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Submitted Article

Do High Food Prices Increase Food Insecurity in the United States?

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Abstract *While research establishing the link between high food prices and increased food insecurity in developing countries is robust, similar research about the United States has been lacking. This has been due in part to a lack of suitable price data, but it has also been due to the assumption that prices matter less in the United States, where households spend a relatively small fraction of their income on food. In this article we examine the role that local food prices play in determining food insecurity in the United States by using newly-developed price data. We examine whether low-income households participating in the Supplemental Nutrition Assistance Program (SNAP, formerly Food Stamps) are more likely to be food insecure in areas where food prices are higher. We find that the average effect of food prices on the probability of food insecurity is positive and significant: a one-standard deviation increase in food prices is associated with increases of 2.7, 2.6, and 3.1 percentage points in household, adult, and child food insecurity, respectively. These marginal effects amount to 5.0%, 5.1%, and 12.4% increases in the prevalence of food insecurity for SNAP households, adults, and children, respectively. These results suggest that indexing SNAP benefits to local food prices could improve the ability of the program to reduce food insecurity and economic hardship more generally in areas with high food prices.*

Key words: Food prices, Food insecurity, SNAP, Treatment effects.

JEL codes: H53, I31, I32.

Food-secure households have access at all times to enough food to ensure active, healthy living for all household members (Anderson 1990). Food-insecure households, on the other hand, lack consistent access to adequate food. Previous research has found that in developing nations food insecurity increases with food prices and price volatility (Shapouri et al. 2009; U.N. Committee on World Food Security 2011). However, the relationship between food prices and food security has not been studied in the U.S. context, in part because suitable food price data have been unavailable, and in part because it has been assumed that food prices do not matter as much in the United States, where the cost of food is low as a proportion of total household expenses, relative to other countries.[1] Recent research, however, indicates significant geographical variation in food prices throughout the United States. Indeed, there is greater variation in food prices across geography than over time—although, in the United States, the Supplemental Nutrition Assistance Program (SNAP, formerly Food Stamps) benefits are adjusted to reflect variation across time but not geography. Moreover, significant variation exists in the prices of healthy relative to less healthy foods across geographic market groups (Todd et al. 2011). Thus, geographic variation in food prices across the United States may affect some low-income households' ability to purchase adequate, healthful food.

Low-income households that rely on SNAP may be particularly vulnerable to high food prices. Maximum SNAP benefit allotments are based on the national average costs of market baskets of food items thought to comprise a healthy diet, consistent with dietary guidelines.[2] Annual cost of living adjustments are made to SNAP benefit levels to account for national inflation in the cost of food for the 48 contiguous states. However, regional variations in food prices are not accounted for. Therefore, households living in areas of the country with food prices that are higher than the national average may be less able to purchase adequate healthy food (Leibtag 2007; Nord and Hopwood 2007; Nord and Leibtag 2005). To the degree that this is true, variations in food prices may affect the extent to which SNAP can ameliorate food insecurity. This is especially true when considering food-at-home prices, because SNAP households spend a higher share of their food budget on food-at-home products.

The effect of prices on food insecurity is important in the context of recent research showing that SNAP reduces food insecurity (DePolt et al. 2009; Nord 2011; Nord and Golla 2009; Ratcliffe et al. 2011; Shaefer and Gutierrez 2012; Yen et al. 2008) and the depth and severity of poverty (Tiehen et al. 2012). Indeed, a particularly relevant recent study by Nord and Prell (2011) showed that the 2009 increase in SNAP benefits resulting from the stimulus package improved food security significantly, suggesting that larger SNAP benefits could help to reduce food insecurity. This may be especially true for households in areas with high food prices. However, a question left unanswered in this literature is whether variation in food prices affects the food security of SNAP participants, and by extension, whether the effectiveness of SNAP in ameliorating food insecurity would be improved by indexing SNAP to local prices.

In this article we estimate the effect of food prices on food insecurity for SNAP recipients using data from the Current Population Survey and the recently published Quarterly Food-At-Home Price Database (QFAHPD) (U.S. Census Bureau [2006]; U.S. Department of Agriculture, Economic Research Service [2012]). We form a local food price index based on amounts of required food for a household of four, as established by the Thrifty Food Plan, a USDA-designed food plan that enumerates the least

[1] *See "Expenditures on food and alcoholic beverages that were consumed at home by selected countries," 2010. http://www.ers.usda.gov/data-products/food-expenditures.aspx.*

[2] *Most SNAP recipients do not receive the maximum benefit. SNAP benefits are a supplement and are not meant to cover a household's entire food budget. Households receiving SNAP are expected to spend 30% of their net monthly income on food.*

expensive basket of foods that is consistent with dietary guidance. We find that the average effect of food prices on the probability of food insecurity for SNAP households is positive and significant: we find that an increase of a little less than one standard deviation in the price of our food basket results in increases of 2.7, 2.6, and 3.1 percentage points in household, adult, and child food insecurity, respectively. These marginal effects amount to 5.0%, 5.1%, and 12.4% increases in the prevalence of food insecurity for SNAP households, adults, and children, respectively. Our model predicts that SNAP participants living in high-priced food areas are roughly 8-10 percentage points (15%-20%) more likely to be food insecure than those participants living in low-priced areas, all other things being equal. In this context, the current study suggests that indexing SNAP benefits to local food prices could improve the ability of the program to ameliorate food insecurity.

This paper proceeds as follows. The next section provides a literature review, followed by a description of the data and sample construction. The proceeding section describes the methods used and, subsequently, the results from estimated models. We summarize and interpret our findings in the final section.

Literature Review

There has been no direct examination of the relationship between food prices and food insecurity for households in the United States. As mentioned above, this is due in part to the relative lack of food price data that can be matched to household behavior. Much of what we know about the relationship between food prices and food security in the United States is thus somewhat descriptive, and relies on our assumptions about the relationship between prices and expenditures, on the one hand, and expenditures and food security, on the other. For example, recent work by Nord (2009b) showed that from 2000 to 2007, as U.S. food prices increased, food spending decreased for low- and middle-income households. At the same time, very low food security increased, but whether the increase in food prices was caused by the increase in food insecurity was not determined.

Research has indicated that regional food price variation is fairly large, but regional measures of food security do not vary positively with prices, as we might expect. For example, one study has found that food prices are lower in the South and Midwest, and higher in the Northeast and West (Leibtag 2007). Households in the West spend between $32 and $48 more per month on food than the U.S. average, while a family in the South or Midwest spends between $12 and $28 dollars less per month for comparable food. At the same time, regional and state variation in food security are inversely, rather than proportionately, related to food prices. Nord et al. (2010) and Nord et al. (2007) indicate that food insecurity is the highest in the South, where food prices are generally lowest.

While there has been little empirical research linking food prices and food security, there is an emerging body of research that links regional price variation to economic wellbeing. On the whole, this research indicates that there is significant variation in the cost of living across the United States, and that it is important to adjust for these costs to understand how this variability affects overall wellbeing.

One thread of this research has examined the sensitivity of poverty measures to variation in prices of housing and other goods. For example, the U.S. Census Bureau's Supplemental Poverty Measures consider regional variations in housing costs to account for the differences in income necessary to meet basic needs across different areas (Short 2011). However, correlations in state rates indicate that the official poverty rate for states is more highly correlated with a state's prevalence of food insecurity than the supplemental poverty measure with geographic adjustment for housing costs (Renwick 2011), perhaps because prices of other goods vary by geography. Curran et al. (2006, 2008) used a market basket approach to more comprehensively account for costs, and found that market-basket-based cost of living adjustments resulted in wide variations in the poverty threshold across large cities.

Another thread of this research has shown that the prices of necessities such as housing and utilities are associated with higher food insecurity. For example, Bartfeld and Dunifon (2006) find that higher median rent is associated with a higher likelihood of food insecurity. Nord (2000) finds that at similar levels of income, urban households are more likely to be food insecure than rural households, suggesting that cost of living is lower in rural areas. However, adjusting for housing costs alone overcorrects for rural/urban cost differences because other costs differ across residence, and some costs are higher in rural areas. In addition, high heating and cooling costs are related to an increased likelihood of food insecurity (Bhattacharya et al. 2003; Nord and Kantor 2006). Taken together, these studies show that the prices households must pay for basic necessities affects food security and other wellbeing outcomes. It follows that variations in food prices would also affect food security.

This article pushes both the geographic cost of living literature and food security literature further by considering the direct effects of food prices on food security. We make a unique contribution by combining household data on household food insecurity with market-level food prices. More comprehensive food price data and precise modeling strategies were developed and incorporated into this study to fully address the relationship between food prices and food security.

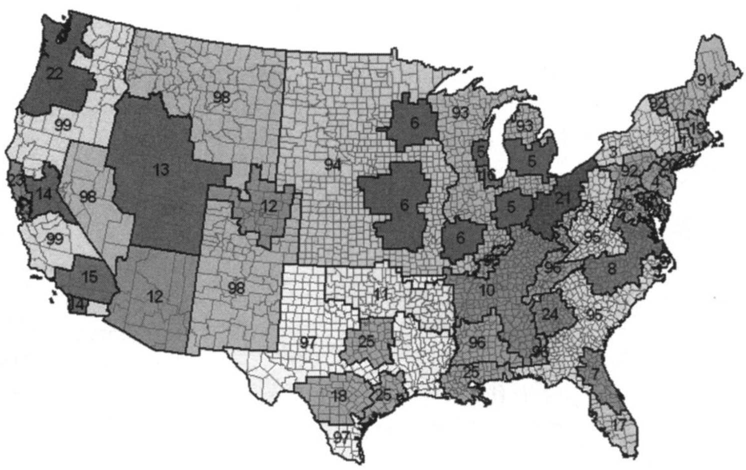
Data

In this section we describe the two primary data sources used for this study: the Quarterly Food-at-Home Price Database (QFAHPD) and the Current Population Survey Food Security Supplement (CPS-FSS). We also discuss how these data sources were matched to each other. In addition, we discuss the source of variables measuring state economic wellbeing, as well as our instrumental variables. We show descriptive statistics for the sample determinants of food insecurity, instrumental variables, and state-level variables.

Quarterly Food-At-Home Price Database: Food Prices

We use the QFAHPD as the source of information about food prices. Researchers from the USDA's Economic Research Service constructed the QFAHPD from Nielsen Homescan data, which follows households over an entire year and tracks both UPC-coded and random-weight food purchases.

Figure 1 QFAHPD market groups



Note: Market groups with identification numbers up to 26 are based on metro areas, which may be spread across different states, while market groups 91 and above are based on Census subregions.

Purchases are aggregated into 52 food groups based on USDA *Dietary Guidelines for Americans* and convenience premiums for certain kinds of processing such as frozen and ready-to-cook. For the years 2002-2006, quarterly prices for these goods are derived for 35 market groups: 26 based on Neilsen households in metropolitan (metro) areas, and 9 based on households in nonmetropolitan (nonmetro) areas. Prices for each good are derived from the average price paid by households in each market area (Todd et al. 2010).[3] The geography of the QFAHPD market groups is shown in figure 1.[4]

We aggregate the prices for individual QFAHPD goods into the price of a food basket based on the Thrifty Food Plan (TFP) for each market group and quarter. The TFP is a representative basket of food considered healthful according to USDA dietary guidance, and is the basis for maximum food stamp allotments. The basket is comprised of recommended amounts of foods, in pounds, in 29 categories and by age group. We match QFAHPD categories for 23 of these groups to form the comparable QFAHPD market basket.[5] For our basket, we use the amounts recommended for a family of four comprised of two adults and two children (one child age 6-8 and the other 9-11 years old). The intersection between TFP foods and QFAHPD foods is shown in table A.1.1.

To obtain the price of each TFP food in the market basket, we use an expenditure-weighted average of the prices for the QFAHPD foods, where

[3]*For a discussion of variation in prices across market groups, see Todd et al. (2010, 2011).*

[4]*These market groups are defined by Nielsen for ERS. Market groups with identification numbers up to 26 are based on metro areas, which may be spread across different states, while market groups 91 and above are based on Census subregions.*

[5]*The remaining 6 TFP groups were not included because their contents were in groups aggregated elsewhere into the TFP basket. For example, popcorn and whole grain snacks and whole grain cereals (including hot cereals) are TFP goods that might have been matched to the QFAHPD categories packaged snacks and whole grain cereal, respectively. However, these QFAHPD goods belong to TFP categories refined grains and whole grains, respectively. Other foods from the TFP that are not explicitly included are bacon, sausages and luncheon meats (including spreads); coffee and tea, and gravies, sauces, condiments and spices. All of these goods, with the possible exception of coffee and tea, are included elsewhere in the QFAHPD basket.*

the weights are a fraction of yearly national expenditures in the TFP category for the QFAHPD good. For example, the TFP good "whole fruit" is comprised of the QFAHPD foods "fresh/frozen fruit" and "canned fruit." In the first quarter of 2002, expenditures on fresh/frozen and canned fruit, in QFAHPD market group 1 (Hartford, Connecticut) were \$35.7 and \$5.8 million, respectively. Thus, the expenditure weights for that TFP good for that market group and quarter are approximately .86 and .13, respectively. The average of all the respective weights for these two goods, for all market groups and all quarters in 2002, will be the weights applied to form the price of whole fruit in Hartford. In 2002, the yearly expenditure weights are .8391 and .1609 for fresh fruit and canned fruit, respectively, meaning that the price for whole fruit in Hartford for the first quarter of 2002 is $.8391 \times \$0.218 + .1609 \times \$0.244 = \$0.222$ per 100 grams, where \$0.218 and \$0.244 are the prices per 100 grams of fresh/frozen and canned fruit in the Hartford market group in the first quarter of 2002, respectively.[6]

CPS: Food Security Status and Household Characteristics

Household data on food security and social demographic characteristics come from the CPS-FSS for 2002-2006. The CPS is the source for federal employment and poverty statistics, and includes data on household demographics, income, and employment. Approximately 50,000 households are interviewed each month. The CPS is nationally representative of the civilian, non-institutionalized population. Each December the Food Security Supplement is added to the basic CPS. Households are asked questions about their ability to meet their basic food needs, their participation in federal and community food assistance programs, and their food spending. The CPS-FSS data from 2002-2006 are used for this analysis to match the years available for 35 market groups in the QFAHPD.

Food security status is measured for the household as a whole and for adults and children separately by assessing answers to the food security survey, which is part of the December CPS. The survey includes 10 questions about the food insecurity conditions experienced by the household and adult members, and 8 items about food security among children. The questions refer to conditions or behaviors experienced in the prior 12 months. Questions range from being worried about running out of food, to cutting or skipping meals, to adults or children not eating for a whole day due to a lack of resources for food.[7] The household food security scale is comprised of the 10 questions about the household and adults members of the household, and for households with children, also includes the 8 questions that pertain to children. Households affirming 3 or more questions are defined as food insecure. Adults are considered food insecure if they affirm 3 or more conditions that pertain to adults in the household, and children are determined to be food insecure if the household reports 2 or more food-insecure conditions for children (Nord 2009a). We use both the household and adult food security scales because the adult scale provides a more comparable measure for households with and without children. We examine child food insecurity because of the policy relevance of child food security. In addition, food prices may have different effects on adult and

[6] *We convert the price per 100 grams into the price for the number of pounds recommended in the TFP by multiplying by .2204622 × the amount in pounds of a given TFP good.*
[7] *The full 18-item questionnaire can be found in Coleman-Jensen et al. (2011).*

Table 1 Rates of Food Insecurity, 2002-06

	2002	2003	2004	2005	2006
All U.S. households (full CPS-FSS sample)	11.1	11.2	11.9	11.0	10.9
CPS-FSS/QFAHPD matched sample	11.0	11.2	11.7	10.8	10.8

Notes: Prevalence of household food security. Estimates for all households come from published ERS reports. Estimates for matched sample weighted using CPS sampling weights. N=177,434.

child food insecurity, as adults often shield children from food insecurity (Nord 2009a).

Households in the CPS were matched to their market groups based on FIPS county codes when available; otherwise, their state or metropolitan information was matched to FIPS county codes and then to QFAHPD.[8] However, due to suppression of geographic identifiers in the CPS, of the 233,275 households in the CPS 2002-2006 sample (excluding Alaska and Hawaii, for which no QFAHPD is available), 24% could not be matched to market groups. This resulted in an initial sample size of 177,434 CPS households with food price information from QFAHPD. We then restricted the sample by income (200% of federal poverty level) for reasons we describe below, resulting in a final estimation sample of 40,617 households.

We restricted our initial CPS-FSS sample to those with geographic information that can be used to match to the QFAHPD. Table 1 compares the full CPS-FSS samples of food insecurity rates and those for the CPS-FSS sample matched to the QFAHPD. In general, the prevalences in both samples hover around 11% for the examined period in question. The full CPS-FSS sample rates are slightly higher than those for the matched sample, but by no more than two-tenths of a percentage point. This suggests that restricting the procedure to the matched sample does not bias our results in terms of food insecurity prevalence.

Table 2 shows regional variation in price and household food insecurity by year for our sample. These aggregates demonstrate two things. First, prices in QFAHPD matched to the CPS sample and averaged by region are consistent with other research about price variation. In general, prices are lower in the South and Midwest, as found by Nord and Leibtag (2005). Second, what correlation there is between prices and food insecurity goes in the opposite direction of expectations: prices are lowest and food security highest in the South, for example. Moreover, the full-sample unconditional correlation between food insecurity and food prices is small and negative.

Determinants of Food Insecurity

As mentioned above, the CPS includes extensive information on demographic and household characteristics that are helpful to our study because they are thought to be correlated with SNAP receipt, food insecurity, or both. We use variables describing human capital—the highest level of household education—and labor market status—an indicator of full-time employment for any adult in the household—because they are strongly related to the financial resources of the household, which we also examine in terms of family income and whether the home is owned or rented. We

[8] *The matching procedure is detailed in the appendix.*

Table 2 Regional Household Food Insecurity (%) and TFP Price ($)

	2002	**2003**	**2004**	**2005**	**2006**
Household food insecurity (%)					
Northeast	9.4	9.7	9.5	8.9	9.0
Midwest	9.8	9.9	11.2	11.7	11.0
South	12.2	12.1	12.7	11.4	11.8
West	11.9	12.2	12.7	10.6	10.6
Sample average	11.0	11.2	11.7	10.8	10.8
TFP price ($)					
Northeast	165.00	168.86	173.39	176.80	183.75
Midwest	152.89	153.98	158.69	158.89	166.05
South	153.07	156.33	160.13	163.21	171.18
West	162.67	166.70	171.50	169.69	176.76
Sample average	157.84	160.96	165.26	166.60	173.97

Notes: Prevalence of household food insecurity (top panel) and means of TFP-price index food basket, per week, for a family of four (two adults and two children, one 6-8, one 9-11 years old, bottom panel). Means weighted using CPS sampling weights. N=177,434.

are also interested in household composition, which affects resources that need to be devoted to food acquisition; variables that address this concern include the number of persons in the household, number of children in the household, number of elderly persons in the household, an indicator for a child under 5 in the household, presence of a teen aged between 15 and 17 in the household, and household structure (i.e., marital status). It will also be important for us to control for factors that describe the economic situation of a given state at any point in time, since those would certainly be correlated with the likelihood of SNAP participation and food insecurity. We use the state unemployment rate, gross state product, and per capita income as measures of state economic health. Furthermore, we include the Federal Home Loan Corporation Home Price Index (FMHPI) as a measure of average state housing costs.

The means of these analysis variables and TFP prices are shown in table 3, stratified by food security status.[9] The average price of the TFP basket faced by food-secure and food-insecure homes, while different statistically, is not so different economically. We also note that the average price is, on average, lower for food-insecure households.[10] The simple means show that food-insecure households are at an economic disadvantage relative to food-secure households because they are less likely to have a member employed full time, have lower family income, are less likely to own their homes, are more likely to have their highest educational attainment be less than a high-school education, and are less likely to have a college degree. Demographically, food-insecure households are more likely to be black or Hispanic, and less likely to be of another race. In terms of household composition and structure, food-insecure households have more children and more persons in the household, are more likely to be comprised of a married couple with children or be single parents, and less likely to be single men or women without children. They are more likely to have a

[9]*Means in table 3 are based on data aggregated over all years covered in the study.*
[10]*The statistical significance of the difference in mean prices is an artifact of sample size.*

Table 3 Summary Statistics by Household Food Security Status

	Food secure	Food insecure
TFP index	163.76	163.03***
	(0.079)	(0.127)
SNAP	0.135	0.353***
	(0.002)	(0.005)
HS dropout	0.203	0.249***
	(0.003)	(0.005)
HS graduate	0.568	0.581*
	(0.003)	(0.005)
College graduate	0.229	0.170***
	(0.003)	(0.004)
Employed full time	0.499	0.488*
	(0.003)	(0.005)
Family income ($ thousands)	17.487	15.515***
	(0.067)	(0.102)
Home owned	0.468	0.301***
	(0.003)	(0.005)
Black	0.181	0.272***
	(0.003)	(0.005)
Hispanic	0.218	0.261***
	(0.003)	(0.005)
Other race	0.058	0.044***
	(0.002)	(0.002)
Number of persons in HH	2.626	2.996***
	(0.011)	(0.019)
Number of children in HH	0.838	1.252***
	(0.008)	(0.015)
Number of elderly in HH	0.381	0.153***
	(0.004)	(0.004)
Child less than 5 in HH	0.190	0.256***
	(0.003)	(0.005)
Teenager in HH	0.099	0.151***
	(0.002)	(0.004)
Multi-adult HH (no children)	0.197	0.121***
	(0.003)	(0.003)
Single parent	0.146	0.280***
	(0.002)	(0.005)
Single male	0.121	0.112**
	(0.002)	(0.003)
Single female	0.214	0.145***
	(0.003)	(0.004)
State unemployment rate	5.463	5.543***
	(0.006)	(0.009)
Gross state product ($ billions)	593.377	600.081
	(3.159)	(5.108)
Per capita income ($ thousands)	33.552	33.221***
	(0.029)	(0.047)
Freddie Mac Home Price Index	136.304	133.828***
	(0.208)	(0.321)
Expanded categorical eligibility	0.209	0.228***
	(0.003)	(0.004)
Simplified reporting	0.684	0.677

Continued

Table 3 *Continued*

	Food secure	Food insecure
	(0.003)	(0.005)
Biometric information	0.361	0.379***
	(0.003)	(0.005)
N	29,380	11,237

*Notes: Summary measures from estimation sample: households at or below 200% of FPL. Data aggregated across all years covered by the study. Asterisks indicate that differences between food-secure and food-insecure households are different at ***p<.01, **p< .05, and *p< .10. Standard Errors appear in parentheses.*

teenager in the household and have fewer elderly persons in the household. Food-insecure households are more likely to participate in SNAP.

Exogenous Variables

One of the problems with estimating the effect of food prices on the probability of food security for SNAP households is that SNAP and food insecurity are correlated for reasons that are unobserved by the researcher. To address this problem, we use a control function approach for modeling unobservables, as detailed below. We include exogenous variables from the Food Stamp rules database, compiled by the Urban Institute (Finegold et al. 2006) and updated by researchers at the Economic Research Service, to identify the probability of SNAP participation. In particular, we use the following state policy variables as instruments to identify SNAP participation:[11]

Expanded Broad-Based Categorical Eligibility

These rules differ from state to state. Many states made all households on TANF (Temporary Assistance for Needy Families), with or without cash assistance, eligible for SNAP. Some states also relax asset tests when considering eligibility criteria.

Simplified Reporting

This sort of reporting indicates that a state had semi-annual reporting or simplified reporting for earners to recertify; simplification differs across states, but usually means that respondents only have to report any change of address and change in income.

Biometric Information

These rules stipulate that SNAP recipients must provide some identifying biological information—usually a fingerprint—before they can receive SNAP benefits.

[11] *We use the term "instruments" even though we do not employ an instrumental variables strategy per se; we find it a convenient shorthand for our exogenous policy variables.*

Table 3 also shows the means of these variables. The probability of expanded categorical eligibility being in place is higher for food-insecure households than for food-secure households, while the probability of simplified reporting policies being in place is the same for food-secure and food-insecure households. The probability of biometric information policies being in place is slightly higher for food-insecure households.

For these variables to be suitable for this application, they need to be strongly correlated with SNAP participation, but uncorrelated with food insecurity, except through SNAP participation. The first requirement can be empirically tested: we show the results of these tests below. The second requirement cannot be empirically verified, but we think there is a strong *a priori* case for these policies being unrelated to food insecurity. The policies have been adopted either to increase (biometric information) or decrease (expanded eligibility) the cost of enrolling in SNAP, or to decrease the cost of remaining enrolled in SNAP (simplified reporting). In addition to there being a strong intuitive case for these policies only affecting food insecurity through SNAP, below we conduct *ad hoc* tests to examine whether the adoption of these policies is related to food insecurity.[12]

State Economic Variables

The model discussed below also contains variables that capture the level of economic wellbeing and state-level variation in housing costs. We include these to capture important aspects of the local environment that might be correlated with both the price level and food security status, but might not be captured by state-level fixed effects. The means of these variables are also shown in table 3.[13] The means of these variables are essentially identical between food-secure and food-insecure households, although the unemployment rate is slightly higher for those in food-insecure households, while income per capita and the home price index are slightly lower. Gross state product is slightly higher for food-insecure households.

Methods

We are interested in the effect of food prices on food insecurity for low-income households, with special attention being paid to SNAP participants. The choice of whether or not to enroll in SNAP is driven by unobserved characteristics that are likely correlated with food security status, so failure to control for the endogeneity of SNAP participation will result in biased parameter estimates. Thus, to accurately estimate the effect that food prices have on SNAP households' food security status, we need to take these unobserved characteristics into account. We do this by using an endogenous switching framework, which allows us to model the unobservables by

[12] *We also note that these variables, alone or in combination with other policy variables, have been used in other studies of the effect of SNAP on food insecurity and health (Yen et al. 2008; Ratcliffe et al. 2011; Meyerhoefer and Pylypchuk, 2008).*

[13] *As detailed in the documentation to the SNAP Policy Database, unemployment rate data come from the Bureau of Labor Statistics, while gross state product and per capita income are derived from Bureau of Economic Analysis data (Economic Research Service, U.S. Department of Agriculture [2013]). The annual home price index is the average of the monthly home price indices, by state, published by Freddie Mac as the Freddie Mac Home Price Index (FMHPI), found at http://www.freddiemac.com/finance/fmhpi/.*

virtue of the parametric form of our regression specification (Lokshin and Sajaia 2011), that is, the control function. For notational simplicity, we let

$$\eta_i = Z_i\delta + TFP_i\gamma$$

and

$$\nu_{\ell i} = X_{\ell i}\beta_\ell + TFP_i\zeta_\ell,\ \ell = (0,1)$$

be linear indices for the propensity to enroll in SNAP (η), and to be food insecure (ν), respectively. Thus, Z is a set of variables that includes household characteristics, state economic indicators, state and year fixed effects, and the state policy variables, and X is a set of variables that determine food insecurity, including household characteristics, state economic indicators, and state and year fixed effects. Both Z and X include the local price index (TFP), while δ, β, γ, and ζ are parameters,[14] and $\ell = 0$ if a household is a SNAP non-participant, and 1 otherwise.

The regression model is:

$$S_i^* = \eta_i + v_i \quad (1)$$
$$F_{\ell i}^* = \nu_{\ell i} + \varepsilon_{\ell i},\ \ell = (0,1) \quad (2)$$

where S^* and F^* are latent variables for the propensity to enroll in SNAP and experience food insecurity, respectively. We estimate a single equation for participation in SNAP, and separate (simultaneous) equations for food security, depending on whether one has enrolled in SNAP or not (as above, $\ell = 0$ for non-participants, 1 for participants), for a total of three simultaneous equations. As is customary, both S^* and F^* are latent variables that are manifest in the data as binary; we assume that they equal one if their respective indices are greater than zero, and are zero otherwise.

The variables v, ε_0, and ε_1 are the unobservables related to SNAP participation, food insecurity for non-participants, and food insecurity for participants, respectively. We assume that these unobservables are jointly normally distributed with a (vector) mean of zero and correlation matrix with parameters ρ_0, ρ_1, and ρ_{10},[15] where ρ_0 and ρ_1 are the correlations between ε and ε_0, and v and ε_1, respectively. However, since we do not observe treated and untreated states in the outcome for any given household, the distribution of $(\varepsilon_1\varepsilon_0)$ is not identified. The model is identified by non-linearities in the functional form of the bivariate normal distribution; nonetheless, we also employ state-level policy variables that affect the cost of enrolling in SNAP (as discussed above) to identify selection into the program.

In general, we are interested in the marginal effects of the *TFP* on food insecurity. Since this model treats food security separately for SNAP participants and non-participants, the marginal effects of *TFP* for SNAP participants and non-participants are based on separate parameter vectors and separate coefficients on TFP, that is, ζ_0 and ζ_1 for non-participants and participants, respectively. If we let the average treatment effect (ATE) of SNAP be defined as the effect of SNAP participation for a person randomly drawn

[14]*Although we could index each of the observations by state, market group, and time, they do not add anything to the elaboration of the model, so we have suppressed them.*
[15]*The diagonal elements of this matrix–the variances of the indices–are assumed to be 1. See Lokshin and Sajaia (2011) for more details.*

from the population, then the marginal effect of food prices on the probability of food insecurity can be found by taking the derivative of the ATE with respect to food prices.[16] For SNAP participants, this is

$$\mu_1 = \frac{1}{N}\sum_{i=1}^{N} \phi(\nu_{1i})\zeta_1 \tag{3}$$

where ϕ is the univariate normal probability density function. For non-participants, the marginal effect of prices is

$$\mu_0 = \frac{1}{N}\sum_{i=1}^{N} \phi(\nu_{0i})\zeta_0. \tag{4}$$

While the ATE measures the effect of SNAP for a person drawn randomly from the population, we might be interested in the effect of SNAP on participants only. That is, we might want to know not whether SNAP would have an ameliorative effect on anyone in the population, but whether it helps those who are most likely to choose it—taking the unobserved characteristics as given. This affect, the average effect of the treatment on the treated (ATT), can be expressed as $P(F_1{=}1|S{=}1,X{=}x)$-$P(F_0{=}1|S{=}1,X{=}x)$. We show this quantity in the results shown below as well.[17]

One important aspect of the estimation procedure is the selection of the study sample. To address sample selection meaningfully, we need to include households that might be on the margin of participating in SNAP. One way to do this would be to include households above the gross income cutoff for participation—130% of the FPL. However, in recent years quite a few states have raised gross income limits to as much as 200% of FPL, so we need to include households with relatively higher levels of income in our sample.[18] Thus, we limit the sample for our main estimates to those households at or below 200% of the federal poverty line.

Results

Parameter Estimates

The parameters from the model outlined above are found in table 4. Each of the columns in the table shows the food security measure used as the dependent variable—household, adult, or child. The table shows the parameter estimates from all three equations—SNAP participation, food insecurity for participants, and food insecurity for non-participants.

Considering the SNAP equation, we can say that the coefficients have the expected signs. Among the state economic indicators, unemployment rate is associated with increases in the probability of SNAP participation. Gross state product and the home price index (FMHPI) have no measurable effect

[16] *The ATE can be represented as* $ATE = \frac{1}{N}\sum_{i=1}^{N} \Phi(\nu_{1i}) - \Phi(\nu_{0i})$. *We calculate standard errors of marginal effects by the delta method.*
[17] *We can estimate this as* $ATT = \frac{1}{S}\sum_{i=1}^{N} (\Phi_2(\eta, \nu_1, \rho_1) - \Phi_2(\eta, \nu_0, \rho_1))/\Phi(\eta)$, *where* Φ_2 *is the bivariate normal cumulative distribution function and S is the size of the SNAP recipient sample.*
[18] *For example, Arizona, Delaware, Maryland, Massachusetts, Washington, and Wisconsin raised the limit to 200%; Maine and Oregon to 185%, and Minnesota and Texas to 165% (Falk and Aussenberg 2012).*

Table 4 Parameter Estimates, Endogenous Switching Probit, SNAP and Food Insecurity

	Food security scale		
	Household	**Adult**	**Child**
SNAP equation			
Unemployment rate	0.0583	0.0598*	0.1354***
	(0.0370)	(0.0358)	(0.0508)
Gross state product	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Per capita income	-0.0210	-0.0198	0.0101
	(0.0345)	(0.0347)	(0.0394)
FMHPI	0.0004	0.0003	0.0005
	(0.0011)	(0.0012)	(0.0013)
HS dropout	0.1545***	0.1576***	0.0954**
	(0.0325)	(0.0325)	(0.0391)
College graduate	-0.1720***	-0.1725***	-0.1489***
	(0.0302)	(0.0307)	(0.0428)
Employed full time	-0.6650***	-0.6665***	-0.6609***
	(0.0261)	(0.0259)	(0.0384)
Family income (thousands)	-0.0411***	-0.0410***	-0.0388***
	(0.0018)	(0.0018)	(0.0020)
Home owned	-0.4541***	-0.4528***	-0.4533***
	(0.0430)	(0.0427)	(0.0383)
Black	0.2962***	0.2970***	0.1776***
	(0.0311)	(0.0307)	(0.0381)
Hispanic	-0.0177	-0.0176	-0.1814***
	(0.0618)	(0.0621)	(0.0619)
Other race	-0.0047	-0.0044	-0.0587
	(0.0410)	(0.0415)	(0.0592)
Number of persons in HH	0.2033***	0.2036***	0.1611***
	(0.0260)	(0.0264)	(0.0248)
Number of children in HH	0.0471**	0.0470*	0.0923***
	(0.0237)	(0.0247)	(0.0248)
Number of elderly in HH	-0.2295***	-0.2309***	0.0388
	(0.0459)	(0.0463)	(0.0368)
Child less than 5 in HH	0.2013***	0.2003***	0.2118***
	(0.0376)	(0.0366)	(0.0339)
Teenager in HH	-0.1633***	-0.1596***	-0.1519***
	(0.0335)	(0.0346)	(0.0356)
Multi-adult HH (no children)	-0.2038***	-0.2046***	
	(0.0770)	(0.0763)	
Single parent	0.3460***	0.3449***	0.3528***
	(0.0359)	(0.0363)	(0.0396)
Single male	-0.3588***	-0.3595***	
	(0.1026)	(0.1019)	
Single female	-0.2646***	-0.2653***	
	(0.0973)	(0.0967)	
Expanded eligibility	0.2085***	0.2450***	0.3124***
	(0.0808)	(0.0835)	(0.1116)
Simplified reporting	0.0986	0.1010	0.1919*
	(0.0715)	(0.0728)	(0.1151)
Biometric information	-0.6960**	-0.7046**	0.0186

Continued

Table 4 *Continued*

	Food security scale		
	Household	**Adult**	**Child**
	(0.3464)	(0.3379)	(0.0938)
TFP	-0.0067*	-0.0067*	-0.0083**
	(0.0036)	(0.0036)	(0.0041)
Food insecurity (SNAP=1)			
Unemployment rate	0.0561	0.0907	0.1424*
	(0.0609)	(0.0601)	(0.0846)
Gross state product	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
Per capita income	-0.0316	-0.0511**	-0.0149
	(0.0284)	(0.0252)	(0.0525)
FMHPI	0.0012	0.0024**	0.0022
	(0.0014)	(0.0011)	(0.0017)
HS dropout	-0.0569	-0.0500	0.0247
	(0.0436)	(0.0423)	(0.0606)
College graduate	-0.0415	-0.0551	-0.0743
	(0.0595)	(0.0673)	(0.0894)
Employed full time	0.0631	0.0084	0.0148
	(0.1004)	(0.0998)	(0.1039)
Family income ($ thousands)	-0.0013	-0.0029	0.0027
	(0.0058)	(0.0066)	(0.0055)
Home owned	0.0452	0.0014	-0.0141
	(0.0727)	(0.0802)	(0.0846)
Black	-0.1353**	-0.1239**	-0.0347
	(0.0565)	(0.0572)	(0.0697)
Hispanic	-0.0763**	-0.1181**	0.0521
	(0.0368)	(0.0518)	(0.0832)
Other race	-0.1450	-0.1739**	0.1300
	(0.0890)	(0.0690)	(0.1100)
Number of persons in HH	0.0149	0.0357	0.0062
	(0.0363)	(0.0425)	(0.0343)
Number of children in HH	-0.0036	-0.0296	0.0378
	(0.0334)	(0.0367)	(0.0376)
Number of elderly in HH	-0.2007***	-0.2649***	-0.1355
	(0.0497)	(0.0538)	(0.0909)
Child less than 5 in HH	-0.3143***	-0.2741***	-0.3364***
	(0.0562)	(0.0495)	(0.0588)
Teenager in HH	0.1295**	0.1191**	0.2393***
	(0.0608)	(0.0578)	(0.0461)
Multi-adult HH (no children)	0.0155	0.2347**	
	(0.1107)	(0.1007)	
Single parent	-0.0878*	-0.0412	-0.0698
	(0.0513)	(0.0727)	(0.0646)
Single male	0.0355	0.2448**	
	(0.1235)	(0.1016)	
Single female	-0.0299	0.1932**	
	(0.1135)	(0.0916)	
TFP	0.0068**	0.0058**	0.0080**
	(0.0028)	(0.0029)	(0.0032)

Continued

Table 4 *Continued*

	Food security scale		
	Household	**Adult**	**Child**
Food insecurity (SNAP=0)			
Unemployment rate	0.0371	0.0389	0.0299
	(0.0258)	(0.0269)	(0.0482)
Gross state product	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
Per capita income	0.0142	0.0140	0.0697***
	(0.0165)	(0.0157)	(0.0217)
FMHPI	-0.0002	0.0000	-0.0019*
	(0.0007)	(0.0009)	(0.0010)
HS dropout	0.1445***	0.1312***	0.1141***
	(0.0247)	(0.0277)	(0.0302)
College graduate	-0.1339***	-0.1367***	-0.1023***
	(0.0243)	(0.0219)	(0.0387)
Employed full time	-0.2918***	-0.2652***	-0.3376***
	(0.0414)	(0.0373)	(0.0737)
Family income ($ thousands)	-0.0235***	-0.0217***	-0.0211***
	(0.0021)	(0.0023)	(0.0040)
Home owned	-0.2851***	-0.2745***	-0.2539***
	(0.0337)	(0.0293)	(0.0621)
Black	0.3074***	0.2869***	0.1054**
	(0.0295)	(0.0333)	(0.0501)
Hispanic	0.0648**	0.0513*	0.0558
	(0.0307)	(0.0270)	(0.0380)
Other race	-0.1017*	-0.1053*	-0.0762
	(0.0543)	(0.0570)	(0.0707)
Number of persons in HH	0.1090***	0.1024***	0.0797***
	(0.0183)	(0.0224)	(0.0147)
Number of children in HH	0.0376**	0.0139	0.0997***
	(0.0189)	(0.0246)	(0.0197)
Number of elderly in HH	-0.4038***	-0.4020***	-0.0673*
	(0.0243)	(0.0244)	(0.0357)
Child less than 5 in HH	-0.0567	-0.0524	-0.1014*
	(0.0492)	(0.0438)	(0.0554)
Teenager in HH	-0.0440*	-0.0189	0.0313
	(0.0252)	(0.0258)	(0.0444)
Multi-adult HH (no children)	-0.2207***	-0.0451	
	(0.0415)	(0.0422)	
Single parent	0.2123***	0.2085***	0.2439***
	(0.0257)	(0.0307)	(0.0388)
Single male	-0.2222***	-0.0359	
	(0.0447)	(0.0464)	
Single female	-0.3161***	-0.1367***	
	(0.0370)	(0.0415)	
TFP	-0.0009	-0.0011	-0.0030
	(0.0020)	(0.0022)	(0.0020)
ρ_1	-0.3434**	-0.2416	-0.2340
	(0.1778)	(0.2033)	(0.2018)
ρ_0	0.5543***	0.4642***	.5534***
	(.1248)	(0.1214)	(0.2091)

Continued

Table 4 *Continued*

	Food security scale		
	Household	**Adult**	**Child**
χ^2_{ind}	13.20***	11.01***	4.78*
χ^2_{IV}	22.80***	26.96***	15.10***
N	40617	40617	17500

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *Parameter estimates of endogenous switching probit: treatment=SNAP, outcome=food insecurity. Standard errors in parentheses. State and year fixed-effects not shown. Household composition reference category is a married couple with children. Sample is comprised of households at or below 200% of the federal poverty line.*

on SNAP participation, and income per capita is inversely related to SNAP participation, though not significantly so. More education is associated with a lower probability of SNAP participation, and employment, family income, and owning one's home are negatively correlated with SNAP participation. Blacks are more likely than whites (the reference group) to be SNAP participants. The number of persons, number of children, the presence of a child younger than 5, and being in a single-parent household are positively related to SNAP participation. Being in a multi-adult household without children, being a single male or female, having a teenager in the household, and the number of elderly persons in the household are all negatively correlated with SNAP participation. The food price index is negatively correlated with SNAP participation in all of the models: given that we have controlled for household income, state per capita income, and gross state product, we think that this suggests that in areas with high food prices, people are less likely to participate in SNAP because the real value of benefits is low. Expanded categorical eligibility is a significant predictor of SNAP participation for all of the models. Policies that require biometric information reduce SNAP participation for all of these models, and simplified reporting is positively related to food security in all of the models, though it is significant only in the child food insecurity model.

In the food security equation for SNAP participants, factors that we might expect to affect food insecurity—such as income, education, and home ownership—do not affect food security status significantly. However, relative to their white counterparts, black and Hispanic households and adults who are SNAP participants are less likely to be food insecure. Participant households with a child less than five years old are significantly less likely to be food insecure. At the same time, households with a teenager in them are more likely to report food insecurity. The number of elderly persons in the household is inversely related to the probability of food insecurity. None of the state economic variables is strongly correlated with food insecurity for SNAP participants, with the exception of per capita income in the adult food insecurity model. The coefficient on the food price index is large and positive for all three models.

In the outcome equation for non-participants, among the state economic variables, only gross state product is significantly associated with food insecurity, but the effect is very small. The FMHPI has no significant correlation with the probability of food security. Factors that increase the likelihood of food insecurity include having attained less than a high school education, the number of persons in the household, the number of children in the household, and being a single parent. Full time employment, higher family income, home ownership, having a college degree, and being a single person with no children are associated with a lower probability of food insecurity among non-participants. As with SNAP participants, elderly members of the household are associated with decreases in the likelihood of food insecurity. The food price index is unrelated to food security for non-participants.

Many of these results are similar to those established in the literature on the determinants of food insecurity. For example, our results for state economic indicators are similar to those in Ratcliffe et al. (2011), who found that similar indicators had the expected signs but were not significant in the presence of state fixed-effects. The parameter estimates for both participants and non-participants also show that each elderly person in the household decreases the probability of food insecurity, which is consistent with the results in Yen et al. (2008), as well as findings that suggest that the elderly are more food secure than the non-elderly (Nord 2002). Higher family income and home ownership are also negatively correlated with food insecurity for non-participants, which is broadly consistent with much research (Coleman-Jensen et al. 2011; DePolt et al. 2009; Ratcliffe et al. 2011; Yen et al. 2008).

This table also shows the values of the parameters ρ_1 and ρ_0, as well as a test of their equivalence, which is a likelihood ratio test of the joint independence of the equations. For all of the models, ρ_1 is negative and ρ_0 is positive, indicating that the unobservables in the SNAP participation and food insecurity equations are negatively correlated for participants, and vice-versa for non-participants. In other words, among the participants, those who are least likely to enroll due to characteristics not observed by the researcher are those who are most likely to be food insecure. At the same time, among non-participants, those who are least likely to enroll are least likely to be food insecure. We find that ρ_0 is significant for all of the models, while ρ_1 is significant only for the household food insecurity model. The table also shows the test statistics and p-values of χ^2_{ind}, which is a likelihood ratio test for the joint independence of the equations; this test statistic is significant for all of the models, suggesting that the regimes of food insecurity for SNAP participants and non-participants are distinct. Put another way, this parameter indicates that this model would be preferred to one in which the food security parameters for SNAP participants and non-participants were assumed to be the same—a bivariate probit, for example.

As noted above, the endogenous switching probit is theoretically identified by functional form. For this application, we also rely on the strength and validity of the state policy variables to help identify the likelihood of SNAP participation. Tests of the instruments' strength in the treatment equation take the values of 22.80, 26.96, and 15.10 ($p<.005$), which are far larger than is recommended to avoid problems with weak instruments in linear models (Staiger and Stock 1997). However, in order to be valid, the policies need to be unrelated to food insecurity. We think there is a strong *a priori* case to be made for the instruments' validity, since the adopted policies change the cost of enrolling (expanded eligibility, biometric information) or staying enrolled (simplified reporting) in SNAP and might affect food insecurity only through SNAP. However, they could still be invalid if they are related to state-level rates of food insecurity—that is, if policy

Table 5 Treatment Effects, 200% FPL

	Household	Adult	Child
SNAP ATE	0.3475***	0.2877**	0.1034
	(0.1051)	(0.1357)	(0.1258)
TFP (SNAP=0) (μ_0)	-0.0001	-0.0001	-0.0007
	(0.0006)	(0.0007)	(0.0006)
TFP (SNAP=1)(μ_1)	0.0027***	0.0026***	0.0031***
	(0.0007)	(0.0009)	(0.0011)
N	40,617	40,617	17,500
SNAP ATT	-0.174**	-0.112*	-0.206**
	(0.085)	(0.066)	(0.086)
N	7,765	7,765	4,897

*Notes: *** p<0.01, ** p<0.05, * p<0.1. Marginal effects adjusted to account for the sampling weights. Standard errors are clustered by state and calculated using the delta method. Selection and outcome equations as specified in text.*

makers adopted them in response to the prevalence of food insecurity. There is no formal test for this, but to examine this possibility, we regressed the current year's policies on the previous year's household food insecurity prevalence: point estimates showed that the policies were uncorrelated with previous years' food security for all three exogenous variables: p-values were .75 (simplified reporting), .25 (expanded eligibility), and .63 (biometric information) for models using household food insecurity, with similar results for adult and child food insecurity models.[19] While not definitive, these results suggest that the systematic variation on SNAP policy is not related to the state history of food insecurity rates, and that our instruments are valid.[20]

Marginal Effects

Table 5 shows marginal effects on the probability of food insecurity. Each column in the table is labeled by the measure of food security used as the outcome variable in question: household, adult, or child. The differences in these outcome measures are described above.[21]

The effect of prices on household, adult, and child food insecurity in SNAP households is large and significant. A $10 increase in the food price index (a little less than one standard deviation) results in an increase in household food insecurity of 2.7 points, and adult food insecurity of 2.6 percentage points, while the same increase in prices results in a 3.1 percentage point increase for child food insecurity.[22] These amount to 5.0%, 5.1%, and 12.4% increases in the prevalence of household, adult, and child food insecurity, respectively. All of the marginal effects are significant at $p<.05$. At

[19]*We used probit models for these regressions. Results are available upon request.*

[20]*These instruments are a similar to those used in other studies, including Ratcliffe et al. (2011), Yen et al. (2008), and Shaefer and Gutierrez (2012).*

[21]*Because the model estimates food insecurity for SNAP participants and non-participants in separate equations, the marginal effects shown for TFP and SNAP × TFP are the marginal effects of food prices on the probability of food insecurity for non-participants and participants, respectively.*

[22]*In the results shown, prices, incomes, and state GDP are all nominal. Results are the same if all of these variables are normalized by relevant CPI measures.*

the same time, the effect of food prices on the food security status of non-participants is essentially zero.

A concern with these estimates is that the average treatment effect (ATE) of SNAP is positive and significant for the household and adult food security models. This runs contrary to recent research on the effect of SNAP on food security (Shaefer and Gutierrez 2012; DePolt et al. 2009; Ratcliffe et al. 2011; Yen et al. 2008). However, the models used in that research assume that the effect of all the observables on food security is the same for SNAP participants and non-participants. Our model relaxes this assumption: we think that SNAP households are more sensitive to food prices than their non-participating counterparts. But it is also plausible that the effect of education or an additional child in the household would differ for SNAP and non-SNAP households—as is borne out by the results shown above. Moreover, as also noted above, the likelihood ratio test for the joint independence of the regimes, χ^2_{ind}, is significant for all of the models, and highly so for the household and adult food security measures.[23] This suggests that the choice to model regimes separately for SNAP participants and non-participants is preferred to a model such as a bivariate probit, which assumes that the parameters in the food security equation for participants and non-participants are the same.

We have also estimated the ATT, shown in the bottom panel of table 5. This is arguably a more policy-relevant effect, because it takes the unobservables that are correlated with both SNAP participation and food insecurity as given, rather than something that can be taken out of the participation dynamic. We find that SNAP has large and significant effects on the probability of food insecurity for participants: SNAP reduces the probability of household, adult, and child food insecurity by 17.4, 11.2, and 20.6 percentage points, which amount to reductions of 33.7%, 24.6%, and 70.3% of prevalence for these populations.

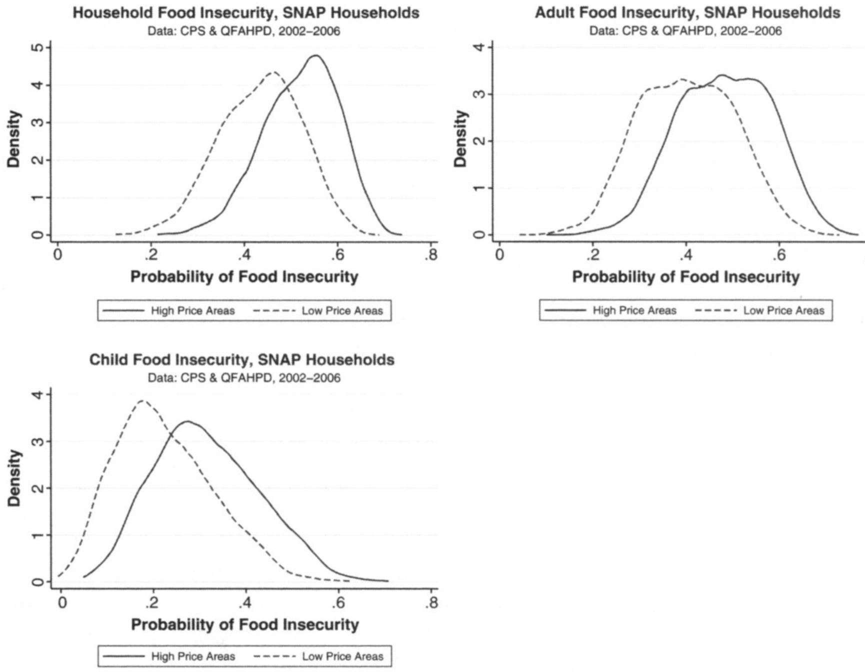
Finally, to show the effects of prices graphically, we estimated the predicted probability of food security for SNAP households in the areas in the highest and lowest quartile of food prices (by year) in our data.[24] The kernel densities of these probabilities are shown in figure 2, with the probability of household, adult, and child food insecurity shown in the top left, top right, and bottom right graphs, respectively. For each of the outcomes, those in the highest-priced areas are significantly more likely to be food insecure: households in high-priced areas are 8.6, 8.3, and 10.0 percentage points more likely to experience household, adult, and child food insecurity, respectively, compared to those in low-priced areas. Kolmogorov-Smirnov tests reject the null hypothesis of the equivalence of these distributions at $p<.001$.

Discussion

Do food prices affect food security? At first glance, the answer seems obvious: yes. But while the link has been established for developing countries, because of data limitations and the assumption that prices would not matter for a rich country such as the United States, until now the question has not been asked with respect to U.S. households. The question is

[23]*We also estimated this model using separate Heckman probit models for SNAP participants and non-participants, as has been done for a different application by Ham et al. (2010). The results are identical.*
[24]*Results are the same if we use quintiles, deciles, or thirds.*

Figure 2 Differences in food insecurity by food prices, SNAP participants in CPS



important because benefits for SNAP—the primary policy defense against food insecurity—are not indexed to local or regional markets, and yet we know that there is a wide variation in food prices within the 48 contiguous states. Holding aside the question of how SNAP benefits might be indexed, we have examined whether evidence exists that local food prices affect levels of food insecurity. Our results confirm our intuition: food prices significantly affect food security for households participating in SNAP that have household incomes of 200% or less of the federal poverty line. Our results suggest that a $10 increase in the price of our TFP basket will lead to 2.5 percentage point increase in household food insecurity, a 2.4 percentage point increase in adult food insecurity, and a 3.1 percentage point increase in child food insecurity. This increase is a little less than 1 standard deviation in the food price level. These marginal effects amount to 5.0%, 5.1%, and 12.4% increases in the prevalence in food insecurity for households, adults, and children, respectively. Our model predicts that SNAP households that live in the places with the highest quartile of food prices are between 8 and 10 percentage points (between 15% and 20%) more likely to be food insecure than those in the lowest quartile of food prices.

Our main results come from a model that accounts for the endogeneity of SNAP participation to food security. The model is a full information maximum likelihood (FIML) model identified by non-linearities in a functional form that includes exogenous state-policy variables, which are strongly related to program participation. The case for the validity of the instruments is strong and we find no evidence that the policy variables that we use for instruments are related to levels of food insecurity. While we do find that our measured ATE of SNAP in our model differs from that in previous research, we find that this is due to specification choice. Moreover, we find that the ATT, an arguably more important measure of policy effectiveness, is consistent with evidence about the efficaciousness of SNAP in reducing food insecurity. In addition, our model parameters suggest that this specification is preferred to a model which assumes that the effect of observed characteristics for SNAP participants and non-participants is the same, as has been assumed in most recent research (Yen et al. 2008; Ratcliffe et al. 2011; Shaefer and Gutierrez 2012).

The food price data that we use are both the study's strength and its limitation. On the one hand, the QFAHPD are based on a nationally-representative sample of households, and give us prices on a wide array of commonly consumed food-at-home products, which is not elsewhere available in the current data environment. On the other hand, our food prices cover varying sizes and kinds of food markets. For example, many of the markets in the West and Midwest are comprised of census subregions, while those in the South and Northeast tend to be smaller and concentrated around metropolitan areas. We have run the models that exclude all of the large census subregion market groups; these models produce results essentially identical to those presented here. Additionally, we have used the CPS-FSS questions about the cost of enough food to estimate the correlation between the respondents' estimates of what it cost for them to purchase enough food (reflecting local food prices) and the TFP basket shown here. The correlation between the measures is .69, which suggests that, sub-market group level variation notwithstanding, our measure of food price variance is strong. We also think that better food price data on both the state and sub-state levels is needed.

The results of this study are important because they contribute to our understanding of the role that SNAP plays in reducing food insecurity and economic hardship more generally. Our results indicate that SNAP could do better to ameliorate food insecurity and its effects by indexing benefits to local prices. Although we think that these effects are important, we are also aware that the question about how to index SNAP benefits is both technically difficult and politically sensitive. Especially since SNAP has become such a large part of income assistance for low-income families, any change in how benefits are calculated will likely have effects beyond households' ability to purchase food. We note, however, the principle of indexing SNAP benefits has already been established by the Food and Nutrition Service, which currently indexes SNAP benefits for recipients in Alaska, Hawaii, Guam, and the U.S. Virgin Islands. Nonetheless, indexing issues, among others, will have to be considered carefully in future research.

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Appendix. CPS: Geographic Matching

The primary geographical identifier by which households in the CPS could be matched to the Quarterly Food at Home Price Database (QFAHPD) is the FIPS county code. However, roughly 60% of CPS household observations from 2002-2006 have FIPS county codes that are suppressed for confidentiality reasons, and so could not ordinarily be matched to the QFAHPD. We match some of these observations to the QFAHPD by means of PMSA/MSA codes (2002 and 2003), CBSA codes (2004-2006), or states (all years) using the procedure described below.[25]

Before doing any geographic matching, there were 233,275 household observations in the sample.[26]

All Years: FIPS County and State Match

For all persons who had county information, we used the FIPS county codes in the CPS to match persons to market groups. Of the almost 90,000 observations with FIPS county codes, 625 were not matched to market groups. These were observations with FIPS code 12025, which was the code in use for Dade County, Florida, in the CPS before 2005. We assigned those observations to market group 17, South Florida. Seven states—Arizona, Maine, Montana, New Mexico, North Dakota, South Dakota, and Utah—each fall entirely within a market group. Households in these states were assigned to the market group for their state.

2002-2003: MSA/PMSA Codes

The 2002-2003 December CPS includes information on MSA/PMSA areas that can be matched to FIPS county codes and then to QFAHPD market groups. To assign MSA/PMSAs to county codes, we use output from the Missouri Census Data Center,[27] which offers a cross reference between MSA/ PMSA codes to FIPS counties for all U.S. states. We first match on MSAs; observations that could not be matched to MSAs are then matched to PMSAs. Table A.1.2 shows the frequencies of potential and actual matches for those without FIPS county codes in 2002-03. All observations with MSA or PMSA codes are matched to the QFAHPD.

Many MSA/PMSAs contain more than one county, so we create a vector of FIPS county codes contained in a given MSA/PMSA, which we then match to QFAHPD market groups. For each MSA/PMSA that contains more than one county, we have assigned one county at random to that MSA/PMSA for the purposes of matching to QFAHPD. Our results are not sensitive to the choice of county within an MSA/PMSA assignment.

[25] *Metropolitan Statistical Areas (MSAs and Primary Metropolitan Statistical Areas (PMSAs) were used before 2004 to identify metropolitan geographic areas. Core-based Statistical Areas (CBSAs) have been used for 2004 and later years.*
[26] *This excludes the 6,035 households in Alaska or Hawaii, for which the QFAHPD has no price information.*
[27] *http://mcdc2.missouri.edu/websas/geocorr2k.html.*

2004-2006: CBSA Codes

The 2004-2006 December CPS includes information on CBSAs for some households. Using the same procedure as for 2001-03, we match CBSA areas to FIPS counties and then to QFAHPD market groups. Table A.1.3 shows the results of this initial matching procedure. As table A.1.3 shows, there were 10,120 observations unmatched with this initial procedure. Using the CBSA codes shown in the CPS documentation (Attachment 11, U.S. Census Bureau 2006), we manually matched those not matched in this process to QFAHPD market groups by visual inspection of Current Division and Region maps. Those matches are shown in table A.1.4. At the end of this matching process, there are no observations in 2004-2006 with CBSA data that remain unmatched to the QFAHPD.

Full Sample

Counting all observations that could be matched to market groups by means of FIPS county, MSA/PMSA, CBSA codes, or states gives 177,434 observations: 89,079 matched to FIPS county codes, 45,843 matched by PMSA/MSA codes, 32,705 matched to CBSA codes, and 9,807 matched to state alone. From this matched sample we derive the estimation sample by imposing one further restriction: namely, we limit the sample to households at or below 200% of the federal poverty line. This leaves a final estimation sample of 40,617 households. The market group breakdown of this sample is shown in table A.1.5.

Table A.1.1 TFP-QFAHPD Food Groups

TFP food	QFAHPD food(s)
Whole fruit	Fresh-frozen fruit
	Canned fruit
Fruit juice	Fruit juice
Dark green vegetables	Fresh-frozen dark green vegetables
	Canned dark green vegetables
Orange vegetables	Fresh-frozen orange vegetables
	Canned orange vegetables
All potatoes	Fresh-frozen starchy vegetables
	Canned starchy vegetables
Other vegetables	Fresh-frozen select nutrient vegetables
	Canned select nutrient vegetables
	Fresh-frozen other vegetables
	Canned other vegetables
Beans & legumes	Fresh-dried legumes
	Canned legumes
Whole grains	Whole grain bread, cereal, pasta
	Whole grain flour-mixes
Refined grains	Other grains
	Other flour-mixes
	Other frozen-ready-to-eat refined grins
	Baked good mixes
	Ready-to-eat bakery items
	Packaged snacks
Low-fat milk, yogurt	Low-fat milk
	Low-fat dairy
Whole milk, yogurt	while milk
	Whole dairy
Milk dessert	Frozen desserts
Cheese	Low-fat cheese
	Whole fat cheese
Beef, pork, etc.	Fresh-frozen low-fat meat
	Fresh-frozen regular fat meat
	Canned meat
Poultry	Fresh-frozen poultry
	Canned poultry
Fish	Fresh-frozen fish
	Canned fish
Nuts	Raw nuts
	Processed nuts
Eggs	Eggs
Fats & oils	Oils
	Solid fats
Soft drinks	Carbonated caloric beverages
	Non-carbonated caloric beverages
Sweets	Raw sugar
	Packaged sweets
Frozen entree	Frozen entrees
Soups	Canned soups and sauces

Table A.1.2 Observations Matched by MSA/PMSA

Total (no FIPS, year 2002-03)	60,016
With MSA/PMSA (potential match)	32,705
Actual match	32,705
Unmatched (of potential)	0

Table A.1.3 Observations Matched by CBSA

Total (no FIPS, years 2004-06)	84,180
With MSA/PMSA (potential match)	45,843
Actual match	35,723
Unmatched (of potential)	10,120

Table A.1.4 CBSA's Manually Matched to QFAHPD Market groups, CPS 2004-2006

CBSA	Freq	CBSA name	Market group match
460	31	Appleton-Oskosh-Neenah	Non Metro East North Central
3,000	102	Grand-Rapids	Metro Midwest 1
3,160	74	Greenville-Spartanburg	Non Metro South Atlantic
3,720	13	Kalamazoo-Battle Creek	Metro Midwest 1
6,450	79	Portsmouth-Rochester	Non Metro New England
22,460	82	Florence	Metro South 2
42,260	178	Sarasota-Bradenton-Venice	South Florida
70,750	235	Bangor	Non Metro New England
70,900	87	Barnstable-Town	Boston
71,650	2234	Boston-Cambridge-Quincy	Boston
71,950	702	Bridgeport-Stamford-Norwalk	Hartford
72,400	566	Burlington	Non Metro New England
72,850	97	Danbury	Hartford
73,450	921	Hartford	Hartford
74,500	63	Leominster	Hartford
74,950	41	Manchester	Boston
75,550	11	New Bedford	Boston
75,700	474	New Haven	Other NY
76,450	168	Norwich-New London	Other NY
76,750	737	Portland	Non Metro New England
77,200	2423	Providence-Fall River	Boston
77,350	216	Rochester-Dover	Non Metro New England
78,100	235	Springfield	Boston
78,700	149	Waterbury	Other NY
79,600	202	Worcester	Boston
Total	10,120		

Table A.1.5 Market group Frequencies, CPS 2002-2006

ID	Market group	N
1	Hartford	495
2	Urban NY	1,285
3	Western NY, PA	1,459
4	Philadelphia	1,340
5	Metro Midwest 1	1,844
6	Metro Midwest 2	2,089
7	North Florida	731
8	Metro South 1	1,107
9	Baltimore	445
10	Metro South 2	1,207
11	Metro South 3	852
12	Metro Mountain	1,799
13	Salt Lake City	958
14	Metro California	627
15	Los Angeles	2,510
16	Chicago	1,114
17	South Florida	1,615
18	San Antonio	445
19	Boston	1,908
20	Other NY	1,012
21	Metro Ohio	1,460
22	North Pacific	1,218
23	San Francisco	439
24	Atlanta	482
25	Metro South 4	1,907
26	Washington, DC	1,442
91	Nonmetro New England	743
92	Nonmetro Middle Atlantic	480
93	Nonmetro East North Central	801
94	Nonmetro West North Central	1,327
95	Nonmetro South Atlantic	1,540
96	Nonmetro East South Central	111
97	Nonmetro West South Central	1,643
98	Nonmetro Mountain	985
99	Nonmetro Pacific	1,197
	Total	40,617