Spatial and Temporal Variation in the Value of the Women, Infants, and Children Program's Fruit and Vegetable Voucher

Metin Çakir, Timothy K.M. Beatty, Michael A. Boland, Timothy A. Park, Samantha Snyder, and Yanghao Wang

Increasing the consumption of fresh fruits and vegetables among children and low-income households is a public health policy priority in the United States. We investigate temporal and spatial price patterns for fresh fruits and vegetables to evaluate the extent to which the value of the fruit and vegetable Cash-Value-Voucher (CVV) of the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) may be affected by unequal price levels and changes in price levels across the United States. Our findings show that price differences over space and time have real and consequential impacts on the purchasing power of the CVV. A WIC Program participant in the highest-cost Metropolitan Statistical Area (MSA) can buy significantly fewer fruits and vegetables than a participant who receives the same benefit in the lowest-cost MSA. Further, we find that the value of the CVV has substantially declined across all MSAs since 2009. We discuss the nutritional implications of the variation in the value of the CVV and evaluate potential mechanisms that could be implemented to maintain equal CVV benefits across time and space.

Key words: Anti-poverty programs, food and nutrition policy, fruits and vegetables, infant health, index numbers, panel price indices, public assistance, purchasing power, SNAP, WIC.

JEL codes: C43, E31, I18, Q11, Q18.

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) is the United States' third largest food and nutrition assistance program behind the Supplemental Nutrition Assistance Program (SNAP), and National School Lunch and School Breakfast programs. The WIC Program reaches a broad and diverse population. The most recent data show that 51% of all infants, around 30% of children under the age of five, pregnant women, and postpartum women were eligible to participate in the program. Participation in WIC is associated with increases in birthweight and decreases in low birthweight (Figlio, Hamersma, and Roth 2009; Hoynes, Page, and Stevens 2011; Rossin-Slater 2013) and improved food security (Bitler, Gundersen, and Marquis 2005). The WIC Program costs the U.S. government approximately $7 billion per year, with additional costs incurred by individual states.

WIC is a national program that provides in-kind food assistance to low-income women, infants, and children who are at risk of poor nutrition. While the nature of the

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benefit depends on participants' circumstances, WIC food packages typically include staples such as infant formula, milk, eggs, and breakfast cereal.[1] The distinguishing feature of the program is that, for the most part, it provides benefits that can be redeemed for specific *quantities* of food such as a gallon of milk or a box of cereal. This ensures that the nutritional value of benefits is the same across the country and remains constant over time. In 2009, the program was revised to offer WIC participants a cash-value voucher (CVV) for the purchase of fruits and vegetables. Currently, a qualifying mother receives $11 and a child receives $8 a month, and these benefits are uniform across states (USDA, Food and Nutrition Services 2016). The CVV makes up approximately 10% of the total pre-rebate WIC food costs, and ranks third after the cost of infant formula and the cost of milk (Oliveira and Frazão 2015). This paper asks how the value of that voucher has changed over time and space since its inception in 2009.

The value of the CVV is linked to the Bureau of Labor Statistics' (BLS) Consumer Price Index (CPI) for fresh fruits and vegetables, such that the base values of $10 for all women and $8 for children will be updated annually, taking fiscal year 2008 as the base year (USDA, Food and Nutrition Services 2014). However, the regulation includes a rounding clause, which states, "if any increase in the adjusted cash value of the voucher is not a multiple of $1, such increase shall be rounded to the next lowest multiple of $1". Due to this, year-to-year values of CVVs have remained almost the same. To date, the value of CVV is still the same as the base value for children, and increased by $1 for women in 2015.

Moreover, if fruit and vegetable prices differ systematically across regions, the real value of CVV will also vary over space, and there is no mechanism by which it is automatically adjusted. This temporal and spatial variability of the value of CVV stands in sharp contrast to the rest of the WIC package. In this paper, we document this variability by constructing panel price indices for fresh fruits and vegetables using store-level scanner data.[2] The panel price indices allow us to make comparisons of price levels (i.e., cost of living comparisons) as well as changes in price levels (i.e., comparisons of inflation rates) and test whether relative price levels converge across U.S. urban markets. The regional CPIs constructed by the BLS can be used to compare inflation rates across regions but cannot be used to make cost of living comparisons.[3] We then investigate the regional and temporal differences in purchasing power of the CVV and their implications for WIC going forward.

The BLS and the USDA Economic Research Service (ERS) are the two primary sources of information on fruit and vegetable prices. However, the data from these sources are insufficiently detailed to address our research questions. BLS publishes fruits and vegetables price indices only at the national level. Regional indices published by BLS are available only for aggregate items such as "Food." The ERS published quarterly fruits and vegetables prices at the metropolitan area level constructed from Nielsen Homescan's UPC-level household food purchase data. However, the average prices are reported for only UPC-coded items. Random weight purchases (items that are not prepackaged or UPC labeled, and sold in variable quantities) are not included, and the dataset was discontinued after 2010.

Our main results are as follows. We find that the value of the CVV diverges by almost 24 percentage points across Metropolitan Statistical Areas (MSA) over the period of our analysis. These differences are economically large and potentially nutritionally important. Moreover, we find that regional differences in the value of the voucher are persistent over time. The estimates of the magnitude of temporal changes in prices are not substantially different across MSAs. Our results have important implications for the future design of the WIC benefit package, which is currently being debated as part of the next Farm Bill.

Our paper also contributes to the broad literature on healthy eating. Poor diet quality

[1] The participant categories are as follows: infants 0–5 months, infants 6–11 months, participants with qualifying conditions, children 1–4 years, pregnant and partially breast-feeding women, postpartum women, and fully breastfeeding women.

[2] We construct price indices for only fresh fruits and vegetables excluding other fruits and vegetables such as frozen or canned.

[3] The Consumer Price Index (CPI) is an indicator of the direction of retail food price movements in the United States. The CPI measures price changes across seven household spending categories: apparel and services, education and communication, food, housing, medical care, recreation, and transportation.

is a risk factor for many chronic diseases. Eating fruits and vegetables is widely accepted as an important part of a healthy diet (World Health Organization 1990; U.S. Department of Health and Human Services 2015). Adequate consumption of fruits and vegetables reduces the risk of obesity, cardiovascular diseases, diabetes, and certain types of cancers (Terry, Terry, and Wolk 2001; Lock et al. 2005; Dauchet, Amouyel, and Dallongeville 2009; Wang, Ouyang, and Liu 2014). However, despite the well-known and well-publicized long-term health benefits, current levels of fruit and vegetable intake among adults and children in the United States remains substantially below the recommended levels provided by the Dietary Guidelines for Americans (Kim et al. 2014). Work by Drewnowski and Specter (2004) and others attribute much of the shortfall to the relatively high cost of healthy foods in general and fruits and vegetables in particular. We shed light on that debate by highlighting persistent differences in prices across the United States.

Finally, our analysis informs the debate on how SNAP might be modified in an effort to improve diet quality. Current proposals either seek to limit spending of benefits on unhealthy foods, specifically sugar-sweetened beverages as noted by Barnhill (2011) or by offering a "healthy incentive" that would lower the cost of fruits and vegetables (Bartlett et al. 2014; Wilde et al. 2015; Grindal et al. 2016; Harnack et al. 2016). Our study adds to this debate by establishing how regional fresh fruit and vegetable price differences impact the purchasing power of households receiving federal food assistance benefits, as these benefit levels are uniformly set for the entire country.

The remainder of the paper is organized as follows. In the next section, we introduce the data used to construct our measure of cost and discuss their main features. Next, we summarize the methods used to construct the measures of spatial and temporal price variation. We then present our findings and relate them to the CVV and potential policy options.

Data

To compute price levels over time and space we use retail point-of-sale scanner data collected by Information Resources, Inc. (IRI).[4] The data consists of weekly sales information at the Universal Product Code (UPC)-level from retailers across the United States from 2009 to 2014. The IRI sample contains more than 40,000 stores reporting both UPC-level and random weight sales information. The surveyed retailers vary by outlet type including grocery stores, mass merchandisers, supercenters, drug stores, and dollar stores. It is unclear whether the sample of surveyed retailers are nationally and regionally representative; however, Muth et al. (2016) show that the estimated coverage of stores in the IRI data is about 41% compared to Census Bureau data in 2012. Similarly, the estimated IRI coverage of food and alcohol sales is about 55% compared to that of the census. In recent years, several studies have been done using similar data (e.g., Villas-Boas 2007; Zhen et al. 2014). However, the point-of-sale scanner data has not been widely available until recently for policy analysis (Muth et al. 2016).

The first step in constructing price indices using the high-frequency scanner data is to determine the unit value prices. A unit value price is an average price of transactions over products, over stores in a geographic region, and over a certain period of time. These prices, and their corresponding quantities, represent the first stage of aggregation that are subsequently used in price index formulae. In our analysis, we construct a unit value price, which is equal to the total sales value divided by the total quantity, for each unique item in a MSA.[5] The items are either unique UPC codes or unique random weight good identifiers, which are both referred to as UPCs.

We obtain the MSA-level aggregation by matching county Federal Information Processing Standard (FIPS) codes provided in the IRI dataset with the census description of MSA. We use MSAs as our unit of geography to allow easy comparison to regional price indices maintained by BLS. For illustration, figure 1 presents the weekly price per

[4] This data was purchased by the Economic Research Service (ERS) of the U.S. Department of Agriculture and made available for use in food policy research under a cooperative agreement (Muth et al. 2016).

[5] The U.S. Census definition is: "Metropolitan and micropolitan statistical areas (metro and micro areas) are geographic entities delineated by the Office of Management and Budget for use by Federal statistical agencies in collecting, tabulating, and publishing Federal statistics."

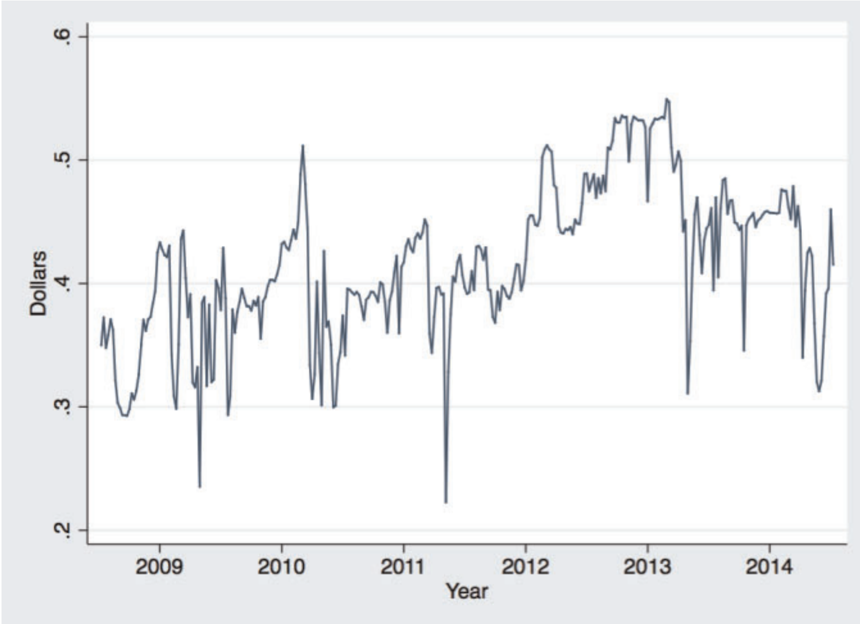

Figure 1. Weekly price per pound of an apple variety at the Universal Product Code level in a metropolitan statistical area

pound of an apple variety for a given MSA. In what follows, we use one-quarter or three months as the unit of time to construct temporal and spatial indices, though results are robust to other choices.

We construct price indices for 26 MSAs, for which at least one price index is reported by the BLS.[6] We follow the hierarchical categorization of the BLS' CPI for fresh fruits and vegetables. Figure 2 presents the hierarchical categorization. At the top is the price index for fresh fruits and vegetables. Next come the two subcategories of fresh fruits and fresh vegetables. The bottom of the hierarchy is comprised of item strata. An item stratum is the lowest level of aggregation for which a price index exists. The BLS categorization includes four strata under fresh vegetables and five strata under fresh fruits. We constructed indices for fresh fruits and vegetables as well as for each of its subcategories. However, for the sake of brevity, we limit our discussion to the indices for fresh fruits and vegetables.

[6] We do not have WIC participation data by MSAs. However, our sample MSA level data are from 19 states and Washington, DC, and cover approximately 67.7% of all WIC participants (Thorn et al. 2015).

To match our indices with the BLS CPIs, we manually sorted all UPCs into BLS categories using IRI-provided product descriptions for fruit and vegetable UPCs. In addition, there is a product dictionary file that provides information on unit of measurement for quantities of packaged products. The unit of measurement for quantities of all random-weight products is expressed in pounds.

A feature of the data is that some retailers provide sales information at the store level, while others provide at the retail market area (RMA) level. An RMA is a retailer-defined geographic area, which can encompass multiple states. For example, retailers such as CVS, Kroger, Safeway, Publix, Walmart and Sam's Club report at the RMA level. Store level data is easily aggregated to the MSA level. However, aggregation or conversion of the RMA level data to the MSA level can be challenging. To this end, we obtained an approximate measure of MSA level sales based on the retailer store counts. Specifically, we first determine the number of MSAs that are covered by an RMA. Then we allocate RMA-level sales to the MSA level in proportion to the number of retailer's stores in each MSA.

I. Fresh Fruits and Fresh Vegetables
   a. Fresh fruits
      i. Apples
      ii. Bananas
      iii. Citrus Fruits (oranges including tangerines)
      iv. Other fresh fruits
   b. Fresh vegetables
      i. Potatoes
      ii. Lettuce
      iii. Tomatoes
      iv. Other fresh vegetables

Figure 2. The hierarchical structure of the U.S. Bureau of Labor Statistics' consumer price index for fresh fruits and vegetables

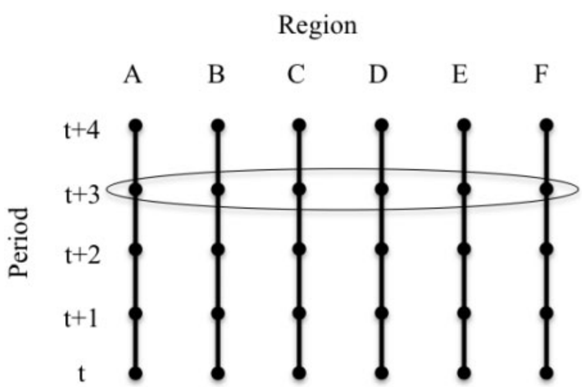

Figure 3. Chronologically chained graph with a spatial comparison in period t+3

Panel Price Indices

We construct panel price indices using the "chronological graph" (CG) method (Hill 2004). The CG method combines temporal price indices, which are strictly chronological, with a reference spatial index in a single period. We chose the CG method since it allows us to construct panel indices that satisfy the desirable properties of temporal fixity and temporal consistency (Hill 2004). A panel price index is temporally fixed if the comparisons are not affected when a new time period is added to the data set, and is temporally consistent if the temporal results of each region do not depend on the other regions in the data set. Hill (2004) provides a review of the panel price index methods and their properties.

Figure 3 illustrates the CG method for a sample of six regions (A to F) and five time periods (t to $t+4$). In the figure, a multilateral spatial comparison in $t+3$ links the temporal indices in each region. Mechanically, we link the indices by multiplying the temporal price indices with each of the regions' corresponding spatial index number. For a numerical example, suppose temporal price indices for regions A and B for three periods (t, t+1, t+2) are given as A= (100, 105, 110) and B= (100, 110, 120). In addition, suppose in period t the spatial index for regions A and B is (100, 110), that is the period t price in region B is 10% higher than the price in region A. By linking the spatial comparison in period t to temporal indices, we can obtain a panel price index as: $(A; B) = (100, 105, 110; 110, 121, 132)$.

One concern is that the resulting panel price indices are sensitive to the choice of reference spatial index (Hill 2004). To this end, we compute a spatial index for each quarter between the 1st quarter of 2009 and the 4th quarter 2014 (twenty quarters). We then construct and compare three sets of panel price indices based on alternative spatial links, denoted as CG_{10}, CG_{12}, and Av(CG). The CG_{10} and CG_{12} indices are linked with spatial indices in 2010 Quarter 3 and 2012 Quarter 3, respectively. The Av(CG) indices are linked with the spatial comparisons that are obtained by taking the geometric mean of spatial price indices over all quarters. In what follows, we present results for the Av(CG) link but note that results are robust to the choice of spatial link.

Applying the CG method requires constructing temporal and spatial price indices for all 26 MSAs simultaneously. We follow the recent literature on the use of scanner data in index number construction. The primary advantage of using scanner data is that prices and quantities are available for all products at the UPC level and at a high frequency (i.e., weekly). This allows us to construct weighted indices at detailed aggregation levels across time, across products, and across regions. Moreover, because of its systematic coverage, indices constructed from scanner data are thought to be less prone to several sources of CPI bias, notably outlet bias, substitution bias, and new goods bias.

Two important characteristics of scanner data are: (*a*) the number and composition of UPCs change week-to-week due to high attrition and introduction of new products, and (*b*) weekly prices and quantities are highly volatile due to sales and promotions. These aspects of the data present challenges to traditional direct or chained temporal index formulae such as the Törnqvist or Fisher. For example, a direct index compares period t prices directly to base period prices. This is problematic when the data display high rates of new and disappearing items over time, such that the basket of goods and their quantities in period t is substantially different than the index basket in the base period.

This particular issue is often addressed by using chained indices; a chained index is made up of links (hence the name) where each link is simply the bilateral direct index of two adjacent periods. The overall index is then constructed by taking product of all of the links. This approach allows the index to incorporate new and disappearing items into estimates of price changes over time as the basket of goods is being updated at every period. However, chained indices may suffer from what is known as "chain drift" that is characterized by indices that do not return to a value of one even when prices return to those in the base period. Chain drift is particularly a problem in indices built with volatile high-frequency data on prices and quantities such as scanner data (Feenstra and Shapiro 2003; de Haan and van der Grient 2011; Ivancic, Diewert, and Cox 2011).

To address chain drift, Ivancic, Diewert, and Cox (2011) propose using the GEKS (Gini, Eltetö, Köves, Szulc) method, which is a kind of hybrid between the traditional direct and chained indices described above. In fact, the GEKS index has important advantages, as it makes maximum use of all possible matches between any two periods—like the chained indices—but is free of chain drift—like the direct indices (de Haan and van der Grient 2011; Ivancic, Diewert, and Fox 2011).

GEKS indices are computed by taking the geometric mean of the product of all bilateral indices between a number of periods, where in turn each period is taken as the base. Formally, let $i = 1, \ldots, N$, and $t = 0, \ldots, T$ denote the set of goods and time periods, respectively, where t takes on a value of zero for the base period. Let p denote prices and q denote quantities. The GEKS-Törnqvist price index—the term indicates that bilateral comparisons that are used in the GEKS formula are obtained using Törnqvist formula—between periods 0 and t is given as

$$(1) \quad \text{GEKS}: \; P_{0t}^{GEKS} = \prod_{s=0}^{T} (P_{0s} \times P_{st})^{1/(T+1)}$$

where P_{st} denotes the Törnqvist index between periods s and t given as

$$(2) \quad \text{Tornqvist}: \; P_{st} = \prod_{i=1}^{N} \left(\frac{p_{it}}{p_{is}} \right)^{(s_{it}+s_{is})/2}$$

where $s_{it} = \frac{p_{it}q_{it}}{\sum_{i=1}^{N} p_{it}q_{it}}$ is the expenditure share of good i in period t. In practice, p_{it} is the unit value of good i in period t. The index formulae are applied using unit values and expenditure shares as weights.

We now turn to the construction of the spatial index necessary to combine temporal indices into a panel price index. Multilateral methods are used to estimate overall differences in price levels across geographical regions. These indices are also referred to as purchasing power parities when applied to compare price levels across countries. A large number of methods can be used to construct aggregate multilateral indexes as described by Hill (1997). Two types of methods are widely used: EKS-type methods and spanning tree methods.[7]

An EKS-type index is obtained by taking the geometric mean of bilateral price indices between regions 1,2,. . .,K and a numeraire region k. An important feature of EKS-type methods is that each bilateral index number comparison between any two regions gets the same weight in the overall index. In other words, the index is "democratic", which could be a shortcoming of the method if the relative price structures across regions are highly heterogeneous.

Alternatively, spanning tree methods make multilateral comparisons among K regions by taking account of the similarity between price structures across regions. Suppose we map K regions on an undirected graph where each vertex (or node) represents a region and each edge, which connects two vertices, represents a bilateral comparison. A spanning tree is a subset of a graph that has all vertices covered with minimum number of edges such that the tree does not contain any cycles—that is, any two vertices are connected by one and only one path of edges. Once a spanning tree of K regions is determined, a multilateral comparison of any two regions is obtained by chaining together the bilateral comparisons along the path of edges.

A key aspect of this methodology is the choice of spanning tree. Note that K^{K-2} spanning trees are defined on a set of K vertices. Because each of the spanning trees comprise a different path of edges between any two vertices, the choice of spanning tree impacts the resulting set of multilateral comparisons. In this paper, we use Hill's (1999) minimum spanning tree (MST) approach. Intuitively, the MST approach finds a path through regions that minimizes a penalty function, where the penalty is based on the similarity of price structures between any two regions. The MST algorithm begins by measuring the dissimilarity between the price structure in each pairwise combination of regions. To measure the relative price dissimilarity between any two regions we use the weighted log quadratic formula given as (Diewert 2009)

$$(3)\quad \text{WLQ}: \Delta_{WLQ}\left(\mathbf{p}_j, \mathbf{p}_k, \mathbf{q}_j, \mathbf{q}_k\right)_{jk} = \sum_{n=1}^{N} \frac{s_j^n + s_k^n}{2}\left[\ln\left(\frac{p_k^n}{p_j^n P_{jk}^T}\right)\right]$$

where $s_i^n = p_i^n q_i^n / \mathbf{p}_i \cdot \mathbf{q}_i \ \forall i \in \{j, k$ is MSA i's expenditure share on product n. Once the similarity scores are assigned to each of the bilateral comparisons, we construct a MST by finding the path between all regions that minimizes the sum of the relative price dissimilarity measures. We follow the literature and use Kruskal's algorithm as described by Hill (1999) to find the shortest path. The spatial indices are then obtained by linking the bilateral comparisons along the path of the two regions. For example, if MSA j is connected with MSA k through MSA l, then the index between MSA j and k is

$$(4)\quad \text{MST}: \ P_{jk}^T = P_{jl}^T P_{lk}^T.$$

We generate a minimum spanning tree for each of the 20 quarters and find that results are largely stable over time. Each pairing of trees between any two quarters share from 15 to 21 common links. Figure 4 shows the spatial minimum spanning tree for the twenty-six MSAs in the third quarter of 2014.

Results

We present the full table of quarterly panel price indices of fresh fruits and vegetables for the period between 2009 and 2014 in the appendix. The table reports indices for the three different spatial links: CG_{10}, CG_{12}, and Av(CG). Because the resulting panel indices are not sensitive to the choice of the spatial link, in what follows we discuss the estimates of the price changes and their implications using the Av(CG) indices.[8]

[7] Hill (2004) provides the taxonomy of multilateral methods as follows: average price methods, EKS-type methods, spanning tree methods, and the weighted-country-product-dummy method. For a detailed review of these methods we refer the reader to Hill (1997) and Hill (2004).

[8] Specifically, each set of indices has the same spread between the largest and the smallest value, which is equal to 35%. Furthermore, the price-level rankings of the three indices are almost identical (i.e., rankings across time and across space). The lowest rank correlation coefficient between the indices generated by each pair of spatial links is equal to 0.987

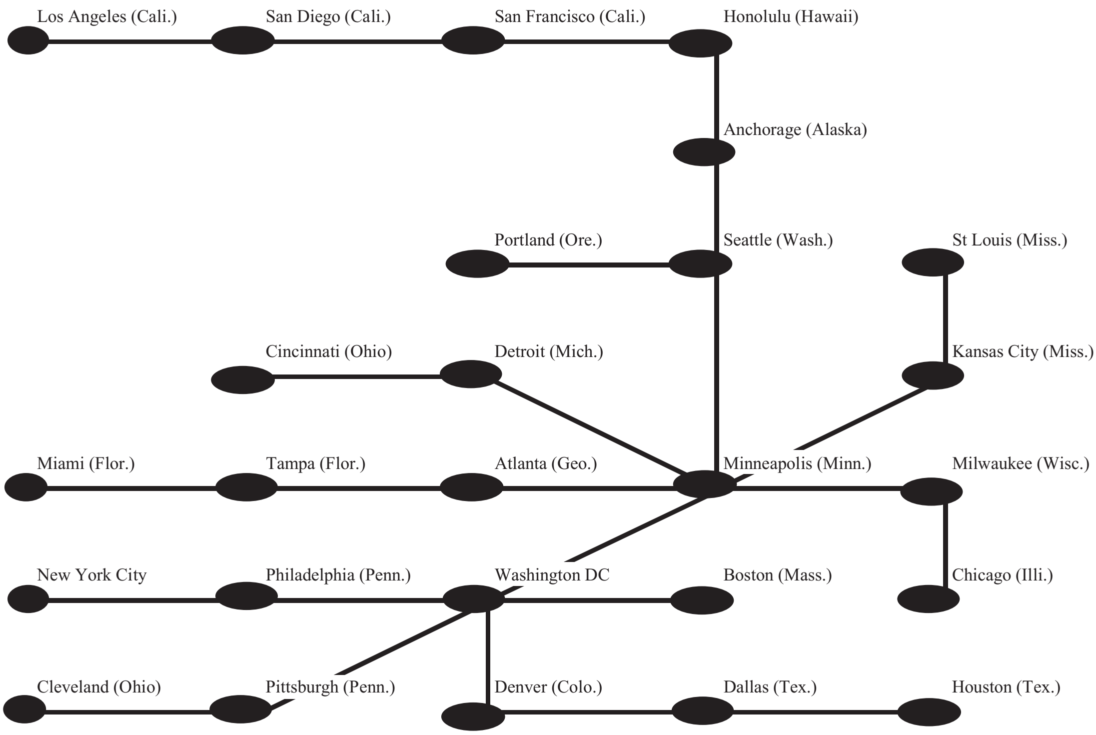

Figure 4. Minimum Spanning Tree of Metropolitan Statistical Areas in 2014, quarter 3

Estimates of Temporal and Spatial Price Changes

Figure 5 presents a comparison of average price levels over all quarters on a map of the twenty-six MSAs. The results show that spatial differences in prices are economically important across the MSAs; the range of differences is 24 percentage points. For example, the same amount of fresh fruits and vegetables that cost \$0.85 in Cincinnati, Ohio, would cost approximately \$1.08 in New York, New York.

Figure 5 also illustrates the fact that price levels have regional patterns. Fruit and vegetable prices in the Northeast and the Southeast MSAs range between \$0.98 and \$1.08 and are higher than prices in the Northwest and Southwest MSAs, which are ranked in the bottom two brackets, ranging between \$0.85 and \$0.98. Prices in the upper Midwest MSAs do not display a clear pattern. However, they are generally lower than the prices in the East but higher than the prices in the South. As expected given their geographic distance, prices in the noncontiguous MSAs (Anchorage, Alaska, and Honolulu, Hawaii) are in the highest bracket.

Table 1 presents full rankings of the average fruit and vegetable price levels of all MSAs. As expected, prices in noncontiguous MSAs, Anchorage and Honolulu, have the second- and third-highest price levels. Among the contiguous states, New York City, Philadelphia, Pennsylvania, and Washington DC have the highest price levels, while Houston, Texas, Portland, Oregon, and Cincinnati, Ohio, have the lowest price levels. We investigate the statistical significance of the rankings of average price levels using the one-sided t-test of mean differences. The results, reported in the last column of table 1, show that differences in rankings are statistically significant. For example, the positive difference between New York City's price level and the price level of any other contiguous MSA is statistically significant. Similarly, Houston's price level is significantly higher than the price levels of Cincinnati and Portland, and is significantly lower than the price level of any other MSA.

Figure 6 shows fruit and vegetable price trends for selected MSAs for the period 2009 to 2014. The Chicago, Illinois price level in

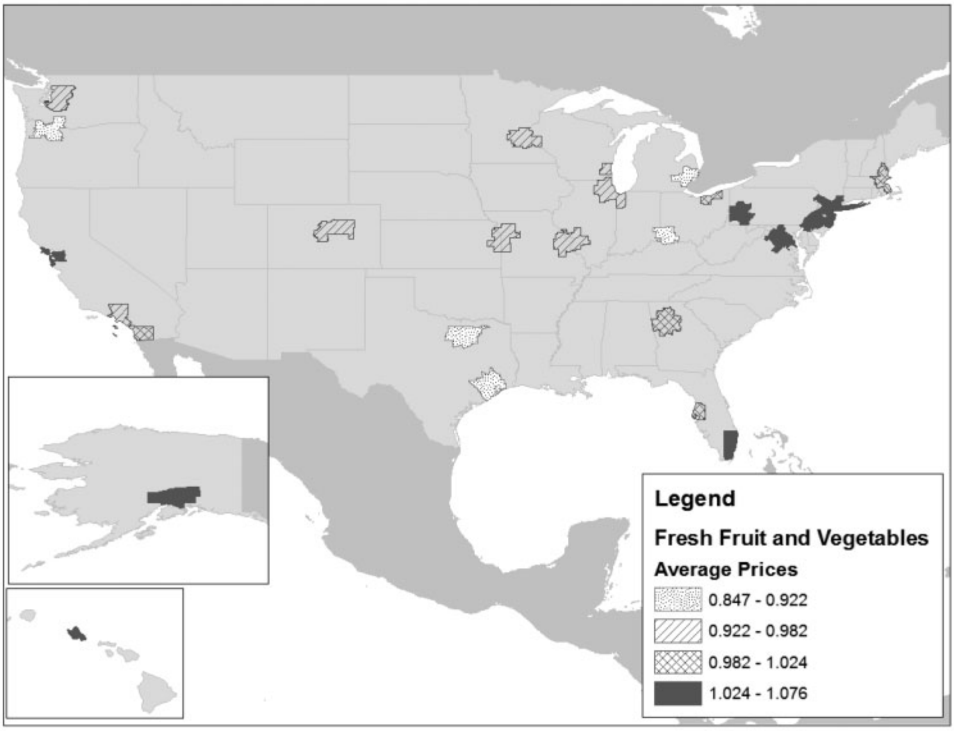

Figure 5. Comparison of fresh fruit and vegetable average prices across Metropolitan Statistical Areas

the first quarter of 2010 is taken as the base value of the panel index as it is the midpoint of the average price level in table 1. Thus, a comparison between all other data points in the figure to the base value provides estimates of the temporal and/or spatial price changes. We find that fruit and vegetable price trends display similar seasonal patterns across MSAs. Unlike the estimates of regional fruit and vegetable price differences, the estimates of the temporal changes in prices are not substantially different across MSAs. For example, between the first quarter of 2011 and the first quarter of 2012, prices are down by 4.6, 4.6, 3.8, and 4.6 percentage points for Chicago, Houston, Philadelphia, and Seattle, respectively.

Convergence of Prices over Time

Next, we ask whether regional fruit and vegetable price levels are converging or diverging over time. In other words, are structural differences pertaining to the demand for and supply of fresh fruits and vegetables persistent across the regions. To this end, following Hill (2004), we calculate the standard deviation of the logarithm of price levels for $k=1,\ldots,K$ regions as

$$\text{(5) WLQ}: \quad \sigma_t = \sqrt{\frac{1}{K-1}\sum_{k=1}^{K}\left[\ln\left(\frac{P_{kt}}{P_{ot}}\right) - \ln\left(\frac{\bar{P}_t}{P_{ot}}\right)\right]^2}$$

where P_o denotes price level in the base region and $\ln\left(\frac{\bar{P}_t}{P_{ot}}\right) = \frac{1}{K}\sum_{k=1}^{K}\ln\left(\frac{P_{kt}}{P_{ot}}\right)$. In other words, σ measures the dispersion of price levels across K regions; a decrease in the value of σ over time would indicate that price levels are converging and an increase in the value of σ over time would indicate that price levels are diverging.

One potential concern is that if noncontiguous MSAs have relatively more persistent structural differences compared to the contiguous MSAs, including prices of the noncontiguous MSAs in the analysis might hide meaningful patterns that could have been detected between price levels of the contiguous states. As a result, we calculate two sets of results, one for all MSAs including

Table 1. Statistical Significance of Differences between Average Price Levels across Metropolitan Statistical Areas[a]

Rank	Metropolitan Statistical Area (MSA)	Average Price Level	MSAs whose Price Levels are Statistically Indifferent[b]
1	New York City, NY	1.08	2, 3
2	Anchorage, AL	1.07	1-3
3	Honolulu, HI	1.06	1-6[c]
4	Philadelphia, PA	1.06	3-8
5	Washington DC	1.05	3-9
6	Miami, FL	1.04	3-10
7	Pittsburgh, PA	1.04	4-10
8	San Francisco, CA	1.04	4-10
9	Tampa Bay, FL	1.02	5-12
10	Cleveland, OH	1.02	6-12
11	Boston, MA	1.01	9-13
12	Atlanta, GA	1.00	9-13
13	San Diego, CA	0.99	11-15
14	Los Angeles, CA	0.98	13-17
15	Saint Louis, MO	0.98	13-17
16	Minneapolis-Saint Paul, MN	0.97	14-19
17	Milwaukee, WI	0.96	14-19
18	Chicago, IL	0.96	16-19
19	Kansas City, KS	0.96	16-20
20	Seattle, WA	0.94	19-21
21	Denver, CO	0.94	20
22	Detroit, MI	0.92	23
23	Dallas, TX	0.92	22
24	Houston, TX	0.90	
25	Portland, OR	0.87	
26	Cincinnati, OH	0.85	

Note: Superscript [a] denotes that the results are based on the one-sided t-test of mean differences at a 0.05 significance level; [b] = MSAs are numbered in column one; [c] = 1–6 indicate that price levels in New York City (1), Anchorage (2), Philadelphia (4), Washington DC (5), and Miami (FL; 6) are statistically indifferent to the price level in Honolulu (3).

Anchorage and Honolulu and another for only contiguous MSAs.

Figure 7 presents the time trend of the standard deviation of log price levels, σ_t. The main result is that price levels show no evidence of convergence across MSAs over the study period. This figure also shows that the result is robust to the inclusion of non-contiguous MSAs. In particular, we observe that differences in price levels remained relatively stable during 2009 and 2010 with a slight trend indicating divergence. During 2011 and 2012, price levels diverged substantially, due in part to a 5.1% decline in the food price index for fresh vegetables due to a very productive growing year in 2011 and 2012 in California, followed by the beginning of the California drought in 2013, but then moved closer in 2013 and 2014. Overall, differences in fruit and vegetable price levels diverged slightly more in 2014 compared to 2009.

Impacts on Purchasing or Buying Power of Consumers

We now turn to the implications of the regional price differences for purchasing power of benefits of the WIC CVV. We perform this analysis using average regional price levels over all quarters. Table 2 presents the purchasing power of federal food assistance benefits earmarked for fruits and vegetable purchases across MSAs. The first column of the table presents the purchasing power of a $19 WIC voucher, which corresponds to the current value of monthly benefits received by a qualifying mother and child. The results show that the basket of fruits and vegetables that costs $19.00 in Chicago costs $16.69 in Cincinnati, and $21.20 in New York City. The range between the highest cost and the lowest cost MSAs is $4.51.

Our results also speak to ongoing proposals to restrict a portion of SNAP benefits to fruits and vegetables. Many researchers and

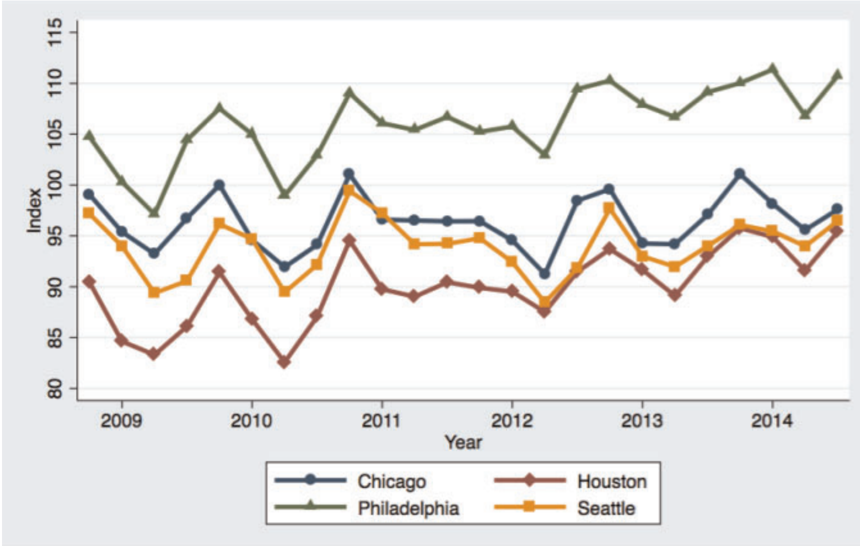

Figure 6. Quarterly fresh fruits and vegetables panel price indices of select Metropolitan Statistical Areas between 2009 and 2014

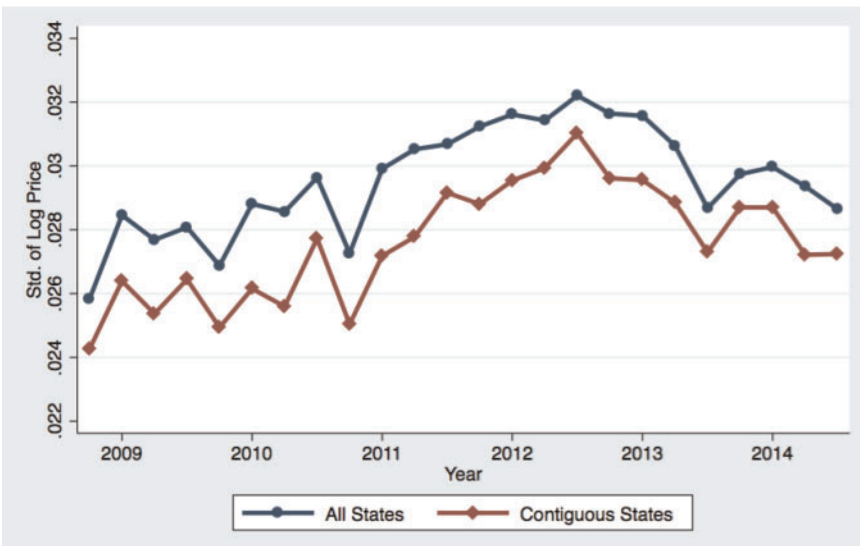

Figure 7. Time trend of the standard deviation of log price levels across All MSAs and across contiguous MSAs between 2009 and 2014

advocacy groups are arguing for changes in SNAP regulations to address nutrition-related health issues. Most recently, the "*American Journal of Preventive Medicine*" published a series of articles from over a dozen researchers in a supplement.[9] One of the proposed policy objectives is to require a portion of SNAP benefits to be spent only on healthful foods such as fruits and vegetables or whole grains, similar to the requirements of the WIC program (e.g., Klerman et al. 2014; Klerman, Collins, and Olsho 2017). Hence, we evaluate a hypothetical regulation that restricts 20% of SNAP benefits to be spent only on fruits and vegetables. Under this rule, a participant family of four with

[9] See *American Journal of Preventive Medicine*, February 2017 Supplement 2, Issue 2, S103-S206.

Table 2. Adjusted $19 WIC and $69.80 SNAP Benefit Amounts Necessary to Provide the Same Basket of Fresh Fruits and Vegetables across 26 Metropolitan Statistical Areas

Metropolitan Statistical Area	Adjusted $19 WIC Benefits (Dollars)	Adjusted $69.80 SNAP Benefits (Dollars)
New York City	21.20	77.88
Anchorage	21.15	77.71
Honolulu	20.90	76.80
Philadelphia	20.82	76.47
Washington DC	20.60	75.68
Miami	20.54	75.45
Pittsburgh	20.44	75.09
San Francisco	20.44	75.09
Tampa Bay	20.19	74.16
Cleveland	20.11	73.88
Boston	19.84	72.90
Atlanta	19.79	72.69
San Diego	19.60	72.00
Los Angeles	19.35	71.07
Saint Louis	19.33	71.01
Minneapolis-Saint Paul	19.16	70.38
Milwaukee	19.02	69.86
Chicago	19.00	69.80
Kansas City	18.90	69.43
Seattle	18.57	68.22
Denver	18.54	68.10
Detroit	18.17	66.75
Dallas	18.05	66.30
Houston	17.65	64.85
Portland	17.06	62.69
Cincinnati	16.69	61.33
Range	4.51	16.55

Note: [a] A $19 WIC voucher for fruits and vegetables corresponds to the total amount of benefits that would be received by a qualifying mother and a child. The value of $69.80 corresponds to 20% of $349 SNAP benefits that would be received by a participant family of four with $1,000 in monthly income.

$1,000 of monthly income, under certain assumptions, would be eligible for $349 in SNAP benefits and would be required to spend $69.80 of their SNAP benefits on fruits and vegetables. In this case, the values in the second column of table 2 show that the range of the difference of real SNAP benefits allotted to fruits and vegetables consumption received by these representative families would be $16.55.

Figure 8 presents the range of purchasing power disparities of the $19 CVV in cup equivalents of edible fresh fruits and vegetables for select MSAs between 2009 and 2014. The figure reports results for two contiguous MSAs with the highest price levels (New York City and Philadelphia), two contiguous states with the lowest price levels (Portland and Cincinnati), and a contiguous state with the median price level (Los Angeles). We assume that one pound of fresh fruits and vegetables is equivalent to two cups of edible mixed fresh fruits and vegetables. This approximation is commonly used by websites that promote healthy diets.[10] Since one pound of water is equivalent to two cups, the approximation may be considered a lower bound for edible fresh fruits and vegetables.

The results show that in 2009 a $19 WIC voucher bought 4.3 more cups of fresh fruits and vegetables in Cincinnati than New York City, corresponding to 0.14-cup equivalents per day.[11] It is important to put this magnitude into context. This regional price difference is of a comparable magnitude to the 0.22 cup equivalents per day increase from the

[10] For example, see http://www.livestrong.com/article/458243-how-many-ounces-are-in-serving-of-vegetables/.

[11] Between 2009 and 2014 the adjusted values of CVV were the same as the base values of $10 for women and $8 for children. The regional purchasing power disparities in cup-equivalents for an $18 CVV are approximately the same as for a $19 CVV.

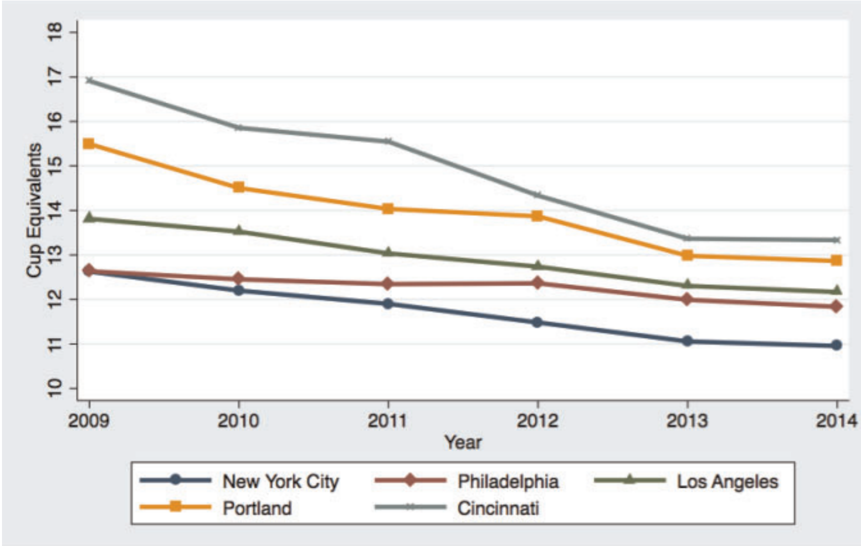

Figure 8. The real value of $19 fruits and vegetables WIC voucher in cup equivalents of fresh fruits and vegetables for select Metropolitan Statistical Areas between 2009 and 2014

Healthy Incentives Pilot program that offered SNAP recipients a 30% subsidy for the purchase of fruits and vegetables (Klerman et al. 2014).

Finally, results show that the cost of fruits and vegetables has significantly increased over time, leading to a decline in the nutritional value of the CVV. Compared to its level in 2009, the purchasing power of the voucher in 2014 decreased by 1.7 (13%), 0.8 (6%), 1.6 (12%), 2.6 (17%), and 3.6 (21%) cups of fresh fruits and vegetables in New York City, Philadelphia, Los Angeles, Portland, and Cincinnati, respectively.

Results above show that the value of the CVV has declined substantially over time and at different rates across MSAs. Indexing these benefits is complicated by the fact that BLS does not publish a regional index for fruits and vegetables. We investigate how much it would have cost to maintain the benefit level in 2009 using three different national indices: the BLS Food CPI, the BLS Fresh Fruits and Vegetables (FFV) price index, and the Av(CG) developed above. Figure 9 shows that indexing the value of the CVV on BLS FFV and Av(CG) provides almost identical results. Accordingly, to maintain the $18 benefit level in 2009, the value of the CVV in 2014 would need to be $19.50. However, due to the rounding clause in the legislation, the benefit levels in 2014 were still at $10 for all women and $8 for all children. In addition, results show that using the BLS Food CPI for indexing results in $20.05, overestimating the change in the real value of the CVV by $0.55.

Discussion and Conclusion

We investigate the spatial and temporal changes in the purchasing power of the WIC Program's fruit and vegetable voucher, and their implications for the design of the WIC food packages going forward. Specifically, using retail point-of-sale scanner data, first we construct panel price indices for fresh fruits and vegetables for a panel of twenty-six MSAs in the United States. Then, we use our estimates to evaluate how the real value of the WIC CVV changes over time and space.

Our main findings show that there are large and statistically significant differences in regional price levels. We find that the difference between the highest and the lowest average price levels is approximately 24 percentage points across the MSAs. New York City, Philadelphia, and Washington DC have the highest price levels; Houston, Portland, Oregon, and Cincinnati have the lowest price levels among the contiguous MSAs. Our results also indicate that regional price differences have diverged slightly during the study period. In contrast, we find that temporal price trends display similar seasonal patterns,

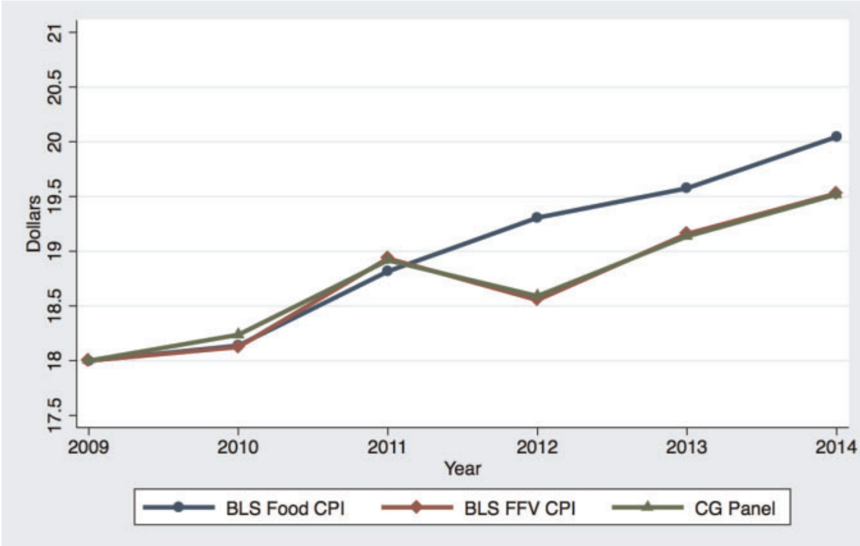

Figure 9. The impact of using BLS indices to measure the national average real value of $18 fruits and vegetables WIC voucher between 2009 and 2014

and that the estimates of temporal changes in prices are not substantially different across MSAs.

These estimates imply that the inequality of real benefits from the WIC CVV across the United States is economically large and potentially nutritionally important. For example, we find that the range in the purchasing power of a $19 WIC voucher is approximately $4.51. This suggests that on average a WIC participant in the highest-cost MSA buys approximately 4.3 cups less, corresponding to 0.14-cup equivalents per day, of fruits and vegetables than the participant that receives the same benefit in the lowest-cost MSA. In addition, our results show that the real value of the voucher has declined substantially between 2009 and 2014—equivalent to a decline of approximately two cups of fruits and vegetables. These results suggest that implementing regional adjustments in the value of the CVV will provide low-income households—especially those that live in high-cost areas such as Anchorage, New York City, Philadelphia, or Honolulu—with real economic benefits. These findings provide evidence on the benefits of implementing alternative mechanisms to automatically adjust the value of the CVV over time and space.

Differences in the purchasing power of the CVV across time and space stand in sharp contrast to the rest of the WIC package design. The WIC CVV was introduced in 2009 to provide WIC participants with benefits earmarked for the purchase of fruits and vegetables. However, all other parts of the WIC food packages are redeemed for specific quantities of food. That is, the WIC program was originally designed to ensure that the nutritional value of benefits is the same across the country and remain the same over time.

The spatial and temporal variation in the value of WIC fruit and vegetable voucher can be avoided by providing in-kind benefits similar to the rest of the WIC food package. Alternatively, our results suggest a straightforward approach to maintaining a roughly constant value of the CVV. First, purchasing power across regions can be equated by introducing regional CVVs that are proportional to regional price levels. A region might be an individual MSA or a group of MSAs for which price levels are similar such as Anchorage, Honolulu, and New York City. Second, regional CVVs can be automatically adjusted using the BLS FFV national price index, which is the current practice, to maintain the real value of the CVVs over time. However, for improved accuracy, the adjusted CVV values should be rounded at lower increments than $1, such as increments of $0.5, $0.25, or $0.10. Also, the regional CVVs might be updated periodically using an updated set of regional price levels.

Finally, our analysis contributes to ongoing debates as part of the next Farm Bill on how SNAP might change to improve diet quality.

Current proposals seek to improve the nutritional impact of SNAP by limiting the spending of benefits by food categories. However, these policy proposals ignore the degree to which relative prices of food categories differ across regions, which has unintended consequences on welfare. Consider two regions, A and B, such that (*a*) the overall food price level is higher in region A than in region B, and (*b*) the prices of fruits and vegetables relative to prices of other SNAP-eligible foods is higher in region A than in region B. In this case, the real benefits that a SNAP participant receives in region A is lower than the participant that receives the same benefits in region B. However, the participant in region A can improve her or his real benefits by allotting a smaller portion of the SNAP dollars to purchases of fruits and vegetables compared to the participant in region B. Therefore, restricting a portion of SNAP benefits to be spent only on fruits and vegetables will exacerbate the effect of differences in regional prices on SNAP participants due to limiting their ability to substitute between food categories.

References

Barnhill, A. 2011. Impact and Ethics of Excluding Sweetened Beverages from the SNAP Program. *American Journal of Public Health* 101: 2037–43.

Bartlett, S., J. Klerman, L. Olsho, L. Logan, M. Blocklin, M. Beauregard, A. Enver, et al. 2014. *Evaluation of the Healthy Incentives Pilot (HIP): Final Report, Food and Nutrition Service*. Prepared by Abt Associates for the U.S. Department of Agriculture. Available at: https://www.fns.usda.gov/sites/default/files/HIP-Final.pdf.

Bitler, M., C. Gundersen, and G.S. Marquis. 2005. Are WIC Nonrecipients at Less Nutritional Risk than Recipients? An Application of the Food Security Measure. *Review of Agricultural Economics* 27 (3): 433–8.

Dauchet, L., P. Amouyel, and J. Dallongeville. 2009. Fruits, Vegetables and Coronary Heart Disease. *Nature Reviews Cardiology* 6 (9): 599–608.

de Haan, J., and H.A. van der Grient. 2011. Eliminating Chain Drift in Price Indexes Based on Scanner Data. *Journal of Econometrics* 161 (11): 36–46.

Diewert, W.E. 2009. Similarity Indexes and Criteria for Spatial Linking. In *Purchasing Power Parities of Currencies: Recent Advances in Methods and Applications*, ed. D.S.P. Rao, 183–216. Cheltenham, UK: Edward Elgar.

Drewnowski, A., and S.E. Specter. 2004. Poverty and Obesity: The Role of Energy Density and Energy Costs. *The American Journal of Clinical Nutrition* 79 (1): 6–16.

Feenstra, R.C., and M.D. Shapiro, eds. 2003. *High-frequency Substitution and the Measurement of Price Indexes*, 123–150. Chicago: University of Chicago Press.

Figlio, D., S. Hamersma, and J. Roth. 2009. Does Prenatal WIC Participation Improve Birth Outcomes? New Evidence from Florida. *Journal of Public Economics* 93 (1): 235–45.

Grindal, T., P. Wilde, G. Schwartz, J. Klerman, S. Bartlett, and D. Berman. 2016. Does Food Retail Access Moderate the Impact of Fruit and Vegetable Incentives for SNAP Participants? Evidence from Western Massachusetts. *Food Policy* 61: 59–69.

Harnack, L., J.M. Oakes, B. Elbel, T. Beatty, S. Rydell, and S. French. 2016. Effects of Subsidies and Prohibitions on Nutrition in a Food Benefit Program: A Randomized Clinical Trial. *JAMA Internal Medicine* 176 (11): 1610–18.

Hill, R.J. 1997. A Taxonomy of Multilateral Methods for Making International Comparisons of Prices and Quantities. *Review of Income and Wealth* 43 (1): 49–69.

———. 1999. Comparing Price Levels across Countries using Minimum-Spanning Trees. *Review of Economics and Statistics* 81 (1): 135–42.

———. 2004. Constructing Price Indexes across Space and Time: The Case of the European Union. *The American Economic Review* 94: 1379–410.

Hoynes, H., M. Page, and A.H. Stevens. 2011. Can Targeted Transfers Improve Birth Outcomes? Evidence from the Introduction of the WIC Program. *Journal of Public Economics* 95 (7): 813–27.

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.

Kim, S.A, L.V. Moore, D. Galuska, A.P. Wright, D. Harris, L.M. Grummer-Strawn, C.L. Merlo, et al. 2014. Vital Signs: Fruit and Vegetable Intake Among Children—United States, 2003–2010. *MMWR Morbidity and Mortality Weekly Report* 63 (31): 671–6.

Klerman, J.A., S. Bartlett, P. Wilde, and L. Olsho. 2014. The Short-Run Impact of the Healthy Incentives Pilot Program on Fruit and Vegetable Intake. *American Journal of Agricultural Economics* 96 (5): 1372–82.

Klerman, J.A., A.M. Collins, and L.E.W. Olsho. 2017. Improving Nutrition by Limiting Choice in the Supplemental Nutrition Assistance Program. *American Journal of Preventive Medicine* 52 (2): S171–8.

Lock, K., J. Pomerleau, L. Causer, D.R. Altmann, and M. McKee. 2005. The Global Burden of Disease Attributable to Low Consumption of Fruit and Vegetables: Implications for the Global Strategy on Diet. *Bulletin of the World Health Organization* 83 (2): 100–8.

Muth, M.K., M. Sweitzer, D. Brown, K. Capogrossi, S. Karns, D. Levin, A. Okrent, et al. 2016. *Understanding IRI Household-Based and Store-Based Scanner Data* TB-1942, U.S. Department of Agriculture, Economic Research Service. Available at: https://www.ers.usda.gov/webdocs/publications/47633/57105_tb-1942.pdf?v=42473.

Oliveira, V., and E. Frazão. 2015. *The WIC program: Background, Trends, and Economic Issues.* 2015 Edition. EIB-134, U.S. Department of Agriculture, Economic Research Service. Available at: https://www.aap.org/en-us/advocacy-and-policy/federal-advocacy/Documents/USDAWIC2015Report.pdf.

Rossin-Slater, M. 2013. WIC in Your Neighborhood: New Evidence on the Impacts of Geographic Access to Clinics. *Journal of Public Economics* 102: 51–69.

Terry, P., J.B. Terry, and A. Wolk. 2001. Fruit and Vegetable Consumption in the Prevention of Cancer: An Update. *Journal of Internal Medicine* 250 (4): 280–90.

Thorn, B., C. Tadler, N. Huret, C. Trippe, E. Ayo, M. Mendelson, K. L. Patlan, et al. 2015. WIC Participant and Program Characteristics 2014. Prepared by Insight Policy Research under Contract No. AG-3198-C- 11-0010. Alexandria, VA: U.S. Department of Agriculture, Food and Nutrition Service.

U.S. Department of Agriculture Food and Nutrition Service. 2016. Supplemental Nutrition Assistance Program Statistics. Available at: https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap.

———. 2014. Special Supplemental Nutrition Program for Women, Infants and Children (WIC): Revisions in the WIC food packages; final rule, 7 C.F.R. § 246. Available at: https://www.gpo.gov/fdsys/pkg/FR-2014-03-04/pdf/2014-04105.pdf.

U.S. Department of Health and Human Services and U.S. Department of Agriculture. 2015 – 2020 Dietary Guidelines for Americans. 8th Edition. December 2015. Available at https://health.gov/dietaryguidelines/2015/guidelines/.

Villas-Boas, S.B. 2007. Using Retail Scanner Data for Upstream Merger Analysis: Counterfactual Experiments in the Retail Coffee Market. *Journal of Competition Law and Economics* 3 (4): 689–715.

Wang, X., Y. Ouyang, J. Liu, M. Zhu, G. Zhao, W. Bao, and F.B. Hu. 2014. Fruit and Vegetable Consumption and Mortality from all Causes, Cardiovascular Disease, and Cancer: Systematic Review and Dose-Response Meta-Analysis of Prospective Cohort Studies. *The BMJ* 349.

Wilde, P., J.A. Klerman, L.E.W. Olsho, and S. Bartlett. 2016. Explaining the Impact of USDA's Healthy Incentives Pilot on Different Spending Outcomes. *Applied Economic Perspectives and Policy* 38 (4): 655–72.

World Health Organization. 1990. *Diet, Nutrition, and the Prevention of Chronic Diseases*. Geneva: WHO.

Zhen, C., E.A. Finkelstein, J.M. Nonnemaker, S.A. Karns, and J.E. Todd. 2014. Predicting the Effects of Sugar-Sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System. *American Journal of Agricultural Economics* 96 (1): 1–25.