Will Fixing Disparities in Food Access Reduce Health Inequity?

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Abstract

I document differences in produce consumption across low and high socioeconomic status (SES) households using a large nationally representative panel. I show that the differences are great enough to be major contributors to disparities in diet-based diseases across SES. I argue that the efficacy of public health policies aimed at improving health disparities by improving access to retailers that offer healthy foods can be gauged by measuring the impact that shifting households' shopping frequency curve has on fresh produce consumption. I estimate a household-level random effects model of households' joint decision of shopping frequency and produce consumption using an instrumental variables approach. The model is a coupled dynamic system that allows me to decompose SES-produce consumption disparities into direct SES effects and indirect SES effects through shopping frequency. I conclude that the indirect effects are not substantial enough to motivate policy intended to reduce health inequity across SES by reducing disparities in access to food retailers that offer healthful food.

Poor people die younger and suffer more from diet-based diseases than rich people (Deaton, 2002). The same is true for other disadvantaged demographic groups such as those with low education attainment and of a minority race (Banks et al., 2009). This has motivated a large policy-relevant literature that serves as a foundation for food-based progressive social programs. Yet, the causes of the socioeconomic status (SES)-health gradient remain not well understood.

Table 1
Percent Men (Aged 55-64) with Select Diet-Based Diseases and SES-Disease Gradients

	Low Income			High Income			***Income Gradient***	
Education	Low	High	***Gradient***	Low	High	***Gradient***	Low	High
Diabetes	23.2	15.2	***-8.0***	8.1	11.0	***2.9***	***-15.1***	***-4.2***
Hypertension	54.5	40.9	***-13.6***	41.9	41.6	***-0.3***	***-12.6***	***-0.7***
Heart Disease	26.7	17.8	***-8.9***	12.8	14.8	***2.0***	***-13.9***	***-3.0***

Note: Adapted from Banks et al. (2009), Table 10.1. Low (high) income refers to the poorest (richest) tercile. Low (high) education indicates less than 12 years (more than 13 years) of schooling. Observe that SES-gradients are steepest in both directions for those with both low income and education attainment.

Building on the observations that SES is positively correlated with (i) health, (ii) food retail access, and (iii) food choice, one hypothesis is that food market failure in low SES communities (Bitler & Haider, 2010) is a major contributing cause of the SES-health gradient. This hypothesis is maintained particularly by public health experts who are not in the habit of conceptualizing supply-side market conditions as equilibrium outcomes. Under their view—that retail presence is exogenous with a strong causal effect on household food decisions—the market can be corrected and community health outcomes can be ameliorated by inducing healthful food grocers to enter "underserved" communities. Such reasoning is the rationale for the $400 million Healthy Food Financing Initiative (HFFI) that was enacted in 2011 (Barnes, 2010). The HFFI aims to improve community health by inducing more supermarkets to enter areas with low SES and poor community health (i.e. food deserts).

In light of no obvious market failure and standard economic theory that says that store density is determined by consumer demand (Salop, 1979), economists have been critical of this view. Simply put, if demand for healthful foods is meager in disadvantaged SES areas and nonresponsive to the presence of retailers, then observed associations between food choice and retail landscapes will be caused entirely by consumer behavior and not retail decisions. Indeed, there is much evidence to suggest that demand for healthful foods is relatively nonresponsive to exogenous changes in retail environments (e.g. Cummins et al., 2014; Atkins, 2013).

As a consequence, many econometricians have been careful to account for the endogeneity of the food retail landscape when studying the relationships between health and the food retail landscape. Results have been mixed and complicated. For example, Dunn (2010) finds that an exogenous increase in fast food restaurant density does not generally cause an increase in obesity rates in rural community, but does increase the BMI of women and non-white consumers in medium-density communities. Courtemanche & Carden (2011) find that exogenous increases in Walmart Supercenters cause a large increase in BMI.

While Dunn's and Courtemanche & Carden's studies represent a substantial advance beyond descriptive analysis, their work does not address the mechanisms through which health benefits are mediated. For example, it could be that Walmart Supercenters make less healthful diets more attractive to consumers through prices and variety (Hausman & Leibtag, 2007) or through decreased shopping frequency that makes storing healthful perishable food difficult. But it could also be the case that obesity levels rise through unconsidered ways such as labor market mechanisms. In an important study, Volpe, Okrent & Leibtag (2013) address indirect possibilities by measuring the impact of supercenters on the healthfulness of grocery purchases and find that supercenters have a negative impact on the healthfulness of food baskets.

In this paper I take this line of inquiry a step further and in a slightly different direction by measuring the effect that *shopping more frequently* has on food choices and how differences in shopping frequency interact with SES. This is an improvement on other studies that proxy for store use (i.e. shopping frequency) by using built environment variables (e.g. store densities). Additionally, physical ounces are used in the analysis that follows as the unit of measurement as opposed to expenditures (cf. Volpe, Okrent & Leibtag, 2013), allowing for the measurements that do not confuse increased expenditures for increased consumption as opposed to higher quality or prices (Aguiar & Hurst, 2005; Kuchler, 2011). Finally, microeconometric analysis is performed on a large data set controlling for household level heterogeneity.

I focus on fresh fruits and vegetables in the analysis for three reasons.[1] First, produce consumption is consistently and strongly positively associated with better health outcomes in meta-analysis studies. Longitudinal (cohort) studies with a combined sample size of 833,000 participants find a 5% reduction in mortality rates from all causes and a and 4% reduction in heart disease for each 1 serving per day increase in fruit and vegetable consumption (Wang et al., 2014). Those that consume fewer than 3 servings of fruits and vegetables per day are 35% more likely to suffer a stroke than those that consume at least 5 servings (He et al., 2006). Controlled experiments and observational studies consistently conclude that produce consumption markedly lowers blood pressure and reduces rates of hypertension (Bazzano, 2006). A one serving increase in fruit or vegetable consumption reduces the relative risk of type 2 diabetes by 7% or 10%, respectively (Li et al., 2014). Finally, analysis of the Nurse's Health Study found that after controlling for an array of factors, those in the highest quintile of increased fruit and vegetable consumption had a 24% lower risk of becoming obese—a condition associated with a myriad of diet-based diseases—after 12 years compared to those in the lowest quintile (He et al., 2004).

[1] Constructing aggregate measures of the healthfulness of household food baskets is difficult. Two recent studies notably advance that effort by creating indexes of aggregate food basket healthfulness (Chen, Jaenicke & Volpe; Volpe, Okrent & Leibtag, 2013). I opt for the more traditional measure, however, because the newly created indexes are not easily related to familiar quantities and link to health outcomes.

Second, produce consumption is by far the most common food group used in epidemiological dose-response and retail food environment[2] studies, making results from this study applicable to the results in a large body of literature.

Third, studies in the food dessert literature argue that low SES households have limited or no access to healthful food baskets primarily with fresh produce in mind.

The rest of the paper is organized as follows. The next section introduces the data. Section 2 describes disparities in produce consumption across SES, and illustrates that those disparities are substantial enough to be major contributors to the SES-health gradient. Section 3 presents the econometric approach that will be used to disentangle demographic factors and to decompose produce consumption into direct effects and indirect effects through shopping frequency. Section 4 presence econometric results. Section 5 concludes.

1. Data

The primary data used in this analysis come from Nielsen Homescan data, years 1998-2006.[3] Homescan households are given barcode scanners similar to those used by retailers to record their grocery purchases. Households are instructed to record all their food at home (FAH) purchases that contain bar codes. A subset of the Homescan households belongs to the Fresh Foods Panel. These households record *all* their FAH purchases including “random weight” purchases that need to be recorded manually because they do not contain (scannable) barcodes. Only Fresh Food Panel households are used in the analysis in this paper. At any point in time there are between 8,000 and 15,000 households in the sample, with a mean participation length of 3½ years. The data include detailed demographics, product characteristics, store descriptors, and the date of purchase.

Households with heads aged 55 or greater are excluded from the sample for two reasons. First, retired consumers have dramatically different purchasing and eating patterns compared to those not retired because retirement frees them to engage in cost saving household production (Aguiar & Hurst, 2005). Second, retired households likely severely under-report Social Security and other non-wage income which would result in estimation bias and muddy conclusions about the effects of income.

Care has been taken to construct (physical) quantity measures since the health impact of produce consumption is a function of the consumed mass, not the price, per se.[4] Quantities are aggregated to the household-month level for econometric analysis. Homescan data is used to construct Fisher ideal price indexes for select food groups used in the analysis. All prices are deflated by BLS’s urban consumer non-food price index.

Household shopping frequency is a crucial variable in the analysis since it represents the extent to which households access retailers. Since policies are particularly concerned with

[2] *At least* 24 studies use fresh produce as a proxy since 2003.
[3] More recent years are available, but are not of use due to problems with quantity variables.
[4] This avoids introducing measurement error stemming from quality adjustments such as organic status (Kuchler, 2011).

access to food retailers that offer fresh produce, only shopping trips to store formats that customarily carry fresh produce are included in the calculation of shopping frequencies. E.g., convenience stores are not included in the calculation.[5] Econometric analysis will make use of household-month average shopping frequency.

Census County Business Pattern (CBP) data of retail store densities (per 1,000 residences) [6] are matched to households and used as controls for food retail environmental (FRE) effects that extend beyond a household's use.[7] Summary statistics are reported in Table 2.

National Oceanic and Atmospheric Administration's (NOAA) "Storm Data" is used as an instrumental variable for shopping frequency. These data are severe weather event records that are likely to affect the likelihood of going shopping. Events are counted and aggregated within county-months, and matched to households-months.[8]

Table 2
Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max
Nielsen Homescan				
Shopping Cycle (*T*)	5.01	3.44	1	29
Produce	5.15	5.24	0	32
FAH[a]	21.76	11.69	0	50
Fresh share	0.20	0.15	0	1
Gas price	1.27	0.30	0.82	2.28
FAFH[b] price	1.00	0.012	0.97	1.03
Produce price	0.97	0.072	0.78	1.15
Other food price	0.93	0.038	0.85	1.02
NOAA Severe Weather Events (Month-County)				
Bad weather	2.92	6.33	0	415
Census Food Retail Densities per 1000 People (County)				
Supermarkets	0.21	0.074	0	0.5
Supercenters+clubs	0.0063	0.0045	0	0.02
Convenience	0.32	0.12	0	0.6
Fast Food Restaurants	0.63	0.16	0	1
Full Service Restaurants	0.63	0.14	0	1

Notes: [a] Food at Home. [b] Food Away From Home. Observations with *Shopping Cycle* > 29, *Fresh* > 32 or *FAH* > were omitted.

[5] But purchases from all store formats are included in the calculation of purchase quantities.
[6] Analysis with store densities per square mile produced similar results.
[7] For example, Hausman & Leibtag (2007) find that Walmart supercenters have a dramatic effect on prices of competing stores
[8] Other aggregation methods were tried such as weighting weather events by the time of day and day of week they occurred according to the likelihood that households shop at time-day as found in the American Time Use Survey. However, doing so did not improve the performance of the instrument.

2. Descriptive Analysis of SES Gradients

In this section I provide graphical evidence of various SES gradients. Statistics calculated from Homescan data are weighted according to Nielsen provided population weights. These weights are based on household demographics and designed to be used for the construction of national statistics.

SES-Produce Gradients

If SES-health gradients are driven at least partially by food choices, and fresh produce consumption in particular, then SES-produce gradients are likely to mimic SES-health gradients. Of course, SES factors are correlated. Conditional correlations will be reported later.

Fresh produce purchase amounts are concave and increase (nearly) monotonically in income. Households with extremely low income buy less than 2.5 oz. per person-day while households with incomes of $85k/yr. or greater purchase 4 oz./person-day.[9]

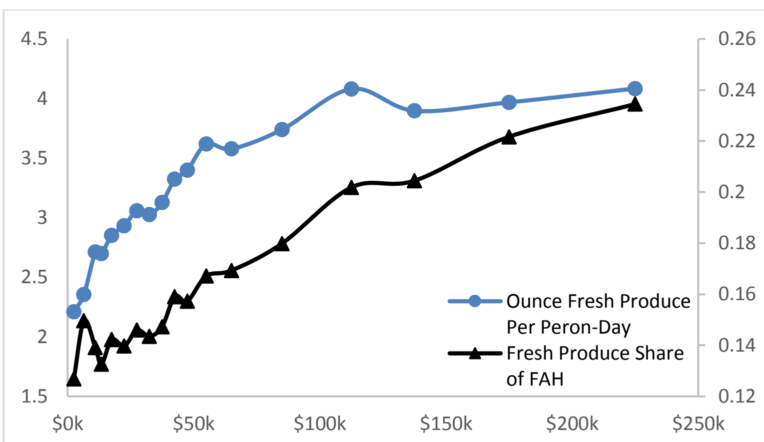

Figure 1. Income-Produce Gradient

From Nielsen Homescan years 1998-2006. Means are calculated using Nielsen provided weights. Error bars represent 95% confidence intervals. Only jointly headed households are considered with both heads aged no older than 55.

These differences may be an artifact of higher income households purchasing more of *everything* (Attanasio & Pistaferri, 2016). However, fresh produce accounts for a higher share of high income households' FAH baskets as well. Fresh produce is more than 20% of purchased FAH of households with incomes above $100k/yr., but below 15% of households with incomes below $50k/yr. (on an oz./oz. basis). Interestingly, produce share of FAH of the poorest

[9] Ounces are the chosen unit of measurement because I suspect the intended audience is less familiar with measuring food in metric units. 1oz. = 28 g.

households with incomes less than $7k.yr. is greater than that of households with incomes between $11-$35k/yr., perhaps reflecting the impact of SNAP.[10]

Household heads—both male and female—with higher education attainment purchase more fresh produce. Dual headed households with either head having graduate school experience purchases 4.5oz./person-day, while those with only a high school diploma purchases 2.7. A common finding in the medical literature is that female—but not male—education level is an important predictor of diet quality. Interestingly, the pattern in Figure 2 suggests that gender differences occur only at the lowest level of education attainment. Even among jointly headed households, the biggest jump in produce purchases is between households with female heads that graduated from high school and those that did not. The same jump is missing for male heads.

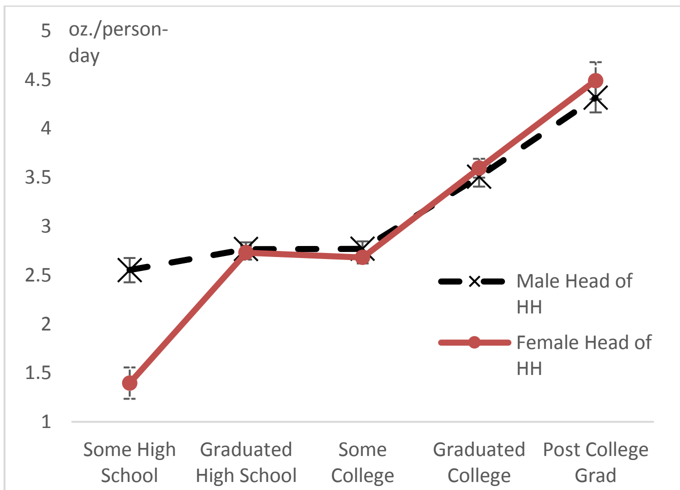

Figure 2. Education-Produce Gradient

From Nielsen Homescan years 1998-2006. Means are calculated using Nielsen provided weights. Error bars represent 95% confidence intervals. Only households are considered with both heads aged no older than 55 to avoid retirement behavior.

Steep produce gradients exist across races and ethnicities. Asian-Americans purchase the most fresh produce (5.2 oz./person-day), followed by white (4.8 oz./person-day), and African Americans (3.4 oz./person-day). Non-Hispanics purchase more than Hispanics (4.7 oz./person-day vs. 4.0 oz./person-day).

[10] Slightly wealthier households that also qualify for SNAP have the lowest produce share of all households. This reflects the difference between inframarginal SNAP households and those that finance all their FAH expenditures through SNAP (Beatty & Tuttle, 2014).

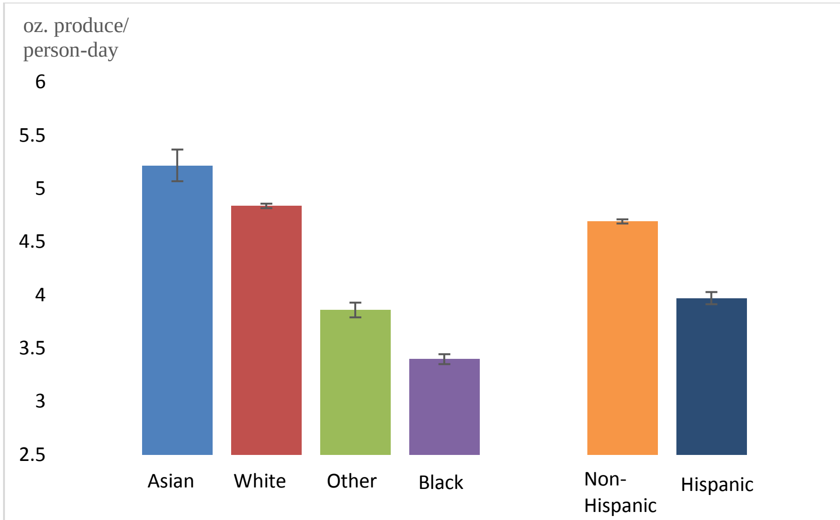

Figure 3. Race-Produce Gradient

From Nielsen Homescan years 1998-2006. Means are calculated using Nielsen provided weights. Error bars represent 95% confidence intervals. Only jointly headed households are considered with both heads aged no older than 55.

In summary, the differences in fresh produce consumption across demographic groups are consistent with the SES-disease gradients reported elsewhere (Table 1).

Food Retail Environment (FRE)-Produce Gradient

The variance of food retail store densities across counties is great enough to cause differences in consumers' access to healthful foods. Consistent with the FRE hypothesis, households in counties with higher densities of supermarkets purchase more fresh produce (Figure 4). Consistent with findings that supercenters have a negative impact on the healthfulness of purchased food baskets (Volpe et al., 2013), households in counties with higher densities of supercenters and club stores purchase less fresh produce. Convenience stores are associated with decreased produce consumption. Finally, higher densities of both full service restaurants and fast food restaurants are associated with more fresh produce purchases. This is consistent with both fresh produce and food away from home (FAFH) being normal goods.[11]

[11] Similar patterns are found using fresh produce share.

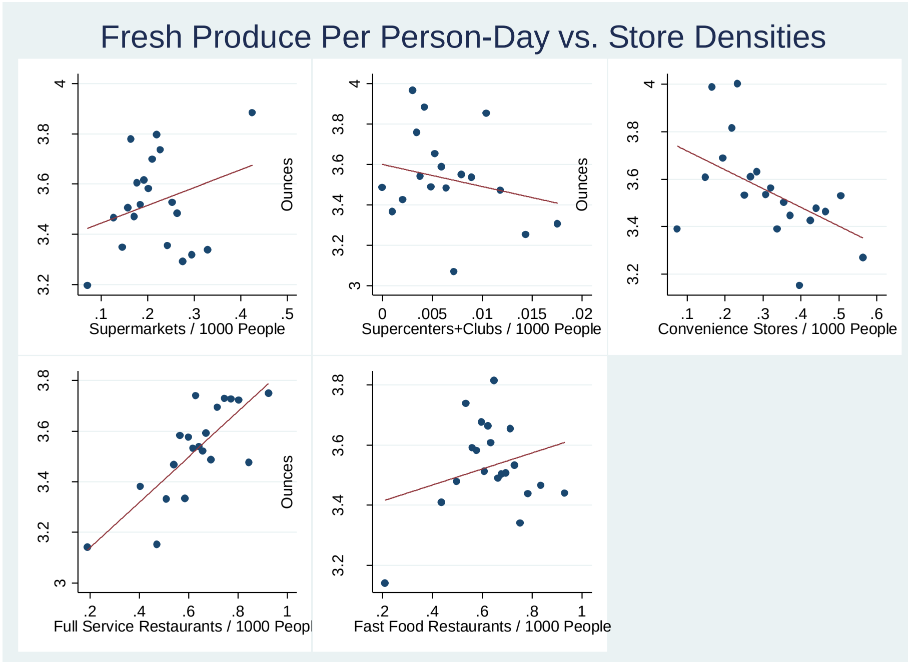

Figure 4.

Note: Calculated from the user-created Binscatter program. Plotting households individually would have completely blackened the plotting region. Instead, dots that represent thousands of households are created. Trend lines are unaltered by binning observations.

SES-Food Retail Environment (FRE) Gradient

Supermarket access has been targeted as a possible key factor affecting FAH diet quality and related health outcomes: more access, better diet and health. Specifically, lack of access has been identified as a possible key factor driving SES-health outcomes (Bitler & Haider, 2010). However, results have been mixed (see. Colby, 2015b).

Homescan panelists with higher incomes live in counties with *fewer* supermarkets per capita.[12] A $10k gain in average household income is associated with a 0.4% decrease in store density (Figure 5). Supercenter and club store density is also decreasing in income, but to a much lesser degree.

[12] Stores per square mile were examined as well. The demographic patterns remained the same.

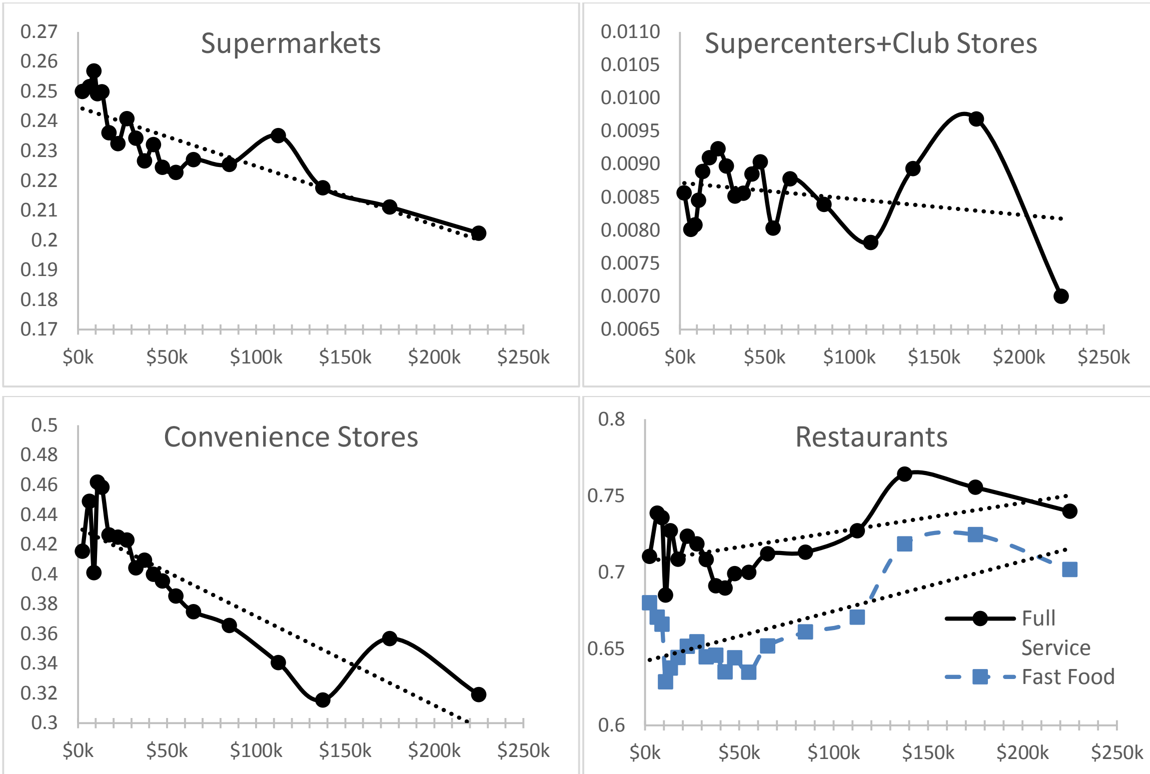

Figure 5. Retail Densities by Income

From Nielsen Homescan years 1998-2006. Densities are in units of restaurants per 1,000 people in the county.

Households with higher incomes tend to live in counties with greater restaurant density, reflecting FAFH being a normal good (McCracken & Brandt, 1987). Importantly, both fast food and full service restaurant density increase with incomes. This is notable because fast food restaurants have been targeted as possible causes of high obesity levels in poor neighborhoods (Hilmers et al., 2012) with the rationale that the inexpensive calories that fast food restaurants offer are especially appealing to low income households (Drewnowski, 2009). Most studies that draw that conclusion, however, are of limited geographic scope or consider limited contexts (e.g. Kwate & Loh, 2010; Bodor et al., 2010), and therefore unlikely to pick up national trends.

Shopping Frequency-Produce Gradient

Improving access to stores that offer healthful foods has become a major strategy for reducing SES-health gradients (Barnes, 2010). Such efforts are predicated on presumption that as the fixed costs of visiting such stores decreases, nearby households will access those stores more frequently, and purchase higher quantities of healthful foods such as fresh produce.

Indeed, households that shop more frequently do purchase higher quantities of produce both in terms of ounces/person-day and household food at home (FAH) basket share (Figure 6). Households that shop on average every other day purchase 5.7 oz./person-day accounting for

20% of their FAH baskets' weight. Those that shop once every ten days purchase 2.7 oz./person-day accounting for only 17% of their FAH baskets' weight.

The lower FAH basket share values are important for two reasons. First, it gives a strong indication that lower levels are not entirely from increased FAFH occasions. Second, it hints at a hidden cost associated with purchasing fresh produce that is decreasing in shopping frequency. Consider a household that shops less frequently. If they try to maintain their former high daily levels of fresh produce consumption, they will face greater food loss from deterioration as they attempt to smooth their consumption over the longer time period between shopping trips (Colby, 2015a).

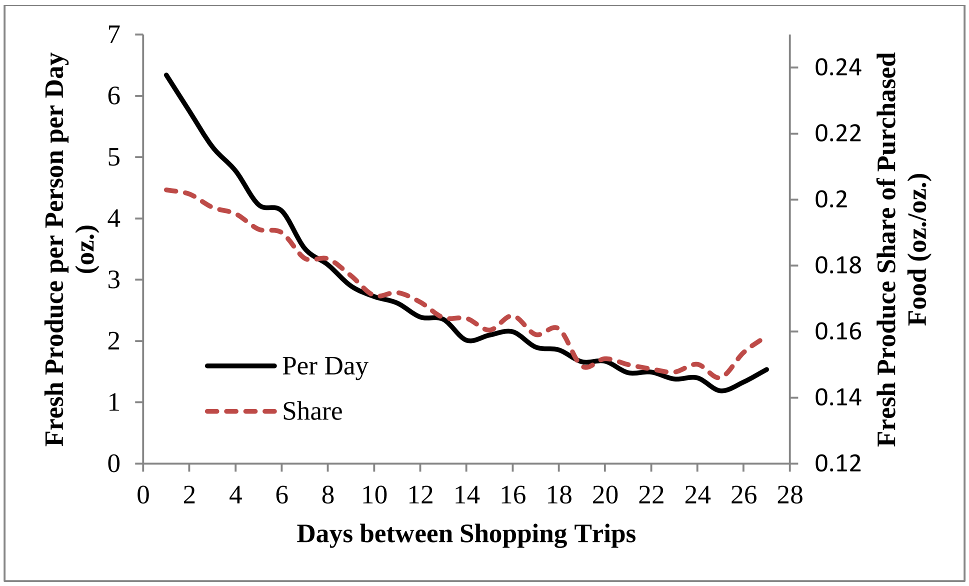

Figure 6. Fresh Produce Consumption vs. Shopping Cycle Length
Note: Author's calculation using the Fresh Food Panel of Nielsen Homescan, 1998-2006.
Trips to convenience stores is not considered since they typically do not carry produce.

Discussion of Descriptive Analysis

The gradients calculated above provide an opportunity to gauge SES-produce gradients' contribution to the SES-health gradient. Household members with the lowest income consume ~1.25 oz. less fresh produce than high income household members. 1.25 oz. corresponds to a third of a serving; an income-produce gradient corresponding to a 1.33% greater chance of death from heart disease per year (Wang et al., 2014), a 3% higher risk of type 2 diabetes (Li et al., 2014), and a 4.5% higher rate of obesity (using estimates from He et al., 2004). Similar differences in health outcomes result from calculations across education levels and racial differences.

These figures correspond to significant contributions to the SES-health gradient. The diabetes consequences of the income-produce gradient corresponds to 41% of the income-diabetes gradient reported in Banks (2009). Similarly, the education-produce gradient between households with females heads who did not complete their high school education and those that completed college accounts for 50% of the education-heart disease gradient. While these rough estimates should be judged with caution, they provide convincing support to the hypothesis that the SES-produce gradient is an important contributor to the SES-health gradient.

The FRE-produce gradients seem less promising as a major contributor to health disparities. While differences between the produce consumption of low and high quartiles of income and education are on the scale of 1-2 oz./person-day, the differences between low and high quartiles of FRE densities are on a scale of 0.2 oz./person day.

However, shopping frequency-produce gradient suggests that if consumers are not only in the vicinity of stores that offer healthful food options, but also *access* the stores, then diets may be ameliorated. Households that shop twice per week purchase 1.5 oz./person-day more produce than households that shop once per week: a difference that is greater the income-produce gradient between high and low income households that we considered above. Conclusions about the effect of shopping frequency on consumption patterns ultimately must be based on sound econometric analysis that accounts the possibility of the arrow of causation pointing in the other direction: high produce demand will cause higher shopping frequency.

As a final note, given that both supermarket density and income are both positively associated with high produce consumption, it is surprising that supermarket densities are lower in counties with high income panelists.[13] This illustrates the danger of reading too far into binary correlations between food retail access, demographics, and food choices. I now turn to more thorough analysis.

3. Econometric Analysis

Analysis is performed on monthly household data. Aggregating up to the month level avoids difficult to model inventory dynamics that are not of interest, and problems stemming from zero demand.

Econometric Model

Since households jointly decide when to shop and what to buy, shopping frequency and fresh produce per person-day will be jointly estimated in a two-equation system,

[13] Recall, correlation is not a transitive relation.

$$T_{nt} = \gamma^T T_{nt-1} + \lambda^T Produce_{nt} \xi^T \cdot \mathbf{r}_{nt} + \delta^T \mathbf{D}_n + \beta^T \cdot \mathbf{p}_{nt}^T + \varphi w_{nt} + \tilde{u}_{nt}^F \tag{1}$$

$$Produce_{nt} = \gamma^F Produce_{nt-1} + \lambda^P T_{nt} + \xi^P \cdot \mathbf{r}_{nt} + \delta^P \mathbf{D}_n + \beta^P \cdot \mathbf{p}_{nt}^P + \tilde{u}_{nt}^P, \tag{2}$$

where *n* is a household identifier, *t* denotes month, T_{nt} is the average number of days between household *n*'s shopping trips in month *t*, $Produce_{nt}$ is oz./person-day that household *n* purchased in month *t*, is the **r** is a vector of food retail environment variables, **D** denotes a vector of demographics, $\mathbf{p}_{nt}^i$ are vectors of prices, and $\tilde{u}_{nt}^i$ are error terms.

$Produce_{nt}$ in equation (1) and T_{nt} in equation (2), respectively, are endogenous. I take an instrumental variables approach. I use a measure of severe weather, w_{nt}, and lagged *T* as instruments for *T*. I use the price of "other food" and lagged *Produce* as instruments for *Produce.* These instruments pass overidentification, underidentification, and weak instrument tests in a companion paper using fixed effects models of shopping frequency and produce consumption (Colby, 2015b).

The panel is unbalanced with households entering and exiting at varying times. The average duration of panel membership is 39 months. Some (but not many) households enter, exit, and reenter. Let *n* = 1,…,*N* denote households; *t* = 1,…,*T* denote time periods; T_n denote the number of periods that household *n* is in the panel; and $M = \sum_{n=1}^{N} T_n$ denote the total number of observations.

I estimate a two-way error components model with $\tilde{u}_{nt} = \alpha_n + \psi_t + \nu_{nt}$ where α_n, ψ_t, and ν_{nt} are unobserved and independent of each other. It is not assumed that $Cov(\mathbf{x}_{it}, \psi_t) = 0$ so that ψ_t cannot be treated as purely random. Instead, each ψ_t is treated as a fixed effect and is estimated directly using a dummy variable. This does not present a problem for estimation because there are no variables of interest that are invariant *across* households, and *T* = 108, which represents a relatively small reduction in degrees of freedom. With time-invariant demographic variables being of primary interest, a similar approach cannot be taken with respect to α_n. To accommodate heterogeneity of unobserved household-specific effects, α_n is treated as a random variable.

The following six assumptions are made. (i) The expected household-specific effects do not depend on demographic or other conditioning variables. This assumption must be made because time-invariant demographic effects are of primary interest, but unobserved household-level effects are sure to vary across households. For example, taste receptors on the tongues of households vary from household to household (Chen et al., 2009; Wooding et al., 2004) and this variation is not likely to be strongly correlated with demographic effects. However, other behavioral factors such as determination to eat a healthful diet and education attainment *are* likely to be correlated making this assumption questionable. For example, a Hausman test in Colby (2015b) finds that a fixed effect model is preferred. However, that result was driven by the large sample size that makes the relative efficiency gains from a random effects model small. Indeed, estimates of coefficients on overlapping variables in both a fixed effect and random effects models are very similar. (ii) Conditioning variables do not affect the dispersion of the household-specific level parameter of similar households. That is to say, the variation among demographically-identical groups does depend on the demographics of the group. For example, childless households do not have more varied household-specific effects. (iii) The impact of households' month-to-month idiosyncratic unobserved factors are free to have different levels of volatility. For example, household *A* may (conditionally) do the same behavior every month while household *B* exhibits inexplicable volatile behavior. This would be the case if household *A* kept a strictly regular consumption and purchasing schedule while household *B* did the same but also had an occupation that required travel. (iv) Time-varying unobserved effects are mean zero and of constant variation for all values of conditioning variables. (v) Time varying idiosyncratic errors are uncorrelated across households. And finally, (vi) errors are not serially correlated. This assumption is almost certainly false but does not sacrifice consistency. Furthermore, the inclusion of lags in dependent variables mitigates any ill-effects from misspecifying the model in this way.

Assumptions (i)-(vi) are made to justify treating the household-specific parameters α_n as random parameters in the EC2SLS estimator and can be written as: (i) $E[\alpha_n \mid \mathbf{x}_{i1},...,\mathbf{x}_{iT_n}] = E[\alpha_n]$, (ii) $E[\alpha_n^2 \mid \mathbf{x}_i] = \sigma_\alpha^2 \ \ \forall n$, (iii) $E[\nu_{nt}^2] = \sigma_n^2$, (iv) $E[\nu_{nt} \mid \mathbf{x}_i, \alpha_i] = 0$, (v) $E[\nu_{nt}\nu_{mt}] = 0 \ \forall n \neq m$, (vi) $E[\nu_{nt}\nu_{ns}] = 0 \ \forall t \neq s$. The inclusion of an intercept term implies (vii) $E[\alpha_n] = 0$.

Let $u_{nt} = \alpha_n + \nu_{tn}$ be the random part of the error net of the time-specific effects. Assumptions (i)-(vi) imply the variance-covariance matrix

$$\Omega = E[\mathbf{uu}'] = \begin{bmatrix} \sigma_1^2 I_{T_1} + \sigma_\alpha^2 \iota_{T_1}\iota_{T_1}' & \sigma_\alpha^2 \iota_{T_1}\iota_{T_2}' & \cdots & \sigma_\alpha^2 \iota_{T_1}\iota_{T_N}' \\ & \sigma_2^2 I_{T_2} + \sigma_\alpha^2 \iota_{T_2}\iota_{T_2}' & & \vdots \\ & & \ddots & \\ \text{symmetric} & & & \sigma_N^2 I_{T_N} + \sigma_\alpha^2 \iota_{T_N}\iota_{T_N}' \end{bmatrix} \tag{3}$$

where ι_A is an *A*-vector of ones, is $M \times M$ and symmetric.

Assumption (i) is an orthogonality condition between α_i and observed conditioning variables, assumption (ii) is homoskedasticity assumption that says the dispersion of idiosyncratic household effects do not depend on demographics, (iii) is a heteroscedasticity assumption that says household *A* may (conditionally) do the same behavior every month while household *B* has volatile behavior, (iv) is strict exogeneity assumption that is needed for consistency, and assumption (v) says that households are uncorrelated.

The error component two-stage least squares (EC2SLS) estimator is used as opposed to generalized two stage least squares (G2SLS) because EC2SLS estimates generally have smaller variances than G2SLS (Baltagi & Liu, 2009).[14]

The inclusion of state-specific effects (e.g. California) is important because in the event that there is correlation between the household-specific effects, α_n, and static demographic variables, state-specific effects likely absorb a sizeable proportion of correlation since state of residence is closely related to demographics such as race and income that are of especially of interest (Wooldridge, 2010 page 328).

4. Results

Equations (1) and (2) form a system of coupled dynamic equations. A permanent increase in a variable, such as income, impacts the demand for produce in complicated ways, but can be decomposed into direct long-term effects which operate through its own equation and long-term indirectly through the equation for *T*. See the Appendix for details of the procedure, and full estimates and decomposition of effect.

Direct Effects of Endogenous Variables

An upward shift in the shopping frequency curve results in households purchasing more produce ($p < 0.001$). However, the amount increased is only on the scale of a tenth on an oz./person-day suggesting that while the economic intuition that increased access to stores that carry healthful foods increases consumption of health foods holds, the impact is likely to be small (see the Appendix for full estimates). Similarly, an exogenous shift in demand for produce increases shopping frequency as households adjust their shopping patterns to avoid costly food waste. Thus the arrow of causation points in both directions as households jointly determine their shopping frequency and produce consumption rates.

Policies such as HFFI are motivated by the assumption that many SES disadvantaged households are discouraged from consuming produce by the burden of going to stores that offer healthful options (e.g. low access). That raises the question: Do SES disadvantaged households increase their consumption of produce in response to a shift in their shopping frequency curve? The most straightforward way to econometrically answer this question would be to interact demographic variables with shopping frequency. IV estimation, however, is not valid if the endogenous variable is interacted with other variables. Fortunately, the data set is large enough to run separate regressions for individual demographic groups. Since I am interested only in the marginal effect of a shift in the shopping frequency curve for each demographic group, interest is no longer in time invariant variables, and a fixed effect (FE) model is applicable.

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[14] Specifically, compared to the variance-covariance matrix of EC2SLS, G2SLS has an additional positive definite matrix that shrinks as the sample size increases. I.e., G2SLS have the same asymptotic properties, but EC2SLS has superior small sample properties.

I estimate separate fixed effect two stage least squared (FE2SLS) for households with varying incomes. A one day exogenous increase in the number of days between shopping trips has a statistically significant negative impact for all households except those with incomes less than $10,000/yr. The poorest households increase their produce consumption in response to a shift in the shopping frequency curve by between ⅓ to ½ of that of higher income households. This suggests that the poorest households may be the least responsive to increased shopping ease since they do not adjust their food choices even if they more frequently enter stores that offer produce.

Table 3

2SLS Fixed Effects Parameter Estimates the Effect of $\hat{T}$ on *Produce* by Income

	< $10k	$10k-$20k	$20k-$50k	$50k-$100k	> $100k
Estimate	-.049	-.15***	-.11***	-.075***	-.14***
Std. Error	(.085)	(.052)	(.039)	(.0021)	(.052)
Observations	19113	66490	317497	159466	191382

Note: Errors clustered by household. *p < .10, **p < .05, ***p < .01. Observations are household-months.

Decomposed Long-Term Effects

Income is associated with greater produce consumption through two mechanisms. First, there is a direct effect on produce consumption. Second, there is an indirect effect that works indirectly through shopping frequency (Figure 7). Structural parameter estimates by household income groups are similar and generally not pairwise statistically significant, but do display a trend indicating that higher income households shop less frequently. This is consistent with higher income households having higher values of time and eating out more often. The direct effect is sizeable. Permanently moving from a poor household to wealthy one increases consumption of produce by about an ounce/person-day (1/4 serving).

Racial differences in produce consumption are entirely explained by a direct effect with negligible indirect effects through shopping frequency. Compared to white Americans, being in an African (Asian) American household reduces (increases) produce consumption by 0.3 ounces/person-day.

Female education level accounts for nearly ½ of an oz./person-day entirely through the direct effect. Shopping frequency does not change with female education. Male head of household levels are the complete opposite. Male heads with higher education attainment shop significantly more frequently causing an indirect increase in produce consumption while the direct effect remains constant.

Female labor participation negatively affects produce consumption significantly both directly as households substitute to less time intensive foods, and indirectly as the household shops less frequently (Figure 9). The indirect effect becomes economically more meaningful relative to the direct effect as the female head works more. Curiously, while the number of hours that the male head works has a small direct effect, shopping frequency is not impacted at all by male labor time allocations.

Older households consume more produce (Figure 10). This is true for both male and female head of households with some differences. As the female head ages, the household shops more frequently which creates an increasing indirect shopping frequency effect. As the male head ages, shopping frequency does not change.

After netting out the effect of shopping frequency, convenience store density and fast food restaurant densities have the most significant impact on produce consumption. Interestingly, both the indirect and direct effects of supercenters+club stores are insignificant. Overall the signs of the coefficients on food retail densities could not have been anticipated.

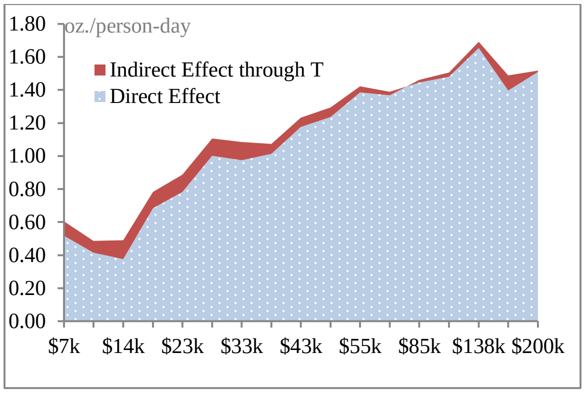

Figure 7. Effect of Income on Produce Consumption

Note: Level effects relative to < $5k.

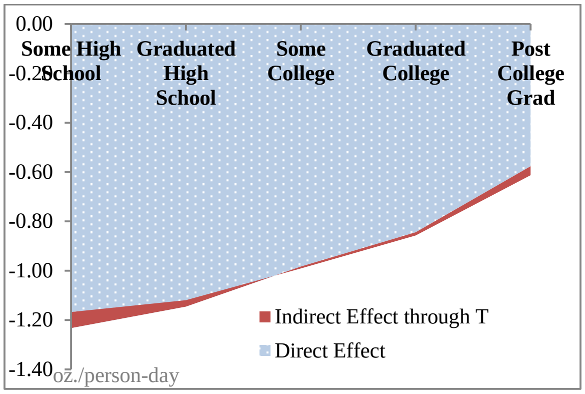

Figure 8. Effect of Female Head's Education on Produce Consumption

Note: Level effects relative to grade school only.

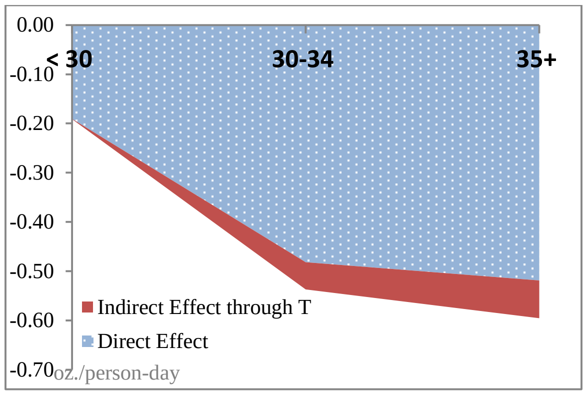

Figure 9. Effect of Female Head Hours Worked on Produce Consumption

Note: Level effects relative to unemployed.

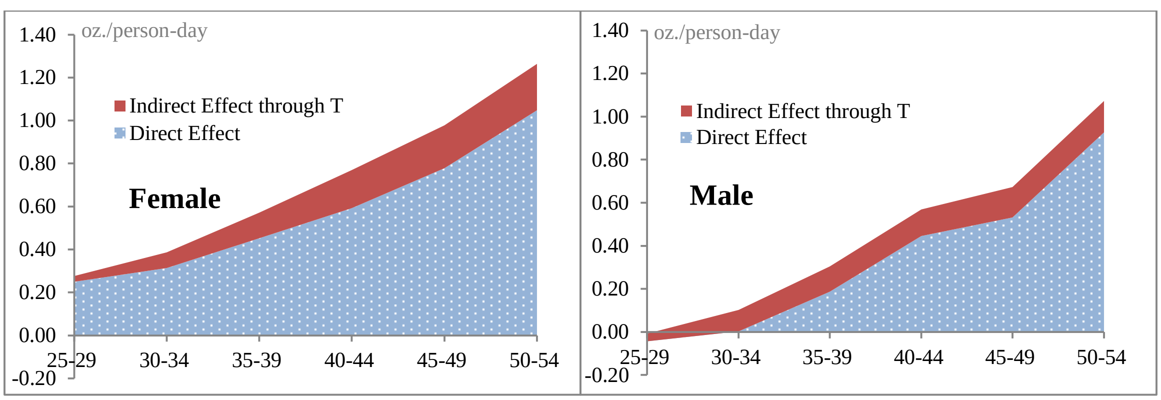

Figure 10. Effects of Head of Households' Age on Produce Consumption

Note: Level effects relative to < 25 y.o.

Table 4
Food Retail Environment Effects on Produce Consumption

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
Supermarkets	0.348***	-0.1000	0.34	-0.06	0.66	0.05	0.71	-0.23	-0.16	-0.39
Supercenters+Clubs	0.536	-1.287	0.40	-1.24	1.02	0.59	1.61	-2.94	-0.24	-3.18
Convenience Stores	-0.394***	-0.159***	-0.42	-0.20	-0.75	0.07	-0.68	-0.36	0.18	-0.18
Fast Food Restaurants	0.190***	-0.141**	0.18	-0.12	0.36	0.06	0.43	-0.32	-0.09	-0.41
Full Service Restaurants	0.0479	0.0472	0.05	0.05	0.09	-0.02	0.07	0.11	-0.02	0.09

Note: Direct long-term effects for *T* are from the impact through *T*'s structural equation accounting for the lag. Indirect long-term effects for *T* are from the impact through *Produce's* equation. Direct and indirect effects for *Produce* are analogous. Only households with 2 heads that are not of retirement age are included in the sample. ***** p < .1, ** p < .05, ***p < .01.

5. Conclusion

There are large disparities between the healthfulness of low and high socioeconomic status (SES) households' diets. These differences resemble the SES-health gradient suggesting that food choice may be a major contributor to health inequity. Based on estimates in epidemiological and medical studies of the impact of produce consumption, I have shown that the differences in produce consumption between low and high SES households is great enough to plausibly explain as much as 40% of the disparities in diet-based diseases such as heart disease, diabetes, and hypertension, as well as substantial differences in obesity rates.

The geographical distribution of food retailers match the geographical distribution of SES status with low SES being correlated with lower densities of food retailers that offer healthful foods. This has led to the concept of food "access" as a component of food security, and the hypothesis that low access has contributed to low SES households' food insecurity and consequent poor health. Based on this, reducing access disparities across SES has become a major policy strategy for alleviating disparities in health across SES.

I assert that measuring the impact of store usage is a way to measure the impact of access. After all, the concern is that low SES households are deterred from *shopping at stores* that have healthful offerings. I decompose the impact of demographic and food retail densities on household produce consumption rates into a direct effect and an indirect effect that works through shopping frequency. While I find that increased shopping frequency does increase produce consumption, the effect is small and can only explain a small fraction of produce consumption disparities across SES. Shifting the shopping frequency curve of low SES households—be it by improving access or some other means—is unlikely to be an effective way to increase produce consumption and flatten the SES-health gradient.

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Appendix

Long-Term Marginal Impacts of Exogenous Variables
Equations (1) and (2) can be rewritten as

$$\underbrace{\begin{bmatrix} 1 & -\lambda^T \\ -\lambda^F & 1 \end{bmatrix}}_{=\Lambda}\underbrace{\begin{bmatrix} T_t \\ Fresh_t \end{bmatrix}}_{=\mathbf{x}_t} = \underbrace{\begin{bmatrix} \gamma^T & 0 \\ 0 & \gamma^F \end{bmatrix}}_{=\Gamma}\underbrace{\begin{bmatrix} T_{t-1} \\ Fresh_{t-1} \end{bmatrix}}_{=\mathbf{x}_{t-1}} + \underbrace{\begin{bmatrix} \mathbf{c}^T & 0 \\ 0 & \mathbf{c}^F \end{bmatrix}}_{=\mathbf{C}}\underbrace{\begin{bmatrix} \mathbf{z}_t^T \\ \mathbf{z}_t^F \end{bmatrix}}_{=\mathbf{z}_t} + \underbrace{\begin{bmatrix} u_t^T \\ u_t^F \end{bmatrix}}_{\mathbf{u}_t} \tag{4}$$

where $\mathbf{z}_t^T$ and $\mathbf{z}_t^F$ are the exogenous variables in equations (1) and (2), respectively. If $\lambda^T\lambda^F \neq 1$, then Λ^{-1} exists and

$$\mathbf{x}_t = \Lambda^{-1}\Gamma\mathbf{x}_{t-1} + \mathbf{C}\mathbf{z}_t + \Lambda^{-1}\mathbf{u}_t \tag{5}$$

with

$$\Lambda^{-1} = \frac{1}{1-\lambda^T\lambda^F}\begin{bmatrix} 1 & \lambda^T \\ \lambda^F & 1 \end{bmatrix}. \tag{6}$$

For any initial values $\mathbf{x}_0$, if $\lim_{t\to\infty}\mathbf{z}_t = \bar{\mathbf{z}} \in (-\infty,\infty)$, Λ^{-1} exists, and $(I-\Lambda^{-1}\Gamma)^{-1}$ exists, then $\lim_{t\to\infty}\mathbf{x}_t = \bar{\mathbf{x}} \in (-\infty,\infty)$ in expectation iff all eigenvalues of $\Lambda^{-1}\Gamma$ are in the unit circle. Specifically,

$$E\left[\bar{\mathbf{x}}\right] = (I-\Lambda^{-1}\Gamma)^{-1}\mathbf{C}\bar{\mathbf{z}}\ . \tag{7}$$

Values from Table III, give eigenvalues of $\Lambda^{-1}\Gamma$ 0.22 and 0.15, both significantly in $(-1,1)$; the (two) hypotheses that $\det(I-\Lambda^{-1}\Gamma)=0$ and $\det(\Lambda)=0$ are both easily rejected. Thus their inverses exist, and $E\left[\bar{\mathbf{x}}\right]$ can be calculated using (7).

Long-term marginal impacts of permanent changes in exogenous variables in $\bar{\mathbf{z}}$ are coefficients of $\mathbf{z}$ in $(I-\Lambda^{-1}\Gamma)^{-1}\mathbf{C}$. These are decomposed through *T* and *Fresh* by calculating the coefficients on $\mathbf{z}_t^T$ and $\mathbf{z}_t^F$, separately. For example, an exogenous variable occurring only in $\mathbf{z}_t^T$ has only one coefficient in $(I-\Lambda^{-1}\Gamma)^{-1}\mathbf{C}$ corresponding to the effect through *T*. An exogenous variable occurring in both $\mathbf{z}_t^T$ and $\mathbf{z}_t^F$ has two coefficients in $(I-\Lambda^{-1}\Gamma)^{-1}\mathbf{C}$ corresponding to effects through *T* and *Fresh*.

Table A
EC2SLS Estimates

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
Endogenous Variables										
Produce	-0.109***									
T		-0.110***								
Prices										
Gas Price	0.0402	-0.0302	0.04	-0.03	0.08	0.01	0.09	-0.07	-0.02	-0.09
FAFH Price	0.275	2.775***	0.58	2.84	0.53	-1.27	-0.74	6.34	-0.13	6.21
Produce Price	0.0291	-1.232***	-0.11	-1.24	0.06	0.56	0.62	-2.81	-0.01	-2.83
Instruments										
Other Foods Price		-0.900	-0.10	-0.91	0.00	0.41	0.41	-2.05	0.00	-2.05
Lagged *Fresh*		0.545***	0.06	0.55	0.00	-0.25	-0.25	1.24	0.00	1.24
Bad Weather	0.00465***		0.005	0.001	0.009	0.000	0.009	0.000	-0.002	-0.002
Lagged *T*	0.449***		0.45	0.05	0.86	0.00	0.86	0.00	-0.21	-0.21
Race & Ethnicity (white omitted)										
Black	-0.00731	-0.294***	-0.04	-0.30	-0.01	0.13	0.12	-0.67	0.00	-0.67
Asian	0.00874	0.309***	0.04	0.31	0.02	-0.14	-0.12	0.71	0.00	0.70
Other	-0.0215	0.0342	-0.02	0.03	-0.04	-0.02	-0.06	0.08	0.01	0.09
Hispanic (yes)	0.0231	0.0588**	0.03	0.06	0.04	-0.03	0.02	0.13	-0.01	0.12
Household Size (2 member households omitted)										
3	-0.143***	-0.722***	-0.22	-0.75	-0.27	0.33	0.06	-1.65	0.07	-1.58
4	-0.290***	-1.072***	-0.41	-1.12	-0.55	0.49	-0.06	-2.45	0.13	-2.32
5	-0.320***	-1.258***	-0.46	-1.31	-0.61	0.57	-0.04	-2.87	0.15	-2.73
6	-0.278***	-1.406***	-0.44	-1.45	-0.53	0.64	0.11	-3.21	0.13	-3.08
7	-0.325***	-1.402***	-0.48	-1.46	-0.62	0.64	0.02	-3.20	0.15	-3.05
8	-0.383***	-1.452***	-0.55	-1.51	-0.73	0.66	-0.07	-3.32	0.17	-3.14
9+	-0.208**	-1.442***	-0.37	-1.48	-0.40	0.66	0.26	-3.29	0.09	-3.20
Age of Female Head (< 25 y.o. omitted)										
25-29	-0.0613	0.109	-0.05	0.10	-0.12	-0.05	-0.17	0.25	0.03	0.28
30-34	-0.163**	0.137*	-0.15	0.12	-0.31	-0.06	-0.37	0.31	0.07	0.39
35-39	-0.261***	0.198***	-0.24	0.17	-0.50	-0.09	-0.59	0.45	0.12	0.57
40-44	-0.389***	0.259***	-0.37	0.22	-0.74	-0.12	-0.86	0.59	0.18	0.77

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
45-49	-0.435***	0.341***	-0.40	0.30	-0.83	-0.16	-0.99	0.78	0.20	0.98
50-54	-0.474***	0.459***	-0.43	0.41	-0.91	-0.21	-1.11	1.05	0.22	1.26
Age of Male Head (< 25 y.o. omitted)										
25-29	-0.0774	-0.0189	-0.08	-0.03	-0.15	0.01	-0.14	-0.04	0.04	-0.01
30-34	-0.219**	0.00117	-0.22	-0.02	-0.42	0.00	-0.42	0.00	0.10	0.10
35-39	-0.257***	0.0819	-0.25	0.05	-0.49	-0.04	-0.53	0.19	0.12	0.30
40-44	-0.272***	0.195*	-0.25	0.17	-0.52	-0.09	-0.61	0.45	0.12	0.57
45-49	-0.308***	0.233**	-0.29	0.20	-0.59	-0.11	-0.69	0.53	0.14	0.67
50-54	-0.320***	0.406***	-0.28	0.38	-0.61	-0.19	-0.80	0.93	0.15	1.07
Education of Female Head (grade school only omitted)										
Some High School	-0.141	-0.540***	-0.20	-0.56	-0.27	0.25	-0.02	-1.23	0.06	-1.17
Graduated High School	-0.0571	-0.502***	-0.11	-0.51	-0.11	0.23	0.12	-1.15	0.03	-1.12
Some College	0.0175	-0.431***	-0.03	-0.43	0.03	0.20	0.23	-0.98	-0.01	-0.99
Graduated College	0.0287	-0.370***	-0.01	-0.37	0.05	0.17	0.22	-0.84	-0.01	-0.86
Post College Grad	0.0787	-0.253**	0.05	-0.25	0.15	0.12	0.27	-0.58	-0.04	-0.61
Education of Male head (grade school only omitted)										
Some High School	-0.0815	-0.0614	-0.09	-0.07	-0.16	0.03	-0.13	-0.14	0.04	-0.10
Graduated High School	-0.166**	-0.0807	-0.18	-0.10	-0.32	0.04	-0.28	-0.18	0.08	-0.11
Some College	-0.205**	-0.113	-0.22	-0.14	-0.39	0.05	-0.34	-0.26	0.09	-0.16
Graduated College	-0.248***	-0.0481	-0.26	-0.08	-0.47	0.02	-0.45	-0.11	0.11	0.00
Post College Grad	-0.230***	0.0887	-0.22	0.06	-0.44	-0.04	-0.48	0.20	0.11	0.31
Children Presence (no children omitted)										
Under 6 only	-0.0468*	0.174***	-0.03	0.17	-0.09	-0.08	-0.17	0.40	0.02	0.42
6-12 only	-0.00917	0.148***	0.01	0.15	-0.02	-0.07	-0.09	0.34	0.00	0.34
13-17 only	-0.0875***	0.0598**	-0.08	0.05	-0.17	-0.03	-0.19	0.14	0.04	0.18
Under 6 & 6-12	-0.0220	0.229***	0.00	0.23	-0.04	-0.10	-0.15	0.52	0.01	0.53
Under 6 & 13-17	-0.0771	0.177***	-0.06	0.17	-0.15	-0.08	-0.23	0.40	0.04	0.44
6-12 & 13-17	-0.112***	0.146***	-0.10	0.14	-0.21	-0.07	-0.28	0.33	0.05	0.38
Under 6 & 6-12 & 13-17	-0.205***	0.138**	-0.19	0.12	-0.39	-0.06	-0.45	0.32	0.09	0.41
Household Income (< $5000 Omitted)										

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
$5000-$7999	-0.190	0.227	-0.17	0.21	-0.36	-0.10	-0.47	0.52	0.09	0.61
$8000-$9999	-0.220	1.021***	-0.11	1.01	-0.42	-0.47	-0.89	2.33	0.10	2.43
$10,000-$11,999	-0.154	0.182	-0.14	0.17	-0.29	-0.08	-0.38	0.42	0.07	0.49
$12,000-$14,999	-0.247*	0.165	-0.23	0.14	-0.47	-0.08	-0.55	0.38	0.11	0.49
$15,000-$19,999	-0.216*	0.300**	-0.19	0.28	-0.41	-0.14	-0.55	0.68	0.10	0.78
$20,000-$24,999	-0.228*	0.343**	-0.19	0.32	-0.44	-0.16	-0.59	0.78	0.10	0.89
$25,000-$29,999	-0.228*	0.439***	-0.18	0.42	-0.44	-0.20	-0.64	1.00	0.10	1.11
$30,000-$34,999	-0.239*	0.427***	-0.19	0.41	-0.46	-0.19	-0.65	0.97	0.11	1.08
$35,000-$39,999	-0.131	0.444***	-0.08	0.43	-0.25	-0.20	-0.45	1.01	0.06	1.07
$40,000-$44,999	-0.123	0.515***	-0.07	0.51	-0.23	-0.24	-0.47	1.18	0.06	1.23
$45,000-$49,999	-0.128	0.541***	-0.07	0.53	-0.24	-0.25	-0.49	1.24	0.06	1.29
$50,000-$59,999	-0.0788	0.607***	-0.01	0.61	-0.15	-0.28	-0.43	1.39	0.04	1.42
$60,000-$69,999	-0.0462	0.599***	0.02	0.60	-0.09	-0.27	-0.36	1.37	0.02	1.39
$70,000-$99,999	0.0346	0.640***	0.11	0.65	0.07	-0.29	-0.23	1.46	-0.02	1.45
$100,000-$124,999	0.0520	0.659***	0.13	0.67	0.10	-0.30	-0.20	1.50	-0.02	1.48
$125,000-$149,999	0.0825	0.741***	0.17	0.76	0.16	-0.34	-0.18	1.69	-0.04	1.65
$150,000-$199,999	0.202	0.652***	0.28	0.68	0.39	-0.30	0.09	1.49	-0.09	1.40
$200,000 +	0.0152	0.664***	0.09	0.67	0.03	-0.30	-0.27	1.52	-0.01	1.51
Hrs./Wk. Worked of Female Head (unemployed omitted)										
< 30	0.000756	-0.0836***	-0.01	-0.08	0.00	0.04	0.04	-0.19	0.00	-0.19
30-34	0.120***	-0.211***	0.10	-0.20	0.23	0.10	0.33	-0.48	-0.05	-0.54
35+	0.169***	-0.227***	0.15	-0.21	0.32	0.10	0.43	-0.52	-0.08	-0.60
Hrs./Wk. Worked of Male Head (unemployed omitted)										
< 30	-0.0532	0.169***	-0.04	0.17	-0.10	-0.08	-0.18	0.39	0.02	0.41
30-34	0.0555	0.0110	0.06	0.02	0.11	-0.01	0.10	0.03	-0.03	0.00
35+	0.0424	0.104***	0.05	0.11	0.08	-0.05	0.03	0.24	-0.02	0.22
Food Retail Densities (per 1000 people in county)										
Supermarkets	0.348***	-0.1000	0.34	-0.06	0.66	0.05	0.71	-0.23	-0.16	-0.39
Supercenters+Clubs	0.536	-1.287	0.40	-1.24	1.02	0.59	1.61	-2.94	-0.24	-3.18
Convenience Stores	-0.394***	-0.159***	-0.42	-0.20	-0.75	0.07	-0.68	-0.36	0.18	-0.18
Fast Food Restaurants	0.190***	-0.141**	0.18	-0.12	0.36	0.06	0.43	-0.32	-0.09	-0.41
Full Service Restaurants	0.0479	0.0472	0.05	0.05	0.09	-0.02	0.07	0.11	-0.02	0.09

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
Months (Feb-98 omitted)										
Mar-98	0.116	-0.0510	0.11	-0.04	0.22	0.02	0.24	-0.12	-0.05	-0.17
Apr-98	0.162*	-0.167*	0.15	-0.15	0.31	0.08	0.39	-0.38	-0.07	-0.46
May-98	0.222***	0.378***	0.27	0.41	0.42	-0.17	0.25	0.86	-0.10	0.76
Jun-98	0.348***	-0.169*	0.33	-0.13	0.66	0.08	0.74	-0.39	-0.16	-0.54
Jul-98	0.381***	-0.0306	0.38	0.01	0.73	0.01	0.74	-0.07	-0.17	-0.24
Aug-98	0.294***	-0.260***	0.27	-0.23	0.56	0.12	0.68	-0.59	-0.13	-0.73
Sep-98	0.249***	-0.581***	0.19	-0.56	0.48	0.27	0.74	-1.33	-0.11	-1.44
Oct-98	0.229***	-0.593***	0.17	-0.57	0.44	0.27	0.71	-1.35	-0.10	-1.46
Nov-98	0.238***	-0.223**	0.22	-0.20	0.45	0.10	0.56	-0.51	-0.11	-0.62
Dec-98	0.218**	-0.826***	0.13	-0.81	0.42	0.38	0.79	-1.89	-0.10	-1.99
Jan-99	0.177*	0.154	0.20	0.18	0.34	-0.07	0.27	0.35	-0.08	0.27
Feb-99	0.0293	-0.410***	-0.02	-0.41	0.06	0.19	0.24	-0.94	-0.01	-0.95
Mar-99	0.0558	-0.208*	0.03	-0.20	0.11	0.09	0.20	-0.47	-0.03	-0.50
Apr-99	0.309***	-0.365***	0.27	-0.34	0.59	0.17	0.76	-0.83	-0.14	-0.97
May-99	0.206**	0.110	0.22	0.13	0.39	-0.05	0.34	0.25	-0.09	0.16
Jun-99	0.422***	-0.172*	0.41	-0.13	0.81	0.08	0.88	-0.39	-0.19	-0.59
Jul-99	0.409***	-0.0572	0.41	-0.01	0.78	0.03	0.81	-0.13	-0.19	-0.32
Aug-99	0.406***	-0.565***	0.35	-0.53	0.78	0.26	1.03	-1.29	-0.19	-1.48
Sep-99	0.323***	-0.480***	0.27	-0.45	0.62	0.22	0.84	-1.10	-0.15	-1.24
Oct-99	0.347***	-0.592***	0.29	-0.56	0.66	0.27	0.93	-1.35	-0.16	-1.51
Nov-99	0.307***	-0.583***	0.25	-0.56	0.59	0.27	0.85	-1.33	-0.14	-1.47
Dec-99	0.132	-1.266***	-0.01	-1.27	0.25	0.58	0.83	-2.89	-0.06	-2.95
Jan-00	1.144***	0.256**	1.19	0.39	2.18	-0.12	2.07	0.58	-0.52	0.06
Feb-00	-0.0129	-0.449***	-0.06	-0.46	-0.02	0.21	0.18	-1.03	0.01	-1.02
Mar-00	0.284***	-0.186	0.27	-0.16	0.54	0.08	0.63	-0.42	-0.13	-0.55
Apr-00	0.511***	-0.156	0.50	-0.10	0.98	0.07	1.05	-0.36	-0.23	-0.59
May-00	0.499***	-0.260**	0.48	-0.21	0.95	0.12	1.07	-0.59	-0.23	-0.82
Jun-00	0.590***	-0.235*	0.57	-0.17	1.13	0.11	1.23	-0.54	-0.27	-0.81
Jul-00	0.556***	-0.119	0.55	-0.06	1.06	0.05	1.12	-0.27	-0.25	-0.53
Aug-00	0.487***	-0.729***	0.41	-0.68	0.93	0.33	1.26	-1.66	-0.22	-1.89
Sep-00	0.513***	-0.415***	0.47	-0.36	0.98	0.19	1.17	-0.95	-0.23	-1.18
Oct-00	0.424***	-0.744***	0.35	-0.71	0.81	0.34	1.15	-1.70	-0.19	-1.89

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
Nov-00	0.407***	-0.441***	0.36	-0.40	0.78	0.20	0.98	-1.01	-0.19	-1.19
Dec-00	0.425***	-0.621***	0.36	-0.58	0.81	0.28	1.10	-1.42	-0.19	-1.61
Jan-01	0.276***	-0.513***	0.22	-0.49	0.53	0.23	0.76	-1.17	-0.13	-1.30
Feb-01	0.408***	-0.293**	0.38	-0.25	0.78	0.13	0.91	-0.67	-0.19	-0.86
Mar-01	0.413***	-0.261*	0.39	-0.22	0.79	0.12	0.91	-0.60	-0.19	-0.78
Apr-01	0.484***	-0.443***	0.44	-0.39	0.92	0.20	1.13	-1.01	-0.22	-1.23
May-01	0.515***	-0.297**	0.49	-0.24	0.98	0.14	1.12	-0.68	-0.24	-0.91
Jun-01	0.442***	-0.147	0.43	-0.10	0.84	0.07	0.91	-0.34	-0.20	-0.54
Jul-01	0.710***	-0.373***	0.68	-0.30	1.36	0.17	1.53	-0.85	-0.32	-1.18
Aug-01	0.466***	-0.672***	0.40	-0.63	0.89	0.31	1.20	-1.53	-0.21	-1.75
Sep-01	0.639***	-0.508***	0.59	-0.44	1.22	0.23	1.45	-1.16	-0.29	-1.45
Oct-01	0.253***	-0.977***	0.15	-0.96	0.48	0.45	0.93	-2.23	-0.12	-2.35
Nov-01	0.470***	-0.450***	0.43	-0.40	0.90	0.21	1.10	-1.03	-0.21	-1.24
Dec-01	0.474***	-0.763***	0.40	-0.72	0.91	0.35	1.25	-1.74	-0.22	-1.96
Jan-02	0.271***	-0.592***	0.21	-0.57	0.52	0.27	0.79	-1.35	-0.12	-1.48
Feb-02	0.326***	-0.489***	0.28	-0.46	0.62	0.22	0.85	-1.12	-0.15	-1.27
Mar-02	0.400***	-0.210*	0.38	-0.17	0.76	0.10	0.86	-0.48	-0.18	-0.66
Apr-02	0.457***	-0.674***	0.39	-0.63	0.87	0.31	1.18	-1.54	-0.21	-1.75
May-02	0.534***	-0.240*	0.51	-0.18	1.02	0.11	1.13	-0.55	-0.24	-0.79
Jun-02	0.652***	0.0192	0.66	0.09	1.25	-0.01	1.24	0.04	-0.30	-0.25
Jul-02	0.476***	-0.519***	0.42	-0.47	0.91	0.24	1.15	-1.18	-0.22	-1.40
Aug-02	0.572***	-0.676***	0.50	-0.62	1.09	0.31	1.40	-1.54	-0.26	-1.80
Sep-02	0.564***	-0.684***	0.50	-0.63	1.08	0.31	1.39	-1.56	-0.26	-1.82
Oct-02	0.199**	-0.937***	0.10	-0.93	0.38	0.43	0.81	-2.14	-0.09	-2.23
Nov-02	0.387***	-0.382***	0.35	-0.34	0.74	0.17	0.91	-0.87	-0.18	-1.05
Dec-02	0.478***	-1.024***	0.37	-0.98	0.91	0.47	1.38	-2.34	-0.22	-2.56
Jan-03	0.214**	-0.266*	0.19	-0.25	0.41	0.12	0.53	-0.61	-0.10	-0.71
Feb-03	0.305***	-0.428***	0.26	-0.40	0.58	0.20	0.78	-0.98	-0.14	-1.12
Mar-03	0.445***	-0.328**	0.41	-0.28	0.85	0.15	1.00	-0.75	-0.20	-0.95
Apr-03	0.509***	-0.589***	0.45	-0.54	0.97	0.27	1.24	-1.34	-0.23	-1.58
May-03	0.448***	-0.315**	0.42	-0.27	0.86	0.14	1.00	-0.72	-0.20	-0.92
Jun-03	0.650***	-0.160	0.64	-0.09	1.24	0.07	1.31	-0.37	-0.30	-0.66
Jul-03	0.666***	-0.429***	0.63	-0.36	1.27	0.20	1.47	-0.98	-0.30	-1.28

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
Aug-03	0.566***	-0.563***	0.51	-0.51	1.08	0.26	1.34	-1.29	-0.26	-1.54
Sep-03	0.526***	-0.783***	0.45	-0.73	1.00	0.36	1.36	-1.79	-0.24	-2.03
Oct-03	0.478***	-0.930***	0.38	-0.89	0.91	0.42	1.34	-2.12	-0.22	-2.34
Nov-03	0.684***	-0.413***	0.65	-0.34	1.31	0.19	1.49	-0.94	-0.31	-1.26
Dec-03	0.307***	-1.146***	0.18	-1.13	0.59	0.52	1.11	-2.62	-0.14	-2.76
Jan-04	0.315***	-0.245*	0.29	-0.21	0.60	0.11	0.71	-0.56	-0.14	-0.70
Feb-04	0.483***	-0.608***	0.42	-0.56	0.92	0.28	1.20	-1.39	-0.22	-1.61
Mar-04	0.339***	-0.516***	0.29	-0.48	0.65	0.24	0.88	-1.18	-0.15	-1.33
Apr-04	0.553***	-0.428***	0.51	-0.37	1.06	0.20	1.25	-0.98	-0.25	-1.23
May-04	0.660***	-0.211	0.64	-0.14	1.26	0.10	1.36	-0.48	-0.30	-0.78
Jun-04	0.520***	-0.528***	0.47	-0.48	0.99	0.24	1.23	-1.21	-0.24	-1.44
Jul-04	0.758***	-0.451***	0.72	-0.37	1.45	0.21	1.65	-1.03	-0.35	-1.38
Aug-04	0.568***	-0.874***	0.48	-0.82	1.08	0.40	1.48	-2.00	-0.26	-2.25
Sep-04	0.547***	-0.745***	0.47	-0.69	1.04	0.34	1.38	-1.70	-0.25	-1.95
Oct-04	0.563***	-0.738***	0.49	-0.68	1.08	0.34	1.41	-1.68	-0.26	-1.94
Nov-04	0.469***	-0.672***	0.40	-0.63	0.90	0.31	1.20	-1.53	-0.21	-1.75
Dec-04	0.488***	-1.037***	0.38	-1.00	0.93	0.47	1.41	-2.37	-0.22	-2.59
Jan-05	0.419***	-0.241	0.40	-0.20	0.80	0.11	0.91	-0.55	-0.19	-0.74
Feb-05	0.362***	-0.753***	0.28	-0.72	0.69	0.34	1.04	-1.72	-0.17	-1.88
Mar-05	0.390***	-0.505***	0.34	-0.47	0.74	0.23	0.98	-1.15	-0.18	-1.33
Apr-05	0.576***	-0.355*	0.54	-0.30	1.10	0.16	1.26	-0.81	-0.26	-1.07
May-05	0.545***	-0.408**	0.51	-0.35	1.04	0.19	1.23	-0.93	-0.25	-1.18
Jun-05	0.739***	-0.434**	0.70	-0.36	1.41	0.20	1.61	-0.99	-0.34	-1.33
Jul-05	0.709***	-0.324*	0.68	-0.25	1.35	0.15	1.50	-0.74	-0.32	-1.06
Aug-05	0.492***	-0.753***	0.41	-0.71	0.94	0.34	1.28	-1.72	-0.22	-1.94
Sep-05	0.684***	-0.820***	0.60	-0.75	1.31	0.37	1.68	-1.87	-0.31	-2.18
Oct-05	0.647***	-0.684***	0.58	-0.62	1.24	0.31	1.55	-1.56	-0.30	-1.86
Nov-05	0.503***	-0.688***	0.43	-0.64	0.96	0.31	1.27	-1.57	-0.23	-1.80
Dec-05	0.486***	-0.805***	0.40	-0.76	0.93	0.37	1.30	-1.84	-0.22	-2.06
Jan-06	0.366**	-0.444**	0.32	-0.41	0.70	0.20	0.90	-1.01	-0.17	-1.18
Feb-06	0.428***	-0.611***	0.37	-0.57	0.82	0.28	1.10	-1.39	-0.20	-1.59
Mar-06	0.416***	-0.418**	0.37	-0.38	0.79	0.19	0.99	-0.95	-0.19	-1.14
Apr-06	0.746***	-0.353	0.72	-0.27	1.42	0.16	1.59	-0.81	-0.34	-1.15

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
May-06	0.660***	-0.406*	0.62	-0.34	1.26	0.19	1.45	-0.93	-0.30	-1.23
Jun-06	0.720***	-0.341	0.69	-0.26	1.37	0.16	1.53	-0.78	-0.33	-1.11
Jul-06	0.797***	-0.185	0.79	-0.10	1.52	0.08	1.61	-0.42	-0.36	-0.79
Aug-06	0.604***	-0.752***	0.53	-0.69	1.15	0.34	1.50	-1.72	-0.28	-1.99
Sep-06	0.742***	-0.709***	0.67	-0.63	1.42	0.32	1.74	-1.62	-0.34	-1.96
Oct-06	0.630***	-0.662***	0.56	-0.60	1.20	0.30	1.51	-1.51	-0.29	-1.80
Nov-06	0.538***	-0.627***	0.48	-0.57	1.03	0.29	1.31	-1.43	-0.25	-1.68
States (AL omitted)										
AZ	0.454***	0.242**	0.49	0.30	0.87	-0.11	0.76	0.55	-0.21	0.35
AR	-0.0316	-0.0957	-0.04	-0.10	-0.06	0.04	-0.02	-0.22	0.01	-0.20
CA	0.167**	0.196**	0.19	0.22	0.32	-0.09	0.23	0.45	-0.08	0.37
CO	0.278**	0.315***	0.32	0.35	0.53	-0.14	0.39	0.72	-0.13	0.59
CT	0.0461	0.717***	0.13	0.73	0.09	-0.33	-0.24	1.64	-0.02	1.62
DE	-0.0338	-0.00726	-0.04	-0.01	-0.06	0.00	-0.06	-0.02	0.02	0.00
DC	0.592***	-0.125	0.59	-0.06	1.13	0.06	1.19	-0.29	-0.27	-0.56
FL	0.348***	0.0699	0.36	0.11	0.66	-0.03	0.63	0.16	-0.16	0.00
GE	0.267***	0.0909	0.28	0.12	0.51	-0.04	0.47	0.21	-0.12	0.09
ID	0.489***	0.218	0.52	0.28	0.93	-0.10	0.83	0.50	-0.22	0.27
IL	0.212***	0.244***	0.24	0.27	0.40	-0.11	0.29	0.56	-0.10	0.46
IN	0.161*	0.108	0.17	0.13	0.31	-0.05	0.26	0.25	-0.07	0.17
IA	-0.0748	0.250**	-0.05	0.24	-0.14	-0.11	-0.26	0.57	0.03	0.60
KS	0.125	0.357***	0.17	0.38	0.24	-0.16	0.08	0.82	-0.06	0.76
KY	0.239**	0.305***	0.28	0.34	0.46	-0.14	0.32	0.70	-0.11	0.59
LA	0.0467	0.166	0.07	0.17	0.09	-0.08	0.01	0.38	-0.02	0.36
ME	0.442***	0.564***	0.51	0.62	0.84	-0.26	0.59	1.29	-0.20	1.09
MD	0.158**	0.136*	0.17	0.16	0.30	-0.06	0.24	0.31	-0.07	0.24
MA	0.236**	0.617***	0.31	0.65	0.45	-0.28	0.17	1.41	-0.11	1.30
MI	0.232***	0.303***	0.27	0.33	0.44	-0.14	0.30	0.69	-0.11	0.59
MN	0.360***	0.366***	0.40	0.41	0.69	-0.17	0.52	0.84	-0.16	0.67
MS	0.831***	0.168	0.86	0.26	1.59	-0.08	1.51	0.38	-0.38	0.00
MO	0.178**	-0.0109	0.18	0.01	0.34	0.00	0.34	-0.02	-0.08	-0.11
MT	0.0749	0.630***	0.15	0.65	0.14	-0.29	-0.14	1.44	-0.03	1.40
NE	0.0521	0.128	0.07	0.14	0.10	-0.06	0.04	0.29	-0.02	0.27

	Short-Term Estimates				Long-Term Effect Estimates					
	Structural		Reduced Form		Direct	Indirect	TOTAL	Direct	Indirect	TOTAL
	T	*Produce*	*T*	*Produce*	*T*	*T*	*T*	*Produce*	*Produce*	*Produce*
NV	0.291*	0.877***	0.39	0.92	0.56	-0.40	0.16	2.00	-0.13	1.87
NH	0.183	1.045***	0.30	1.08	0.35	-0.48	-0.13	2.39	-0.08	2.30
NJ	0.108	0.380***	0.15	0.40	0.21	-0.17	0.03	0.87	-0.05	0.82
NM	0.0363	0.166	0.06	0.17	0.07	-0.08	-0.01	0.38	-0.02	0.36
NY	0.105	0.243***	0.13	0.26	0.20	-0.11	0.09	0.55	-0.05	0.51
NC	0.184**	0.231**	0.21	0.25	0.35	-0.11	0.25	0.53	-0.08	0.44
ND	-0.147	0.119	-0.14	0.10	-0.28	-0.05	-0.34	0.27	0.07	0.34
OH	0.124	0.259***	0.15	0.28	0.24	-0.12	0.12	0.59	-0.06	0.53
OK	0.236*	0.243*	0.27	0.27	0.45	-0.11	0.34	0.55	-0.11	0.45
OR	0.0384	0.391***	0.08	0.40	0.07	-0.18	-0.11	0.89	-0.02	0.88
PA	0.148*	0.275***	0.18	0.29	0.28	-0.13	0.16	0.63	-0.07	0.56
RI	0.00484	1.113***	0.13	1.13	0.01	-0.51	-0.50	2.54	0.00	2.54
SC	0.154	0.382***	0.20	0.40	0.29	-0.17	0.12	0.87	-0.07	0.80
SD	0.249	-0.0602	0.25	-0.03	0.48	0.03	0.50	-0.14	-0.11	-0.25
TN	0.202**	0.175*	0.22	0.20	0.39	-0.08	0.31	0.40	-0.09	0.31
TX	0.265***	0.240***	0.29	0.27	0.51	-0.11	0.40	0.55	-0.12	0.43
UT	0.287***	0.395***	0.33	0.43	0.55	-0.18	0.37	0.90	-0.13	0.77
VT	-0.00726	0.758***	0.08	0.77	-0.01	-0.35	-0.36	1.73	0.00	1.73
VA	0.0388	0.291***	0.07	0.30	0.07	-0.13	-0.06	0.66	-0.02	0.65
WA	-0.0149	0.262**	0.01	0.26	-0.03	-0.12	-0.15	0.60	0.01	0.60
WV	0.834***	0.00609	0.84	0.10	1.59	0.00	1.59	0.01	-0.38	-0.37
WI	0.171*	0.364***	0.21	0.39	0.33	-0.17	0.16	0.83	-0.08	0.75
WA	1.063***	0.0192	1.08	0.14	2.03	-0.01	2.02	0.04	-0.49	-0.44
Constant	2.910***	1.988	3.16	2.34	5.56	-0.91	4.65	4.54	-1.33	3.21
R-Squared	0.33	0.44								
between	0.84	0.9								
within	0.08	0.08								
N	261097	261097								

Note: Direct long-term effects for *T* are from the impact through *T*'s structural equation accounting for the lag. Indirect long-term effects for *T* are from the impact through *Produce's* equation. Direct and indirect effects for *Produce* are analogous. Only households with 2 heads that are not of retirement age are included in the sample. ***** p < .1, ** p < .05, ***p < .01.