From Paper to Plastic: Understanding the Impact of EBT on WIC Recipient Behavior

Andrew S. Hanks, PhD[1,3], Carolyn Gunther, PhD[1], Dean Lillard, PhD[1,4], Robert L. Scharff, PhD[1]

Key Words: Transaction costs, assistance programs, social benefits, stigma, redemptions

JEL Codes: D12

Acknowledgments: We would like to thank participants at the 2016 NBER Health Economics Summer Institute and Lauren Jones for their valuable input. We also thank Employees of state WIC agencies in Texas, Ohio, Oregon, New Mexico, Nevada, Massachusetts, Connecticut, Florida, West Virginia, Virginia, Kentucky, Michigan, Wisconsin, Iowa, Vermont, and Wyoming for helping us gather WIC EBT implementation data.

Funding: This manuscript was partially funded by the Duke-UNC USDA Center for Behavioral Economics and Healthy Food Choice Research (BECR), which is funded by grant 59-5000-4-0062 from the U.S. Department of Agriculture.

1. Consumer Sciences, Department of Human Sciences, College of Education and Human Ecology, The Ohio State University
2. Human Nutrition, Department of Human Sciences, College of Education and Human Ecology, The Ohio State University
3. Corresponding author: 130A Campbell Hall, 1787 Neil Ave., Columbus, OH, 43210; hanks.46@osu.edu; Office -- 614-688-1787; Cell – 607-339-6942
4. Deutsches Institut für Wirtschaftsforschung – Berlin (DIW-Berlin), National Bureau of Economic Research

From Paper to Plastic: Understanding the Impact of EBT on WIC Recipient Behavior

Abstract

Only about 60% of eligible people participate in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) and evidence indicates that these recipients do not claim all of the benefits available to them. Transaction costs and negative stigma associated with participating in the program are likely to discourage eligible people from enrolling, and enrollees from redeeming all of their benefits. As of November 2016, sixteen states have implemented Electronic Benefits Transfer (EBT) for WIC, potentially reducing the amount of time required for each transaction and making it more difficult to identify beneficiaries. In this manuscript we analyze the impact the transition to WIC EBT has on enrollment, WIC benefits redemption, and non-WIC food expenditures using enrollment data for five states, and expenditure data for 17,714 households enrolled in WIC. We find no evidence that EBT increases the chance that eligible people enroll in the WIC program. We do find evidence that WIC recipients redeem more benefits two to four months after the transition, and there is no evidence that they increase expenditures on non-WIC foods.

The Healthy, Hunger-Free Kids act mandates that by October 2020 all states in the Union must deliver benefits for the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) through Electronic Benefit Transfer systems (EBT). This system of benefit delivery has the potential to reduce transaction costs for WIC recipients, cut down on employee time dedicated to conducting these transactions, and not force other shoppers to wait in line for a longer period of time. In addition, it is possible that psychological stigma experienced by the WIC recipient decreases since other shoppers may have a more difficult time identifying a shopper as a WIC recipient. Given the reduction in transaction time and costs, and potentially the decrease in stigma, it is not unrealistic to expect that purchasing patterns of WIC recipients might change and that eligible individuals just on the margin of enrolling will matriculate in the program (where funds are available). Our objective is to use exogenous variation in WIC EBT implementation to measure the impact that this transition has on enrollment, WIC redemptions, and non-WIC food expenditures.

One of the current challenges in measuring the impact of the transition to EBT on WIC recipient behavior is the lack of available data. Only select WIC enrollment data are available on the USDA website and transaction level data commonly used in research do not indicate whether or not foods are redeemed with WIC benefits, or paid for out-of-pocked. In addition, state information for WIC EBT implementation is not always readily available or well archived.

For this study we attempted to overcome some of these data challenges by collecting EBT rollout information for fifteen of the sixteen states currently using WIC

EBT. We then match these data to monthly WIC enrollment data for five states. In addition, we received transaction records from a grocer in Ohio for 17,714 WIC households who hold also hold a loyalty card for this grocer. These transaction data include 75 weeks of WIC redemptions and expenditures on non-WIC foods and covers most of the EBT transition period in Ohio. We match these transaction records to the implementation schedule for Ohio.

In brief, our results indicate that WIC EBT has no impact on enrollment and measurable impact on WIC redemptions. We also find significant county and state variation suggesting that time-variant state and even county effects can significantly influence responses to this and similar programs. We provide more details regarding our data and empirical specifications below.

Background

In 2015, $104.1 billion were delivered in food benefits through in-kind food assistance programs (Oliveira 2016). Despite the debate surrounding efficiencies of in-kind transfer programs in general, these types of programs may be able to effectively deliver specific benefits to intended recipients (see Cunha 2014; Ben-Shalom, Moffitt, and Scholz 2012; Currie and Gahvari 2008), and minimize the potential political ramifications of recipients utilizing benefits contrary to how tax payers think the benefits should be spent (Currie and Gahvari 2008).

The most well-known in-kind food assistance programs currently administered by the Federal government are the Supplemental Nutrition Assistance Program (SNAP), National School Lunch Program (NSLP), WIC, and the School Breakfast Program (SBP).

These programs account for 93% of total benefits delivered for food assistance nationally (Oliveira, 2016).

WIC provides food assistance for lower income pregnant, breast-feeding, and post-partum women, infants and children ages 1-4, making it an extremely valuable and consequential food assistance program. In 2015, WIC accounted for 6% of federal dollars allocated to in-kind food assistance programs, benefitting 8 million recipients (Oliveira 2016). Yet only 60% of eligible people are enrolled in the program (Johnson et al. 2015) and in some cases, only 12.6% of recipients redeem all of their benefits (Phillips et al. 2015)

Of the many acclaimed benefits attributed to the WIC program, the most widely accepted, though still debated benefit (Joyce, Gibson, and Colman 2005; Joyce, Racine, and Yunzal-Butler 2008), is the improvement in birth weight among infants (Currie and Rajani 2015; Rossin-Slater 2013; Hoynes, Page, and Stevens 2011; Bitler and Currie 2005). There is some evidence that food insecurity is reduced (Kreider, Pepper, and Roy 2016; Metallinos et al. 2011; Black et al. 2004) leading to an improvement in dietary and health outcomes for women and children (Lee and Mackey-Bilaver 2007). There is also limited evidenced of cognitive benefits to children (Jackson, 2015) and even potential spill-over effects for older siblings of young participants (Robinson 2013).

Redeeming WIC Benefits: Vouchers vs. EBT

One of the factors affecting the 40% of eligible people that do not participate, and that might result in left-over WIC benefits, is the way in which benefits are delivered (Johnson et al. 2015). Since WIC began in 1972, recipients have redeemed benefits through paper vouchers. To redeem food items using vouchers, beneficiaries follow a specific routine at the check-out line. They first separate WIC-eligible and WIC-non-eligible items and then present their vouchers to the cashier who verifies that the selected items are WIC-eligible and notes which benefits are redeemed. If the beneficiary does not redeem all items on the voucher, in some states, she can pick up those items at a later date. If a beneficiary mistakenly includes a non WIC-eligible item in the WIC-eligible pile, the cashier informs her and gives her the choice to either pay cash for the item in a separate transaction or to return it to the shelf. Because this part of the process slows down the check-out line and potentially embarrasses the WIC beneficiary, a beneficiary may face higher transaction and stigma costs when she redeems WIC benefits with paper vouchers.

In contrast to benefit redemption using paper vouchers, under EBT, store clerks electronically scan the Uniform Product Code label of all items all at once. The WIC beneficiary then swipes her EBT card, which is like a debit card, enters her PIN, and the computer program automatically determines which items are WIC-eligible. Next, the computer deducts the dollar amount of the WIC approved items from the total bill and the recipient is responsible to pay the remainder out of her own pocket. This streamlined process most likely reduces the amount of time each transaction takes. Fellow shoppers do not need to wait behind recipients as long and it is more difficult to identify WIC recipients, potentially reducing negative stigma (Manchester and Mumford 2010, 2012).

In addition to improving the efficiency of the WIC benefit redemption process, EBT systems also place more responsibility on WIC beneficiaries. Since the cashier is no longer validating the eligibility of selected items, it is up to the WIC recipient to make sure she selects the correct foods. If not, she either must pause the transaction right after swiping her EBT card to identify which foods are not covered, or simply pay for them out of pocket. The complex and burdensome foods list published by many states can make it difficult for WIC beneficiaries to easily identify WIC eligible foods, and use of these documents in the store easily identifies someone as a WIC recipient, potentially resulting in stigma. In addition, foods are often not well marked in the stores increasing the difficulty of correctly selecting the appropriate foods.

Descriptive Model of WIC Recipient Behavior

Researchers have modeled a person's decision to enroll in (or to enroll one's eligible child) and redeem WIC benefits as a function of transaction costs and the stigma associated with participating in government assistance programs (see Manchester and Mumford, 2010, 2012; Currie 2004 for good discussions on stigma). These transaction costs are a function of the effort required to enroll in the program (travel to clinic and fill out forms), the effort and time required to identify which food are part of the WIC program and properly select these foods, and the effort and time required to redeem benefits at the check-out line. In addition, these costs include the effort to initially enroll in the program and the effort required to learn which foods are part of the WIC package. There are also monthly costs that include the time required to renew benefits every three months, the time required for mandatory visits (6 months for women, 1 year for children), and the time required redeem benefits at check-out.

In addition to transaction costs, WIC recipients might also pay stigma costs for participation in the program. We assume these psychological costs are borne by the recipient when someone else identifies the recipient as participating in the welfare program. This occurs with greatest accuracy at check-out when the recipient gives the cashier a paper voucher to redeem benefits. This clearly signals the recipient's participation in the program and shoppers behind the recipient may become impatient, frustrated, or angry. The cashier might even show frustration or appear annoyed when conducting the transaction.

Both transaction and stigma costs can reduce the chance that a person will enroll in WIC and/or redeem all of their benefits. At the margin, the value of WIC benefits must equal or be greater than transaction and stigma costs combined for enrollment and/or benefit redemption to occur, holding income and other variables constant. An increase in the size of the benefit can increase the chance that a person enrolls and redeems benefits. This is most clearly demonstrated by recent statistics indicating that 60.2% of all eligible people enroll in WIC, where 84.4% of these enrollees are infants and 49.8% children ages 1-4 (Johnson et al. 2015). Infant formula is costly and the flexibility it provides women who wish to return to work is also valuable, thus it is no surprise that a high percentage of eligible infants are enrolled in the program.

When EBT is introduced into the WIC benefits redemption process, the nominal value of benefits does not change, though transaction costs, and potentially stigma costs, do change. Specifically, transaction costs fall because the recipient no longer needs to separate goods into WIC and non-WIC food piles. Also, the cashier no longer verifies foods as WIC eligible using a paper voucher. Instead the computerized system determines which foods are WIC eligible and applies the appropriate benefits to these foods. Finally, shoppers behind the WIC recipient may not be able to identify the shopper as a WIC recipient, potentially reducing stigma costs. Given the change in these costs as a result of EBT, the following behavioral predictions can be made:

1. Eligible people will be more likely to enroll in the program
2. Benefits redeemed will increase

Under the voucher system, the cashier alerts the recipient if a non-WIC item is mistakenly submitted for redemption, giving the recipient the choice whether to purchase the item, replace it with an eligible item, or not make the purchase. When EBT is used, the recipient scans WIC and non-WIC items together and WIC benefits are automatically applied. If the enrollee is not fully paying attention, there is the potential for a non-WIC item to be inadvertently purchased. If enrollees mistakenly choose non-eligible foods and attempt to redeem them with their WIC benefits, the following prediction can also be made:

3. Expenditures on non-WIC foods will increase initially, but as WIC recipients learn about the process, these expenditures will decline over time.

If WIC recipients were already making errors in selecting their foods, there is no reason this error rate will increase, but the cost of the errors will now be borne by the recipients, instead of the store. In other words, the recipient will need to pay for the additional goods out of pocket instead of the store cashier taking time to verify the eligibility of the food. It is possible that recipients may quickly learn which foods are part of the WIC program and not repeat the mistakes over an extended period of time.

Data

To carry out this study we use four types of data: WIC enrollment data, county level population data, WIC EBT implementation data, and WIC household grocery purchase data. We merge the WIC EBT implementation data with the enrollment and purchase data to estimate the effect of the transition on WIC recipient behavior. We describe the data in detail below.

State Enrollment and Population Data

The United States Department of Agriculture publishes monthly WIC enrollment data by state from Oct 2009 through May 2016. These data include total WIC enrollment numbers as well as the number of enrolled people in specific WIC groups of pregnant women, post-partum women, infants, and children. While WIC enrollment and benefits are all handled at the county or WIC agency level, these data are only at the state level so we cannot take advantage of county or WIC agency level variation.

For our analyses with enrollment data, we also collected county level population estimates for 2010-2015. These data are annual by county, so we use linear interpolation methods to calculate monthly population estimates for each county in each state in the US. We then aggregate these population values by state and merge them to the enrollment data.

WIC EBT Implementation Data

We collected EBT rollout information for 15 of the 16 states that currently use WIC EBT (Nevada is the only state for which information is missing). In most of the states that have implemented EBT, the state WIC agencies proceeded with the transition on a county or WIC agency basis. In addition, most of these states handled the implementation over a period of several months. Some of the first states to transition to WIC EBT took more than one year to complete implementation. Even though we have implementation data for all but one of the states that has transitioned to EBT, we only have enrollment data and population estimates that span both the pre- and post EBT periods for 5 states: Kentucky, Ohio, Massachusetts, Virginia, and Wisconsin. Thus we restrict our analysis of enrollment data to these states.

Since the population data are at the county level and some states implemented EBT on a WIC agency instead of county basis, we use the geographic area the agency covers and based on county lines, calculate the share of a county's population within that WIC agency area. This allows us greater precision in determining the share of each county exposed to WIC EBT in any given month. Since the monthly enrollment data are at the state level, we aggregate these population data up to the state-month level. While we do not have county or WIC agency level variation, we still have monthly variation in the share of the state's population exposed to WIC EBT. We then merge these population data to the enrollment data. Finally, we characterize a state as having transitioned to EBT once 95% of the state's population has been exposed.

Household Grocery Purchase Data

Through a cooperative agreement with a supermarket chain in Ohio, we obtained weekly expenditure data for households participating in the Ohio WIC program. These households are taken from the grocer's database of 6 million households tracked through a loyalty card shopper program. Households enter into this panel if they hold a loyalty card and if they spend a certain amount each month and year. The grocer sets this minimum spending limit to make sure the households in the database represent regular shoppers in the store. Households enter this panel through the loyalty card program. This panel includes weekly expenditure data, both on WIC redemptions and non-WIC food expenditures, for 73,331 total households.

Data for this study spans from December 2013 to June 2015, a total of 75 weeks, and covers 56 of the 88 Ohio counties. This time frame includes all but one of the EBT transition phases for Ohio, the transition that occurred on July 1, 2015. Thus in this sample, stores in the counties scheduled to transition to EBT on July 1 redeemed voucher benefits only. In regards to the 32 missing counties, there is no store from the grocery chain in these counties, thus they are not present in the data. See table 1 for specific counties that appear in the data. Also, see figure 1 for an illustration of the staggered WIC EBT rollout across Ohio.

While the data do include expenditures, these expenditures are aggregated at the weekly level for each household. We also know the store and county where most a household made most of their purchases that week. In addition, the data are aggregated at the product category level: bakery, deli, deli packaged, floral, fresh prepared, fresh produce, general merchandise, grocery, health and beauty care, liquor, meat, natural foods, packaged produce, pharmacy, packaged meat, packaged seafood, seafood, and supplies. Expenditures for each of these categories are separated into WIC redemptions and non-WIC expenditures. In addition, WIC redemptions are flagged as purchases using WIC vouchers or EBT. The following categories include WIC eligible foods: fresh produce, grocery, health and beauty care (infant formula), and packaged seafood. We only use the first three categories in our analyses since packaged seafood is rarely purchased.

Household expenditures are only recorded when a purchase is made at one of the grocer's stores, creating an unbalanced panel. We fill in missing weeks with zeros. Notably, these zeros mean one of three things: 1) the household did not buy anything or redeem WIC benefits that week; 2) the household purchased groceries or redeemed benefits at a different store; 3) the household purchased groceries without the loyalty card and did not redeem benefits. Moreover, there is no county or store associated with these weeks. We fill in stores and counties for these cases by inserting the store and county where the household shopped the most frequently on the weeks when transactions were logged. If there were two or more stores or counties where a household shopped that tied for highest frequency of household visits, we randomly selected one of the highest frequency stores and counties and used those as the store and county proxies.

We also note that households are in the sample if they redeemed WIC benefits any time in 2014 or 2015. Thus some households can be in the sample and not have WIC redemptions recorded until the end of the sample period, or vice versa. In addition, some households may not redeem all of their benefits, or may redeem benefits at other stores.

In order to adequately measure WIC shopper behavior in this sample we restrict the sample to households that make a WIC purchase an average of once every month, and we do this for several reasons. First, this ensures, with high probability, that a household has WIC benefit redemption data recorded both before and after the EBT transition. Second, since WIC benefits are distributed at three-month intervals, recipients have to show up at a clinic every three months to either pick up the new vouchers or have the benefits “loaded” onto the card. It is plausible that a household member on WIC does not visit a clinic at the beginning of the cycle to retrieve the new vouchers or re-load the EBT card. As a result, there may be cases where WIC data are not recorded for a household for multiple weeks, but the household still has a member enrolled in the WIC program. Third, this ensures, with high probability, that a household is registered for the WIC program throughout the whole sample period. This leaves us with 17,714 (N=1,328,550) households in the final sample of data.

Finally, we aggregate expenditures by month to remove weekly cyclicality in purchase behavior. Since we received weekly data, we construct months by setting the first week as the week when the first day of the month occurs (the first week of the data includes January 1, 2014). With this structure we create some months with four weeks and some with five. We note that this has little impact on our regression results.

Empirical Specification

To measure the impact of EBT on enrollment and household shopping behavior we rely on an event-study approach (Binder 1998; Khotari and Warner 2006). The event-study approach allows us to use the staggered implementation of EBT across counties and states as our identification strategy, and convert it to a difference-in-difference design. In addition, this approach allows us to track behavior in relation to EBT implementation and to see how long behavior persists over time, if at all. In this approach, the baseline period, is coded as zero and all the preceding and subsequent periods are coded as indicator variables. In the enrollment data, the baseline period is the month prior to the month when 95% of the state population is exposed to EBT. For the grocery purchase data, the baseline period is the month prior to the county's implementation month. In both cases, all pre- and post-months are relative to the baseline month.

For our empirical specification for the enrollment data, we include indicator variables for six months prior and six months post EBT implementation. We include an event horizon of this length because this is the time for which we have a balanced panel for the five states of interest. This limits us to a sample size of 65. We also include a monthly indicator variable and use state fixed effects. The empirical model is as follows:

$$Enrollment\ Share_{it} = \beta_0 + \boldsymbol{PreEvent} * \mathbf{B}_{\boldsymbol{pre}} + \boldsymbol{PostEvent} * \mathbf{B}_{\boldsymbol{post}} + \boldsymbol{Month} * \mathbf{B}_{\boldsymbol{month}} + \boldsymbol{State} * \mathbf{B}_{\mathbf{state}} + \nu_i, \tag{1}$$

where each B represents a vector of coefficients to be estimated. The variables *PreEvent* and *PostEvent* are both matrices of indicator variables for the pre and post EBT months, respectively. *State* and *Month* are matrices of state and month fixed effects, respectively. We also estimate robust standard errors. Our outcome variables are total state enrollment share of the state population, and then each WIC enrollment group's share of total WIC enrollment.

In our models with transaction data, we use a similar model, but only include a five-month event horizon. To make the most use of our data, we use unbalanced panel data since the last two enrollment groups in Ohio only have one or three months after the baseline month. Furthermore, the first county to implement EBT only has five months prior to the baseline month. In addition, we run multiple robustness checks to verify the outcomes we estimate.

In our empirical specification for the transaction data, we estimate month and county fixed effects models and include the indicator variables for five months before and after the baseline month. We also estimate robust standard errors. Our empirical model follows the form:

$$y_{it} = \alpha_0 + \boldsymbol{PreEvent} * \mathbf{A}_{\boldsymbol{pre}} + \boldsymbol{PostEvent} * \mathbf{A}_{\boldsymbol{post}} + \boldsymbol{Month} * \mathbf{A}_{\boldsymbol{month}} + \boldsymbol{County} * \mathbf{A}_{\mathbf{county}} + \nu_i. \qquad (2)$$

Outcome variables of interest are total WIC redemptions and non-WIC expenditures, and non-WIC expenditures and WIC redemptions for general grocery foods, all produce, and infant formula.

Results

In table 2, we present data on the counties represented in the sample of transaction data from Ohio, and group them by EBT transition. Notably, after the pilot phases, population density gradually increases by phase, indicating that larger, more population dense counties transitioned later. There is less variation in the percentage of the county's population in poverty, with the highest percentage at 21.46% in the seven counties that began the transition on January 26, 2015. Racial profiles, based on percentage of Caucasians in the county, were similar too, though Greene County has the lowest percentage at 86.60%. Finally, there is variation in the percentage of the population with a college degree. Notably, on average 13.8% of the residents in the counties that transitioned on March 23, 2016 have a college degree while on average more than one-fifth of the residents of the counties that transitioned on May 1 and July 1, 2015 have a college degree.

Enrollment

Now we consider the impact that the transition to EBT has on program enrollment. The first column in table 3 reports the impact of the EBT transition on WIC enrollment's share of the state population. Based on our specification, there is no evidence that EBT has any impact on WIC enrollment in general.

It is plausible, however, that enrollment in different recipient groups in the WIC program change. In columns 2-8 in table 3, we report results for the different groups in the WIC program. Overall for each of these groups, we find limited evidence that the transition to EBT has any impact on enrollment.

What limited evidence we have of any impact appears in month three or later after the baseline month, though these are primarily significant at the 0.1 level. Two notable exceptions are the significant increases in month six for fully breast fed infants and conversely women who fully breast feed their infants. We determine whether or not these results are state specific by running the regressions and removing one state at a time. We find that when we remove Ohio, these two significant results are eliminated, suggesting something other than EBT is driving the result.

Household Grocery Purchases

Even though EBT does not seem to increase the chance a women, infant, or child enrolls in WIC, we find evidence in the transaction data that EBT positively influences WIC benefit redemptions purchases. We also find evidence that expenditures on non-WIC foods increase after EBT, though it is not clear this is a result of EBT.

Results in table 4 indicate that households redeem more WIC benefits beginning at two months after the baseline month. These redemptions increase in magnitude from $3.69 in month two to $17.14 additional dollars in month five. This increase in redemptions is driven by redemptions of foods in the grocery category, which includes items such as cereal, bread, peanut butter, and juice. There are also increases in infant formula redemptions, though this increase is statistically significant at the 0.05 level only in month 5. Produce redemptions are not influenced by the transition.

When we estimate our expenditure model with non-WIC food expenditures, we find some evidence that expenditures increased. In table 5 we report that in the fifth month after the transition, all non-WIC expenditures increased by $28.16. This increase is driven by items from all three categories, though expenditures on grocery items increased by $16.94. We note that expenditures on produce and health and beauty care increase relative to the baseline month as early as month three.

It is important to note that for Ohio, month five in the grocery purchase data is not the same calendar month as month five in the enrollment data. Month five in the enrollment data corresponds to November, 2015, while month 5 in the grocery purchase data depends on implementation date. Since the grocery purchase data do not extend through November 2015, then no month five in these data corresponds to month five in the enrollment data.

Robustness Checks

We conduct a series of robustness checks to determine the validity of our transaction results. These robustness checks include event horizons of one and three-month duration, as well as estimation with a balanced panel with one, three, and five months in the event horizon. We also estimate models in which we remove households that purchased baby formula at least once during the study. In addition, we estimate the models and remove one implementation group at a time. We conduct this set of regressions with both unbalanced and balanced panels. Finally, we estimate a set of regression models in which we parse the sample into one-person, two-person, three-person, four-person, and five or more person households. We use information from the BLS on monthly food expenditures for each of these households sizes to separate the data into these groups. All of the results for our robustness checks are available in our supplemental material.

From our robustness checks, we find consistent evidence for increases in WIC redemptions beginning somewhere between month two and four after the baseline month. These results are eliminated only when we remove households that purchased baby formula at least once during the study period. The decrease in expenditures for all WIC redemptions and redemptions of foods in grocery and produce prior to EBT (table 4) are not robust to the different specifications so these are likely the result of county or implementation phase-specific variation. Similarly, the increase in non-WIC expenditures post-EBT and the decrease in expenditures pre-EBT observed in table 5 are not robust to the various specifications.

Discussion

In this study, we focus on the impact that the transition to EBT has on enrollment decisions and shopping behavior of WIC recipients. First, we use enrollment data for five states currently with WIC EBT to estimate the impact of the transition on WIC enrollment. Then we utilize a set of transaction data from a major grocer in Ohio that tracks purchases of more than 17,000 WIC households across 56 counties over a 75 week period. In both cases, we identify the causal impact of EBT by relying on variation in benefit transmission across counties and regions to estimate a difference in differences model. Most importantly, we find no evidence that the transition to EBT influences enrollment decisions. We do find evidence that the transition increases WIC redemptions but this increase usually occurs somewhere between two to four months once EBT has been implemented.

This primary finding from our research highlights an important administrative complexity in the transition process. WIC benefits are distributed on a three-month basis. When counties in Ohio transitioned to EBT, people in these counties had up to three months to use their vouchers. Once this three-month period ended, all recipients in the county received benefits via EBT. For example, if a WIC recipient received three months of vouchers the day before the EBT transition, then this person could still use those vouchers for three months. This provides insights into our results that WIC redemptions began to increase somewhere between month two and four after baseline. Redemptions in those first months included both voucher and EBT redemptions but by month four, all benefits should be redeemed via EBT.

We also highlight the sets of counties in the transaction records for which data appear in the event horizon months. Counties that implemented EBT in Ohio on May 1, 2015 only have one month of data post baseline, though these counties appear in all months prior to the baseline month. Those counties that implemented EBT in Ohio on March 23, 2015 have three months of data post baseline, and those that implemented EBT on January 26, 2015 have five. The pilot counties appear in all five months of the event horizon (refer to table 1 and figure 1). We note that the counties that appear in months three through five after the reference month are primarily Appalachian counties. Thus it is very possible that our results are driven by this specific set of WIC recipients. Our robustness checks do suggest this to a certain degree. Unfortunately, our limited time frame does not allow us to explore this further.

In addition to our limited time-frame for both the enrollment and food purchase data, we also recognize that our enrollment data are only for five states and at the state level. This limits our ability to detect any potential effects from EBT. Furthermore, the lack of demographic data with the expenditure data diminishes our ability to precisely identify specific WIC households in the data, such as those with a pregnant woman and those with children. In addition, we only have transaction data for WIC households, and only for foods purchased at this particular location. Furthermore, we do not know what percentage of benefits are redeemed, and on which specific items. Yet we emphasize the novelty of the data and its value in providing a glimpse into the impact that the transition to EBT has on WIC recipient behavior.

Conclusions

This study is unique because we leverage variation in EBT implementation across states, and across counties in Ohio, to identify the causal impact of the transition on enrollment and shopping decisions. This is the first study to empirically study these questions and we also use unique transaction data. Given that 16 of the 50 states currently distribute benefits with EBT and the remainder will do so in the next several years, this is a very timely research topic. Additionally, WIC reaches some of the country's most vulnerable populations – pregnant and postpartum women, infants, and young children – highlighting the importance of this research. Proper nutrition for pregnant women is essential to ensure a healthy birth, and children need an appropriate diet to develop well. Results from this research can inform policy makers of the benefits and challenges associated with WIC EBT, as well as potential improvements to benefit delivery.

References

Ben-Shalom, Yonatan, Moffitt, Robert A., Scholz, John Karl. "An Assessment of the Effectiveness of Anti-Poverty Programs in the United States." *In Oxford Handbook of the Economics of Poverty*, ed. P. Jefferson (Oxford University Press, 2012).

Binder JJ. "The Event Study Methodology Since 1969." *Review of Quantitative Finance and Accounting* 11 (1998):111-137.

Bitler, Marianne P., Janet Currie. "Does WIC Work? The effects of WIC on pregnancy and birth outcomes. *Journal of Policy Analysis and Management* 24, no. 1 (2005): 73-91.

Black, Maureen M., Diana B. Cutts, Deborah A. Frank, Joni Geppert, Anne Skalicky, Suzette Levenson, Patrick H. Casey et al. "Special Supplemental Nutrition Program for Women, Infants, and Children participation and infants' growth and health: a multisite surveillance study." *Pediatrics* 114, no. 1 (2004): 169-176.

CDC National Immunization Survey: Breastfeeding among U.S. Children Born 2002-2012. URL: https://www.cdc.gov/breastfeeding/data/NIS_data/. Accessed July 22, 2015.

Currie, Janet. "Welfare and the Well-being of Children: The Relative Effectiveness of Cash and in-kind Transfers." In *Tax Policy and the Economy, Volume 8* (MIT Press, 1994), pp. 1-44.

Currie, Janet, and Ishita Rajani. "Within-mother estimates of the effects of WIC on birth outcomes in New York City". *Economic Inquiry* 53, no. 4 (2015):1691-1701.

Currie, Janet, and Firouz Gahvari. “Transfers in Cash and In-Kind: Theory Meets the Data.” *Journal of Economic Literature* 46, no. 2 (2008): 333-383.

Cunha, Jesse M. “Testing paternalism: Cash versus in-kind transfers.” *American Economic Journal. Applied Economics* 6, no. 2 (2014): 195-230

Hoynes, Hilary, Marianne Page, and Ann Huff Stevens. “Can targeted transfers improve birth outcomes?: Evidence from the introduction of the WIC program.” *Journal of Public Economics* 95, no. 7 (2011): 813-827.

Jackson, Margot I. “Early childhood WIC participation, cognitive development and academic achievement.” *Social Science & Medicine* 126 (2015): 145-153.

Johnson Paul, Erika Huber, Linda Giannarelli, David Betson , and Grant Lovellette. “National and state-level estimates of Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) eligibles and program reach, 2013.” *Alexandria, VA, United States Department of Agriculture Food and Nutrition Service, Office of Policy Support* (2015). URL: http://www.fns.usda.gov/sites/default/files/ops/WICEligibles2013-Volume1.pdf. Accessed on March 28, 2016.

Joyce, Ted, Diane Gibson, and Silvie Colman. “The changing association between prenatal participation in WIC and birth outcomes in New York City.” *Journal of Policy Analysis and Management* 24, no. 4 (2005): 661-685.

Joyce, Ted, Andrew Racine, and Cristina Yunzal-Butler. “Reassessing the WIC Effect: Evidence from the Pregnancy Surveillance System.” *Journal of Policy Analysis and Management* 27, no. 2 (2008): 277-303.

Kohtari, S.P. and Warner, J.B. Econometrics of Event Studies. Chapter 1 in *Handbook of Corporate Finance: Empirical Corporate Finance, Volume A*. Ed. B. Espen Eckbo. (Elsevier/North-Holland, 2006).

Kreider, Brent, John V. Pepper, and Manan Roy. "Identifying the Effects of WIC on Food Insecurity Among Infants and Children." *Southern Economic Journal* (2016). DOI: 10.1002/soej.12078.

Lee, Bong Joo, and Lucy Mackey-Bilaver. "Effects of WIC and Food Stamp Program participation on child outcomes." *Children and Youth Services Review* 29, no. 4 (2007): 501-517.

Manchester, Colleen Flaherty, and Kevin J. Mumford. "Welfare stigma due to public disapproval." *Minneapolis, MN: Department of Applied Economics, University of Minnesota* (2010). URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.617.4266&rep=rep1&type=pdf. Accessed on April 5, 2016.

Manchester, Colleen Flaherty, and Kevin J. Mumford. "How Costly is Welfare Stigma? Separating Psychological Costs from Time Costs in Food Assistance Programs." *Available at SSRN 1544601* (2011). Manuscript. URL: http://www.krannert.purdue.edu/faculty/kjmumfor/papers/stigma.pdf. Accessed on April 12, 2016.

Metallinos-Katsaras, Elizabeth, Kathleen S. Gorman, Parke Wilde, and Jan Kallio. "A longitudinal study of WIC participation on household food insecurity." *Maternal and Child Health Journal* 15, no. 5 (2011): 627-633.

Official USDA Food Plans: Cost of Food at Home at Four Levels, U.S. Average, April 2015. URL: http://www.cnpp.usda.gov/sites/default/files/CostofFoodApr2015.pdf. Accessed July 22, 2016.

Oliveira, Victor. The Food Assistance Landscape: FY 2015 Annual Report, EIB-150. U.S. Department of Agriculture, Economic Research Service, March 2016.

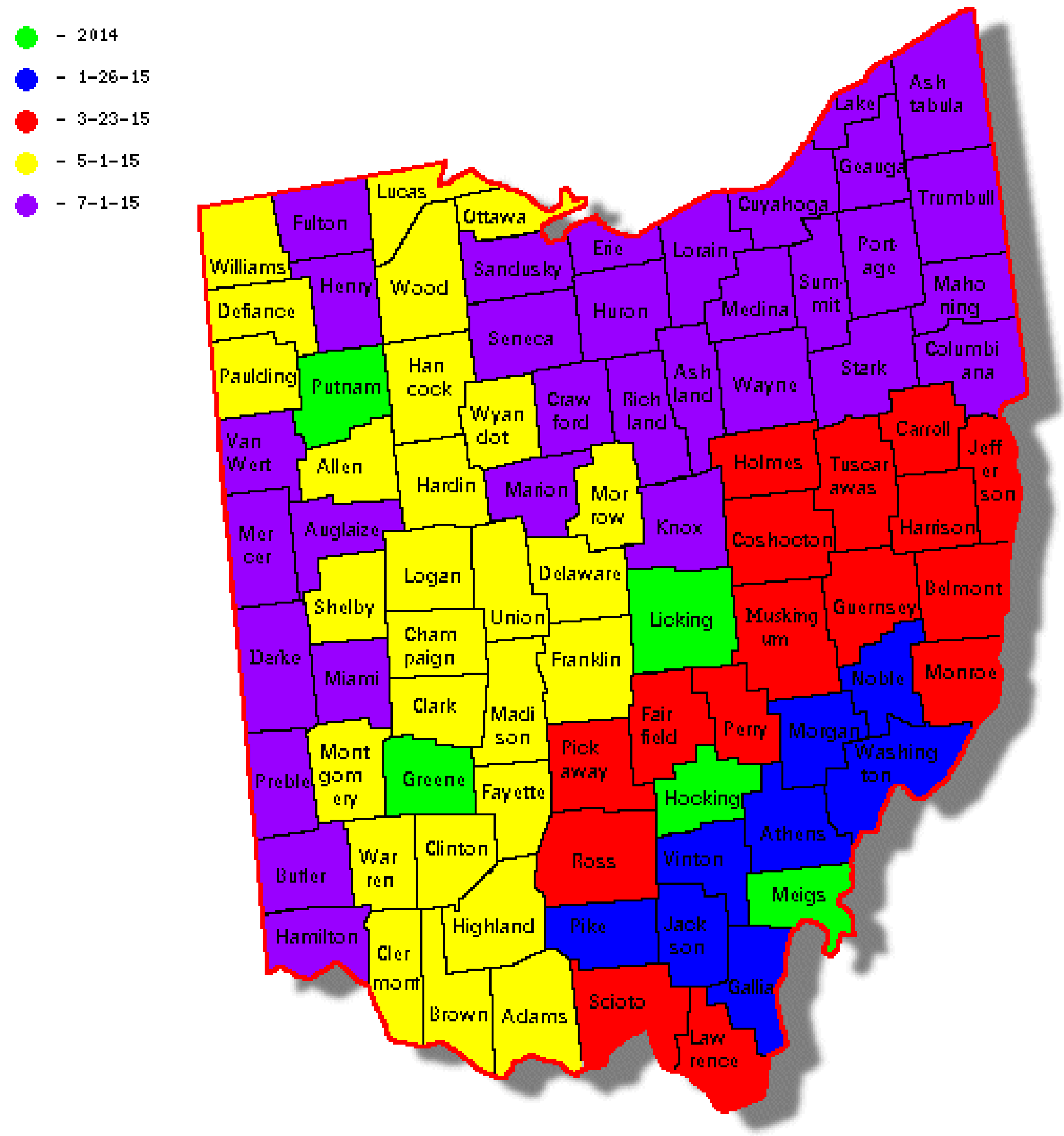
Phillips, Diane, Loren Bell, Ruth Morgan, and Jennifer Pooler. "Transition to EBT in WIC: Review of Impact and Examination of Participant Redemption Patterns."

Rossin-Slater, Maya. "WIC in your neighborhood: New evidence on the impacts of geographic access to clinics." *Journal of Public Economics* 102 (2013): 51-69.

Robinson, Christina. "Younger siblings can be good for your health: An examination of spillover benefits from the Supplemental Nutrition Program for Women, Infants, and Children (WIC)." *Journal of Family and Economic Issues* 34, no. 2 (2013): 172-184.

WIC EBT Activity, July 2016. URL: http://www.fns.usda.gov/sites/default/files/wic/July2016EBTStatusColorMap.pdf Accessed on July 22, 2016

Figure 1: WIC Electronic Benefits Transfer Rollout in Ohio



Source: diymaps.net (c)

Table 1: Timeline for WIC Electronic Benefits Transfer Transition in Ohio[a]

Pilot Studies	January 26, 2015	March 23, 2015	May 1, 2015	July 1, 2015[c]
Jul 14, 2014[b]	**Athens**	**Belmont**	Adams/**Brown**	Ashtabula
Licking	Gallia	Carroll	**Allen**	**Auglaize**
Aug 4, 2014[b]	**Jackson**	Coshocton	**Champaign**	**Butler**
Greene	Noble	**Fairfield**	**Clark**	**Crawford**
Oct 19, 2014[b]	**Pike**	Guernsey	**Clermont**	Cuyahoga
Hocking	Vinton	Harrison	**Clinton**	**Darke/Mercer**
Meigs, Putnam	**Washington/Morgan**	Holmes	**Defiance**	**Erie**/Huron
		Jefferson	**Delaware/Morrow/Union**	**Fulton**/Henry
		Lawrence	**Fayette**	Geauga
		Monroe	**Franklin**	**Hamilton**
		Muskingum	**Hancock/Hardin**	**Knox**
		Perry	**Highland**	Lake
		Ross/Pickaway	**Logan**	Lorain
		Scioto	**Lucas**	Mahoning
		Tuscarawas	**Madison**	**Marion**
			Montgomery	Medina
			Ottawa	**Miami**
			Paulding	**Preble**
			Shelby	Portage/Columbiana
			Warren	**Richland**/Ashland
			Williams	**Sandusky**
			Wood	**Seneca**

			Wyandot	Stark Summit Trumbull **Van Wert** Wayne

a. Bolded counties appear in the data.

b. These are the three pilot phase dates. In the October pilot, the EBT transition occurred sometime during the week of the 19th.

c. Data for this study precedes this rollout date

Table 2: County Demographics by WIC Electronic Benefits Transfer Rollout Date (standard deviation in parentheses[a])

EBT Rollout Date	Percent Caucasian	% with College Degree	Per Capita Income	% in Poverty	Population Density
July 14, 2014[b]	92.90%	22.60%	$27,082.00	13.50%	243.9
	--	--	--	--	--
August 4, 2014[b]	86.60%	36.90%	$30,629.00	13.20%	390.5
	--	--	--	--	--
October 19, 2014[b]	96.83%	15.27%	$22,136.67	15.97%	65.5
	(0.175)	(0.360)	(3564.617)	(0.366)	(7.250)
January 29, 2015	95.30%	14.71%	$20,313.88	21.46%	67.8
	(0.212)	(0.354)	(2047.160)	(0.411)	(31.484)
March 23, 2015	95.03%	13.79%	$21,980.69	16.68%	115.8
	(0.217)	(0.345)	(2258.433)	(0.373)	(59.384)
May 1, 2015	91.71%	20.29%	$24,954.19	14.04%	314.2
	(0.276)	(0.402)	(4711.970)	(0.347)	(477.890)
July 1, 2015[c]	91.05%	20.15%	$25,083.97	14.04%	447.4
	(0.285)	(0.401)	(3325.461)	(0.347)	(595.480)

a. **The first two rollouts in 2014 included one county each, thus there is no standard deviation**

b. **These are the three pilot phase dates. In the October pilot, the EBT transition occurred sometime during the week of the 19th.**

c. **Data for this study precedes this rollout date**

Table 3: WIC EBT Impact on Enrollment (standard errors in parentheses)

	Share of State Population	Share of WIC Enrollment							
	WIC Enrollment	Children	Fully Breast Fed Infants	Fully Formula Fed Infants	Partially Breast Fed Infants	Post-Partum Women	Pregnant Women	Women Fully Breast Feeding Infant	Women Partially Breast Feeding Infant
T-6	0.14%**	-1.52%	0.14%	1.48%	-0.23%	0.43%	0.06%	-0.03%	-0.33%**
	(0.001)	(0.011)	(0.003)	(0.013)	(0.010)	(0.003)	(0.003)	(0.001)	(0.001)
T-5	0.14%**	-1.16%	0.11%	1.11%	0.00%	0.29%	-0.03%	-0.05%	-0.28%*
	(0.001)	(0.010)	(0.003)	(0.012)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
T-4	0.12%*	-1.39%	0.06%	1.10%	0.11%	0.38%	-0.06%	-0.03%	-0.16%
	(0.001)	(0.011)	(0.003)	(0.012)	(0.010)	(0.003)	(0.003)	(0.001)	(0.001)
T-3	0.10%	-1.32%	0.12%	0.96%	0.13%	0.31%	-0.08%	-0.02%	-0.11%
	(0.001)	(0.010)	(0.003)	(0.012)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
T-2	0.01%	-0.18%	-0.08%	-0.64%	0.93%	-0.02%	0.11%	-0.06%	-0.06%
	(0.001)	(0.010)	(0.003)	(0.012)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
T-1	0.03%	-0.23%	0.00%	-0.15%	0.37%	0.03%	-0.01%	0.00%	-0.01%
	(0.001)	(0.010)	(0.003)	(0.012)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
T+1	0.01%	-0.90%	0.29%	1.20%	-0.68%	0.11%	-0.09%	0.09%	-0.01%

	(0.001)	(0.010)	(0.002)	(0.012)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
T+2	-0.01%	-0.84%	0.29%	1.51%	-0.92%	0.17%	-0.19%	0.12%	-0.14%
	(0.001)	(0.010)	(0.002)	(0.012)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
T+3	0.01%	-1.34%	0.37%	2.12%*	-1.36%	0.34%	-0.15%	0.18%	-0.16%
	(0.001)	(0.010)	(0.002)	(0.012)	(0.009)	(0.003)	(0.003)	(0.001)	(0.001)
T+4	0.01%	-1.61%	0.33%	2.11%*	-1.05%	0.28%	0.01%	0.19%	-0.27%*
	(0.001)	(0.011)	(0.003)	(0.012)	(0.010)	(0.003)	(0.003)	(0.001)	(0.001)
T+5	-0.03%	-1.57%	0.51%*	2.23%*	-1.39%	0.18%	0.09%	0.231%*	-0.28%*
	(0.001)	(0.011)	(0.003)	(0.013)	(0.010)	(0.003)	(0.003)	(0.001)	(0.002)
T+6	-0.01%	-2.11%*	0.79%***	2.45%*	-1.37%	-0.19%	0.28%	0.36%**	-0.21%
	(0.001)	(0.012)	(0.003)	(0.013)	(0.011)	(0.003)	(0.003)	(0.001)	(0.002)
Constant	2.01%***	53.2%***	2.30%***	17.1%***	04.00%***	7.82%***	9.83%***	2.45%***	3.22%***
	(0.001)	(0.012)	(0.003)	(0.013)	(0.011)	(0.003)	(0.003)	(0.001)	(0.002)
N	63	63	63	63	63	63	63	63	63

Results are from fixed effects regression with month and state fixed effects and robust standard errors.

***p<0.1. **p<0.05. ***p<0.01.**

Table 4: WIC Food Expenditures with Five Month Event Horizon(standard errors in parentheses)

	All WIC Redemptions	WIC Redemptions in Grocery	WIC Redemptions in Produce	WIC Redemptions in Baby Formula
T-5	-$5.34***	-$2.78***	-$0.55***	-$0.96
	(1.929)	(0.727)	(0.164)	(1.664)
T-4	-$2.75	-$2.38***	-$0.71***	$0.74
	(1.890)	(0.714)	(0.167)	(1.613)
T-3	-$2.35	-$1.34*	-$0.26	$0.17
	(2.074)	(0.773)	(0.180)	(1.772)
T-2	-$2.45	-$0.99*	-$0.45***	-$0.75
	(1.518)	(0.559)	(0.142)	(1.309)
T-1	-$1.66	-$0.36	-$0.01	-$0.65
	(1.938)	(0.733)	(0.170)	(1.663)
T+1	-$1.73	-$0.28	$0.25	-$0.96
	(1.914)	(0.713)	(0.167)	(1.625)
T+2	$3.69**	$0.85	-$0.02	$1.46
	(1.707)	(0.612)	(0.154)	(1.434)
T+3	$9.49***	$2.61***	$0.07	$3.10*
	(2.230)	(0.806)	(0.181)	(1.852)
T+4	$14.33***	$4.21***	$0.03	$3.58*
	(2.410)	(0.898)	(0.185)	(1.915)
T+5	$17.14***	$4.42***	-$0.25	$5.14**
	(2.822)	(1.030)	(0.206)	(2.264)

Constant	\$50.65***	\$25.91***	\$4.93***	\$16.95***
	(2.411)	(0.950)	(0.216)	(2.024)
N	91013	91013	91013	91013

Results are from OLS regression with month and county fixed effects and robust standard errors. A five-month event horizon indicates that we include in the regression five months before and after the reference month.

***p<0.1. **p<0.05. ***p<0.01.**

Table 5: Non-WIC Food Expenditures with Five Month Event Horizon(standard errors in parentheses)

	Non-WIC Purchases	Non-WIC Grocery	Non-WIC Produce	Non-WIC Health/Beauty Care
T-5	-$41.00***	-18.84***	-4.002***	-7.104***
	(9.890)	(6.117)	(0.836)	(1.672)
T-4	-$44.06***	-20.88***	-3.459***	-6.258***
	(10.770)	(6.798)	(0.886)	(1.615)
T-3	-$29.13***	-15.94**	-2.652***	-3.425**
	(10.900)	(6.824)	(0.918)	(1.685)
T-2	-$23.13**	-$11.65	-2.481***	-2.960**
	(11.260)	(7.345)	(0.944)	(1.293)
T-1	-$9.93	-$4.37	-$1.35	-$1.08
	(10.930)	(6.924)	(0.942)	(1.562)
T+1	$4.26	-$0.08	$0.66	$0.95
	(9.831)	(6.113)	(0.852)	(1.525)
T+2	$8.33	$2.30	1.407*	2.985**
	(9.404)	(5.840)	(0.775)	(1.393)
T+3	$14.92	$7.20	2.421**	3.583**
	(10.930)	(6.774)	(0.945)	(1.768)
T+4	$15.50	$7.53	3.390***	5.157***
	(10.920)	(6.655)	(0.931)	(1.925)
T+5	$28.16**	16.94**	4.706***	6.594***
	(13.450)	(8.324)	(1.144)	(2.248)
Constant	$487.90***	287.2***	35.89***	45.14***

	(13.050)	(8.105)	(1.099)	(2.080)
N	91013	91013	91013	91013

Results are from OLS regression with month and county fixed effects and robust standard errors. A five-month event horizon indicates that we include in the regression five months before and after the reference month.

***p<0.1. **p<0.05. ***p<0.01.**