns 1 and 2, we find that a ten percent increase in the real value of SNAP benefits increases the SNAP caseload per capita by 1.2 and 0.9 percentage points, respectively, and that both coefficients are statistically significant. This result differs from the findings of the prior studies that used an unadjusted TFP index. For example, Bronchetti et al. (2019) found no statistically significant relationship between SNAP purchasing power and per-capita SNAP participation after controlling for the unemployment rate. In columns (3) and (4), we present findings for SNAP caseload per eligible individual. The results suggest that a ten percent increase in the SNAP purchasing power leads to a 6.5 to 8.1 percentage point increase in SNAP participation among eligible individuals. These results corroborate the findings of Finkelstein and Notowidigdo (2019) that reducing transaction costs can increase the SNAP participation among eligible individuals.

[39] The eight policy indicators include simplified reporting, recertification lengths, interview format, establishment of call centers, online applications, Supplemental Security Income Combined Application Project, vehicle exemptions, and broad-based categorical eligibility.
[40] We do not have data on the policy index for 2016, so we have fewer observations in the results in columns (2) and (4).

Next, we examine whether the relationship holds if we calculate the SNAP purchasing power using the unadjusted TFP price index, i.e., calculated using TFP recommended expenditure weights and without an adjustment for outlet bias. Table 4 presents the same specifications as Table 3, with the unadjusted SNAP purchasing power being the only difference. The results show that none of the SNAP purchasing power coefficients are statistically significant. That is, ignoring the expenditure and outlet biases is consequential. Using the TFP recommended weights to examine the relationship between local food prices and SNAP-related outcomes would lead to potentially inaccurate estimates.

7 Conclusion

SNAP benefit levels are fixed across the contiguous United States and have remained relatively stable in recent years. However, food prices vary over time and across regions resulting in inequality of real SNAP benefits. To examine the extent to which inequality of real SNAP benefits exists, we construct the TFP panel price index. Our panel index estimates monthly price changes from 2006 to 2016 and the spatial price differences across 48 contiguous states and the District of Columbia.

Our TFP panel index shows that price levels and inflation rates differ substantially across states. These findings are concordant with previous studies on regional food prices. Differently, we show that constructing the TFP price index using the TFP recommended expenditure weights are subject to expenditure and outlet biases. The expenditure bias exists since SNAP recipients do not closely follow the TFP recommendation, while the outlet bias exists since the sample of outlets is not representative of the outlets used by SNAP households. After correcting for expenditure and outlet biases, the range of spatial price differences decreases by 51 percent.

Our findings also suggest that spatial variation in SNAP purchasing power is considerable, although less than what has been found in previous studies that use TFP recommendation weights to estimate the prices. The gap between the highest and the lowest SNAP purchasing power among contiguous states is between 5 and 9 percent. These estimates correspond to about 27 to 58 dollars of monthly benefits for a household of four. Our analysis of the convergence of prices suggests that the inequality of the SNAP purchasing power across states is likely to persist over time.

In addition to the spatial variation, we find that the inflation in TFP prices varies across states. Exploiting the variation in temporal trends of SNAP purchasing power across states, we examine the impact of real SNAP benefits on SNAP participation. Our results show that a ten percent increase in the real value of SNAP benefits leads to a 0.9 percentage point increase in SNAP participation per capita and an 8.1 percentage point increase in SNAP participation among eligible individuals. These effects become statistically insignificant if the TFP index is not corrected for expenditure and outlet biases.

Our results have direct implications for measuring regional price changes and the SNAP program. First, the regional TFP food price index used in most prior studies overstates the variation in food prices for SNAP households as it does not account for expenditure bias and outlet bias. Also, we find that regional inequalities in SNAP purchasing power are significant. Consequently, using nominal SNAP benefits to measure the impacts on key program outcomes such as household participation and food insecurity might lead to inaccurate results. Last, our findings suggest that policy mechanisms targeted to increase the real value of SNAP benefits would significantly increase the program participation.

References

Bitler, M., and H. Hoynes. 2016. "The more things change, the more they stay the same? The safety net and poverty in the Great Recession." *Journal of Labor Economics*, 34(S1): S403-S444.

Bronchetti, E.T., G. Christensen, and H.W. Hoynes. 2019. "Local Food Prices, SNAP Purchasing Power, and Child Health." *Journal of Health Economics 68*:102231.

Çakır, M., T.K. Beatty, M., Boland, M.A., Park, T.A., Snyder, S., and Y. Wang. 2018. "Spatial and Temporal Variation in the Value of the Women, Infants, and Children Program's Fruit and Vegetable Voucher." *American Journal of Agricultural Economics* 100(3):691–706.

Carlson, A., M. Lino, W. Juan, K. Hanson, and P.P. Basiotis. 2007. *Thrifty food plan*, *2006* (No. 1472-2016-120690).

Carlson, A., M. Lino, and T. Fungwe. 2007. *The Low-Cost, Moderate-Cost, and Liberal Food Plans, 2007 (CNPP-20).* U.S. Department of Agriculture, Center for Nutrition Policy and Promotion.

Caves, D.W., L. R. Christensen, and W.E. Diewert. 1982. "Multilateral comparisons of output, input, and productivity using superlative index numbers." *The Economic Journal* 92(365):73-86.

Christensen, G., and E.T. Bronchetti. 2020. "Local food prices and the purchasing power of SNAP benefits." *Food Policy* 95:101937.

Currie, J. 2006. "The Take-up of Social Benefits of Poverty, the Distribution of Income, and Public Policy." In A. Auerbach, D. Card, and J. Quigley, ed. *Poverty, The Distribution of Income, and Public Policy.* New York: Russel Sage.

De Haan, J., and F. Krsinich. 2014. “Scanner data and the treatment of quality change in nonrevisable price indexes.” *Journal of Business & Economic Statistics* 32(3):341-358.

De Haan, J., and H.A. Van der Grient. 2011. “Eliminating Chain Drift in Price Indexes Based on Scanner Data.” *Journal of Econometrics* 161(1):36–46.

De Haan, J.,L. Willenborg, A.G. Chessa, and J. Verburg. 2016. “An overview of price index methods for scanner data.” In Paper for the UNECE-ILO Meeting of the Group of Experts on Consumer Price Indices, pp. 2-4.

Dean, S., and D. Rosenbaum. 2013. “SNAP benefits will be cut for nearly all participants in November 2013.” Center on Budget and Policy Priorities, Washington, DC.

Diewert, W.E. 1999. “Axiomatic and economic approaches to international comparisons.” In *International and Interarea Comparisons of Income, Output, and Prices.* University of Chicago Press, pp. 13-107.

Diewert, W.E. 2009. “Similarity indexes and criteria for spatial linking.” In *Purchasing power parities of currencies: Recent advances in methods and applications*, pp. 183-216.

East, C.N. 2020. “The Effect of Food Stamps on Children’s Health Evidence from Immigrants’ Changing Eligibility.” *Journal of Human Resources* 55(2):387-427.

Eltetö, O., and P. Köves. 1964. “On a Problem of Index Number Computation Relating to International Comparison.” *Statisztikai Szemle* 42(10):507–518.

Feenstra, R.C., and M.D. Shapiro. 2003. “High-frequency substitution and the measurement of price indexes” In *Scanner Data and Price Indexes.* University of Chicago Press, pp. 123-150.

Finkelstein, A., and M.J. Notowidigdo. 2019. “Take-up and targeting: Experimental evidence from SNAP.” *The Quarterly Journal of Economics* 134(3):1505-1556.

Gini, C. 1931. “On the Circular Test of Index Numbers.” *Metron* 9(9):3–24.

Greenlees, J.S., and R. McClelland. 2011. “New evidence on outlet substitution effects in consumer price index data.” *Review of Economics and Statistics* 93(2):632-646.

Gregory, C.A., and A. Coleman-Jensen. 2013. “Do High Food Prices Increase Food Insecurity in the United States?” *Applied Economic Perspectives and Policy 35*(4):679–707.

Gregory, C.A., and P. Deb. 2015. “Does SNAP improve your health?” *Food Policy 50*:11–19.

Gundersen, C., A. Dewey, A. Crumbaugh, M. Kato, and E. Engelhard. 2018. *Map the Meal Gap 2018*: A report on county and congressional district food insecurity and county food cost in the United States in 2016. USA: Feeding America.

Gundersen, C. 2016. *Construction of Weekly Store-Level Food Basket Costs*: Documentation.

Gundersen, C., and J.P. Ziliak. 2018. “Food Insecurity Research in the United States: Where We Have Been and Where We Need to Go.” *Applied Economic Perspectives and Policy* 40(1):119–135.

Hausman, J. 2003. “Sources of bias and solutions to bias in the consumer price index.” *Journal of Economic Perspectives* 17(1):23-44.

Hausman, J., and E. Leibtag. 2009. “CPI bias from supercenters: does the BLS know that Wal-Mart exists?” In *Price Index Concepts and Measurement*, pp. 203-231. University of Chicago Press.

Hill, R.J. 1999. “Comparing Price Levels Across Countries using Minimum-Spanning Trees.” *Review of Economics and Statistics* 81(1):135–142.

Hill, R.J. 2004. “Constructing Price Indexes across Space and Time: The Case of the European Union.” *American Economic Review 94*(5):1379–1410.

Hoynes, H., D.W. Schanzenbach, and D. Almond. 2016. “Long-Run Impacts of Childhood Access to the Safety Net.” *American Economic Review 106*(4):903–934.

Hoynes, H., and D.W. Schanzenbach. 2020. *Policies to strengthen our nation’s Supplemental Nutrition Assistance Program*. Accessed 22 April 2021 at https://equitablegrowth.org/policies-to-strengthen-our-nations-supplemental-nutrition-assistance-program/.

Ivancic, L., W.E. Diewert, and K.J. Fox. 2011. “Scanner data, time aggregation and the construction of price indexes.” *Journal of Econometrics 161*(1):24–35.

Keith-Jennings, B., and D. Rosenbaum. 2015. “SNAP benefit boost in 2009 recovery act provided economic stimulus and reduced hardship.” Center on Budget and Policy Priorities, Washington, DC

Mykerezi, E., and B. Mills. 2010. “The impact of food stamp program participation on household food insecurity.” *American Journal of Agricultural Economics* 92(5):1379-1391.

Nord, M. 2013. “Effects of the Decline in the Real Value of SNAP Benefits From 2009 to 2011.” Economic Research Report No. 151. U.S. Department of Agriculture, Economic Research Service.

Nord, M., and P. Mark. 2011. “Food Security Improved Following the 2009 ARRA Increase in SNAP Benefits.” Economic Research Report No. 116. U.S. Department of Agriculture, Economic Research Service.

Rosenbaum, D., and B. Keith-Jennings. 2019. “SNAP Caseload and Spending Declines Have Accelerated in Recent Years.” Center for Budget and Policy Priorities.

Sanjeevi, N., J.H. Freeland-Graves, P.K. Sachdev, and J. Sands. 2018. "Do food expenditure patterns of supplemental nutrition assistance program households meet thrifty food plan recommendations?" *Journal of Hunger & Environmental Nutrition.*

Schmidt, L., L. Shore-Sheppard, and T. Watson. 2016. "The Effect of Safety-Net Programs on Food Insecurity." *Journal of Human Resources 51*(3):589–614.

Szulc, B. 1964. "Indices for Multiregional comparisons." *Przeglad statystyczny* 3:239–254.

Todd, J.E., E. Leibtag, and C. Penberthy. 2011. *Geographic differences in the relative price of healthy foods.* DIANE Publishing.

U.S. Department of Agriculture Food and Nutrition Service. 2017. "2016 SNAP Retailer Management Year End Summary." Accessed 2 October 2020 at https://fns-prod.azureedge.net/sites/default/files/media/file/2016SNAPRetailerManagementYearEndSummary.pdf.

U.S. Energy Information Administration. 2013. *North Dakota sees increases in real GDP per capita following Bakken production.* Accessed 22 April 2021 at https://www.eia.gov/todayinenergy/detail.php?id=12071.

Zhen, C., E.A. Finkelstein, S.A. Karns, E.S. Leibtag, and C. Zhang. 2019. "Scanner Data-Based Panel Price Indexes." *American Journal of Agricultural Economics* 101(1):311–329.

Ziliak, J.P. 2016. *Modernizing SNAP Benefits.* The Hamilton Project, Policy Proposal 2016–06.

Table 1. TFP-Basket and Nielsen Retail Scanner Food Categories

TFP Food Types	Food Categories	Nielsen Retail Food Categories
1.1 Grains	Whole grain bread, rice, pasta, pastries (incl whole grain flours)	Bread and Baked Goods
1.2 Grains	Whole grain cereals incl hot cereal mixes	Cereal
1.3 Grains	Popcorn and other whole grain snacks	Flour
1.4 Grains	Non-whole grain breads, cereal, rice, pasta, pies, pastries, snacks, and flours	Grains - Dried
		Pasta
		Pasta - Refrigerated
		Snacks
2.1 Vegetables	All potato products	Fresh Produce - Fresh Vegetables
2.2 Vegetables	Dark green vegetables	Vegetables - Dried
2.3 Vegetables	Orange vegetables	Vegetables - Canned
2.4 Vegetables	Canned and dry beans, lentils, and peas or legumes Other vegetables	Vegetables - Frozen
2.5 Vegetables	Other vegetables	
3.1 Fruit	Whole fruit	Fresh Produce - Fresh Fruits
3.2 Fruit	Fruit juices	Frozen Fruits
		Fruit - Canned
		Fruit - Dried
		Fruit - Refrigerated
		Fruit Juice - Canned, Bottled
		Juices, Drinks - Frozen
4.1 Milk products	Whole milk, yogurt, and cream	Milk
4.2 Milk products	Low-fat and skim milk and low-fat yogurt	Yogurt
4.3 Milk products	All cheese, including cheese soups and sauces	Cheese
4.4 Milk products	Milk drinks and milk desserts	Cot Cheese, Sour Cream, Toppings
		Packaged Milk and Modifiers

Table 1. TFP-Basket and Nielsen Retail Scanner Food Categories – Continued

5.1 Meat and beans	Beef, pork, veal, lamb, and game	Fresh Meat; Packaged Meats – Deli;
5.2 Meat and beans	Chicken, turkey, and game birds	Seafood – Canned; Seafood –
5.3 Meat and beans	Fish and fish products	Refrigerated; Unprep
5.4 Meat and beans	Bacon, sausage, and lunch meats including spreads Nuts, nut butters,	Meat/Poultry/Seafood – Frozen;
5.5 Meat and beans	and seeds	Eggs
5.6 Meat and beans	Egg and egg mixtures	Nuts
	Nuts, nut butters, and seeds	
6.1 Other foods	Table fats, oils, and salad dressings	Salad Dressings, Mayo, Toppings; Salad Dressing – Refrigerated; Shortening, Oil
6.2 Other foods	Gravies, sauces, condiments, and spices	Condiments, Gravies, and Sauces Spices, Seasoning, Extracts
6.3 Other foods	Coffee and tea	Coffee; Tea
6.4 Other foods	Soft drinks, sodas, fruit drinks, and ades incl rice beverages	Carbonated Beverages; Fruit Drinks – Frozen; Fruit Drinks – Canned/Other Container; Soft Drinks-Non-Carbonated
6.5 Other foods	Sugars, sweets, and candies	Candy; Sugar, Sweeteners
6.6 Other foods	Soups (ready-to-serve and condensed)	Soup
6.7 Other foods	Soups (dry)	
6.8 Other foods	Frozen/refrigerated entrees incl pizza, fish sticks, and frozen meals	Entrees – Refrigerated; Sandwiches - Refrigerated/Frozen; Pizza/Snacks/Hors Doeurves - Frozen; Pizza – Refrigerated; Prepared Foods - Frozen

Notes: The TFP food types and food categories are from Thrifty Food Plan report (Carlson et al., 2007).

Table 2. SNAP Allotments

Fiscal Year	Max Benefit for 1	Max Benefit for 4	Average Benefit Per Person
2006	$152	$506	$95
2007	$155	$518	$96
2008	$162	$542	$102
2009-1	$176	$588	$125
2009-2	$200	$668	$125
2010	$200	$668	$134
2011	$200	$668	$134
2012	$200	$668	$133
2013	$200	$668	$133
2014	$189	$632	$125
2015	$194	$649	$127
2016	$194	$649	$125
2017	$194	$649	$126

Notes: This table presents maximum and average allotments for the 48 States and the District of Columbia from 2006 to 2017. The period that SNAP benefits cover each year is from the from October in the past year through September this year (e.g. the allotments for 2012 are from October 1, 2011 through September 30, 2012). There was a change in SNAP benefits in 2009 due to the American Recovery and Reinvestment Act (ARRA) in responding to the Great Recession. Thus, in this table “2009-1” covers October 1, 2008 through March 31, 2009, and “2009-2” covers April 1, 2009 through September 30, 2009.
Source: USDA Food and Nutrition Service.

Table 3. SNAP Purchasing Power and SNAP Participation

	(1) Caseload per Capita	(2) Caseload per Capita	(3) Caseload per Eligible	(4) Caseload per Eligible
Log Real SNAP Benefits	0.123***	0.088***	0.647***	0.812***
	(0.017)	(0.017)	(0.192)	(0.199)
State Unemployment		0.004***		0.000
		(0.000)		(0.002)
Policy Index		-0.004***		-0.016
		(0.002)		(0.018)
State Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	6,468	5,880	6,468	5,880
Adjusted R-squared	0.927	0.939	0.740	0.757

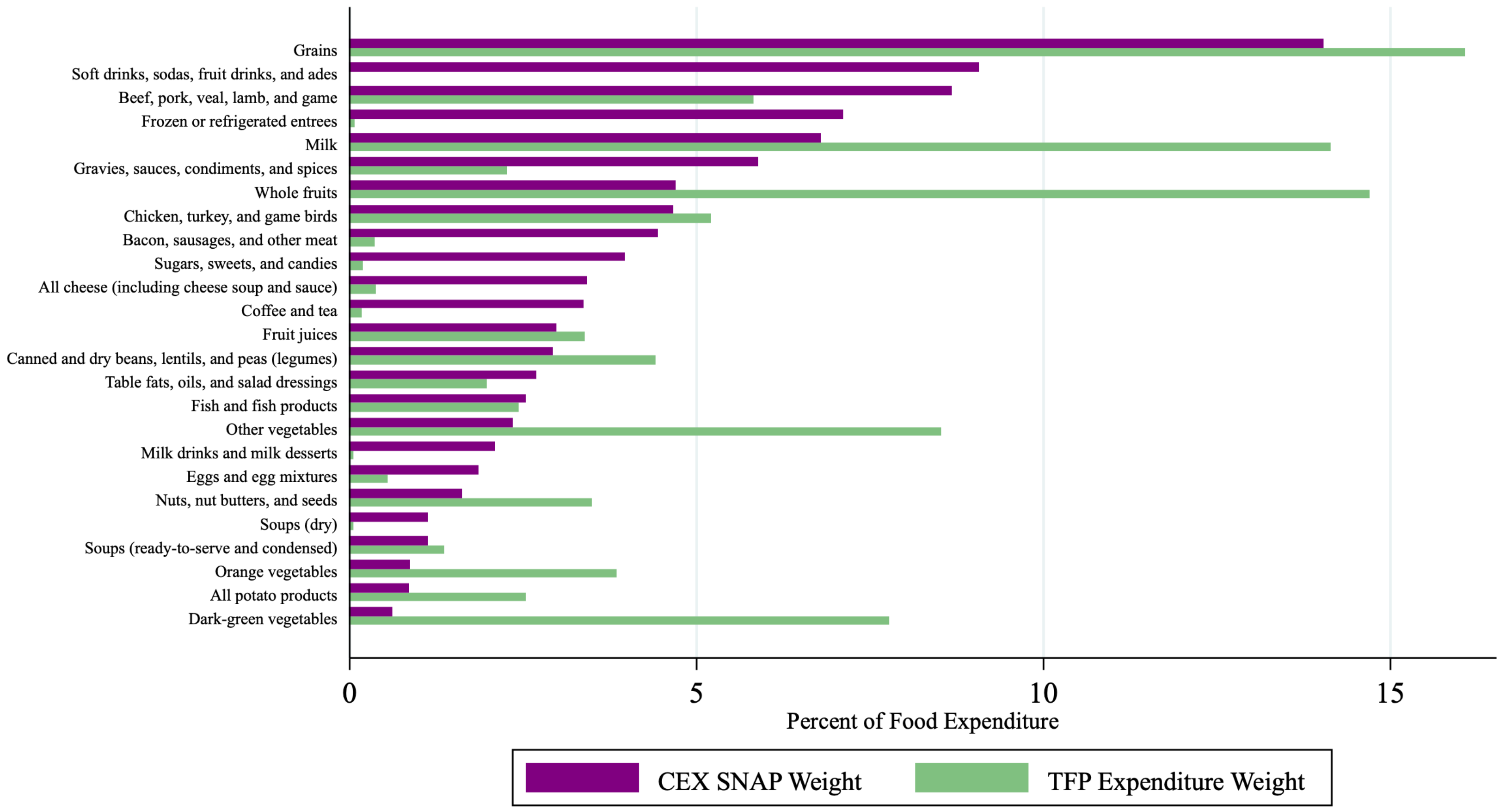
Notes: This table presents the results of equation (7) with two different specifications. The dependent variables include per-capita SNAP participation and a ratio of SNAP participation to the state population below the poverty line. The key independent variable is the log of the real value of SNAP benefits. The controls we include in columns (2) and (4) are the monthly unemployment rate of the state and the policy index from Ganong and Liebman (2018). The policy index does not cover 2016, and thus regressions with the policy index included have fewer observations. Heteroskedasticity-robust standard errors in parentheses. Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.

Table 4. Unadjusted SNAP Purchasing Power and SNAP Participation

	(1)	(2)	(3)	(4)
	Caseload per Capita	Caseload per Capita	Caseload per Eligible	Caseload per Eligible
Log Real SNAP Benefits	0.009	0.004	-0.013	0.106
	(0.010)	(0.011)	(0.106)	(0.113)
State Unemployment		0.004***		-0.001
		(0.000)		(0.002)
Policy Index		-0.005***		-0.021
		(0.002)		(0.019)
State Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	6,468	5,880	6,468	5,880
Adjusted R-squared	0.927	0.939	0.740	0.756

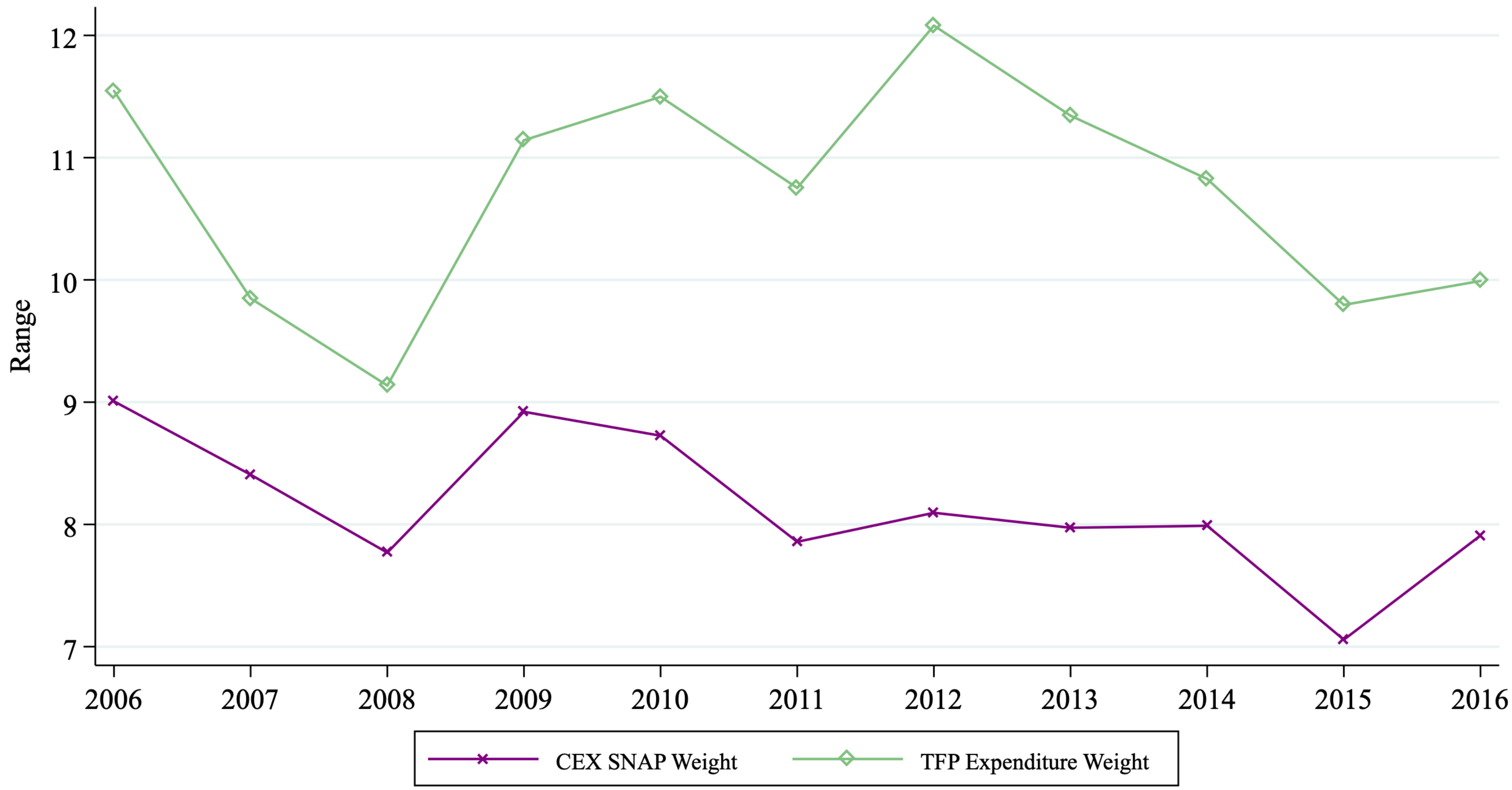
Notes: This table presents the results of equation (7) with 2 different specifications. The dependent variables include per-capita SNAP participation and a ratio of SNAP participation to the state population below the poverty line. The key independent variable is the log of the *unadjusted* real value of SNAP benefits. The controls we include in columns (2) and (4) are the monthly unemployment rate of the state and the policy index from Ganong and Liebman (2018). The policy index does not cover 2016, and thus regressions with the policy index included have fewer observations. Heteroskedasticity-robust standard errors in parentheses. Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.

Figure 1. SNAP Household Expenditure Weights versus TFP Expenditure Weights



Notes: This figure shows the actual expenditure weights of TFP food categories of SNAP households from the Consumer Expenditure Surveys and the TFP recommended expenditure weights. To match the CEX categories with TFP categories, we aggregate the four categories in the "Grains" TFP food type, and thus we have 25 food categories. The TFP recommended weights are based on the expenditure shares for a household of four (two adults and two children) in Carlson et al., (2007).

Figure 2. The Range of Spatial Price Index Values by Alternative Expenditure Weights



Notes: The figure displays the range of the spatial TFP index values estimated using the SNAP household expenditure weight and the TFP recommended expenditure weight for contiguous states between 2006 and 2016. The range is the difference between states with the highest index value and the lowest index value.

Figure 3. SNAP Redemption and Authorized Stores by Outlet Type

Notes: This figure displays the percentage of SNAP benefits redeemed and authorized store counts for grocery, mass merchandise, convenience, and other outlets between 2010 and 2016. The grocery outlet includes supermarkets and grocery stores. The mass merchandisers are the supercenters, such as Walmart and Target.
Source: USDA Food and Nutrition Service.

Figure 4. The Range of Spatial Price Index Values by Outlet Type

Notes: The range of the SNAP household expenditure weighted spatial indices is plotted using three alternative samples: grocery stores and mass merchandisers combined, only grocery stores, and only mass merchandisers. The range is the difference between states with the highest index value and the lowest index value.

Figure 5. Spatial Price Differences Before and After Adjustments for SNAP Expenditure and Outlet Weights

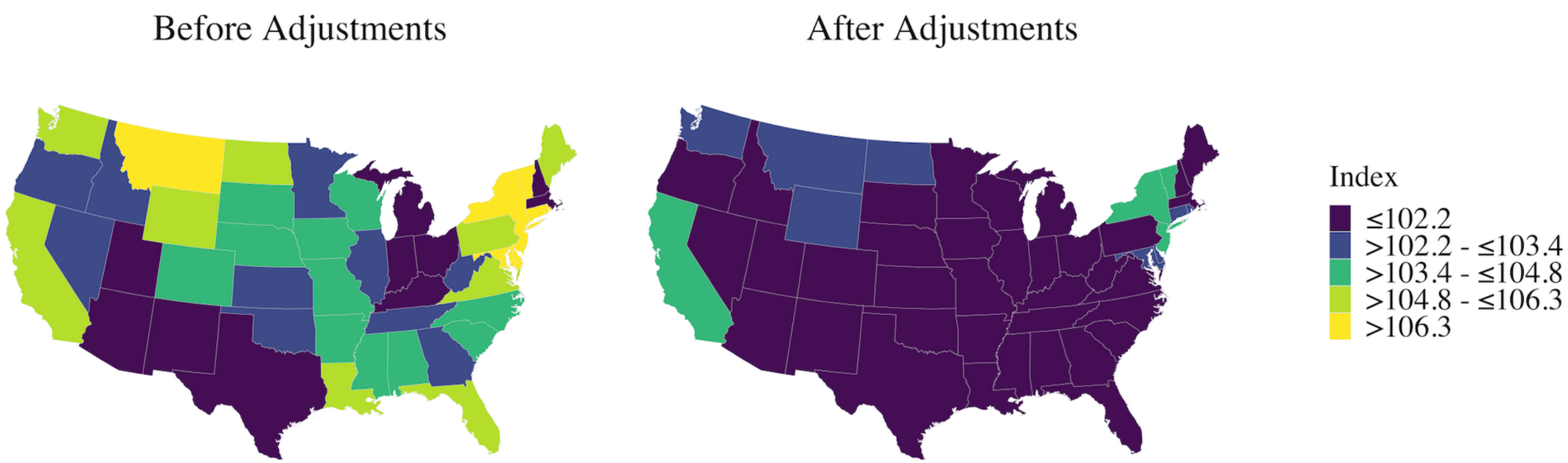
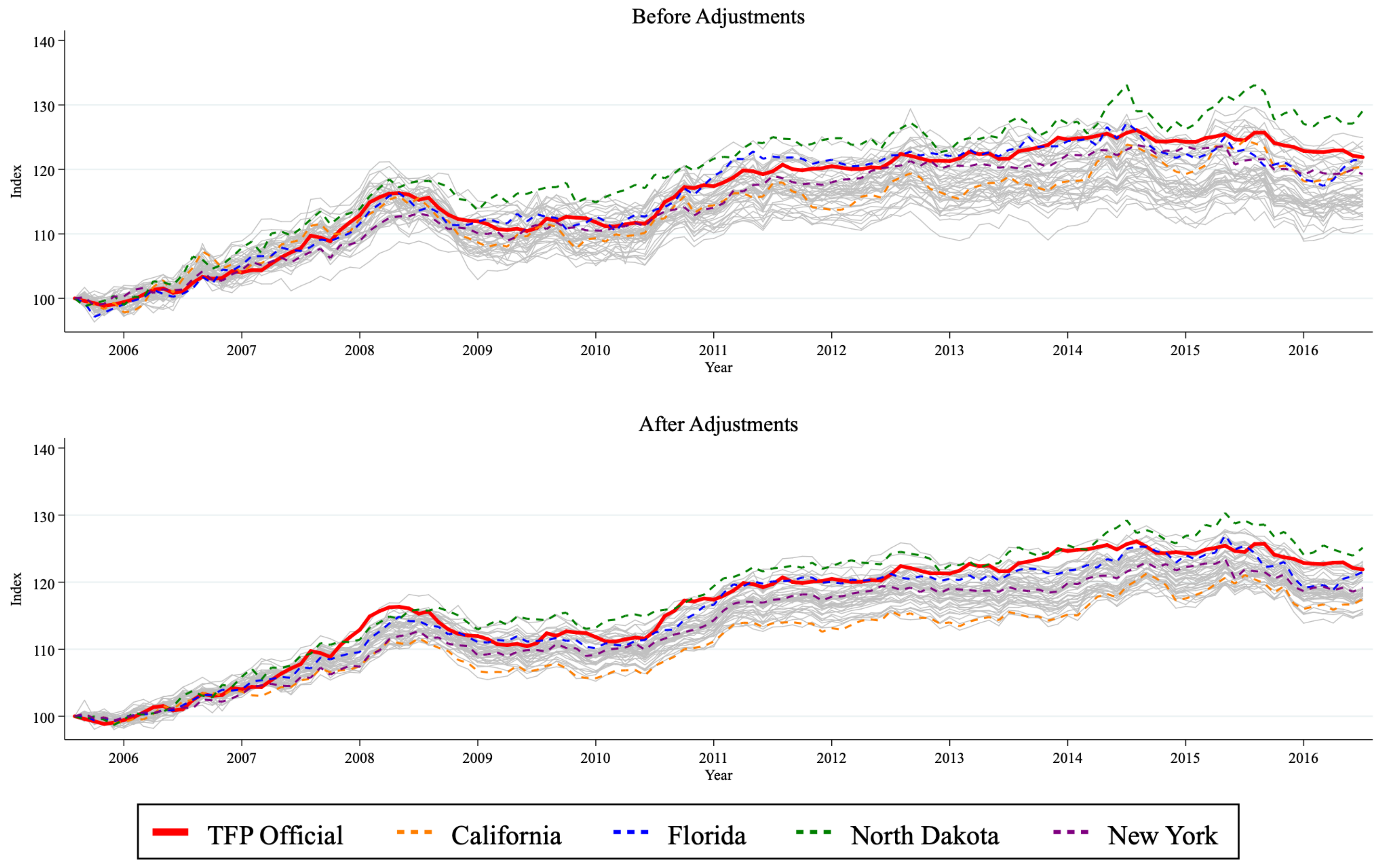
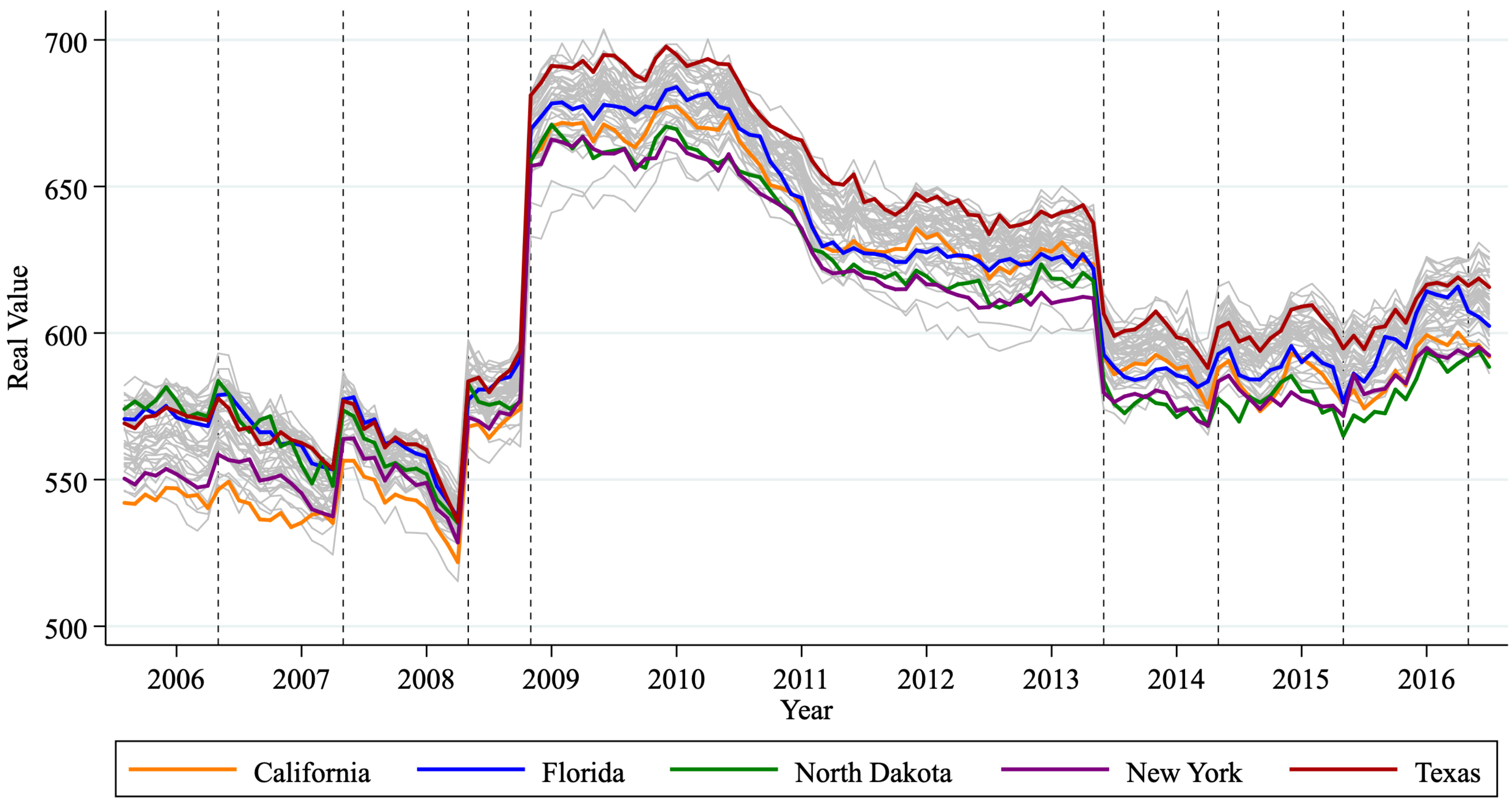


Figure 6. Temporal Price Changes Before and After Adjustments for SNAP Expenditure and Outlet Weights



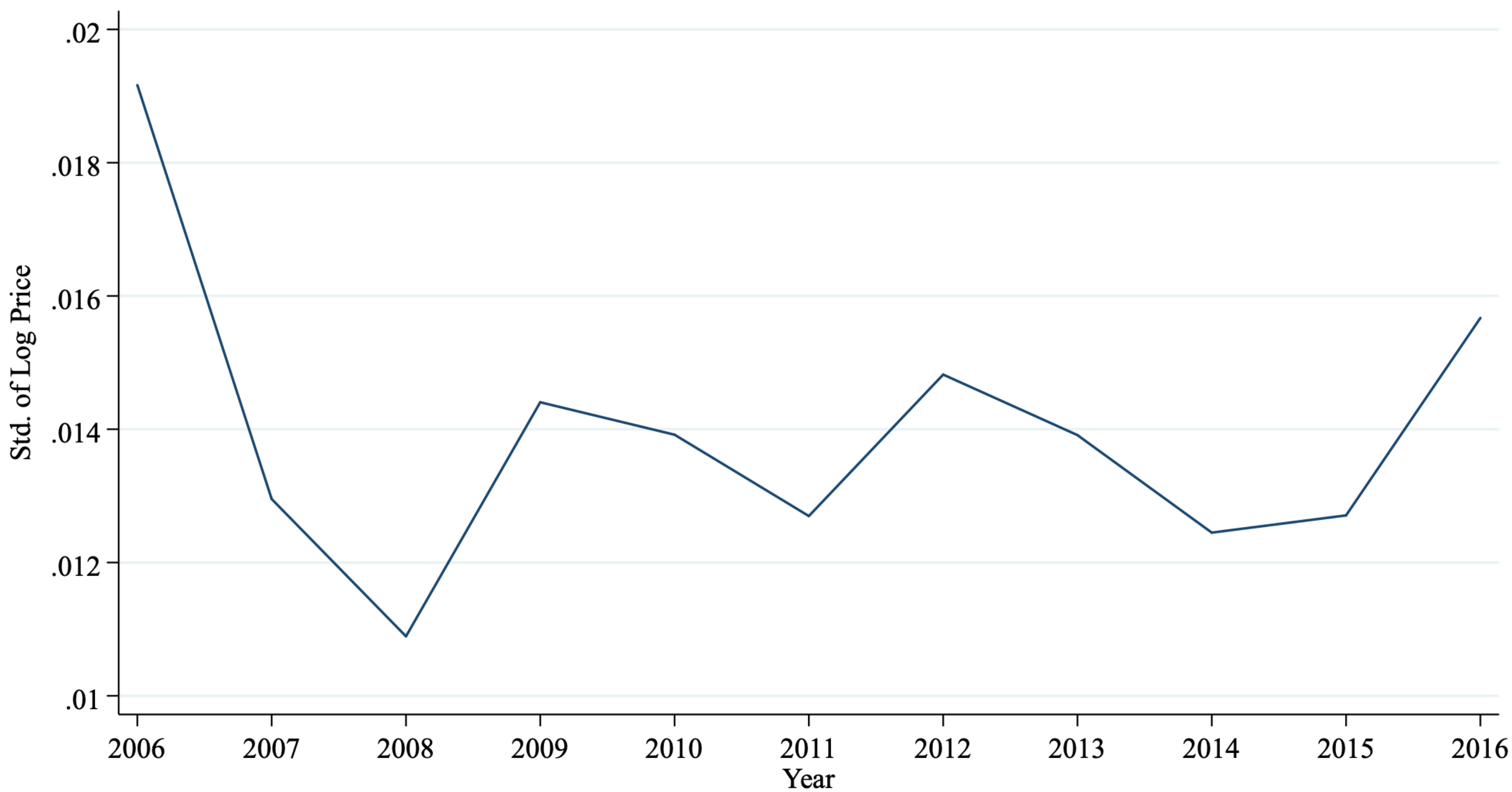
Notes: TFP official refers to the official TFP cost, which is updated monthly by the USDA.

Figure 7. The SNAP Purchasing Power across States between 2006 and 2016



Notes: This figure presents the real value of SNAP max benefits for a household of four. The vertical dashed lines indicate the time when official SNAP adjustments were made in each fiscal year.

Figure 8. Convergence of Price Levels Across States between 2006 and 2016



Notes: A decreasing trend indicates convergence of price levels across the contiguous states and vice versa.

Appendix Table A1. Steps of Calculating TFP Price Indices

Step 1	Extract weekly transaction data between 2006 and 2016 for each of the selected 40 food categories from all stores in the Nielsen retail scanner data.
Step 2	For each UPC in the sample, aggregate store-level sales and quantity to state-level using the geographic code for the grocery stores and the mass merchandisers.
Step 3	Aggregate data from weekly to monthly (for temporal index) and yearly (for spatial index). For straddling weeks, split the sales and quantity by the number of days in each month.
Step 4	Match the food categories in the Nielsen retail scanner data with the TFP categories.
Step 5	Construct temporal price indices for each TFP category sold in each retail channel for each contiguous state using the GEKS method.
Step 6	Construct spatial price indices for each TFP category sold in each retail channel for each year between 2006 and 2016 using the MST method.
Step 7	Adjust for the expenditure bias and the outlet bias, and then generate the TFP temporal and spatial price indices.
Step 8	Construct TFP panel price indices using the CG method.

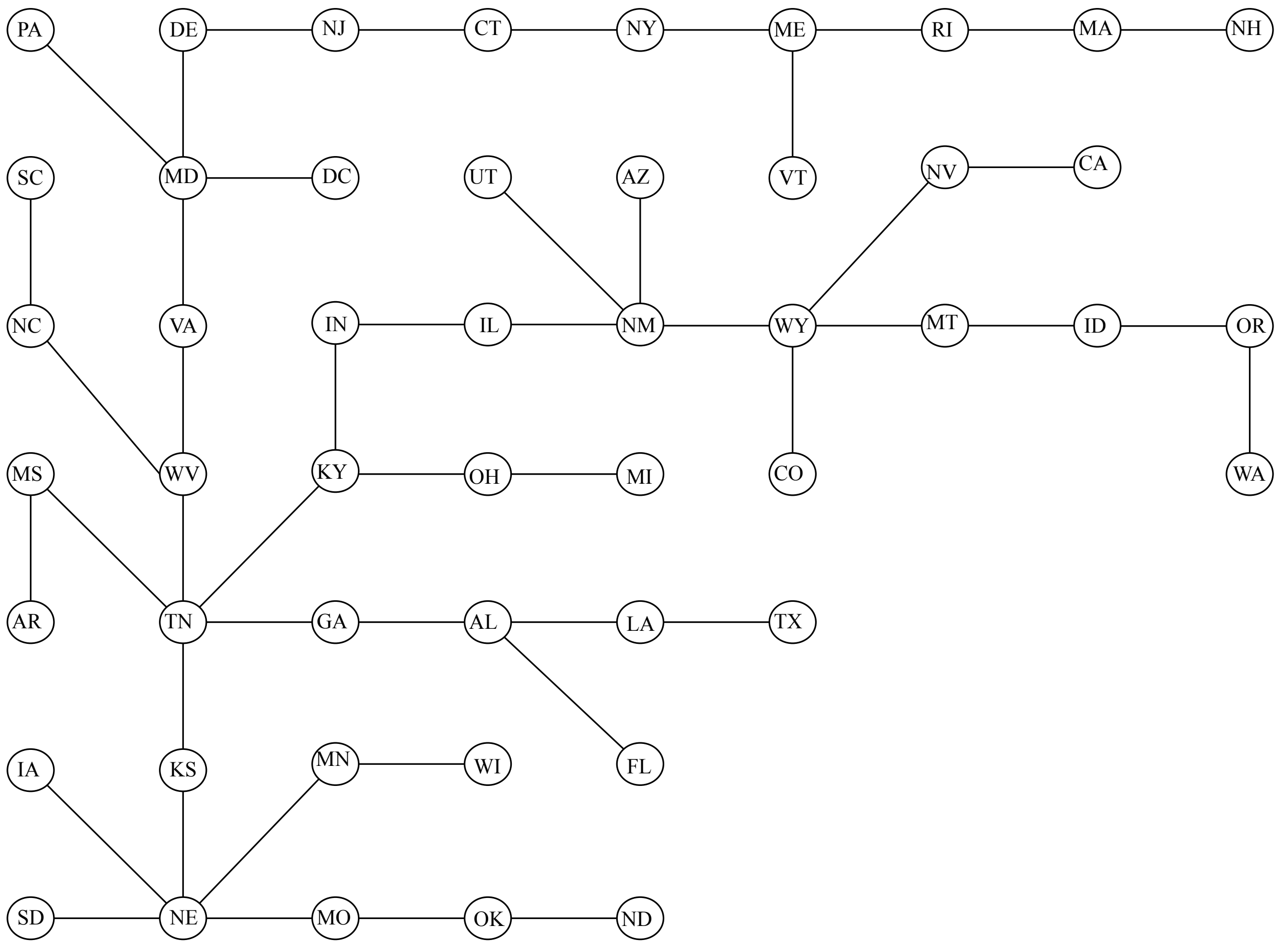
Notes: This table presents an overview of steps required to compute our TFP price indices.

Appendix Table A2. TFP and CEX Matching

TFP Food Categories	CEX Food Categories
Soft drinks, sodas, fruit drinks, and ades	Cola; Other carbonated drinks; Noncarbonated fruit flavored drinks, including non-frozen lemonade; Bottled water; Sports drinks; Nonalcoholic beer
Frozen or refrigerated entrees	Frozen prepared foods
Bacon, sausages, and other meat	Bacon; Ham; Sausage; Other meats
Sugars, sweets, and candies	Sugar and other sweets
Gravies, sauces, condiments, and spices	Condiments and seasonings
Coffee and tea	Tea; Coffee
All cheese (including cheese soup and sauce)	Cheese
Beef, pork, veal, lamb, and game	Beef; Pork chops; Lamb, organ meats and others
Milk drinks and milk desserts	Ice cream and related products; Miscellaneous dairy products; Cream
Eggs and egg mixtures	Eggs
Soups (dry)	Canned and packaged soup
Table fats, oils, and salad dressings	Fats and oils
Fish and fish products	Fish and seafood
Soups (ready-to-serve and condensed)	Canned and packaged soups
Fruit juices	Frozen orange juice; Frozen fruit juices; Fresh fruit juice; Canned and bottled fruit juice
Chicken, turkey, and game birds	Poultry
Canned and dry beans, lentils, and peas (legumes)	Canned beans; Canned corn; Dried peas; Canned miscellaneous vegetables; Dried peas; Dried beans; Dried miscellaneous vegetables; Dried processed vegetables
All potato products	Potatoes
Nuts, nut butters, and seeds	Nuts
Grains	Cereals and bakery products
Orange vegetables	Tomatoes
Other vegetables	Other fresh vegetables
Dark-green vegetables	Lettuce
Milk	Fresh milk, all types
Whole fruits	Fresh fruits

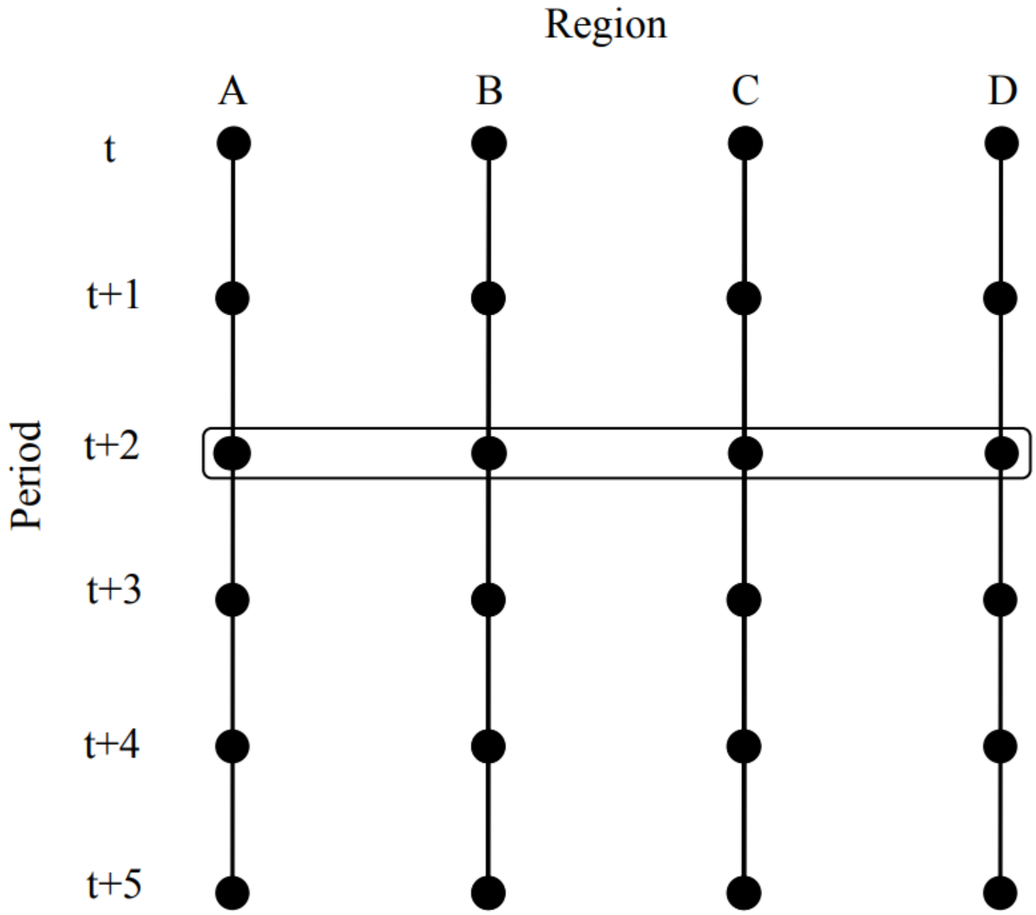
Notes: The CEX categories are from the CEX Table 1101. Quintiles of income before taxes: Average annual expenditures and characteristics.

Appendix Figure B1. Minimum Spanning Tree



Notes: This figure presents the Minimum Spanning Tree of contiguous states in the first quarter of 2012. Each cell represents a state. AL: Alabama; AZ: Arizona; AR: Arkansas; CA: California; CO: Colorado; CT: Connecticut; DE: Delaware; DC: District of Columbia; FL: Florida; GA: Georgia; ID: Idaho; IL: Illinois; IN: Indiana; IA: Iowa; KS: Kansas; KY: Kentucky; LA: Louisiana; ME: Maine; MD: Maryland; MA: Massachusetts; MI: Michigan; MN: Minnesota; MS: Mississippi; MO: Missouri; MT: Montana; NE: Nebraska; NV: Nevada; NH: New Hampshire; NJ: New Jersey; NM: New Mexico; NY: New York; NC: North Carolina; ND: North Dakota; OH: Ohio; OK: Oklahoma; OR: Oregon; PA: Pennsylvania; RI: Rhode Island; SC: South Carolina; SD: South Dakota; TN: Tennessee; TX: Texas; UT: Utah; VT: Vermont; VA: Virginia; WA: Washington; WV: West Virginia; WI: Wisconsin; WY: Wyoming.

Appendix Figure B2. Chronologically Chained Graph



Notes: This figure presents a chronologically chained graph with a spatial comparison in one of the periods. In this example, we select *t*+2 as the spatial comparison reference.