Thrifty Food Plan Panel Price Index and the Real Value of SNAP Benefits

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Abstract

This paper uses retail scanner data to construct panel price indices for the Thrifty Food Plan (TFP) basket and uses the indices to estimate the real value of SNAP benefits. We find that the inflation rates and the price levels of TFP basket vary substantially across the 48 contiguous states and the District of Columbia. Using the TFP price indices, we show that from 2006 to 2016, the range of the difference in the real SNAP benefits for a household of four among states is between 7 to 16 percentage points, which converts to about 39 to 90 pounds of food per month. The result of our price convergence test suggests that this inequality would persist for a long time in the absence of regional adjustments of the SNAP benefits. Using the variation in the real value of SNAP benefits, we find that a one-percent increase in the real value of SNAP benefits is associated with a 0.5 percentage point increase in the SNAP participation rate among low-income population.

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Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.
All errors and omissions are our own.

1 Introduction

The Supplemental Nutrition Assistant Program (SNAP), formerly the Food Stamp Program, is the largest nutrition assistance program in the United States. In 2019, 38 million people in the United States, about 12 percent of the total population, were enrolled in the SNAP. Serving as a key component of the social safety net programs, SNAP has been shown to have significant improvements in food insecurity (Nord and Prell, 2011; Schmidt et al., 2016; Mykerezi and Mills, 2010), health outcomes (Bronchetti et al., 2019; Gregroy and Deb, 2015), and economic self-sufficiency (Hoynes et al., 2016) of the participants. Despite the success in achieving the main goal of reducing food insecurity and improving the well-being of low-income households, the program has room for improvement as there are still millions of households that remain food insecure or lack of sufficient nutrients (Ziliak, 2016). Specifically, Ziliak (2016) proposes that accounting for the time cost in food preparation, updating the Thrifty Food Plan (TFP), and adjusting for the regional difference in cost of living would modernize and improve the effectiveness of SNAP. In this paper, we provide a comprehensive study on the regional variations in the real value of SNAP benefits and suggest a potential method for the regional adjustment in SNAP benefits.

Food prices vary substantially across regions in the United States (e.g. Todd et al., 2011; Gregory and Coleman-Jensen, 2013). The SNAP benefits, however, are fixed across all regions in the contiguous United States. This creates inequalities in real SNAP benefits as the participants in different regions would not be able to purchase the same amount of food due to the spatial differences in food prices. In other words, such inequalities would indicate that some of the neediest households who live in high-price regions would receive less benefits. However, the periodic measurement of real SNAP benefits is a challenging task since we do not have systematic information on the regional price differences in the United States. The limited information on regional price differences could also have important implications for the program evaluation. To the extent that inequalities in real SNAP benefits exist, the impact of the nominal SNAP benefits on key outcomes such as household participation and food insecurity may not be measured accurately. In this paper, we address each of these issues in turn. In particular, using state-of-art methods of index number theory, we construct TFP panel price indices to measure changes in real SNAP benefits over time and across space. Furthermore, we test whether the relative price levels of the TFP basket converge across the contiguous United States. Lastly, we investigate the impact of the real SNAP benefits on program participation.

We use detailed retail scanner data obtained from 48 contiguous states and the District of Columbia from 2006 to 2016 to construct panel price indices for the TFP basket.[1] Retail scanner data provide high-frequency store-level price and sales information on consumer purchases and allow us to construct monthly panel price indices. We construct state-level indices as they may be more flexible for policy to apply, and examine the month-to-month differences as SNAP benefits as distributed monthly.

To construct the TFP panel price indices, we follow a similar approach as described by Çakır et al. (2018). Using fresh fruits and vegetables as the basket, Çakır et al. (2018) construct panel indices to estimate the real value of the Special Supplemental Nutrition Program for

[1] 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.

Women, Infants, and Children (WIC) cash-value voucher and find that there are substantial differences across regions and over time. Specifically, we use the GEKS method to construct the temporal index.[2] When using scanner data, GEKS method has the advantage of both chained indices, which allow the introduction of the new products and the deletion of obsolete products, and fixed base indices, which are free of 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 suggested by Hill (2004). We address the base dependent limitation in the CG method to provide a consistent and transitive panel index.

Our results indicate that from 2006 to 2016, the real value of SNAP benefits changes over time and varies substantially across contiguous states. We find that households of four living the states with the highest real SNAP benefits can purchase 39 to 90 pounds more food in the TFP basket per month than the household living in the states with the lowest real SNAP benefits. Our price convergence estimates suggest that without regional adjustments, the inequalities in the real value of SNAP benefits are likely to persist over time. Using the variation in the real value of SNAP benefits, we find that each one-percent increase in the real value of SNAP benefits is associated with a 0.5 percentage point increase in the SNAP participation rate among the low-income population. Our finding is different from a previous study (Bronchetti et al. 2019) that uses yearly household data and a different approach to generate the real value of SNAP benefits, in which they did not find a statistically significant relationship between SNAP purchasing power and SNAP participation. In general, these results have direct implications for SNAP administration: regional adjustments of SNAP benefits would be necessary for reducing the nutrition deficit for SNAP participants living in states with low real SNAP benefits; prompt and accurate adjustment could lead to higher SNAP participation.

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 our results and Section 6 concludes.

2 SNAP Overview and Previous Literature

2.1 SNAP Overview

SNAP provides low-income households with monthly benefits to purchase eligible food products. SNAP benefits can be used by households via an electronic benefit transfer card to purchase food for the household. Not all foods, however, are eligible for purchase using SNAP benefits. For instance, hot foods and prepared foods for immediate consumption are not eligible. To be eligible for SNAP, households need to meet three tests: (1) the gross monthly income of the household needs to be less than 130 percent of the poverty line; (2) household income after deductions must be at or less than the poverty line; (3) assets must be $2,250 or less.[3] Eligible households receive SNAP benefits equal to the maximum benefit for that household size minus 30 percent of the household's net income. The maximum value of SNAP is determined by the

[2] GEKS is named after Gini (1931), Elteto and Koves (1964), and Szulc (1964).
[3] 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.

cost of the TFP, which is designed by the USDA to serve as a representative standard for people to obtain a nutritious diet at a minimal cost. The SNAP benefits are updated every fiscal year based on the Consumer Price Index (CPI) for the 29 food categories in the TFP (Carlson et al. 2007).[4]

In 2009, the American Recovery and Reinvestment Act (ARRA) boosted the SNAP benefits by 13.6 percent per month in responding to the Great Recession. The ARRA specified that the SNAP benefits would not be adjusted for inflation until the food prices eliminate the purchasing power of the benefit amounts. Nord and Prell (2011) show that the increase in SNAP benefits increased food spending and reduced food insecurity among SNAP participating households. However, as the real value of SNAP benefits declined due to inflation, the food spending declined, and food security worsened for SNAP participating households (Nord, 2013). In October 2013, SNAP lowered the benefits by around 5 percent since the food price inflation rate is lower than expected.[5]

2.2 Previous Literature

Previous studies use various data and methods to generate the basket price of TFP. Gregory and Coleman-Jensen (2013) and Bronchetti et al. (2019) use data from the Quarterly Food-at-Home Price Database (QFAHPD) to generate the TFP price for designated market groups in the United States.[6] Both studies use expenditure weighted average prices of products in the TFP category to construct annual price estimates for the TFP for markets across the United States. Gregory and Coleman-Jensen (2013) use the TFP price to examine the link between food prices and food insecurity in the United States. Bronchetti et al. (2019) calculate the SNAP purchasing power using the TFP price and estimate the relationship between the local purchasing power of SNAP and health outcomes. Feeding America for the Map the Meal Gap (Gundersen et al. 2018) uses Nielsen household scanner and store scanner data to construct the TFP basket price and estimate the relative pricing between counties. This project uses expenditure weighted prices from a 4-week period in October to generate annual TFP basket prices for each county from 2009 to 2017. Another project by Gundersen et al. (2016) uses Information Resources, Inc. (IRI) store scanner data and calculates a weekly TFP basket price for stores by taking the median price per pound for each TFP category multiply by pounds prescribed for purchase by the TFP.

The TFP prices constructed in the extant literature are inadequate to provide a general inference in the real SNAP benefit variations due to two important limitations. First, household scanner data used in the previous studies have a relatively small sample in each region. Since the TFP basket includes a large number of food categories, a sample with an inadequate number of households is likely to lead to inaccurate results. For instance, the San Francisco market group in QFAHPD data have less than 100 households in the year 1999, 2002, and 2003, and less than 400 households in the years 2004 to 2006.[7] Unlike household scanner data that collect data from selected households, retail scanner data contain all the transactions generated by point-of-sale

[4] 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.

[5] This is also called the sunset of the ARRA benefit boost.

[6] 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.

[7] See Todd et al. (2010) for details on the number of households by market and year.

systems and refrain from several information biases that household scanner data face.[8] Another advantage of using retailer scanner data is that the data are collected from retailers, which is similar to the CPI price collection approach. The current procedure for CPI price collection is by having BLS data collectors visit or call retail stores over the United States to obtain data on the prices of products. Thus, regional adjustments relying on price indices generated by this type of data may be more flexible for policymakers.[9] Second, the methods used to construct the TFP price could potentially subject to biases, such as product heterogeneity bias and variety bias. Heterogeneity bias occurs when comparing products in different regions or time periods and variety bias arises from the fact that products may be unavailable in some regions. Handbury and Weinstein (2015) show that controlling for these biases reverses the finding that prices increase with city size.[10] Thus, it is important to consider these biases when constructing price indices for the TFP basket.

Our methods address some of the biases given their nature of index construction. For the product heterogeneity bias, since we match products at the Universal Product Code (UPC) level in both the GEKS and the MST methods, we resolve the product heterogeneity bias that arises from the comparison of aggregated goods (Handbury and Weinstein, 2015). The MST approach mitigates the variety bias as it links the regions that have a similar price structure when making spatial comparisons.

3 Data

We use retail scanner data collected by the Nielsen Company (US), LLC, to construct the price indices.[11] Retail scanner data offers detailed information on all consumer purchases at high frequency (i.e. weekly) at the UPC (or barcode) level and provides great potential to improve the quality of price index construction. Furthermore, retail scanner data avoid major types of information bias due to survey or diary collection techniques that other kinds of data may have such as observer bias, recall bias, and strategic bias. The data include weekly retail prices and sales from more than 35,000 stores comprising more than 50 and 30 percent of the total sales volume of grocery and drug stores and mass merchandiser stores of the United States, respectively.[12] 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 95 percent of all food sales in the TFP basket. There are more than 2 million products in the data, and the products are disaggregated to the UPC level. The high frequency and the availability of both price and quantity allow us to generate weighted indices at detailed aggregation levels. Similar to the

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[8] Zhen et al. (2018) show that there exist significant differences between retail scanner data index and household scanner data based index.

[9] The BLS has not started to use retail scanner data for index construction, but there are seven countries (Australia, Belgium, Denmark, the Netherlands, Norway, Sweden, and Switzerland) that used scanner data in compiling their CPI. A recent study suggests that the number of countries is likely to increase in the future (de Haan et al., 2016).

[10] Fan et al. (2018) calculated the Exact Price Index (EPI) proposed by Handbury and Weinstein (2015) for the TFP basket using IRI retail scanner data in 2012 to examine whether a nutritious diet cost more in food deserts. The EPI is a spatial price index that eliminates the heterogeneity and variety biases. Fan et al. (2018) use the food group elasticities in 2012 from Handbury and Weinstein (2015) to construct the EPI. We are not able to use the same approach as we are constructing a panel index instead of a spatial index for a specific year.

[11] The data are provided for research purposes by the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business.

[12] The average number of stores from 2006 to 2016 in our data is 37,183. The specific store channels that the data include are convenience, drug, food, and mass merchandiser.

approach suggested by Handbury and Weinstein (2015), using the comprehensive UPC level data allows us to correct for the product heterogeneity bias in the price index we construct.

Our sample includes all categories listed in TFP, thus allowing us to generate indices using TFP as the basket. We match the 29 food categories in the TFP basket to the product categories in the Nielsen retail scanner data. Specifically, we select all available categories in Nielsen retail scanner data that match the categories in each TFP food type and include them as our sample. Table 1 presents how we match the food categories in Nielsen retail scanner data to the food categories in the TFP basket. After matching, our sample consists of 640,679 UPCs from 412 product groups of the 40 matched categories. There are four units of measurement for products in the TFP basket from the Nielsen retail scanner data, including ounce ("OZ"), pound ("PO"), liter ("LI"), and count ("CT"). Because we are making apples-to-apples comparison when we construct the price indices, it is not necessary for us to convert to unified units.[13]

Since SNAP benefits are provided monthly, we aggregate the weekly store-level average price to the monthly state-level price for each unique UPC as the unit value price.[14] We use states including the District of Columbia as our geographic unit as it is more likely for SNAP benefits to adjust at that level. Thus, we aggregate store-level data to the state-level, and each state, on average, includes data from more than 750 stores. The number of stores in our data varies by the population of the state, for instance, the top 3 states are California, Texas, and Florida. Our 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.[15]

We collect data on SNAP benefits from the USDA Food and Nutrition Service. Table 2 presents the maximum allotments for a household size of one and four and the average monthly benefits of SNAP. The maximum SNAP benefits vary by household size but are identical across the contiguous United States. We include the year 2017 since the SNAP benefits are in effect each year from October in the past year through September this year (i.e., the allotments for 2017 are from October 1, 2016, through September 30, 2017). The average annual increase in max 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 that lead a 14 percent increase in the max SNAP benefits for a household of four. Other than the 5 percent decrease in 2014 and a 3 percent increase in the year after, the allotment amount has remained stable after the ARRA.

4 Price Indices

To investigate the changes in TFP basket cost, we use index number methods to construct price indices. We first construct the temporal indices and the spatial indices, and then link them using the "chronological" (CG) method proposed by Hill (2004) to create the panel indices.[16] Panel price index allows us to make apples-to-apples comparison of cost of living (real value) in different regions and different periods in the United States. To address the product heterogeneity bias, the items in all equations are unique UPC codes.

[13] This also avoids the potential measurement error caused by the unit conversion.

[14] Specifically, we take the expenditure weighted average of weekly store-level prices to generate monthly prices.

[15] The retail scanner data cover years 2006 to 2017, but there was a dramatic change in store composition after 2016. Thus, we use data from 2006 to 2016.

[16] The term "temporal" in our paper refers to comparisons for a given region or state across different point of time, and the term "spatial" refers to comparisons across regions or states in a specific point of time.

4.1 Temporal Indices

There are many different index number formulas available to calculate the temporal price change. Bilateral index formulas such as Laspeyres, Paasche, Fisher, and Törnqvist are commonly used. Fisher and Törnqvist are also called "superlative" indices and are considered to be theoretically more attractive since they approximate to the second order of the underlying cost-of-living index (Diewert, 1976).[17] For comparisons between two periods *0* and *t* with common items $i = 1, \ldots, N$, the Laspeyres price index (direct) is defined as follows:

$$P_L^{0,t} = \frac{\sum_{i=1}^{N} p_i^t q_i^0}{\sum_{i=1}^{N} p_i^0 q_i^0} \tag{1}$$

where p_i^0 is the price of item *i* in period 0, p_i^t is the price of item *i* in period *t*, and q_i^0 is the quantity of item *i* in period 0. The common counterpart to the Laspeyres price index, the Paasche price index (direct) can be written as:

$$P_P^{0,t} = \frac{\sum_{i=1}^{N} p_i^t q_i^t}{\sum_{i=1}^{N} p_i^0 q_i^t} \tag{2}$$

where p_i^t is the price of item *i* in period t. The Fisher index formula is defined as the geometric mean of Laspeyres and Paasche price indices:

$$P_F^{0,t} = \left(P_L^{0,t} \times P_P^{0,t}\right)^{\frac{1}{2}} \tag{3}$$

The formula for the Törnqvist price index is:

$$P_T^{0,t} = \prod_{i=1}^{N} \left(\frac{p_i^t}{p_i^0}\right)^{\frac{s_i^0 + s_i^t}{2}} \tag{4}$$

where s_i^0 and s_i^t are the expenditure shares of item *i* in period 0 and *t* for set of items available in both periods, respectively.

When constructing indices, we need to decide using direct indices (also known as fixed base indices) or chained indices. Direct indices compare the current period directly with a fixed base period, and the basket of goods is fixed over time. Chained indices compare the current period to the base period by taking the product of all chain links, which are the bilateral indices of two adjacent periods, between the two periods. Chained indices incorporate the new and disappearing items in the estimate of price change since the basket of goods is updated every period by the chain links. Since scanner data have high attrition and quality changes (which can lead to product heterogeneity bias) in the basket of goods due to the high frequency feature, chained indices are usually preferred to the direct indices. However, chained indices suffer from

[17] Fisher and Törnqvist are the two most widely used superlative indices and are usually numerically very close. The Fisher index is exact for the quadratic mean of order two unit cost functions and the Törnqvist index is exact for the translog cost function (Diewert, 1976).

chain drift, which means that the indices do not return to a value of 1 even when prices return to those in the base period. The chain drift issue is a series problem when using scanner data due to the data attrition and oscillation features, and is usually attributed to promotions triggering consumers' stockpiling behavior (Feenstra and Shapiro 2003; de Haan and van der Grient 2011; Ivancic, Diewert, and Fox, 2011).

To address the chain drift, Ivancic, Diewert, and Fox (2011) proposed an approach that uses a multilateral index number method of Gini (1931), Elteto and Koves (1964), and Szulc (1964). Studies have shown that the GEKS method performs well with scanner data (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 period j and k can be expressed as follows:

$$P_{GEKS}^{j,k} = \prod_{l=0}^{T} \left[P^{j,l} \times P^{l,k} \right]^{\frac{1}{T+1}} \tag{5}$$

where $P^{j,l}$ and $P^{l,k}$ are bilateral indices. Both the Fisher index and the Törnqvist index can be used to generate the GEKS-Fisher index and the GEKS-Törnqvist index, respectively.[18] The GEKS index has the advantages of both fixed base index and chained index. Since the GEKS method uses each of the possible matches over time period under consideration, each period is considered in turn as the base and therefore is free from chain drift. The maximum use of all possible matches between any two periods also allows the GEKS index to deal with the high attrition rate of items.

4.2 Spatial Indices

The GEKS method we use for temporal indices can also be used in spatial price comparisons.[19] However, since the GEKS method assigns equal weight to each bilateral index number comparison between any two regions, the overall results would be less promising if the price structures differ across regions. Hill (2004) suggests the minimum spanning tree (MST) approach that accounts for price structure differences between regions to reconcile this issue in EKS-type methods.[20] 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.[21] In our spatial comparisons, each region represents a vertex and each edge connects the two vertices. We present the MST of states in one of the quarters in Appendix Figure 1 as an example.

[18] The GEKS-Törnqvist index can also be referred to as CCD (Caves, Christensen, and Diewert, 1982) index.

[19] In fact, multilateral index methods are often used for spatial comparisons (e.g. Caves et al., 1982; Diewert, 1999, Zhen et al. 2018). Hill (2004) provides a general taxonomy of index methods that can be used to compute spatial indices.

[20] In general, GEKS and EKS usually refer to the same method of making bilateral index formula transitive by taking the geometric mean. The practice of adding Gini to EKS came in recently, and Hill used EKS in the paper.

[21] For a set of M vertices, we can have a maximum M^{M-2} number of spanning trees.

To apply the MST approach, we first need to measure the dissimilarity between the price structure of all region pairs to use as the edge weights. 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*:

$$\Delta_{PLQ}(p^m, p^n, q^m, q^n) = \sum_{i=1}^{N} \left(\frac{1}{2}\right)(s_i^m + s_i^n)\left[\ln\left(\frac{p_i^n}{p_i^m P^{m,n}}\right)\right]^2 \tag{6}$$

where any superlative price index formula can be used as $P^{m,n}$ to calculate the dissimilarity scores. 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.

After we generate the relative price dissimilarity scores for each pair of regions, we follow Hill (1999) and use Kruskal's algorithm to find the path with the least sum of dissimilarity scores between all regions to obtain the MST. 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 region *m* and *n* can be calculated as:

$$P^{m,n} = P^{m,l} \times P^{l,n} \tag{7}$$

where $P^{m,l}$ and $P^{l,n}$ denote superlative price indices we choose.

4.3 Panel Indices

We combine the temporal and spatial indices using the "chronological graph" (CG) method introduced by Hill (2004). The CG method allows for both temporal fixity and temporally consistency, which are very desirable properties for a panel method. Temporal fixity means that adding new periods to the data does not affect the results of the previous periods. Temporal consistency means that the 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. a MST in one of the periods) we select. Figure 1 presents a chronologically chained graph with a spatial comparison in one of the periods. In Figure 1, we link temporal indices from January 2010 to June 2010 with the spatial indices for Massachusetts, California, Illinois, and Minnesota using March 2010 as the spatial comparison reference. Since we apply the CG method to construct the panel indices, the choice of reference spatial comparison is important. Therefore, we choose the spatial reference that is obtained by taking the geometric mean of all spatial price indices over all periods as suggested by Hill (2004).

A limitation of this approach is that it is base dependent, in other words, the choice of the base period for the temporal indices would have an impact on the panel index value. To address this issue, we take an approach that uses the geometric mean of all available periods as the base to link the temporal and spatial indices to generate a consistent and transitive panel index.

5 Results

5.1 TFP Price Indices

We begin by estimating the temporal and spatial changes in TFP prices. We first construct the temporal and spatial indices using GEKS and MST approaches, respectively. Figure 2 illustrates the temporal movements in the TFP prices for contiguous states from 2006 to 2016 and compares with the national average Consumer Price Index (CPI) for food and beverages constructed by the BLS during the same period. In general, the temporal trend of TFP price changes follows a similar pattern for all states and is analogous to the CPI: the prices were increasing from 2006 to 2008 but dropped a bit in 2009, then the prices went up gradually and started to decrease again in 2016. Nevertheless, there still exist substantial differences in the temporal movements of different states. For instance, compared to the base period (i.e., January 2006), the TFP price in North Dakota has increased 30 percent in January 2016, but South Dakota and California have only increased 25 percent and 18 percent during the same period, respectively. The difference in TFP price inflation among states in our study period can be more than 17 percent. The high temporal price movement in North Dakota may be due to the oil boom started in 2006 that leads to a substantial growth job in population and per capita gross domestic product (U.S. Energy Information Administration 2013). In general, these results suggest that a fixed adjustment for all states may not be sufficient for SNAP as the temporal TFP price movements could be substantially different across states.

The temporal indices give insight into the changes in prices individually for each state, and thus, we cannot make comparisons on the value of the prices across states with them. Instead, we use spatial indices to achieve the regional comparisons in each period. Figure 3 presents the average spatial variation in TFP prices for the contiguous states from 2006 to 2016. The darker shading in the figure represents a higher price in the state. We find that the range of the average spatial TFP price difference between the highest cost and the lowest cost states during our study period is 8 percentage points. The figure illustrates that price levels, in general, are higher in the east and west coastal states and suggests that the spatial difference in TFP prices are economically important across states.

Similar to the mechanism of the temporal indices, the spatial indices we construct cannot make temporal comparisons for each state. Therefore, we link the temporal and spatial indices to generate the panel price indices to allows us to make comparisons of TFP price levels over time and across space. That is, we can compare the TFP price level in Florida in January 2006 with the price in Michigan in August 2013 using the panel indices.

5.2 Real Value of SNAP Benefits

We adjust the SNAP benefits of each state during each period from 2006 to 2016 using the TFP panel price indices. Table 3 displays the average real value of SNAP max benefits for a household of four in each SNAP fiscal year. Despite the nominal SNAP benefits are identical across states, the real value of SNAP benefits is changing over time and is different across states. From 2006 to 2016, on average, Indiana, Utah, Kentucky, and Oklahoma have the highest adjusted SNAP benefits, while District of Columbia, Vermont, New York, and New Jersey have the lowest adjusted SNAP benefits.

The differences between the highest and the lowest real value of SNAP benefits are substantial. For instance, in the 2007 fiscal year, a household of four living in Indiana can use their maximum SNAP benefits to purchase about 9 percent more of the same goods in the TFP basket each month than a household of four living in Washington state could purchase. In general, our results show that the range among contiguous states in our study period is between 7 to 16 percentage points, which is about 45 to 85 dollars of food for a household of four per month.[22] Since the SNAP benefits are adjusted every fiscal year, the difference in the SNAP real value would create an inequality of at least 540 dollars of food per household between states with the highest and the lowest SNAP purchasing power each fiscal year.

To further illustrate the significance of the inequality in the real value of SNAP benefits, we convert the difference in nutritional value. The TFP basket for a household of four contains 130.61 pounds of food that provides approximately 62,895 kilocalories (kcal) of total energy per week (Carlson et al. 2007).[23] Assuming that households living in the state with the highest SNAP real benefits could purchase a full amount of the TFP, then the 7 to 16 percentage point difference in the real value of SNAP indicates a deficit of 39 to 90 pounds of food and about 18,867 to 43,128 kcal energy per month for a household of four living in the state with the lowest real value of SNAP benefits. This gap in nutritional values could have important health impacts on the SNAP participants.

5.3 Convergence of Prices over Time

Next, we investigate whether the inequality in the real value of SNAP benefits persists over time to infer the need for regional adjustment in the SNAP benefits. With the panel indices, we examine the trends of relative regional prices across the contiguous United States for the TFP basket. That is, we test if the prices of the TFP basket are converging or diverging over time. If the TFP prices are converging, then the national uniformed SNAP benefit adjustment using the TFP basket as a reference may be sufficient in the future, and vice versa.

Following the approach in Hill (2004), we calculate the standard deviation of the logarithm of price levels for *k=1,…,K* states in each period t as:

$$\sigma_t = \sqrt{\frac{1}{K-1}\sum_{k=1}^{K}\left[\ln\left(\frac{\mathrm{P_{kt}}}{\mathrm{P_{ot}}}\right) - \overline{\ln\left(\frac{\mathrm{P_t}}{\mathrm{P_{ot}}}\right)}\right]^2} \tag{8}$$

where P_o denotes the price level in the base state and $\overline{\ln\left(\frac{P_t}{P_{ot}}\right)} = \frac{1}{K}\sum_{k=1}^{K}\ln\left(\frac{P_{kt}}{P_{ot}}\right)$.[24] A decrease in σ_t signals that price levels are converging over time and an increase in σ_t signals that price levels are diverging.

We present the trends of relative regional prices across the contiguous United States from 2006 to 2016 in Figure 4. In general, there is no obvious evidence of convergence across or divergence across the contiguous states over the period. There was a substantial decrease in σ_t during late 2006 and the end of 2007, suggesting that the price levels were converging in the period. After that, the value of σ_t fluctuated and did not show an obvious pattern until the start of 2015. Starting from 2015, the price levels diverged gradually but did not reach the peak value in 2006. Overall, the differences in TFP price levels have been going up and down with a slight trend suggesting divergence in 2016. This finding suggests that the TFP price levels are likely to remain heterogeneously changing for states over time. Thus, without regional adjustments, the

[22] This result is robust to the choice of excluding the District of Columbia in the comparison.
[23] The reference household of four consists of male and female adults ages 19 to 50 and two children ages 6 to 8 and 9 to 11.
[24] We choice California as the base state as it has the most SNAP participant. Nevertheless, σ_t is invariant to the choice of base state (Hill, 2004).

inequalities in the real value of SNAP benefits among contiguous states are likely to persist over time.

5.4 Real Value of SNAP Benefits and SNAP Participation

The number of people participating in SNAP has been decreasing in the past several years. This decline is mainly due to the recovery of the economy; however, the number of eligible people is still larger than the number of SNAP participation. 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. While unemployment is shown to be a key determinant of SNAP caseloads (Bilter and Hoynes, 2016), the variation in the real value of SNAP benefits could also have an impact on SNAP participation. Thus, we apply the real value of SNAP benefits we construct in this paper to investigate whether there exist correlations between the real value of SNAP and the SNAP participation rate for each state.[25]

We collect monthly data on SNAP participation for each state from the USDA Food and Nutrition Service. We then link the data with the state-level number of poor and poverty rate data by Current Population Survey (CPS) to generate the SNAP participation rate as a ratio of SNAP participation to the state population below the poverty line. We examine the relationships based on the following model:

$$y_{it} = \beta \ln(SNAP_{it}) + \alpha_i + \boldsymbol{\lambda}_t + \boldsymbol{X}_{it} + \varepsilon_{it}, \tag{9}$$

where y_{it} is the ratio of the SNAP participation number to the number of people below the poverty line for state i in time t. The key independent variable $\ln(SNAP_{it})$ is the log of the real value of SNAP benefits for state i in time t. The vector $\boldsymbol{X}_{it}$ is a set of controls including state unemployment rate, state minimum wage, state market rent, and regional CPIs for apparel, commodities, education, medical, recreation, services less rent of shelter, transportation, and other goods and services. We include state fixed effects (α_i), and month of sample fixed effects and year of sample fixed effects in a vector $\boldsymbol{\lambda}_t$. We cluster the standard errors at the state level in all models.

Table 4 presents the results of equation (9) with 3 different specifications. In column 1, we perform OLS regression and include the fixed effects. We control for monthly state unemployment rate in column 2, and column 3 includes all the other controls including state minimum wage, state market rent, and regional CPIs for apparel, commodities, education, medical, recreation, services less rent of shelter, transportation, and other goods and services.

The results show that the real value of SNAP benefits has a positive and significant effect on SNAP participation. When only the state and time fixed effects are included, we find that a one percent increase in the real value of SNAP benefits is associated with a 0.5 percentage point increase in the number of SNAP participants. Adding unemployment, which is a determinant of SNAP participation (Bitler and Hoynes, 2016), has a negligible impact on the coefficient. The addition of the other controls also does not alter much, and the estimated coefficient on the real value of SNAP remains positive and significant. In general, the findings suggest that a one

[25] In a recent study, Bronchetti et al. (2019) use yearly household data from 1999 to 2010, and find no statistically significant relationship between SNAP purchasing power on the SNAP participation. Since our paper uses monthly retail scanner data and the real value of SNAP benefits constructed from a completely different approach, we expect the additional variation by the monthly data and the more precise temporal and spatial adjustment would provide different findings.

percent increase in the real value of SNAP benefits is associated with a 0.5 percentage point increase in the rate of the SNAP participation among the population below the poverty line.

6 Conclusion

The SNAP benefit levels are fixed across the continental United States and remain relatively stable in recent years, but food prices vary over time and across regions. Consequently, in some regions, low-income households that rely on SNAP would face inequality of SNAP benefits. Adjusting SNAP benefits to more accurately align with the regional cost of food could help reduce this inequality and improve the effectiveness of SNAP. To examine the real value of SNAP benefits, we construct panel price indices for foods in the TFP basket since TFP is the basis for legislated SNAP benefits. Our panel price indices present the monthly change in TFP food prices from 2006 to 2016 and the spatial difference over 48 contiguous states and the District of Columbia.

Our panel price indices show that the price levels of the TFP basket change at a different rate for each state over time, and the price levels across space are also substantially different. On average, the TFP price inflated 16 percent from 2006 to 2016, and the average spatial price difference between the highest cost and the lowest cost states is 8 percentage points. Using the price indices, we generate the real value of SNAP benefits and present the change over time and across contiguous states. We show that the range of the difference in the real SNAP benefits for a household of four among states is between 7 to 16 percentage points, which converts to about 39 to 90 pounds of food per month. This finding suggests that implementing regional adjustments in the SNAP benefits could provide low-income households, especially those who live in states with high food cost areas such as District of Columbia, Vermont, New York, and New Jersey, with real economic benefits. In addition, we find that the trends of relative regional TFP prices across the United States do not show a clear trend of divergence or convergence. This result implies that in the absence of regional price adjustments, the gap in the real value of SNAP benefits across states could persist over time.

In addition to the examination of the variation in SNAP real benefits, we leverage the variation to examine the relationship between the rate of SNAP participation among the population below the poverty line. We find that the real value of SNAP benefits is associated with a significantly higher rate of SNAP participation. This finding presents one of the potential benefits of adjusting SNAP benefits to account for the variation in regional food prices.

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Table 1. TFP-Basket and Nielsen Retail Scanner Product Categories Matching

TFP Food Type	Food Category	Nielsen Retail Food Category
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 Product Categories Matching – 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 Type and Food Category 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. The Real Value of SNAP Benefits across States from Fiscal Years 2006 to 2016

	2006	2007	2008	2009-1	2009-2	2010	2011	2012	2013	2014	2015	2016
Alabama	593.95	585.00	574.23	598.62	696.94	698.42	672.59	652.19	655.73	616.27	632.41	648.05
Arkansas	603.03	588.43	574.53	603.54	710.68	702.41	679.01	659.42	661.06	617.42	627.93	634.35
Arizona	586.52	571.95	561.23	601.36	713.35	715.66	694.98	679.39	675.97	635.07	648.85	660.35
California	556.71	549.66	546.37	580.56	680.80	687.41	670.10	656.44	656.06	615.03	616.35	616.37
Colorado	572.12	568.49	560.21	596.29	707.71	708.72	683.84	666.01	664.10	623.22	637.24	643.92
Connecticut	546.59	550.07	561.37	588.05	678.90	678.22	661.97	644.18	642.23	603.12	610.94	619.99
District of Columbia	548.50	541.36	541.98	572.64	658.12	670.13	652.27	630.13	629.86	596.67	611.25	612.28
Delaware	568.61	564.26	559.95	586.16	679.23	683.57	662.51	642.86	644.86	612.41	624.64	629.19
Florida	590.41	584.23	576.79	602.29	699.89	701.88	675.61	651.49	655.86	613.62	626.14	644.06
Georgia	597.85	589.49	581.36	613.14	724.06	721.14	692.03	668.20	669.00	626.00	638.40	650.44
Iowa	618.33	604.87	590.08	620.39	727.42	719.19	687.93	664.63	659.42	613.51	628.81	630.92
Idaho	581.29	575.32	565.66	597.30	697.74	702.33	677.12	659.11	666.46	630.83	644.11	650.10
Illinois	579.23	575.94	571.87	603.14	707.47	713.88	691.05	674.35	687.82	645.80	650.86	657.91
Indiana	611.37	600.64	590.71	615.62	734.15	733.31	703.82	683.61	685.22	637.68	648.99	657.85
Kansas	605.45	592.51	576.85	608.30	714.69	713.63	689.76	674.36	675.25	630.19	640.45	650.03
Kentucky	604.15	593.65	585.73	613.33	726.72	726.45	698.86	679.48	679.89	635.55	649.92	658.39
Louisiana	596.08	589.11	579.68	599.17	695.36	696.85	672.16	651.08	649.86	607.90	618.64	636.52
Massachusetts	589.15	582.04	578.05	601.69	703.12	705.26	689.60	675.49	677.09	639.09	647.85	651.37
Maryland	568.61	564.50	563.88	590.99	681.13	685.94	668.55	647.66	649.70	614.69	628.99	631.01
Maine	579.60	568.20	562.86	586.53	686.03	680.94	660.57	638.71	642.43	614.70	631.81	638.03
Michigan	586.27	577.61	565.80	603.32	712.23	714.76	694.27	677.12	677.22	636.52	653.20	658.64
Minnesota	608.08	598.57	585.99	614.79	721.01	728.13	700.36	679.06	674.60	630.33	636.91	640.18
Missouri	593.28	586.29	578.71	609.96	715.41	717.64	695.20	673.08	669.53	622.55	630.27	630.00
Mississippi	597.30	586.54	574.91	598.80	704.83	701.35	676.19	656.08	660.57	620.52	633.78	643.85
Montana	583.29	569.52	552.83	580.37	670.88	678.12	649.71	627.51	635.60	600.68	614.97	621.41
North Carolina	587.85	581.27	572.74	600.63	704.05	705.54	682.93	661.75	661.11	622.45	641.40	646.86

Table 3. The Real Value of SNAP Benefits across States from Fiscal Years 2006 to 2016 – Continued

North Dakota	611.17	594.32	580.18	603.86	701.30	697.92	674.97	649.91	649.28	605.51	607.94	609.30
Nebraska	611.74	597.63	586.65	617.03	722.13	716.08	687.83	665.88	661.96	618.30	627.23	630.09
New Hampshire	594.71	587.58	582.93	605.37	711.25	713.51	696.64	684.53	684.79	643.69	652.39	654.89
New Jersey	564.59	559.97	560.02	586.16	678.04	679.20	658.63	642.06	638.56	599.76	604.17	612.19
New Mexico	584.64	580.72	573.52	603.35	708.06	712.78	689.08	670.48	672.97	626.54	635.30	644.19
Nevada	578.01	571.26	567.24	598.76	707.59	711.95	688.05	669.03	670.91	634.12	639.08	644.58
New York	564.67	561.12	560.63	586.16	678.04	673.14	654.44	635.18	631.68	593.73	600.84	615.77
Ohio	598.43	589.94	578.73	609.69	721.14	718.82	693.27	672.91	672.69	630.59	643.01	652.24
Oklahoma	611.60	601.95	594.26	622.81	723.29	722.23	699.34	677.48	670.28	629.90	636.43	634.76
Oregon	561.79	562.45	560.35	593.70	694.62	703.92	684.47	666.45	667.96	627.15	630.79	635.05
Pennsylvania	590.66	585.19	579.79	606.70	708.00	705.33	681.85	662.81	661.23	621.02	628.37	621.26
Rhode Island	561.89	555.62	558.86	581.99	668.88	673.08	658.22	639.54	644.55	618.30	633.76	635.14
South Carolina	596.25	588.17	576.77	604.87	708.88	707.41	682.04	657.10	656.51	614.62	630.07	643.93
South Dakota	607.68	593.90	581.60	615.10	716.09	711.83	684.53	661.98	660.01	615.34	626.99	631.92
Tennessee	593.71	584.84	573.48	603.58	711.07	714.63	691.27	670.09	669.65	626.89	643.03	651.38
Texas	595.96	588.21	579.88	610.48	719.21	724.55	703.36	683.09	679.98	635.67	643.15	650.32
Utah	599.00	593.12	585.86	618.61	725.76	729.99	700.51	682.53	677.88	638.37	652.43	663.70
Virginia	577.63	572.95	567.34	594.46	693.81	697.29	676.53	658.98	661.36	622.64	640.37	645.22
Vermont	576.37	564.81	556.22	576.92	673.06	671.16	656.06	631.47	626.24	588.65	603.30	611.50
Washington	554.46	552.77	551.15	583.30	681.65	691.70	671.46	658.32	660.76	620.87	623.46	626.92
Wisconsin	615.04	597.52	587.59	612.38	716.41	704.55	685.28	663.98	656.33	610.82	622.48	631.54
West Virginia	601.99	595.33	580.56	607.68	717.53	714.48	690.07	670.16	668.09	628.92	646.41	656.33
Wyoming	575.41	568.31	556.72	587.45	684.49	692.63	666.09	645.78	648.30	609.79	624.61	635.44

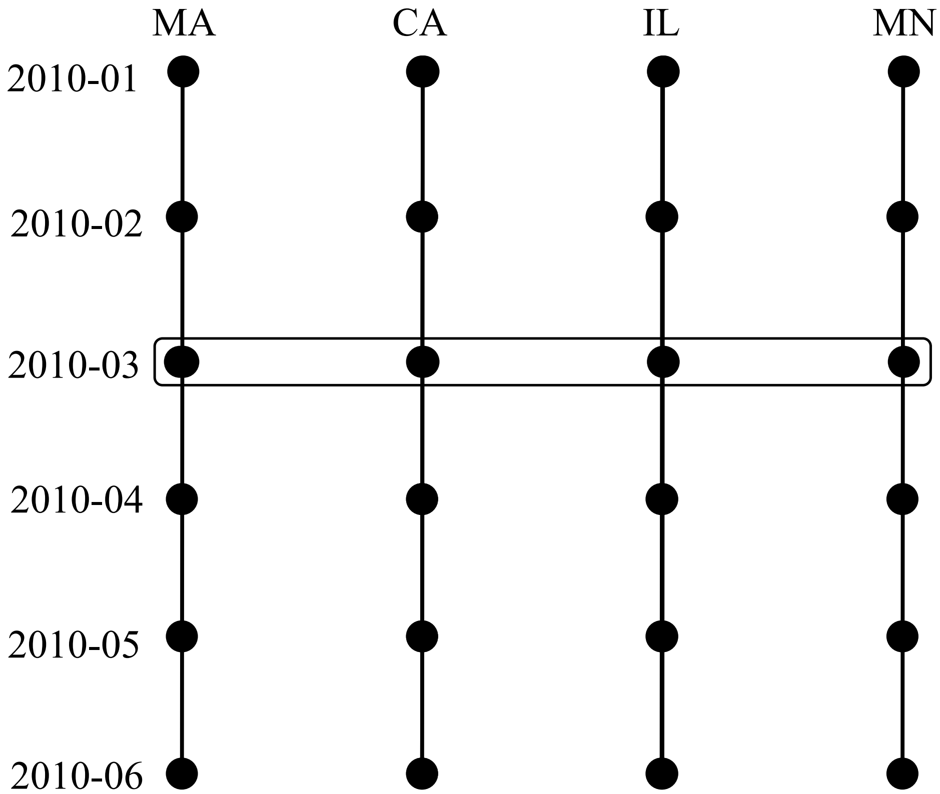
Notes: The adjusted real value of SNAP benefits in this table is the max benefit for a household of four. The value each year is the average of all monthly real value of SNAP benefits. The years present the SNAP fiscal year that is from October in the past year through September this year (e.g. the allotments 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 here “2009-1” covers October 1, 2008 through March 31, 2009, and “2009-2” covers April 1, 2009 through September 30, 2009.

Table 4. Effects of the Real Value of SNAP Benefits on SNAP Participation

Dependent Variable: SNAP Participation/Population below Poverty Line	(1)	(2)	(3)
ln(SNAP_Real)	0.500***	0.498***	0.502***
	(0.159)	(0.166)	(0.164)
Observations	6,468	6,468	6,468
R^2	0.743	0.743	0.748
Month fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
State UER	No	Yes	Yes
Other controls	No	No	Yes

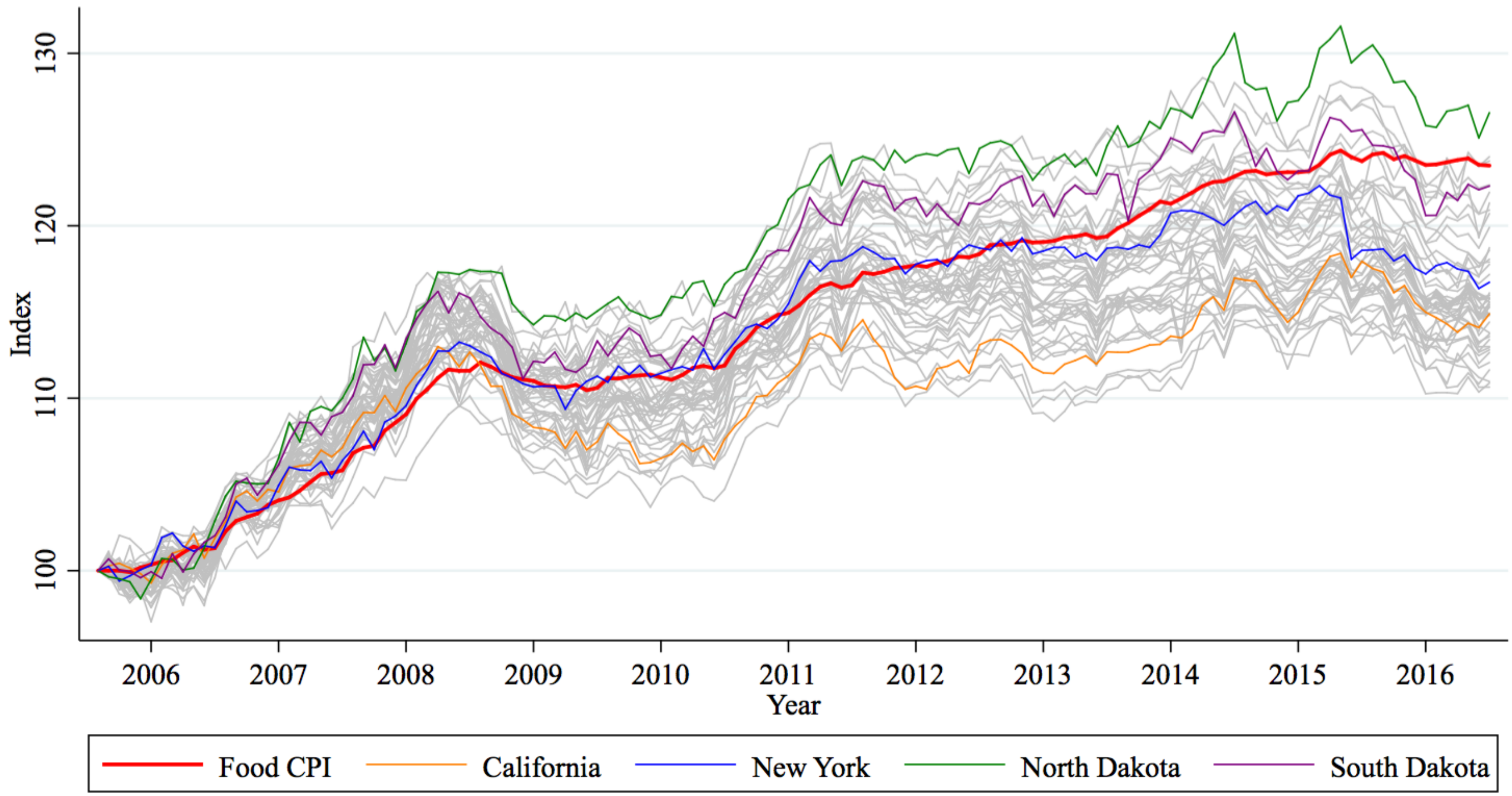
Notes: This table presents the results of equation (9) with 3 different specifications. The dependent variable is the ratio of the SNAP participation number to the number of people below poverty line, and the key independent variable ln $(SNAP_{it})$ is the log of the real value of SNAP benefits. Control variables include state unemployment rate, state minimum wage, state market rent, and regional CPIs for apparel, commodities, education, medical, recreation, services less rent of shelter, transportation, and other goods and services. Standard errors in parentheses are clustered at state level. Stars indicate significance at 10% (*), 5% (**), and 1% (***) levels.

Figure 1. Chronologically Chained Graph with a Spatial Comparison in period March 2010



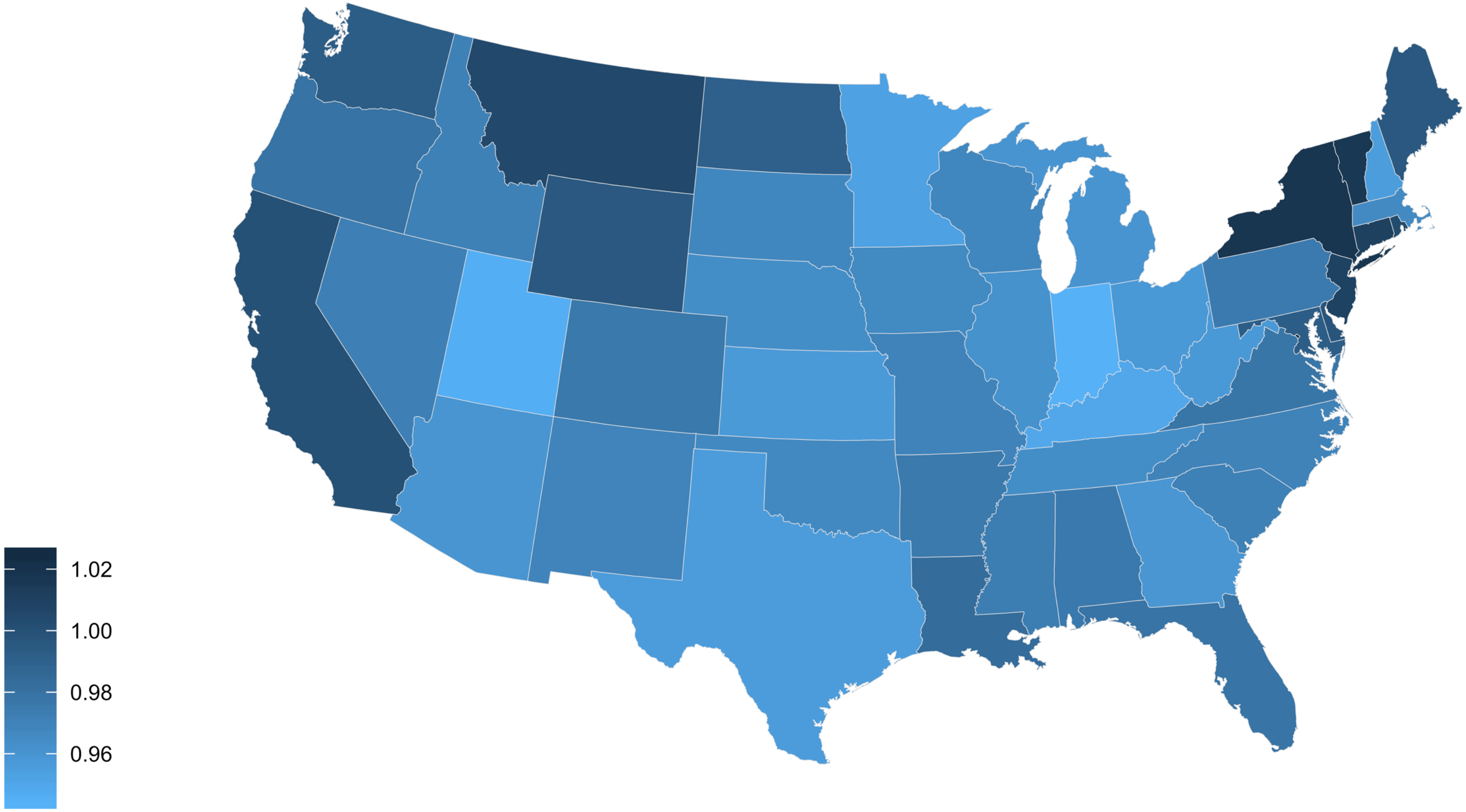
Notes: This figure presents a chronologically chained graph with a spatial comparison in one of the periods. In this example, we select 2010-03 as the spatial comparison reference.

Figure 2. Temporal Movements in the TFP Price across Contiguous United States from 2006 to 2016



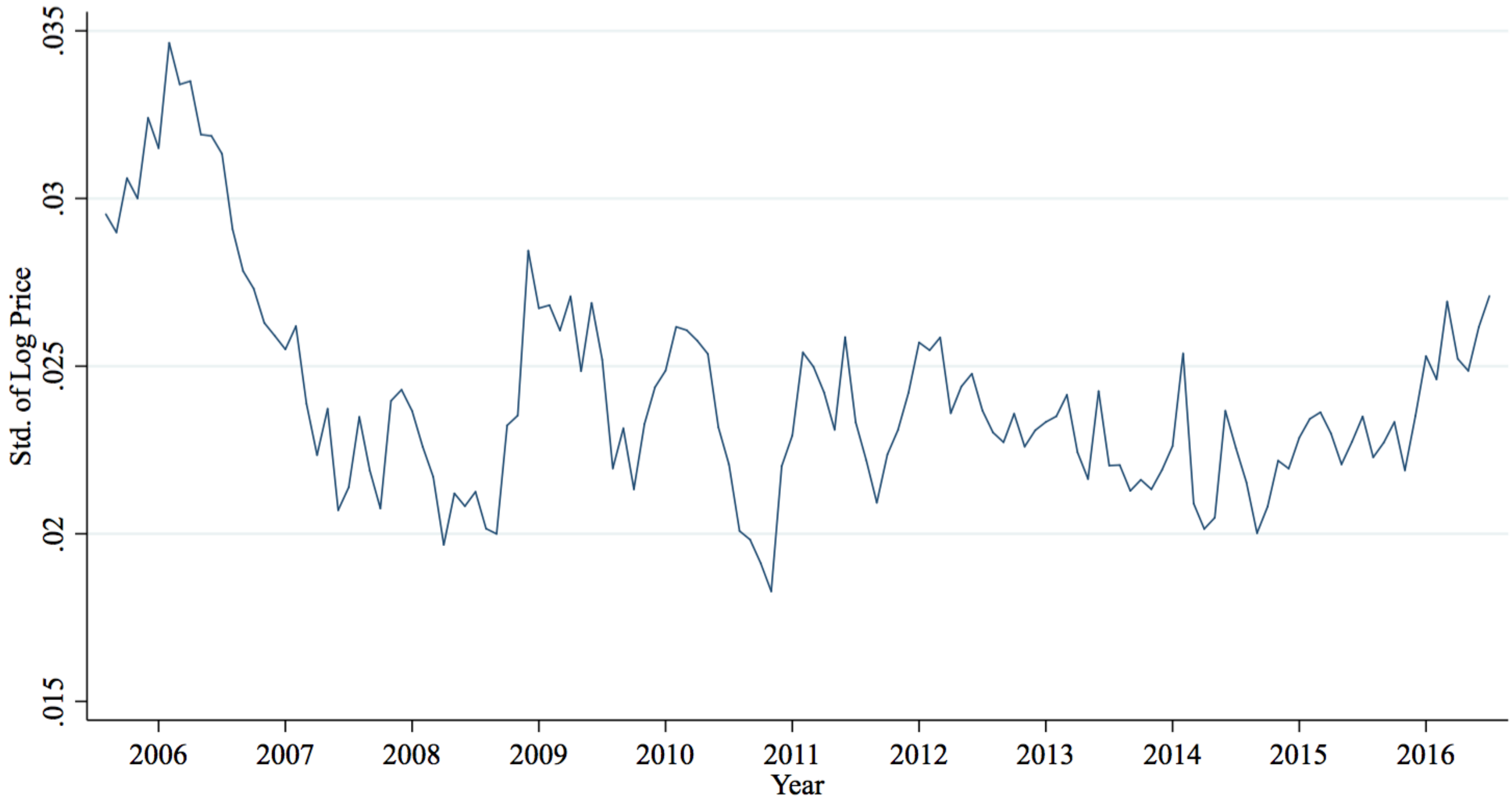
Notes: This figure presents the temporal movements in the TFP prices for contiguous states from 2006 to 2016 and compares with the national average Consumer Price Index (CPI) for food and beverages constructed by the BLS during the same period. January 2006 is the base period for all states in this figure.

Figure 3. Spatial Variation in TFP Price across Contiguous United States



Notes: This figure presents the average of the spatial indices over all periods (2006 to 2016) in our sample.

Figure 4. Temporal Trend of the Standard Deviation of Log Price Levels across the Contiguous United States between 2006 and 2016



Notes: This figure presents the trends of relative regional prices across the contiguous United States from 2006 to 2016. A decrease in the value signals that price levels are converging over time and an increase in value signals that price levels are diverging.