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The Relationship Between Patronizing Direct-to-Consumer Outlets and a Household's Demand for Fruits and Vegetables

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Abstract

Farmers markets, roadside stands, and other direct-to-consumer (DTC) outlets can be an important sales channel for small farmers. However, it is unclear what, if any, impact shopping at DTC outlets has on consumer food-purchase behavior. This study uses the National Household Food Acquisition and Purchase Survey to investigate the relationship between buying fruits and vegetables at DTC outlets and spending on these food groups by U.S. households. While American households are found to patronize DTC outlets infrequently, on average, study results show that encouraging them to do so more frequently could lead to higher levels of fruit and vegetable spending across all outlets types—including both DTC and nondirect retailers.

Keywords: direct-to-consumer marketing, farmers markets, fruits and vegetables, roadside stands, food expenditures, FoodAPS data

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Contents

USDA
United States Department of Agriculture

A report summary from the Economic Research Service *January 2018*

The Relationship Between Patronizing Direct-to-Consumer Outlets and a Household's Demand for Fruits and Vegetables

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What Is the Issue?

USDA seeks to develop, improve, and expand direct-to-consumer (DTC) marketing channels such as farmers markets and roadside stands. The Farmers Market Promotion Program (FMPP), for one, awards grants to agricultural groups and others who use these funds for a variety of activities that support the sale of agricultural products directly to consumers. Several other efforts help participants in USDA food and nutrition assistance programs to acquire foods through DTC outlets.

Farmers markets, roadside stands, and other DTC outlets can be important to small farmers. Many further hope that consumers who patronize these outlets will buy and consume a greater quantity and variety of fruits and vegetables. However, it is not clear how patronizing DTC outlets affects a typical consumer's behavior, if at all. This study investigates whether patronizing a DTC outlet increases a household's demand for fruits and vegetables as measured by its expenditures on these foods, including purchases at both DTC and nondirect retailers.

What Did the Study Find?

USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) offers unique insights into the food shopping behavior of U.S. households. Among 4,826 FoodAPS households that reported their food acquisitions over a 1-week period, 231 bought food from a farmers market or other DTC outlet. Fruits and vegetables were the most frequently purchased type of food at such places. Among the 231 households that bought food at a DTC outlet, 170 bought fruits and vegetables.

Households that bought fruits and vegetables directly from farmers spent more money on these two food groups across all outlet types, including both DTC and nondirect retailers:

- Among 170 FoodAPS households that bought fruits and vegetables at DTC outlets, weekly total fruit and vegetable spending averaged $28.36.
- Among 3,388 FoodAPS households that also bought fruits and vegetables but did not patronize DTC outlets, weekly total fruit and vegetable spending averaged $16.53.

ERS is a primary source of economic research and analysis from the U.S. Department of Agriculture, providing timely information on economic and policy issues related to agriculture, food, the environment, and rural America.

- Average fruit and vegetable spending across all 4,826 FoodAPS households was $12.60, including those who made zero purchases.

Analysis of the data, including the estimation of an econometric model, revealed factors like education and interest in health and nutrition that are closely associated with buying fruits and vegetables at DTC outlets. However, Americans tend to do so infrequently:

- The probability to buy fruits and vegetables at DTC outlets in a given week averaged 3.5 percent across all FoodAPS households. In other words, the average household buys these foods directly from farmers during roughly 3.5 out of every 100 weeks, or between 1 and 2 weeks each year.

Encouraging households to shop at DTC outlets more frequently could increase Americans' fruit and vegetable expenditures. Model results further show that:

- Increasing a household's probability to patronize DTC outlets in any given week by 2 percentage points from 3.5 to 5.5 percent (which is roughly equivalent to buying at a DTC outlet one more time per year) could raise the household's weekly-average fruit and vegetable spending by 60 cents.

- For a household that already spends $12.60 per week on fruits and vegetables (the mean level of spending across all surveyed households), spending 60 cents more per week would represent a 5-percent increase in expenditures.

Higher levels of fruit and vegetable spending associated with patronizing DTC outlets may reflect a variety of behaviors. Some households may be willing to pay higher prices when buying directly from farmers. This could represent additional revenue to small farmers, helping them to maintain operations, which is a goal of USDA programs like the FMPP. Households that patronize DTC outlets may also purchase a greater quantity and/or a different variety of fruits and vegetables. Additional research is needed to better understand these changes in demand and their health implications. For example, a household may choose grapes instead of bananas, or leafy lettuce instead of iceberg. Such changes in the mix of products bought by households could, in turn, affect their diet quality for better or worse.

How Was the Study Conducted?

Using data from FoodAPS, researchers compared households that bought fruits and vegetables at DTC outlets and households that also bought fruits and vegetables but patronized only supermarkets and other nondirect retailers. The main empirical analysis involved modeling a household's level of fruit and vegetable spending as a function of its income and demographic characteristics, attitudes and behaviors toward food and nutrition, and tendency to patronize DTC outlets, among other potential demand determinants. Statistical techniques (including the method of instrumental variables) were used to measure the effect that patronizing DTC outlets has on a household's fruit and vegetable spending.

Introduction

Farmers markets, roadside stands, community-supported agriculture (CSA) networks,[1] and other direct-to-consumer (DTC) outlets account for less than 0.5 percent of U.S. agricultural sales.[2] Nonetheless, they can be a boon to small and beginning farmers who may be unable to satisfy the supply requirements of buyers for supermarkets and chain restaurants who demand large volumes (Low and Vogel, 2011; Martinez et al., 2010). DTC outlets are also important to consumers who value a source of locally grown food. Fresh fruits and vegetables, in particular, are "at the heart of the U.S. farmers market business model" (USDA, AMS, 2015, p. 1), and it is widely hoped that consumers who patronize DTC outlets will buy and consume a greater quantity and variety of fruits and vegetables (e.g., McCormack et al., 2010). Most Americans do not satisfy Federal dietary recommendations for these foods (e.g., Dong and Lin, 2009; Wang et al., 2014).

Given the potential benefits of DTC outlets for both producers and consumers, USDA maintains programs to develop, improve, and expand these operations (e.g., USDA, OC, 2013; Low et al., 2015). The Farmers Market Promotion Program (FMPP) is among these efforts (e.g., USDA, AMS, 2017a). It awards competitive grants to agricultural groups and others who, in turn, use these funds to build capacity, facilitate marketing, and provide technical assistance to farmers and ranchers selling through DTC outlets. This may be especially helpful for small farmers. While small, medium, and large farms all market food directly to consumers, some small producers rely disproportionately on DTC outlets. Using the 2007 Census of Agriculture, Martinez et al. (2010) find that, among small farms that sell through DTC outlets, direct marketing represented about 35 percent of total agricultural product sales. By contrast, among medium and large farms that also sell through DTC channels, direct marketing represented only 17 percent and 7.5 percent of total agricultural product sales, respectively.[3]

Other USDA programs that support DTC outlets focus on participants in food and nutrition assistance programs. The Farmers' Market Nutrition Program (FMNP) helps participants in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) to acquire food through DTC outlets. Still another effort, the Senior Farmers' Market Nutrition Program (SFMNP), provides low-income seniors with coupons and vouchers for purchasing eligible foods at farmers markets, CSAs, and roadside stands.

Previous research shows that providing SFMNP and FMNP participants with financial incentives to buy fruits and vegetables at DTC outlets can be effective (e.g., Racine et al., 2010; Baronberg et al., 2013; Dimitri et al., 2015). In Washington, DC, and Charlotte, NC, Racine et al. (2010) survey a total of 179 African-American women participating in WIC. Women who received and redeemed

[1]Households that join community-supported agriculture networks share in the risks and benefits of food production. Typically, members pledge in advance to cover the anticipated costs of a farm operation and the farmer's salary. In return, they receive a share of the farm's output (e.g., a box of fresh vegetables each week throughout the farming season).

[2]Every 5 years, USDA conducts a census of U.S. farms and ranches. Information is collected about the value of products produced and sold directly to individuals for human consumption from roadside stands, farmers markets, and other direct-to-consumer (DTC) outlets. Estimates of DTC agricultural sales exclude non-edible products such as craft items and processed food products such as jellies, sausages, hams, cider, and wine. DTC sales accounted for 0.3 percent of total agriculture sales in 2012, 0.4 percent in 2007, and 0.4 percent in 2002.

[3] Martinez et al. (2010) defines small farms to include operators who reported less than $50,000 in agricultural sales across all marketing channels.

FMNP vouchers reported they were more likely to purchase fruits and vegetables at farmers markets than if they had not received program benefits.

Other research further suggests that opening DTC outlets in low-income/low-access communities may increase fruit and vegetable consumption among the residents of those areas (e.g., Larsen and Gilliland, 2009; Evans et al., 2012). In Texas, Evans et al. (2012) placed farm stands in low-income communities where few retailers offered fresh produce. Residents were surveyed about their fruit and vegetable intake before and after the opening of the farm stands. Responses show the presence of DTC outlets led to increases in consumption of tomatoes, green salad, other vegetables, and fruit. However, since such experiments have only been conducted in a small number of places, it remains unclear whether similar results could be expected in other low-income/low-access communities in general.

Even less clear is what effect, if any, patronizing DTC outlets has on a household's demand for fruits and vegetables outside of low-income/low-access communities when financial incentives are not provided. On the one hand, it might be hoped that households shopping at DTC outlets will see a variety of farm-fresh products, interact with growers, witness nutrition education activities, and watch cooking demonstrations. These experiences could, in turn, increase their demand for fruits and vegetables. On the other hand, households buying fruits and vegetables through DTC outlets may simply curtail their spending at supermarkets, warehouse club stores, and other nondirect retailers by an equally large amount. If so, the net effect of patronizing DTC outlets could be zero, and encouraging these households to buy directly from farmers would have little effect on their overall demand for fruits and vegetables.

In this study, we use data from the National Household Food Acquisition and Purchase Survey (FoodAPS) to test whether shopping at DTC outlets affects a household's level of spending on fruits and vegetables. Expenditures are a broad measure of consumer demand for food products and determine the quantity and variety of specific products a household can buy at a given set of prices. We begin by comparing FoodAPS households that bought fruits and vegetables at DTC outlets and households that also bought fruits and vegetables, but patronized only supermarkets and other nondirect retailers. We then estimate an econometric model to understand how a household's propensity to patronize DTC outlets may affect its weekly-average level of spending on these two food groups. Statistical techniques (including the method of instrumental variables) are used to obtain an unbiased, causal measure of this effect, if any. We also control for other factors that might affect fruit and vegetable demand, such as a household's income, demographics, and attitudes toward food, shopping, and nutrition.

How Much Americans Spend for Fruits and Vegetables and Where They Spend It

USDA's FoodAPS offers unique insights into the food shopping behavior of U.S. households, including where they buy fruits and vegetables and how much they spend. When designing the survey, USDA divided the continental United States into 948 counties or groups of contiguous counties, which served as primary sampling units (PSUs). A stratified sample of 50 PSUs was then selected with probability proportional to size.[4] Finally, a sample of 4,826 households was drawn. Each household participated for a 1-week period between mid-April 2012 and late January 2013.

Detailed information is available about surveyed households. In each household, the main meal planner (primary respondent) reported the household's income as well as demographic information for each household member including the gender, age, education level, race, and ethnicity. Data collectors further questioned primary respondents about their own attitudes and behaviors toward food and nutrition. Below, we begin by examining fruit and vegetable spending by FoodAPS households as well as their tendency to patronize DTC outlets. This provides insights into the characteristics of FoodAPS households, such as how many patronized DTC outlets during their week of participation in the survey and how the attitudes and behaviors of those patrons compares with the characteristics of other FoodAPS households who did not report buying food directly from farmers.

During their 1 week of participation in the survey, almost 74 percent of FoodAPS households (3,558 out of 4,826 households) bought fruits and vegetables for at-home consumption at one or more types of store, including DTC and/or nondirect retail outlets. This includes 68 percent (3,300 households) who bought fresh products and 48 percent (2,312 households) who bought processed products. For this study, we define processed products to include canned, frozen, dried, and juiced foods like frozen peas, 100-percent juice, and canned tomatoes. However, we exclude purchases of some highly processed products, such as fruit drinks containing less than 100 percent juice, canned tomato paste, and frozen potato products. While the consumption of juice drinks, tomato paste, and french fries counts toward an individual's fruit or vegetable consumption, these foods are unlike the fresh products commonly sold at DTC outlets, and it is unlikely that patronizing a DTC outlet would affect demand for them.

Of all 4,826 FoodAPS households, only 231 reported buying food from a farmers market, roadside stand, fruit stand, or other DTC outlet.[5] However, fruits and vegetables were the most frequently purchased type of food at such places. Among the 231 households that bought food at a DTC outlet, 170 bought fruits and vegetables, including 169 who bought fresh products and 10 who bought processed products. Similarly, when Gumirakiza et al. (2014) interviewed 1,488 consumers at 16 farmers markets in Nevada and Utah, 73 percent of respondents reported that buying fresh fruits and vegetables was their primary motivation for visiting the market.

FoodAPS households that bought fruits and vegetables at a DTC outlet were more likely to report having certain attitudes and behaviors than other survey participants who also bought fruits and

[4]Within each of the 50 primary sampling units, USDA further selected 8 secondary sampling units (SSUs) with probability proportional to size. Each SSU comprises one or more contiguous Census Block Groups.

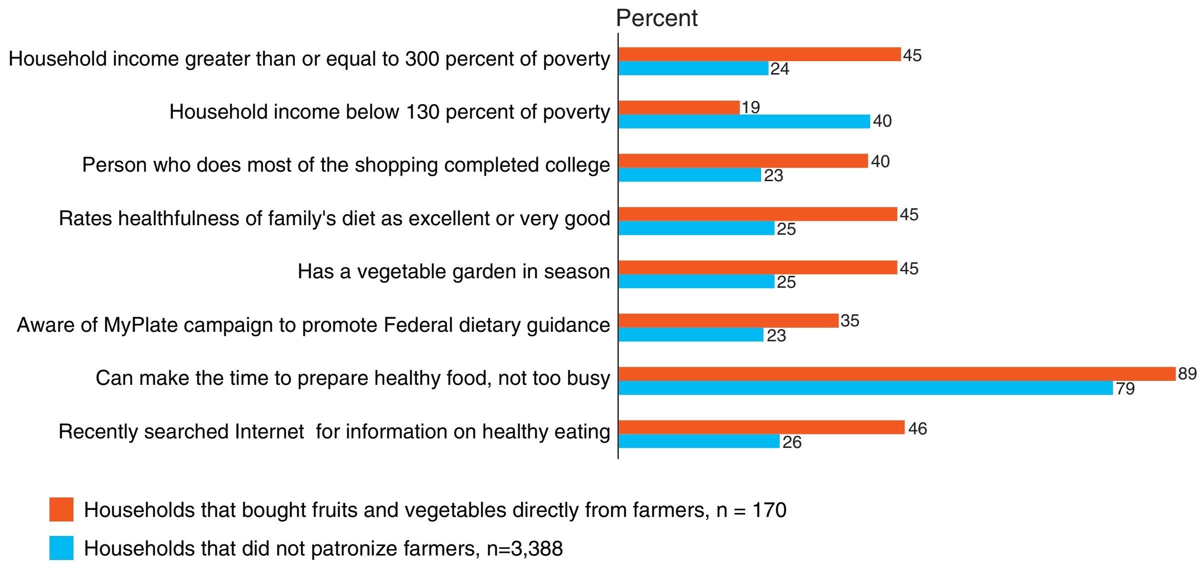
[5]This does not include 17 households that received free food from a DTC outlet.

vegetables but patronized only nondirect retailers (fig. 1).[6] For example, buying fruits and vegetables directly from farmers is positively associated with having a garden (45 percent versus 25 percent for non-DTC shoppers). Households that bought fruits and vegetables at DTC outlets were also more likely than other households to know of USDA's MyPlate campaign to promote Federal dietary guidance (35 percent versus 23 percent) and consider their overall diet quality to be excellent or very good (45 percent versus 25 percent). These results are consistent with a large body of research investigating the attitudes and behaviors of households that patronize DTC outlets, such as Gumirakiza et al. (2014); Maples et al. (2013); Webber et al. (2013); Zepeda and Li (2006); and McGarry Wolf et al. (2005).

DTC shopping households were also more likely than non-DTC shopping households to exhibit certain economic and demographic characteristics (fig. 1).[7] One notable contrast is income—45 percent of DTC shopping households reported incomes at 300 percent or more of the poverty level, compared with 24 percent of non-DTC households. Among the two household categories, those that shopped for fruits and vegetables at DTC outlets were also more likely to have a college-educated main meal planner. Similarly, Onianwa et al. (2005) and McGarry Wolf et al. (2005) find that households with a higher level of education are more likely to shop at farmers markets. However, McGarry Wolf et al. (2005) do not find a significant difference in income between households who shop at farmers markets and other households. In Onianwa et al. (2005), income by itself was not significant, although families with children were more likely to shop at DTC outlets as their income increased.

Figure 1

Households that bought at least some fruits and vegetables directly from farmers have higher incomes and tend to express certain attitudes and behaviors about food and nutrition



Note: Differences reported in the figure are statistically significant at the 5-percent level. Results are based on 3,588 households that bought fruits and vegetables during a 1-week period during which they participated in a survey. Among these households, 170 bought at least some of their fruits and vegetables directly from farmers, and 3,388 patronized only nondirect retail outlets. All estimated percentages are unweighted (see table 2 notes).
Source: USDA, Economic Research Service using the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

[6]All differences in this paragraph are significant at the 5-percent level.

[7]All differences in this paragraph are significant at the 5-percent level.

Consumers may face different prices when shopping at DTC and other retail food stores—even for similar products. FoodAPS participants made 810 purchases of fresh fruits and vegetables at DTC outlets during the period studied. Complete price information is available for 103 of these 810 purchases.[8, 9] Moreover, we can use our price information for these 103 purchases to estimate the average price paid per pound at DTC outlets for 42 different types of produce, such as fresh apples, carrots, and watermelon, since multiple purchases are observed for many produce types. Finally, we compare these price estimates with the average price paid per pound by FoodAPS households for the same 42 types of produce at nondirect retailers (table 1). These price estimates are very broad averages. We do not control for the type of DTC outlet, household characteristics, the season or region in which purchases were made, or the quality of the items acquired. Moreover, while we find that DTC prices were higher for 24 types of produce and lower for 18 types, we do not test whether these price differences were statistically significant.[10] Instead, we merely observe that FoodAPS households sometimes paid more money for fruits and vegetables when shopping at DTC outlets, and sometimes they paid less. This is consistent with a number of studies that find DTC prices can be higher or lower than prices at nondirect retail stores. However, it remains unclear whether either type of outlet charges higher or lower prices than the other, on average (see box "Little Consensus Exists About the Cost of Food at Direct-to-Consumer Outlets Versus Other Retail Food Stores").

To calculate each FoodAPS household's total fruit and vegetable expenditures, we aggregate purchases at DTC outlets and other retail stores. Expenditure information is missing for about 5 percent of all purchases.[11] In such cases, we assume that each fresh item cost $2.12 and each processed item cost $2.01, the average amounts spent per item of fruits and vegetables at nondirect retail stores.[12] By this method, we estimate that the 3,558 FoodAPS households that bought fruits and vegetables during their week of participation in the survey spent $17.09, on average. Among these same households, spending for fresh products exceeded spending for processed products as defined in this study ($12.52 versus $4.57, on average).

Key to this study is whether buying directly from farmers increases a household's demand for fruits and vegetables as measured by its expenditures on these foods across all types of outlets—direct and nondirect. Our data show that overall spending is higher among households that bought some fruits and vegetables at DTC outlets than among households that also bought fruits and vegetables but made all their purchases exclusively at nondirect retailers ($28.36 versus $16.53) (fig. 2).[13] This

[8]In FoodAPS, information on households' expenditures is recorded fairly well. Hypothetically, we may know that a household spent $20 at a roadside stand. We may also know that the household bought apples, cucumbers, and tomatoes. However, in the case of DTC outlets, we often do not know the amount spent on each individual item; rather, we only know the total amount spent on the shopping trip. Quantity information may also be missing. For example, we may know that the household bought apples, but it may be unclear whether the amount purchased was 1 pound of apples, 1 apple, or 1 bag of apples.

[9]These 103 particular purchases were made by 36 different households at 24 different DTC outlets.

[10]We do not attempt to calculate whether these differences are statistically significant given sample sizes.

[11]As noted in footnote 8, we may know that a hypothetical household spent $20 at a roadside stand. We may also know that it bought apples, cucumbers, and tomatoes. As long as the household only bought produce, we do not need to know each item's individual price. It is only problematic if the household also bought nonproduce items on the same shopping occasion. In this case, we must impute the value of the produce items.

[12]Since we are testing whether patronizing a DTC outlet affects a household's total fruit and vegetable expenditures, we use the same average value for all purchases with missing data to be conservative. Assuming no differences in prices biases us toward finding no statistically significant difference in spending between households that buy directly from farmers and other households.

[13]The difference is statistically significant at the 5-percent level.

reflects greater purchases of fresh products ($23.04 versus $12.00).[14] Among both household types, spending for processed products is not significantly different ($5.32 versus $4.53, on average).[15] However, these findings are merely correlations and do not provide a causal measure of whether buying directly from farmers raises a household's total demand for fruits and vegetables.

Table 1
Prices paid for fresh fruits and vegetables at direct-to-consumer (DTC) and nondirect (other) retail food stores

	Average price ($) paid per pound	
	DTC outlets	Other stores
Apples	1.19	1.58
Apricots	1.88	3.88
Arugula	15.00	9.02
Asparagus	5.55	3.58
Bananas	0.69	0.66
Blueberries	9.31	4.00
Broccoli	0.60	1.51
Carrots	1.16	1.31
Cherries, red or black	2.75	2.73
Collard greens	3.20	1.83
Corn	1.35	1.12
Cucumber, regular	2.08	1.57
Eggplant, regular	3.99	1.22
Grapes, blue, black, or red	2.79	2.25
Grapes, white or green	1.41	1.87
Green beans	1.55	1.84
Guineito	1.67	0.77
Kiwifruit	0.55	2.25
Mushrooms, cremini, brown, or swiss brown	5.25	3.50
Mushrooms, regular or button	2.76	3.68
Onions, red	1.24	1.34
Onions, vidalia	0.45	1.13
Onions, yellow or brown	1.34	1.09
Oranges	0.81	1.34
Peaches	1.68	1.50
Pepper, bell	2.49	2.05
Pepper, elongated	3.41	4.05
Pepper, poblano	3.54	1.40
Pepper, red cheese	3.29	2.17
Potatoes, red	0.25	0.86

[14]The difference is statistically significant at the 5-percent level.

[15]This difference is not statistically significant at the 5-percent or 10-percent level.

Table 1

Prices paid for fresh fruits and vegetables at direct-to-consumer (DTC) and nondirect (other) retail food stores—continued

	Average price ($) paid per pound	
	DTC outlets	Other stores
Potatoes, russet	0.36	0.92
Potatoes, white	1.00	0.57
Spinach	4.39	2.56
Spinach, baby	7.38	4.99
Squash, acorn	1.12	1.11
Squash, yellow	0.85	1.26
Squash, zucchini or courgette	1.48	1.25
Strawberries	3.50	2.81
Tomatoes	1.47	1.50
Tomatoes, cherry	1.99	3.39
Tomatoes, grape	1.29	3.34
Tomatoes, plum or roma	2.29	1.05

Note: Average prices reported for DTC outlets are based on 103 purchases. These purchases were made by 36 households at 24 different outlets and are the only fresh fruit and vegetable purchases at DTC outlets for which complete information was provided on both the item's weight and cost. Moreover, we do not control for the type of DTC outlet, the characteristics of purchasing households, the season or region in which purchases were made, or the quality of the fruits and vegetables acquired. We also do not test for differences in statistical significance given small sample sizes; rather, we merely observe that FoodAPS households sometimes paid more money for fruits and vegetables when shopping at DTC outlets, and sometimes they paid less. Data are unweighted.

Source: USDA, Economic Research Service using the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Box 1

Little Consensus Exists About the Cost of Food at Direct-to-Consumer Outlets Versus Other Retail Food Stores

Households that buy fruits and vegetables directly from farmers may face a different set of prices and product assortment than households that shop exclusively at nondirect retail stores. A review of existing research revealed four studies from the past decade in peer-reviewed academic journals and U.S. Government reports that investigate fruit and vegetable prices at DTC outlets (Valpiani et al., 2016; Low et al., 2015; Wheeler and Chapman-Novakofski, 2014; McGuirt et al., 2011). Overall, it appears that households sometimes pay more money when shopping at DTC outlets and sometimes pay less. However, it is unclear whether DTC outlets charge higher or lower prices, on average, because these four studies reach mixed results. Further confounding efforts to reach a consensus are differences across the studies in how researchers measure prices, differences in the variety of products researchers consider, and the geographic scope of the analyses.

continued—

In one study, McGuirt et al. (2011) examine fruit and vegetable prices in 12 North Carolina counties. The researchers first identified the largest farmers market in each of those counties. One researcher then visited each of the 12 identified farmers markets. He recorded vendor prices for all types of fresh fruits and vegetables available at the markets. After visiting each farmers market, he also visited two nearby supermarkets where he recorded prices for the same types of fruits and vegetables. Finally, the researchers compared the average cost of each type of fruit or vegetable at each farmers market with the average cost of similar products at the two supermarkets. For conventionally grown produce, McGuirt et al. (2011) find that the mean DTC price was 18 percent less than the mean supermarket price, which indicates an overall price savings to consumers who shop at farmers markets.

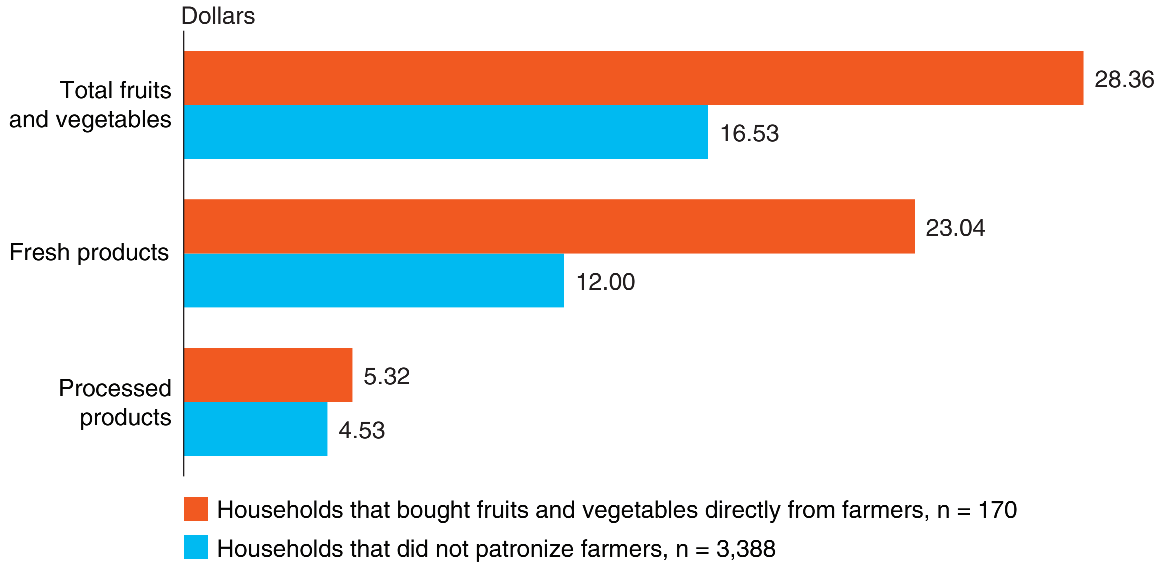
A second study by Low et al. (2015) reaches a similar conclusion. That study uses Nielsen Homescan panel data to compare U.S. average prices for five types of produce at DTC outlets, grocery stores, and supercenters. Though prices are generally lower at DTC outlets, Low et al.'s (2015) results vary by season of the year, by region of the country, and between grocery stores and supercenters. The researchers find, for example, that tomatoes are less expensive at DTC outlets, on average, throughout the year. In the summer, when this vegetable is generally in season, DTC outlets charge 25 percent less than grocery stores. Somewhat surprisingly, the U.S. average price discount for fresh tomatoes at DTC outlets as a share of the grocery store price rises to 38 percent in the winter. However, Low et al. (2015) do not control for produce availability or quality. For example, it is possible that relatively few DTC outlets sell tomatoes in the winter and, among outlets that do sell tomatoes, many may offer hard pink ones picked green in the fields of, say, Florida. Supermarkets and club warehouse stores remain open nationwide and may tend to sell a greater variety of fresh tomato products including hothouse and greenhouse-grown varieties, which can be more expensive.

In contrast to Low et al. (2015) and McGuirt et al. (2011), Wheeler and Chapman-Novakofski (2014) conclude that DTC prices are higher than prices at nondirect retail outlets. That study examines prices at three farmers markets in Urbana, IL. The researchers converted prices for competing products to a dollars-per-pound basis, and identified the least-cost way to buy each of 15 types of fruits and vegetables at each of the 3 farmers markets. They similarly identified the least-cost way to buy each of the same 15 types of fruits and vegetables at 5 nearby grocery stores. Finally, Wheeler and Chapman-Novakofski (2014) compared each item's average cheapest price across the three farmers markets with its average cheapest price across the five grocery stores. Grocery stores offered the lowest prices. Raspberries sold for the greatest premium at DTC outlets (118 percent), followed by peaches (91 percent) and tomatoes (63 percent). Corn (38 percent) and squash (25 percent) commanded smaller premiums at the farmers markets. No significant price differences were found for apples; green bell peppers; or red, yellow, and orange bell peppers.

In a fourth study, Valpiani et al. (2016) compare prices at farmers markets, roadside stands, and supermarkets across North Carolina. Both farmers markets and roadside stands charged less money than supermarkets for watermelon, cantaloupe, and plums, for example, but more money for carrots and potatoes. However, Valpiani et al. (2016) find no significant price difference for most of the 29 fruits and vegetables they consider.

Figure 2

Households that bought at least some fruits and vegetable directly from farmers had higher overall expenditures



Note: Differences reported in the figure are statistically significant at the 5-percent level for only total fruits and vegetables and fresh products. Those for processed products are statistically insignificant. Results are based on 3,588 households that bought fruits and vegetables during a 1-week period during which they participated in a survey. Among these households, 170 bought at least some of their fruits and vegetables directly from farmers, and 3,388 patronized only nondirect retail outlets. All estimated percentages are unweighted (see table 2 notes).
Source: USDA, Economic Research Service using the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Theoretical Framework

Households that buy directly from farmers may substitute purchases of fruits and vegetables at DTC outlets for purchases of the same types of foods at other retail stores. In theory, it is generally assumed that households engage in a multistage budgeting process. A household allocates its financial resources across housing, transportation, medical care, food, and other needs and wants. Spending on food is then divided across meats, dairy products, and fruits and vegetables, among other food groups. The decision of where to buy specific food products comes later (e.g., Bhatnagar and Ratchford, 2004; Staus, 2009; Dong and Stewart, 2012). In a study of how consumers allocate their food dollars between competing retail formats, Staus (2009), for one, assumes that households choose a particular type of store to patronize only after they have already determined whether they need to shop and decided on what purchases they need to make. Thus, by this theoretical framework, a household sets its level of fruit and vegetable purchases before it allocates those purchases across different types of stores, and buying more at one place is likely associated with buying equally less elsewhere.

To our knowledge, no previous study empirically tests whether patronizing DTC outlets affects a household's total fruit and vegetable expenditures, though some studies do suggest that such purchasing behavior may lead to improvements in a household's overall diet quality. Berning (2012), for one, investigates the relationship between an individual's body mass index (BMI) and the number of farmers markets and CSAs in his or her community of residence. The study finds that greater access to DTC outlets has a negative association with individual weight outcomes. Leung et al. (2011) similarly find that greater access to produce stores/farmers markets reduces a child's BMI. Thilmany McFadden and Low (2012) explore the health status of residents in 2,990 U.S. counties. Using data from USDA's Census of Agriculture, the authors find that the number of CSAs and the number of farmers markets are negatively correlated with poor health outcomes, including the adult obesity rate, at the county level.

To formally test whether patronizing DTC outlets increases fruit and vegetable demand, we model spending by FoodAPS households for fruits and vegetables across all types of retailers, including DTC outlets, supermarkets, supercenters, warehouse clubs, and other nondirect retailers. If patronizing a DTC outlet has no impact on total expenditures, we assume that buying fruits and vegetables directly from farmers crowds out spending for these same foods elsewhere. If, on the other hand, patronizing a DTC outlet increases total fruit and vegetable expenditures, we assume that it generates a "patronage" effect. Kinnucan et al. (1997), Capps and Park (2002), and Zheng and Kaiser (2008), among other studies, demonstrate how health information and advertising can influence a consumer's tastes and preferences for a food, driving them to purchase more of the food. Patronizing a DTC outlet might similarly affect a household's tastes and preferences for fruits and vegetables, as consumers shopping at DTC outlets may see a variety of fresh products and interact with growers. About 81 percent of farmers markets further sponsor nutrition education activities like distributing recipe cards or cooking demonstrations (USDA, AMS, 2015). Any of these experiences could heighten interest in fruits and vegetables among DTC shoppers, which may, in turn, prompt these individuals to allocate more money to these food groups during the assumed multistage budgeting process.

A household's demand for food can be measured by its expenditures or by the physical amount of products it purchases. Beatty and Tuttle (2015), for example, examine how changes in food and nutrition assistance benefits influence a household's food-at-home expenditures. Liu et al. (2013) study spending by U.S. households on food away from home. Studies that focus specifically on fruit and vegetable spending include Stewart et al. (2003) and Gustavsen and Rickertsen (2006), among others. In the current study, we similarly focus on fruit and vegetable expenditures. Nelson (1991) argues that expenditures are a better measure of demand when consumers buy heterogeneous goods, including products with different quality attributes. Since expenditures are also the starting point of the household's multistage budgeting process, this study approach further accounts for all of the possible ways in which buying fruits and vegetables directly from farmers could affect demand.[16] Changes in expenditures should precede and capture any changes that may occur in prices paid for fruits and vegetables, the variety of a household's purchases, or the quantity of a household's purchases as a result of patronizing DTC outlets.

Changes in fruit and vegetable spending associated with buying directly from farmers may partly reflect price differences between DTC and nondirect retailers. Thilmany et al. (2008), for one, show that some consumers are willing to pay a premium for local foods. Some may allocate more money to fruits and vegetables because they intend to buy from local producers and are willing to pay more money at a DTC outlet than they would pay for similar foods elsewhere. Higher unit prices paid by these households could generate extra revenue for small farmers, helping them to maintain operations, which is a goal of USDA programs like the FMPP.

Changes in fruit and vegetable spending associated with buying directly from farmers may also reflect changes in the quantity and/or variety of products bought. Indeed, since prices paid at DTC outlets do not appear to be consistently higher or lower than those at other, nondirect retailers (table 1; box "Little Consensus Exists About the Cost of Food at Direct-to-Consumer Outlets Versus Other Retail Food Stores"), large expenditure increases would suggest one of the following:

1. Households may buy more expensive types of fruits and vegetables at DTC outlets. For example, a household may buy grapes instead of bananas, or leafy lettuce instead of iceberg.

2. Households may buy more expensive types of fruits and vegetables at supermarkets after having tried those foods at DTC outlets.

3. Households may buy some products at a farmers market or other DTC outlet that they would not have otherwise purchased, leading to an increase in the total quantity of fruits and vegetables acquired.

4. Households may continue to buy additional items at a supermarket after having tried them at a DTC outlet, leading to an increase in the total quantity of fruits and vegetables acquired.

5. Any combination of the above.

[16]In addition to these theoretical considerations, it also happens that FoodAPS better recorded households' expenditures on fruits and vegetables than it did the physical quantities they purchased. See footnote 8.

Modeling Fruit and Vegetable Expenditures Over 1 Week

To date, it is not clear whether buying fruits and vegetables directly from farmers affects a household's overall demand for these foods. In this study, we first compared fruit and vegetable spending between households that patronized DTC outlets and households that also bought fruits and vegetables but patronized only nondirect retailers. However, this exercise reveals only correlations. It is premature to assume that buying directly from farmers causes or leads to higher levels of fruit and vegetable spending. Other factors like a household's concern for nutrition may affect both its propensity to patronize DTC outlets and its level of fruit and vegetable spending, even if no direct relationship exists between the two behaviors. Appropriate econometric and statistical tools must be used to test for and measure a causal relationship. As described below, we model a household's weekly-average expenditures on fruits and vegetables using an instrumental variable procedure to gain a causal measure of the relationship, if any, between a household's propensity to patronize DTC outlets and its spending on fruits and vegetables.

Following our theoretical discussion of how consumers allocate their budgets to various goods and services, we model a household's fruit and vegetable spending (M) as a function of its financial resources (F), propensity to buy fruits and vegetables at DTC outlets (*DTCFV*), other household characteristics (X), and prices in its community of residence (P). This relationship is specified below in equation 1:

$$M = M(F, P, X, DTCFV) \qquad (1)$$

where F, P, and X each contain a number of independent variables that may predict M. Educational attainment, ethnicity, age, and a household's attitudes toward health and nutrition, for example, are included in X among our household-characteristic variables since they may influence tastes and preferences. Households who care more about health and nutrition may purchase more fruits and vegetables, all else constant.

Our goal in estimating the above model is to test whether patronizing DTC outlets affects a household's expenditures on fruits and vegetables, and *DTCFV* is therefore our independent variable of primary interest. We define this variable to equal a household's probability to buy fruits and vegetables at a DTC outlet in any given week. For example, if *DTCFV* = 0.0192 for a particular household, then that household shops at DTC outlets with probability 1.92 percent in a given week. In other words, since there are 52 weeks in a year, the household buys fruits and vegetables at DTC outlets during roughly 1 week each year.[17] Raising the value of *DTCFV* for that household from 0.0192 to 0.0384 is likewise equivalent to increasing the number of weeks during which the household patronizes DTC outlets from one to two.

Defining *DTCFV* based on a household's probability to buy fruits and vegetables directly from farmers in a given week has the key advantage of accounting for all of the different ways that consumer demand might be affected. As discussed earlier, households that purchase directly from farmers may have greater expenditures because they spend extra money beyond their normal budgets during the weeks they shop at a DTC outlet. However, they may also spend more money during other weeks when they do not patronize a DTC outlet, if, for example, they first tried a food at a

[17]If, on average, a household patronizes DTC outlets with probability 0.0192 each week, then we should expect the household to do so once each year since 52 times 0.0192 equals 1.

farmers markets and continued to buy it at their regular store(s). Our definition of *DTCFV* accounts for both possibilities. We might predict, for example, that a household's weekly-average expenditures are $1 higher because it patronizes DTC outlets a couple times per year. Of course, the household may not consume the same amount each week. The extra money may be spent during only a few weeks of the year or it could be spread out evenly across a large number of weeks. The average or expected size of the increase in weekly-average expenditures only need be $1.

The method of instrumental variables is used to generate values of *DTCFV*, which, when included in our model, will allow us to make a causal statement about whether patronizing DTC outlets increases, decreases, or has no effect on weekly-average fruit and vegetable spending. For this procedure, we estimate a separate probability model. First, we model the probability that a FoodAPS household bought fruits and vegetables directly from farmers during its week of participation in the survey as a function of F, P, X, and some additional (instrumental) variables that do not appear in our main expenditure model. Second, we use our estimation results for this auxiliary probability model to estimate each household's likelihood to buy fruits and vegetables at a DTC outlet in any given week. Finally, following a procedure outlined by Wooldridge (2010) and Angrist and Pischke (2009), we include these predicted values for *DTCFV* in our main model of households' weekly-average fruit and vegetable spending.[18]

Variables Used in the Analysis

As shown in the model just discussed, a household's weekly-average expenditures for fruits and vegetables are hypothesized to depend on a number of independent variables. These variables were defined using data from FoodAPS, the 2012 Census of Agriculture, and the Council for Community and Economic Research (C2ER).[19] An outline of some of the independent variables used in the analysis follows. Table 2 provides a full list of all independent variables along with a definition and the variable's mean value.

A household's fruit and vegetable expenditures may depend on its financial resources and on food prices in its community of residence. *INCOME* and *SNAP* (Supplemental Nutrition Assistance Program) are therefore included among our independent variables. We expect that both factors lead to higher levels of spending. We also considered different measures of food prices. One possible measure of food prices is the cost of a basket of foods based on USDA's Thrifty Food Plan.[20] Researchers at the University of Illinois used retail scanner data provided by market research firm IRI to estimate the cost of such a basket in each FoodAPS household's county of residence. An alternative measure of food prices is a cost-of-living index calculated by C2ER.[21] This index measures the cost of food at grocery stores. It is based on prices for 25 at-home foods, such as ground beef, bread, and orange juice. Data are available for each of 345 metropolitan and micropolitan statis-

[18]Following Wooldridge (2010) and Angrist and Pischke (2009), we first generate values of *DTCFV* for each household using a probit model. Second, we estimate an additional linear probability model. Finally, we use the fitted values from this second-step regression for *DTCFV* in our main expenditure model in lieu of the original, first-step values based on a probit model.

[19]C2ER was formerly known as the American Chamber of Commerce Researchers Association (ACCRA).

[20]USDA's Center for Nutrition Policy and Promotion has developed four food plans. Each shows how a nutritious diet can be achieved at a different cost level. The Thrifty Food Plan in particular represents a healthy, minimal-cost meal plan that can be achieved with limited resources and is used as the basis for SNAP allotments.

[21]C2ER publishes a number of cost-of-living indices. The goal of these indices is to measure the cost of living in different parts of the United States for professional and executive households in the top income quintile.

tical areas for April 2011 through March 2012.[22] In this study, we obtained similar results using the indices created by the University of Illinois and C2ER. Here, we report results using the latter, which we denote as *GROCERYPRICE*.

Table 2
Definitions and means of independent variables used in the study[1]

Variable name	Variable definition	Mean
Household economic and demographic characteristics		
INCOME	Total monthly household income ($1,000)	3.811
SNAP	Used SNAP benefits during survey week (0/1)	0.198
COLLEGE	Main meal planner completed college (0/1)	0.211
AGE	Age of household's main meal planner (decades)	4.600
EMPLOYED	Main meal planner works at a job or business (0/1)	0.451
ASIAN	Main meal planner is Asian (0/1)	0.040
HISPANIC	Main meal planner is Hispanic (0/1)	0.194
BLACK	Main meal planner is Black (0/1)	0.146
NOCAR	Household does not have access to a car (0/1)	0.046
GUESTS	Household provided a meal or snack to a guest (0/1)	0.286
HHMEMBERS	Number of people living in the household	2.967
ADULTMALE	Number of males aged more than 18 years	0.922
ADULTFEMALE	Number of females aged more than 18 years	1.091
MALETEE*N*	Number of males aged 14 to 18 years	0.12
FEMALETEEN	Number of females aged 14 to 18 years	0.121
MALEYOUTH	Number of males aged 11 to 13 years	0.076
FEMALEYOUTH	Number of females aged 11 to 13 years	0.069
MALECHILD	Number of males aged 0 to 10 years	0.289
FEMALECHILD	Number of females aged 0 to 10 years	0.278
Attitudes toward health and nutrition		
GARDEN	Has a vegetable garden in season (0/1)	0.238
MYPLATE	Main meal planner is aware of MyPlate (0/1)	0.219
INTERNET	Searched internet for information on healthy eating (0/1)	0.265
HEALTHYDIET	Rates own diet as very good or excellent (0/1)	0.234
TIME	Makes the time to prepare healthy food, not too busy (0/1)	0.797
Seasonality variables		
SPRING	Surveyed during the spring (0/1)	0.146
SUMMER	Surveyed during the summer (0/1)	0.437
FALL	Surveyed during the fall (0/1)	0.376
Community characteristics and marketing variables		
COUNTYOBESITY	Percentage of county's residents who are obese	28.407
COUNTYBLACK	Percentage of county's residents who are Black	9.708

[22]We were generally able to match a FoodAPS household's county of residence directly to a metropolitan or micropolitan statistical area for which C2ER provides data. In the remaining cases, we merge a respondent's record with the value of C2ER's grocery price index for the nearest metropolitan or micropolitan statistical area for which data are available.

Table 2
Definitions and means of independent variables used in the study[1]—continued

Variable name	Variable definition	Mean
COUNTYASIAN	Percentage of county's residents who are Asian	4.598
COUNTYHISPANIC	Percentage of county's residents who are Hispanic	15.710
COUNTYINCOME	Median income in the household's county	50,105.310
POPDENSITY	Population per square mile in household's county	1,465.330
GROCERYPRICE	Cost-of-groceries index divided by 100	1.009
Identifying instruments		
PEAKSEASON	Surveyed between June 3 and September 30 (0/1)	0.589
DTCFARMERS	Number of DTC farmers in the household's State (# per sq. mile)	0.079
Propensity to patronize DTC outlets		
DTCFV	Estimated probability to buy fruits and vegetables at DTC outlets divided by 100	0.035

SNAP = Supplemental Nutrition Assistance Program. FoodAPS = National Household Food Acquisition and Purchase Survey. DTC = direct-to-consumer.

[1]Means are unweighted. If calculated using sample weights, sample means are not only representative of FoodAPS households, but may be representative of all households living in the contiguous United States as well. Each FoodAPS household is assigned a sample weight based on the survey design and its own economic and demographic characteristics. However, in this study, it is unclear whether using sample weights would make our particular results representative of the U.S. population as a whole. Census of Agriculture data show that the number of DTC outlets in business across the United States varies widely from State to State, and FoodAPS may either under- or over-represent higher access States. Since FoodAPS sample weights were not calculated in a manner that explicitly accounts for this variation, we do not use them. We instead examine only the characteristics of the sample and rely on our statistical model to test hypotheses that may be generalized to the U.S. population. Unlike descriptive measures of population characteristics, such as population averages and ratios, it is possible to estimate a statistical model without using sample weights and still obtain appropriate (unbiased and consistent) estimates of any relationships that exist among the variables (e.g., DuMouchel and Duncan, 1983; Winship and Radbill, 1994).

Source: USDA, Economic Research Service using the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

In our demand model, it may be especially important to control for a household's tastes and preferences with respect to the importance that it places on home-cooked meals and nutrition. We therefore include the main meal planner's age (*AGE*), a binary indicator of whether this person has completed college (*COLLEGE*), a binary indicator of whether this person has a job (*EMPLOYED*), and three binary indicator variables for the same person's race/ethnicity (*ASIAN*, *HISPANIC*, and *BLACK*). Previous research shows that these demographic characteristics of a household can be strong predictors of fruit and vegetable demand (e.g., Stewart et al., 2003; Dong and Lin, 2009).

In addition to the major demographic characteristics of households, we also add direct measures of a household's attitudes and behaviors. These include two binary indicator variables to capture a household's interest in and knowledge of nutrition. One measures whether the main meal planner is aware of USDA's MyPlate campaign to promote Federal dietary guidance (*MYPLATE*), and the other measures whether the household has recently searched the Internet for information on healthy eating (*INTERNET*). To further account for the importance that a household places on diet quality, we include a binary indicator of whether the main meal planner rates his or her family's diet quality as very good or excellent (*HEALTHYDIET*). To account for whether a household prioritizes cooking and family meals, we include a fourth binary indicator variable for whether the main meal planner reports being able to make the time in his or her schedule to prepare healthy meals (*TIME*). Finally, we include a fifth binary indicator variable to account for whether the household has a garden in season (*GARDEN*), since this may be associated with interest in fresh produce. If the major demographic characteristics of households do not already well enough proxy for key tastes and preferences, then including these variables in our model may help to isolate and test the effect of DTC patronage on fruit and vegetable spending.

Finally, we create our independent variable of primary interest, *DTCFV*, using an instrumental variable procedure as described earlier. The likelihood that a household purchases fruits and vegetables directly from farmers in any given week is estimated for each household. Among the independent variables in this auxiliary model, we include *INCOME*, *SNAP*, demographics, and a household's attitudes toward food and nutrition. We also include two variables excluded from our main expenditure model that serve as identifying instruments and are particularly important since they will enable us to identify the effect of *DTCFV* on M in equation (1). Both of our selected instruments proxy for a household's access to DTC outlets. Building on theoretical models like Salop's (1979) transportation cost model in which individuals choose the closest location, it can be hypothesized that the greater a household's access to DTC outlets, the lower should be its time and money costs for patronizing one of them. Indeed, when McGarry Wolf et al. (2005) interviewed customers at food stores in California, they found that the primary barrier to patronizing a farmers market is a lack of convenience. Similarly, when Abello et al. (2014) interviewed customers at two Texas farmers markets, they found that increases in the distance needed to travel to a DTC outlet tend to decrease the frequency of patronage.

Our first identifying instrument is a proxy for the number of DTC outlets likely located around a FoodAPS participant. One such possible measure is the number of farmers engaged in DTC marketing in a household's State of residence as reported in USDA's 2012 Census of Agriculture. To control for differences in State sizes, we can further divide the reported number by the size of the household's State in square miles. However, this measure may still be less precise for large States like California or Texas than for small States like Delaware or Rhode Island. It may also be less precise for households living near the border of two States. Another possible measure is the number of farmers markets in a household's county of residence as reported in the ERS Food Environment Atlas. However, this measure has other limitations: (1) Many FoodAPS households shopped outside of their own county, and (2) Many FoodAPS households bought fruits and vegetables at a roadside stand, CSA, or other type of DTC outlet besides a farmers market. In this study, we found that State-level data from the Census of Agriculture better explained a household's propensity to patronize DTC outlets than county-level data on only the number of farmers markets from the ERS Food Environment Atlas. We therefore report results using the former, which we denote as *DTCFARMERS*.

Our second identifying instrument proxies for whether the DTC outlets around a household were open while it participated in FoodAPS. Most DTC outlets operate seasonally. A USDA-maintained list of farmers markets across the United States, for example, shows that many open in May and close in October (USDA, AMS, 2017b). It is likewise reasonable to consider June through September a peak period for shopping at DTC outlets, and we define our instrument accordingly. Specifically, *PEAKSEASON* is a binary indicator variable for whether a household participated in FoodAPS between June 3 and September 30, when USDA's own farmers market in Washington, DC, is open during both daytime and nighttime hours.

Model Estimation and Results

Using data on 4,826 FoodAPS households, we estimated our model of weekly-average fruit and vegetable spending based on equation (1) above. Because only 74 percent of surveyed households bought fruits and vegetables while participating in FoodAPS, we used Blundell and Meghir's (1987) infrequency of purchase framework to specify our empirical model. In this framework, it is assumed that the other 26 percent of households did not shop for fruits and vegetables because they already had an ample stock of these foods at home. Indeed, several types of fresh fruits and vegetables have a shelf life greater than 1 week. These include tomatoes (2 weeks), apples (1-2 months), oranges (1-2 months), and potatoes (2-4 months), among others (eatbydate.com, 2017). By contrast, strawberries (5-7 days) and packaged lettuce (3-5 days) last less than 1 week. Thus, depending on what types of produce it consumes, a household may buy fruits and vegetables as frequently as every few days or as seldom as every several weeks. A detailed discussion of Blundell and Meghir's (1987) infrequency of purchase model is presented in appendix 1.

Because FoodAPS was collected using a form of cluster sampling, we further calculated robust standard errors for all model estimates.[23, 24] A bootstrap procedure with 250 replications was used. Following Deaton (1997), we created each bootstrap sample by first resampling at the PSU-level and then randomly resampling households within PSUs. Efron and Tibshirani (1998, p. 52) report that 100 replications "gives quite satisfactory results" and "very seldom" are more than 200 replications needed.

Additional analysis was also undertaken to ensure the quality of *DTCFARMERS* and *PEAKSEASON* as instrumental variables, given their special role in identifying how changes in *DTCFV* affect weekly-average fruit and vegetable spending. A detailed discussion of this analysis is available in appendix 2.

Finally, we estimated our model of household spending for total, fresh, and processed fruits and vegetables.[25] We then used our estimates of the model's parameters to determine how a change in any independent variable might affect a household's weekly-average expenditures on each type of product. Marginal effects for total, fresh, and processed fruits and vegetables are reported in tables 3 through 5.

In this section, we summarize our results beginning with a brief discussion of the estimated marginal effects: how changes in an independent variable affect a household's weekly-average fruit and vegetable expenditures. We then use our model results to develop two simulations. In the first simulation, we lay out the behavior of a representative household that does not shop at DTC outlets. In the second simulation, we assume that the same household starts to buy fruits and vegetables at DTC outlets during a single week each year and, holding all else constant, examine how this affects the household's weekly-average fruit and vegetable expenditures.

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[23]As described above, USDA first divided the continental United States into 948 counties or groups of contiguous counties, which served as primary sampling units (PSUs). Fifty of these 948 PSUs were then selected. Finally, samples of households were drawn from each of the 50 selected PSUs. This is a form of cluster sampling. Standard errors calculated in the traditional manner will be underestimated.

[24]Standard errors calculated in the traditional manner will be further underestimated because we used predicted values for *DTCFV* in estimating the model.

[25]Gauss software was used.

Table 3
Marginal effects, total fruit and vegetable spending

	Marginal effect	Standard error
Household economic and demographic characteristics		
INCOME	0.25**	0.107
SNAP	3.292**	0.68
COLLEGE	2.992**	0.776
AGE	0.596**	0.189
EMPLOYED	0.446	0.545
ASIAN	2.73*	1.54
HISPANIC	1.293	0.905
BLACK	-1.618*	0.836
NOCAR	-1.522	1.276
GUESTS	0.995*	0.527
ADULTMALE	1.115**	0.401
ADULTFEMALE	0.98*	0.583
MALETEEN	0.152	0.73
FEMALETEEN	1.431*	0.843
MALEYOUTH	-0.19	0.914
FEMALEYOUTH	1.312	0.992
MALECHILD	1.061**	0.483
FEMALECHILD	1.041**	0.508
Attitudes toward health and nutrition		
GARDEN	0.559	0.628
MYPLATE	0.328	0.616
INTERNET	1.73**	0.625
HEALTHYDIET	1.705**	0.764
TIME	1.177*	0.634
Seasonality variables		
SPRING	-0.105	1.569
SUMMER	-0.325	1.439
FALL	-1.116	1.384
Community characteristics and marketing variables		
COUNTYOBESITY	-0.276**	0.139
COUNTYBLACK	0.026	0.036
COUNTYASIAN	0.062	0.115
COUNTYHISPANIC	0.027	0.031
COUNTYINCOME	0.0001	0.00005
POPDENSITY	0.00004	0.0002
GROCERYPRICE	-3.396	4.316
Propensity to patronize DTC outlets		
DTCFV	31.343**	11.214

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Marginal effects are evaluated at the mean of the sample data (table 2). Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. Sample weights not used.
Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Table 4
Marginal effects, fresh fruit and vegetable spending

	Marginal effect	Standard error
Household economic and demographic characteristics		
INCOME	0.175**	0.08
SNAP	2.177**	0.537
COLLEGE	2.205**	0.61
AGE	0.442**	0.136
EMPLOYED	0.117	0.459
ASIAN	3.283**	1.349
HISPANIC	1.842**	0.707
BLACK	-1.42**	0.688
NOCAR	-1.21	0.941
GUESTS	0.736*	0.42
ADULTMALE	0.815**	0.29
ADULTFEMALE	0.711	0.462
MALETEEN	0.316	0.618
FEMALETEEN	1.12*	0.641
MALEYOUTH	0.303	0.726
FEMALEYOUTH	1.152	0.82
MALECHILD	0.679*	0.382
FEMALECHILD	0.511	0.419
Attitudes toward health and nutrition		
GARDEN	0.467	0.502
MYPLATE	0.12	0.521
INTERNET	1.405**	0.47
HEALTHYDIET	1.261**	0.567
TIME	0.732	0.531
Seasonality variables		
SPRING	1.167	1.225
SUMMER	0.824	1.124
FALL	-0.008	1.082
Community characteristics and marketing variables		
COUNTYOBESITY	-0.186	0.117
COUNTYBLACK	0.027	0.03
COUNTYASIAN	0.031	0.092
COUNTYHISPANIC	0.019	0.024
COUNTYINCOME	0.00006	0.00004
POPDENSITY	0.00008	0.00017
GROCERYPRICE	-2.443	3.627
Propensity to patronize DTC outlets		
DTCFV	26.422**	9.215

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Marginal effects are evaluated at the mean of the sample data (table 2). Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. Sample weights not used.
Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Table 5
Marginal effects, processed fruit and vegetable spending

	Marginal effect	Standard error
Household economic and demographic characteristics		
INCOME	0.001	0.027
SNAP	0.711**	0.192
COLLEGE	0.665**	0.21
AGE	0.065	0.073
EMPLOYED	-0.064	0.151
ASIAN	-1.014**	0.484
HISPANIC	-0.555**	0.301
BLACK	-0.467*	0.256
NOCAR	-0.485	0.396
GUESTS	0.088	0.18
ADULTMALE	0.223	0.137
ADULTFEMALE	0.135	0.131
MALETEEN	-0.026	0.217
FEMALETEEN	0.323	0.268
MALEYOUTH	0.042	0.317
FEMALEYOUTH	0.225	0.298
MALECHILD	0.32**	0.16
FEMALECHILD	0.33**	0.168
Attitudes toward health and nutrition		
GARDEN	0.2	0.196
MYPLATE	0.157	0.179
INTERNET	0.466**	0.202
HEALTHYDIET	0.133	0.207
TIME	0.16	0.162
Seasonality variables		
SPRING	-0.776*	0.433
SUMMER	-0.801*	0.436
FALL	-0.812**	0.388
Community characteristics and marketing variables		
COUNTYOBESITY	-0.032	0.04
COUNTYBLACK	-0.004	0.011
COUNTYASIAN	0.027	0.027
COUNTYHISPANIC	0.005	0.008
COUNTYINCOME	0.000005	0.00001
POPDENSITY	-0.00002	0.00005
GROCERYPRICE	-0.573	1.258
Propensity to patronize DTC outlets		
DTCFV	2.781	3.335

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = drect-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Marginal effects are evaluated at the mean of the sample data (table 2). Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. Sample weights not used.
Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Marginal Effects

Almost 74 percent of FoodAPS households bought fruits and vegetables at some type of retail store—DTC or other format—during their week of participation in the survey. Among these purchasing households, the average level of spending was $17.09. Across all FoodAPS households, including fruit and vegetable buyers and nonbuyers, spending averaged $12.60 (calculated as 0.737 x $17.09). Estimation of our econometric model further reveals that:

- The amount a household spends on fruits and vegetables increases with the age of the main meal planner. Increasing the age of a household's main meal planner by 10 years raises the household's weekly-average expenditures by $0.60 (table 3).

- Education is positively associated with fruit and vegetable demand. Households with a college-educated main meal planner spend $2.99 more on fruits and vegetables per week than households in which the main meal planner does not have a college degree (table 3).

- Patronizing DTC outlets appears to increase consumer demand for fruits and vegetables as measured by a household's willingness to spend money on these foods, but the effect is limited to fresh products (tables 3-5).

Of primary interest are results on our patronage variable, *DTCFV*. From the estimated marginal effect (see table 3), we find that increasing *DTCFV* from zero to 0.01 would increase a household's weekly-average fruit and vegetable expenditures by about $0.31 (calculated as 0.01 times 31.343). Similarly, a 1.92-percentage-point increase in *DTCFV* would raise weekly-average expenditures by $0.60 (calculated as 0.0192 times 31.343). For a household that did not previously patronize DTC outlets, this is roughly equivalent to increasing the number of weeks during which a visit is made from 0 to 1.[26] Moreover, for a household that already spends $12.60 per week, on average, including weeks when it does and does not buy fruits and vegetables, 60 additional cents would represent a 5-percent increase in expenditures.

However, increasing the probability that a household buys fruits and vegetables through DTC outlets in a given week raises expenditures on fresh products only (table 4). Such an increase has no impact on the demand for processed products. For processed fruits and vegetables, the estimated marginal effect of *DTCFV* is not statistically different than zero (table 5). Consumers patronizing DTC outlets are exposed primarily to fresh products, and increases in demand associated with buying directly from farmers seem limited to fresh fruits and vegetables.

Simulation

Buying directly from farmers appears to increase consumer demand for fruits and vegetables, as measured by a household's willingness to spend money on these foods. To better understand the magnitude of this relationship and to more generally illustrate the type of household behavior that our model implies, we conducted a simulation. In the following section, using our estimation results, we lay out the behavior of a representative household that does not patronize DTC outlets. We then assume that the household starts to buy fruits and vegetables at a combination of DTC and nondirect retailers during only 1 week each year. Finally, we compare the household's expected fruit and vegetable expenditures in the two scenarios and ask whether price differences between DTC outlets and nondirect retailers are likely to explain the identified differences in spending (table 6).

[26]The household may make one or more visits to a DTC outlet during that 1 week.

Table 6

Household's predicted fruit and vegetable expenditures when it never patronizes DTC outlets and when it buys directly from farmers during 1 week each year, simulation results

	Never shops at DTC outlets	Shops at both DTC and nondirect retailers during 1 week each year		
		Mean	Lower bound	Upper bound
Average weekly expenditures ($)	12	12.60	12.18	13.01
Number of weeks household shops	39	39	39	39
Number of weeks household buys at DTC outlet	0	1	1	1
Average expenditures during shopping weeks ($)	16	16.79	16.24	17.35
Annual expenditures ($)	624	654.97	633.25	676.68

Note: DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. Simulations are based on estimated marginal effects shown in table 3. Results are provided for the mean, lower bound, and upper bound estimates of a 95-percent confidence interval for the marginal effect of *DTCFV,* which measures a household's propensity to patronize DTC outlets.
Source: USDA, Economic Research Service.

We begin our simulation by assuming that a representative household's fruit and vegetable spending averages $12 per week (slightly below the mean level of actual spending across all sampled households), or, equivalently, $624 per year (calculated as $12 x 52). Moreover, we assume that the household buys fruits and vegetables during 39 weeks each year (75 percent of 52 weeks). It spends $16 during each of these weeks, on average (calculated as 12/0.75). However, the household patronizes only nondirect retailers. It never buys fruits and vegetables directly from farmers (i.e., *DTCFV* = 0).

For the second part of our simulation, we now assume that the same household starts to buy fruits and vegetables at a combination of DTC and nondirect retailers during 1 week each year (i.e., *DTCFV* = 0.019). Using our results in table 3, we can create a confidence interval for the household's new level of fruit and vegetable expenditures in this alternative scenario. Based on the estimated marginal effect of *DTCFV* and its associated standard error, we predict with 95 percent certainty that the household now spends between $633.25 and $676.68 on fruits and vegetables over the course of 1 year. This represents an overall increase in annual spending of $9.25 to $52.68 on these two food groups. Patronizing DTC outlets during 1 week each year does not change the household's overall purchase frequency. It still shops 39 out of 52 weeks.[27]

Increased spending by our representative household in the alternative scenario as a result of patronizing a DTC outlet during 1 week each year could represent many things. It could reflect price differences between DTC outlets and nondirect retail stores. As noted earlier, higher unit prices paid by some DTC patrons could represent revenue to small farmers, helping them to maintain operations, which is a goal of USDA programs like the FMPP. The household may also be purchasing a different quantity and/or variety of items. Moreover, all additional money could be spent exclusively at DTC outlets, or some could be spent at nondirect retailers. As noted, for example, a household

[27]As shown in table 3, the marginal effect of *DTCFV* is 31.34 with a standard error of 11.21. A 10-percentage-point increase in *DTCFV* would raise a household's weekly rate of fruit and vegetable usage by $3.13. A 1.9-percentage-point increase would likewise raise it by $0.60 (calculated as 0.019 x 31.34 ≈ 0.60). Of course, 31.34 is only a point estimate. To generate a 95-percent confidence interval for the marginal effect, we calculate 31.34 plus or minus 1.96 standard errors.

could try a food at a DTC outlet, like it, and continue to buy the same or similar products at the household's regular store(s), affecting purchases in other weeks, too.

For the final part of our simulation, we assume that higher levels of spending in the alternative scenario in table 6 reflect only higher prices paid for fruits and vegetables at DTC outlets during the 1 week that the household also buys directly from these places. In other words, we assume that our representative household continues to buy the same quantity and variety of foods during all 39 shopping weeks. If so, during 38 weeks each year, it must continue to spend $16 for the same foods as before at nondirect retailers. Its fruit and vegetable expenditures remain $608 (calculated as 38 x $16) during those weeks when it does not patronize DTC outlets. Furthermore, since the household's annual expenditures are now between $633.25 and $676.68, it must spend $25.25 (calculated $633.25 – $608) to $68.68 (calculated $676.68 – $608) during the 1 week that it now patronizes a combination of DTC and nondirect retailers. However, if the household were to spend only $8 at nondirect retailers during that week, it would need to spend the rest of the week's budget at DTC outlets for the same quantity and variety of foods it previously bought at nondirect retailers with the other $8 of its usual $16 budget. This would require DTC prices to range between two and three times higher than supermarket prices, which appears unlikely given the average price data we sampled (see table 1) and the existing literature (see box "Little Consensus Exists About the Cost of Food at Direct-to-Consumer Outlets Versus Other Retail Food Stores"). Thus, it is more likely that the increase in annual spending reflects both price differences and some changes in the quantity and/or variety of fruits and vegetables bought on at least some weeks.

Conclusions

USDA works to develop, improve, and expand DTC outlets. In this study, we ask whether buying directly from farmers increases a household's overall level of spending for fruits and vegetables, including purchases at nondirect retailers, or, alternatively, crowds out spending for these same foods elsewhere in the budget. Using data from USDA's FoodAPS, we initially compared fruit and vegetable spending between households that did and did not patronize DTC outlets. After estimating an econometric model, we further confirmed that patronizing DTC outlets raises a household's demand for fresh products, as measured by the household's total expenditures, but has no impact on spending for processed products.

Higher levels of spending associated with buying directly from farmers may partially reflect price differences between DTC and nondirect outlets. Some households may allocate more money to fruits and vegetables because they intend to buy from local producers and are willing to pay more money at a DTC outlet than they would pay for similar foods elsewhere. Previous research shows that some consumers will pay a premium for local foods, partly because they want to support local producers (Thilmany et al., 2008). The willingness of these households to pay a premium at DTC outlets, in turn, could represent revenues to small farmers, helping them to maintain operations.

Spending increases associated with buying directly from farmers may also reflect changes in the mix of foods purchased. Households that patronize DTC outlets more often appear to buy a larger quantity and/or a different variety of fresh fruits and vegetables than other households. This, in turn, could affect their diet quality for better or worse. Additional research is needed to better understand these changes in demand and their health implications.

Additional research is also needed to better understand any effects that USDA programs may have on a household's overall demand for fruits and vegetables. In this study, we make no effort to account for the impact on consumers of programs that support DTC outlets. Moreover, we make no attempt to investigate whether the relationship between a household's fruit and vegetable spending and its tendency to patronize DTC outlets varies for particular segments of the population, such as low-income households or high-income households.

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Appendix 1: The Infrequency of Purchase Model

In this study, using FoodAPS data, we model a household's average-weekly spending on fruits and vegetables. Our goal is to test whether households that patronize DTC outlets more frequently than other households spend more money on these food groups across all outlet types—DTC and nondirect retailers. However, because 24 percent of FoodAPS households reported zero fruit and vegetable spending, we cannot use traditional regression procedures when modeling equation (1) in the text. These procedures could produce biased estimates.

Following Deaton and Irish (1984) and Blundell and Meghir (1987), we assume that FoodAPS survey participants who reported zero fruit and vegetable expenditures already had an ample stock of these foods at home. They consumed out of storage and simply did not need to shop for additional items. Indeed, even among households that bought fruits and vegetables, we believe that FoodAPS survey records may be a poor measure of weekly-average spending. Some of these households may have bought more than they consumed during the survey week, saving items for consumption in a future period. To model demand in this type of situation, Deaton and Irish (1984) and Blundell and Meghir (1987) developed the infrequency of purchase model (IPM). Variations of the IPM have been estimated by Gould (1992), who studies U.S. cheese consumption; Blisard and Blaylock (1993), who investigate spending on butter by U.S. households; Newman et al. (2001), who analyze household meat expenditures in Ireland; and Gibson and Kim (2012), who investigate the consumption of various commodities in Papua New Guinea.

Following Blundell and Meghir's (1987) IPM framework, we can infer the dollar value of the fruits and vegetables that a FoodAPS household typically consumes each week, even though raw survey records provide a poor measure of weekly-average spending. For households that made a purchase during the survey week, we assume that

(A1.1) $Y_i L_i = M_i$

where Y_i is observed expenditures, L_i is the likelihood or probability that i shops for fruits and vegetables in any given week, and M_i represents a household's rate of fruit and vegetable usage in dollar terms over 1 week (hereafter termed its "latent expenditures"). For example, if a household spent \$10 for fruits and vegetables in 1 week ($Y_i = 10$) and it typically shops for these foods every 2 weeks ($L_i = 0.5$), then its latent expenditures are \$5 worth of fruits and vegetables per week ($M_i = 5$).

In the IPM framework, it is also hypothesized that households that shop more often buy less on each purchase occasion, all else constant. Manipulating (A1.1) further shows that a household's observed or conditional spending is:

(A1.2) $$Y_i = M_i / L_i$$

where, holding M_i constant, an increase in L_i would lower the amount of money the household spends when purchases are made. Notably, conditional purchases approach latent expenditures as L_i approaches 1, which we would expect if a survey were collected over a long enough period.

To estimate an IPM for a household's weekly-average fruit and vegetable spending, we begin by specifying the probability that the household buys fruits and vegetables at any type of store during a given week, L_i. This probability is:

$$(A1.3) \qquad \begin{aligned} L_i &= \text{Probabilty}(SHOPFV_i > 0) \\ &= \text{Probabilty}(\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i + w_i > 0) \\ &= \Phi(\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i) \end{aligned}$$

where $SHOPFV_i$ measures the benefit to household i from shopping, F_i includes household i's income and other financial resources, P_i captures the price level that i faces, and Z_i is a vector of other independent variables. These independent variables may include demographic characteristics and a household's attitudes and behaviors toward food and nutrition. For example, households that do not own cars may shop for fruits and vegetables less often than car-owning households. By contrast, if Asian and Hispanic households tend to consume a greater variety of fruits and vegetables, including products with shorter shelf lives, then such households may shop for fruits and vegetables more often than households of other race and ethnicity types. θ_0, θ_1, θ_2, and θ_3 are parameters and w_i is a standard normal error term. Finally, $\Phi(\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i)$ denotes the standard normal CDF evaluated at $\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i$.

Next, we complete the IPM's specification by writing the relationship between weekly-average expenditures, M_i, and observed purchases, Y_i, for purchasing households as

$$(A1.4) \qquad \begin{aligned} \Phi(\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i) Y_i &= M_i + v_i \\ &= (\beta_0 + \beta_1 F_i + \beta_2 P_i + \beta_3 X_i + \delta DTCFV_i + e_i) + v_i \\ &= \beta_0 + \beta_1 F_i + \beta_2 P_i + \beta_3 X_i + \delta DTCFV_i + u_i \end{aligned}$$

which is based on equations (A1.1) and (A1.3) where X_i is a vector containing many of the same independent variables in Z_i and $DTCFV_i$ captures i's propensity to buy fruits and vegetables at DTC outlets. Whereas $SHOPFV_i$ from equation (A1.3) captures how often a household buys fruits and vegetables at any outlet type, $DTCFV_i$ captures exclusively how often it buys fruits and vegetables directly from farmers. β_0, β_1, β_2, β_3, and δ are parameters. Both v_i and e_i are normally distributed error terms with mean zero while $u_i = (e_i + v_i)$ is revealed to be a composite error term with mean zero and a variance of σ_u^2.

Finally, assuming that the error terms in (A1.3) and (A1.4) are independent, Blundell and Meghir (1987) show that the log-likelihood function becomes

$$(A1.5) \qquad \begin{aligned} \ln L = {} & \textstyle\sum_0 \ln (1 - \Phi(\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i)) \\ & + \textstyle\sum_+ [2\ln (\Phi(\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i)) - \ln\sigma_u + \ln\varphi(\psi)] \end{aligned}$$

where $\psi = (\Phi(\theta_0 + \theta_1 F_i + \theta_2 P_i + \theta_3 Z_i) Y_i - \beta_0 - \beta_1 F_i - \beta_2 P_i - \beta_3 X_i - \delta DTCFV_i)/\sigma_u$. Also, Σ_0 and Σ_+ refer to the summation over households with zero and positive purchases, respectively, and φ denotes the standard normal PDF. Estimates of the parameters can be obtained through the maximization of (A1.5).

Given estimates of the model's parameters, it is also possible to predict how changes in the independent variable affect a household's weekly-average fruit and vegetable expenditures, M. Using latent expenditures as modeled in the IPM framework to measure weekly-average spending, and taking expectations, we find that $E(M) = \beta_0 + \beta_1 F + \beta_2 P + \beta_3 X + \delta E(DTCFV)$, where $E(DTCFV)$ is the expected value of a household's propensity to buy fruits and vegetables at DTC outlets from the instrumental regression. Since this is a linear model, we can use the estimated values of β_0, β_1, β_2, β_3, and δ to measure the change in a representative household's latent expenditures following a change in an independent variable, say X_j or *DTCFV*, respectively, for all continuous and binary variables.

For this study, we estimated an IPM by maximum likelihood using an instrumental variable procedure as well as a bootstrap procedure to generate robust standard errors as described in the text. Estimation results for total fruit and vegetable spending are shown in appendix tables A1.1a-1b. Both *DTCFARMERS* and *PEAKSEASON* determine whether households patronized a DTC outlet (appendix table A1.1a), and *DTCFV* is a significant determinant of fruit and vegetable spending (appendix table A1.1b).

Appendix table A1.1a

Coefficient estimates for model of probability that households buy fruits and vegetables directly from farmers in a given week

	Coefficient	Standard error
Constant	-4.336**	1.026
INCOME	0.018**	0.009
SNAP	-0.091	0.177
COLLEGE	0.166	0.149
AGE	0.125**	0.039
ASIAN	0.01	0.341
HISPANIC	-0.42	0.294
BLACK	-0.499**	0.254
GARDEN	0.238**	0.115
MYPLATE	0.164	0.117
INTERNET	0.331**	0.137
HEALTHYDIET	0.252**	0.109
WORTHTIME	0.171	0.175
COUNTYOBESITY	0.03	0.029
COUNTYBLACK	0.002	0.01
COUNTYASIAN	0.027	0.02
COUNTYHISPANIC	-0.004	0.01
MEDIANINCOME	-0.000002	0.000008
POPDENSITY	-0.00001	0.00007
PEAKSEASON	0.391**	0.163
DTCFARMERS	3.492**	1.34
Model fit statistics		
F-statistic for PEAKSEASON and DTCFARMERS		7.62

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A1.1b

Coefficient estimates for infrequency of purchase model, total fruit and vegetable expenditures

	Coefficient	Standard error	Coefficient	Standard error
Constant	1.018**	0.444	7.869	6.716
INCOME	0.003	0.013	0.25**	0.107
SNAP	0.355**	0.101	3.292**	0.68
COLLEGE	-0.019	0.088	2.992**	0.776
AGE	0.077**	0.022	0.596**	0.189
EMPLOYED	-0.036	0.088	0.446	0.545
ASIAN	0.311	0.2	2.73*	1.54
HISPANIC	0.224*	0.122	1.293	0.905
BLACK	-0.074	0.1	-1.618*	0.836
GARDEN	0.182**	0.092	0.559	0.628
MYPLATE	0.114	0.092	0.328	0.616
INTERNET	0.106	0.078	1.73**	0.625
HEALTHYDIET	0.023	0.1	1.705**	0.764
TIME	0.018	0.078	1.177*	0.634
SPRING	-0.132	0.147	-0.105	1.569
SUMMER	-0.018	0.127	-0.325	1.439
FALL	-0.113	0.133	-1.116	1.384
NOCAR	-0.113	0.149	-1.522	1.276
GUESTS	0.149**	0.075	0.995*	0.527
HHMEMBERS	-0.055	0.04		
ADULTMALE			1.115**	0.401
ADULTFEMALE			0.98*	0.583
MALETEEN			0.152	0.73
FEMALETEEN			1.431*	0.843
MALEYOUTH			-0.19	0.914
FEMALEYOUTH			1.312	0.992
MALECHILD			1.061**	0.483
FEMALECHILD			1.041**	0.508
COUNTYOBESITY			-0.276**	0.139
COUNTYBLACK			0.026	0.036
COUNTYASIAN			0.062	0.115
COUNTYHISPANIC			0.028	0.027
COUNTYINCOME			0.00006	0.00005
POPDENSITY			0.00004	0.0002
GROCERYPRICE	-0.74*	0.431	-3.396	4.316
DTCFV			31.343**	11.214
Error term			11.48**	0.597

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix 2: Instrumental Variable Estimation

Our goal is to measure the relationship between a household's weekly-average fruit and vegetable expenditures and *DTCFV* (its propensity to patronize DTC outlets). Assuming a linear relationship between spending and our independent variables in equation (1) of the text, our model becomes:

(A2.1) $$M = \beta_0 + \beta_1 F + \beta_2 P + \beta_3 X + \delta DTCFV + u$$

where F represents a household's financial resources and P is a measure of prices. To further account for tastes and preferences, we include X among our model's independent variables. X includes measures of a household's educational attainment, ethnicity, and attitudes towards health and nutrition. However, *DTCFV* is our independent variable of primary interest. To obtain an unbiased estimate of δ, which measures the relationship between M and *DTCFV*, we take steps to guard against endogeneity bias. Specifically, we take steps to minimize any correlation between u and *DTCFV* in equation (A2.1). Either omitted variables or simultaneity between *DTCFV* and M could otherwise cause such a correlation and bias our estimate of δ (e.g., Murray, 2006).

When researchers are concerned about potential endogeneity bias, they may use an instrumental variable (IV) procedure. In this study, that involves modeling a household's probability to buy fruits and vegetables directly from farmers in any given week. We assume each household that participated in FoodAPS compared its utility associated with patronizing DTC outlets, U^1, against its utility associated with not doing so, U^0:

(A2.2) $$D = \begin{cases} 1 \text{ if } D^* = U^1 - U^0 > 0 \\ 0 \text{ otherwise} \end{cases}$$

where D equals 1 if the household bought fruits and vegetables directly from farmers, and 0 otherwise. D^* is the difference between the two utilities and represents a household's net benefit from patronizing DTC outlets. Moreover, we model this variable as:

(A2.3) $$D^* = \eta T + \varepsilon$$

where ε is a normally distributed error term with a mean of zero and a variance of one. Included in T are many of the same independent variables that also appear in our main expenditure model and two variables excluded from our main model. These identifying instruments are *DTCFARMERS* and *PEAKSEASON*. Using a probit model, we estimate the vector of parameters η. Next, we generate values of *DTCFV* for each of our 4,826 FoodAPS households as $DTCFV_i$ = Probability$(D_i^* > 0) = \Phi(\hat{\eta}T_i)$ where $\Phi(\hat{\eta}T_i)$ denotes the standard normal CDF evaluated at $\hat{\eta}T_i$, and $\hat{\eta}$ is the estimated value of η. Finally, using a method described in Angrist and Pischke (2009) and Wooldridge (2010), we estimate our main model with *DTCFV* among the independent variables.[28]

Both economic theory and the existing literature guided our choice of *DTCFARMERS* and *PEAKSEASON* as identifying instruments. Building on Salop's (1979) transportation cost model,

[28]We first generate values of *DTCFV* for each household using a probit model as already described. Secondly, we estimate an additional linear probability model. The dependent variable in this second-step again equals one for each FoodAPS household that bought fruits and vegetables directly from farmers and zero for all other households. The independent variables include F, P, X, and *DTCFV*. Thirdly, we estimate our main expenditure model using the fitted values from this second-step regression for *DTCFV* in lieu of the original, first-step values of *DTCFV* based on a probit model.

we theorize that households with lower time and money costs for patronizing DTC outlets should exhibit a greater propensity to buy fruits and vegetables directly from farmers, all else constant. Indeed, empirical studies confirm that convenience is a prime determinant of patronage (e.g., McGarry Wolf et al., 2005; Abello et al., 2014). Moreover, both Leung et al. (2011) and Berning (2012) find a positive association between access to DTC outlets and health status. Berning (2012), for one, regresses an individual's body mass index (BMI) on the number of farmers markets and CSAs in his or her county (similar to *DTCFARMERS*). Endogeneity tests are conducted for both variables. Berning (2012) finds no evidence of endogeniety for farmers markets. Although he does find some evidence of endogeneity for community-supported agriculture operations, it has little effect on his results.

While instrumental variables are widely used in economic research, the efficacy of IV procedures depends on the quality of the identifying instruments (e.g., Murray, 2006; Stock et al., 2002; Stock and Yogo, 2001). First, the identifying instrument(s) must be "valid" meaning that they are themselves uncorrelated with the error term (i.e., there should be a zero correlation between our instruments and u in equation (A2.1)). As discussed below, we believe *DTCFARMERS* and *PEAKSEASON* are valid after the addition of a few more variables to our model. If so, our estimate of δ will be consistent, though it is still possible for our estimate of δ to suffer from finite sample bias. The second requirement of quality instruments is that they are relevant. In the present study, *DTCFARMERS* and *PEAKSEASON* should be highly significant predictors of whether a household buys fruits and vegetables directly from farmers.

We believe that *DTCFARMERS* is a valid instrument. However, as Murray (2006) recommends, we also attempt to anticipate arguments about why it might be invalid. On the one hand, the number of farmers who sell directly to consumers should be independent of any individual FoodAPS household's fruit and vegetable spending. This is a reasonable assumption given that any single household's demand is small relative to the overall market. It is also consistent with most demand models in which individuals are assumed to be "price takers." On the other hand, DTC outlets may locate in communities where aggregate demand is strong. For example, there should be more DTC farmers where a greater proportion of all households care about nutrition and consume more fruits and vegetables, all else constant. Moreover, if a household lives in such a community, then those attitudes could "rub off" on the household, causing it to feel and act similarly. A correlation would then exist between *DTCFARMERS* and unaccounted for fruit and vegetable spending by individual households, u. Both would be positively correlated with the share of all households that care about nutrition. Following Murray (2006), we account for this possibility by adding *COUNTYOBESITY*, *COUNTYINCOME*, *POPDENSITY*, *COUNTYBLACK*, *COUNTYASIAN*, and *COUNTYHISPANIC* to both our main expenditure and our auxiliary probit models. These variables control for the characteristics and health attitudes of the households in a FoodAPS participant's community, and their inclusion in our models should prevent any "rubbing off" effect from influencing estimation results on our independent variable of primary interest, *DTCFV*.

We also believe that *PEAKSEASON* is a valid instrument. However, since FoodAPS households were surveyed during different seasons of the year, seasonal variation in product assortment and prices could contribute to differences in fruit and vegetable spending between the households. If so, this could lead to some correlation between *PEAKSEASON* and unaccounted for fruit and vegetable spending by individual households, u. To account for this possibility, we include binary indicator variables for whether a household joined FoodAPS between June and August (*SUMMER*), September and November (*FALL*), or March and May (*SPRING*).[29]

As a final check of the validity of our instruments, we followed Murray's (2006) recommendation and re-estimated our model using only one identifying instrument, *DTCFARMERS* or *PEAKSEASON*, but not both. This test is similar in spirit to Sargan's (1958) test of over-identifying restrictions (Murray, 2006, pg. 119). "Getting similar results from alternative instruments enhances the credibility of instrumental variable estimates" (Murray, 2006, pg. 118). Our results are shown in appendix tables A2.1a-1b and A2.2a-2b. Indeed, using either identifying instrument, we get very similar results on *DTCFV* as compared with results for our full model using both instruments in appendix tables A1.1a-1b.

Relevancy is the other criterion for judging the quality of identifying instruments. Even if instruments are valid, Murray (2006), Stock et al. (2002), and Stock and Yogo (2001) show that our estimates of δ could suffer from finite sample bias. Moreover, standard methods for testing the parameter's statistical significance based on the assumption of a normal distribution may not be sufficiently conservative. For example, if we test the parameter's significance at the 5-percent level, the actual size of our test (i.e., the risk of committing a type 1 error) may be greater than 5 percent. This depends on both the strength of our instruments and the extent of bias in our main IPM (i.e., the degree of correlation between the error terms in equations (A2.1) and (A2.3)).

To judge the relevancy of identifying instruments in an IV regression, Murray (2006), Stock et al. (2002), and Stock and Yogo (2001) suggest reporting F-statistics for the joint significance of identifying instruments in the auxiliary model used to generate predicted values of the potentially endogenous variable (equation (A2.3)). As a rule of thumb, instruments with an F-statistic greater than 10 are "strong" while 5 indicates "moderately weak" instruments and 1 indicates "very weak" instruments (Stock et al., 2002). In our analysis, the F-statistic for *DTCFARMERS* and *PEAKSEASON* is 7.62, which is somewhere between strong and moderately weak (appendix 1, table A1.1a).

Given our results, we tested the sensitivity of our estimates to endogeneity bias. The most likely source of endogeneity bias appears to be omitted attitudes and behaviors toward food and nutrition that drive a household to both patronize DTC outlets and consume more fruits and vegetables. We therefore re-estimated our model excluding *GARDEN*, *MYPLATE*, *INTERNET*, *TIME*, and *HEALTHYDIET*. The effects of these variables now enter u and ε (the error terms in equation (A2.1) and (A2.3)). These error terms should now be highly correlated, if the potential for endogeneity bias due to omitted attitudes and behaviors toward food and nutrition is high. Estimation results should also be biased and different than results in appendix 1 (table A1.1b) for our full model. That model including all five direct measures of a household's attitudes and behaviors toward food and nutrition should represent a significant improvement. However, after re-estimating our model, results for *DTCFV* were little affected, which suggests that the potential for endogeneity in our model is limited. Results are shown in appendix tables A2.3a-3b.

[29]As described in the text, we consider June through September a peak period for shopping at DTC outlets, and define *PEAKSEASON* accordingly. This binary variable indicates whether a household participated in FoodAPS between June 3 and September 30, when USDA's own farmers market in Washington, DC, is open during both daytime and nighttime hours. Among all 4,826 FoodAPS participants, *PEAKSEASON* =1 for 2,844 households. Among these 2,844 survey participants, *SPRING* = 1 for 103 households, *SUMMER* = 1 for 2,108 households, and *FALL* = 1 for 633 households. Thus, while *PEAKSEASON* is positively correlated with *SUMMER*, the two variables are not perfectly collinear. Some households, for example, joined FoodAPS in late May but continued to participate into early June.

Another possible source of endogeneity bias is omitted characteristics of a household's community and its surrounding retail food marketing environment. As noted above, we include variables like *COUNTYOBESITY* and *POPDENSITY* to account for "rubbing off." These variables should also capture relevant aspects of the retail food marketing environment around a household. Wilde et al. (2014), for one, show that population density is a good proxy for the number of stores in a community. Thus, if the potential for endogeneity bias due to omitted characteristics of a household's community or its surrounding retail food marketing environment is high, then dropping *POPDENSITY* along with *COUNTYOBESITY*, *COUNTYINCOME*, *COUNTYBLACK*, *COUNTYASIAN*, and *COUNTYHISPANIC* should increase any correlation between u and ε, and further bias our estimation results. Estimation results should also be different than our full model results in appendix 1 (table A1.1b). However, after re-estimating our model without these variables, results for *DTCFV* were again little affected, which continues to suggest that the potential for endogeneity in our model is limited, and our results are not very sensitive to omitted variable bias. Results are shown in appendix tables A2.4a-4b.

As a final test of our IV results, we judged the statistical significance of *DTCFV* using a bootstrap confidence interval (CI). As noted above, when instruments are weak and the potential for endogeneity severe, the asymptotic distribution of IV estimates is not normal and standard tests of significance based on the assumption of a normal distribution are not sufficiently conservative. By contrast, bootstrap confidence intervals do not rely on any assumption about a parameter's sampling distribution. We re-estimated our model 250 times. Results reveal empirically how parameter estimates would vary if FoodAPS were re-administered this many times and we re-estimated our model with each survey. Creating bootstrap confidence intervals for δ based on its empirical sampling distribution, we find that *DTCFV* remains statistically significant at the 10-percent level (90-percent bootstrap CI = (9.09, 41.35)) and at the 5-percent level (95-percent bootstrap CI = (6.15, 49.43)), which again suggests that the potential for endogeneity in our model is limited.

Appendix table A2.1a

Coefficient estimates for model of probability that households buy fruits and vegetables directly from farmers in a given week; only identifying instrument is DTCFARMERS

	Coefficient	Standard error
Constant	-4.013**	0.979
INCOME	0.018**	0.009
SNAP	-0.119	0.174
COLLEGE	0.172	0.148
AGE	0.126**	0.039
ASIAN	-0.05	0.335
HISPANIC	-0.414	0.29
BLACK	-0.506**	0.247
GARDEN	0.236**	0.113
MYPLATE	0.18	0.117
INTERNET	0.336**	0.133
HEALTHYDIET	0.251**	0.109
WORTHTIME	0.153	0.174
COUNTYOBESITY	0.028	0.028
COUNTYBLACK	0.001	0.01
COUNTYASIAN	0.028	0.02
COUNTYHISPANIC	-0.004	0.01
MEDIANINCOME	-0.000002	0.00001
POPDENSITY	-0.00001	0.00007
DTCFARMERS	3.564**	1.314
Model fit statistics		
F-statistic for DTCFARMERS		7.36

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A2.1b

Coefficient estimates for infrequency of purchase model, total fruit and vegetable expenditures; sole instrument is DTCFARMERS

	Coefficient	Standard error	Coefficient	Standard error
Constant	0.965**	0.442	6.232	6.73
INCOME	0.003	0.013	0.264**	0.111
SNAP	0.351**	0.102	3.298**	0.696
COLLEGE	-0.017	0.09	3.084**	0.785
AGE	0.077**	0.022	0.633**	0.187
EMPLOYED	-0.036	0.088	0.42	0.547
ASIAN	0.295	0.201	2.522*	1.494
HISPANIC	0.223*	0.12	1.182	0.94
BLACK	-0.073	0.1	-1.707**	0.83
GARDEN	0.179*	0.093	0.595	0.641
MYPLATE	0.113	0.092	0.338	0.607
INTERNET	0.111	0.079	1.827**	0.639
HEALTHYDIET	0.025	0.101	1.778**	0.815
TIME	0.016	0.078	1.182*	0.638
NOCAR	-0.113	0.148	-1.573	1.228
GUESTS	0.153**	0.075	1.065**	0.542
HHMEMBERS	-0.055	0.041		
ADULTMALE			1.115**	0.404
ADULTFEMALE			0.975*	0.588
MALETEEN			0.163	0.731
FEMALETEEN			1.407*	0.843
MALEYOUTH			-0.14	0.914
FEMALEYOUTH			1.328	1.006
MALECHILD			1.062**	0.483
FEMALECHILD			1.065**	0.506
COUNTYOBESITY			-0.255*	0.134
COUNTYBLACK			0.024	0.036
COUNTYASIAN			0.063	0.114
COUNTYHISPANIC			0.026	0.031
COUNTYINCOME			0.0001	0.0001
POPDENSITY			0.0001	0.0002
GROCERYPRICE	-0.758*	0.43	-3.036	4.384
DTCFV			28.494**	12.957
Error term			11.521**	0.606

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A2.2a

Coefficient estimates for model of probability that households buy fruits and vegetables directly from farmers in a given week; only identifying instrument is PEAKSEASON

	Coefficient	Standard error
Constant	-3.236**	0.268
INCOME	0.022**	0.009
SNAP	-0.085	0.176
COLLEGE	0.186	0.144
AGE	0.131**	0.038
ASIAN	0.012	0.299
HISPANIC	-0.479**	0.227
BLACK	-0.444*	0.253
GARDEN	0.237**	0.112
MYPLATE	0.139	0.113
INTERNET	0.319**	0.135
HEALTHYDIET	0.258**	0.103
WORTHTIME	0.181	0.169
PEAKSEASON	0.403**	0.163
Model fit statistics		
F-statistic for PEAKSEASON		6.11

Note: SNAP = Supplemental Nutrition Assistance Program. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A2.2b

Coefficient estimates for infrequency of purchase model, total fruit and vegetable expenditures; sole instrument is PEAKSEASON

	Coefficient	Standard error	Coefficient	Standard error
Constant	1.077**	0.453	-6.103	4.714
INCOME	0.003	0.012	0.27**	0.118
SNAP	0.358**	0.101	3.158**	0.667
COLLEGE	-0.018	0.088	3.231**	0.809
AGE	0.077**	0.022	0.632**	0.208
EMPLOYED	-0.031	0.087	0.436	0.552
ASIAN	0.312	0.203	3.786**	1.464
HISPANIC	0.23*	0.122	2.86**	0.839
BLACK	-0.072	0.099	-1.485*	0.84
GARDEN	0.183**	0.092	0.185	0.654
MYPLATE	0.118	0.092	0.255	0.637
INTERNET	0.107	0.079	1.878**	0.703
HEALTHYDIET	0.023	0.099	1.788**	0.787
TIME	0.014	0.078	1.044	0.647
SPRING	-0.128	0.147	0.274	1.563
SUMMER	-0.014	0.125	0.278	1.517
FALL	-0.109	0.132	-0.484	1.459
NOCAR	-0.110	0.151	-0.962	1.305
GUESTS	0.149**	0.074	0.932*	0.564
HHMEMBERS	-0.054	0.039		
ADULTMALE			1.122**	0.402
ADULTFEMALE			1.104*	0.591
MALETEEN			0.093	0.761
FEMALETEEN			1.436*	0.863
MALEYOUTH			-0.139	0.94
FEMALEYOUTH			1.437	1.049
MALECHILD			1.067**	0.484
FEMALECHILD			1.068**	0.528
GROCERYPRICE	-0.807*	0.436	5.662	4.161
DTCFV			32.662**	15.02
Error term			11.544	0.6

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A2.3a

Coefficient estimates for model of probability that households buy fruits and vegetables directly from farmers in a given week, excluding variables for households' attitudes toward food and nutrition

	Coefficient	Standard error
Constant	-3.527**	0.997
INCOME	0.024**	0.009
SNAP	-0.102	0.17
COLLEGE	0.286**	0.138
AGE	0.111**	0.033
ASIAN	-0.085	0.331
HISPANIC	-0.523*	0.289
BLACK	-0.555	0.245
COUNTYOBESITY	0.021	0.028
COUNTYBLACK	0.0001	0.01
COUNTYASIAN	0.027	0.02
COUNTYHISPANIC	-0.006	0.011
MEDIANINCOME	0.000002	0.00001
POPDENSITY	0.00001	0.00008
PEAKSEASON	0.396**	0.158
DTCFARMERS	3.236**	1.375
Model fit statistics		
F-statistic for PEAKSEASON and DTCFARMERS		6.88

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A2.3b

Coefficient estimates for infrequency of purchase model, total fruit and vegetable expenditures, excluding variables for households' attitudes toward food and nutrition

	Coefficient	Standard error	Coefficient	Standard error
Constant	1.096**	0.427	10.099	7.469
INCOME	0.003	0.013	0.278**	0.122
SNAP	0.344**	0.1	3.227**	0.701
COLLEGE	0.004	0.092	3.427**	0.847
AGE	0.079**	0.023	0.596**	0.205
EMPLOYED	-0.024	0.084	0.372	0.565
ASIAN	0.299	0.202	2.711*	1.544
HISPANIC	0.189	0.116	1.031	0.977
BLACK	-0.121	0.093	-1.994**	0.928
SPRING	-0.135	0.15	-0.243	1.602
SUMMER	-0.022	0.128	-0.402	1.489
FALL	-0.117	0.135	-1.219	1.385
NOCAR	-0.136	0.147	-1.558	1.267
GUESTS	0.162**	0.076	1.102*	0.589
HHMEMBERS	-0.047	0.039		
ADULTMALE			1.134**	0.41
ADULTFEMALE			1.061*	0.583
MALETEEN			0.14	0.741
FEMALETEEN			1.419	0.866
MALEYOUTH			-0.043	0.948
FEMALEYOUTH			1.308	0.989
MALECHILD			1.138**	0.501
FEMALECHILD			1.24**	0.554
COUNTYOBESITY			-0.291*	0.152
COUNTYBLACK			0.03	0.039
COUNTYASIAN			0.064	0.118
COUNTYHISPANIC			0.025	0.032
COUNTYINCOME			0.00007	0.00005
POPDENSITY			0.00004	0.0002
GROCERYPRICE	-0.733*	0.428	-3.539	4.638
DTCFV			31.32**	14.733
Error term			11.540**	0.607

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A2.4a

Coefficient estimates for model of probability that households buy fruits and vegetables directly from farmers in a given week, excluding community characteristic variables

	Coefficient	Std. error
Constant	-3.455**	0.277
INCOME	0.02**	0.008
SNAP	-0.091	0.174
COLLEGE	0.177	0.147
AGE	0.125**	0.038
ASIAN	0.072	0.303
HISPANIC	-0.446*	0.232
BLACK	-0.463*	0.264
GARDEN	0.237**	0.112
MYPLATE	0.151	0.113
INTERNET	0.329**	0.136
HEALTHYDIET	0.249**	0.105
WORTHTIME	0.176	0.172
PEAKSEASON	0.394**	0.16
DTCFARMERS	2.879**	1.158
Model fit statistics		
F-statistic for PEAKSEASON and DTCFARMERS		8.09

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).

Appendix table A2.4b

Coefficient estimates for infrequency of purchase model, total fruit and vegetable expenditures, excluding variables for the characteristics of a household's community

	Coefficient	Standard error	Coefficient	Standard error
Constant	1.064**	0.455	-6.119	4.17
INCOME	0.002	0.012	0.274**	0.114
SNAP	0.358**	0.101	3.166**	0.668
COLLEGE	-0.016	0.088	3.251**	0.792
AGE	0.077**	0.022	0.633**	0.19
EMPLOYED	-0.03	0.088	0.431	0.557
ASIAN	0.319	0.201	3.835**	1.43
HISPANIC	0.23*	0.122	2.854**	0.798
BLACK	-0.073	0.099	-1.499*	0.792
GARDEN	0.183**	0.092	0.191	0.635
MYPLATE	0.118	0.092	0.262	0.628
INTERNET	0.106	0.078	1.861**	0.641
HEALTHYDIET	0.022	0.099	1.799**	0.783
TIME	0.016	0.078	1.051*	0.626
SPRING	-0.13	0.147	0.242	1.564
SUMMER	-0.014	0.125	0.279	1.515
FALL	-0.109	0.133	-0.495	1.466
NOCAR	-0.112	0.151	-0.959	1.294
GUESTS	0.149**	0.075	0.925*	0.545
HHMEMBERS	-0.054	0.039		
ADULTMALE			1.121**	0.413
ADULTFEMALE			1.11*	0.589
MALETEEN			0.089	0.744
FEMALETEEN			1.435*	0.841
MALEYOUTH			-0.138	0.932
FEMALEYOUTH			1.434	1.035
MALECHILD			1.055**	0.482
FEMALECHILD			1.074**	-0.52
GROCERYPRICE	-0.795*	0.438	5.672	3.788
DTCFV			32.217**	12.247
Error term			11.54**	0.602

Note: SNAP = Supplemental Nutrition Assistance Program. DTC = direct-to-consumer. DTCFV = propensity to buy fruits and vegetables at a DTC outlet. **, * = significant at the 5-percent and 10-percent levels, respectively. Standard errors are estimated using a bootstrap method with 250 replications. Each bootstrap sample was created by first resampling at the primary sampling unit (PSU) level and then randomly sampling households within PSUs. FoodAPS sample weights not used.

Source: USDA, Economic Research Service analysis of the 2012-13 National Household Food Acquisition and Purchase Survey (FoodAPS).