How long do healthy habits last? The role of prices*

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Abstract

When a policy gives temporary incentives for healthy behaviors, how long does the impact last? I study the U.S. Special Supplemental Nutrition Program for Women, Infants, and Children, which gives vouchers for healthy foods. Using household-level scanner data, I find that the effect of the program diminishes when households become ineligible. Demand model estimates show that price differences between healthy and unhealthy foods play a large role in the decrease of the program's impact. The estimates imply that the program has a persistent effect, in that it increases the impact of subsequent policies like subsidies on healthy foods.

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1 Introduction

Obesity is a public health problem that leads to higher medical care costs and imposes negative externalities (Cawley, 2015). One of the causes of obesity is an unhealthy diet. While a diet is an individual's optimal choice given budget and other constraints, the negative externalities of obesity provide a rationale for a government intervention. Indeed, governments

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use various policies to improve diets, like fat and sugar taxes and regulation of nutrition labeling and advertising. To reduce costs, some policies are designed to give only temporary incentives, like vouchers and subsidies on healthy foods and paying people to lose weight. When designing and evaluating a policy that gives only temporary incentives, it is important to take into account whether it has a long-term impact.

This paper studies two questions. First, when a policy gives temporary incentives for a healthy diet, how long does the impact last? Second, I analyze the role of prices in affecting the persistence of the policy impact. Specifically, I study a U.S. federal program, the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), which gives vouchers for healthy foods. Literature has shown that food vouchers limited to healthy foods change diets in the intended direction while participating in the program.[1] Much less is known about the impact of the program after incentives end.

I study the effect of the program on both, the observed behavior and underlying preferences. Why is it important to understand the impact on preferences? Often the healthy product is more expensive than its unhealthy substitute. A price sensitive person, even when she otherwise prefers a healthy option, might not buy it because of the price difference. Hence, temporary incentives might not change the long-run behavior even if these did change preferences. Why would underlying preferences matter if these won't affect behavior? Changes in preferences are important when implementing subsequent policies, like taxes and subsidies.

In this paper, I focus on the WIC program. The program is important in itself. In 2016, eight million people participated in WIC per month. Moreover, WIC provides a good setting for the study. Participation eligibility is restricted to children up to their fifth birthday and pregnant, postpartum, and breastfeeding women. WIC food vouchers are restricted to specific foods. In particular, in some food categories, the vouchers are restricted only to healthier products. By providing free healthy products, the program gives incentives to eat more healthily. The incentives are temporary, lasting until the child's fifth birthday.

In the analysis, I use Nielsen household-level scanner data of grocery purchases. The dataset includes information on households' WIC status, composition, and income. The dataset covers ten years, 2006–2015. I restrict attention to purchases of milk and bread because these are product categories that most households buy. Moreover, in these product categories, since 2009 WIC food vouchers are limited to the healthy versions of products — low-fat milk and whole wheat bread. Data on product prices is obtained from the Nielsen

[1] For an overview of the results from the WIC program see Schultz, Byker Shanks, and Houghtaling (2015). Griffith, von Hinke, and Smith (2018) provide evidence based on a similar program in the UK.

Retail Scanner Data.

My analysis starts by using a panel data fixed effects model to estimate the long-term impact of WIC assistance on grocery purchases. The analysis focuses on a panel of households whose purchases I observe before they receive WIC assistance, while they receive it, and after they become ineligible to receive it. My estimates confirm that from 2009, when a household starts to receive WIC assistance, its grocery purchases indeed become healthier, as was intended by the program. However, I find that the effect diminishes shortly after the household becomes ineligible for WIC. The effect is less persistent in the case of bread than milk. Note that bread has a large price difference between the healthy and unhealthy versions, while milk products are more homogeneously priced. This raises the question whether the difference can be explained by prices?

To examine the role of prices I estimate a demand model and perform counterfactual exercises. I model demand using a discrete choice random coefficient multinomial logit model allowing household heterogeneity in preferences. In the model, past purchases are allowed to affect current tastes. This is a channel how temporary incentives can have a more persistent effect. I use the control function approach and production input prices as instruments to address price endogeneity. The estimates of the demand model show that both prices and past purchases matter for current choices. The results illustrate that prices cause the actual purchases to differ from the tastes for the products. In the case of bread, higher whole wheat (healthy) bread prices lead to lower purchases. Prices affect milk purchases too, but the effect is smaller due to smaller price differences.

The counterfactual analysis studies two questions. First, how do prices affect the persistence of the program's impact? This is relevant when choosing which products to include in the program if the goal is to obtain a long-term change. In the case of bread, the healthy option (whole wheat bread) is currently more expensive than unhealthy alternatives. Suppose bread prices were all equal, then WIC's impact would be more persistent. In contrast to bread, in the case of milk, the healthy option (low-fat milk) is currently on average cheaper than the unhealthy alternative. If prices were equal, the healthy option would become relatively more expensive, which would make WIC's impact less persistent. The results suggest that if a goal of the program is to obtain a long-term change in diet, then it would be more effective to include in the program product categories in which the healthy option is not much more expensive.

In the second counterfactual, I study how much the change in tastes induced by the program decreases a subsequent subsidy needed for a given change in purchases? I simulate the impact of a ten cent subsidy on whole wheat bread and low-fat milk. The results show that the change in tastes induced by WIC magnifies the impact of subsequent policies; in the case of bread, it doubles the effect of the subsidy.

The paper builds on the literature in economics that studies nutritional choices. The literature has shown that prices matter, but also that nutritional choices are persistent and difficult to change.[2] For example, Dubois, Griffith, and Nevo (2014), using scanner data from different countries, showed that price differences explain a large share of the difference in calories consumed between France and the U.S. In the case of milk, which is one of the products studied in this paper, Khan, Misra, and Singh (2016) showed that even small price differences lead to large differences in fat consumption. Atkin (2013, 2016), using data of migration, has provided evidence of habit formation and quantified the costs of the persistence of nutritional choices. Oster (2018), using Nielsen scanner data, showed that individuals are reluctant to make large changes to their diets even when diagnosed with a diet-related disease. To my knowledge, the current paper is the first to analyze the role of prices and the persistence of nutritional choices together when studying the impact of a public policy.[3]

The paper is also related to the literature on the impact of the WIC program. Literature in economics studying the program has concentrated mostly on birth outcomes (Figlio, Hamersma, and Roth, 2009; Hoynes, Page, and Stevens, 2011), participation (Rossin-Slater, 2013), and the impact of WIC on market outcomes (Meckel, 2016).[4] Literature in nutrition science has shown that the 2009 change in WIC food packages increased the healthiness of WIC participants' food consumption.[5] My work confirms the findings and extends the literature by analyzing the long-term effect of WIC on nutritional choices taking into account the role of prices.

The rest of the paper is organized as follows. Section 2 describes the WIC program and data. Section 3 estimates how long do the healthy changes last after the end of WIC eligibility. Section 4 analyzes the impact of prices. It first provides estimates from a demand model and

[2]Other topics this literature has studied include the role of restaurants (Anderson and Matsa, 2011; Currie, DellaVigna, Moretti, and Pathania, 2010), nutritional information (Bollinger, Leslie, and Sorensen, 2011), food availability and food deserts (Handbury, Rahkovsky, and Schnell, 2015), advertising (Dubois, Griffith, and O'Connell, 2017), and weight loss programs (Uetake and Yang, 2018). For an overview of the literature on the economics of nutrition and obesity, see Cawley (2015).

[3]Long-term effects of temporary policies on consumption choices have been studied in other contexts. For example, Kueng and Yakovlev (2017) find evidence of a temporary regulation having long-lasting effects on alcohol consumption. There is also a growing experimental literature analyzing long-term impacts of temporary incentives on nutritional choices (including List and Samek, 2015; Belot, Berlin, James, and Skafida, 2018).

[4]Hoynes and Schanzenbach (2015) provide a recent overview of the literature on WIC.

[5]For an overview, see Schultz, Byker Shanks, and Houghtaling (2015).

then uses these estimates in the counterfactual analysis. Section 5 concludes.

2 Background on WIC and data

2.1 Background on WIC

WIC is a U.S. in-kind food and nutrition assistance program targeted at women and children 0–4 years old. In 2016, eight million people participated in WIC per month and it accounted for six percent of U.S. food and nutrition assistance expenditures (Oliveira, 2017). The average monthly WIC program cost for food per participant was 43 dollars.

The following categories of people are eligible to participate in WIC: pregnant, breastfeeding (up to child's first birthday), and postpartum women (up to six months after birth), and children up to their fifth birthday.[6] The income eligibilibility requirement to participate in WIC is income not exceeding 185 percent of the federal poverty guidelines.[7] Income eligibility requirement is automatically satisfied if the individual or a family member is eligible for SNAP, Medicaid, or Temporary Assistance for Needy Families benefits (for more see Oliveira, 2017). A large share of families with small children participate in WIC. According to the USDA report (Oliveira and Frazao, 2015), in 2012, 51 percent of infants (up to their first birthday) and almost 30 percent of pregnant and postpatrum women and children aged 1–4 participated in WIC. Not everyone who is eligible participates in WIC. According to the USDA report (Johnson, Giannarelli, Huber, and Betson, 2014), in 2011, the rate at which eligible individuals participated in WIC was highest among infants (83%) and postpartum non-breastfeeding women (81%), and lowest among children aged 1–4 (54%). Those who participate tend to have lower income.[8]

WIC benefits are in the form of quantity vouchers for specific food items (with the exception of fruits and vegetables, which is a cash voucher). The set of foods in the WIC food package is rather small. Children aged 1–4 and women receive regular food items, which until 2009 included mainly milk, juice, cereal, eggs, legumes, and peanut butter. Infants until their first birthday receive infant formula, infant cereal, and infant juice.

[6]USDA. Food and Nutrition Service. "WIC Eligibility Requirements." Last published: August 3, 2016. https://www.fns.usda.gov/wic/wic-eligibility-requirements.

[7]States are allowed to decrease the eligible income cutoff, but in practice in all states, it equals the 185 percent of the federal poverty guidelines (Oliveira and Frazao, 2015).

[8]More than two thirds of WIC participants have income below the federal poverty level (Oliveira and Frazao, 2015). Less than three percent of the partipants have income above the upper limit. The fact that income can be above the limit is explained by automatic eligilibility through Medicaid and SNAP, which have higher income limits in some states.

In 2009, there was a major change in the types of foods provided by WIC. The goal of the change was to make WIC food packages consistent with new dietary guidelines. While WIC was established to fight malnutrition in low-income families, over time obesity became a problem and concerns were raised whether WIC contributes to child obesity (Oliveira and Frazao, 2009). The change added new foods: whole grain products, fruits, and vegetables. Specifically, it added whole wheat bread. The change also introduced restrictions on the fat percentage of milk. Specifically, whole milk is no longer allowed, except for one-year-old children. Altogether, the 2009 reform was cost neutral as it reduced the quantities of some foods (including milk, juice, and eggs).[9] An example of a WIC food package is shown in table A1 in appendix A.

2.2 Data

In the paper, the main data source is the Nielsen Homescan Consumer Panel. Data on product prices is obtained from the Nielsen Retail Scanner Data.[10] The consumer panel is representative of the U.S. population. The participating households in the panel are asked to scan all their grocery purchases bought for personal at home consumption. The dataset includes UPC level information of the purchased quantities. Reliability of the data has been analyzed by Einav, Leibtag, and Nevo (2010). In addition to purchases, Nielsen collects information on household demographic characteristics using annual surveys. The demographic characteristics include household income and composition, employment status and education of household heads, and the month of birth of each child. Starting from 2006 the dataset includes information on household WIC status. In the analysis, I use the Nielsen data that covers ten years, 2006–2015.

I focus attention on purchases of milk and bread, specifically, white dairy refrigerated milk and loaves of bread. These are product categories that most households regularly buy. Households on average spend a relatively large share of their food grocery purchases on these categories: about 3% on milk and about 2% on bread. Both product categories are in the standard WIC food package. I focus on product type (fat percentage for milk and grain

[9] In 2014, there were additional small modifications to the food package. These changes reduced milk fat percentage even further, allowing only low-fat (1%) or non-fat milks for children 2-4 years of age and women, and increased the cash voucher for fruits and vegetables. It also allowed states to authorize whole wheat macaroni (pasta) products as substitutes for whole wheat bread and allowed partial substitution of milk with yogurt.

[10] Both datasets are from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data is available at http://research.chicagobooth.edu/nielsen.

characteristics for bread) and aggregate purchases across brands, package sizes, and other product characteristics.

The analysis will focus on households for whom I can infer that they receive WIC assistance and the timing of their WIC eligibility. To do that, I combine survey data of household self-reporting receiving the assistance with WIC age eligibility requirements, and the data about the month of birth of each child. I assume that a household is receiving WIC assistance in a given month if it self-reported receiving WIC assistance that year and if it has a WIC age-eligible child (or expecting mother) that month. Combining the two requirements gives some validity to the survey data and a more precise timing because the survey data about receiving WIC assistance is available only yearly. In the following part of the paper, when as a short-hand I say that a household is receiving WIC assistance then I mean the above assumption.

Next I outline the choices made in construction of the datasets used in the estimation. Further details of dataset construction are provided in appendix B.

Dataset to estimate long-term effects: construction and descriptive statistics. In section 3, the panel data fixed effects analysis focuses on a balanced panel of households that report receiving WIC assistance after the 2009 policy change and whose purchases I observe before they receive WIC assistance (or before the policy reform), while they receive it, and during the first year when they become ineligible to receive it. I use households who have not reported receiving WIC assistance after the 2009 policy change as a control group. The control group includes households who report receiving WIC assistance before the policy change or report having received it in the past (at an unspecified time before the survey).

Table 1 presents demographic characteristics of the households. It compares the treatment group, that is, those that receive WIC assistance after the policy change (column 1), to those receiving it earlier (columns 2 and 3), and to the remaining households (column 4). Households receiving WIC assistance on average have lower income, larger household size, and are more likely to be racial minorities.

Figure 1 presents the average percentage of whole wheat bread (panel 1a) and low-fat milk (panel 1b) from all bread and milk purchases by household type. Figure 1 illustrates that since the policy change households purchase relatively more whole wheat bread and low-fat milk while receiving WIC assistance. Table 2 presents summary statistics of bread and milk purchases.

Dataset to estimate the demand model: construction and descriptive statistics. In section 4, to keep the demand model estimation manageable, I restrict attention to a smaller sample of households who all have reported receiving WIC assistance. Specifically, in the estimation, I use the households in columns 1–3 of table 1 and additional households who did report receiving WIC assistance after the policy change in 2009 but were not in the Nielsen panel long enough to be included in the balanced sample (column 1 in table 1). The sample is further restricted in the following ways. First, to be able to estimate how prices affect purchases, I have to exclude time periods when a household received the products for free while receiving WIC assistance. Because milk was always in the WIC food package, for milk, I exclude all time periods when a household received WIC assistance. Because bread was included only since the policy change, for bread, I exclude time periods when a household received WIC assistance after the policy change in 2009. Second, to construct a household-specific measure of past market shares I use purchases of the previous twelve months and I exclude time periods when a household has fewer than ten purchases during the past twelve months. Third, to ensure a sufficient number of observations per household, I exclude households for whom the remaining number of purchases is less than ten. Table 3 describes demographic characteristics of households used in the demand model estimation.

To obtain prices of available products I use the Nielsen store dataset. Because the store dataset does not cover all stores, I'm not able to obtain prices from the same exact store the household visited. Instead, I calculate weighted average prices at the state level. To alleviate the concern that more price sensitive households are more likely to buy generic products and larger packages, I use the same weight for each brand (and package) across products (fat percentage or grain type) in a given state in a given year.[11]

To estimate demand for bread, I aggregate all types of bread into four products. The cheapest product is *white bread* with the median price about $1.5 per pound. It is a non-whole-grain bread made from white refined flour. I differentiate between two types of whole grain breads. First, following WIC regulation, I classify bread as *whole wheat bread* if it contains 100% whole wheat flour. Second, I call bread that is only partially made with whole wheat flour or contains any other type of whole grain flour or rye flour *whole grain bread*. Both whole wheat bread and whole grain bread are about 40 cents more expensive than

[11] To explain the concern, let's consider a simplified example. Suppose there are two milk brands, one cheaper than the other, which each set equal prices across fat percentages, and suppose households who like whole milk buy the cheaper brand. Weighted aggregate prices, correctly, would be equal across fat percentages. However, unweighted aggregate prices would imply that whole milk is cheaper, even though noone can save money by switching to whole milk.

white bread. Finally, *other bread* aggregates together all other non-whole-grain bread types (like Cinnamon Raisin, Cinnamon Swirl, etc.) and it is, typically, slightly cheaper than whole grain or whole wheat bread. To estimate demand for milk, I aggregate all types of milk into two products. The median price for a gallon of whole milk is 5 cents higher than for low-fat milk. Table 3 presents summary statistics of prices of each product.

3 How long do the healthy changes last?

This section presents results of the analysis of how long the changes to the purchases last after WIC eligibility ends.

Empirical strategy. I focus attention on the balanced panel of households that report receiving WIC assistance after the 2009 policy change and whose purchases I observe before they receive WIC assistance (or before the policy reform), while they receive it, and in the first year when they become ineligible to receive it. The comparision is for each household over time (before WIC and after). Households who have not reported receiving WIC assistance after the policy change are used as a control group. Including a control group is needed to separate the effect of having a young child from WIC assistance, and to control for the overall decrease over time in the consumption of milk and bread (see figure A1 in appendix A).

Using household-level monthly data I estimate the following panel data regression with household fixed effects:

$$\begin{aligned} Y_{it} = {} & \beta_1 WIC_{it} + \beta_2 StillElig_{it} + \beta_3 Q1_{it} + \beta_4 Q2ToQ4_{it} + \beta_5 Later_{it} \\ & + HHFE_i + YearMonthFE_t + \alpha X_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

The outcome variable (Y) is the logarithm of the quantity of a given type of milk or bread purchased. The coefficients of interest, β-s, measure the impact of receiving WIC assistance (WIC), being still eligible for WIC assistance but not receiving it ($StillElig$), the first quarter when becoming ineligible ($Q1$), the second until the fourth quarter ($Q2ToQ4$), and the period after that ($Later$). The time period before receiving WIC assistance forms the baseline for each household. The regressions include household fixed effects ($HHFE$), fixed effects for each time period ($YearMonthFE$), and time-varying household characteristics (X). The time-varying household characteristics include logarithm of income and indicator variables for the period before the child is born, up to the child's 1st birthday, 1-year old, up to 4-years old, the first quarter when the child is 5 years old, quarters 2-4 when the child is 5 years old, 6-12 year old children, 13-17 year old children, a male in the household, female household head not employed, and each specific household size (from two household members to nine household members). For milk, the regression also includes an interaction term for WIC and 1-year-old child to take into account that for one-year-old children WIC food vouchers give whole milk.

Identification is based on the assumption that the timing of WIC assistance is exogeneous to the household's purchases of milk and bread. For the start of the WIC period, I use either the 2009 policy change or when the household first reports being on WIC. For the end, I use the end of eligibility of WIC assistance (the child's fifth birthday). The exogeneity of the timing of WIC assistance is a reasonable assumption because WIC assistance is related to the birth of a child.

Main results. First, I present the estimates graphically. Figure 2 shows a large increase in low-fat milk purchases and decrease in whole milk purchases when the household starts to receive WIC assistance compared to the period before. It also shows that the effect on low-fat milk is rather persistent throughout the first four quarters when the household becomes ineligible for WIC. In the case of whole milk, households return to their before WIC level purchases when they become ineligible for the program.

Figure 3 shows that the impact on bread is less persistent than on milk. It shows an increase in whole wheat bread purchases when the household starts to receive WIC assistance compared to the period before. The effect decreases substantially during the first year when the household becomes ineligible. The same results in regression form are presented in column 1 in tables A2 and A3 in appendix A.

Robustness. Robustness of these results is analyzed in tables A2 – A5 in appendix A. Overall the conclusion remains that while receiving WIC assistance households' purchases change in the intended direction, and when WIC eligibility ends the effect seems to be more persistent in the case of milk.

The first concern addresses the control group. In the analysis, the comparison is within the same household over time. The goal of the control group is to control for the overall trends in purchases and to distinguish the effect of WIC from the effect of a child of a certain age. Columns 2-5 in tables A2 and A3 restrict the control group to subsets of households. In column 2, the control group consists of households in columns 2-3 in table 1, who have received WIC assistance in the past. In column 3, the control group is limited to households with children, and in column 4, to households with lower income (having had income below the WIC eligible income level). Column 5 repeats the estimation with the same past-WIC control group as in column 2, but now the outcome variable is the residualized logarithm of quantity. The residualized variable is obtained from the first stage regression of logarithm of quantity on year-month fixed effects using the full sample. Hence, in column 5, the first stage regression pins down the year-month effects using the full sample, and then estimates the effect of WIC using only the past-WIC sample. The results remain largely the same.

The second concern addresses the outcome variable (columns 1-2 in tables A4 and A5). In the main analysis, the outcome variable is the logarithm of quantity purchased. The transformation puts less weight on potentially large values, which might otherwise drive the estimates. However, a question can arise whether the results might depend on this particular transformation. For robustness, I estimate regressions with the following outcome variables: quantity purchased (column 1) and a zero-one indicator for purchasing the product in a given month (column 2). The results are similar.

In the main analysis, in the case of milk, I included an interaction term of WIC status and a one-year-old child to account for the fact that for a one-year-old child WIC allows whole milk. In column 3 in table A4, I estimate a regression without this interaction term. The effect of the policy is even more persistent.

In column 3 in table A5, the outcome variables are logarithm of quantity of whole grain and non-whole-grain bread. This is to broaden the category of whole wheat bread. The results are similar.

Finally, the main analysis uses the sample restricted to households without large purchases in order to avoid large purchases driving the estimation results. Columns 4-5 in tables A4 and A5 use alternative thresholds for large purchases. In column 4, a large purchase is defined as above three times the 99th percentile, and in column 5, as above the 99th percentile. The results remain largely the same.

Limitations. The analysis faces several limitations. First, it focuses on households who report receiving WIC assistance. The remaining households are included in the control group. Some households who received WIC assistance might also be included in the control group. This could lead to underestimation of the effect of the program.

Second, as is always the case with scanner data, it includes information only on purchases, not consumption nor food waste. If households were more likely to discard food that they received for free, then the impact of the program would be overestimated. Fortunately, this affects only the impact while households receive the food vouchers, not the long-term impact when they have to pay for the products.

4 The role of prices

In this section, I analyze the role of prices. First, I estimate a demand model. Then I use these estimates for counterfactual analysis. The counterfactual analysis answers two questions. First, how do prices affect the persistence of the program's impact? This is relevant when choosing which products to include in the program if the goal is to obtain a long-term change. Second, how much does the program decrease a tax or a subsidy needed to obtain a given change in the healthiness of purchases?

4.1 Demand model

I model demand using a discrete choice multinomial logit model with random coefficients. Motivated by results in section 3, past purchases are allowed to affect current tastes. This is a channel how temporary incentives can have a more persistent effect.

The indirect utility of household i from purchasing product j in week t equals:

$$u_{ijt} = \alpha_i p_{jt} + \beta_{ij} x_j + \gamma_i log(ProductShareInPrevYear_{ijt}) + \varepsilon_{ijt} \tag{2}$$

where p_{jt} is price, x_j is a product dummy capturing time invariant characteristics of product j, and ε_{ijt} is a taste shock that is independent across households, products, and time, and distributed according to a type 1 extreme value distribution. The persistence of tastes is captured by the logarithm of the share of product j in household i's purchases during the previous twelve months, $log(ProductShareInPrevYear)_{ijt}$. Across the available products in each category, the shares sum up to one (for each consumer in each time period). I construct the variable in this form for the ease of interpretation of the estimates. A coefficient larger than zero means that there is no preference reversal – the products that a consumer bought more previously, he still buys more than other products. A coefficient larger than one implies the concentration of tastes on favorite products – over time a consumer buys even more the products that he bought more earlier.

The model allows household heterogeneity in preferences in the marginal utility of income (α_i), taste for products (β_{ij}), and persistence of tastes (γ_i). I model heterogeneity as a linear combination of households' observed characteristics and unobserved characteristics, except for persistence (γ_i), in which case I allow only unobserved characteristics. In the case of all the heterogeneity parameters, the unobserved characteristics are captured by a household-specific random term which is independent across households distributed according to a normal distribution, the parameters of which will be estimated. The observed characteristics include logarithm of household income, household size, age, and race. For example, household i's marginal utility of income equals $\alpha_i = \mathbf{v}_i' \boldsymbol{\alpha}_1 + \mu_i$, where $\mathbf{v}_i$ is a vector of the household's observed characteristics, $\boldsymbol{\alpha}_1$ is a vector of parameters to be estimated, and μ_i captures unobserved characteristics (normally distributed). I estimate the model with alternative specifications, because milk and bread seem to differ in terms of which household characteristics drive the demand. In the case of bread, due to a larger number of products, I assume household observed characteristics affect the taste for whole grain and whole wheat in the same way. That is, I assume that household i's taste for whole grain bread, $j = WholeGrain$, equals:

$$\beta_{ij} = \mathbf{v}_i' \boldsymbol{\beta}_{1k} + \eta_{ij} \tag{3}$$

where $\mathbf{v}_i$ is the vector of the household's observed characteristics, η_{ij} captures the household's unobserved taste for whole grain bread (normally distributed), and $\boldsymbol{\beta}_{1k}$ is the vector of estimated parameters, which is restricted to be the same as for whole wheat bread.

In the model, I don't include measures of promotion, because promotion typically varies by brand and not by product characteristics. That is, typically, when whole milk is on promotion then so is the low-fat milk of the same brand. Following most of the discrete choice demand literature, I don't model the purchase quantity decision nor purchasing more than one product on a given trip (for the details of the dataset construction, see appendix B).

Control function. To address the concern of price endogeneity, I estimate the model using a control function. Following Petrin and Train (2010), I assume the pricing function takes the following form where the price of product j in week t in market m equals

$$p_{jtm} = \mathbf{z'}_{jtm} \boldsymbol{\delta} + \xi_{jtm} \tag{4}$$

where $\mathbf{z}_{jtm}$ is the vector of exogeneous instruments and ξ_{jtm} is the unobserved price shock. The pricing function is estimated at the market (state) level, because price variables are constructed so that these vary only by market, not by consumer. Typically, when estimating a demand model, we are concerned that prices might depend on the unobserved factors that directly affect demand. In the control function approach, the identifying assumption is that prices and taste shocks, ε, are independent conditional on the unobserved factors affecting price, ξ.

For instruments I use the input prices interacted with product fixed effects (following Villas-Boas, 2007), and I also include state fixed effects. Interacting input prices with product fixed effects allows the cost of input to affect each product's price to a different extent. In the case of milk, the input price is the regulated raw milk price, which varies across both time and regions. In the case of bread, the instrument is the price of wheat, which varies across time.

I estimate the model in two steps. First, I estimate the reduced form pricing regression (equation 4) with ordinary least squares to recover the residuals ξ_{jtm}. Then I include these residuals as an additional regressor (control function) in the indirect utility (equation 2), and estimate the demand model.

4.2 Estimation results

The estimates of the demand model are presented in table 4 for bread and table 5 for milk. In each table, columns 1 and 2 present estimates without and with a control function, respectively. The estimates are otherwise mostly similar, but, as expected, the coefficient on price is larger in absolute value with a control function. Furthermore, including the control function decreases the taste for the bread that costs the least. The first stage control function estimates are presented in tables A6 and A7 in appendix A.

The demand model estimates show that both previous purchases and prices matter. In the case of bread, the impact of prices varies substantially by observable household characteristics. Low-income, larger, and younger households tend to be more price sensitive. Preferences for the type of bread and milk also vary by household characteristics. High-income and smaller households tend to prefer whole grain/wheat bread. Low-income, older, and non-white households tend to prefer whole milk. Demand model estimates with a larger set of household characteristics are presented in tables A8 and A9 in appendix A.

Since consumers care about prices, it causes preferences for product characteristics and actual purchases to differ. This is especially the case for the bread category, which has large price differences. Table 6 presents the actual market shares, predicted market shares, and predicted market shares if prices were equal (using estimates with a control function in tables 4 and 5).[12] In columns 1 and 2, actual and predicted market shares with actual prices

[12] All the market shares are calculated only based on the sample used in the demand model estimation. Because the sample includes only households who received WIC assistance, the market shares don't necessarily

show that the model fit is good. Column 3 presents predicted market shares if prices for all products in all time periods would be equal. Column 4 calculates the percentage change in the market shares if prices were equal compared to the actual prices. With equal prices the market share of white bread (which was the cheapest) would decrease, while the shares of other types of bread would increase. Note that the largest increase would be for the *other* bread category, which consists of non-whole-grain breads including breads like cinnamon raisin. Similarly, in the case of milk, with equal prices the market share of whole milk (which was more expensive) would increase.

4.3 How do prices affect the persistence of the program's impact?

I use the demand model estimates to understand the role of prices in affecting how long the impact of the program lasts.

Figure 4 presents the simulated average share of whole wheat bread in bread purchases over the first four years after WIC eligibility ends with different prices. It compares these to the benchmark which is the actual share while receiving WIC assistance (grey dashed line). First, it shows that the simulated average share with current prices (red line with square markers) decreases considerably compared to the benchmark. Second, it presents the average share of whole wheat bread if all bread prices were equal (blue line with diamond markers). With equal prices the share of whole wheat bread is larger than with current prices, but both are similarly decreasing over time. Recall that the demand model estimates imply that households on average don't like whole wheat bread, instead they favor the *other* bread category (the base group in the demand model). This suggests that with equal prices households would substitute mostly to the other bread category and not to whole wheat bread. If instead a 20 cent subsidy was applied on whole wheat bread, then the average whole wheat share (green line with circles) remains at a considerably higher level.

A similar exercise for milk is presented on figure 5. It shows that the share of low-fat milk decreases much less with current prices (in red) compared to equal prices (in blue). This is because low-fat milk is currently cheaper.

4.4 Analysis of subsidies

Next I use the demand model estimates to simulate the impact of subsidies. The demand model estimates imply that past purchases affect current tastes. This has implications on

represent overall market shares.

policy. Suppose the policy maker would like to use subsidies for healthy or taxes on unhealthy products to change consumption. After WIC the size of a tax or a subsidy required to obtain a given change is smaller than before.

Table 7 describes the impact of tastes and subsidies in the first year after WIC. In the demand model, tastes had two components: the time invariant part (β_{ij}-s) and the time varying part captured by the logarithm of each product's share in purchases during the previous year. Through the time varying part WIC affects tastes. Panel A presents the impact on purchases of a 10 cent subsidy on whole wheat bread, and panel B, of a 10 cent subsidy on low-fat milk. Columns 1 and 3 present the predicted market shares calculated with old (before WIC) tastes, and columns 2 and 4 with new (after WIC) tastes. The old tastes are calculated using the average product shares of the households before they start receiving WIC assistance. The new tastes are calculated using the average product shares of the same group of households during the first year after their WIC eligibility ended. In columns 3 and 4, the market shares are simulated with a 10 cent subsidy on healthy products (whole wheat bread and low-fat milk).

Columns 5-7 measure the relative contribution of tastes and subsidies on the change in market shares. They show that the change in tastes magnifies the impact of the subsidy. It more than doubles the impact of the 10 cent subsidy on the market share of whole wheat bread. In other words, after WIC the subsidy needed to obtain a given level of increase in the whole wheat bread market share is only half of that without the WIC program.

5 Conclusion

In this paper, I study the long-term impact of vouchers for healthy foods on food purchases, taking into account the role of prices. I confirm that households make healthier dietary choices while participating in the program. However, I find that the effect diminishes after the end of eligibility for the program. This is especially the case for bread, for which healthy product types are more expensive. The estimates from a demand model show that both prices and past purchases matter for current choices. The estimates imply that even if the program's impact on purchases is not long-lasting, it induces a change in tastes which is relevant for subsequent policies. After the program compared to before, a tax or a subsidy needed to obtain a given level of change in the healthiness of purchases is smaller.

In addition to the caveats discussed in section 3, the study faces limitations in terms of generalizability of results. The study focuses on households that have lower income and hence are likely to be more price sensitive. Because price sensitivity limits the long-term impact of the policy, the impact could be more persistent in the general population. On the other hand, less price sensitive households probably need stronger incentives to change their consumption in the first place. Furthermore, the analysis focuses on choices between similar products, such as one type of bread versus another. Because the products are similar, individuals might be willing to switch to the healthy option rather easily. When a policy would require a larger change, for example, reducing the consumption of sweets and increasing consumption of vegetables, the impact might be less persistent. Further research is needed to understand whether the results hold for the general population and different products.

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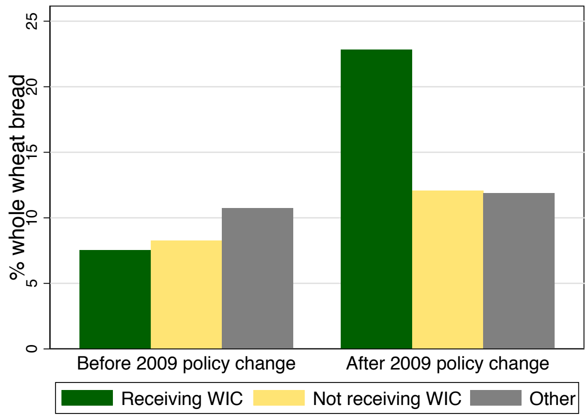
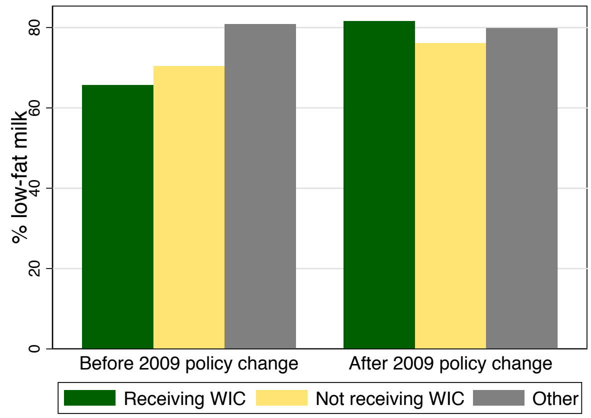
Tables and figures



(a) % whole wheat bread



(b) % low-fat milk

Figure 1: Percentage of whole wheat bread and low-fat milk from all bread and milk purchases

Note: *Receiving WIC* are households in columns 1-2 of table 1 during months when they receive WIC assistance. *Not receiving WIC* are the same households during months when they don't receive WIC assistance (either before or after they have received the assistance). *Other* are households in columns 3-4 of table 1. The percentage is calculated from weight for bread and volume for milk.

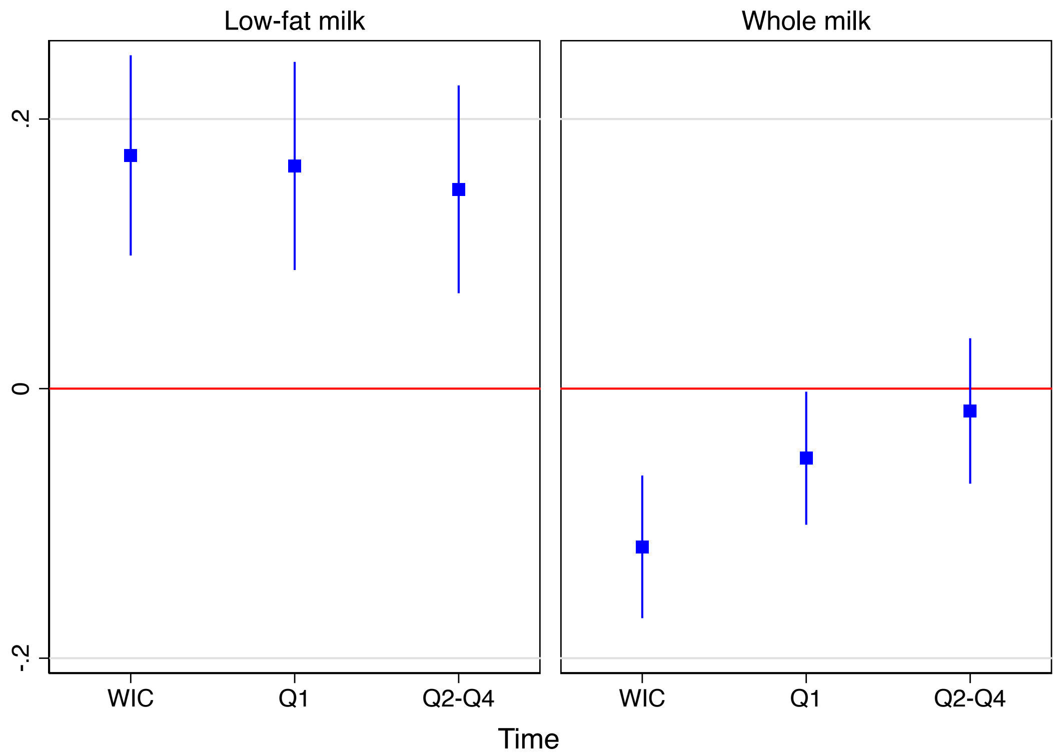


Figure 2: Estimated effect of WIC assistance on milk purchases

Note: The graph presents point estimates and confidence intervals of the impact of receiving WIC assistance (WIC), the first quarter ($Q1$) and the second until the fourth quarter ($Q2-Q4$) when becoming ineligible for the assistance. Time period before receiving WIC assistance forms the baseline value for each household. Each panel presents estimates from a separate panel data fixed effects regression. Dependant variable is logarithm of gallons of low-fat milk (left panel) and whole milk (right panel). Regressions include an indicator for being still eligible for WIC but not receiving it, an indicator for time period after the first year of not being eligible ends, dummies for period before child is born, up to child's 1st birthday, 1-year old, up to 4-years old, first quarter when child is 5 years old, quarters 2-4 when child is 5 years old, 6-12 years old children, 13-17 years old children, a male in the household, female household head not employed, indicators for household size equal to $2, \ldots, 9$, an interaction term for WIC and 1-year-old child, and logarithm of income. 90% confidence intervals are presented using standard errors clustered by household. The estimates of the regressions are presented in column 1 in table A2 in Appendix A.

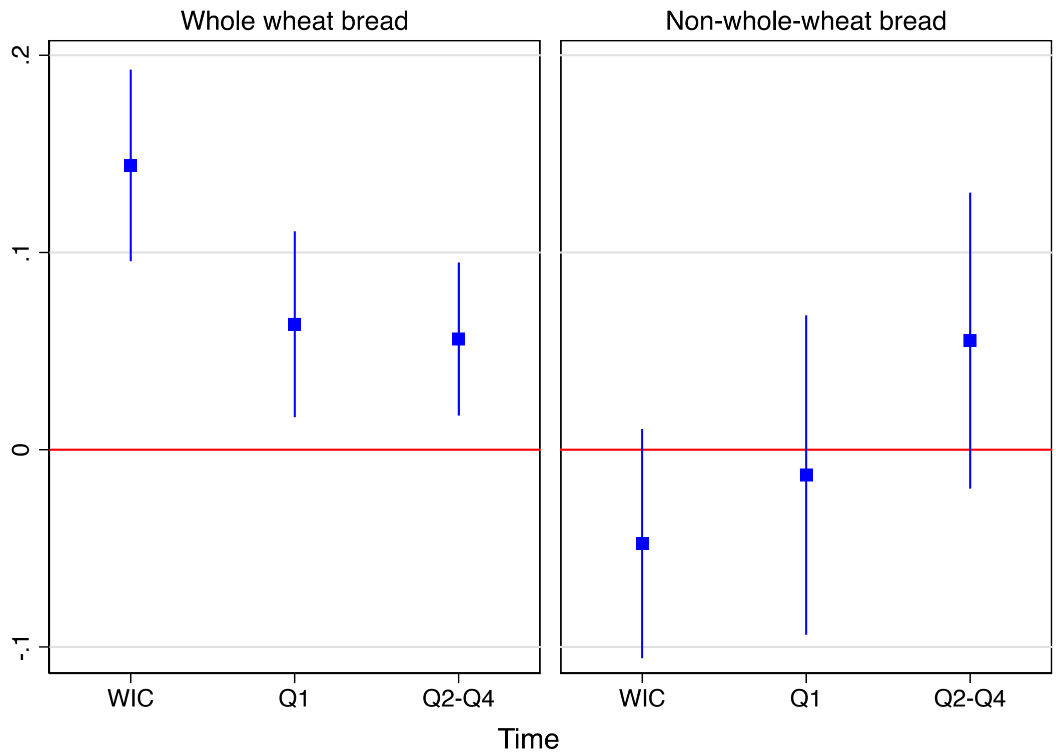


Figure 3: Estimated effect of WIC assistance on bread purchases

Note: The graph presents point estimates and confidence intervals of the impact of receiving WIC assistance (WIC), the first quarter ($Q1$) and the second until the fourth quarter ($Q2-Q4$) when becoming ineligible for the assistance. Time period before receiving WIC assistance forms the baseline value for each household. Each panel presents estimates from a separate panel data fixed effects regression. Dependant variable is logarithm of whole wheat bread quantity (left panel) and logarithm of non-whole-wheat bread quantity (right panel). Regressions include an indicator for being still eligible for WIC but not receiving it, an indicator for time period after the first year of not being eligible ends, dummies for period before child is born, up to child's 1st birthday, 1-year old, up to 4-years old, first quarter when child is 5 years old, quarters 2-4 when child is 5 years old, 6-12 years old children, 13-17 years old children, a male in the household, female household head not employed, indicators for household size equal to $2, \ldots, 9$, and logarithm of income. 90% confidence intervals are presented using standard errors clustered by household. The estimates of the regressions are presented in column 1 in table A3 in Appendix A.

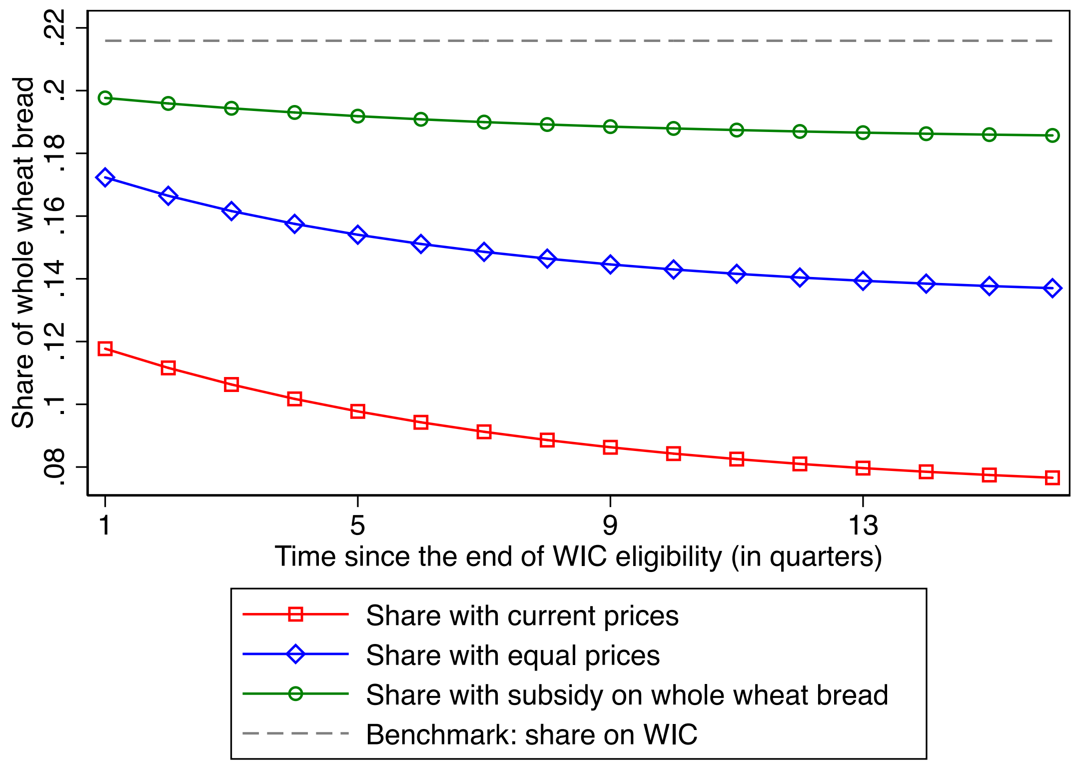


Figure 4: Share of whole wheat bread over time with different prices

Note: Predicted average share of whole wheat bread from all bread purchases is calculated using estimates with control function (model 2) in table 4. It is calculated over the set of households whose purchases I observe during the first quarter after their WIC eligibility ends and who report receiving WIC assistance at least up to 6 months before their WIC eligibility ends. *Benchmark* is their average share of whole wheat bread during the last 12 months of WIC eligibility. *Subsidy* is a 20 cent subsidy on whole wheat bread. In simulations, when updating the past share of purchases, I assume that each household purchases 6 times per quarter, which is the median in this sample.

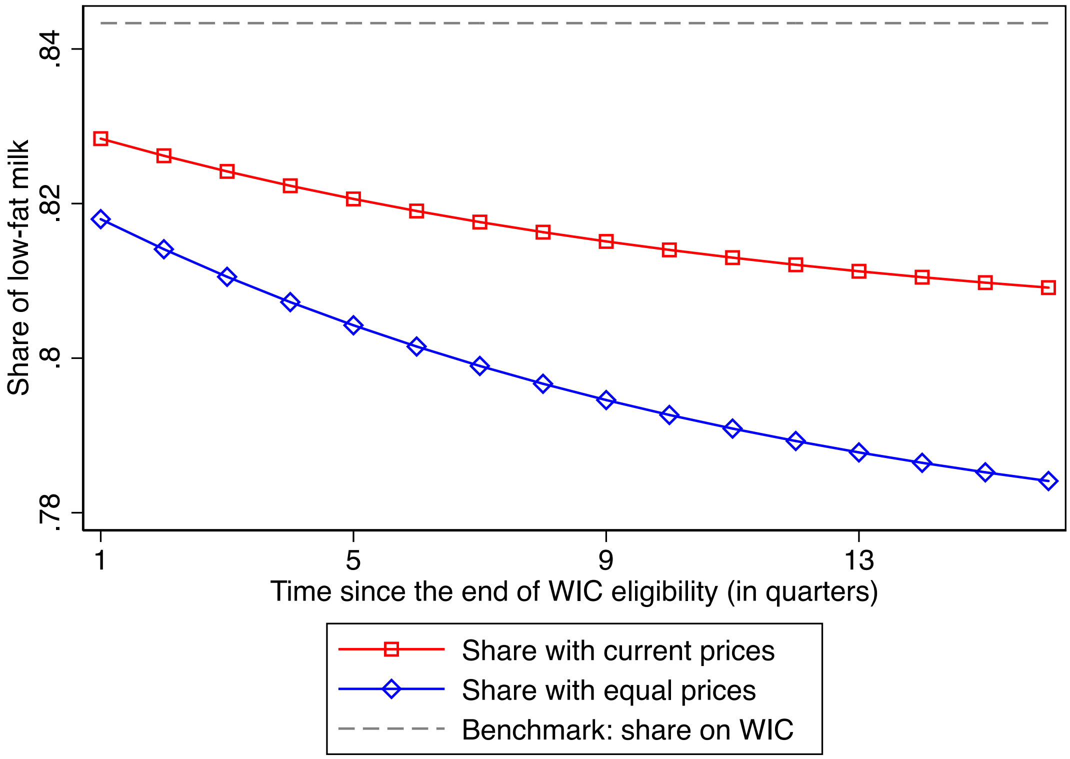


Figure 5: Share of low-fat milk over time with current and equal prices

Note: Predicted average share of low-fat milk from all milk purchases is calculated using estimates with control function (model 2) in table 5. It is calculated over the set of households whose purchases I observe during the first quarter after their WIC eligibility ends and who report receiving WIC assistance at least up to 6 months before their WIC eligibility ends. *Benchmark* is the average share of low-fat milk during the last 12 months of WIC eligibility. In simulations, when updating the past share of purchases, I assume that each household purchases 7 times per quarter, which is the median in this sample.

Table 1: Household demographic characteristics

	Treatment group	Control groups		
	WIC after 2009	WIC before 2009	WIC in the past	Other
	(1)	(2)	(3)	(4)
Household income	44135.5	42042.5	50909.4	59345.3
Household size	4.3	4.3	3.7	2.2
Household head at least college	0.498	0.383	0.415	0.527
Female not employed	0.517	0.510	0.370	0.387
Male in the household	0.810	0.816	0.774	0.741
Race: white non-Hispanic	0.687	0.715	0.701	0.817
Households	196	778	12027	132904
Household-years	1391	2857	43855	534858

Note: An observation is a household-year pair. Sample consists of household-years in the panel data fixed effects regressions. Column 1 consists of the balanced panel of households who received WIC assistance after the 2009 policy change. Column 2 includes households who received WIC assistance only before the 2009 policy change. Column 3 includes households who received WIC assistance in the past (before the survey) and at least during one year of the survey still had children under the age 18 in the household. Column 4 includes the remaining households.

Table 2: Summary statistics of purchases

	WIC households		Other
	Receiving WIC	Not receiving WIC	
	(1)	(2)	(3)
	Panel A: Before 2009 policy change		
Whole wheat bread: lb per household/month	0.27	0.27	0.27
Bread: lb per household/month	3.66	3.38	2.59
Low fat milk: gallons per household/month	2.38	2.10	1.68
Milk: gallons per household/month	3.58	2.96	2.04
Food grocery expenditures $ per household/month	247.31	238.94	190.84
Expenditure share (%): milk	5.13	4.11	3.73
Expenditure share (%): bread	1.92	1.89	2.18
	Panel B: After 2009 policy change		
Whole wheat bread: lb per household/month	0.67	0.33	0.25
Bread: lb per household/month	3.50	3.09	2.15
Low fat milk: gallons per household/month	2.63	2.05	1.36
Milk: gallons per household/month	3.24	2.66	1.66
Food grocery expenditures $ per household/month	287.04	257.94	206.05
Expenditure share (%): milk	4.00	3.60	2.92
Expenditure share (%): bread	2.02	1.76	1.83

Note: An observation is a household-month pair. In column 1, the sample consists of households in columns 1-2 of table 1 during months when they receive WIC assistance. In column 2, the sample consists of the same households during months when they don't receive WIC assistance. In column 3, the sample consists of households in columns 3-4 of table 1.

Table 3: Summary statistics of demand model datasets

	Mean	SD	Min	P. 25	Median	P. 75	Max	N
			Panel A: Households in bread demand model					
Household income	49.95	27.73	2.50	27.50	42.50	65.00	115.00	33274
Household size	3.83	1.44	1.00	3.00	4.00	5.00	9.00	33274
Age	44.43	8.70	18.00	38.50	44.00	50.00	72.00	33274
Race: non-white	0.27	0.44	0.00	0.00	0.00	1.00	1.00	33274
			Panel B: Bread prices					
Other	1.87	0.31	1.06	1.66	1.83	2.04	2.94	24316
Whole grain	1.91	0.28	1.13	1.71	1.88	2.07	5.70	24316
Whole wheat	1.87	0.32	1.00	1.64	1.87	2.07	2.97	24316
White	1.50	0.24	0.91	1.34	1.47	1.65	2.28	24316
			Panel C: Households in milk demand model					
Household income	50.62	27.82	2.50	27.50	47.50	65.00	115.00	35037
Household size	3.80	1.44	1.00	3.00	4.00	5.00	9.00	35037
Age	44.23	8.53	18.00	38.00	44.00	49.50	72.00	35037
Race: non-white	0.25	0.43	0.00	0.00	0.00	1.00	1.00	35037
			Panel D: Milk prices					
Low-fat	3.54	0.60	1.55	3.10	3.54	3.99	5.23	24532
Whole	3.58	0.61	1.52	3.12	3.59	4.05	5.09	24532

Note: In panels A and C, a unit of observation is a household-year pair, and in panels B and D, a state-week pair. *Household income* is annual, measured in thousands of dollars. *Age* is the average age of household heads measured at the baseline. Price of bread is measured in dollars per pound and price of milk in dollars per gallon.

Table 4: Demand model estimates: bread

	No control function		Control function	
	(1)		(2)	
	Estim.	SE	Estim.	SE
Mean				
Price	−1.474∗∗∗	(0.456)	−4.186∗∗∗	(0.952)
Price: log. income	0.107∗∗∗	(0.039)	0.106∗∗∗	(0.039)
Price: household size	−0.036∗∗	(0.015)	−0.036∗∗	(0.015)
Price: age	0.006∗	(0.003)	0.006∗	(0.003)
Whole grain/wheat: log. income	0.089∗∗∗	(0.016)	0.089∗∗∗	(0.016)
Whole grain/wheat: household size	−0.030∗∗∗	(0.006)	−0.030∗∗∗	(0.006)
Whole grain/wheat: age	−0.003∗∗∗	(0.001)	−0.003∗∗∗	(0.001)
Log. past product share	0.461∗∗∗	(0.004)	0.461∗∗∗	(0.004)
Whole grain bread	−1.116∗∗∗	(0.184)	−1.029∗∗∗	(0.187)
Whole wheat bread	−1.548∗∗∗	(0.184)	−1.562∗∗∗	(0.184)
White bread	−0.065∗∗∗	(0.021)	−1.071∗∗∗	(0.310)
Residual			2.712∗∗∗	(0.833)
Standard Deviation				
Price	0.653∗∗∗	(0.073)	0.654∗∗∗	(0.072)
Log. past product share	0.133∗∗∗	(0.004)	0.133∗∗∗	(0.004)
Whole grain bread	0.639∗∗∗	(0.015)	0.639∗∗∗	(0.015)
Whole wheat bread	0.773∗∗∗	(0.019)	0.773∗∗∗	(0.019)
White bread	0.870∗∗∗	(0.021)	0.869∗∗∗	(0.021)
Log-likelihood	-421399.6		-421387.4	
Number of choices	2224448		2224448	
Number of households	8188		8188	

Note: The table presents estimates from 2 random coefficient logit models. For each model, the first column presents parameter estimates and the second column standard errors. The lower part of the table presents standard deviations of the distributions of random coefficients. The base type of bread is *other* bread. Standard errors are clustered at the household level. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table 5: Demand model estimates: milk

	No control function		Control function	
	(1)		(2)	
	Estim.	SE	Estim.	SE
Mean				
Price	$-0.623**$	(0.313)	$-5.372*$	(2.828)
Log. past product share	$0.711***$	(0.007)	$0.711***$	(0.007)
Whole milk	0.400	(0.535)	0.590	(0.574)
Whole milk: log. income	$-0.133***$	(0.050)	$-0.133**$	(0.052)
Whole milk: age	$0.006**$	(0.003)	$0.006**$	(0.003)
Whole milk: non-white	$0.301***$	(0.116)	$0.299**$	(0.122)
Residual			$4.735*$	(2.795)
Standard Deviation				
Price	$4.743***$	(0.956)	$4.733***$	(0.980)
Log. past product share	$0.247***$	(0.009)	$0.246***$	(0.009)
Whole milk	$1.248***$	(0.092)	$1.246***$	(0.097)
Log-likelihood	-99333.53		-99327.36	
Number of choices	1403726		1403726	
Number of households	8929		8929	

Note: The table presents estimates from two random coefficient logit models. For each model, the first column presents parameter estimates and the second column standard errors. The lower part of the table presents standard deviations of the distributions of random coefficients. The base type of milk is low-fat milk. Standard errors are clustered at the household level. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table 6: Actual and predicted market shares

	Market shares by product type			Difference
	Actual data	Predicted with actual prices	Predicted with equal prices	in market shares
		Panel A: Bread		
Other bread	35.79	35.90	43.10	7.2
Whole grain bread	15.28	15.19	19.64	4.4
Whole wheat bread	7.83	7.68	8.84	1.2
White bread	41.09	41.23	28.41	-12.8
		Panel B: Milk		
Low-fat milk	76.20	76.33	75.84	-0.5
Whole milk	23.80	23.67	24.16	0.5

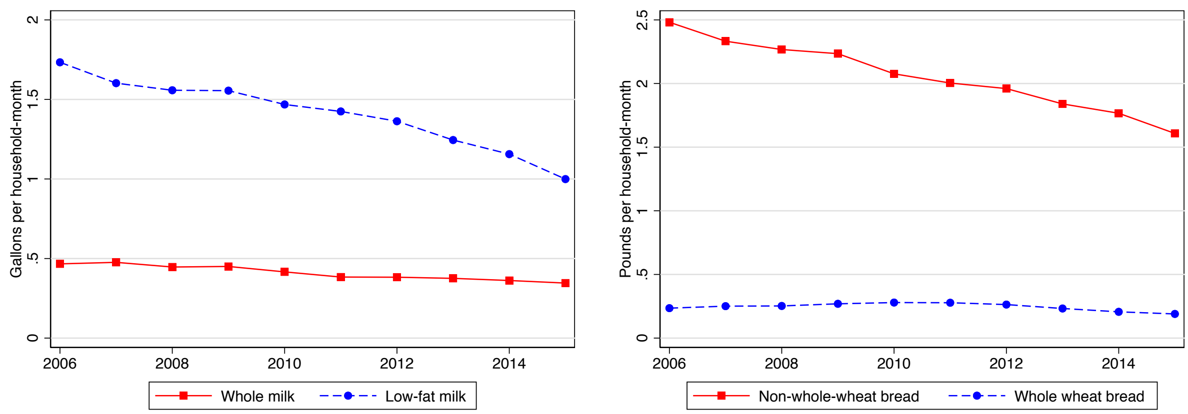
Note: Market shares sum up to 100. Predicted market shares are calculated using estimates with control function (model 2) in tables 4 and 5.

Table 7: The impact of whole wheat bread subsidy and low-fat milk subsidy

	Predicted market shares				Percentage change in market shares		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tastes	Old	New	Old	New	Δ Tastes	-	Δ Tastes
Subsidy	No	No	Yes	Yes	-	Δ Subsidy	Δ Subsidy
				Panel A: Whole wheat bread subsidy			
Other bread	32.3	29.5	31.2	28.2	-8.7	-3.4	-12.6
Whole grain bread	15.8	13.7	15.3	13.1	-13.2	-3.4	-16.8
Whole wheat bread	10.2	13.0	12.9	16.3	27.8	26.9	60.2
White bread	41.7	43.8	40.6	42.4	4.9	-2.6	1.5
				Panel B: Low-fat milk subsidy			
Low-fat milk	81.9	84.0	87.6	89.1	2.5	6.9	8.7
Whole milk	18.1	16.0	12.4	10.9	-11.4	-31.3	-39.6

Note: The impact of a 10 cent subsidy on whole wheat bread (panel A) and the impact of a 10 cent tax on whole milk (panel B) on the market shares in the first year after WIC eligibility ends. Market shares sum up to 100. Predicted market shares are calculated using estimates with control function (model 2) in tables 4 and 5.

A Online Appendix: Additional tables and figures



(a) Milk

(b) Bread

Figure A1: Quantity over time

Note: Sample is restricted to households who have not reported receiving WIC after the 2009 policy change (households in columns 2-4 in table 1). Calculated as an average over household-years and weighted by Nielsen projection weights.

Table A1: WIC food package, per month, 2009 - 2014

	Children	Women		
	1–4 years	Pregnant, partially breastfeeding	Postpartum	Breastfeeding
Milk (gallons)	4	5.5	4	6
Whole wheat/grain bread (lb)	2	1	-	1
Juice (gallons)	1	1.125	0.75	1.125
Breakfast cereal (oz)	36	36	36	36
Cheese (lb)	-	-	-	1
Eggs	12	12	12	24
Fresh fruits and vegetables ($)	6	8	8	10
Canned fish (oz)	-	-	-	30
Legumes (lb)	1	1	1	1
And/or peanut butter (oz)	Or 18	And 18	Or 18	And 18

Note: Whole milk is the standard milk for 1-year-old children. Reduced fat (2%) milks are the standard milk for children 2-4 years of age and women. Milk is allowed to be partially substituted by cheese. As substitutes to bread, states are allowed to authorize brown rice, bulgur, oatmeal, whole-grain barley, or soft corn or whole wheat tortillas on an equal weight basis.
Source: Federal Register, 2007, Vol. 72, No. 234, pp. 68989–68990.

Table A2: Dependent variable: logarithm of gallons of milk purchased

	All	Past WIC	Children	Lower income	Past WIC Resid. log(Q)
	(1)	(2)	(3)	(4)	(5)
			Panel A: Low-fat milk		
WIC	0.173***	0.201***	0.206***	0.171***	0.158***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Post WIC: Q1 not eligible	0.165***	0.171***	0.207***	0.145***	0.123***
	(0.047)	(0.048)	(0.047)	(0.047)	(0.048)
Post WIC: Q2-Q4 not eligible	0.148***	0.157***	0.193***	0.129***	0.105**
	(0.047)	(0.048)	(0.047)	(0.047)	(0.047)
Year-month FE	Yes	Yes	Yes	Yes	No
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	188	188	188	188	188
Households	138246	12646	48547	53942	12646
Household-months	6745752	563208	1991892	2838660	563208
			Panel B: Whole milk		
WIC	-0.117***	-0.092***	-0.096***	-0.126***	-0.130***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
Post WIC: Q1 not eligible	-0.052*	-0.034	-0.031	-0.063**	-0.071**
	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)
Post WIC: Q2-Q4 not eligible	-0.017	0.008	0.005	-0.028	-0.031
	(0.033)	(0.034)	(0.033)	(0.033)	(0.034)
Year-month FE	Yes	Yes	Yes	Yes	No
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	188	188	188	188	188
Households	138246	12646	48547	53942	12646
Household-months	6745752	563208	1991892	2838660	563208

Note: A unit of observation is a household and month pair. Each column presents estimates from a separate panel data fixed effects regression. Dependant variable is logarithm of gallons of low-fat milk (panel A) and whole milk (panel B). All regressions include an indicator for being still eligible for WIC but not receiving it, an indicator for time period after the first year of not being eligible ends, dummies for period before child is born, up to child's 1st birthday, 1-year old, up to 4-years old, first quarter when child is 5 years old, quarters 2-4 when child is 5 years old, 6-12 years old children, 13-17 years old children, a male in the household, female household head not employed, indicators for household size equal to $2, \ldots, 9$, an interaction term for WIC and 1-year-old child, and logarithm of income. Columns present estimates with different control groups: in column 1, all households; in columns 2 and 5, households that received WIC assistance in the past (columns 2–3 in table 1); in column 3, households with children; in column 4, households that have had income below the WIC eligible income threshold. In column 5, the outcome variable is the residualized logarithm of quantity, that is, the logarithm of quantity is residualized with respect to the year-month fixed effects using the full sample. Standard errors clustered on household-level are included in parenthesis. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table A3: Dependent variable: logarithm of pounds of bread purchased

	All	Past WIC	Children	Lower income	Past WIC Resid. log(Q)
	(1)	(2)	(3)	(4)	(5)
			Panel A: Whole wheat bread		
WIC	0.144***	0.129***	0.141***	0.140***	0.138***
	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)
Post WIC: Q1 not eligible	0.064**	0.041	0.063**	0.055*	0.045
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Post WIC: Q2-Q4 not eligible	0.056**	0.036	0.056**	0.049**	0.039
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Year-month FE	Yes	Yes	Yes	Yes	No
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	193	193	193	193	193
Households	141724	12713	49386	55019	12713
Household-months	6854532	562920	2011368	2876136	562920
			Panel B: Non-whole-wheat bread		
WIC	-0.048	-0.142***	-0.009	-0.054	-0.059*
	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)
Post WIC: Q1 not eligible	-0.013	-0.117**	0.031	-0.023	-0.012
	(0.049)	(0.050)	(0.050)	(0.050)	(0.050)
Post WIC: Q2-Q4 not eligible	0.055	-0.061	0.101**	0.047	0.051
	(0.046)	(0.047)	(0.046)	(0.046)	(0.046)
Year-month FE	Yes	No	Yes	Yes	No
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	193	193	193	193	193
Households	141724	12713	49386	55019	12713
Household-months	6854532	562920	2011368	2876136	562920

Note: A unit of observation is a household and month pair. Each column presents estimates from a separate panel data fixed effects regression. Dependent variable is logarithm of pounds of whole wheat bread (panel A) and non-whole-wheat bread (panel B). All regressions include an indicator for being still eligible for WIC but not receiving it, an indicator for time period after the first year of not being eligible ends, dummies for period before child is born, up to child's 1st birthday, 1-year old, up to 4-years old, first quarter when child is 5 years old, quarters 2-4 when child is 5 years old, 6-12 years old children, 13-17 years old children, a male in the household, female household head not employed, indicators for household size equal to $2, \ldots, 9$, and logarithm of income. Columns present estimates with different control groups: in column 1, all households; in columns 2 and 5, households that received WIC assistance in the past (columns 2–3 in table 1); in column 3, households with children; in column 4, households that have had income below the WIC eligible income threshold. In column 5, the outcome variable is the residualized logarithm of quantity, that is, the logarithm of quantity is residualized with respect to the year-month fixed effects using the full sample. Standard errors clustered on household-level are included in parenthesis. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table A4: Dependent variables: measures of quantity of milk

	Quantity	Prob. of purchase	Fewer controls	Fewer large purch. excl.	More large purch. excl.
	(1)	(2)	(3)	(4)	(5)
			Panel A: Low-fat milk		
WIC	0.464***	0.115***	0.145***	0.175***	0.125**
	(0.152)	(0.029)	(0.043)	(0.044)	(0.050)
Post WIC: Q1 not eligible	0.358**	0.115***	0.165***	0.167***	0.166***
	(0.171)	(0.031)	(0.047)	(0.047)	(0.050)
Post WIC: Q2-Q4 not eligible	0.266	0.124***	0.147***	0.143***	0.168***
	(0.175)	(0.030)	(0.047)	(0.047)	(0.049)
Year-month FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	188	188	188	192	148
Households	138246	138246	138246	138753	131839
Household-months	6745752	6745752	6745752	6781344	6355728
			Panel B: Whole milk		
WIC	-0.325***	-0.080***	-0.072**	-0.109***	-0.102***
	(0.091)	(0.022)	(0.034)	(0.032)	(0.035)
Post WIC: Q1 not eligible	-0.174**	-0.036	-0.051*	-0.044	-0.030
	(0.084)	(0.023)	(0.030)	(0.030)	(0.033)
Post WIC: Q2-Q4 not eligible	-0.086	0.002	-0.015	-0.011	-0.017
	(0.096)	(0.026)	(0.033)	(0.032)	(0.036)
Year-month FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	188	188	188	192	148
Households	138246	138246	138246	138753	131839
Household-months	6745752	6745752	6745752	6781344	6355728

Note: Note: A unit of observation is a household and month pair. Each column presents estimates from a separate panel data fixed effects regression. Dependent variable is a measure of low-fat milk (panel A) or whole milk (panel B). Specifically, dependent variable is gallons of milk (column 1); indicator for purchasing milk (column 2), logarithm of gallons of milk (columns 4-5). Sample in column 4 is restricted to households whose quantity of milk purchased don't exceed 3 times the 99th percentile across all households; and in column 5, one time the 99th percentile. All regressions include an indicator for being still eligible for WIC but not receiving it, an indicator for time period after the first year of not being eligible ends, dummies for period before child is born, up to child's 1st birthday, 1-year old, up to 4-years old, first quarter when child is 5 years old, quarters 2-4 when child is 5 years old, 6-12 years old children, 13-17 years old children, a male in the household, female household head not employed, indicators for household size equal to $2, \ldots, 9$, an interaction term for WIC and 1-year-old child, and logarithm of income. Standard errors clustered on household-level are included in parenthesis. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table A5: Dependent variables: measures of quantity of bread

	Quantity	Prob. of purchase	Whole grain	Fewer large purch. excl.	More large purch. excl.
	(1)	(2)	(3)	(4)	(5)
			Panel A: Whole wheat bread		
WIC	0.274***	0.140***	0.144***	0.140***	0.120***
	(0.075)	(0.023)	(0.036)	(0.029)	(0.026)
Post WIC: Q1 not eligible	0.101	0.071***	0.082**	0.063**	0.050
	(0.071)	(0.024)	(0.038)	(0.029)	(0.031)
Post WIC: Q2-Q4 not eligible	0.126**	0.046**	0.082**	0.056**	0.038
	(0.062)	(0.018)	(0.033)	(0.023)	(0.024)
Year-month FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	193	193	193	194	141
Households	141724	141724	141724	142440	132223
Household-months	6854532	6854532	6854532	6905160	6237960
			Panel B: Non-whole-wheat bread		
WIC	-0.234	-0.012	-0.055	-0.043	-0.073**
	(0.150)	(0.017)	(0.034)	(0.035)	(0.036)
Post WIC: Q1 not eligible	-0.139	0.012	-0.035	-0.013	-0.006
	(0.204)	(0.027)	(0.047)	(0.049)	(0.052)
Post WIC: Q2-Q4 not eligible	0.031	0.054**	0.033	0.050	0.063
	(0.189)	(0.022)	(0.044)	(0.046)	(0.049)
Year-month FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
WIC households	193	193	193	194	141
Households	141724	141724	141724	142440	132223
Household-months	6854532	6854532	6854532	6905160	6237960

Note: A unit of observation is a household and month pair. Each column presents estimates from a separate panel data fixed effects regression. Dependent variable is a measure of whole wheat bread (panel A) or non-whole-wheat bread (panel B). Specifically, dependent variable is pounds of bread (column 1); indicator for purchasing bread (column 2), logarithm of pounds of (non-)whole-grain bread (column 3), and logarithm of pounds of (non-)whole-wheat bread (columns 4-5). Sample in column 4 is restricted to households whose quantity of bread purchased don't exceed 3 times the 99th percentile across all households; and in column 5, one time the 99th percentile. All regressions include an indicator for being still eligible for WIC but not receiving it, an indicator for time period after the first year of not being eligible ends, dummies for period before child is born, up to child's 1st birthday, 1-year old, up to 4-years old, first quarter when child is 5 years old, quarters 2-4 when child is 5 years old, 6-12 years old children, 13-17 years old children, a male in the household, female household head not employed, indicators for household size equal to $2, \ldots, 9$, and logarithm of income. Standard errors clustered on household-level are included in parenthesis. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table A6: Control function estimation. Dependent variable: price of bread

	Estimate	SE
Wheat price	0.629***	(0.022)
Wheat price: white bread	-0.080***	(0.028)
Wheat price: whole grain bread	0.009	(0.032)
Wheat price: whole wheat bread	0.151***	(0.035)
White bread	-0.352***	(0.007)
Whole-grain bread	0.030***	(0.008)
Whole-wheat bread	-0.041***	(0.009)
Constant	1.713***	(0.008)
State FE	Yes	
R-squared	0.682	
Number of observations	97264	

Note: A unit of observation is a bread type (white, whole grain, whole wheat, or other), state, and week triplet. Price of bread is measured as dollars per pound. Price of wheat is measured as dollars per kg. Robust standard errors are included in parenthesis. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table A7: Control function estimation. Dependent variable: price of milk

	Estimate	SE
Raw milk price	0.841***	(0.005)
Whole milk: Raw milk price	-0.017**	(0.007)
Whole milk	0.070***	(0.012)
Constant	2.415***	(0.011)
State FE	Yes	
R-squared	0.834	
Number of observations	49064	

Note: A unit of observation is a milk type (whole or low-fat), state, and week triplet. Robust standard errors are included in parenthesis. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table A8: Demand model estimates: bread, robustness

	No control function		Control function	
	(1)		(2)	
	Estim.	SE	Estim.	SE
Mean				
Price	−1.469∗∗∗	(0.455)	−4.178∗∗∗	(0.952)
Price: log. income	0.106∗∗∗	(0.039)	0.106∗∗∗	(0.039)
Price: household size	−0.036∗∗	(0.015)	−0.036∗∗	(0.015)
Price: age	0.006∗	(0.003)	0.006∗	(0.003)
Price: non-white	−0.010	(0.060)	−0.009	(0.060)
Whole grain/wheat: log. income	0.089∗∗∗	(0.016)	0.089∗∗∗	(0.016)
Whole grain/wheat: household size	−0.030∗∗∗	(0.006)	−0.030∗∗∗	(0.006)
Whole grain/wheat: age	−0.003∗∗	(0.001)	−0.003∗∗	(0.001)
Whole grain/wheat: non-white	−0.018	(0.028)	−0.017	(0.028)
Log. past product share	0.461∗∗∗	(0.004)	0.461∗∗∗	(0.004)
Whole grain bread	−1.117∗∗∗	(0.184)	−1.031∗∗∗	(0.187)
Whole wheat bread	−1.550∗∗∗	(0.184)	−1.563∗∗∗	(0.184)
White bread	−0.064∗∗∗	(0.021)	−1.069∗∗∗	(0.310)
Residual			2.707∗∗∗	(0.833)
Standard Deviation				
Price	0.655∗∗∗	(0.072)	0.656∗∗∗	(0.072)
Log. past product share	0.133∗∗∗	(0.004)	0.133∗∗∗	(0.004)
Whole grain bread	0.639∗∗∗	(0.015)	0.639∗∗∗	(0.015)
Whole wheat bread	0.773∗∗∗	(0.019)	0.773∗∗∗	(0.019)
White bread	0.869∗∗∗	(0.021)	0.869∗∗∗	(0.021)
Log-likelihood	-421399		-421386.9	
Number of choices	2224448		2224448	
Number of households	8188		8188	

Note: The table presents estimates from two random coefficient logit models. For each model, the first column presents parameter estimates and the second column standard errors. The lower part of the table presents standard deviations of the distributions of random coefficients. The base type of bread is *other* bread. Standard errors are clustered at the household level. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

Table A9: Demand model estimates: milk, robustness

	No control function (1)		Control function (2)	
	Estim.	SE	Estim.	SE
Mean				
Price	-1.458	(3.369)	-6.521	(5.003)
Price: log. income	-0.086	(0.284)	-0.078	(0.313)
Price: age	0.033	(0.025)	0.033	(0.026)
Price: non-white	0.581*	(0.350)	0.614	(0.411)
Price: household size	0.020	(0.152)	0.018	(0.153)
Log. past product share	0.710***	(0.007)	0.710***	(0.007)
Whole milk	0.419	(0.469)	0.624	(0.602)
Whole milk: log. income	-0.140***	(0.040)	-0.142***	(0.048)
Whole milk: age	0.007**	(0.003)	0.007*	(0.004)
Whole milk: non-white	0.304***	(0.072)	0.302***	(0.072)
Whole milk: household size	0.011	(0.016)	0.013	(0.016)
Residual			4.931*	(2.815)
Standard Deviation				
Price	4.857***	(0.535)	4.873***	(0.684)
Log. past product share	0.247***	(0.008)	0.246***	(0.008)
Whole milk	1.240***	(0.057)	1.236***	(0.073)
Log-likelihood	-99328.27		-99321.6	
Number of choices	1403726		1403726	
Number of households	8929		8929	

Note: The table presents estimates from two random coefficient logit models. For each model, the first column presents parameter estimates and the second column standard errors. The lower part of the table presents standard deviations of the distributions of random coefficients. The base type of milk is low-fat milk. Standard errors are clustered at the household level. *** Indicates significance at the 1 percent level, ** at 5 percent level, * at 10 percent level.

B Online Appendix: Dataset construction

In this Appendix, I describe the construction of the dataset from the Nielsen Homescan consumer panel and Retail Scanner dataset from years 2006–2015. Retail Scanner dataset is used to construct price variables and Homescan consumer panel is used for purchases.

Milk purchases. I concentrate on dairy white fluid refridgerated milk. I exclude goat milk, lactose free milk, and organic milk. I also drop multi-unit products, and unusual package sizes. That is, the package sizes which I keep are: one gallon, half a gallon, and a quart (0.25 gallon). Note that in the majority of states, only one gallon package size is allowed as a WIC product, a few states also allow half a gallon and a quart. I keep only packages which are either plastic or carton, and drop glass bottles and other unusual packages. These exclusions lead to about 9 percent reduction in purchases (household store trip and upc combinations).

Bread purchases. I concentrate on loaves of bread. I exclude organic products, multi-unit produts, and unusual package sizes. That is, I restrict the sample to four most common package sizes: 16, 20, 22, and 24 oz. Note that in the majority of states, only 16 oz package bread is allowed as a WIC product, some states also allow 24 oz packages. These exclusions lead to about 13 percent decrease in purchases.

Product definition and aggregation of purchases in panel data fixed effects analysis (section 3). In section 3, in each category, the main analysis aggregates all purchases to two products – for milk, low-fat and whole milk; for bread, whole wheat bread and non-whole-wheat bread. Following WIC regulations, I classify a bread as whole wheat bread if it is made using 100% whole wheat flour. A bread that only partially is made using whole wheat flour is classified as non-whole-wheat. For robustness analysis, I use an alternative classification: whole grain bread and non-whole-grain bread. I classify bread as whole grain if it contains whole wheat, other whole grain, or rye. Note that whole grain bread is a less strict classification including breads that are not 100% whole wheat/grain. Purchases of each product are summed up to monthly level.

Product definition and aggregation of purchases in demand model estimation (section 4). In section 4, for milk I use the same classification of products as described above. I group bread into four products: whole wheat, whole grain, white, and other. Whole wheat bread is defined as before if bread is made with 100% whole wheat flour, whole grain contains whole wheat, whole grain, or rye flour (except 100% whole wheat), white bread is from white refined flour, and other bread aggregates together all other non-whole-grain bread types. Purchases of each product are aggregated to weekly level. When household purchased more than one product in a week, then I only include the largest (in terms of weight for bread and volume for milk) purchase.

Sample of households: In the Nielsen Homescan dataset, there are about 150 thousand households that have made food purchases in the ten years 2006–2015. Of these households 97% have made milk purchases and 98% bread purchases.

In section 3, in the main panel data fixed effects specification, separately for each product category, I exclude households that have ever had a monthly purchase quantity larger than two times the 99th percentile (conditional on a purchase in the category). The 99th percentile equals 13 gallons for milk, 15 pounds for bread. I exclude these households because I don't want the extremely large purchases to drive the estimation results. The restriction excludes less than one percent of households. In robustness analysis, I use two alternative thresholds: purchase quantity larger than one or three times the 99th percentile.

Underreporting of WIC status. In the survey data, household's WIC status seems to be underreported. The information on WIC status is collected via a survey question, which households are not required to answer. Therefore, as expected, in the dataset, the reported share of households receiving WIC assistance is lower than in the administrative data. Figure B2 shows the percentage of income eligible households who report receiving WIC assistance, by the age of the youngest child. The figure illustrates two aspects of the data. First, the magnitude of underreporting. Back-of-the-envelope calculations suggest that about forty percent of WIC participants report it in the survey.[13] Second, the households' reported WIC participation mirrors well the pattern in the administrative data. Namely, WIC participation is the highest during the calendar year when the child is born and decreases after that up to the child's fifth birthday. In the analysis, I focus on households who report receiving WIC assistance.

Product input prices as instruments. For milk input prices I use raw milk prices from USDA. The minimum raw milk prices that the dairy processors and manufacturers must pay

[13] According to the USDA report (Johnson, Giannarelli, Huber, and Betson, 2014), around 80% of eligible infants (up to their first birthday) receive WIC. However, in this dataset, the reported WIC participation of the corresponding households is 35%. According to the administrative data, participation of children aged 1–4 is about 50%, but in this dataset, only around 20%.

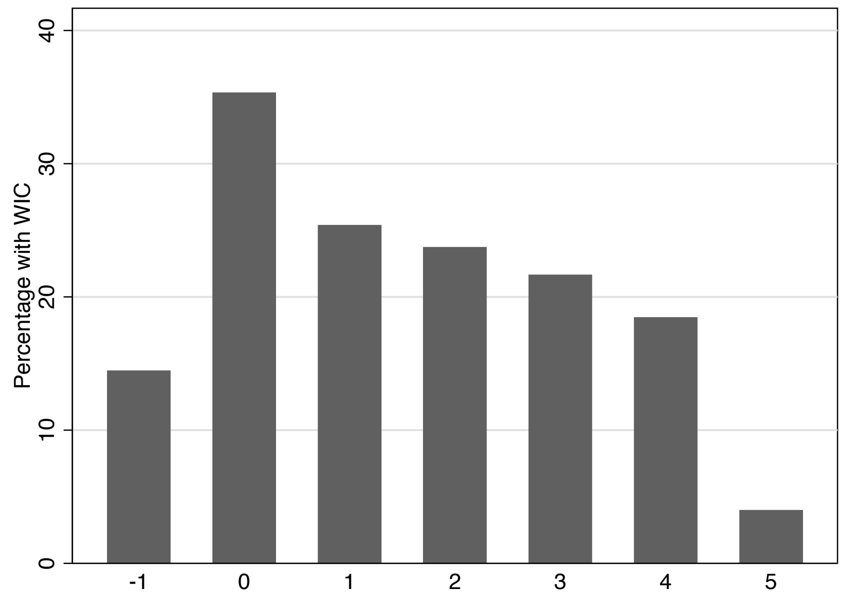


Figure B2: Percentage of households reporting receiving WIC assistance, by the years since the youngest child is born

Note: Sample is restricted to WIC income eligible households. Calculated as an average over household-years and weighted by Nielsen projection weights. Year 0 indicates that the youngest child is born during the current panel year. Income eligibility is calculated using the mid-point value of Nielsen reported household income interval.

to the dairy farmers are set by the Federal Milk Marketing Orders. The raw milk prices are set monthly and vary by county. For bread input prices, I use the global price of wheat from IMF. It's the average price per month representative of the global market.

Construction of variables. I generate *Income* variable as the mid-point of the reported income interval. Except for the highest income group, for which the mid-point cannot be calculated as no highest level is reported. For that group I assume that their household annual income equals 115,000 dollars, which is consistent with the current income distribution. In the demand model, *Age* is the average age of household heads at the baseline, that is, during the first year when they are in the sample. The variable is calculated at the baseline and kept constant for each household over time to capture the impact of age and not the possible trend over time. To avoid that the impact of age is mainly driven by the upper tail, I cap the age at the 99th percentile.