Do Food Prices Affect Food Security? Evidence from the CPS 2002-2006

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Abstract:

In this paper, 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. We form a local food price index based on amounts of food for a household of four as established by the Thrifty Food Plan. We use an econometric model that accounts for the endogeneity of SNAP receipt to food insecurity and for household-level unobservables. We find that the average effect of food prices on the probability of food insecurity is positive and significant: an increase of one standard deviation in the price of our food basket is associated with an increase in food insecurity of between 1.3 and 2 percentage points for SNAP households. These results are fairly large in terms of the prevalence of food insecurity in our sample. An increase in food insecurity of this magnitude would be about 8 percent of total food insecurity prevalence for the populations in question. These results suggest that indexing SNAP benefits to local food prices could improve its ability to ameliorate the effects of food insecurity.

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1 Introduction

Food insecurity refers to a family's ability to acquire adequate food for all household members. We know that in developing nations food insecurity increases with food prices(Shapouri et al., 2009). However, food insecurity has not been as closely linked to food prices in the U.S. context, perhaps because the cost of food is low as a proportion of total household expenses, relative to the cost of food in other countries.[1] Nonetheless, it is reasonable to assume that geographic variation in food prices may affect the ability to purchase adequate, healthful food for some low-income households. Indeed, food price variation may explain some regional variation in food security.[2]

Households that rely on SNAP (the Supplemental Nutrition Assistance Program, formerly Food Stamps) may be particularly vulnerable to high food prices. SNAP benefit levels are fixed at the national average costs of market baskets of food items that comprise the Thrifty Food Plan (TFP), a representative diet developed for low-income households by USDA based on dietary guidelines. Annual cost of living adjustments are made to SNAP benefit levels to account for inflation in the cost of food. 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). In areas with higher costs of food, the SNAP benefit allotment may be significantly less than that needed to purchase the Thrifty Food Plan. To the degree that this is true, variation in food prices may affect whether SNAP can ameliorate food insecurity and its effects.

In this paper, 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). We form a local food price index based on amounts of food for a household of four as established by the Thrifty Food Plan and use an econometric model that accounts for the endogeneity of SNAP receipt to food insecurity and for household-level unobservables. Our results suggest that the average effect of food prices on food insecurity is positive and significant: an increase of one standard deviation in the price of our food basket is associated with an increase in food insecurity of between 1.3 and 2 percentage points for SNAP households. These results are fairly large in terms of the prevalence of food insecurity in our sample. An increase in food insecurity of this magnitude would be about 8 percent of total food insecurity prevalence for the population that we study. These results suggest that indexing SNAP benefits to local food prices could improve its ability to ameliorate the effects of food insecurity.

2 Variation in Food Prices and Food Insecurity

Food prices vary considerably across regions within the U.S. Studies have found that food prices are lower in the South and Midwest and higher in the Northeast and West (Leibtag,

[1] See Table 97 in the ERS Food CPI and Expenditures Briefing Room, `http://www.ers.usda.gov/Briefing/CPIFoodAndExpenditures/Data/Table_97/2009table97.htm`

[2] Although there has been no direct examination of the relationship between regional food prices and food insecurity, we do know 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 (Nord, 2009).

2007). This regional variation in food prices can have a meaningful impact on household food budgets. Leibtag (2007) estimates that a family of four in the East or West regions would spend 32-48 dollars more per month on food than the U.S. average, while a family in the South or Midwest would spend 12-28 less per month for comparable food. The variation in food prices paid by region is consistent with variation by region in what households report as the minimum cost of enough food to meet basic needs: Nord and Leibtag (2005) found that the cost-of-enough-food was lowest in the Midwest and South, higher in the Northeast and West.

The hypothesis of this study is that, in regions with high prices, the maximum SNAP benefit will purchase less food and could reduce the ability of the SNAP program to promote household food security. If this is true, we would expect regions with higher food prices to have higher levels of food insecurity. We examine this possibility in tables 1 and 2. In table 1, we show estimates of weekly food prices for a family of four, using data described below, by Census region and year.[3] Table 2 shows rates of food insecurity, also based on our data, by region and year.

The descriptive measures shown in table 1 yield results similar to those of Leibtag (2007): in each year, households in the Midwest and South pay 5-8 dollars per week less than the national family on average, meaning that they pay about 20-32 dollars less per month for food; meanwhile, households in the Northeast and West pay 3-10 dollars more per week for food, meaning they pay between 12-40 dollars more per month for food. We also see that, whereas the Northeast has the highest food prices in these years, it has the lowest rates of food insecurity, as shown in table 2; similarly, the South, whose prices are relatively low compared to the national average, has the highest rates of food insecurity in general. In fact, the simple correlation between household food insecurity and food prices in our data is -.04; moreover, the relationship shown here with respect to census regions also holds with our smaller market groups defined below: there is a small but significant negative correlation between food prices and levels of food insecurity.[4] This suggests the effect of confounding variables–income, among others–that are correlated with both food insecurity and food prices and the need for multivariate models.[5] We describe those models and the results from estimating them below.

3 Data

3.1 Quarterly Food At Home Price Database: Food Prices

We use the Quarterly Food At Home Price Database (QFAHPD) as the source of information about food prices. ERS researchers constructed the QFAHPD from Nielsen Homescan data, which follows households over an entire year and tracks both UPC-coded and random-weight food purchases. Purchases are aggregated into 52 food groups based on the USDA *Dietary Guidelines for Americans* and convenience premiums for certain kinds of processing–i.e. frozen and ready-to-cook. Quarterly prices for these goods are derived for 35 marketgroups: 26 formed on the basis of Neilsen households found in metropolitan (metro) areas, and 9 on the basis of households in nonmetropolitan (nonmetro) areas. Prices for each good are derived from the

[3] Estimates are weighted using Census probability weights.

[4] We do not show this analysis in the interests of space. Results available from the authors.

[5] Adult and child food insecurity also have negative correlations with food prices.

average price paid by households in each market area (Todd et al., 2010). The geography of the QFAHPD market groups is shown in figure 1.

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, by age group. We match QFAHPD categories for 23 of these groups to form the comparable QFAHPD market basket.[6] For our basket, we use the amounts recommended for a family of four, two adults and two children (one 6-8, the other 9-11 years old). The crosswalk between TFP foods and QFAHPD foods is shown in table 3.[7]

To get the price of each TFP food in the market basket, we use an expenditure weighted average of the prices for the QFAHPD foods, where the weights are the fraction of yearly national expenditures in the TFP category for the QFAHPD good. For example, the TFP food 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, respectively, in QFAHPD marketgroup 1 (Hartford) were \$35.7 and \$5.8 million. 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 marketgroups and 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 and canned fruit, respectively, meaning that the price for whole fruit in Hartford for the first quarter of 2002 is $.8391 \times .218 + .1609 \times .244 = \$.222$ per 100 grams, where .218 and .244 are the prices per 100 grams of fresh/frozen and canned fruit in the Hartford marketgroup in the first quarter of 2002, respectively.[8]

3.2 CPS: Geographic Matching

Our data on food security and household characteristics come from Current Population Survey Food Security Supplement (CPS-FSS). This dataset includes information on a rich set of demographics and labor market characteristics for approximately 60,000 households per year and is currently used for benchmark estimates of food security in the United States (Nord et al., 2010). The CPS is especially useful for the current application because it allows geographical matching by state, FIPS county or MSA/PMSA/CBSA codes to the Quarterly Food At Home Price Database.

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,

[6]The remaining 6 TFP groups were not included to 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.

[7]For more on the TFP, see Carlson et al. (2007).

[8]We convert the price per 100 grams into the price for the number of pounds recommended in the TFP by multiplying by .2204622 $\times$ the amount in pounds of a given TFP good.

roughly 60% of CPS household observations in 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.[9]

Before doing any geographic matching, there were 233,275 household observations in the sample.[10]

3.2.1 2001-2003: MSA/PMSA Codes

The 2001-2003 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,[11] which offers a crosswalk between MSA/ PMSA codes to FIPS counties for all US states. We first match on MSAs; observations which could not be matched to MSAs are then matched to PMSAs. Table 4 shows the frequencies of potential and actual matches for those without FIPS county codes in 2001-03. 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.

3.2.2 2004-2006

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 5 shows the results of this initial matching procedure. As table 5 shows, there were 10,120 observations unmatched with this initial procedure. Using the CBSA codes shown in the CPS documentation (Attachment 11) (CPS, 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 6. At the end of this matching process, there are no observations in 2004-2006 with CBSA data that remain unmatched to the QFAHPD.

3.2.3 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. Those were observations with FIPS code 12025, which was the code use for Dade County, Florida in the CPS before 2005. We assigned those observations to market group 17, South Florida. Finally, households not otherwise identified who resided

[9]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.

[10]This excludes the 6,035 households in Alaska or Hawaii, for which the QFAHPD has no price information.

[11]`http://mcdc2.missouri.edu/websas/geocorr2k.html`

in seven states–Arizona, Maine, Montana, New Mexico, North Dakota, South Dakota, and Utah–were identified because their states lie entirely within a marketgroup.

3.2.4 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 by imposing two further restrictions. First, we limit the sample to households that are only observed once or to the first observation of households that are observed twice. We do this to limit problems in estimating time invariant unobservables at the household level. Second, we limit the sample to households at or below 200% of the federal poverty line. That leaves a final estimation sample of 28,719 households. The market group breakdown of this sample is shown in table 7.

3.3 Means of Explanatory Variables

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. Of these, only race could arguably be considered exogenous to SNAP receipt and food insecurity, although race is strongly correlated with other characteristics that might affect food insecurity or SNAP receipt. Among other important variables are those describing human capital–highest level of household education–and labor market status–an indicator of full time employment for any adult in the household. We are interested in these variables because they are strongly related to the financial resources of the household, which we also examine in terms of family income. We additionally are interested in household composition, since that will affect resources that need to be devoted to food acquisition; variables that address this concern include the number of children in the household, number of persons in the household, whether the house is owned or rented, an indicator for a child under 5 in the household, household structure (i.e. marital status), number of elderly persons in the household, and presence of a teen between 15 and 17 in the household. Finally, we are interested in distinguishing the effect of SNAP from other food assistance programs, so we also examine participation in other federal food programs including WIC, school lunch or school breakfast, and head start.

The means of these analysis variables and TFP price are shown in table 8, stratified by food security status. Noteworthy is that the average price of the TFP basket faced by food secure and food insecure homes is essentially identical, even while other important labor market and family composition variables differ. As has been found in other studies, food insecure households are much more likely to receive SNAP. Food secure households have higher income, are more likely to own their home or have someone who has graduated high school in them, are less likely to be single-parent families, and less likely to participate in other food assistance programs. These means confirm the conventional findings about the relationship between food security, SNAP and demographic variables. They also suggest that the relationship between food prices and food security may not be straightforward. We look at multivariate methods of determining the relationship between food prices and food security below.

4 Empirical Strategy

A simple model of the effect of food prices on food security might look something like

$$FS_i^* = X_i\beta + SNAP_i\gamma_1 + TFP\gamma_2 + SNAP \times TFP\gamma_3 + \varsigma_i, \quad (1)$$

where i indexes the household, FS^* represents a latent index of food insecurity, TFP, $SNAP$, and $SNAP \times TFP$ are a food price index, an indicator of SNAP receipt, and an interaction of the two. X is a vector of exogenous variables. As is well understood, food security and SNAP participation are determined simultaneously, and both are likely influenced by factors that are unobserved by the researcher. For a long time, this was an intractable problem for researchers interested in the effect of SNAP on food security. However, recent research has addressed this problem by using a variety of methods, including single- and multi-equation (quasi-) fixed-effect models and multivariate normal models with and without instrumental variables. (DePolt et al., 2009; Yen et al., 2008; Ratcliffe and McKernan, 2010; Wilde and Nord, 2005; Gundersen and Oliveira, 2001; Nord and Golla, 2009).

An additional complication in this context is that the quantity of interest is the marginal effect of an endogenous binary variable (SNAP) interacted with a continuous exogenous variable. Holding aside the problem of the endogenous binary itself, conventional two-stage least squares will not offer consistent estimates of this effect, because the interaction between the instruments (for the endogenous binary regressor) and the continuous variable is not a consistent estimate of this interaction.[12] Nonetheless, it is still possible to use an instrumental variables strategy that does not rely on linear form restrictions or two-stage modeling in this case. We model the decision to participate in SNAP, to be food insecure, and the interaction of SNAP participation and TFP price jointly, estimating the parameters by maximum likelihood; we use policy instruments to identify SNAP participation, and the interaction of policy instruments and TFP price to model the $SNAP \times TFP$ interaction. Our model consists of three equations:

$$\begin{aligned} S_i^* &= X_i\beta + Z_i\gamma + \tilde{\varepsilon}_i & (2)\\ I_i &= X_i\beta + (Z_i \times TFP)\delta + \upsilon_i & (3)\\ F_i^* &= X_i\beta + W_i\theta + \tilde{\varsigma}_i, & (4) \end{aligned}$$

where S^* and F^* are latent variables indicating propensity to participate in SNAP and be food insecure, respectively, and I is the interaction of SNAP participation and TFP.[13] Z are instruments for SNAP participation (discussed below); W is a vector that includes the dollar amount of the most recent SNAP benefits, an indicator of SNAP participation, the price of the market level TFP, and an interaction of these two. X is a vector containing variables about household characteristics, state fixed effects, a linear trend, linear state trends and indicators for other food assistance programs (WIC, school lunch, school breakfast, Head Start Food Programs).[14]

[12] See Wooldridge (2002) pp.477ff on the limitations of linear models for binary endogenous regressors.

[13] As is conventionally done, for the purposes of estimation we assume that S^* and $F^* = 1$ if their respective right-hand-side indexes are greater than zero, and that 0 otherwise.

[14] Household characteristics include race of reference person, number of children in the household, number of

We assume that $\tilde{\varsigma}$ and $\tilde{\varepsilon}$ are correlated, conditional on the instrumental variables, due to the presence of unobserved household heterogenity that is independent of X, Z, and W. Thus, the error terms of the first and third equations have the structure

$$\begin{aligned} \tilde{\varepsilon}_i &= \sum_{c=1}^{C} \pi_c * \eta_c^1 + \varepsilon_i \\ \tilde{\varsigma}_i &= \sum_{c=1}^{C} \pi_c * \eta_c^3 + \varsigma_i, \end{aligned} \tag{5}$$

where η are the latent household effects and π_c constant probabilities; $\sum_{c=1}^{C} \pi_c = 1$. We normalize this distribution to be mean zero, so one point of support in each distribution is identified by

$$\eta_C^j = -\frac{1}{\pi_C} \sum_{c=1}^{C-1} \pi_c * \eta_c^j. \tag{6}$$

We assume that the correlation between $\tilde{\varepsilon}$ and $\tilde{\varsigma}$ is completely accounted for by this distribution; that is, we identify the correlation in the unobservables that contribute to SNAP receipt and food security status by means of this non-parametric error structure. Finally, we assume that, conditional on the estimates of the unobserved heterogeneity in the SNAP and Food Security equations, υ, ε and ς are mutually independent; finally, υ is distributed normally, ε and ς are extreme value (logit).

The contribution to the log likelihood of household i is

$$l_i = ln\{\phi(\upsilon_i; \sigma_I)\{\sum_{c=1}^{C} \pi_c \prod_{i=1}^{N} \Phi(d_i^j(X_i\beta + Z_i\gamma + \eta_c^j))\Phi(d_i^j(X_i\beta + W_i\theta + \eta_c^j))\}\}, \tag{7}$$

where, once again, c, j, and i index points of support in the distribution of latent variables, equations 1 and 3 in the likelihood, and households, respectively; σ_I is the variance of υ and ϕ is the normal density function. We set $d_i^j = 2y_i^j - 1$, to differentiate observations for which the respective variables are 1 ($d = 1$) and 0 ($d = -1$).

This model estimates the correlation between the unobservables in the SNAP and food security equations non-parametrically; we use this approach for two reasons. First, while models employing continuous distributions for unobserved heterogeneity have been fruitful in applications that involve bivariate normals (Yen et al., 2008; Ratcliffe and McKernan, 2010), for this application, the choice of multivariate distribution is less straightforward. The model we employ represents an intuitively plausible simplification of what could be a much more complicated problem. Second, as was first argued by Heckman and Singer (1984), modeling unobserved heterogeneity non-parametrically is preferable if one has any doubts about the distribution of the latent variables: if one uses a parametric form for the latent variable distribution but one's assumptions are incorrect, then the model is misspecified and parameter estimates will be biased.

persons in the household, an indicator for full-time employment by any adult in the household, family income, whether the house is owned or rented, highest level of household education, indicator for a child under 5 in the household, household structure (childless married couple= reference group), number of elderly persons, and presence of a teen between 15 and 17 in the household. The level of TFP prices is also included in the SNAP equation.

Moreover, Heckman and Singer (1984), Mroz (1999), and Deb (2001) have shown that the discrete factor approach for group or person level latent variables is robust in circumstances when the distribution of unobservables is not normal. Finally, these models have been successfully used in a wide variety of contexts, both with and without panel data (Bhattacharya et al., 2003; Meyerhoefer and Pylypchuk, 2008).

Although we view the use of the discrete distribution for the latent factors as important, the strength of these estimates relies on the plausibility of our instruments. We use the following 8 policy instruments to identify participation in SNAP:

1. **Biometric.** An indicator for whether the state collects biometric information (typically a fingerprint image) as a condition of SNAP participation.

2. **Short Recertification Period.** This is the fraction of the state's working households that have to re-certify their eligibility in every 3 months or less.

3. **Ads.** An indicator that any media market in the state had a SNAP media campaign in the year.

4. **Simplifed Reporting.** An indicator for whether the state takes part in a simplified reporting program, which reduces the information that SNAP participants need to provide to DHHS each month. In simplified reporting, SNAP households only need to report changes if their address changes or gross income exceeds a limit that varies by family size.

5. **Expanded Eligibility.** These differ from state-to-state, but most include relaxation of income limits and/or asset tests for SNAP eligibility, or count households who qualify for Temporary Assistance to Needy Families (TANF) as eligible for SNAP.

6. **EITC.** This is the real dollar amount of federal and state EITC money received in the fiscal year.

7. **Transitional Benefits.** This is an indicator variable for whether the state provides transitional SNAP benefits for households that move off of TANF. These benefits can be offered for up to 5 months.

8. **All Vehicle Exemption.** This is an indicator for whether the state exempts all vehicles from asset calculations for SNAP qualifications.

For these variables to be valid instruments, they need to be strongly related to SNAP participation but unrelated to reporting food insecurity except through SNAP. While the first condition can be empirically tested, the second is not empirically verifiable. Since most of the changes in policies increase or decrease the cost of enrolling or participating in SNAP, we think it is reasonable to view them as affecting food insecurity reporting only through SNAP participation, conditional on the other covariates in the model. One concern that might arise is that the policy level variables will be correlated with the general political and cultural environment in the state, which could certainly affect the level of stigma attached to SNAP receipt and the levels food insecurity reported. We expect that these concerns will be addressed by the inclusion of state fixed effects and state linear trends.

5 Results

Before we discuss the results of our previously described preferred model, we present results from a simpler model that addresses the endogeneity of SNAP to food security in an *ad hoc* but still informative way. Table 9 shows the results of the following specification:

$$\{(FS_i^* = X_i\beta + TFP\gamma_1 + \varsigma_i)|SNAP = 1\}, \tag{8}$$

which is our original "naïve" specification, restricted to SNAP households. This model addresses the endogeneity problem by means of a technicality–the SNAP indicator is not on the right hand side of the model. But it is informative because it looks at whether the variation in the TFP has any effect on the likelihood of food insecurity for those households only.

The left panel of the table shows results for households at or below 200% of the federal poverty line (FPL), the right panel for households at or below 150% of the FPL. In each panel the leftmost two specifications show results for all households, and the rightmost three for households with children. The name at the top of each column indicates the food security measure to which the estimates in that column pertain. Household food insecurity is based on the full 18 item food security module, also the basis for most Federal food security statistics. Adult food security is based on the 10 items that refer to food insecurity conditions among adults and provides a more comparable measure of food insecurity for households with and without children. Child food insecurity is based on the 8 items that refer only to food insecurity conditions among children.[15] We show the marginal effects for the most recent SNAP amount (in $) and for the TFP.[16]

There are two characteristics of the results that stand out. First, the SNAP dollar amount has a significant negative effect on the probability of being food insecure in all specifications. These results suggest that an extra $100 in the most recent SNAP benefits would decrease food insecurity between 3 and 4 percentage points. All of these estimates are statistically significant. Second, the effect of the TFP price is positive and significant in seven of the ten specifications; the effect of an increase in the TFP price of ten dollars–a little less than a standard deviation–would be to increase the likelihood of food insecurity by between 3 and 3.7 percent. As we might expect, this effect is stronger for households in the lower income sample.

Table 10 shows the results for our preferred model, once again for households at or below 200% and 150% of the FPL in the left and right panels, respectively. All households are shown in the left two specifications in each panel, and households with children in the rightmost three specifications. For these models, we show the marginal effects of being in SNAP, the most recent SNAP amount, the TFP average effect for the entire sample, and the TFP effect for SNAP households.[17] The table also shows the parameters latent variable distribution, which we estimate with two points of support, as well as F-statistics for tests of the instruments.

Our results for the marginal effect of SNAP on food insecurity are consistent with recent findings that show that SNAP participation decreases the probability of food insecurity (Yen et al., 2008; Ratcliffe and McKernan, 2010; DePolt et al., 2009). The marginal effects are negative for eight of the specifications, and large and significant in three specifications. In the

[15] For more, see Nord et al. (2010).

[16] For all specifications, we use the delta method to compute standard errors.

[17] On the calculation of marginal effects of interactions, see Edward C. Norton and Hua Wang and Chungrong Ai (2004).

specifications in which this marginal effect is not negative, it is small and insignificant. The results indicate that SNAP reduces the probability of child food insecurity for households at or below 200% of the FPL by 13 percentage points. For households at or below 150% of the FPL, SNAP participation reduces child food insecurity by almost 15 percentage points and adult food insecurity in households with children by 14 percentage points.[18]

As in the naïve specification above the effect of the most recent amount of SNAP benefits reduces the probability of food insecurity in all specifications. The effects are smaller–between 2 and 3 percentage points for each $100 in benefits. These estimates are significant in all specifications.

The model suggests that the effect of food prices is fairly large and significant for both the sample as a whole and for SNAP participants. For households at or below 200% of the FPL, the effect of a ten dollar increase in the TFP price would be to increase food insecurity by between .7 and 1.9 percentage points. For SNAP households, the effects are similar: a ten dollar increase in the TFP increases the probability of food insecurity by between 1.3 and 1.8 percentage points. For the 150% of the FPL sample, the effects are larger, as we might expect: a ten dollar increase in the TFP will increase food insecurity by between 2 and 2.7 percentage points, on average; for SNAP households, the effects are similar, with a 10 dollar increase bringing a 1.6-2.0 percentage point increase in food insecurity.

Table 10 also reports the probabilities for each of the points of support of the latent variable distribution. The distributions of latent variables are consistently highly skewed in all specifications except for the household food security models for all households (the leftmost specification in each panel). In all other specifications, with probability above .92, households would draw the first point of support of the SNAP and food insecurity latent variables. The values of those latent variables ($\eta_1^{SNAP}, \eta_1^{FS}$) are negative and small, indicating that these households would be a little less likely than average to receive SNAP and be food insecure. But there is a small probability that households would draw the second value of the random intercept distribution ($\eta_2^{SNAP}, \eta_2^{FS}$): the values of these draws is very large and positive. This indicates that there is a small part of the sample whose latent characteristics imply that they will both participate in SNAP and be food insecure with near certainty.[19]

Finally, we report the F-statistics on the instrumental variables for both SNAP and the SNAP-TFP interaction. Although there is no canonical test statistic for instrumental variables in this kind of model, we note that all of the F-statistics are above 10; as expected, the significance decreases when we reduce the sample size.

6 Discussion

Do food prices affect food security? The question is important because benefits for SNAP–the primary policy defense against food insecurity–are not indexed to local or regional markets,

[18]This estimate is similar to that found by Ratcliffe and McKernan (2010) for household food insecurity. However, it is far larger in relative magnitude: this estimate suggests that SNAP decreases the probability of food insecurity for this population by about one half.

[19]We have also estimated some of these models with three points of support in the latent variable distribution. The results are very similar in meaning to those here. The distribution is quite skewed, with a very small probability of drawing values in the latent variable distribution that imply both SNAP receipt and food insecurity with near certainty. Those results are available upon request.

and yet we know that there is wide variation in food prices across the United States. Holding aside the question of how SNAP benefits might be indexed, we have examined whether there is evidence that local food prices affect levels of food security. Our results confirm our intuition in this case: food prices significantly effect food security for low income households with children. Our results suggest that a 10 dollar increase in the price of the TFP basket will lead to about a 2 percentage point increase in child food insecurity; similar results hold for adult food insecurity measures in households with children. Additionally, our models confirm recent studies that estimate the effect of SNAP on food security is strong, negative and significant, and we find that the dollar amount of SNAP benefits also has a significant effect on the likelihood of food insecurity.

One aspect of our model is the inclusion of household latent effects, which we estimate along with the correlation of unobservables in the SNAP receipt and food insecurity equations of our model. As expected, we find that the unobservables from the respective equations have a strong positive correlation. Additionally, our models suggest that these effects are highly skewed, with a small portion of the population being likely to receive SNAP and be food insecure with certainty. This aspect of the model is intuitively appealing, as it suggests that there are two kinds of households in the survey: the majority, for whom there is some small amount of stigma associated with SNAP receipt and for claiming food insecurity, and a very small minority, who will have no reluctance whatsoever to receive SNAP benefits and are food insecure with certainty.

The marginal effects that we present here indicate that food prices have substantive effects of food insecurity. For example, our results for those at 150% of the FPL suggest that a roughly one standard deviation increase in food prices would increase child food insecurity by 1.7 percentage points, or about 8 percent of the total food insecurity for this subpopulation. (About 21 percent of households at this level of income report child food insecurity.) Results for adults in families with children suggest similar results: one standard deviation price increase would increase food insecurity by 8 percent of the total prevalence for this income group. The results with respect to children are particularly important, since food insecurity among children has been shown to be associated with developmental problems (Cook and Frank, 2008; Rose-Jacobs et al., 2008).

Although we think that these effects are important, we are also aware that the question about just how to index SNAP benefits is both technically difficult and politically sensitive. Especially since SNAP has become such a large part of income assistance to low-income families, any change in how benefits are calculated will likely have effects beyond households' ability to purchase food. These issues, among others, will have to be considered carefully in future research in this area.

7 Tables and Figures

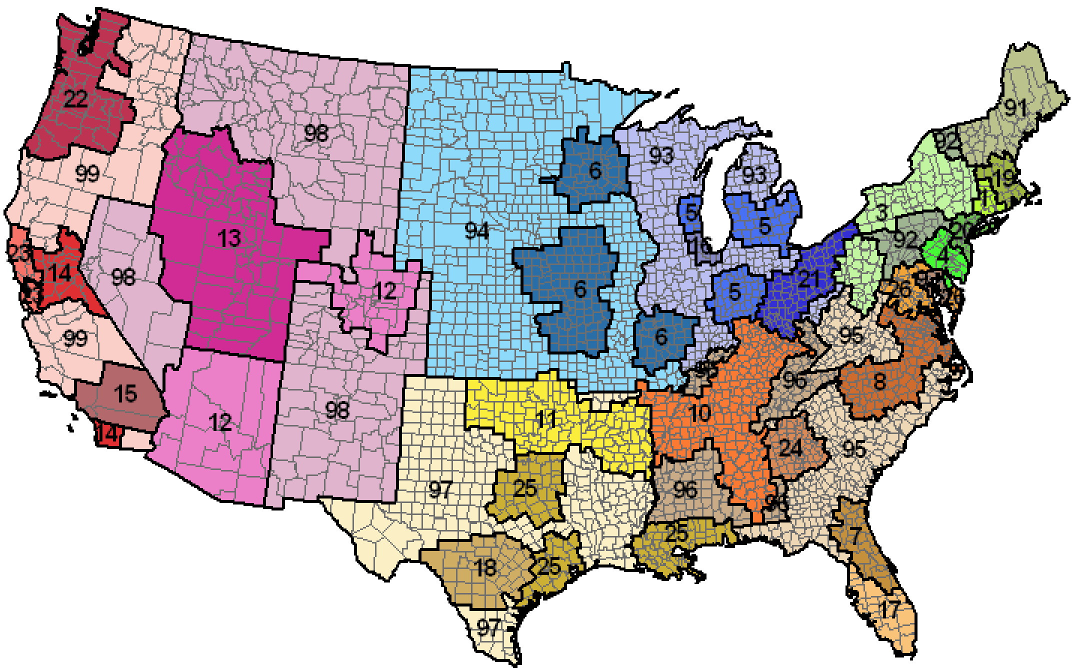

Figure 1: QFAHPD Marketgroups

Table 1: Regional Price Variation: TFP Market Basket ($)

	2002	2003	2004	2005	2006
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
Average	157.84	160.96	165.26	166.60	173.97

Table 2: Regional Variation in Food Insecurity 2002-06

	2002	2003	2004	2005	2006
Northeast	0.094	0.097	0.095	0.089	0.090
Midwest	0.098	0.099	0.112	0.117	0.110
South	0.122	0.121	0.127	0.114	0.118
West	0.119	0.122	0.127	0.106	0.106
Average	0.110	0.112	0.117	0.108	0.108

Table 3: 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 4: Observations Matched by MSA/PMSA

Total (No FIPS, Year 2001-03)	60,016
With MSA/PMSA (Potential Match)	32,705
Actual Match	32,705
Unmatched (of Potential)	0

Table 5: 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 6: Missing CBSA Replacement Marketgroups, CPS 2004-06

CBSA	Freq	CBSA Name	MarketGroup Match
460	31	Appleton-Oskosh-Neenah	Non Metro East North Central
3000	102	Grand-Rapids	Metro Midwest 1
3160	74	Greenville-Spartanburg	Non Metro South Atlantic
3720	13	Kalamazoo-Battlecreek	Metro Midwest 1
6450	79	Portsmouth-Rochester	Non Metro New England
22460	82	Florence	Metro South 2
42260	178	Sarasota-Bradenton-Venice	South Florida
70750	235	Bangor	Non Metro New England
70900	87	Barnstable-Town	Boston
71650	2234	Boston-Cambridge-Quincy	Boston
71950	702	Bridgeport-Stamford-Norwalk	Hartford
72400	566	Burlington	Non Metro New England
72850	97	Danbury	Hartford
73450	921	Hartford	Hartford
74500	63	Leominster	Hartford
74950	41	Manchester	Boston
75550	11	Newbedford	Boston
75700	474	Newhaven	Other NY
76450	168	Norwich-New London	Other NY
76750	737	Portland	Non Metro New England
77200	2423	Providence-Fall River	Boston
77350	216	Rochester-Dover	Non Metro New England
78100	235	Springfield	Boston
78700	149	Waterbury	Other NY
79600	202	Worcester	Boston
Total	10,120		

Table 7: Marketgroup Frequencies, CPS 2002-06

ID	MarketGroup	N
1	Hartford	363
2	Urban NY	968
3	Western NY, PA	918
4	Philadelphia	908
5	Metro Midwest 1	1,303
6	Metro Midwest 2	1,095
7	North Florida	508
8	Metro South 1	740
9	Baltimore	323
10	Metro South 2	854
11	Metro South 3	599
12	Metro Mountain	1,236
13	Salt Lake City	765
14	Metro California	444
15	Los Angeles	1,747
16	Chicago	770
17	South Florida	1,147
18	San Antonio	368
19	Boston	1,322
20	Other NY	667
21	Metro Ohio	1,017
22	North Pacific	847
23	San Francisco	372
24	Atlanta	334
25	Metro South 4	1,353
26	Washington, DC	917
91	Nonmetro New England	419
92	Nonmetro Middle Atlantic	328
93	Nonmetro East North Central	535
94	Nonmetro West North Central	1,370
95	Nonmetro South Atlantic	1,068
96	Nonmetro East South Central	82
97	Nonmetro West South Central	825
98	Nonmetro Mountain	1,389
99	Nonmetro Pacific	818
	Total	28,719

Table 8: Means of Analysis Variables: CPS/TFP 200% FPL

	Food Secure	Food Insecure
TFP	162.952	162.517
	(11.769)	(11.788)
SNAP	0.128	0.356
	(0.334)	(0.479)
Number of Children in HH	0.814	1.221
	(1.236)	(1.401)
Number of Persons in HH	2.589	2.943
	(1.678)	(1.789)
Non-Hispanic Black	0.164	0.248
	(0.371)	(0.432)
Hispanic	0.187	0.239
	(0.390)	(0.426)
Other Race	0.052	0.049
	(0.222)	(0.217)
Family Income (000's)	17.339	15.489
	(10.023)	(9.646)
Home Owned	0.459	0.289
	(0.498)	(0.453)
HS Graduate	0.802	0.753
	(0.398)	(0.431)
Child Less Than 5 in HH	0.183	0.248
	(0.387)	(0.432)
Single Parent	0.143	0.277
	(0.350)	(0.448)
Single Male	0.117	0.112
	(0.322)	(0.315)
Single Female	0.223	0.156
	(0.416)	(0.363)
Teen in HH	0.098	0.146
	(0.297)	(0.353)
Number of Elderly in HH	0.375	0.149
	(0.616)	(0.418)
Someone in HH Full Time	0.496	0.493
	(0.500)	(0.500)
School Lunch	0.148	0.340
	(0.355)	(0.474)
School Breakfast	0.104	0.253
	(0.305)	(0.435)
Food @ Head Start	0.028	0.067
	(0.166)	(0.250)
WIC	0.069	0.127
	(0.253)	(0.333)
Most Recent SNAP Amount[1]	202.472	199.204
	(130.271)	(130.140)
N	28,719	

[1] Conditional on receiving SNAP Benefits.

Table 9: Marginal Effects: Fully Interacted Model[1]

	200% FPL					150% FPL				
	All Families		Families with Children			All Families		Families with Children		
	Household	Adult	Child	Adult	Household	Household	Adult	Child	Adult	Household
SNAP Amount	-0.0003***	-0.0004***	-0.0003***	-0.0004***	-0.0003***	-0.0003***	-0.0004***	-0.0003***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
TFP	0.0029*	0.0030**	0.0033*	0.0026	0.0025	0.0031**	0.0034**	0.0037**	0.0033*	0.0029
	(0.0015)	(0.0015)	(0.0017)	(0.0019)	(0.0019)	(0.0016)	(0.0016)	(0.0018)	(0.0019)	(0.0019)
N	5,193	5,193	3,349	3,349	3,349	4,788	4,788	3,059	3,059	3,059

[1] Results fully-interacted models of food insecurity conditional on TFP prices. Specifications include household characteristics, a linear trend, state fixed-effects, a state linear trend, and a vector of indicators for participation in school lunch, school breakfast, WIC, and food programs associated with Head Start. Household characteristics as specified in text. Marginal effects shown for most recent amount of SNAP benefits and market TFP price. Standard errors in parenthesis.

Table 10: Marginal Effects: IV Discrete Factor Model[1]

	200% FPL					150% FPL				
	All Families		Families with Children			All Families		Families with Children		
	Household	Adult	Child	Adult	Household	Household	Adult	Child	Adult	Household
SNAP	-0.0373	0.0122	-0.1328**	-0.1093	-0.1251	0.0059	-0.0418	-0.1467**	-0.1413**	-0.1554
	(0.0704)	(0.1079)	(0.0591)	(0.0776)	(0.0805)	(0.0383)	(0.1131)	(0.0717)	(0.0660)	(0.6034)
SNAP Amount	-0.0002***	-0.0004***	-0.0002***	-0.0003***	-0.0003***	-0.0000	-0.0004***	-0.0003***	-0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
TFP	0.0007*	0.0014**	0.0014*	0.0018**	0.0019**	0.0001	0.0021**	0.0020**	0.0027**	0.0026
	(0.0004)	(0.0005)	(0.0007)	(0.0008)	(0.0009)	(0.0005)	(0.0008)	(0.0009)	(0.0011)	(0.0026)
SNAP × TFP	0.0008	0.0013*	0.0016**	0.0017**	0.0018**	0.0008	0.0016*	0.0017**	0.0020**	0.0021
	(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0077)	(0.0008)	(0.0008)	(0.0008)	(0.0017)
π_1	0.696	0.969	0.997	0.994	0.992	0.413	0.935	0.992	0.991	0.926
π_2	0.304	0.031	0.003	0.006	0.008	0.587	0.065	0.008	0.009	0.074
η_1^{SNAP}	-0.597	-0.071	-0.063	-0.096	-0.187	0.001	-0.119	-0.150	-0.158	-0.167
η_2^{SNAP}	1.365	2.229	18.535	17.038	22.799	-0.001	1.729	19.362	18.215	2.083
η_1^{FS}	-0.633	-1.011	-2.929	-0.135	-0.126	-3.470	-2.213	-0.017	-0.115	-0.224
η_2^{FS}	1.445	31.897	863.548	23.833	15.420	2.438	32.052	2.207	13.238	2.802
F_{SNAP_IV}	15.97	17.58	13.27	12.78	12.00	15.25	15.40	13.48	13.82	12.50
F_{INT_IV}	18.39	18.39	12.03	12.03	12.03	15.18	15.18	10.96	10.96	10.96
N	28,719	28,719	12,470	12,470	12,470	20,444	20,444	8,827	8,827	8,827

[1] Results from 3 equation IV discrete factor specification; all equations include household characteristics, a linear trend, state fixed-effects, a state linear trend, and a vector of indicators for participation in school lunch, school breakfast, wic, and food programs associated with Head Start. Household characteristics as specified in text. SNAP and SNAP interaction equations include instrumental variables as specified in text. Food security equation includes a vector of SNAP variables including an indicator of participation, the amount of benefits, market TFP price and SNAP × TFP interactions. Standard errors in parenthesis.

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