Is the Cure Worse than the Disease? Unintended Consequences of Fraud Reduction in Transfer Programs*

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Abstract

Many U.S. safety net programs involve in-kind transfers, which are used in order to both alter consumption patterns among recipients and limit take-up by ineligibles. However, in the absence of its own network of providers, the government must rely on private vendors to serve as its agents in rendering transfers, giving rise to two types of agency problems: (1) vendors may refuse to participate in government programs, leaving needy people unserved or (2) vendors may engage in fraud in order to increase their payoff from participation. A separate issue arises when government intervention in private markets causes general equilibrium effects on third parties.

This paper examines attempts to reduce vendor fraud in the Supplemental Nutrition Program for Women, Infants, and Children (WIC) using data on the staggered rollout of a fraud reduction program in Texas. Vendors were required to move to an electronic payment system, which allowed regulators to more easily verify reimbursement claims. I show that the program was effective in reducing fraud, but also that it increased vendor non-participation, leading to a reduction in WIC take-up among eligible women. I also show that the fraud reduction program increased prices paid by non-WIC shoppers by 9%. My results indicate that the effectiveness of policies intended to alter consumption patterns among welfare recipients depend crucially on the incentives of providers and that enforcement measures interact with these incentives.

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1 Introduction

A large and growing share of safety net programs in the U.S. and other developed countries involve in-kind transfers. In-kind transfers are used in order to limit take-up among ineligibles and to alter consumption patterns among recipients (Besley and Coate, 1992; Blackorby and Donaldson, 1988; Nichols and Zeckhauser, 1982). A potential drawback of in-kind transfers is the fact that, absent its own network of providers, the government must rely on private vendors to distribute transfers, which creates the potential for agency problems as well general equilibrium effects in the private market for program goods.

In particular, contracting out the distribution of in-kind transfers to private vendors gives rise to two types of agency problems: (1) vendors may refuse to participate in government programs, leaving needy people unserved or (2) they may engage in wasteful strategies (e.g., fraud) in order to increase their payoff from participation. In fact, a growing body of literature finds that vendors in safety net programs respond strategically to program incentives in order to maximize their own profits, suggesting that they may play an important role in program incidence.

My paper examines attempts to reduce vendor fraud in the Supplemental Nutrition Program for Women, Infants, and Children (WIC) — which currently serves over half of pregnant women and infants in the U.S. — using data on the staggered county-level roll out of a fraud reduction program in Texas. Vendors were required to move to an electronic payment system that allowed regulators to more easily verify reimbursement claims. I show that the fraud reduction program was effective, but also that it increased vendor non-participation, leading to a reduction in WIC participation among eligible women and infants. I also show that smaller vendors increase the prices charged to non-WIC shoppers for program eligible foods by 9%.

This paper is the first to consider the relationship between opportunities for vendor fraud, vendor participation in a transfer program, the participation of potential recipients of government transfer programs, and general equilibrium effects on prices. I am able to consider all of these aspects by constructing a unique data set combining administrative data about WIC vendors in Texas, information about prices from Nielsen scanner data, and information about the participation of pregnant women from individual birth records. Because my study encompasses all of these elements, it is possible to consider the effect of fraud reduction on social welfare. My findings suggest that fraud reduction, while effective in terms of achieving its stated goal, reduced social welfare by 3-4% of the value of benefits received.

Further analysis suggests that fraud subsidizes vendor participation in high poverty areas, where reduced consumption of fresh foods implies higher fixed costs associated with stocking and storing WIC-eligible products (e.g. milk, eggs, cheese). A welfare improving program would therefore combine fraud reduction with measures to increase vendor participation in underserved areas.

My analysis proceeds as follows. I first motivate my findings by modeling vendor profits as a function of WIC program incentives. Because WIC participants receive set quantities and types of food regardless of price, they are price inelastic. Therefore, vendors — retail grocery stores — can increase profits by price discriminating between their WIC and non-WIC customers, charging the former a mark-up over the latter, which is considered fraud. The anti-fraud reform forces stores to charge a pooling price to both types of customers, so the price paid by non-WIC customers increases. In addition, program profits for stores fall, reducing the store incentive to participate.

Using administrative data on WIC stores in Texas, I find that *ex-ante* rates of fraud are high among single outlet grocery stores and low among grocery chains. However, single outlet stores are the predominant type of groceries in high-poverty areas, making them potentially important for access. I use the staggered county-level rollout of the antifraud reform to show that (1) it eliminates most pre-existing fraud among stores and (2) it causes 10-26% of single outlets to drop out of WIC (no change for chains).

Next, using individual birth records for the state of Texas, I find a corresponding decrease in WIC participation among eligible mothers by 3-5%. In addition, using the fact that the birth records include ZIP code of residence of the mother, I show directly that the reform reduced the likelihood a mother has at least one WIC store in her ZIP code. Note that my results likely understate overall reductions in access, as I do not observe more intensive-margin outcomes such as how *much* food she receives, the distance she needs to travel to the nearest store, whether her "usual" grocery store offers WIC, etc. I provide corroborating evidence on the importance of WIC vendor supply to take-up among eligibles by studying a moratorium on new vendors in California's WIC program.

Using the Nielsen Homescan dataset, I then evaluate the effect of the reform on prices paid by *non-WIC* shoppers. I use precise information on WIC product eligibility and the location of WIC stores to show that prices on WIC products within single outlet WIC stores increased after the reform by 9%. There is no change for chains, which follows from the fact that chains did not price discriminate *ex-ante*. I also find no price movements in the various untreated subsets (WIC products in non-WIC stores; non-WIC products in WIC stores, etc.), in line with my predictions and also providing evidence against alternative hypotheses. In general, my empirical results on prices and participation among stores and eligible women are highly robust to different specifications, controls and data sources.

Finally, I synthesize my empirical results to estimate the overall impact on social welfare of the anti-fraud reform. I find that while program costs decreased due to both the reduction in fraud as well as the decline in benefit take-up, the costs to participants, non-participants and stores outweigh these savings. I estimate that the reform decreased welfare by at least 3-4% of the value of benefits received.

Subsample analyses reveal that the largest proportional declines in WIC participation among stores and women occur in high-poverty ZIP codes. I provide evidence from the Nielsen dataset that the consumption of fresh foods is low in high-poverty ZIP codes, suggesting that there are higher fixed costs associated with stocking and storing the foods required by WIC (e.g. cold storage). As a result, only fraudulent stores select into the program in high-poverty areas, suggesting that fraud implicitly subsidizes program access in these areas. A welfare improving program would therefore combine fraud reduction with measures to increase vendor participation in underserved areas.

The paper is organized as follows: Section 2 discusses related literature; Section 3 describes the institutional details of WIC and EBT; Section 4 formalizes incentives in the WIC program; Section 5 provides social welfare analysis of EBT reform; Section 6 discusses the data; Section 7 presents the empirical methods; Section 8 describes the empirical results; Section 9 estimates the overall social welfare impact; Section 10 reviews alternative hypotheses; Section 11 concludes by discussing various policies, including targeted vendor subsidies, restricted cash vouchers for participants, and public distribution of WIC foods.

2 Related Literature

Many safety net programs in the U.S. and other developed countries provide benefits in-kind rather than in cash (Currie and Gahvari, 2008). In the U.S., in-kind benefits include healthcare, nutrition, housing, childcare and education. A particularly large share of benefits provided to families with children, the targeted population for WIC, are made in-kind — Currie and Gahvari (2008) estimate the percentage to be 92.6% for 2002.

Justifications for providing benefits in-kind include a desire to limit take-up by ineligibles as well as a desire to alter consumption choices among recipients (i.e., paternalism) (Blackorby and Donaldson, 1988; Besley and Coate, 1992; Nichols and Zeckhauser, 1982). In-kind transfers can be used to avoid take-up by ineligibles if they involve goods which provide higher utility to program eligibles than ineligibles, known as "indicator goods" (Blackorby and Donaldson, 1988). In the setting of the WIC program, for example, infant formula is an indicator good, as eligible mothers likely value the transfer more than ineligible groups, such as women without children.

Research on indicator goods falls more broadly into the literature on targeting efficiency in safety net programs, which analyzes ways to minimize take-up by ineligibles while ensuring access among eligibles (Diamond and Mirrlees, 1978; Nichols and Zeckhauser, 1982; Besley and Coate, 1992; Kleven and Kopczuk, 2011).[1] The use of indicator goods may be preferred to strengthening eligibility rules as a way to limit take-up by ineligibles, for example, because the latter could simultaneously increase the likelihood that eligibles are inadvertently denied access.

In addition to limiting take-up by ineligibles, another justification for in-kind transfers involves paternalism — the desire to alter consumption patterns among recipients. Paternalism can be be welfare improving if the unconstrained consumption choices of recipients create utility losses for society (see Currie and Gahvari (2008) for a review of the literature). For example, a WIC mother may not fully internalize her child's utility, undervaluing the importance of infant nutrition and health screenings. In fact, recent political debate has focused on ways to use tax/transfer programs to restrict unhealthy food choice in light of increasing childhood obesity.[2]

In-kind transfers can therefore be used as a way to address agency problems between the government and consumers. A drawback of providing in-kind transfers, however, is the potential for agency problems between the government and private vendors. In the absence of its own network of suppliers, the government relies on private vendors to procure and distribute in-kind transfers. If, however, providers respond strategically to program incentives to maximize profits, they may have important effects on program efficacy as well as the private market for program goods. In fact, a growing literature on the role of providers in safety net programs finds evidence along both of these dimensions. I describe existing findings below.

2.1 Providers Respond to Program Incentives to Maximize Profits

Several recent papers find that private vendors in safety net programs respond to program incentives to maximize their profits. Hastings and Washington (2010) find that supermarkets increase prices on SNAP benefit issuance days, in response to surges in demand among program recipients. Research on Medicare has found evidence that providers increase quantity to maximize reimbursements (e.g. Alpert *et al.*, 2013; Brown *et al.*, 2011; Silverman and Skinner, 2004). These findings suggest that profit-maximizing behavior among vendors can reduce program efficacy by increasing costs.

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[1] Akerlof (1978) referred to these screening mechanisms as tagging in the tax literature.

[2] Some examples include Nikki Haley's push to restrict food eligibility in SNAP (`http://thinkprogress.org/health/2013/02/28/1636211/nikki-haley-food-stamps/`) and former Mayor Bloomberg's tax on soda (`http://en.wikipedia.org/wiki/New_York_City_soft_drink_size_limit`)

2.2 Provider Responses Can Affect Third Parties

Provider response to program incentives can also distort private market equilibria, affecting third parties. Duggan and Scott Morton (2006) find that prescription drug makers with significant market share mark up the prices they charge non-Medicaid customers, in order to maximize their Medicaid reimbursements, which are calculated as a function of market price. Rothstein (2010) finds that employers lower wages in response to increases in labor supply due to the Earned Income Tax Credit (EITC), thereby non-EITC labor. Clemens and Gottlieb (2013) show that Medicare's reimbursement rates are reference points for private rates charged by physicians. Overall, these findings suggest that social welfare analyses of safety net programs should take into account third parties.

2.3 Incentives vary by Provider Type

Additionally, the effects of safety net programs on private markets may vary importantly by provider type. For example, I find that small WIC groceries mark up their prices in response to price-inelastic WIC demand, while chains, in general, do not. Similarly, Kopczuk *et al.* (2013) show that the pass-though to consumers of a diesel tax, which is affected by whether the producer evades the tax, varies with the type of producer: retail gas stations (likely to evade taxes) versus diesel wholesalers (not likely).

2.4 Provider Behavior Affects Program Access

Finally, research finds that providers play an important role in take-up of safety net benefits by eligibles. For example, Kopczuk and Pop-Eleches (2007) find that tax preparers increase take-up of the Earned Income Tax Credit (EITC) when the option of electronic filing is available. E-filing results in a quicker refund but used to involve a complicated application, and tax preparers capitalized on this trade-off. Aizer (2007) finds that offering community based organization compensation for each approved Medicaid application substantially increases take-up. Finally, a number of papers suggest that healthcare plans and providers in Medicaid and Medicare strategically reduce access for high cost patients, a tactic called "cream-skimming" (Baicker and Dow, 2009; Currie and Fahr, 2005; Kuziemko *et al.*, 2013a; Newhouse, 2006, e.g.).

These papers relate more broadly to literature on the determinants of take-up in safety net programs. Common hypotheses for incomplete take-up include welfare stigma, information asymmetry and transaction costs. Welfare stigma occurs when eligibles associate participation in welfare programs with shame (Moffitt, 1983). Transaction costs may include documentation requirements, waiting periods, re-certification appointments, travel to and from the benefit site and program office, etc. Available evidence suggests that transaction costs may be more important than stigma or informational asymmetry in determining take-up (Currie, 2006). Indeed, my work suggests that distance to the nearest WIC store (i.e., travel cost) is an important predictor of take-up.

Finally, low-income pregnant women and single mothers with young children are likely especially constrained by transaction costs. Previous work finds that single mothers enter the labor force when offered free public preschool (Cascio, 2009); pregnant women in low-income areas have fewer prenatal care visits when public transportation is unavailable (Evans and Lien, 2005); preventive care among inner city black children declines with distance to hospital (Currie and Reagan, 2003); and the opening of a WIC clinic (where food vouchers are distributed) increases WIC participation within-ZIP code (Rossin-Slater, 2013).

My paper is the first to consider together the different elements of provider behavior summarized above. I show that the antifraud reform reduces provider payoff, leading to welfare loss among participants as well as non-participants, as providers face reduced incentive to participate in the program and those that remain are incentivized to increase their market prices. I also demonstrate that heterogeneity in provider fixed costs (provider type) generates variance in these responses.

A second contribution to existing literature is my use of the Nielsen scanner data to analyze the incidence of a tax-transfer program, as I am among the first to do so (to my knowledge, existing work focuses on excise taxes: Espinosa and Evans, 2012; Harding *et al.*, 2012). The Nielsen Homescan Panel is a nationally representative panel of consumers with product level-data on all purchases from any outlet. Its level of detail, on the types of products purchased, the date and location of the purchase, and on the purchaser, is not often used in similar work on incidence, which often employs aggregate data or micro data from a single provider or geographical area. Additionally, while other analyses of pricing in safety net programs usually utilize data from the government or providers, Nielsen is recorded by parties neutral to program incentives (i.e. not the WIC program or WIC stores).

Finally, my use of the staggered county-level rollout as an identification design links my paper to other recent work on the effects of nutrition assistance programs. For example, Hoynes *et al.* (2011b) exploit county level variation in the introduction of the WIC program during the 1970s to identify its effects, finding increases in birthweight among participating infants. Similarly, Almond *et al.* (2011) and Hoynes *et al.* (2012) utilize the staggered county level introduction of Food Stamps during the 1960s and 1970s, finding that it increases birthweight and reduces disease later in life.

3 Institutional Background

The Special Supplemental Nutrition Program for Women, Infants and Children (WIC) is a federal assistance program of the United States Department of Agriculture (USDA) whose aim is to ensure the nutritional well-being of low-income mothers and their young children. Participants are issued monthly vouchers that they exchange at participating retail groceries for a pre-specified basket of nutritious foods, including milk, cheese, and eggs. In addition to foods distributed, the WIC program provides participants with health screenings, nutrition education, and referrals to other social services. WIC has been found to have large positive effects on infant health, maternal health, and access to Medicaid (Bitler and Currie, 2005; Figlio *et al.*, 2009; Hoynes *et al.*, 2011a; Rossin-Slater, 2013).

Participants include pregnant and postpartum mothers up to one year after birth, infants, and children up to age 5. To be eligible, households must make less than 185% of the poverty line — currently $44,123 for a family of four — and be deemed "at nutritional risk," although the latter requirement is rarely used to restrict participation (IOM, 2000).[3] WIC is a widely used program, currently serving 53% of infants and about 20% of households in the U.S. (of the 63% and 30% eligible, respectively).[4][5]

WIC foods sales totaled $6.7 billion in 2010, and the average monthly benefit was worth $56.80 per participant.[6] For a mother and infant, the monthly WIC benefit in 2010 was around $150-$165, plus an additional $40 per child ages 1-5.[7] The value of WIC benefits is therefore comparable that of Food Stamps; in 2010, the monthly Food Stamps benefit was worth $133.79 per participant and $289.60 per household.[8]

Note that WIC benefits differ importantly those used in Food Stamps because WIC

[3]Source for current income eligibility cut-offs : `http://www.fns.usda.gov/sites/default/files/wic/FY2014-2015_WIC_IEGs_WEB.pdf`.

[4]Source: `http://www.fns.usda.gov/wic/about-wic-wic-glance`. 32.4% of households lived below 185% of the poverty line in 2012: Source: American Community Survey, 2012, `http://frac.org/pdf/2013_09_19_acs_state_poverty_lessthan185all_2012.pdf`. Of the 32.4%, I impute a take-up rate of 20% using the 60.1% take-up rate overall. Source for take-up rates: `http://www.urban.org/UploadedPDF/412549-WIC-Participants-and-Their-Growing-Need-for-Coverage.pdf`

[5]Note that Medicaid participants are adjunctively eligible for WIC, and Medicaid eligibility thresholds are much higher (300-400% of the FPL in some states). This is why WIC caseloads are so large.

[6]Sources: USDA/Urban Institute for overall WIC sales and average monthly benefit, website: `http://www.urban.org/UploadedPDF/412893-fiscal-year-2010-wic.pdf`. All years are fiscal years (October of previous year to November of current year). Note that the national average ($56.80) is similar to that of Texas, on which I focus my analyses. In 2009 (closest year to 2010 available), the benefit in Texas was $51.14. To calculate this number, I accessed financial reports on archived versions of this page from Texas' WIC website (here: `http://www.dshs.state.tx.us/wichd/fin/finrpt.shtm`), and divided gross outlays on food for the year ($609,063,433) by the sum of total participation per month across all 12 months (11,905,455).

[7]A range is given because different packages are available for breastfeeding vs. non-breastfeeding mothers.

[8]Source for Food Stamps figure: `http://www.fns.usda.gov/sites/default/files/pd/19SNAPavg$HH.pdf`.

vouchers are exchanged for *set quantities* of foods, rather than having a cash value. For example, a postpartum women on WIC receives a monthly voucher for 4.5 gallons of milk, 2 lbs. of cheese and 2 dozen eggs, among other foods (Table 1). WIC products are further restricted by size, type (e.g. flavor) and sometimes brand (Appendix Table 1).

Because WIC benefits are distributed as specific types and quantities of foods, participants are price-inelastic — that is, they receive the same basket of foods regardless of shelf prices. WIC retailers are therefore incentivized to price discriminate between WIC and non-WIC customers, charging the former a mark-up over the latter. The cost of price discrimination is the risk of sanctions, as it is considered fraud.

Fraudulent price discrimination between WIC and non-WIC customers is feasible before the reform because the technologies for charging each type of customer are separate. Whereas non-WIC purchases are processed through the cash register, the WIC transaction is recorded on the paper WIC voucher. The cashier records by hand the prices of foods allotted, and then the voucher is mailed to the state for reimbursement. No receipts are required for reimbursement. See Appendix Figure 1 for a picture of the paper voucher.[9]

Of course, stores will only find it worthwhile to price discriminate if they have "enough" WIC business (e.g., to cover expected sanctions). I use redemptions data provided to me by Kansas' WIC Program to estimate average monthly WIC sales per WIC store.[10] Appendix Table 2 presents average monthly WIC sales per store and WIC sales over total store revenue. Estimates are shown separately for chain versus independent groceries.

Average monthly WIC sales for independent stores is $19,942.90, or 28% of total monthly revenue.[11] For chain stores, the respective numbers are $37,690.74 and 6%. WIC sales therefore seem to comprise a non-negligible fraction of total revenue in participating groceries, but are of much greater importance to independent stores.

[9]Specifically, the WIC transaction proceeds as follows: the WIC customer gathers her allotted basket of foods within the store and presents the voucher to a cashier. The cashier then writes on the voucher the total price of the foods distributed (e.g. "$5 for 2 lbs cheese, $8 for 36 oz. cereal"). The retailer then mails the voucher (only) to the state WIC office for reimbursement. Stores are reimbursed only up to maximum price marked on the voucher, which is set high enough to allow for geographic variation in prices. In separate analysis of average WIC reimbursement prices at the county and store-size level, these maximum prices are not binding.

[10]Kansas is used because it is the only state to make store level redemptions data available to me. Note Kansas does not use EBT

[11]Please see the notes for Appendix Table 2 for further detail on the construction of these estimates. I proxy for total sales per WIC store using estimates of store revenue by store size (across the nation) from the Census Bureau and the County Business Patterns. To proxy for chains and independent store classifications in the national sales data, I use NAICS code 4451: "Supermarkets and Other Grocery" and NAICS 44512: "Convenience Stores," respectively.

3.1 Price Discrimination Before Anti-Fraud Reform

Recent media coverage suggests that small WIC groceries frequently price discriminate between their WIC and non-WIC customers in states that have not adopted the anti-fraud reform. As reported in the *New York Times*, journalists entered WIC stores in the San Francisco area to find separate WIC and non-WIC aisles:[12]

> "At Rancho Grande Supermarket...[in] the WIC section, a 64-ounce bottle of Hansens brand orange juice was $7.99, while the same bottle of orange juice in another part of the store cost $4.69....A box of Cheerios [was] on sale for $9.94 in [the] special WIC section..."

The reporters also noticed incentive items, used to attract lucrative WIC business:

> "A flier for Rancho Grande Supermarket promises Free Gift! For Redeeming Your Vouchers over pictures of a blender, a rice cooker and an iron....At 23rd and Sanford Market in San Pablo, just over a mile from the Rancho Grande Supermarket, free items offered to WIC shoppers include a bottle of Jarritos, a sugary soft drink, and Abuelita, a hot chocolate mix."

Government reports confirm that price discrimination, which is referred to as "overcharging" by WIC, occurs relatively frequently, but also that overcharges comprise a small share of the overall program budget, as nearly all overcharging occurs at small groceries. For example, USDA estimates that in 2010, 9.3% of WIC stores overcharged, amounting 1% of federal outlays on food (Mantovani, 2012).[13][14] Saitone *et al.* (2013) find that the smaller retailers in California WIC charge the program up to 50% more than large chains for the same products, and conclude that the markup is not explained by variation in food costs, but point out that budget impacts are limited because small stores only account for 11-15% of reimbursements. Stlll, even when small, fraud can threaten the viability of safety net programs viability through public outrage and political channels (Kuziemko *et al.*, 2013b).

WIC agencies have two strategies for monitoring overcharging — they use either undercover buys or audits to collect the shelf prices paid by non-WIC customers and then compare those to reimbursement claims. Government reports suggest that these monitoring strategies are resource-intensive for state offices (GAO, 1999), which explains why states let overcharging persist. In addition, because WIC is fully federally funded, states have little

[12]Mieszkowski, Katharine. "Gouged by Some Small Groceries, WIC Program Cracks Down." The New York Times. April 21, 2012. URL: `http://www.nytimes.com/2012/04/22/us/wic-caps-california-reimbursements-after-stores-raise-food-prices.html?_r=0`

[13]It should be noted that USDA methodology, by its own admission, likely underestimates overcharging. USDA bases overcharging estimates on covert undercover buys during which a WIC official recorded the shelf price of WIC foods for later comparison to submitted prices. However, given unmarked prices at many small stores, around a fifth of undercover buys were unusable (Bell *et al.*, 2007).

[14]Note also that estimates of overcharging frequency vary by methodology — in comparison to the USDA figure of 9.3% in 2010, state reports estimate an overall overcharge rate of 20% of vendors. Source: `http://www.fns.usda.gov/sites/default/files/WICErroneousPayment_2011.pdf`, pg. 17

stake in reducing waste (Oliveira and Frazao, 2009), particularly when facing opposition from grocery lobbies.[15] All major cost-containment reforms in WIC have been federal.

3.2 Electronic Benefit Transfer (EBT)

The transition from paper vouchers to EBT constitutes the latest federal cost containment reform in the WIC Program. EBT was mandated as part of the Healthy, Hunger-Free Kids Act of 2010 (Pub.L. 111296), a federal bill reauthorizing funding for child nutrition programs. States are required to transition their WIC programs by October 1, 2020. Currently, there are six states using EBT: Texas, New Mexico, Wyoming, Kentucky, Michigan, and Nevada.[16]

The EBT card functions like a debit card in the grocery checkout lane, authorizing a participant's allotted WIC products. Appendix Figure 2 shows an image of the card. Data from transactions tendered with the EBT card are uploaded directly from the store's electronic cash register (ECR) to the state WIC office for reimbursement.

By integrating the technology used to process WIC and non-WIC transactions (i.e. the ECR), EBT ensures that both types of customers are charged the same price. An ECR stores a one-to-one mapping from a product's Universal Product Code (UPC) to its price. When UPCs are scanned during checkouts, corresponding prices are assessed. The total purchase is then tendered with cash, a credit or debit card, or an EBT card. Importantly, the mapping between price and quantity is *independent* of the type of tender. In other words, by accessing data from the store's ECR, the government *directly observes a store's prices.*

Government officials portray EBT as a tool for mitigating overcharges. For example, USDA's 5 Year Plan for WIC EBT lists "identified positive outcomes" of EBT: "Ensures that retailer claims are no more than shelf price."[17] The National WIC Association (NWA), a group comprised of State WIC Directors and other WIC officials, writes of EBT: "The retailer cannot claim more than the shelf price thus decreasing overcharges."[18] JP Morgan, the primary contractor used in EBT implementation, describes EBT: "Prevents store overcharges by relying on point-of-sale technology to enforce the price at which food is redeemed" (Kibble-Smith, 2009).[19]

[15] State WIC agencies have had difficulty passing store cost-containment regulations through state legislatures, where they face opposition by grocery lobbies. For example, around 2004 the California WIC agency wanted to institute a cap on reimbursements to WIC-only stores. The grocery lobby representing WIC-only stores opposed the cap and, with little political support in the state legislature, it was defeated. See Oliveira and Frazao (2009), page 37-40.

[16] Other state agencies are in the design and development phase or planning stage. For current status by state, see `http://www.fns.usda.gov/wic/wic-ebt-technology-wic-program`.

[17] Source: `www.fns.usda.gov/sites/default/files/WICEBT5-yearPlan-FINAL3-1-06.pdf`

[18] Source: `http://s3.amazonaws.com/aws.upl/nwica.org/Delivering_WIC_Food_Benefits_EBT.pdf` and `https://s3.amazonaws.com/aws.upl/nwica.org/unitedstates2014.pdf`

[19] JP Morgan oversaw the establishment of EBT in SNAP in 40 states and partners with several state WIC programs in transitioning to EBT.

In addition, some recent studies find lower overcharging rates in EBT states vs. non-EBT states. For example, OIG (2013) found patterns of overcharging in IL and FL, but none in MI, where EBT is used. Another study finds overcharging is 1.2 to 3.0 times *less* likely in states with EBT.[20] The response of groceries to EBT is also telling, as stores tend to support EBT in Food Stamps, where cash vouchers make overcharging less feasible, but not in WIC (Hamilton *et al.*, 1997). However, there may be other ways in which a store could price discriminate under EBT; for example, stores could offer coupons to non-WIC customers.[21]

4 Formalizing Incentives

In this section, I formalize incentives for grocery stores participating in the WIC program. I assume that retail groceries are local monopolists, following existing research on the grocery market, which assumes that consumers are locally constrained due to travel costs and perishable groceries (e.g Ellickson *et al.*, 2013; Ellickson and Grieco, 2013; Ellickson, 2006).

Let $\pi = (p - c)q(p)$ represent grocery store profits, where c is marginal cost, and the stores sell a single good. Define p^* as the profit maximizing price and $q(p^*)$ as equilibrium demand.

Now suppose that a store participates in the WIC program (pre EBT reform). The store charges WIC customers p_w using paper vouchers and distributes q_w. Note that q_w is a constant, set by WIC eligibility rules and unaffected by prices. The WIC store charges its non-WIC customers price p_{nw} (which I have differentiated from p, the price charged to non-WIC customers in non-WIC stores).

Price discrimination (overcharging) occurs when $p_w > p_{nw}$. Sanctions for overcharging are given by $\mu\left(p_w, p_w - p_{nw}\right)$. γ^w is the fixed cost of joining WIC (e.g. training cashiers, labeling foods, cold storage for the fresh foods required by WIC, etc.). Then, stores choose p_w and p_{nw} to maximize profits:

$$\pi^w = (p_w - c - \mu_s\left(p_w,\, p_w - p_{nw}\right))q_w + (p_{nw} - c)q\left(p_{nw}\right) - \gamma^w$$

I assign the following functional form to sanctions, $\mu_s\left(p_w,\, p_w - p_{nw}\right) = \theta(p_w)(p_w - p_{nw})$, where $\theta\left(p_w\right)$ is the likelihood that stores are investigated and $\left(p_w - p_{nw}\right)$ is the amount of the sanction conditional on investigation. I assume $\theta'\left(p_w\right) > 0$ and $\theta''\left(p_w\right) > 0$.[22]

This functional form follows directly from Texas WIC policy. WIC officials monitor sub-

[20] The upper bound (3.0) is for states which do not require receipts be given to the WIC participant (like Texas).

[21] Fortunately, the Nielsen price scanner data I use includes records coupons and other discounts.

[22] To specify θ as a true likelihood (i.e. always between 0 and 1) a logistic function could be used, which is convex for some values of p_w, in place of a convex function. The main point is just that θ is convex in the relative range of p_w.

mitted vouchers (p_w) for suspicious patterns, including whether redemptions are "unusually high," and initiate investigations based on this evidence.[23] During an investigation, WIC officials conduct undercover buys, enabling observation of p_{nw}. If price discrimination is discovered, Texas WIC fines the store the full amount: $(p_w - p_{nw})$.[24] Note that the sanction form is the same as Becker's crime penalty function — probability of apprehension times fine if apprehended (Becker, 1968).

Then, if we define $p^*_{nw}, p^*_w = \arg\max \pi_w$ and $p^* = \arg\max \pi$, stores participate in WIC if profits are higher with WIC than without WIC, $\pi_w(p^*_{nw}, p^*_w) > \pi(p^*)$, or:

$$\left(p^*_w - c - \theta\left(p^*_w\right)(p^*_w - p^*_{nw})\right) q_w + \left(p^*_{nw} - c\right) q\left(p^*_{nw}\right) - \gamma^w > \left(p^* - c\right) q\left(p^*\right)$$

[25]

Now consider store profits after EBT. Stores can no longer price discriminate ($p_{nw} = p_w$) and must set a single EBT price. I denote the EBT price p_{ebt}. Profits from participating in WIC are now:

$$\pi_{ebt} = (p_{ebt} - c)(q_w + q\left(p_{ebt}\right)) - \gamma^w$$

Note, that π^{ebt} is in fact a constrained version of π^w — if we set $p_{nw} = p_w = p_{ebt}$ in π^w, the expression reduces to π^{ebt} because $\mu\left(p_{nw} = p_w\right) = 0$. Therefore, it must be that $\pi^{ebt}(p^*_{ebt}) \leq \pi^w(p^*_{nw}, p^*_w)$. Conceptually, EBT reduces the rent stores used to get from price discrimination. Therefore:

Prediction 1. *Some stores will drop out of WIC after EBT ($\pi^*_{ebt} \leq \pi^*_w$)*

Suppose we allow for heterogeneity by store in the fixed costs of joining WIC, γ^w_s.

Then:

Prediction 2. *Stores with higher fixed costs of joining WIC, γ^w_s, will be more likely to drop out after EBT.*[26]

[23] I provide a full list of reasons used to open compliance investigations in the data section below; they are nearly all related to suspiciously large or high redemptions.

[24] In addition, if 3 instances of overcharging are observed in a 24 month period, a store can be disqualified for 3 years. In practice, disqualification rarely happens — less than 1% of stores in my data are disqualified. Source of Texas WIC store rules: Texas WIC Policy WV 01.1 `http://www.dshs.state.tx.us/wichd/vo/policy.shtm`

[25] Note, importantly, that when a store drops out of WIC, it does not necessarily exit (shut down). I assess the extent to which EBT induces grocery store exit below.

[26] What about heterogeneity in the WIC share of customers, $\frac{q^w}{q^w + q^{nw}}$? Appendix Section A provides a short proof that among stores of a similar size, those with a higher share of WIC customers are *less* likely to drop

4.1 Comparing Equilibrium Prices

Prediction 3. *For sufficiently bounded θ and θ', the price paid by non-WIC customers increases once EBT is introduced: $p^*_{nw} < p^*_{ebt}$*

Conceptually, the EBT price reflects pooled WIC (inelastic) and non-WIC (elastic) demand and therefore should lie somewhere in the middle of the separate prices charged pre-EBT ($p^*_{nw} < p^*_{ebt} < p^*_w$). Appendix Section B provides short proofs. Some upper bounds on θ and θ' are necessary to to guarantee $p^*_{ebt} < p^*_w$. Conceptually, if sanctions are too high, stores will not want to increase p_w. I provide direct evidence that sanction rates are very low. Further, note that the sanction function puts upward pressure on p^*_{nw}, so that if sanctions were large, we would expect $p^*_{nw} > p^*$. In fact, I find no evidence that p^*_{nw} is different from p^*; prices on WIC goods in WIC stores are comparable to prices on the same goods in non-WIC stores.[27]

5 Social Welfare and EBT

I now use these predictions to account for the different effects of EBT on social welfare. Figure 2(a) shows outcomes in the market consisting of the WIC grocery store and non-WIC consumer: the consumer pays p^*_{nw} and consumes q^*_{nw}. Also shown on Figure 2(a) are outcomes in the case in which the grocery store did not participate in WIC (p^*, q^*) — recall that the WIC store sets $p^*_{nw} > p^*$ because WIC sanctions are decreasing in p^*_{nw}.[28] Figure 2(b) shows that after EBT is introduced and the store can no longer price discriminate, it sets the pooling price to p^*_{ebt} and both consumer and store surplus are reduced.

Figure 2 shows social welfare for WIC beneficiaries and the government. The government spends $p^*_w q_w$ to purchase WIC foods from grocery stores, who retain $(p^*_w - c)q_w$ in profits. The social benefit of WIC to participants, who pay nothing, is represented by the area under the demand curve up to q_w. Note that the demand curve is not necessarily that of the WIC participant, but represents the benefit to society of the transfers. A WIC mother's demand curve for WIC foods might lie below society's valuation, if, for example, she faces informational constraints regarding the importance of nutrition for her children.[29] After EBT is rolled out, the government saves money from (1) the drop in prices paid to WIC stores ($p^*_{ebt} < p^*_{nw}$) and (2) the fact that fewer stores are willing to participate (meaning fewer WIC participants). At the same time, the social benefit of the program is reduced because fewer

out of WIC after EBT. To the extent that poorer neighborhoods have a higher share of WIC customers and higher fixed costs γ^w_s, as I demonstrate, this effect will work against Prediction 2.

[27] Results available on request.

[28] Although I find no empirical evidence of this effect (i.e. no evidence that $p^*_{nw} > p^*$), I allow for the possibility that it exists for the purpose of this analysis.

[29] This scenario is in fact one of the arguments for the existence of WIC.

mothers participate.

Figure 2(c) and Figure 3(c) graph and label the changes in market and WIC program surplus as a result of EBT. Using the numeric labels for reference, the total change in social welfare is given as follows, where λ denotes the shadow price of government funds and m denotes the stores' profit margin ($m(p^*_w)q_w = (p^*_w - c)q_w$).

$$\begin{aligned}\Delta\text{Social Welfare} =& (\lambda-1)(\boldsymbol{D})\text{store transfer to WIC} + (\lambda-1)(\boldsymbol{F})\text{store transfer to WIC}\\ &+ \lambda(\boldsymbol{G})\text{WIC savings} - (\boldsymbol{B})\text{loss non-WIC consumer welfare}\\ &- (\boldsymbol{C})\text{loss store profits} - (\boldsymbol{E}+\boldsymbol{F}+\boldsymbol{G})\text{loss WIC benefit}\end{aligned}$$

Of the two store transfers to WIC, $(\boldsymbol{D})$ is due to the fact that WIC stores charge the WIC program less after EBT ($p^*_{ebt} < p^*_{nw}$), and $(\boldsymbol{F})$ is due to the decrease in store participation after EBT. Note that $(\boldsymbol{D})$ represents intended savings (i.e. the reduction in fraud), whereas $(\boldsymbol{F})$ and $(\boldsymbol{G})$ represent unintended savings (store dropout). These transfers are multiplied by λ because the government saves the efficiency costs of raising funds (taxation, e.g.).

Note that the latter three terms, $(\boldsymbol{B})$, $(\boldsymbol{C})$ and $(\boldsymbol{E}+\boldsymbol{F}+\boldsymbol{G})$, are the deadweight loss caused by EBT reform, whereas $(\boldsymbol{D})$, $(\boldsymbol{F})$, $(\boldsymbol{G})$ and $(\boldsymbol{A})$ represent transfers between consumers, stores, and the government. There will be a net loss associated with EBT if the costs to consumers, stores and participants outweigh government savings. In the following sections, I estimate the different components of this sum.

6 Data

I compile data from a variety of different sources to create a rich picture of the effects of EBT.

6.1 Nielsen Data

The Nielsen Consumer Panel consists of 40,000-60,000 households who provide information on all products they buy starting in 2004. Households are recruited through the mail and internet and the sample is designed and maintained to be representative of households overall and within individual markets throughout the U.S.[30] Households are given incentives to join and stay active such as monthly prize drawings and gift points for participation.

Participating households use in-home optical scanners to scan the Universal Product

[30] The Consumer Panel documentation states: "The Nielsen Company uses a stratified, proportionate sample for the Homescan Consumer Panel...The design calls for the recruitment of a sample of households that match a selected group of demographic characteristics (see below) at the total U.S., major market and remaining Census Region levels. The total sample includes 125,000 households and is stratified into 61 geographic areas."

Codes (read from barcodes) found on their purchases, and then hand-enter price, number of units purchased, whether a coupon was involved (and for how much) and where and when the purchases were made. For certain stores, Nielsen independently receives point of sale data; the prices of purchases at these stores are verified by Nielsen.[31]

Each observation in the data is therefore a purchase of a given UPC on a given day by a given household at a given store. In addition to price and quantity, the data include detailed information stored in the UPC code, such as brand, size, category and other descriptors (e.g., flavor). Participating households also provide demographic information on an annual basis, including, importantly for my purposes, ZIP code of residence. I limit my sample to purchases made by residents of the state of Texas during the years FY 2005-2009 (10/2004-9/2009), as the WIC food package was substantially redesigned in FY 2010.

The Nielsen sample therefore provides a measure of the prices paid by non-WIC customers across different ZIP codes before and after EBT (p^*_{nw} and p^*_{ebt}, respectively). Importantly, that WIC purchases made pre-EBT with a voucher (p^*_w) are not recorded in the data — if these purchases were recorded, my price results would be biased downward.[32] Also importantly, any coupons or discounts are recorded, and my price measure is net of these reductions (recall that a post EBT strategy for price discrimination could be selective coupon use). A particularly nice feature of the data is that it is recorded by parties neutral to WIC incentives (i.e. not the WIC program or WIC stores).

According to my predictions, we should observe an increase in the prices paid by non-WIC consumers (i.e. Nielsen prices) after EBT for WIC-eligible products in *ex-ante* fraudulent WIC stores. To identify WIC-eligible goods, I use archived lists of WIC products authorized by Texas. I focus on purchases of cheese and eggs, for which I observe complete UPC-level eligibility during the sample period, and which are also main WIC foods. Appendix Table 1 gives a breakdown of WIC versus non-WIC cheese and egg products.

I then proxy for whether the purchase occurred at a WIC store using an indicator for whether there existed a WIC store of the given size (chain vs. independent) in the ZIP code of residence of the household in the year and month of the purchase.[33] A proxy is necessary because Nielsen does not release identifying information on stores. I am able to observe a retailer code for the majority of chains in the sample, however, and use the presence of a retailer code to infer chain status. Appendix Section C gives more precise detail on the steps involved in the sample construction and Appendix Table 4 provides summary statistics. Although my proxy indicators for WIC store and chain status will contain some measurement

[31]See Einav *et al.* (2010) for a recent validation study of the prices reported in the Homescan panel.

[32]Nielsen purchases are not recorded when a receipt is not given and Texas WIC vendors do not distribute receipts to recipients pre-EBT.

[33]I observe location and size of all WIC stores in administrative WIC data described next.

error, my ability to difference across UPCs, stores, and dates (year-month) should help net out some of this error.[34]

6.2 Administrative Data on WIC Groceries in Texas

State WIC agencies maintain annual administrative records on participating grocery stores. Included in each record is the store's name, address, months of participation and the following information on monitoring and compliance: whether the store was investigated and the type of investigation, the reason the store was investigated, and whether the investigation resulted in any sanctions.[35] I received these data for fiscal years 2007-2010 from the Texas Department of State Health Services. I matched stores across years using physical location (address, city and zip code) to create a panel of store-months. I match on physical location rather than store name because Texas WIC's reporting of store names changes across fiscal years due to changes in abbreviations, spelling, etc.[36]

I indicate that a WIC store is a chain if (1) the store is assigned an outlet ID (indicating multiple outlets exist) or (2) if there are 2 or more stores of the same name in the given year-month.[37] For example, there's a store called "Bob's Supermarket" in Austin and a store called "Bob's Supermarket" in Dallas. To mitigate classification errors due to common store names, I then calculate within-store mode of my chain indicator.[38] Out of 3,015 WIC stores in my sample, 2,569 are classified as chains and 438 are single outlets. Note WIC stores comprise about 15% of grocery stores in Texas.[39]

Chains in my data include large national companies such as Wal-Mart, Target, and Kroger, large Texas based companies such as H-E-B, Brookshire and David's; and local companies with a few outlets, such as Terry's "El Mariachi" Supermarket, serving Dallas-

[34] Error in assigning purchases to WIC stores will be higher in ZIP codes with more grocery stores. For the purpose of my analysis, I focus on high poverty ZIP codes, where grocery options are limited, so this aspect of my analysis should also serve to minimize error.

[35] Also included is why a sanction was given, but, in nearly all cases, Texas WIC does not indicate a reason. Therefore, I use the detailed reasons given for the investigation to infer the type of fraud occurring.

[36] Of course, some physical locations will host different stores during my time period; examination of my data suggests that all such changes are chain-to-chain or independent-to-independent, rather than a switch between chain and independent, so these changes should not affect my results.

[37] Chains assign outlet IDs to identify a store's location— for example, "H-E-B #39" is in San Antonio — so any store with an outlet number is, by definition, part of a chain. Some smaller chains don't use outlet numbers, however. I therefore additionally designate a store a chain if the store's name is common to at least two WIC stores in a given year-month.

[38] My analyses are unaffected by using alternative classifications, including the underlying indicator or whether a given store is *ever* classified as a chain.

[39] Percentage is for Texas only and FY 2013 and is calculated by comparing total WIC stores to total SNAP stores during my time period. Current SNAP store totals by state found here: `http://www.fns.usda.gov/snap/retailerlocator`. Because almost all grocery stores accept SNAP, their total proxies for total grocery stores, as explained by a USDA official to the author. The official relayed that grocery stores think participating in SNAP as an "entitlement" for their store, but that WIC is much harder to be approved for because of concerns over fraudulent overcharging.

Forth Worth and Culebra Meat Market, with 3 locations in San Antonio. Finally, the single outlet (independent) stores include, for example, Country Boy Store, Neighborhood Grocery, and San Juan Food Mart.

Table 5 presents summary statistics for the sample of Texas WIC stores. Each observation represents one store that participated in WIC at some point during FY 2007-2010. Means are shown separately for chains and independent stores.

Independent WIC stores tend to participate in the program for a shorter amount of time than large chains. Independent stores are also much more likely to be located in high-poverty ZIP codes, indicating that they are potentially important for access. Existing research finds that chain supermarkets rarely locate in high poverty areas (Morland *et al.*, 2002).

The remainder of the table summarizes the monitoring and compliance variables. State WIC programs routinely monitor WIC stores through analysis of their redemptions (vouchers) and in-store visits. If WIC officials suspect a store of violating program rules, a compliance investigation is initiated. During a compliance investigation, the store is investigated through undercover buys and/or audits. Sanctions are levied if violations are observed during compliance investigations.

Table 5 indicates that 18.9% of chains versus 41.9% of independent stores receive at least one compliance investigation during my sample period. The vast majority of these investigations are initiated because of suspicious redemption prices (100% for independent stores).[40] All investigations are indicated as undercover buys, meaning that no audits were performed — this suggests that audits may be too resource-intensive. Finally, independent WIC stores are much more likely to receive a sanction than are chains (20.2% vs. 6.3%), even *conditional* on compliance investigation (48.2% vs. 33.3%).

In sum, Table 5 suggests the following: (1) most non-compliance is price discrimination; (2) independent stores are more fraudulent, even conditional on being investigated, but are

[40]More detailed reasons for the compliance investigation are listed in the data. The category of suspicious prices includes the following detailed reasons: Unusually high average prices – submitting extremely high average food instruments compared with similar stores; Extremely small amount of variation in food instrument prices the individual food instrument prices do not vary substantially from the average price.; Large percent of food instruments redeemed at same price; Unusually high average food instrument prices - submitting extremely high average food instruments compared with similar stores.; Redeemed prices are higher than their price list.; Large percent of high-priced food instruments.; Large increase of dollar volume of food instruments redeemed over time; Large percent of the areas total WIC redemptions; WIC sales are an unusually high percent of store's total sales; High WIC to Food Stamps redemption ratios; Volume of WIC business high; WIC and Food Stamp sales are an unusually high percentage of total sales. Other flags, not related to redemptions include: Participant complaints; Large number of participants redeeming food instruments who are considered to be at high health risk; Large number of participants redeeming food instruments outside of their health service area; Large number of food instruments with consecutive serial numbers; Large percentage of manually issued food instruments; Excessive number of returned checks due to errors; Past history of violations and disqualifications; Associations with known violators; Multiple ownerships which include known violators; Short on authorized food items or no inventory; Other.

also important for access; and (3) most stores investigated are not sanctioned, which may be due to costly and/or ineffective surveillance methods.

Note that I am not able to distinguish precisely *why* independent groceries are more fraudulent than chains. One possibility is that chains have more potential whistleblowers (employees) because they are larger. Another possibility is that, the cost of WIC fraud could be very high for chains — a national chain could lose its WIC business across many states for fraud committed in only one.[41]

Another possibility is that single outlets have higher program fixed costs (γ), so only those willing to fraudulently price discriminate *select in*. Fixed costs associated with WIC include stocking and storing program foods (some of which require refrigeration), training cashiers, maintaining proper signage, etc.[42] I investigate these hypotheses further below.

6.3 Births Data

To measure WIC participation among eligible pregnant mothers, I use Texas birth certificate data for the years 2005-2009, which I received from the Texas Department of State Health Services (DSHS). These data consist of the universe of births in Texas for each year and contain detailed information on maternal demographics and health outcomes and also her ZIP code of residence.

Mothers are asked to respond "yes" or "no" to the following question: "Did you receive any WIC food during your pregnancy?" The percentage responding "yes" in my sample is 53.12%, equal to the current national average of 53%.[43] Note that this measure of WIC usage is extensive margin and understates other changes to maternal WIC usage, including *how much* food she received, how far she had to travel to find a WIC grocery, etc.

I limit my sample to mothers who are Texas residents and have non-missing information on the birth date, gestation and mothers county and ZIP of residence. In addition, I create control variables including mother's marital status, education (no HS diploma, high school, some college, advanced degree), mom's race and ethnicity (black, Hispanic, other), mom's age (less than 20, 20-24, 25-29, 30-39), child's parity (1,2,3,4+).

Appendix Table 6 shows summary statistics for all births (Column 1) and births to mothers who participated in WIC (Column 2). As would be expected, WIC mothers are of lower socioeconomic status: less likely to be married (44.3% vs. 59.3%), more likely to have

[41]Conversation with a Texas WIC state office further revealed that for independent stores, conversely, reputation costs of fraud can be small — after losing WIC eligibility, some stores have changed their names/owners and successfully re-applied.

[42]Training cashiers is one cost for which there are likely increasing returns to scale; WAL-Mart makes available a single WIC cashier handbook available online and H-E-B, a Texas chain, has "WIC Champions," employees knowledgeable about the program and charged with providing training to H-E-B employees across the state.

[43]Source: http://www.fns.usda.gov/wic/about-wic-wic-glance

low levels of education (76.3% vs. 56.6%) and more likely to be Hispanic or black (79.3% vs. 62.1%).

Subsample analysis reveals that the proportion of mothers on WIC is 70% for each of: minority mothers (which I define to include blacks and Hispanics), unmarried mothers, and low-education mothers. In interacting these subsamples, the group with the highest WIC usage is minority mothers with less than a high school education (78%). In analysis below I therefore use minority mothers (largest sample size) and minority mothers with less than a high school education as proxies for high-poverty WIC eligibles.

7 Empirical Method

7.1 EBT Rollout

In order to assess the causal effects of the switch from paper vouchers to EBT, I exploit variation in the exact timing of the EBT implementation across counties. Appendix Table 3 shows the date of EBT rollout for each county. My design assumes that the rollout timing is uncorrelated with other variation at the county or county-group level. It is therefore reassuring that the rollout schedule was set by the state WIC agency and not by counties themselves. I provide additional tests of endogeneity below.

The first counties to transition to EBT were El Paso and Hudspeth in June 2004. These counties were chosen because they border New Mexico, which was already using EBT in 2004 — in fact, WIC staff and retailers from New Mexico came over to Texas to help with the initial roll out. Subsequent EBT expansions took place in small metropolitan or rural counties in Texas about every 6 months during 2005-2007. In 2008, having accumulated sufficient experience, the state agency began monthly expansions, which included the larger metropolitan areas (Dallas, Houston, Fort Worth). Figure 3 graphs the share of WIC participants using EBT over time.

7.2 Estimating Equations

My main estimating equation exploits variation in the exact timing of EBT rollout across counties and takes the form:

$$Y_{ymc} = \alpha + \beta_1\, AfterEBT_{ymc} + \mu_c + \gamma_y + \nu_m + \epsilon \tag{1}$$

for a given outcome Y in county c, year y, and month m. EBT_{ymc} is an indicator that equals 1 if ym is after the EBT rollout date in county c. μ_c are county fixed effects, γ_y are year fixed effects, ν_m are month fixed effects, and ϵ is the error term, which I cluster by county. The key coefficient is β_1, which measures the effect of EBT on the outcome of interest. This specification is a difference-in-difference design (across counties and dates).

Additionally, I estimate a variation of this specification (and the ones below) including county specific linear time trends in year ($\mu_c{*}tt$) and month-year fixed effects (the interaction of month and year, rather than month and year separately). Finally, for the purposes of displaying the results graphically, I substitute the EBT indicator with dummy variables for the 18 months before and after EBT implementation (normalizing the month before implementation to 0) and plot these event-time coefficients.

My identification strategy assumes that the exact timing of EBT rollout is uncorrelated with endogenous trends. I test this assumption by estimating Eq. 1 on different maternal demographic indicators in the births sample. Table 2 presents the results. Estimates of β_1 are uniformly small and insignificant for a range of outcomes including maternal education, age, race, and marital status, lending credibility to my identifying assumption that the timing of EBT rollout is exogenous.

In order to assess the effects of EBT on outcomes *within* stores, I also estimate a variation of Eq. 1 which adds store fixed effects:

$$Y_{yms} = \alpha + \beta_2\, AfterEBT_{ymc} + \phi_s + \gamma_y + \nu_m + \epsilon \tag{2}$$

in which s indexes the stores, ϕ_s are store fixed effects and ϵ is clustered by store. The remaining terms are defined as in Eq. 1.

Lastly, I interact the difference-in-difference terms from Eq. 2 with indicators for WIC productn and WIC store. The outcome is logged price and each observation represents a transaction of a certain UPC.

$$\begin{aligned}\ln p_{usym} = \alpha + \beta_3\, AfterEBT_{ymc}\, WICprod_u\, WICstore_{yms} + \delta\, AfterEBT_{ymc}\, WICprod_u + \\ \zeta\, AfterEBT_{ymc}\, WICstore_{yms} + \xi\, WICprod_u\, WICstore_{yms} + \rho\, WICstore_{yms} + \\ \upsilon\, AfterEBT_{ymc} + \phi_s + \psi_u + \gamma_y + \nu_m + \tau_w + \epsilon\end{aligned} \tag{3}$$

where p_{usym} is the price of product UPC u sold in store s on date ym. $AfterEBT_{ymc}$ indicates that a purchase took place on date ym after the EBT rollout date in county c. $WICprod_u$ indicates the UPC is WIC-eligible and $WICstore_{yms}$ is a proxy for whether store s participates in WIC on date ym . ϕ_s are store fixed effects and ψ_u are UPC fixed effects (so that the effects are identified *within-UPC*. Like in the previous expressions, γ_y are year fixed effects, ν_m are month fixed effects, τ_w are weekday fixed effects.[44] ϵ_{usym} is the error

[44] As explained in Appendix Section C, ϕ_s is a proxy for store ID FE, consisting of two vectors: store ID

term, which I cluster by store. The key coefficient is β_3, which measures the relative price on WIC products in WIC stores compared to non-WIC products and non-WIC stores. Note that the indicator for whether a store participates in WIC, $WICstore_{yms}$, is not collinear because stores may participate in some month-years and not others.

8 Results

8.1 Effect of EBT on Price Discrimination

To test whether EBT reduces price discrimination (fraud), I use the vendor dataset to estimate the effect of EBT on the likelihood a store is sanctioned. Recall that the majority of sanctions I observe are related to suspicious redemption patterns, so I infer that they correlate highly with price discrimination. I first estimate the effect of EBT on monitoring. If selection into being monitored is changing with EBT, then changes in the sanction rate may reflect this rather than changes in underlying fraudulent activity. Table 3, Columns (1) and (3), present the results of estimating the store FE model (Eq. 2) on monitoring. Selection into being monitored did, in fact, change with EBT (within stores) — chains are less likely to be monitored and single outlets are more likely to be monitored.

To avoid confounding changes in the propensity to commit fraud with changes in monitoring, I therefore estimate the effect of EBT on store sanctions using a subsample of "high-risk" stores chosen *at random* for investigation by the state agency (Columns (2) and (4)).[45] Sample means in Columns (2) and (4) confirm that the stores are "high-risk" — 48% of the independent stores and 31% of the chain stores are found to be in violation (compare to much lower means in Table 5). Columns (2) and (4) show, however, that violations are dramatically lower for those stores in this sample who have EBT at the time of their random compliance investigation — by around 1/3 to 2/3 of the sample means. This table therefore suggests that sanctionable offenses — which I infer are mostly overcharging — decrease among stores following EBT.[46][47]

FE and ZIP code of residence FE.

[45] The state agency is required to perform random compliance investigations on stores they identify as "high risk." "High risk" stores are denoted based on certain characteristics such as their size, location, volume of WIC business, etc. Because there is only one observation per store, the regressions do not include store fixed effects and are cross-sectional (Eq. 1).

[46] Given that the regressions are cross sectional, rather than *within-store* it could be that drop outs after EBT (compositional change) are driving the post EBT change in violations. Including only stores who are present at least 6 months before and 6 months after EBT actually increases the size and precision of the results (not reported). Therefore, compositional effects do not seem to be driving the results.

[47] One might expect that non-compliance should drop 100% after EBT. However, (1) the broad compliance checks will pick up smaller and more common, sources of non-compliance, such as improper signage or labeling (2) high-risk stores may find ways to commit price discrimination even post EBT (e.g. selective coupon usage).

8.2 Effect of EBT on WIC Food Costs

Figure 3 graphs WIC food costs per participant for Texas during the EBT expansion.[48] Also shown are corresponding food costs for Oklahoma, which serves as a control state.[49] Note that the Texas food expenditures represent average p^*_w in non-EBT (paper voucher) counties, and average p^*_{ebt} in counties using EBT (so that the statewide measure shown is an average both). Because $p^*_{ebt} > p^*_w$, we would expect Texas expenditures to fall as EBT is expanded.

As expected, Texas food costs start to decrease, diverging from Oklahoma costs, exactly when EBT is introduced (June 2004) and fall most sharply during the big EBT expansions in 2008-2009. Additionally, the largest month-to-month decrease in Texas food costs directly follows the largest month-to-month expansion in EBT (November 2008). Using Oklahoma as a counterfactual, the graph suggests that EBT saved the TX WIC program 11.7% of food costs.[50] Comparing the change in food costs to the change in EBT share for October 2008 to February 2009, the period of largest expansion, produces a similar estimate of 11.4% in savings in per person food costs over the entire rollout.

In sum, EBT appears to be an effective cost-containment tool, saving Texas WIC somewhere between 11-12% total on per-participant food costs (through a combination of reduction in price discrimination and changes in WIC store and participant composition).

8.3 Effect of EBT on Prices Paid by Non-WIC Customers

Second, I estimate the effects of EBT on the prices paid by non-WIC consumers for WIC UPCs in WIC stores (Eq. 3, store and UPC fixed effects model). As discussed above, I predict an increase in prices after EBT ($p^*_{ebt} > p^*_{nw}$). This increase should only occur within stores that price discriminated before EBT (i.e., single outlets).

Table 4 presents the results of estimating Eq. 3 using the full Nielsen sample. The coefficient on the interaction term of interest is significant for single outlet WIC stores, implying a price increase on WIC products of 8.94%, whereas there is no effect for chains.[51] To check that the price effects occur in the expected subsample, I plot event time coefficients in Fig-

[48] County level food expenditures are not available, so I use statewide variation in this section to assess the effect of EBT on costs.

[49] Oklahoma is used as a control state because it is the only state in USDA WIC's "Southwest Region" (regions are overseen by a WIC regional office and chosen because they have similar food prices), which includes Texas, Arkansas, New Mexico and Oklahoma, which didn't use EBT at the time of Texas' rollout. If I instead use population-weighted average food cost for Oklahoma and Louisiana, another non-EBT state contiguous to Texas, as the control, the graph looks very similar. Additionally, note that graphing *total costs*, rather than per-participant costs, produces a very similar graph, indicating that movements in per-participant costs are not driven by changes in participation.

[50] I subtracted \$4.00 from the September 2009 OK-TX difference in food costs to get \$4.40, or 11.7% of Oklahoma's per person cost in 2009. The reduction of \$4.00 accounts for the fact that OK food costs are \$4.00 higher in Oct 2000

[51] The remaining coefficients from the quadruple difference are reported in Appendix Table 7.

ures 4 and 5 using the subsample of WIC products and WIC stores *only* ($WICprod_u = 1$ and $WICstore_{ts} = 1$ in Eq. 3). As predicted, prices increase on WIC products in single outlets after EBT, whereas there is no effect in chains. Note that the effect for single outlets shows up exactly after a 6 month probationary period — stores were required to maintain low prices during this period to qualify for reimbursement for EBT technology.[52] Figure 3 presents results using variations of the main specification and the effects appear robust.

In addition, we should see no effects in the other subsamples: non-WIC stores and non-WIC products. Appendix Figures 4 and 6 estimate the same event-time coefficients for the following subsamples: WIC products in non-WIC stores and non-WIC products in WIC stores, separately for chains and single outlets. As expected, I see no effects in these subsamples.

How reasonable are the price increases of 9-10%? Note that, under the simplest conditions, the new pooling price should lie approximately at the average of the *ex-ante* separating prices (p^*_w and p^*_{nw}), weighted by proportion of WIC and non-WIC customers. I estimate that p^*_w is 35% higher than p^*_{nw} *ex-ante*.[53] Given that 30% of single outlets' sales is WIC, then the pooling price p^*_{ebt} should lie about 30% of 35% above the separating price, p^*_{nw}, which is approximately 10%, the exact magnitude of my estimate.

In sum, EBT reform results in an increase in the shelf prices of WIC products in single outlet WIC stores of 9-10%, and no offsetting effects are observed in other subsets.

8.4 Effect of EBT on Store Participation in WIC

The model also predicts that, given the reduction in rent from fraud, some *ex-ante* fraudulent stores (i.e. single outlets) will drop out of WIC after EBT. To asses this hypothesis, I estimate the event-time version of Eq. 1 on total WIC stores per county, year and month, separately for single outlets and chains. The results are plotted Figures 6-7. Figure 6 shows a drop in single outlet stores coincident with the timing of EBT rollout, whereas no change is seen for chain stores in Figure 7. Appendix Figures 8- 9 present the same results, adding county-specific linear time trends, and the graphs are very similar.

The fact that the drop in Figure 6 is *immediate* follows from the way EBT rollout worked. The EBT date is the point after which WIC stores were required to have EBT technology (i.e., were only allowed to use EBT technology to process WIC transactions). In the months leading up to EBT, on the other hand, stores were still able to accept paper vouchers.

[52] More detail on Texas WIC rules regarding reimbursement is given in Section 10.2

[53] Recall that Saitone *et al.* (2013) find that independent WIC stores charge WIC 50% more than chain WIC groceries. Using data from the Census' Retail Trade Report, I estimate that 15 percentage points of the 50% is the difference in mark-ups between independent and chain stores, and the remaining 35 percentage points is price discrimination *within* single outlet stores (i.e. the gap between p^*_w and p^*_{nw}). See calculation of ***(C)*** *Loss in store profits* below for more detail regarding the Trade Report calculations.

Therefore, stores who intend to drop out of WIC WIC after EBT are incentivized to exit the program exactly on the EBT date.

Table 5 presents the corresponding regression results — estimating Eq. 1) on total WIC stores per county and month, separately for chains and independent stores. EBT is associated with a significant decrease in independent WIC stores per county, but has no effect on chain stores. The effects are robust to the inclusion of year*month fixed effects and county-specific linear time trends. The coefficient estimates imply a decrease in total independent WIC stores per county of 10.0%-25.9% of the mean.[54]

The fact that there are fewer single outlet WIC stores after EBT may be because existing WIC stores dropped out of WIC or because would-be WIC stores decided not to join.[55] In Table 6, I test whether EBT increases the likelihood that existing stores exited, which is specifically implied by my model. I use the store data in panel form to estimate the store fixed effects model (Eq. 2), regressing the likelihood store s exits in period t on an indicator for whether t occurs after EBT.[56][57] Panel A of Table 6 presents the results, which indicates that dropouts increase among single outlets by around 2.1 to 2.5 percentage points (about 100% of mean). There is no effect for chains.[58][59]

Per my theoretical framework above, single outlets are more likely than chains to drop out after EBT because they were more fraudulent *ex-ante*. One possibility as to why single

[54] As a robustness check, I estimated the same specifications using a different dataset of Texas WIC stores I read in using web crawls of the Texas WIC website. A list of WIC stores and addresses are posted here: `http://www.dshs.state.tx.us/wichd/vo/vlist.shtm`. I compiled previous versions of the lists using archived versions of the website on following dates: 8/2006, 6/2007, 9/2007, 5/2008, 12/2008, 6/2009, and 7/2010. This data provide a check for possible error in the string cleaning and month imputation processes used in creating my main data sample. Appendix Table 8 presents analogous results to Table 5. The coefficients are highly similar, showing a negative effect on independent stores and no effect for chains.

[55] Note that applications are accepted on a rolling basis, so stores can start offering WIC in any month.

[56] Note that if the store never exits or exits after the end of my sample then the exit indicator is 0 in each period.

[57] Store fixed effects help adjust for differences in entry date, as stores with earlier entry dates will tend to exit earlier, all else equal.

[58] In addition, Appendix Table 9 presents alternative estimates of the effects of EBT on store exit using a Cox proportional hazard model, which accounts for the fact that store participation spells are right censored at the end of my sample period (FY 2010), imposes no restrictions on the baseline hazard function, and models independent variables as having a proportional effect on the hazard rate:

$$h(t) = h_{0c}(t) * \exp\left(\beta_5\, EBT_{tc} + \gamma_y + \nu_m + \mu_c * y + \epsilon_{tc}\right) \tag{4}$$

Appendix Table 9 reports the implied hazard ratios, e^{β_5}. Single outlet stores are 1.86 to 2.51 more likely to exit after EBT, whereas there is no change for chains. Note that the standard errors shown are those on the underlying coefficients (β_5). Standard errors are clustered on county and I allow for heterogeneity in hazard rate by county.

[59] Note that because EBT reduces WIC store profits, it may induce some stores to exit (shut down). Using establishment counts for grocery stores, I do not find evidence that EBT is associated with a change in the number of grocery stores at the county-year level, either independent or chain (Appendix Table 10), however.

outlets in WIC tend to be fraudulent *ex-ante* is they face higher fixed costs of joining WIC (γ), so that only the fraudulent ones *select in*. Recall that single outlets are more likely to be located in high poverty areas. I hypothesize that stores in high poverty areas face higher fixed costs associated with carrying the healthy and/or fresh foods required by WIC.

Specifically, following Waldfogel (2009), if we assume there is a fixed cost of carrying any given product, then grocery stores will only carry products which reflect the tastes of the majority of their customers.[60] Therefore, if customers in high-poverty areas don't tend to purchase the healthy/fresh foods required by WIC, then stores in these areas will face higher fixed costs of participating in WIC — namely the costs of adding these foods to their inventory.[61] Adding fresh foods may involve fixed costs such as purchasing extra cold storage, establishing new supply routes, inability to stockpile, etc. Empirically, it is well established that grocery stores in high poverty areas, which are predominantly small single outlet stores, carry very limited quantities of healthy and fresh foods (Chung and Myers, 1999; Morland *et al.*, 2002; Zenk *et al.*, 2005).[62]

In order to test my hypothesis, I first investigate whether WIC stores in high poverty ZIP codes are more likely drop out following EBT. I re-estimate the store panel model (Eq. 2), interacting "after EBT" with poverty in the store's ZIP code. Panel B of Table 6 presents the results. As expected, store dropout increases with ZIP poverty, and the pattern holds for chains as well as single outlet stores.[63]

Next, I use the Nielsen Consumer Panel to investigate whether WIC food types are less likely to be purchased in high poverty areas. Table 7 correlates the share of household food expenditures spent on WIC food categories (purchases of any kinds of eggs, milk, fruit juice, cereal, beans or peanut butter) with the poverty level of the household's ZIP code.[64] Column

[60] Technically, this prediction applies when there are any fixed costs of entry.

[61] WIC stores must keep a minimum inventory of *all* WIC foods on their clients' vouchers, to serve them, including cheese, eggs, low fat and whole milk, etc. Some of these foods may already be part of stores' inventories (and customer demand), while some others are not — for example, whole milk vs. low fat milk

[62] Andreyeva *et al.* (2011) conducted interviews with "corner and convenience" stores in high poverty neighborhoods in Connecticut in 2009, asking why they chose not to carry healthy and fresh foods. The majority of retailers identified low customer demand as the main reason. Recently, in order to address the lack of fresh foods in inner city neighborhoods, the federal government has made grants to several U.S. cities with the express purpose of covering fixed costs of carrying fresh foods in corner and convenience stores and bodegas. These programs include Fresh Bodega (NYC), Food Trust (Philadelphia), and Baltimarket Fresh Stores (Baltimore). Through the grants, small groceries receive grants for cold storage, training on how to connect with local suppliers and store and purchase fresh foods, and other services.

[63] Note that these results suggest that the differences in behavior I observe between WIC chains and single outlets are driven by differences in store location, rather than something else distinguishing the two types of stores (more whistleblowers, differences in audit probability, etc.).

[64] Note that the local market for WIC type foods in high poverty area may by affected by the WIC program itself. To avoid these confounding effects, I limit the sample to purchases made in Mississippi (where WIC foods are distributed directly through government warehouses rather than though the retail sector) and also limit the sample to households without children (to avoid households potentially participating in WIC).

(1) shows that households on average spend 11.1% of their food expenditures on WIC food types. This share falls with ZIP code poverty—a 10 percentage point increase in the share of a ZIP under the poverty line implies an 0.8% decrease in WIC food expenditures (7% of mean).[65] Restricting to households without children to avoid WIC recipients (Column (2)) actually increases the effect to 8% of the mean, although precision is somewhat reduced due to the large drop in sample size. In sum, the evidence suggests that markets for WIC-type foods are thin in high poverty areas, implying that WIC stores in these areas may face higher fixed costs of stocking WIC foods.

Finally, I test whether stores which exit WIC after EBT drop WIC-eligible UPCs (consistent with demand being too low to cover fixed costs). Appendix Table 11 regresses the share of a store's transactions that involve WIC-eligible products on whether a store is in WIC, using the sample of stores which exit WIC upon EBT rollout. In the baseline specification (Cols. (1) and (4)), I find that the WIC-eligible share of transactions decreases 33% for independent stores and 20% for chains.[66] Adding time trends reduces the magnitude and precision for independent stores, although it is plausible that these smaller stores can only gradually change their inventory.

In sum, EBT is associated with a decrease in WIC stores, predominantly those located in higher poverty areas. Evidence suggests that these stores face may higher fixed costs of joining WIC, γ_s, associated with carrying healthy/fresh foods due to low neighborhood demand. Before EBT, revenue from price discrimination acts as an implicit subsidy to cover these fixed costs.

8.5 Effect of EBT on Access in WIC

Given that EBT reduces the number of WIC stores in high poverty areas, there may be negative impacts on access among women and children. I investigate whether EBT leads to a reduction in WIC take-up by estimating Eq. 1 using the sample of Texas birth certificates, where the outcome of interest is whether a mother reports receiving any WIC food during her pregnancy. Note that the reduction in stores associated with EBT may affect whether a mother ends up receiving any WIC foods (my outcome) even if it occurs partway through pregnancy, as the majority of pregnant mothers Texas don't enroll until their second or third

[65] As explained in the notes to Table 7, the coefficients are from a regression of the WIC food expenditure share measure on ZIP poverty and also control for year and household ID fixed effects. Household ID FE control for autocorrelation in tastes, so that the coefficients can be interpreted as the covariance between a given household's purchasing patterns and neighborhood poverty.

[66] The fact that these decreases are not 100% suggests non-WIC consumers demand *some* WIC foods. Continuing the example above, non-WIC customers may demand whole milk but not low fat milk — WIC stores are required to carry both. That non-WIC customers demand *some* WIC products implies that they are affected by price increases on WIC products in WIC stores after EBT.

trimester.[67]

I calculate total births as well as total births for which the mother reports receiving WIC (WIC births, from now on) per county, year and month. I also calculate WIC births as a a share of total births per county-year-month cell. Births are considered treated if they occur after EBT rollout, meaning that mothers for whom EBT occurred partway through pregnancy are part of the treatment group.

Figure 8 plots coefficients from the event-time version of Eq. 1 with log WIC births as the outcome. WIC participation falls roughly 5% between births born before EBT rollout and those born afterwards. As expected, WIC participation among mothers for whom rollout occurred during pregnancy is somewhere in between these two levels.[68]

Table 8 presents regression results from estimating Eq. 1, using log total WIC births and share WIC births. Appendix Table 12 shows the corresponding results for total WIC births. In addition, Appendix Table 13 presents results using the individual-level births sample, in which I add individual level maternal demographic controls.

Table 8 shows that the decrease in WIC usage is 3.1-3.3% (from the log specification in Columns 1-3) and significant across all specifications. The effects are *proportionally* larger among the subset of minority mothers, at 3.4-3.8%, which is consistent with the fact that higher poverty neighborhoods see the largest decrease in store participation. Appendix Table 13, Panels A and B, presents corresponding estimates from the individual-level regressions — including maternal demographic controls does not seem to affect the results, suggesting that endogenous trends in maternal demographics are not driving my results.

So far, we have seen the EBT reduces the number of WIC stores as well as WIC participation among mothers, but not that the first necessarily causes the second. In particular, even if WIC stores exit, it could be that there are still "enough" WIC stores to which women have access. In Appendix Table 15, I estimate the effect of EBT on the likelihood that a ZIP code has *at least one WIC store* in a given month and year, weighted by the number of low-SES mothers residing in that ZIP code.

As mentioned above, within-ZIP access to benefits has been found to be an important predictor of take-up in previous work.[69] Appendix Table 15 shows that EBT reduces the likelihood there is at least one WIC store in a pregnant woman's ZIP code by around 1 percentage point, and that the effect is most pronounced when ZIPs are weighted by the

[67]Source for enrollment in Texas among pregnant women: See `https://www.dshs.state.tx.us/wichd/fin/ParticipantProgramCharacteristics.pdf`

[68]Because the cell sizes used to create the point estimates are small on average, I exclude standard errors from the graph, reserving significance testing for the differences-in-differences specification.

[69]However, it is likely that pregnant mothers and mothers with young children are especially constrained by small costs. Having at least one WIC store per ZIP code can be seen as a conservative measure of access.

highest-poverty mothers.[70] Of course, these results likely understate the total changes in access associated with EBT because they ignore things like the distance a mother needs to the nearest WIC store or whether her "usual" grocery store offers WIC.[71]

Finally, as additional evidence on the impact that WIC store supply can have on WIC take-up, I analyze as a case study the effects of a vendor moratorium in California WIC on participation. In response to an escalation in fraud among smaller groceries, California WIC implemented a moratorium on *all* new store applications in April 2011.[72] Note also that such moratoriums are not unique to California — similar USDA-directed bans on new WIC stores are also currently in place in Louisiana and Georgia.[73]

Media coverage suggests that the moratorium has caused unintended reductions in access, as newly opened grocery stores in poor neighborhoods cannot offer WIC.[74] Appendix Figure 10 shows total monthly WIC participation in California as a fraction of the state population.[75] There is, in fact, a striking 15% decline in the WIC-to-population participation ratio after the moratorium was imposed in 2011. Note that this decrease is *twice* as large as the increase in WIC participation during the recession seen on the graph.[76]

[70] For comparison, 37% of Texas ZIP codes have a WIC store during my sample.

[71] Note that effects on access are largest when I weight ZIP codes by the number of mothers who are minorities *and* do not have a high school education. Correspondingly, we might expect that this specific subset of mothers has the largest proportional declines in WIC usage following EBT. In fact, the evidence is mixed. If I recreate Table 8) using log total share WIC mothers who are minority *and* have no high school diploma, I find the same magnitude declines as for *all* minority mothers (not reported). Conversely, if I estimate the effect of EBT on access using individual level regressions with demographic controls, as reported in Panel C of Appendix Table 13, I *do* find that minority mothers with a high school education have the largest proportional declines. It may be that adding demographic controls helps adjust for trends among this specific subset of high poverty mothers. Conversely, although reductions in store participation are greatest in the highest poverty neighborhoods, slightly higher SES mothers may be more responsive to distance costs, given that their marginal utility of WIC may be lower. More sensitive measures of both access to WIC as well as the costs of participating may be necessary.

[72] California WIC Association reported the rise of a middleman business, which set up "ready-to-go" fraudulent WIC stores: We had WIC participants complaining of the high and different prices being charged to them. Some [of the] small store owners appear to be receiving assistance from knowledgeable and centralized WIC middlemen or brokers. See: `www.cdph.ca.gov/programs/wicworks/Documents/storeAlerts/WIC-store-Alert-2012-10.pdf` and `/www.cpehn.org/pdfs/CWA%20WIC%20Stores%203-12.pdf`. USDA extended the ban until June 2014, writing that CA WIC needed to demonstrate its ability to "develop and fully implement an effective cost containment and store management system."

[73] See `http://new.dhh.louisiana.gov/assets/oph/nutrition/WIC/alerts/storeAlerts2014/storeNotice_FederalMoratorium52214.pdf` and `http://www.georgiahealthnews.com/2011/06/state-targets-fraud-nutrition-program/`

[74] E.g. Gutierrez, Melody and Will Kane. "Needy Families hit roadblock to using WIC food vouchers," *San Francisco Chronicle*, May 14, 2014. Available here: `http://www.sfgate.com/default/article/Needy-families-hit-roadblock-to-using-WIC-food-5482223.php`.

[75] California WIC participation totals were received by the author from USDA through a Freedom of Information Act (FOIA) request. The non-civilian resident population for the state of California is estimated by the Census Bureau and reported in the following link by the Bureau of Labor Statistics (BLS) (Source: `http://www.bls.gov/lau/rdscnp16.htm`

[76] Note also that the sharp decline in CA WIC participation from 2012-2013 is not exhibited in neighboring

Appendix Figure 10 therefore presents supporting evidence that WIC store participation — perhaps particularly small and/or fraudulent stores, at whom the moratorium was aimed — is important for take-up among eligibles.

9 Welfare Calculations

In this section, I use the estimates generated above to calculate the overall impact of EBT on social welfare. Recall from Section 5 that we want to calculate the following sum (letters refer to labeled areas of Figure 1 and Figure 2).

$$\begin{aligned}\Delta\text{Social Welfare} =& (\lambda-1)(\boldsymbol{D})\text{store transfer to WIC} + (\lambda-1)(\boldsymbol{F})\text{store transfer to WIC} \\ &+ \lambda(\boldsymbol{G})\text{WIC savings} - (\boldsymbol{B})\text{loss non-WIC consumer welfare} \\ &- (\boldsymbol{C})\text{loss store profits} - (\boldsymbol{E}+\boldsymbol{F}+\boldsymbol{G})\text{loss WIC benefit}\end{aligned}$$

(*D*) *Store transfer to WIC*

The store transfer to WIC denoted **(*D*)** is due to the elimination of overcharging (price discrimination) after EBT — $p^*_{ebt} < p^*_w$ *within* WIC stores. I combine the USDA's estimate that overcharging comprises 1% of WIC food expenditures with my estimate that WIC paid \$31.61 per participant-month in Texas for FY 2005 to calculate the amount saved, $p^*_{ebt} - p^*_w = 0.01 * \$31.61 = 0.32$ per participant-month.[77] The area **(*D*)** is equal to $q'_w(p^*_w - p^*_{ebt})$, where q'_w is post EBT (reduced) participation, which I estimate at 75,195,398.50 monthly benefits per year.[78] I therefore estimate the store transfer to WIC to be $\$0.32 * 75,195,398.50 = \$24,062,527.52$.

(*F*) *Store transfer to WIC* and **(*G*)** *WIC savings*

The store transfer to WIC denoted **(*F*)** occurs because of the reduction in store participation after EBT (and resulting decline in take-up / benefits issues to mothers). The savings to the government are the pre-EBT food costs (p^*_w) multiplied by the decrease in benefits distributed ($q_w - q'_w$). Of this amount, the stores only lose their WIC *profits*, which

states. Figures available upon request from author. Source: USDA, state-year total participation counts `http://www.fns.usda.gov/pd/wic-program`.

[77] I calculate \$31.61 by averaging food costs per person in Texas in 2005 using Texas WIC financial records.

[78] I estimate reduced participation $q'_w = (1 - 3.3\%$ reduction in WIC participation among pregnant women)$*200,712$ pregnant women who receive WIC in 2005$*12$ months of benefits*13.05 US to Texas population ratio in 2005$*2.474$ avg. number of WIC beneficiaries per mother, incl. mother$= 75,195,398.50$. I calculate the avg. number of WIC beneficiaries per mother in the next paragraph. Source for WIC participation among pregnant women: 2005 Texas birth certificates. Source for Texas and US population in 2005: Census Bureau.

are equal to $(\boldsymbol{F}) = m((\boldsymbol{F}) + (\boldsymbol{G}))$, where m is the store mark-up (estimated below), and $(\boldsymbol{G})$ is additional savings from the cost of producing WIC foods.

To estimate the food costs of a mother participating (p^*_w), I add up the monthly cost for mother and infant ($31.61+$31.61) as well as for an additional child under 5 ($31.61) multiplied by the probability the mother has another child under 5 (47.4%), which is a total of $p^*_w = \$78.20$.[79] I multiply $78.20 by 12 months of benefits, the 0.033 reduction in participation, the 200,712 pregnant women on WIC in Texas in 2005, and the US-Texas population ratio of 13.05 in 2005, which amounts to $(\boldsymbol{F})+\boldsymbol{G} = (q_w - q'_w)p^*_w = \$81,112,126.84$.

$(\boldsymbol{B})$ *Loss in non-WIC consumer welfare*:

To calculate the loss in non-WIC consumer welfare $(\boldsymbol{B})$, I first estimate total demand for WIC-eligible products in single outlet WIC stores. I add up sales of food at home for 2005 in the following types of grocery stores, which I use to proxy for single outlets: convenience stores, small groceries, and specialty food stores, which is $37,537 million.[80] I then use the Nielsen data sample to estimate the fraction of sales in single outlet groceries that are of WIC eligible products at WIC stores at 4.2%.[81]

I combine these estimates to calculate annual sales of WIC products at single outlets to be $37,537 million*4.2% = $1,576.55 million (specifically, this sum represents pre-EBT sales of WIC-eligible products in WIC stores, $p^*_{nw}q^*_{nw}$). The triangle $(\boldsymbol{B}) = 1/2(p^*_{ebt} - p^*_{nw})(q^*_{nw} - q^*_{ebt})$, which can be re-written using non-WIC consumer price elasticity of demand, ϵ_p, as $1/2(0.0894p^*_{nw})(q^*_{nw}\epsilon_p 0.0894) = (0.0040)\$1,576.55 \text{ million } *\epsilon_p = \$6.30 \text{ million } *\epsilon_p$, where I have also plugged in my estimate of the non-WIC price increase (8.94%). ϵ_p is the demand elasticity for WIC foods; I discuss bounds below.

[79] Children are eligible for WIC up to age 5. I calculate the probability a new mother has another child under 5 from the Texas birth certificate data, which records the age of the mothers previous child. I dont observe any additional children under 5 (which would increase the transfer further), so my estimate of $78.20 serves as a lower bound.

[80] Data Source: Sales are calculated by the Economic Research Service, USDA, from various data sets from the U.S. Census Bureau and the Bureau of Labor Statistics. Table 14, Sales of food at home by type of outlet (including sales tax), which is available here: `http://www.ers.usda.gov/data-products/food-expenditures.aspx`. I sum sales in: Convenience Stores, defined as "Small stores that stock a range of everyday items such as groceries, toiletries, and newspapers," Other Grocery, defined as "Smaller grocery stores that sell a range of groceries, meats, and produce." and Specialty Food Stores, defined as "Stores that sell a small range of specific foods such as bakeries or meat markets."

[81] I define food at home to include the following Nielsen categories (in order to best overlap with the ERS food at home category): Meat, Dairy, Fresh Produce, Frozen, and Dry Grocery, excluding Alcoholic Beverages, Deli, Non-Food, Health & Beauty Care, General Merchandise, and Magnet data (a special category of Nielsen products for which UPC level information is not recorded). I add up all sales in these categories at single outlets (as elsewhere in my analysis, I denote a store as a single outlet if it has no retailer/store outlet code) and then take the fraction of sales of WIC products at single outlets (6%). Note that because I don't observe exact UPC-level eligibility for all WIC product categories, my estimate is approximate. I then multiply this fraction by the percent of sales in these categories that occur in WIC stores, which is 0.71

(C) *Loss in store profits*

The loss in store profits ***(C)*** comes from the fact that stores can no longer price discriminate. Stores' profits decrease by $\boldsymbol{(C)} = (q^*_{nw} - q^*_{ebt})(p^*_{nw} - c)$. To estimate the mark-up of the non-WIC price over cost, $(p^*_{nw} - c)$, I use the Census Bureau's Retail Trade Report for 2005, which reports profits as a percent of sales for grocery stores at 28.6%.[82] Therefore, we have $(q^*_{nw} - q^*_{ebt})(p^*_{nw} - c) = (q^*_{nw} - q^*_{ebt})0.286p^*_{nw}$. Substituting in the demand elasticity, ϵ_p, and my estimate of the non-WIC price increase (8.94%), the expression becomes $(q^*_{nw} - q^*_{ebt})0.286p^*_{nw} = (0.0894 * 0.286q^*_{nw}p^*_{nw}\epsilon_p) = 0.0894 * 0.286 * \$1,576.55$ million $*\epsilon_p = \$40.31$ million (ϵ_p). Again, we need the non-WIC demand elasticity.

(E + F + G) *Loss in WIC benefit*

The loss in WIC benefit is equal to the reduction in take-up multiplied by the social value of WIC participation. From my births sample, I have that 200,712 pregnant women participated in WIC in Texas in 2005. Multiplying by 12 months of benefits, my estimated reduction in access (3.3%) and then scaling up by the U.S.-to-Texas population ratio (13.05), I estimate a reduction in take-up of 1,037,239.47 mother participation-months.

Estimating the social value of an additional woman participating in WIC (which includes benefits to her children, as in my calculations above) is not as straightforward. In addition to the immediate value of foods provided, WIC has been found to have positive effects on health outcomes such as birthweight, pregnancy weight gain and breastfeeding (Bitler and Currie, 2005; Figlio *et al.*, 2009; Hoynes *et al.*, 2011a; Rossin-Slater, 2013). Additional benefits comes from the referrals to other social services, health screenings, and health education WIC provides. Further, the (regular) transfer may have insurance value for beneficiaries. I discuss bounds below.

I set $\lambda = 1.3$, following standard practice (Saez *et al.*, 2012).[83] I calculate m, the profit margin of p^*_w over c at 0.34.[84] Then the multiplier on this transfer becomes $\lambda - 0.34$ (WIC gains the transfer*multiplier, store loses its profit margin on transfer).

The change in social welfare is then given by:

[82] The Retail Trade report can be found here: `https://www.census.gov/retail/`. The relevant table is Gross Margin as a Percentage of Sales, 1993-2012 and the industry is NAICS code 4451 (grocery stores). The Census Bureau defines the Gross Margin as: "The measure of gross margin represents total sales less cost of goods sold."

[83] The value of λ is calculated as $\frac{1}{1-\epsilon*t/(1-t)}$ where ϵ is the elasticity of taxable income and t is the top tax rate. $\epsilon = 4$ is a standard value (Saez *et al.*, 2012). With t roughly $= 0.4$, λ is equal to 1.3.

[84] I calculate m by combining the mark-up of p^*_{nw} over c (0.286), the mark-up of p^*_{ebt} over p^*_{nw} (0.894) and the mark up of p^*_w over p^*_{ebt} (0.01). The full calculation is as follows: $0.01 + (1 - .01) * (0.0894/1.0894) + (1 - 0.01)(0.286)(1 - (0.0894/1.0894)) = 0.34$

$$
\begin{aligned}
\Delta\text{Social Welfare} =&(1.3-1)\$24,062,527.52+(1.3-0.34)\$81,112,126.84\\
&+\$40,309,861.02(\epsilon_p)+\$6,300,177.58(\epsilon_p)\\
&-1,037,239.47(\text{Social Value WIC})
\end{aligned}
$$

which reduces to:

$$
\Delta\text{Social Welfare} =\$85,086,400.02+\$46,610,038.60(\epsilon_p)+1,037,239.47(\text{Social Value WIC})
$$

As for ϵ_p, Andreyeva *et al.* (2010) review literature on the price elasticity of demand for groceries, specifically, reviewing estimates from around 500 studies. They find a range from 0.27 to 0.81 (absolute value). Plugging in -0.81 (-0.27) to the equation above implies that if the social value of one month's participation for a mother and her children is above \$45.63 (\$69.90), then EBT created a net loss in social welfare. As I discuss further in the next section, the magnitude of ϵ_p may be affected by several additional factors. If consumers can easily substitute between WIC and non-WIC goods, for example, it may be larger than the overall demand elasticities for groceries. On the other hand, WIC products, like milk and eggs, are staples, implying a less elastic demand.

As a conservative measure of the value of WIC participation, I use the market value of WIC foods— that is, how much it would cost a mother to purchase the food she receives, which excludes any additional benefits she receives from the program. I calculate the market value of the average WIC transfer in 2005 at \$172.80 for the mother's household, well above the break-even cutoffs.[85] Plugging \$172.8 to the equation above, and using the range of elasticities, I calculate a conservative estimate of the annual loss associated with EBT of \$106-130 million, or 3-4% of the value of benefits received (2-3% of total program budget, which includes employee salaries).

Finally, note that, in addition to non-food benefits, my estimates exclude some of the costs involved in the implementation of EBT. The CBO estimates EBT will cost \$652 million over 2011-2015 (the rollout of EBT is planned to extend to 2020).[86]

[85] I use the value of WIC benefits estimated in 2005 by the USDA: `http://www.fns.usda.gov/sites/default/files/FY2005.pdf`. I calculate the average benefit by averaging the benefits breastfeeding and non breastfeeding mothers, weighted by participation of the two groups (in the report).I add the mother's monthly benefit (\$39.09), her infant's benefit (\$99.57) and her other child under 5's benefit multiplied by the likelihood she has a child under 5 (47.4%*\$39.97=\$18.94). Note that the market value of WIC foods is more than the government spends because the government receives post-transaction rebates from the manufacturers of WIC-eligible products. Rebates are established through competitive bidding from manufacturers, who win the right for their products to be WIC-eligible. The government therefore saves by using monopsony power.

[86] Source: `http://www.gpo.gov/fdsys/pkg/CRPT-111srpt178/html/CRPT-111srpt178.htm`.

10 Alternative Hypotheses

In this section, I explain why a few alternative hypotheses do not explain my pattern of results.

10.1 EBT Reduces Stigma

Advocates for EBT argue that it reduces stigma in the grocery checkout line because the EBT card functions like a debit card, so WIC mothers are not easily identifiable. However, if EBT were to reduce stigma, we should see a positive effect on participation, whereas I find a negative effect on participation. In addition, research on the rollout of EBT in the Food Stamps program does not evidence in support of stigma effects (Currie and Grogger, 2001).

10.2 EBT Imposes Other Costs on Store and Participants

EBT may involve greater fixed costs for retailers than the paper voucher system if, for example, installation, use and upkeep of the EBT technology is costly. Such increased costs would be consistent with the fact that stores drop out after EBT, but would not be consistent with the price effects I find.

In addition, the government has explicitly specified that EBT transition be cost-neutral for grocery stores. Because groceries are required to have certain types of ECR hardware and software to be EBT-compatible, states were awarded grants to reimburse stores for these purchases.[87] In Texas, stores were reimbursed up to $11,000 per lane for new equipment and $200 per lane for new software, *conditional* on being compliant with all program regulations during a probationary 6 month period after EBT rollout.[88]

EBT might reduce the value of the program to participants because it was easier to make fraudulent substitutions with paper vouchers (e.g. exchange the voucher for cigarettes). As mentioned, the EBT card will only provide stores with reimbursement if the correct UPCs are scanned, so stores have less incentive to collude with participants who want substitutions. This hypothesis would account for reductions in store and participant participation but would *not* be consistent with the price effects I find. In addition, research finds negligible rates of participant fraud in the WIC program, as discussed above (e.g. 0.14% of participants commit fraud (GAO, 1999)). In my store data, 0 investigations are initiated based on evidence of participant fraud within the store.

[87] CBO estimates that EBT implementation over 2011-2015 will cost a total of $652 million over 2011-2015. Source: `http://www.gpo.gov/fdsys/pkg/CRPT-111srpt178/html/CRPT-111srpt178.htm`.

[88] The state was also directly involved in the purchasing of EBT equipment for stores, suggesting that they tried to reduce the burden of switching to EBT on stores. E.g., from October 2006, Texas WIC store Bulletin: "Approximately nine months prior to rollout in your area, the State will sponsor a store Expo in your area that will provide both general information about the rollout and a forum for all certified ECR stores to demonstrate their systems to you. The side-by-side comparison of ECR systems and demonstrations may help you determine which system will best meet your business needs."

10.3 Substitution Effects

If non-WIC customers are able to to find close substitutes for WIC-eligible products, then when the prices on WIC goods increase as a result of EBT, non-WIC customers may be able to mitigate welfare losses. The evidence appears to indicate, however, that customers are not fully substituting. First, note that the single outlet stores in question do not carry a wide variety of products so opportunities for substitution may be limited. Second, within product category, WIC eligible foods tend to be the low cost ones (e.g. organic foods are not allowed). Third, if there were large substitution effects (that is, demand shifts outwards for, e.g., Swiss cheese), we would expect to see price movements for non-WIC products, which I do not observe.

A different substitution effect concerns the extent to which stores make small substitutions of non-WIC products for WIC products (e.g. Swiss cheese for American cheese). Recall that EBT eliminates the possibility of any substitutions. Stores might want to make small substitutions if they run out of stock of certain WIC products (not only might re-stocking be expensive, but they might lose WIC business if they can't distribute the allotted quantities).[89] Conceptually, the ability to make substitutions is part of the profit margins on WIC goods, as it reduces marginal cost (so c would increase after EBT in my model). Because EBT eliminates the possibility of close substitutions, profit margins would decrease, leading to store dropout, so substitutions could be easily incorporated into the story of EBT presented above.[90] Because I can not directly observe substituting behavior in WIC stores before EBT, I do not model it explicitly above.

11 Conclusion

A large and growing share of safety net programs in the U.S. and other developed countries involve in-kind transfers. In-kind transfers are used in order to limit take-up among ineligibles and to alter consumption patterns among recipients (Besley and Coate, 1992; Blackorby and Donaldson, 1988; Nichols and Zeckhauser, 1982). However, absent its own network of providers, the government must rely on private vendors to distribute transfers, which creates the potential for agency problems (e.g. fraud), as well general equilibrium effects in the private market for program goods.

In this paper, I study the introduction of an antifraud technology (EBT) in the WIC

[89] Stores might also switch WIC products for close substitutes of lower marginal cost, but this effect is likely to be small because WIC eligibility is usually assigned to the lowest cost products in a given category.

[90] Of course, the price relationship $p < p_{nw} < p_{ebt}$ would still hold because the shelf price increases with EBT to reflect pooled demand. That I find an decrease in p_w with EBT rollout (as well as evidence presented next) shows that reducing overcharging is a key function of EBT, possibly in addition to reducing substitutions.

Program, which allows for easier verification of vendor reimbursement claims. I show that EBT was effective in reducing fraud, but also that it increased vendor non-participation, leading to a reduction in WIC participation among eligible women and infants. In addition, I find that WIC vendors increased the prices charged to *non-WIC* shoppers for program-eligible foods.

This paper is the first to consider the relationship between opportunities for vendor fraud, vendor participation in a transfer program, the participation of potential recipients of government transfer programs, and general equilibrium effects on prices. I am able to consider all of these aspects by constructing a unique data set combining administrative data about WIC vendors in Texas, information about prices from Nielsen scanner data, and information about the participation of pregnant women from individual birth records. Because my study encompasses all of these elements, it is possible to consider the effect of fraud reduction on social welfare. My findings suggest that fraud reduction, while effective in terms of achieving its stated goal, reduced social welfare by 3-4% of the value of benefits received.

Given my findings, efforts to reduce vendor fraud in safety net programs should consider the potential for offsetting effects, such as the fact that vendors may be less willing to participate in the program. In order to understand these offsetting effects, it is important to recognize the function served by the fraud *ex-ante*. In the case of WIC, I find that, before EBT, vendor fraud subsidizes vendor participation in high poverty areas (as well as reducing program-related market distortions). Therefore, one welfare improving policy might be to combine EBT with subsidies for vendors in high-poverty areas.

Suppose WIC adds to EBT a lump sum subsidy for vendors in high poverty areas. Presumably, the subsidy would be better targeted (and cheaper) than the *ex-ante* fraud. To further refine targeting, WIC could restrict the subsidy to certain, documentable, vendor fixed costs (e.g., refrigerators).[91] Adding a lump sum subsidy to EBT would increase vendor participation but would not address the increase in non-WIC prices that occurs with EBT, however. In order to address this issue, we would have to additionally allow WIC vendors to price discriminate. In fact, allowing for a fixed amount of price discrimination would be technologically easy — for example, the WIC program could reimburse stores at some fixed mark up over their non-WIC price, $p^*_w = \alpha + p^*_{nw}$ (replacing the current EBT requirement that $p^*_w = p^*_{nw} = p^*_{ebt}$).

A second policy option would be to provide WIC participants with restricted cash transfers rather than the current in-kind transfer. For example, participants could be issued a

[91]Of course, vendors could always quit the program and resell the refrigerators. In fact, Texas struggled with a similar problem when EBT was first rolled out – a few smaller vendors, upon receiving reimbursement for their new electronic cash register, quit WIC and re-sold the valuable machines.

voucher worth "10 dollars for any cheese, eggs or cereal." Doing so would make participants sensitive to prices but might undermine the goals of the program – would Velveeta be allowed?

A third policy option is that the government could directly provide WIC foods, rather than contracting with retail grocery stores. In fact, a few different locations — Mississippi, the South Side of Chicago, and Vermont — currently use direct distribution, providing WIC foods from government warehouses.[92] When the WIC program was first introduced, a number of states used direct distribution, but most have since switched to retail grocery distribution.[93]

In 1976, the USDA commissioned a report from the Urban Institute on the different distribution systems used in WIC (Institute *et al.*, 1976). At that time, only 73% of 325 WIC clinics nationwide used retail distribution, while the others used direct distribution. The report found that direct distribution was the cheaper distribution system, both for food *and* administrative expenditures. Per-person food costs were 21% higher for retail distribution than direct distribution, for example. However, the authors also found that direct distribution imposed higher travel costs on participants (local groceries being more convenient).

Further research is needed to fully evaluate these different policy options. In general, given that U.S. safety net programs are increasingly contracted out, it is important to understand which program designs are effective at alleviating poverty *and* incentive-compatible for vendors. This topic remains a fruitful area for future research.

[92] From the following report: `http://www.gao.gov/archive/1999/rc99224.pdf`, "In Chicago, many small vendors selling primarily alcohol and tobacco have been replaced by 15 food centers operated through a partnership between the state WIC agency and Catholic Charities of the Archdiocese of Chicago. These food centers distribute WIC products [directly]". That there are few grocery options on the South side of Chicago, and the ones that exist are wasteful, aligns with the narrative of this article.

[93] Government documents suggest that the switch to retail grocery was due to the fact that, pre-1990, the federal grant to states for WIC's administrative costs (i.e., non-food costs), which is used to pay employee salaries, was set at a fixed percentage of the food grant — so when food costs are higher, the administrative grant is higher. States opted for retail grocery distribution because it involved higher food costs than direct distribution (likely in part or completely due to vendor price discrimination).

References

Aizer, A. (2007). Public Health Insurance, Program Take-Up, and Child Health. *The Review of Economics and Statistics*, **89** (3), 400–415.

Akerlof, G. A. (1978). The economics of "tagging" as applied to optimal income tax, welfare programs, and manpower planning. *The American Economic Review*, **68** (1), 8–19.

Almond, D., Mazumder, B. and van Ewijk, R. (2011). *Fasting During Pregnancy and Children's Academic Performance*. NBER Working Papers 17713, National Bureau of Economic Research, Inc.

Alpert, A., Duggan, M. and Hellerstein, J. K. (2013). Perverse reverse price competition: Average wholesale prices and medicaid pharmaceutical spending. *Journal of Public Economics*, **108** (0), 44 – 62.

Andreyeva, T., Long, M. W. and Brownell, K. D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American journal of public health*, **100** (2), 216.

—, Middleton, A. E., Long, M. W., Luedicke, J. and Schwartz, M. B. (2011). Food retailer practices, attitudes and beliefs about the supply of healthy foods. *Public health nutrition*, **14** (06), 1024–1031.

Baicker, K. and Dow, W. H. (2009). Risk selection and risk adjustment: Improving insurance in the individual and small group markets. *Inquiry*, **46** (2), 215–228.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy*, **76**, 169.

Bell, L., Ledsky, R., Sternesky, L., Gleason, S., Ritu, T., Smith, D., Eicheldinger, C. and Kirkpatrick, G. (2007). *2005 WIC Vendor Management Study: Final Report*. Tech. Rep. WIC-06-WICVM-02, Office of Analysis, Nutrition and Evaluation, Food and Nutrition Service, U.S. Department of Agriculture, Alexandria, Virginia, project Officer: Sheku G. Kamara.

Besley, T. and Coate, S. (1992). Understanding Welfare Stigma: Taxpayer Resentment and Statistical Discrimination. *Journal of Public Economics*, **48** (2), 165–183.

Bitler, M. P. and Currie, J. (2005). Does WIC work? The effects of WIC on pregnancy and birth outcomes. *Journal of Policy Analysis and Management*, **24** (1), 73–91.

Blackorby, C. and Donaldson, D. (1988). Cash versus Kind, Self-selection, and Efficient Transfers. *American Economic Review*, **78** (4), 691–700.

Brown, J., Duggan, M., Kuziemko, I. and Woolston, W. (2011). *How does Risk-selection Respond to Risk-adjustment? Evidence from the Medicare Advantage Program.* Discussion papers, Stanford Institute for Economic Policy Research.

Cascio, E. U. (2009). Maternal Labor Supply and the Introduction of Kindergartens into American Public Schools. *Journal of Human Resources*, **44** (1).

Chung, C. and Myers, S. L. (1999). Do the poor pay more for food? an analysis of grocery store availability and food price disparities. *Journal of Consumer Affairs*, **33** (2), 276–296.

Clemens, J. and Gottlieb, J. D. (2013). *Bargaining in the Shadow of a Giant: Medicare's Influence on Private Payment Systems.* Working Paper 19503, National Bureau of Economic Research.

Currie, J. (2006). The take-up of social benefits. In A. Auerbach, D. Card and J. Quigley (eds.), *Poverty, the Distribution of Income, and Public Policy*, New York: Russell Sage, pp. 80–148.

— and Fahr, J. (2005). Medicaid Managed Care: Effects on Children's Medicaid Coverage and Utilization. *Journal of Public Economics*, **89** (1), 85–108.

— and Gahvari, F. (2008). Transfers in Cash and In-Kind: Theory Meets the Data. *Journal of Economic Literature*, **46** (2), 333–83.

— and Grogger, J. (2001). Explaining recent declines in food stamp program participation. *Brookings-Wharton Papers on Urban Affairs*, **1**, 203–244.

— and Reagan, P. B. (2003). Distance to hospital and children's use of preventive care: Is being closer better, and for whom? *Economic Inquiry*, **41** (3), 378–391.

Diamond, P. A. and Mirrlees, J. A. (1978). A Model of Social Insurance with Variable Retirement. *Journal of Public Economics*, **10** (3), 295–336.

Duggan, M. and Scott Morton, F. (2006). The Distortionary Effects of Government Procurement: Evidence from Medicaid Prescription Drug Purchasing. *The Quarterly Journal of Economics*, **121** (1), 1–30.

Einav, L., Leibtag, E. and Nevo, A. (2010). Recording discrepancies in nielsen homescan data: Are they present and do they matter? *Quantitative Marketing and Economics*, **8** (1), 207–239.

Ellickson, P. B. (2006). Quality competition in retailing: A structural analysis. *International Journal of Industrial Organization*, **24** (3), 521 – 540.

— and Grieco, P. L. (2013). Wal-mart and the geography of grocery retailing. *Journal of Urban Economics*, **75** (0), 1 – 14.

—, Houghton, S. and Timmins, C. (2013). Estimating network economies in retail chains: a revealed preference approach. *The RAND Journal of Economics*, **44** (2), 169–193.

Espinosa, J. and Evans, W. N. (2012). Excise taxes, tax incidence, and the flight to quality: evidence from scanner data. *Public Finance Review*, p. 1091142112460724.

Evans, W. N. and Lien, D. S. (2005). The benefits of prenatal care: evidence from the PAT bus strike. *Journal of Econometrics*, **125** (1-2), 207–239.

Figlio, D., Hamersma, S. and Roth, J. (2009). Does prenatal wic participation improve birth outcomes? new evidence from florida. *Journal of Public Economics*, **93** (1-2), 235–245.

GAO (1999). *Efforts To Control Fraud and Abuse in the WIC Program Can Be Strengthened*. Report to Congressional Committee GAO/RCED-99224, Government Accountability Office.

Hamilton, W., Elwood, P., Ciurea, M., St. George, A. and Porcari, D. (1997). *Costs and Impacts of the Wyoming Smartcard EBT System: Evaluation of the Wyoming EBT system for WIC and the Food Stamp Program*. Tech. rep., U.S. Department of Agriculture, Food and Nutrition Service.

Harding, M., Leibtag, E. and Lovenheim, M. F. (2012). The heterogeneous geographic and socioeconomic incidence of cigarette taxes: Evidence from nielsen homescan data. *American Economic Journal: Economic Policy*, **4** (4), 169–98.

Hastings, J. S. and Washington, E. (2010). The first of the month effect: Consumer behavior and store responses. *American Economic Journal: Economic Policy*, **2** (2), 142–62.

Hoynes, H., Miller, D. and Simon, D. (2011a). Income, the earned income tax credit, and infant health, mimeo, U.C. Davis.

—, Page, M. and Stevens, A. H. (2011b). Can targeted transfers improve birth outcomes?: Evidence from the introduction of the wic program. *Journal of Public Economics*, **95** (78), 813 – 827.

Hoynes, H. W., Schanzenbach, D. W. and Almond, D. (2012). *Long Run Impacts of Childhood Access to the Safety Net*. Working Paper 18535, National Bureau of Economic Research.

Institute, U., Food, U. S., Service, N. and Bendick, M. (1976). *Efficiency and Effectiveness in the W.I.C. Program Delivery System: The Special Supplemental Food Program for Women, Infants, and Children*. Miscellaneous publication, U.S. Dept. of Agriculture, Food and Nutrition Service.

IOM (2000). *Framework for Dietary Risk Assessment in the WIC Program: Interim Report.* Tech. rep., Institute of Medicine.

Kibble-Smith, B. (2009). *WIC EBT: The Future is Now: Moving Government from Policy to Results.* Tech. Rep. W6660209, J.P. Morgan.

Kleven, H. J. and Kopczuk, W. (2011). Transfer Program Complexity and the Take-Up of Social Benefits. *American Economic Journal: Economic Policy*, **3** (1), 54–90.

Kopczuk, W., Marion, J., Muehlegger, E. and Slemrod, J. (2013). *Do the Laws of Tax Incidence Hold? Point of Collection and the Pass-through of State Diesel Taxes.* NBER Working Papers 19410, National Bureau of Economic Research, Inc.

— and Pop-Eleches, C. (2007). Electronic filing, tax preparers and participation in the earned income tax credit. *Journal of Public Economics*, **91** (7-8), 1351–1367.

Kuziemko, I., Meckel, K. and Rossin-Slater, M. (2013a). *Do Insurers Risk-Select Against Each Other? Evidence from Medicaid and Implications for Health Reform.* Working Paper 19198, National Bureau of Economic Research.

—, Norton, M. I., Saez, E. and Stantcheva, S. (2013b). *How Elastic Are Preferences for Redistribution? Evidence from Randomized Survey Experiments.* Working Paper 18865, National Bureau of Economic Research.

Mantovani, R. (2012). *Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) Erroneous Payments to Vendors: Annual Estimates for Fiscal Year 2010.* Tech. Rep. WIC-12-EP2010, Office of Research and Analysis, Food and Nutrition Service, U.S. Department of Agriculture, Alexandria, Virginia, project Officer: Grant Lovellette.

Moffitt, R. (1983). An Economic Model of Welfare Stigma. *American Economic Review*, **73** (5), 1023–35.

Morland, K., Wing, S., Diez Roux, A. and Poole, C. (2002). Neighborhood Characteristics Associated with the Location of Food Stores and Food Service Places. *American Journal of Preventive Medicine*, **22** (1), 23–29.

Newhouse, J. P. (2006). Reconsidering the moral hazard-risk avoidance tradeoff. *Journal of Health Economics*, **25** (5), 1005–1014.

Nichols, A. L. and Zeckhauser, R. J. (1982). Targeting Transfers through Restrictions on Recipients. *American Economic Review*, **72** (2), 372–77.

OIG (2013). *Vendor Management in the Food and Nutrition Service's Special Supplemental Nutrition Program for Women, Infants and Children (WIC).* Tech. Rep. 2760-0038-Ch, Office of Inspector General.

Oliveira, V. and Frazao, E. (2009). *The WIC Program: Background, Trends, and Economic Issues, 2009 Edition*. Economic Research Report 55839, United States Department of Agriculture, Economic Research Service.

Rossin-Slater, M. (2013). WIC in Your Neighborhood: New evidence on the Impacts of Geographic Access to Clinics. *Journal of Public Economics*, **102** (C), 51–69.

Rothstein, J. (2010). Is the EITC as Good as an NIT? Conditional Cash Transfers and Tax Incidence. *American Economic Journal: Economic Policy*, **2** (1), 177–208.

Saez, E., Slemrod, J. and Giertz, S. H. (2012). The Elasticity of Taxable Income with Respect to Marginal Tax Rates: A Critical Review. *Journal of Economic Literature*, **50** (1), 3–50.

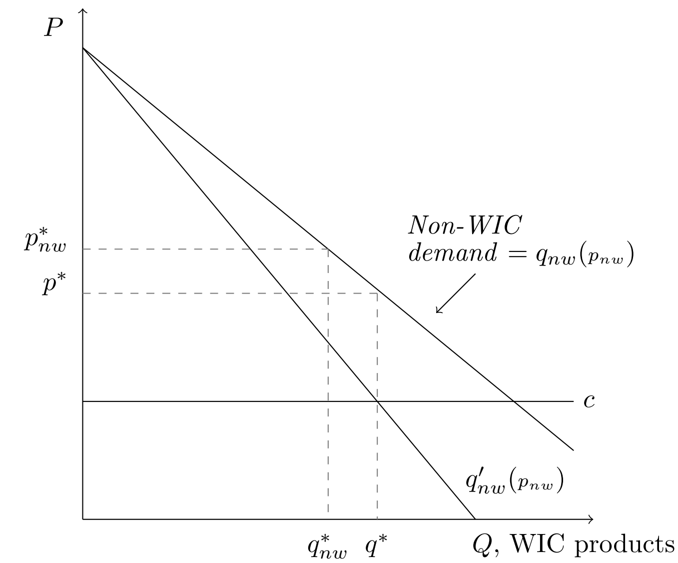
Saitone, T. L., Sexton, R. J. and Volpe, R. J. (2013). *A WICked Problem? Cost Containment in the Women, Infants and Children Program*. Working paper, seminar, Washington State University.

Silverman, E. and Skinner, J. (2004). Medicare upcoding and hospital ownership. *Journal of Health Economics*, **23** (2), 369–389.

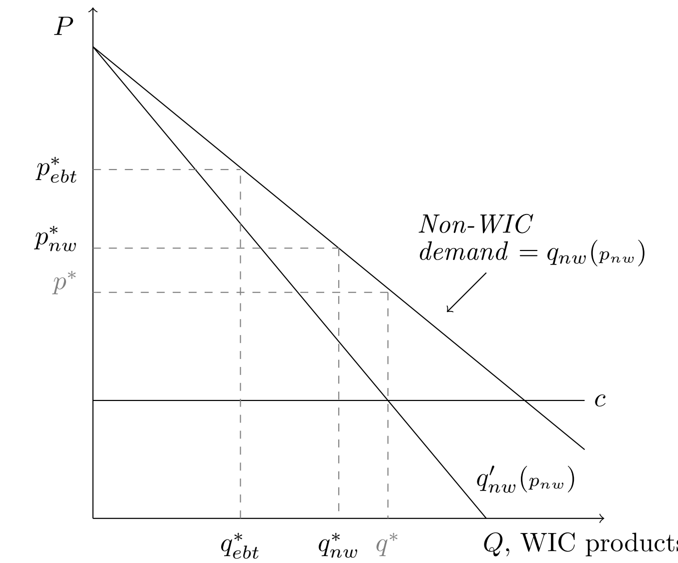
Waldfogel, J. (2009). *The Tyranny of the Market: why you can't always get what you want*. Harvard University Press.

Zenk, S. N., Schulz, A. J., Israel, B. A., James, S. A., Bao, S. and Wilson, M. L. (2005). Neighborhood racial composition, neighborhood poverty, and the spatial accessibility of supermarkets in metropolitan detroit. *Journal Information*, **95** (4).

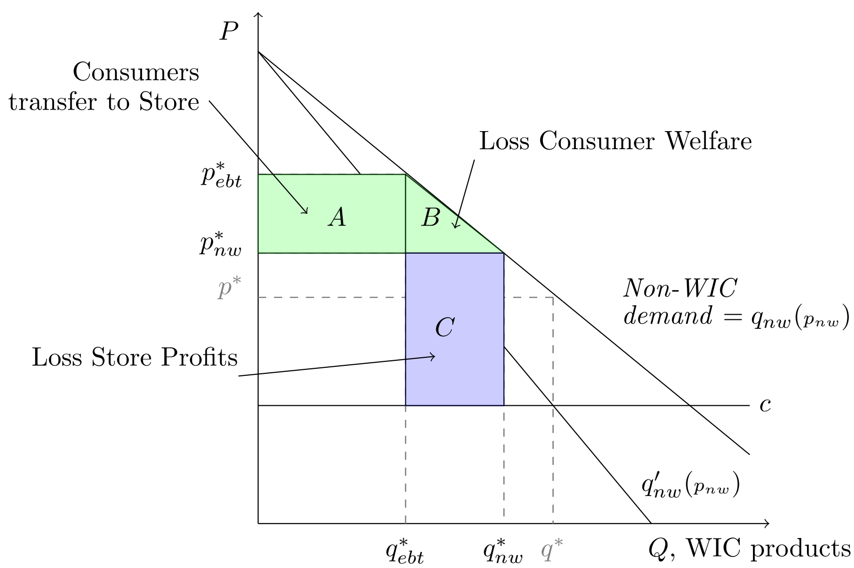
Figure 1: Effect of EBT on Social Welfare: WIC Stores and non-WIC Consumers



(A) *Before EBT*: Stores participating in WIC charge non-WIC consumers p^*_{nw} for WIC-eligible products. Stores not participating in WIC charge p^*. $p^*_{nw} > p^*$ because WIC sanctions μ decrease in p^{nw} $(\mu = \theta(p_w - p_{nw}))$.

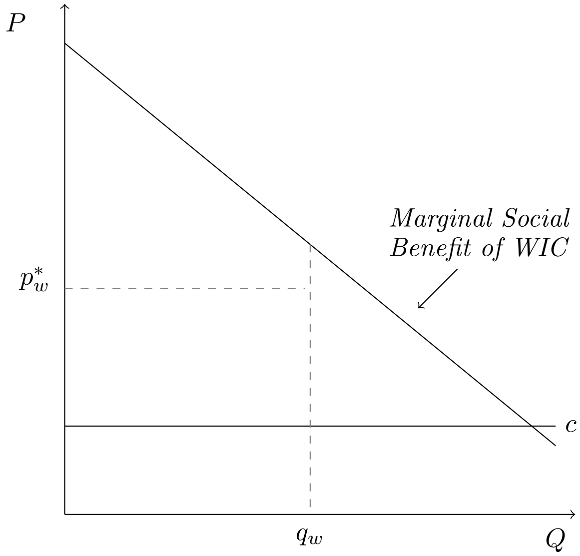


(B) *After EBT*: WIC stores charge their non-WIC and WIC customers p^*_{ebt}. Because p^*_{ebt} reflects pooled WIC and non-WIC demand, and WIC demand is inelastic, $p^*_{ebt} > p^*_{nw}$.

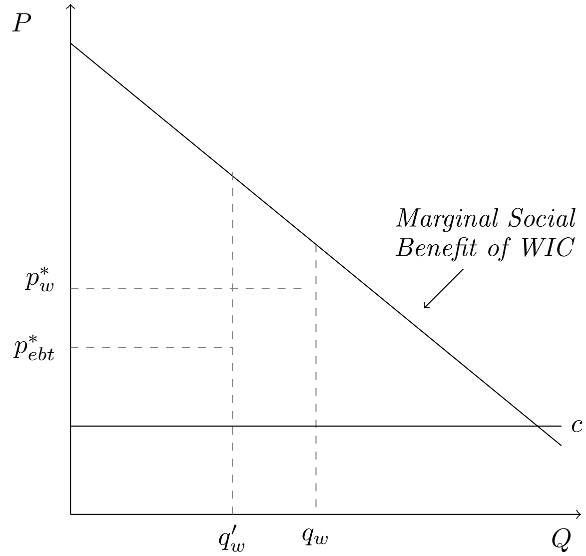


(C) *Change in Welfare Associated with EBT*

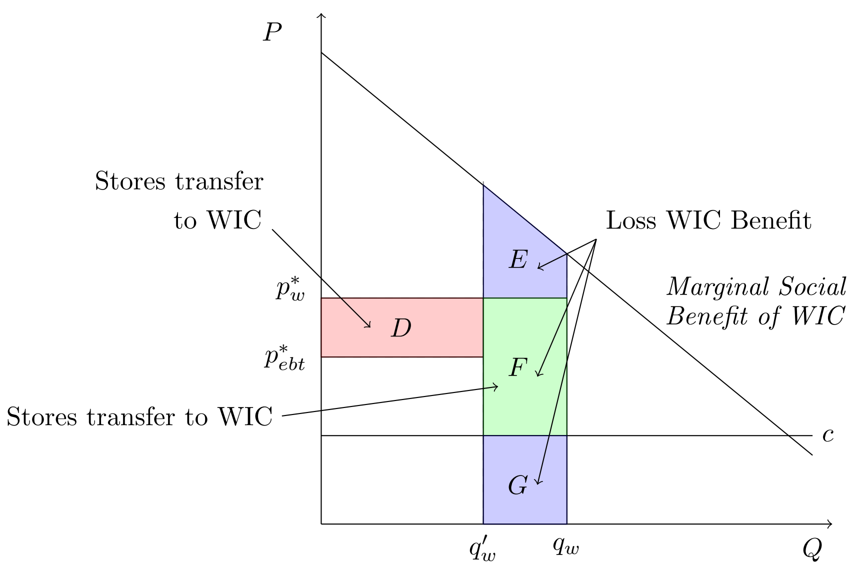
Figure 2: Effect of EBT on Social Welfare: WIC Participation and Program Expenditures



(A) *Before EBT*: Stores distribute benefits q^w and charge WIC customers p_w^* (using paper vouchers). WIC sets q^w; stores choose p_w^* based on sanction rate θ. WIC program surplus = area under the MSB curve up to q^w − program budget, $p_w^* q_w$.

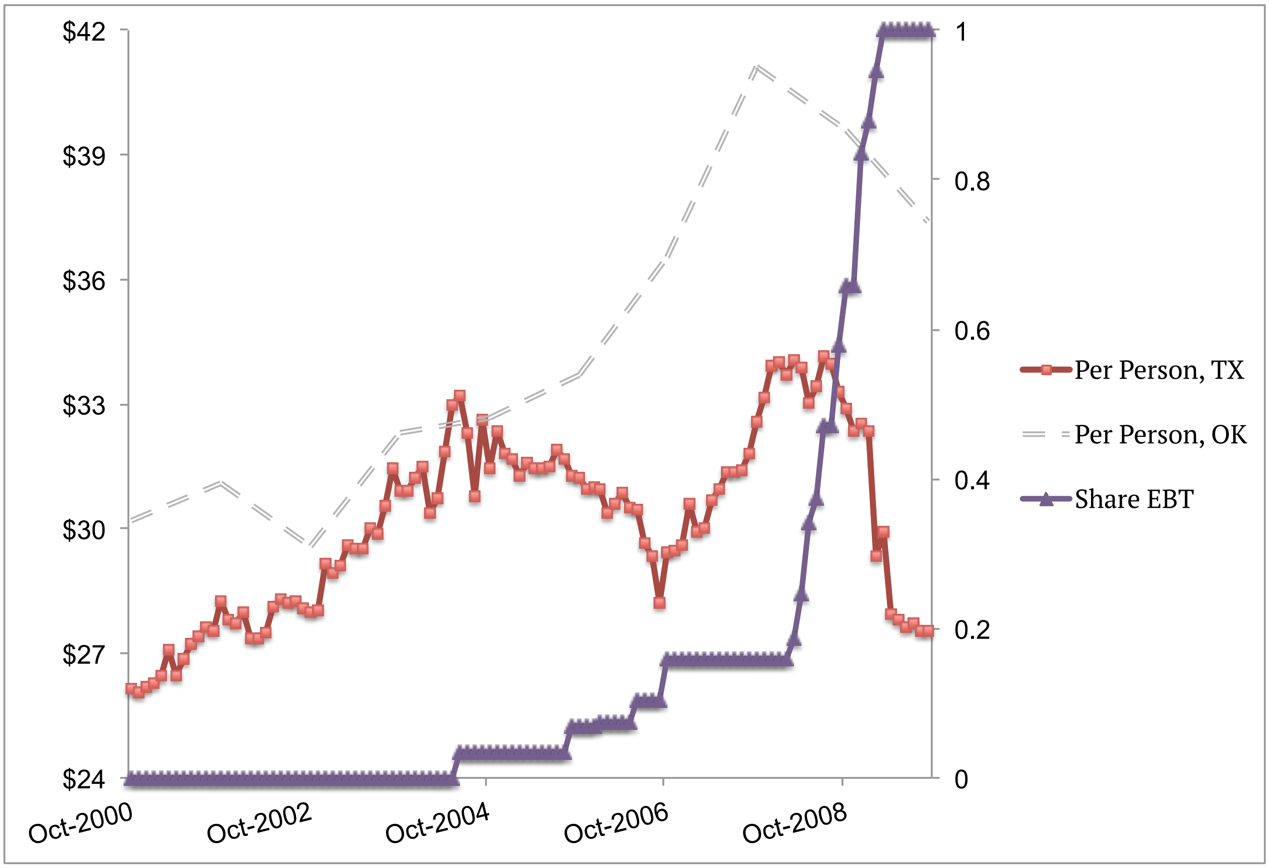


(B) *After EBT*: Stores charge pooling price p_{ebt} to WIC and non-WIC customers. WIC profits fall w/ loss of price discrimination → stores leave WIC → take-up falls ($q^w \rightarrow q^{w\prime}$).



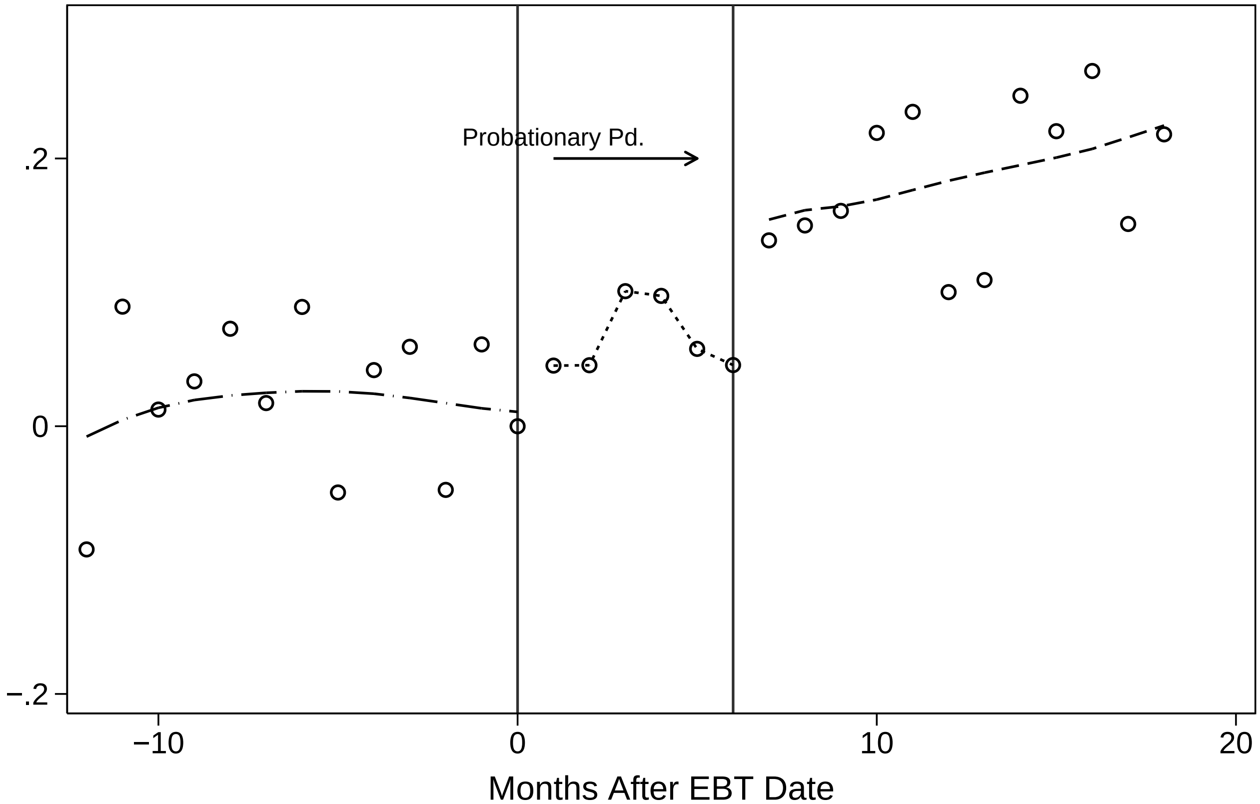
(C) *Change in Welfare Associated with EBT*

Figure 3: Monthly Food Costs During EBT Rollout, Texas WIC



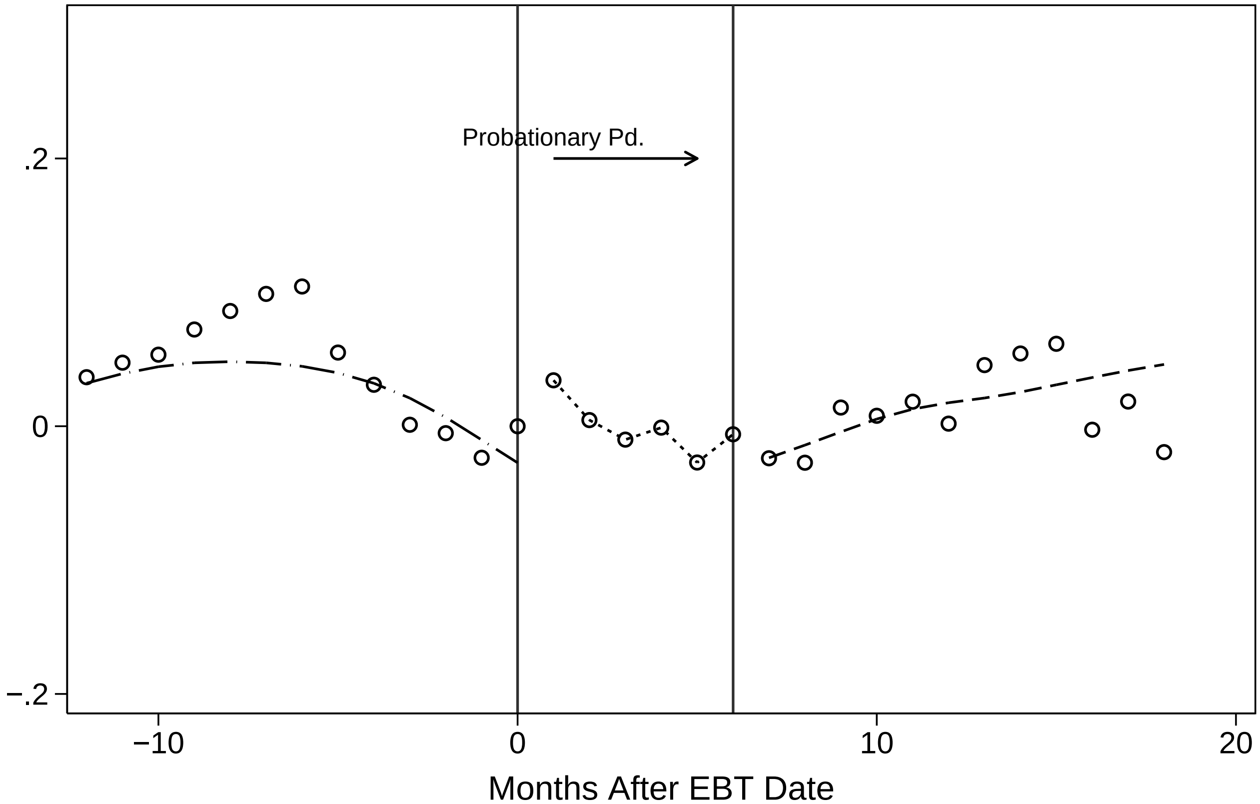
Notes: Share of WIC recipients using EBT is calculated from the births sample as the fraction of mothers residing in counties using EBT. Total monthly post-rebate food outlays and participation for Texas were collected from web crawls of the agency website. Food cost per participant is calculated by dividing food outlays by participation. An accounting change regarding infant formula rebates in June 2007 creates a fixed shift upward in post-rebate food outlays —this difference is subtracted post June 2007. Yearly post-rebate food costs per participant for Oklahoma WIC are from the USDA.

Figure 4: Shelf Prices and EBT, Independent Stores



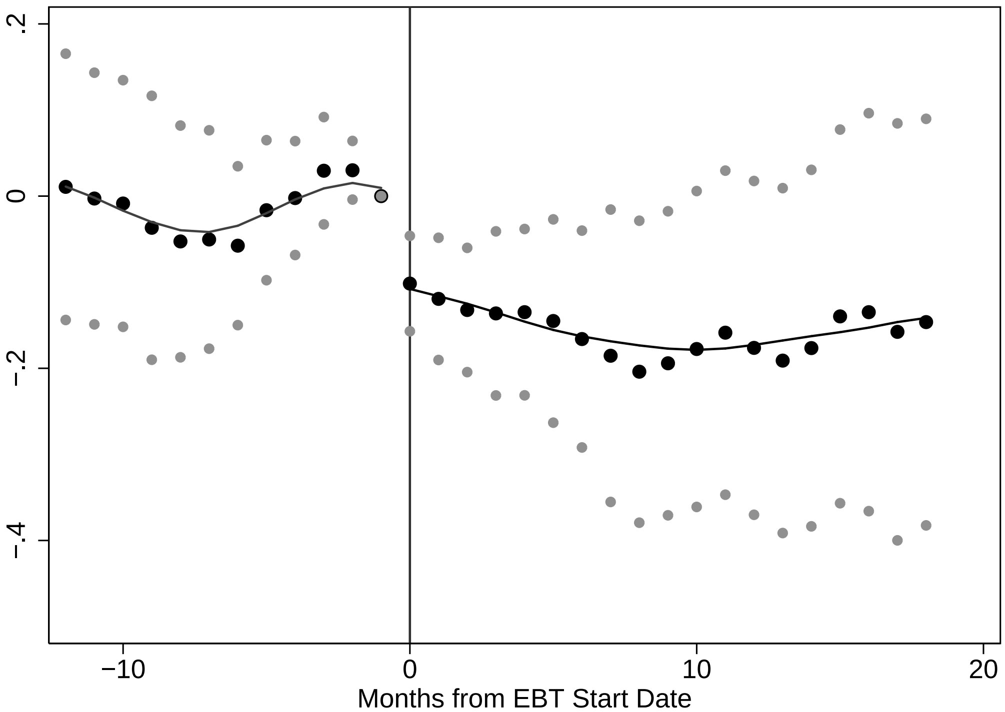
Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of WIC products at single outlet WIC stores only.

Figure 5: Shelf Prices and EBT, Chain Stores



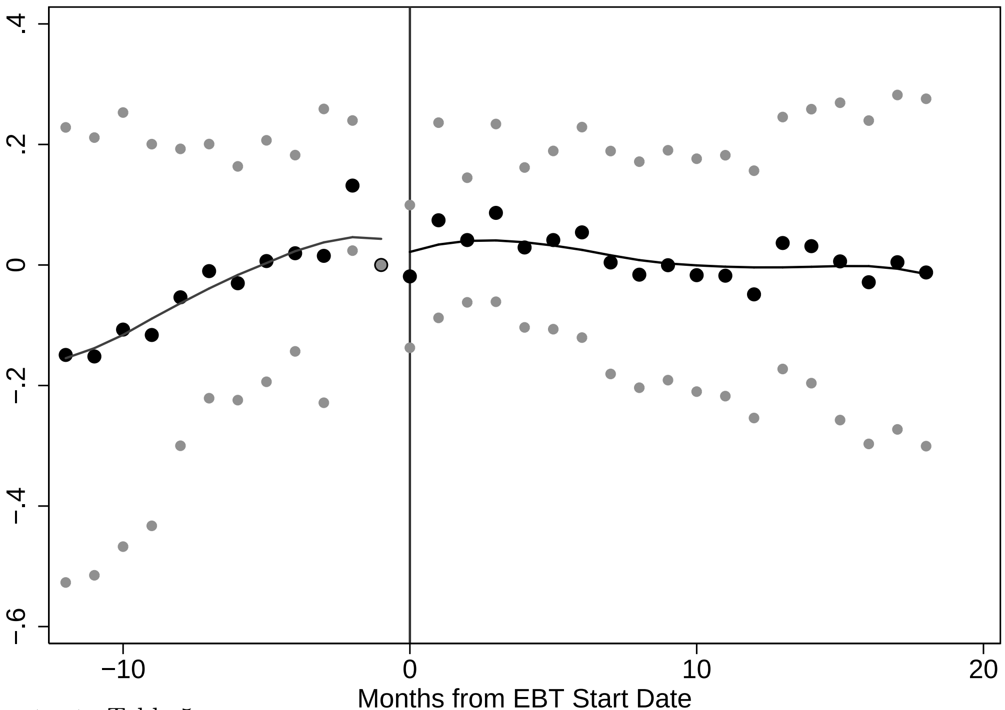
Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of WIC products at chain WIC stores only.

Figure 6: Independent WIC stores and EBT



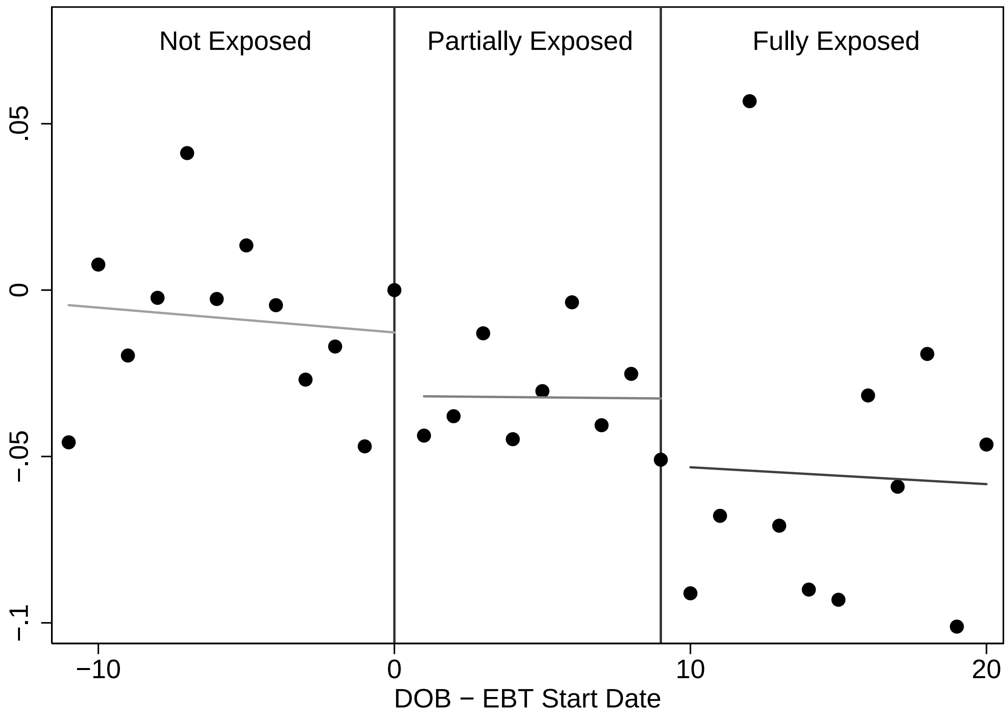
Please see notes to Table 5

Figure 7: Chain WIC stores and EBT



Please see notes to Table 5

Figure 8: Log Total WIC Participation and EBT



Notes: Data are from births records. “Not Exposed” means that the infant was born before EBT, “Partially Exposed” means that EBT rollout occurred during pregnancy, and “Fully Exposed” means that the infant was born after EBT. The outcome is the log of total births per county, year and month. Please see the notes to Table 8 for further details on the sample construction.

Table 1: Example Food Packages

Recipient		Formula/Milk	Cheese	Cereal	Juice	Eggs	PB	Beans
Women	**Pregnant and Breastfeeding**	5 ½ gallons	2 lbs	36 oz Adult	6 Juices: 46 fl oz. or 12 oz. frozen	2 doz	18 oz PB OR 1 lb beans	
Women	**Postpartum**	4½ gallons	2 lbs	36 oz Adult	4 Juices: 46 fl oz. or 12 oz. frozen	2 doz		
Infants, Formula Fed	**0 - 3 Months**	Formula, Assorted Amounts						
	4 - 5 Months	Formula, Assorted Amounts		16 oz Infant				
	6 - 11 Months	Formula, Assorted Amounts		16 oz Infant	2 Juices: 46 fl oz. or 12 oz. frozen			
Infants, Breastfed Only	**0 - 3 Months**							
	4 - 5 Month			16 oz Infant				
	6 -11 Months			16 oz Infant	2 Juices: 46 fl oz. or 12 oz. frozen			
Children	**Age 1**	4½ gallons, Whole Milk only	2 lbs	36 oz Adult	4 Juices: 46 fl oz. or 12 oz. frozen	2 doz		1 lb
	Ages 2-4	4½ gallons	2 lbs	36 oz Adult	4 Juices: 46 fl oz. or 12 oz. frozen	2 doz	18 oz PB OR 1 lb beans	

Notes: foods shown are standard monthly food packages in FY 2007 from Texas WIC. Pregnant women, breastfeeding women and children over 2 also have a choice of either 1 lb dried beans or 18 oz peanut butter. Modifications to the standard food package are made for groups with special needs. Some examples: exclusively breastfeeding mothers additionally receive tuna and carrots; lactose intolerant participants can receive lactose free milk in place of regular milk; families with no refrigeration receive dry powdered milk and extra beans and peanut butter in place of eggs and cheese. Author's analysis of food packages distributed by Texas WIC in March 2014 reveals that 94% of these packages are the standard version summarized above for FY 2007.

Table 2: Timing of EBT Rollout and Mother Characteristics

Outcome:			
LTHS	0.0028 0.0005 (0.0037) (0.0039)	Teen Mom	-0.0027** -0.0014 (0.0011) (0.0010)
HS	-0.0011 -0.0015 (0.0040) (0.0044)	Age 20-24	0.0000 0.0008 (0.0013) (0.0014)
Some College	-0.0020 0.0000 (0.0023) (0.0015)	Age 25-29	0.0009 0.0001 (0.0014) (0.0014)
College	-0.0002 0.0011 (0.0015) (0.0011)	Age 30-39	0.0018 0.0003 (0.0019) (0.0012)
Adv Degree	0.0000 -0.0002 (0.0008) (0.0006)	Age 45+	0.0000 0.0002 (0.0005) (0.0005)
Hispanic	0.0022 0.0002 (0.0026) (0.0017)	Infant Female	-0.0005 0.0006 (0.0015) (0.0014)
Non-Hisp Black	0.0006 0.0008 (0.0007) (0.0007)	Parity = 1	-0.0028 -0.0023 (0.0025) (0.0023)
Non-Hisp White	-0.0017 0.0004 (0.0026) (0.0018)	Parity = 2	0.0029 0.0019 (0.0018) (0.0018)
Other race	-0.0011 -0.0015** (0.0006) (0.0007)	Parity = 3	0.0012 0.0010 (0.0012) (0.0011)
Married	0.0036 0.0018 (0.0026) (0.0026)	Parity = 4	-0.0010 -0.0006 (0.0008) (0.0008)
Reported Occ	0.0028 -0.0055 (0.0098) (0.0074)	Parity = 5	0.0001 0.0001 (0.0004) (0.0004)
N	1,923,827 1,923,827		1,923,827 1,92,3827
Time Trends	No Yes		No Yes

Notes: The sample consists of the universe of births in Texas from 2005-2009 and the level of observation is an individual birth. Each coefficient and standard error is from a separate regression where the outcome indicated is the dependent variable. The coefficient reported is on “After EBT,” an indicator for whether the date of birth is on or after the county’s EBT roll-out date. All regressions contain birth year, birth month, and county fixed effects and standard errors are clustered on county of residence. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Table 3: Effect of EBT on Store Monitoring and Violations

	Independent		Chain	
	(1)	(2)	(3)	(4)
	Any Monitoring	Violation Found	Any Monitoring	Violation Found
after EBT	0.0543+	-0.1522**	-0.0295***	-0.1559***
	(0.0304)	(0.0649)	(0.0078)	(0.0379)
N	11,618	1,264	88,182	5,622
Mean, Dep. Var.	0.2423	0.4802	0.1014	0.3095
Sample:	All	Rand. Samp.	All	Rand. Samp.
TT	yes	yes	yes	yes

Notes: The data source is Texas WIC administrative vendor records for FY 2007-2010. The regression sample is an unbalanced panel with one observation for each year-month-WIC store. "Random Sample" refers to a subsample of all Texas stores chosen at random from a pool of "high-risk" stores by the Texas WIC state agency for compliance investigations from 2006-2008. "Any Violations" therefore refers to the outcome of a single compliance investigation per store, and time periods before the compliance investigation are dropped from the sample. Regressions in Columns (1) and (3) include store ID, year, and month fixed effects and cluster on the store ID, comparing likelihood of monitoring before and after EBT *within* store. "Any Violations" regressions in Columns (2) and (4) include county, year and month fixed effects and cluster on store ID, comparing the likelihood of violation *across* stores who have EBT or not at the time of their random compliance investigation. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Table 4: Effect of EBT on Shelf Prices of WIC Foods

	(1)	(2)
WIC Chain*WIC Product*After EBT	-0.0034	-0.0016
	(0.0097)	(0.0099)
Independent WIC Store*WIC Product*After EBT	0.0960***	0.0894**
	(0.0335)	(0.0375)
Purchases	430,587	430,587
Cluster on	Store	Store
Zip Code Controls	No	Yes

Notes: The sample is drawn from the Nielsen Consumer Panel, 2004-2009, and contains all purchases of cheese and eggs made by residents of Texas. The outcome is log price, where price is net of any discounts or coupons. "WIC Product" indicates the product purchased is WIC-eligible (see Appendix Table 1). "WIC Chain" or "WIC Independent Store" is a proxy indicator for whether the product is purchased at WIC store. The remaining triple difference coefficients are reported in Table **??**. Each specification includes fixed effects for store, county of residence of the panelist, purchase month, year and weekday, and UPC. County specific time trends are included. Standard errors are clustered on county. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Table 5: Effect of EBT on Total WIC Stores by County

	Independent			Chain		
	(1)	(2)	(3)	(4)	(5)	(6)
after EBT	-0.2635***	-0.2750***	-0.0998**	0.0558	0.0351	-0.0045
	(0.0982)	(0.1033)	(0.0434)	(0.1217)	(0.1246)	(0.0802)
N	11,424	11,424	11,424	11,424	11,424	11,424
Mean, Dep. Var.	1.0170	1.0170	1.0170	7.7190	7.7190	7.7190
Time Trends	No	No	Yes	No	No	Yes
Year*Month FE	No	Yes	No	No	Yes	No

Notes: The sample consists of administrative records on WIC stores collected by the Texas State WIC Agency for 10/2006 to 9/2010. The observation level is county-year-month and the outcome is the number of WIC stores per county-year-month cell, separately for chain versus independent stores. Chain status is determined based on (1) whether the store has an outlet ID (2) whether 2 or more stores of the same name participate in WIC in the given year-month. Pharmacies, military commissaries and WIC-only stores are excluded. Month of entry and exit for each store is determined using reported redemption months per year and whether the store is a new store in the given year. All regressions include year, month and county fixed effects and standard errors are clustered on county. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Table 6: Effect of EBT on Likelihood a Store Exits WIC

	Independent			Chain		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline						
after EBT	0.0240***	0.0255***	0.0211***	0.0005	0.0022	-0.0006
	(0.0065)	(0.0065)	(0.0067)	(0.0021)	(0.0022)	(0.0027)
Panel B: Add Interaction with ZIP Poverty						
after EBT*ZIP Poverty	0.1226***	0.1248***	0.0714+	0.0319**	0.0288**	0.0281**
	(0.0329)	(0.0337)	(0.0391)	(0.0112)	(0.0115)	(0.0112)
after EBT	-0.0081	-0.0067	-0.0011	-0.0042**	-0.0028	-0.0042+
	(0.0106)	(0.0103)	(0.0132)	(0.0019)	(0.0022)	(0.0024)
N	11,529	11,529	11,529	87,643	87,643	87,643
Mean, Dep. Var.	0.0228	0.0228	0.0228	0.0093	0.0093	0.0093
Time Trends	No	No	Yes	No	No	Yes
Year*Month FE	No	Yes	No	No	Yes	No

Notes: This table presents the estimates from two separate specifications. The upper panel shows coefficients from the baseline store fixed effects model (Equation 2) and the lower panel re-estimates the same model, adding an interaction between $AfterEBT_{tc}$ and ZIP code poverty. Each coefficient and standard error pair are from a distinct regression. The sample is an unbalanced panel of WIC stores with one observation for each year-month a store participated in Texas WIC during FY 2007-2010. Pharmacies, military commissaries and WIC-only stores are excluded. The outcome is whether a stores exits the WIC program in a given month-year. If a store exits after the end of my sample period, then the exit outcome equals 0 for all periods. ZIP code poverty is a continuous variable equal to the percentage of residents living under the Federal Poverty Level in the ZIP code of a WIC store (Source: US Census Bureau, American Community Survey, 2011 5 year estimates, 2007-2011, Table S1701). All regressions include year, month and store ID fixed effects. Robust standard errors are clustered on county. Store Fixed effects adjust for differences in entry date across stores. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Table 7: Propensity to Purchase WIC Foods, by Neighborhood Poverty

	(1)	(2)
Percent of ZIP in Poverty	-0.0839**	-0.0879+
	(0.0408)	(0.0511)
Obs.	2,347	1,683
Mean, Dep. Var.	0.1110	0.1123
Households:	All	No Kids

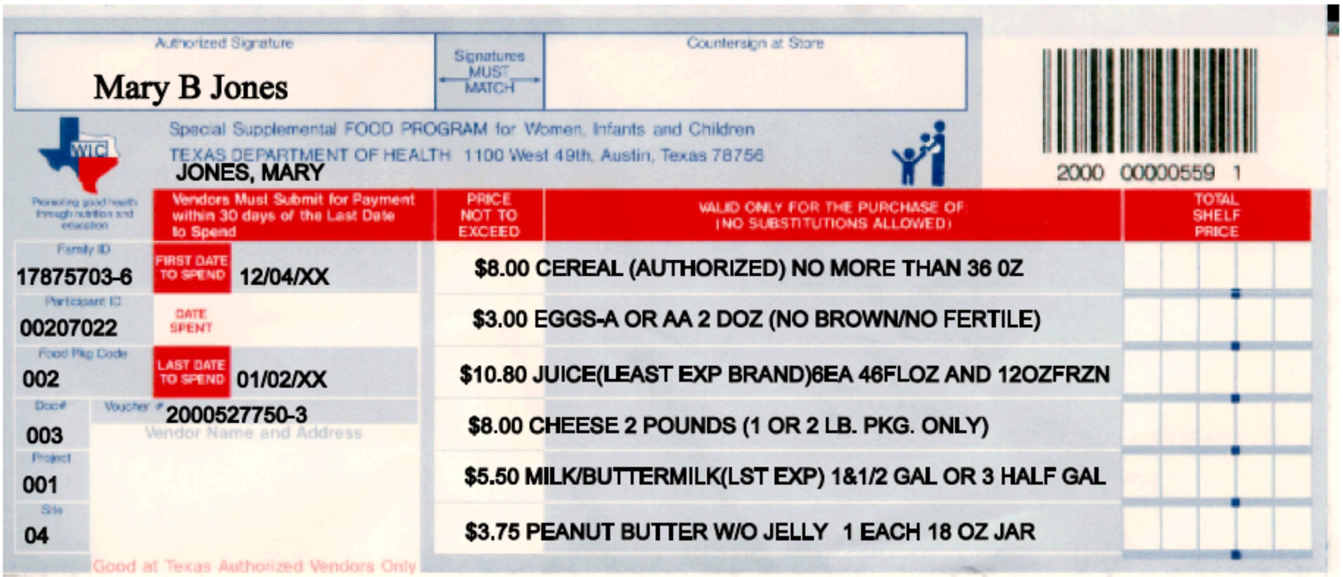
Notes: The sample is drawn from the Nielsen Homescan Consumer Panel, 2004-2009. Each observation is a household-year and the sample is restricted to households living in Mississippi. The outcome is the percent of the household's annual food expenditures spent on nutritional foods, as defined by the WIC program (I count any purchases of milk, cheese, eggs, peanut butter, dry beans, and juice). I define food expenditures as total purchases of the following categories: alcoholic beverages, dairy, deli, dry grocery, fresh produce, frozen food, and meat. "No kids" excludes any household without any co-resident children under the age of 18 in the year of purchase.The table presents the result of regressing the outcome on the percent of residents living under the poverty level in the household's ZIP code. ZIP code poverty for Mississippi comes from the US Census Bureau, 2011 American Community Survey, 5 year estimates, 2007-2011, Table S1701. Also include in the regression are year and household ID fixed effects (coefficients not shown). + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Table 8: Effect of EBT on WIC Participation

	Log WIC Births			Share WIC Births		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Births						
After EBT	-0.0312***	-0.0332***	-0.0334***	-0.0142***	-0.0123**	-0.0154***
	(0.0115)	(0.0119)	(0.0110)	(0.0050)	(0.0048)	(0.0051)
N	13,786	13,786	13,786	14,167	14,167	14,167
Panel B: Births to Minority Moms						
After EBT	-0.0344**	-0.0345**	-0.0377***	-0.0175**	-0.0146**	-0.0224***
	(0.0135)	(0.0139)	(0.0132)	(0.0071)	(0.0069)	(0.0076)
N	12,988	12,988	12,988	13,441	13,441	13,441
Year-Month FE		Yes			Yes	
Time Trends			Yes			Yes

Notes: The sample consists of the universe of birth certificates in Texas during 2005-2009. "After EBT" indicates the date of birth is on or after the county's EBT roll-out date. Texas birth certificates report whether the mother received WIC at all during her pregnancy. The outcome is the sum of WIC births at the county-year-month level—in Columns 1-3, the sum is logged, whereas in Columns 4-6, it is expressed as the share of total births per county-year-month cell. The level of observation is county-year-month. All regressions contain birth year, birth month, and county fixed effects and standard errors are clustered on county of residence. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Figure 1: Paper Voucher, Texas WIC

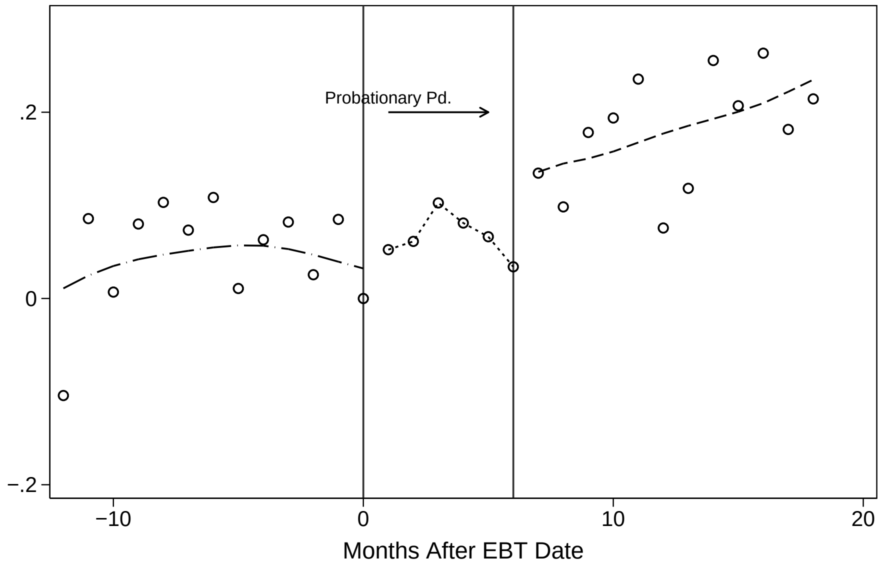


Source: Texas WIC: `http://www.dshs.state.tx.us/wichd/`

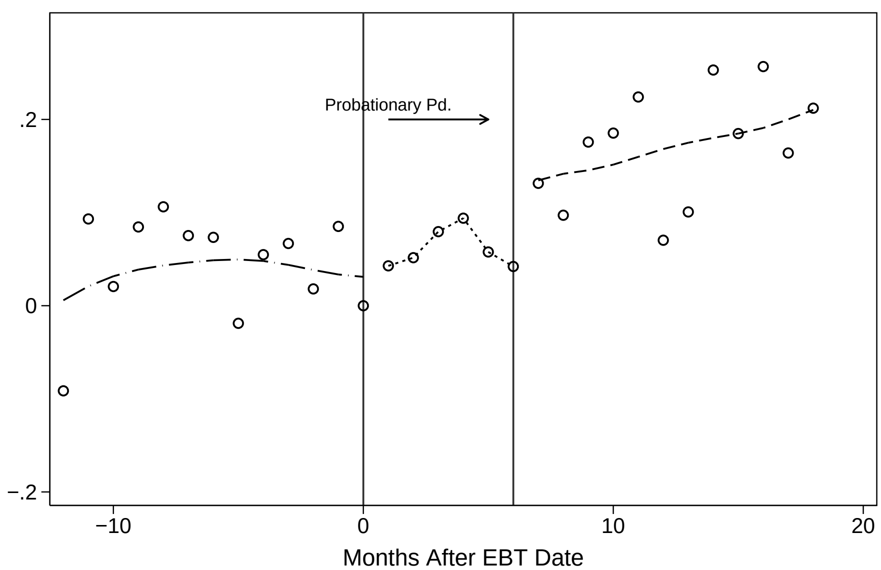
Appendix Figure 2: EBT Card, Texas WIC

Source: Texas WIC: `http://www.dshs.state.tx.us/wichd/`

Appendix Figure 3: Shelf Prices and EBT, Single Outlets, Other Spec'ns

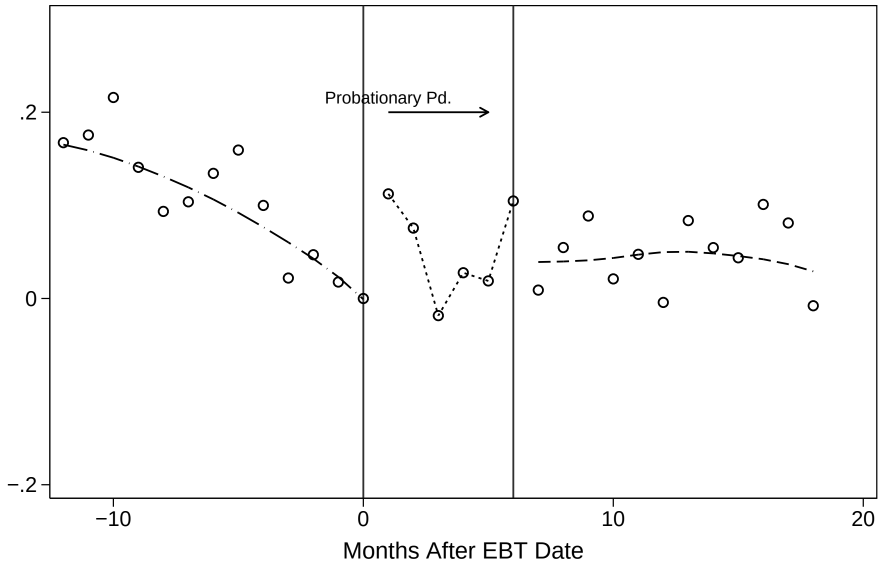


Add Store ID and ZIP Code Interactions. Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of WIC products at single outlet WIC stores only.



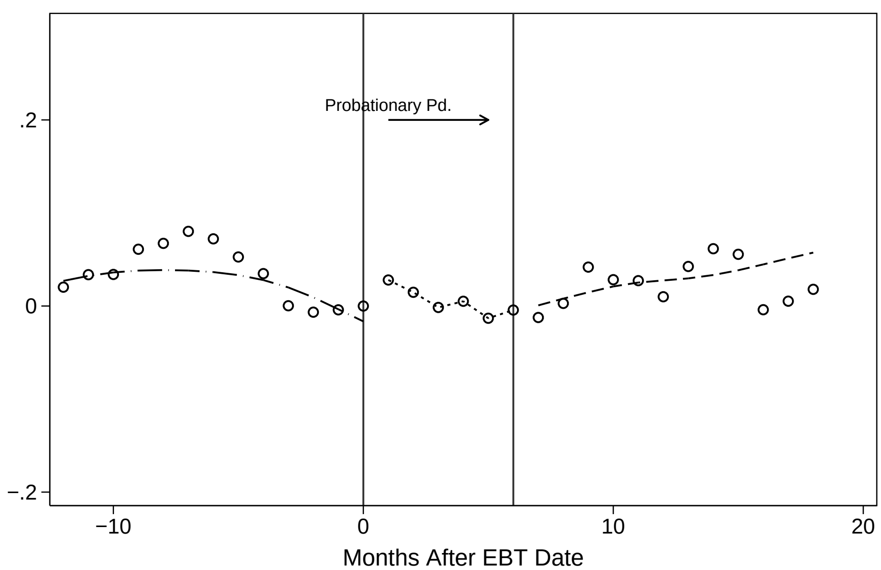
Add County Specific Linear Time Trends. Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of WIC products at single outlet WIC stores only.

Appendix Figure 4: Shelf Prices and EBT: non-WIC Products, Single Outlet WIC Stores



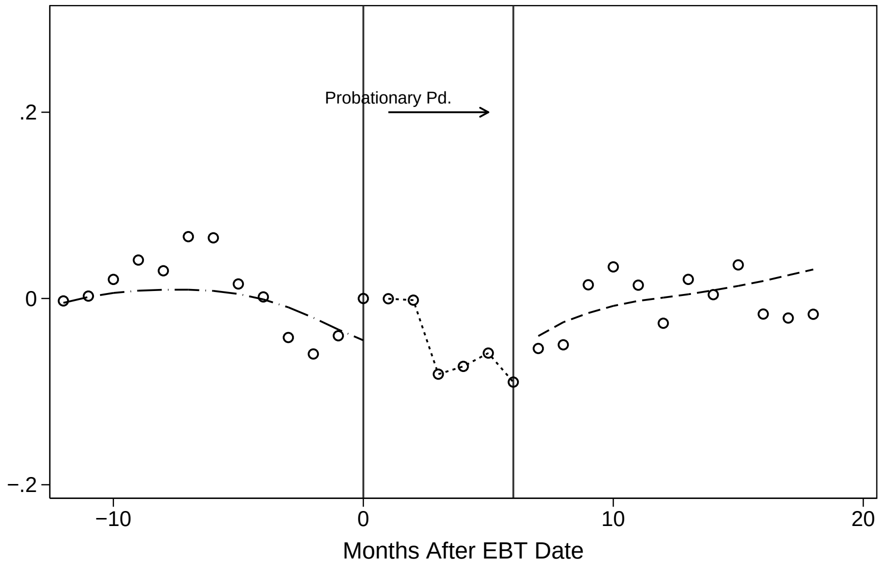
Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of non-WIC products at single outlet WIC stores only.

Appendix Figure 5: Shelf Prices and EBT: non-WIC Products, Chain WIC Stores



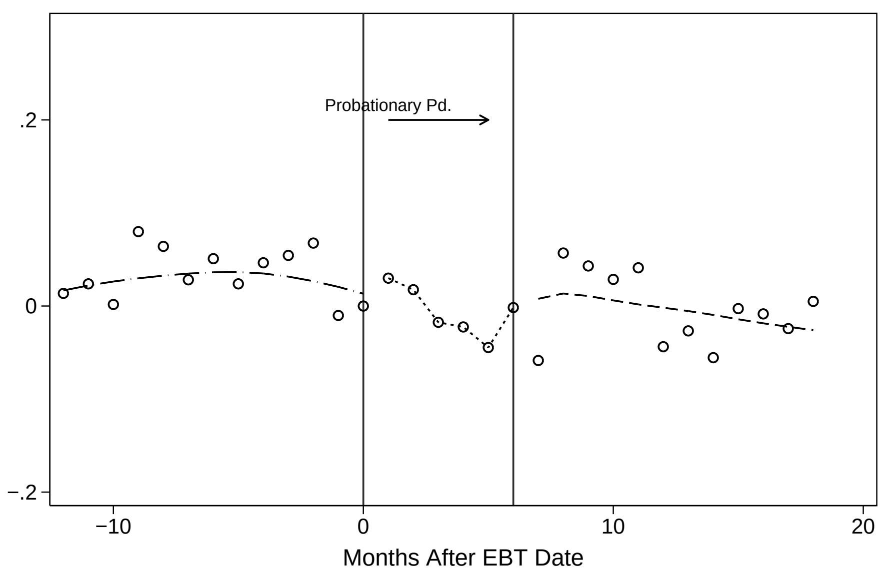
Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of non-WIC products at single outlet WIC stores only.

Appendix Figure 6: Shelf Prices and EBT: WIC Products, non-WIC Stores, Single Outlets



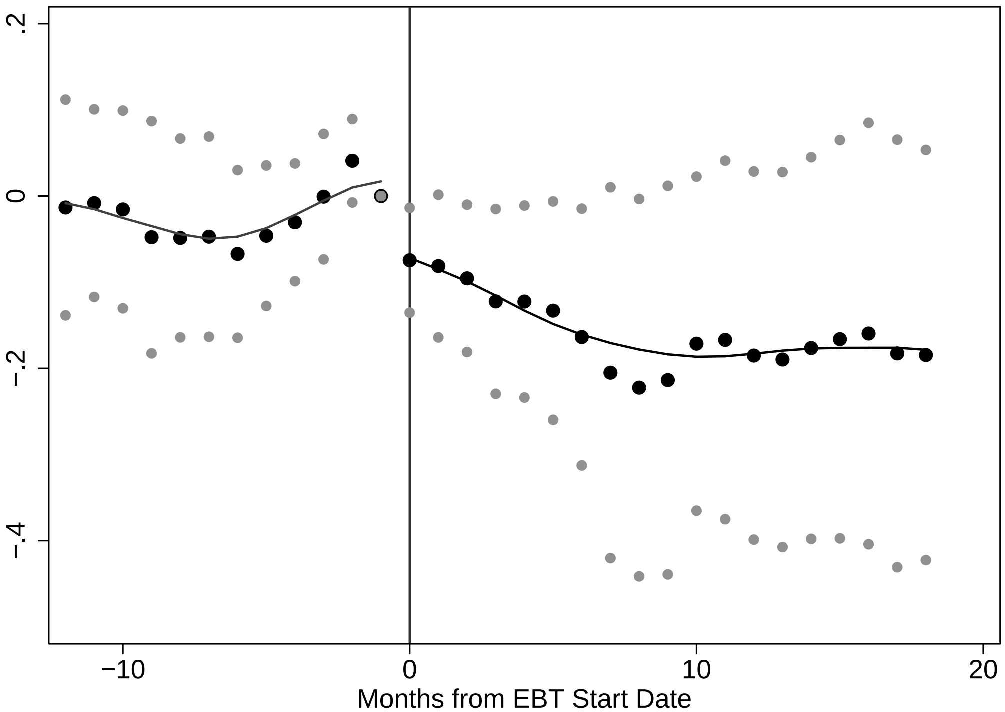
Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of WIC products at non-WIC single outlet stores only.

Appendix Figure 7: Shelf Prices and EBT: WIC Products, non-WIC Stores, Chains



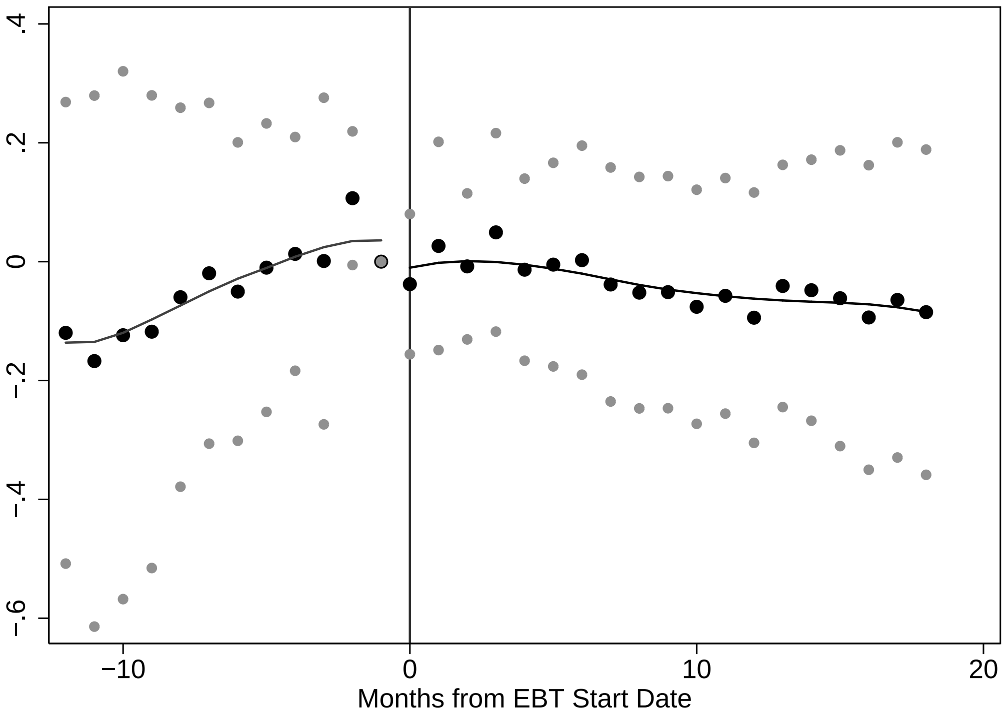
Please see notes to Table 4. The sample used to produce this graph is restricted to purchases of WIC products at non-WIC chain stores only.

Appendix Figure 8: Independent WIC stores and EBT, add Time Trends



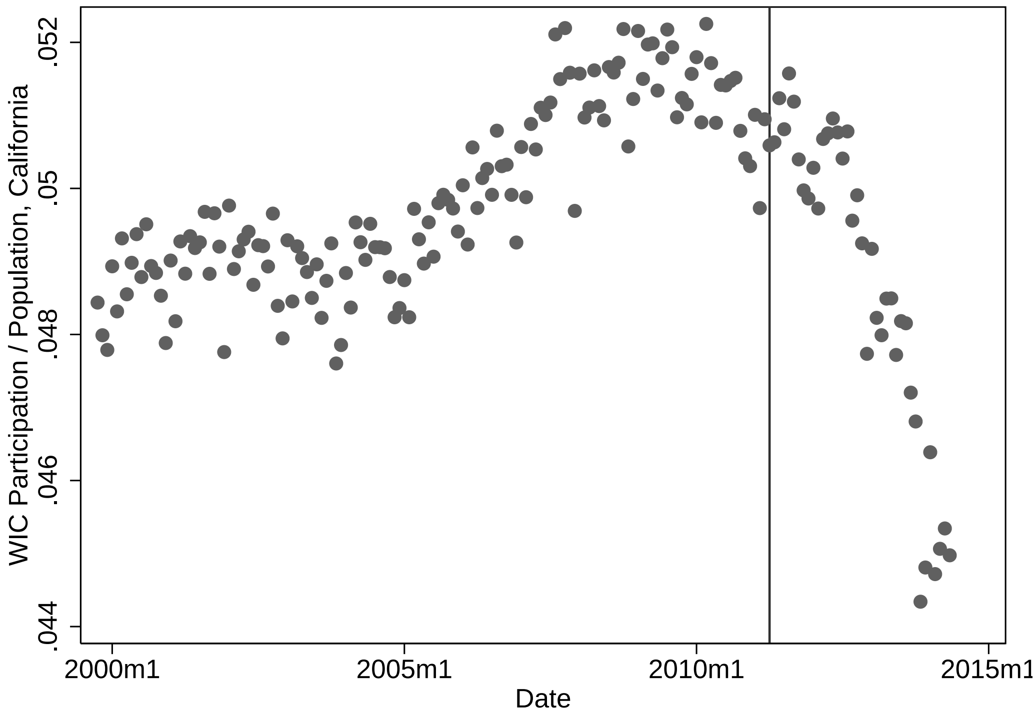
Please see notes to Table 5 for information on the sample. This specification adds county-specific linear time trends as controls.

Appendix Figure 9: Chain WIC stores and EBT, add Time Trends



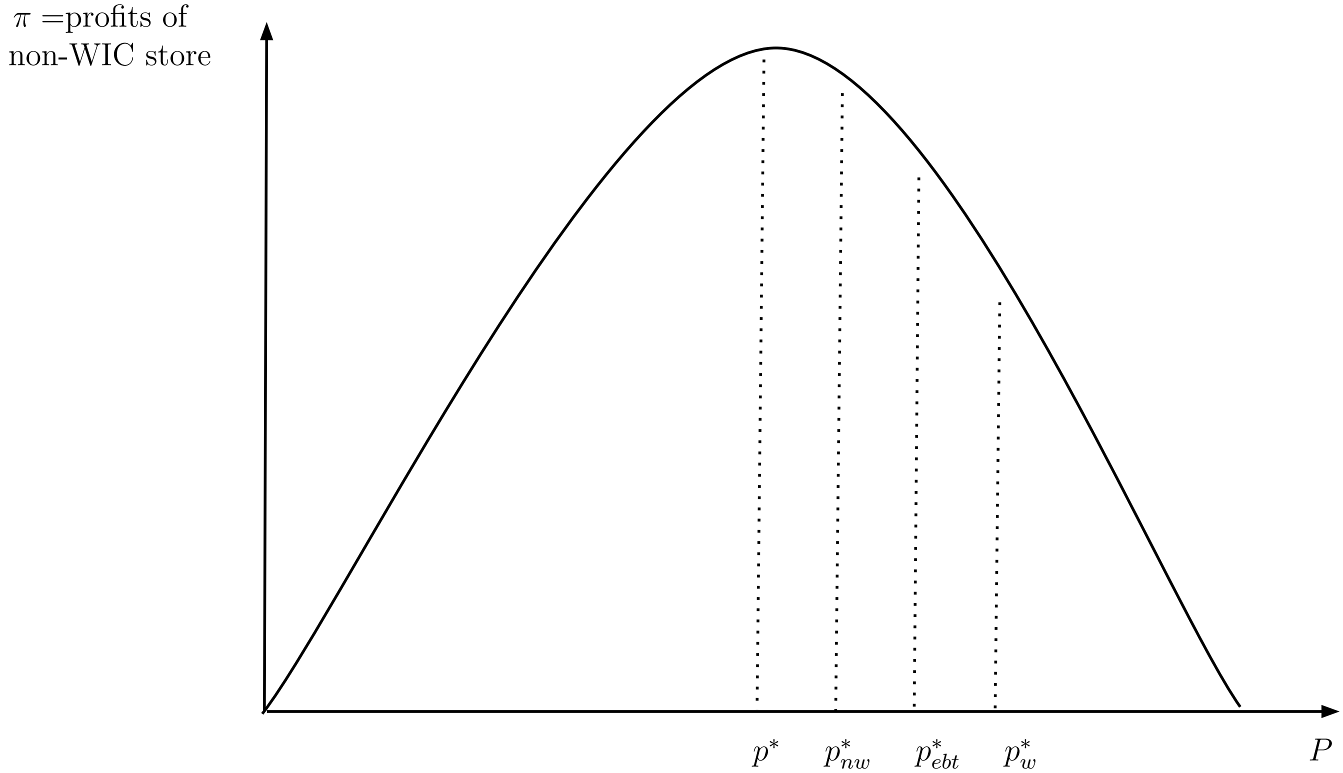
Please see notes to Table 5 for information on the sample. This specification adds county specific linear time trends as controls.

Appendix Figure 10: Moratorium on New stores and WIC Participation, California



Notes: Data used in this figure is from the USDA. Monthly WIC participation for California for FY 2008-present are found here: `http://www.fns.usda.gov/pd/wic-program`. WIC participation for FY 2000-2007 was obtained through a Freedom of Information Act (FOIA) request made by the author to the FNS WIC office. Total participation counts all women, children and infants issued food vouchers in a given month. Monthly population is measured by the Census Bureau as the civilian noninstitutional persons 16 years of age and older residing in California (Source: `http://www.bls.gov/lau/rdscnp16.htm`). The X-line indicates April 2011, the date the USDA imposed a moratorium on all new WIC store authorizations in California.

Appendix Figure 11: Equilibrium Prices and a Non-WIC Store's Profit Function



Appendix Table 1: WIC Food Specifications

	WIC Foods	Non-WIC Foods
Eggs	Large, Medium or Small Grade A or AA 1 dozen	Extra Large, Jumbo Grade B 6, 18 count Brown, Fertile, Free-Range, Organic
Cheese	American, Cheddar, Colby, Colby-Jack, Longhorn, Monterey-Jack, Mozzarella Sliced or block 1 or 2 pound packages	Peppercorn, Muenster, Swiss, processed cheese food (Velveeta) Individually wrapped slices, shredded, cheese from deli 1/2 pound package, 7 oz. package
Peanut Butter	Creamy or Crunchy 18-oz. jar	With honey, jelly or candy pieces, reduced fat 28 oz., 40 oz., etc.

Notes: This information is compiled from archived versions of the WIC food list on the Texas WIC website, available here: `http://www.dshs.state.tx.us/wichd/vo/flist.shtm`

Appendix Table 2: WIC Sales, by Grocery Store Type

	Grocery Chains	Single Outlet Stores
Monthly WIC Sales	$37,690.74	$19,942.90
- as a Fraction of Total Sales	0.0640	0.2846
Total Grocery Stores	67,300	28,700

Notes: Total monthly sales per grocery store for the years 2005-2008 is calculated by combining data from (a) the Monthly and Annual Retail Trade report from the Census bureau and (b) the number of establishments by industry from the County Business Patterns (see Tables 1048 and 1051 in the 2012 Statistical Abstract of the U.S., Census Bureau, section "Wholesale and Retail Trade": `https://www.census.gov/prod/2011pubs/12statab/domtrade.pdf`. Previous statistical abstracts were also used to supplement some years of establishment counts). The industry classification used is NAICS 4451, Grocery Stores, which are classified either as "Supermarkets and other groceries (non-convenience)" (NAICS 44511) or "Convenience Stores" (NAICS 44512). Second, to estimate average WIC sales per store, I multiply the per participant value of the monthly WIC transfer $58.60, (Source: See 6.) by average monthly participants per store. I proxy for average monthly participants per store nationwide using figures from State of Kansas' WIC Program, the only state to release store-level participant counts and store size classifications. I calculate average participants per month and store for 2004-2009, separately for independent stores versus chain stores, where store type is coded by Kansas WIC (note that because the NAICS classification differentiate between supermarkets and convenience stores, the Kansas classification system is not exactly comparable, but serves as a proxy classification).

Appendix Table 3: Roll Out Schedule for Texas MMC

Date	Counties
Jun 2004	El Paso, Hudspeth
Sep 2005	Collin
Jan 2006	Grayson
Jun 2006	Andrews, Brewster, Coke, Coleman, Concho, Crane, Crockett, Culberson, Ector, Howard, Jeff Davis, Kimble, Martin, Mason Mcculloch, Menard, Midland, Pecos, Presidio, Reagan, Reeves, Runnels, Schleicher, Sutton, Taylor, Tom Green, Upton, Ward, Winkler
Oct 2006	Archer, Armstrong, Bailey, Baylor, Brown, Callahan, Carson, Castro, Childress, Clay, Cochran, Collingsworth, Cottle, Crosby, Dallam, Dawson, Deaf Smith, Dickens, Donley, Eastland, Floyd, Foard, Gaines, Garza, Gray, Hale, Hall, , Hansford, Hardeman, Haskell, Hemphill, Hockley, Hutchinson, Jones, Knox, Lamb, Lipscomb, Lubbock, Lynn, Mitchell, Moore, Motley, Nolan, Ochiltree, Parmer, Potter, Randall, Scurry, Shackelford, Sherman, Stephens, Stonewall Swisher, Terry, Wheeler, Wichita, Wilbarger, Yoakum, Young,
Mar 2008	Denton
Apr 2008	Bastrop, Bell, Brazos, Burleson, Caldwell, Comal, Coryell, Grimes, Guadalupe, Hays, Leon, Madison, Mclennan, Milam, Robertson, Travis, Washington
May 2008	Bexar, Bosque, Freestone, Hill, Limestone, Williamson
Jun 2008	Atascosa, Bandera, Bee, Blanco, Edwards, Fayette, Frio, Gillespie, Gonzales, Hardin, Jefferson, Karnes, Kendall, Kerr, Lavaca, Lee, Medina, Real, Wilson
Jul 2008	Anderson, Angelina, Bowie, Camp, Cass, Chambers, Cherokee, Delta, Fort, Bend, Franklin, Galveston, Gregg, Harrison, Henderson, Hopkins, Jasper, Marion, Morris, Navarro, Newton, Panola, Rains, Red, River, Rusk, Sabine, San Augustine, Smith, Titus, Upshur, Van Zandt, Wharton, Wood
Sep 2008	Dallas
Oct 2008	Tarrant
Dec 2008	Harris
Jan 2009	Austin, Brazoria, Colorado, Liberty, Matagorda, Montgomery, Waller
Feb 2009	Aransas, Brooks, Calhoun, De Witt, Dimmit, Duval, Goliad, Houston, Jackson, Jim Hogg, Jim Wells, Kinney, Kleberg, La Salle, Live Oak, Maverick, Nacogdoches, Nueces, Orange, Polk, Refugio, San Jacinto, San Patricio, Shelby, Trinity, Tyler, Uvalde, Val Verde, Victoria, Walker, Webb, Willacy, Zapata, Zavala
Mar 2009	Cameron, Hidalgo, Starr

Source: Texas WIC Staff, Department of State Health Services

Appendix Table 4: Summary Statistics, Nielsen Sample, 2004-2009

Purchase is:	Mean
WIC Product	0.2696
at a WIC Chain	0.7425
at a WIC Independent Store	0.0172
WIC Chain & WIC Product	0.2025
WIC Indep. & WIC Product	0.0045
Purchases	430,587

Notes: The sample contains purchases of cheese, eggs or peanut butter made by residents of Texas in the Nielsen Consumer Panel, 2004-2009. WIC products are identified using lists of WIC-eligible products for each year. Whether a purchase is made at WIC store is proxied using an indicator for whether there was a WIC store in the consumer's zip code of residence in the year and month of purchase. Chains are differentiated from independent stores using Nielsen's retailer code (exists for chains only).

Appendix Table 5: Summary Statistics, WIC stores, FY 2007-2010

	(1) Chain	(2) Independent
Months in WIC	33.80	26.62
	(15.69)	(16.31)
Share of Store ZIP in Poverty	0.172	0.244
	(9.656)	(11.50)
Investigation	0.189	0.419
	(0.392)	(0.494)
— *b/c of suspicious prices*	0.168	0.419
	(0.374)	(0.494)
Sanction	0.0627	0.202
	(0.242)	(0.402)
Sanction / Investigation	0.3317	0.4821
Stores	2,569	446

Notes: The data is administrative records on WIC stores from the Texas State WIC Agency. The sample contains one observation for any grocery store which participated in the Texas WIC program from 10/2006 to 9/2010. Months of participation is the total months a store participated in WIC from 10/2006 to 9/2010, so the upper bound is 48. Similarly, "Investigated" indicates the store was ever flagged for investigation *between* 10/2006 and 9/2010 (and likewise for "Sanction"). Data on % households living under the Federal poverty line by zip code is taken from 2007-2011 American Community Survey file.

Appendix Table 6: Maternal Demographics, Texas Birth Certificates, 2005-2009

	(1) All Moms	(2) Moms on WIC
Married	0.593	0.443
Less than H.S.	0.295	0.421
H.S. Diploma	0.271	0.342
Hispanic	0.510	0.665
Non-Hispanic Black	0.111	0.128
WIC	0.531	1
N	1,974,980	1,043,180

Notes: Sample includes the universe of births to residents of Texas from 2005-2009.

Appendix Table 7: Effect of EBT on Shelf Prices of WIC Foods, Remaining Coeff's

	(1)	(2)
Chain*After EBT	-0.0218+	-0.0243+
	(0.0132)	(0.0139)
Single Outlet*After EBT	-0.0225	-0.0201
	(0.0179)	(0.0180)
Chain*WIC Product	0.0073**	0.0073**
	(0.0033)	(0.0033)
Single Outlet*WIC Product	-0.0504+	-0.0487+
	(0.0270)	(0.0268)
WIC Product*After EBT	-0.0146	-0.0147
	(0.0094)	(0.0097)
Chain	0.0053	0.0023
	(0.0037)	(0.0056)
Single Outlet	0.0084	0.0073
	(0.0066)	(0.0059)
After	-0.0147	-0.0159
	(0.0115)	(0.0124)
WIC Product	0.0320	0.0281
	(0.0276)	(0.0261)
Cluster on	Store	Store
Zip Code Controls	No	Yes
	430,587	430,587

Notes: The data sample is from the Nielsen Consumer Panel 2004-2009 and contains all purchases of cheese and eggs made by residents of Texas. The outcome is log price, where price is net of any discounts or coupons. "WIC Product" indicates the product purchased is WIC-eligible (see Table 1). "WIC Chain" or "WIC Independent Store" is a proxy indicator for whether the product is purchased at WIC store. Each specification includes fixed effects for store, county of residence of the panelist, purchase month, year and weekday, and UPC. County specific time trends are included. Standard errors are clustered on county. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 8: Effect of EBT on Total stores by County, Webcrawls Data

	Independent			Chain		
	(1)	(2)	(3)	(4)	(5)	(6)
after EBT	-0.2176**	-0.2176**	-0.1825**	0.0975	0.0975	0.0381
	(0.0917)	(0.0917)	(0.0780)	(0.1392)	(0.1392)	(0.1177)
N	1,667	1,667	1,667	1,658	1,658	1,658
Mean, Dep. Var.	1.5003	1.5003	1.5003	7.8254	7.8254	7.8254
Time Trends	No	No	Yes	No	No	Yes
Year*Month FE	No	Yes	No	No	Yes	No

Notes: The observation level is county-year-month and the outcome is the number of WIC stores per county-year-month cell. Separate sums for chain and independent stores are used as outcomes. The data source is archived versions of store lists available publicly on the Texas WIC website. store lists for the following dates are used: 08/2006, 06/2007, 09/2007, 05/2008, 12/2008, 06/2009, and 07/2010. All regressions include year, month and county fixed effects and standard errors are clustered on county. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 9: Effect of EBT on Store Exit, Cox PH Model

	Independent			Chain		
	(1)	(2)	(3)	(4)	(5)	(6)
after EBT	1.8559**	2.01283	2.5072**	1.09043	0.99683	1.05065
	(0.58324)	(0.93055)	(0.0067)	(0.48098)	(0.3857)	(0.5972)
N	11,618	11,618	11,618	88,182	88,182	88,182
Time Trends	No	No	Yes	No	No	Yes
Year*Month FE	No	Yes	No	No	Yes	No

Notes: The sample is an unbalanced panel of WIC stores with one observation for each year-month a store participated in Texas WIC during FY 2007-2010. Pharmacies, military commissaries and WIC-only stores are excluded. The hazard refers to the likelihood a store exits the WIC program in a given month-year. All regressions include year and month fixed effects and the baseline hazard is allowed to vary by county. Robust standard errors are clustered on county. Hazard ratios and standard errors on the underlying coefficients are reported. Observations in which store exited on the same month/year as entry are not used in estimation (3,066 obs. or 3% of the sample).+ indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 10: Effect of EBT on Grocery Store Exits

	Grocery Chains		Convenience Stores	
	(1)	(2)	(3)	(4)
	est	est	est	est
after EBT	2.383*	-0.0560	-0.635	0.433
	(1.306)	(0.314)	(0.492)	(0.406)
Mean, dept. var.	23.11	23.11	14.40	14.40
N	2952	2952	2952	2952
Time Trends	No	Yes	No	Yes

Notes: The outcome is total establishments per county and year for the state of Texas from 1998-2009. The data is taken from the Census County Business Patterns and can be found here: `https://www.census.gov/econ/cbp/index.html`. The first two columns use (as a proxy for chain groceries) NAICS category 445110: "Supermarkets and Other Grocery (except Convenience) Stores." Columns 3 and 4 use as a proxy for independent grocery stores NAICS category 445120: "Convenience Stores." All regressions include year and county fixed effects and robust standard errors are clustered on county. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 11: Do Stores Drop WIC Products After Exiting WIC?

	Independent			Chain		
	(1)	(2)	(3)	(4)	(5)	(6)
after store exits WIC	-0.1308***	-0.1372***	-0.0559+	-0.0476**	-0.0407**	-0.0542**
	(0.0422)	(0.0417)	(0.0336)	(0.0191)	(0.0201)	(0.0260)
N	89,408	89,408	89,408	282,775	282,775	282,775
Mean, Dep. Var.	0.3943	0.3943	0.3943	0.2509	0.2509	0.2509
Time Trends	No	No	Yes	No	No	Yes
Year*Month FE	No	Yes	No	No	Yes	No

Notes: The sample is the Nielsen sample used Table 4, limited to the subset of WIC stores which drop out of WIC following EBT rollout (but do not shut down). The outcome is an indicator for whether the product purchased is WIC-eligible (see Appendix Table 1). "After store exits WIC" indicates the year-month of purchase occurs after the store drops out following EBT rollout. Each specification includes fixed effects for store, ZIP code of residence of the panelist, purchase month and year FE. Linear time trends are county specific and standard errors are clustered on county. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 12: Effect of EBT on Total WIC Births Per County-Year-Month

	(1)	(2)	(3)
Panel A: All Births			
After EBT	-4.4935**	-4.4928**	-4.2284**
	(2.2450)	(2.2518)	(1.9389)
N	14,167	14,167	14167
Panel B: Births to Minority Moms			
After EBT	-4.1815+	-4.1893+	-3.9072**
	(2.2364)	(2.2572)	(1.8888)
N	14,167	14,167	14,167
Year-Month FE		Yes	
Time Trends			Yes

Notes: The sample consists of the universe of birth certificates in Texas during 2005-2009. “After EBT” indicates the date of birth is on or after the county’s EBT roll-out date. Texas birth certificates report whether the mother received WIC at all during her pregnancy. The outcome is the sum of WIC births at the county-year-month level. The level of observation is county-year-month. All regressions contain birth year, birth month, and county fixed effects and standard errors are clustered on county of residence. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 13: Effect of EBT on WIC Participation, Individual Levels Regs.

	(1)	(2)	(3)	(4)
Panel A: All Births				
After EBT	-0.0139***	-0.0139***	-0.0126***	-0.0146***
	(0.0038)	(0.0031)	(0.0032)	(0.0031)
Births	1,923,827	1,923,827	1,923,827	1,923,827
Mean WIC	0.5367	0.5367	0.5367	0.5367
Panel B: Births to Minority Moms				
After EBT	-0.0162**	-0.0156**	-0.0141**	-0.0182**
	(0.0055)	(0.0048)	(0.0051)	(0.0043)
Births	1,187,368	1,187,368	1,187,368	1,187,368
Mean WIC	0.6912	0.6912	0.6912	0.6912
Panel C: Births to Minority Moms with <HS Diploma				
After EBT	-0.0234**	-0.0231**	-0.0204**	-0.0229**
	(0.0068)	(0.0067)	(0.0058)	(0.0066)
Births	486,593	486,593	486,593	486,593
Mean WIC	0.7891	0.7891	0.7891	0.7891
Controls		Yes	Yes	Yes
Year*Month FE			Yes	
Time Trends				Yes

Notes: The sample consists of the universe of births in Texas from 2005-2009. "After EBT" indicates the date of birth is on or after the county's EBT roll-out date. The outcome is whether the mother reports receiving WIC at all during her pregnancy. All regressions contain birth year, birth month, and county fixed effects and standard errors are clustered on county of residence. Also included are the following controls: mother's marital status, child sex, education (no HS diploma, high school, some college, advanced degree), mom's age (<20, 20-24, 25-29, 30-39, 40+), whether mother lists an occupation, and child's parity (1,2,3,4). + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 14: Effect of EBT on WIC, High SES Mothers

	College+ and White			College+, White, and Married		
	(1)	(2)	(3)	(4)	(5)	(6)
After EBT	-0.0031	-0.0030	-0.0025	-0.0023	-0.0024	-0.0019
	(0.0020)	(0.0021)	(0.0019)	(0.0019)	(0.0022)	(0.0019)
N	223,789	223,789	223,789	215,549	215,549	215,549
Mean, Dep. Var.	0.1163	0.1163	0.1163	0.1120	0.1120	0.1120
Year-Month FE		Yes			Yes	
Time Trends			Yes			Yes

Notes: The sample consists of the universe of births in Texas from 2005-2009 in the given SES sample. "After EBT" indicates the date of birth is on or after the county's EBT roll-out date. The outcome is whether the mother reports receiving WIC at all during her pregnancy. All regressions contain birth year, birth month, and county fixed effects and standard errors are clustered on county of residence. Also included are the following controls: mother's marital status, child sex, education (no HS diploma, high school, some college, advanced degree), mom's race and ethnicity (Hispanic, non-Hispanic white, non-Hispanic black, other), mom's age (<20, 20-24, 25-29, 30-39, 40+), whether mother lists an occupation, and child's parity (1,2,3,4). + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Table 15: Effect of EBT on ZIP-Level Access

	(1)	(2)	(3)
Panel A: ZIP Weights = All Moms			
after EBT	-0.0064	-0.0057	-0.0057+
	(0.0039)	(0.0041)	(0.0038)
N	103,584	103,584	103,584
Sum of Weight	18,874,368	18,874,368	18,874,368
Panel B: ZIP Weights = Mom is Minority			
after EBT	-0.0067	-0.0058	-0.0064+
	(0.0047)	(0.0049)	(0.0047)
N	91,536	91,536	91,536
Sum of Weight	11,684,448	11,684,448	11,684,448
Panel C: ZIP Weights = Mom is Minority, no H.S.			
after EBT	-0.0094**	-0.0088**	-0.0079+
	(0.0043)	(0.0044)	(0.0046)
N	78,240	78,240	78,240
Sum of Weight	4,772,544	4,772,544	4,772,544
Year-Month FE	No	Yes	No
Time Trends	No	No	Yes

Notes: The observation level is zip code-year-month and the outcome is an indicator for whether there is at least one WIC store in that ZIP code, year and month. The sample is constructed using WIC administrative data on stores for FY 2007-2010. Observations are weighted by total births per ZIP code for FY 2007 to mothers in the indicated demographic subset, where ZIP code refers to the mother's residence and FY 2007 is used because it is the base year. All regressions include year, month and ZIP code fixed effects and standard errors are clustered on ZIP code. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$

Appendix Section A Heterogeneity in Share WIC Customers

Does heterogeneity in the WIC share of customers predict store dropout following EBT? In particular, stores in high poverty areas have a higher WIC share of customers and higher dropout after EBT, — perhaps higher WIC share, rather than fixed costs, causes dropout. I demonstrate below, however, that stores with a higher WIC share (all else equal) in fact have *less* incentive to leave WIC after EBT.

Suppose there exist two identical WIC, differentiated only by their share of customers in WIC, $m < n$.

The conditions for these stores to drop out of WIC after EBT (set marginal costs = 0) are as follows:

Store n: $np_{ebt}^{n*} > (1-n)(p^*q(p^*) - p_{ebt}^* q_{nw}(p_{ebt}^*)) + \gamma$
Store m: $mp_{ebt}^{m*} > (1-m)(p^*q(p^*) - p_{ebt}^* q_{nw}(p_{ebt}^*)) + \gamma$

Note $np_{ebt}^{n*} > mp_{ebt}^{m*}$ because $n > m$ and $p_{ebt}^{n*} > p_{ebt}^{m*}$

Intuition: higher q_w $\rightarrow$ higher p_{ebt}^* because there are more inelastic WIC customers, which means higher revenue *ex-post* ($p_{ebt}^* q_w$) $\rightarrow$ stores with more WIC customers are *less* likely to drop out following EBT $\rightarrow$ heterogeneity in WIC share of customers does not explain dropout pattern

Appendix Section B Short Proofs, Price Predictions

Recall that a store's profit function if it does not participate in WIC is:

$$\pi = (p - c)q(p)$$

If the store participates in WIC pre-EBT, profits are:

$$\pi^w = (p_w - c - \theta(p_w)(p_w - p_{nw}))q_w - \gamma^w + (p_{nw} - c)q(p_{nw}) = (p_w - c - \theta(p_w)(p_w - p_{nw}))q_w - \gamma^w + \pi(p_{nw})$$

Similarly, post EBT:

$$\pi^{ebt} = (p_{ebt} - c)(q_w + q(p_{ebt})) - \gamma^w = (p_{ebt} - c)(q_w) - \gamma^w + \pi(p_{ebt})$$

Appendix Section B.1 $p^{w*} > p^*_{nw}$

From the FOC for p_w, we have $p^{w*} = p^*_{nw} + \frac{1-\theta}{\theta'}$, so $p^{w*} > p_{nw}$ if $\theta < 1$ and $\theta' > 0$ (✓, assumed).
→ *Intuition:* Inelastic WIC demand leads to a mark up over elastic non-WIC demand.

Appendix Section B.2 $p^*_{ebt} > p^*_{nw}$

Taking the FOCs for p_{nw}, p^*_{ebt}, and p and we have

$$\pi'(p^*) = 0$$

$$\pi'(p^*_{nw}) = -\theta q_w$$

$$\pi'(p^*_{ebt}) = -q_w$$

Therefore, we can easily see that, assuming a concave profit function, $p^* < p^*_{nw} < p^*_{ebt}$ if $\theta > 0$ (✓, assumed). This is visualized in Appendix Figure 11.

→ *Intuition:* Sanction function pushes p^*_{nw} above p^*; the pooling price, p_{ebt} lies above the separating price charged to non-WIC customers, p^*_{nw}

Appendix Section B.3 $p^{w*} > p^*_{ebt}$

The FOC for p^{w*} is $1 - \theta(p^{w*}) - \theta'(p^{w*})(p^{w*} - p_{nw}) = 0$

If we were to evaluate this at the EBT price, we would have $1 - \theta(p^*_{ebt}) - \theta'(p^*_{ebt})(p^*_{ebt} - p_{nw})$. Because we assumed the profit function is concave, then if $p^{w*} > p^*_{ebt}$, it must be that $1 - \theta(p^*_{ebt}) - \theta'(p^*_{ebt})(p^*_{ebt} - p^*_{nw}) < 0$, which implies that $p^*_{ebt} - p_{nw} < \frac{1-\theta(p^*_{nw})}{\theta'(p^*_{nw})}$. Without imposing further functional form, the condition can be re-arranged as:

$f(\pi', q_w) < \frac{1-\theta(p^*_{ebt})}{\theta'(p^*_{ebt})}$, where we know that $f(\pi', q_w) = p^*_{ebt} > p^*_{nw} > 0$ (shown above).

$\rightarrow$ *Intuition:* Additional bounds on the derivative of the sanction likelihood function at the EBT price must be established to ensure that $p^{w*} > p^*_{ebt}$ (if sanctions increase too much, it will not be optimal to set WIC prices price above p^*_{ebt})

Appendix Section C Construction of Nielsen Sample

I limit the sample from the Nielsen Consumer Panel, 2004-2009 to residents of Texas and transactions involving any of the following food types (types of food are coded by Nielsen): cheese, eggs, peanut butter. I limit my sample to cheese, eggs, and peanut butter because (1) I can observe WIC eligibility at the UPC level from the product lists and (2) they are included in the most common food package (cheese and eggs are in all packages, peanut butter is in some). Product restrictions for milk, beans, cereal and juice, are store-specific and not given by the product lists, and tuna, carrots, buttermilk, nonfat dry milk, and evaporated milk are rarely distributed (e.g. "home lacks refrigeration) and comprise less than 3% of redemptions. While cheese and eggs are distributed in all packages, peanut butter is only distributed in some, so my main estimates of WIC prices (p_w) use the cheese and egg purchases.[94]

To proxy for whether a purchase occurred at a WIC store, I use an indicator for whether a WIC store of the given size (chain vs. independent) existed in the ZIP code of residence of the consumer in the year and month of purchase. Nielsen does not release store identifiers, including ZIP code, which is why I use the ZIP code of the consumer, assuming that consumers shop for groceries near their residence (reasonable due to the perishable nature of groceries). I then indicate whether the store is a chain based on whether Nielsen indicates a store ID and retailer ID for the purchase (purchases at non-chains have missing values).

To generate the store fixed effects used in Equation 3, I create a new store ID using Nielsen's store ID if it is non-missing and Nielsen's retailer ID if the store ID is missing (in fact, when Nielsen's store ID is missing, meaning that the store is not a chain, the retailer ID contains codes representing industry groups, rather than actual retailers). I also include (separately) fixed effects for the consumer's ZIP code of residence. Therefore, the store fixed effects represented in Equation 3 stand for two sets of fixed effects: my new store ID and ZIP code. In some of the price graphs, I further interact ZIP and store ID (as indicated), and interacting vs. separate FE does not produce noticeably different results (as shown).

Appendix Table 4 shows the percentage of purchases in my sample matched to WIC products and WIC stores. 50.53% of purchases are made at chains that accept WIC and 1.68% are at independent stores that accept WIC. 14.50% purchases are both of WIC UPCs and at WIC chains, compared to 0.48% purchases are of WIC UPCs at single outlets in WIC. While the fraction of WIC purchases at single outlet WIC stores is small, it still amounts to a relatively large number of purchases—2,330—due to the underlying sample size. To mitigate noise in price reporting, I have performed the same analysis first dropping any prices which are over 3 times or less than 1/3 of the within-UPC mean price (for all of Texas and all years), and the results are not noticeably different.

[94]For FY 2005, cheese comprised 13.4% Appendix Table 1 lists the eligibility requirements, which I found by accessing archived versions of WIC-eligible product lists, found here: `www.dshs.state.tx.us/wichd/vo/TexasWICApprovedFoods.pdf`.