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The Impact of Expanding Public Health Insurance on Safety Net Program Participation: Evidence from the ACA Medicaid Expansion
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ABSTRACT

The expansion of public insurance eligibility that occurred with the Affordable Care Act (ACA) Medicaid expansions may have spillover effects to other public assistance programs. We explore the impact of the ACA on two large safety net programs: the Earned Income Tax Credit (EITC) and the Supplemental Nutrition Assistance Program (SNAP). We use a county border-pair research design, examining county-level administrative measures of EITC and SNAP participation in contiguous county pairs that cross state lines where the county on one side of the border experienced the Medicaid expansion and the county on the other side did not. This approach allows us to focus narrowly on differences arising from the ACA Medicaid expansion choice, implicitly controlling for local economic trends that could affect safety net participation. Our results suggest that the Medicaid expansion increased participation in SNAP, and possibly in the EITC, in counties that expanded relative to nearby counties that did not expand. We corroborate and extend these results using individual level data from the American Community Survey (ACS). Our results show that access to one safety net program may increase take-up of others.

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I. Introduction

The safety net is a nexus of public programs addressing a partially overlapping set of needs and serving a partially overlapping set of beneficiaries. The Affordable Care Act (ACA) expanded the availability of one such program, Medicaid, to individuals who were previously categorically ineligible and to individuals who had been categorically eligible such as parents, but at lower means-tested income limits. Given connections across programs, the expansion of public insurance eligibility may have had spillover effects to other forms of public assistance. In this paper we explore the impact of expanded Medicaid access through the ACA on participation in the two most widely used and broadly available non-health safety net programs: the Earned Income Tax Credit (EITC) and the Supplemental Nutrition Assistance Program (SNAP). Understanding how participation in EITC and SNAP increases or decreases as the result of public health insurance expansions contributes to the policy evaluation of the ACA and could inform future state and federal expansion decisions.

EITC and SNAP are two of the most important components of the U.S. safety net. The EITC, a refundable tax credit targeting low-income workers, is the largest cash assistance program for the non-elderly in the United States, with 26.7 million recipients in 2013 (Nichols and Rothstein 2016). SNAP (formerly known as Food Stamps) provides food assistance to more than one out of seven Americans (Hoynes and Schanzenbach 2016). In addition to having large numbers of recipients, spending on both programs is substantial, with federal expenditures of $63 billion for the EITC in 2013 (Nichols and Rothstein 2016) and SNAP expenditures of $74.2 billion in 2014 (Hoynes and Schanzenbach 2016). Both EITC and SNAP are also notable because unlike many U.S. safety net programs, they have no categorical requirements such as age, presence of children, or disability status, although their eligibility standards do depend somewhat on such criteria. Nevertheless, they are in principle available to anyone, and thus when Medicaid expanded under the ACA to low-income non-disabled workers, including those without children, individuals newly eligible for Medicaid may well have been in a position to qualify for, or were already participating in, these programs.

Expansion of Medicaid eligibility has several potential impacts on participation in the EITC and SNAP. First, individuals may be induced to reduce their income below the Medicaid income limit to qualify for Medicaid, potentially increasing eligibility for means-tested programs. Alternatively, the newly increased income limit relative to previous limits for some groups could allow individuals to have more earnings while still qualifying for Medicaid, potentially changing cash and food program eligibility and participation. Finally, expanding Medicaid access may draw individuals' attention to the existence of other public programs or reduce the marginal cost of enrolling in additional programs while enrolling in Medicaid.

The interconnected nature of safety net program eligibility and receipt makes examining the impacts on other programs an important aspect of evaluating the effect of changes in program eligibility. However, there has been relatively little work on the impact of recent Medicaid expansions on cash and food program participation. Baicker et al. (2014) analyze the Oregon Medicaid Experiment, in which permission to apply for Medicaid was randomly assigned among a set of low-income adults. They find no effects of Medicaid expansion on Temporary Assistance to Needy Families receipt, but they find small positive effects on the probability of SNAP receipt. Burney, Boehm, and Lopez (2018) use a state difference-in-difference specification and report positive impacts of the ACA Medicaid expansion on SNAP. To our knowledge, no other work examines how the ACA Medicaid expansions affected EITC receipt.[1]

In this paper, we exploit the fact that the Supreme Court decision of June 2012 made the Medicaid expansion optional for the states, but we focus on identification of the effect of the Medicaid expansion by comparing changes in county-level measures of EITC and SNAP participation in contiguous county pairs that cross state lines where the county on one side of the border experienced the Medicaid expansion and the county on the other side did not. This approach allows us to focus narrowly on differences arising from the ACA Medicaid expansion choice, abstracting from potential heterogeneity in trends across broader geographic areas. We also exploit preexisting differences in Medicaid generosity across states.

Using this county border pair method, we begin by presenting evidence of increases in insurance coverage due to the ACA Medicaid expansion. The county-level data are obtained from the Census Bureau's Small Area Health Insurance Estimates (SAHIE) program. We find positive insurance impacts that are of magnitudes similar to those found by other authors using state difference-in-difference and state synthetic control methods (Kaestner et al. 2017, Courtemanche et al. 2017).

For our main analyses of EITC and SNAP, we use county-level data on the number of tax returns claiming the EITC from the Internal Revenue Service Statistics of Income and county-level data on the number of SNAP participants reported to the US Department of Agriculture (for a subset of states). Our estimates for the EITC are fairly imprecise, but are suggestive of small

[1] In related work, Chatterji, Liu, and Yörük (2019) examine the effect of the ACA's dependent care provision on family structure and program participation. They find that coverage for young adults under the age of 26 reduces single parenthood and reduces participation in SNAP, TANF, and WIC.

increases in the number of returns with an EITC claim per 100 working adults as a result of the Medicaid expansion. For SNAP, we find that the Medicaid expansion led to a statistically significant increase in participation. This is consistent with results from the Oregon experiment (Baicker et al. 2014).

We examine some of the mechanisms behind these results and explore heterogeneity in the impacts of the expansion using individual-level American Community Survey (ACS) data on SNAP participation, imputed EITC eligibility, and various labor supply measures. This supplemental analysis uses a Public-Use Microdata Area (PUMA)-pair design, since county of residence is not identified in the public-use data. Our ACS analysis confirms significant effects of the Medicaid expansion on health insurance coverage and SNAP participation. We find little evidence of labor supply-related changes in SNAP eligibility in the population, suggesting that information and/or transaction costs may be the main explanation for the observed association between Medicaid eligibility and SNAP participation. Our results suggest a small increase in imputed EITC eligibility and a small increase in the labor supply of single parents on the extensive margin. Overall, our results indicate that access to one safety net program may increase participation in others, highlighting the important connections across the safety net.

II. Background

The 2010 Affordable Care Act was arguably the most important piece of health care legislation in a generation. It aimed to reduce uninsurance by mandating that individuals obtain health insurance, by improving the functioning and regulation of the private market, and by significantly expanding access to public health insurance through Medicaid. In particular, it sought to expand eligibility for Medicaid to all those under 138% of the poverty line, representing a major change in most states. The change was especially pronounced for non-disabled adults without dependents who had been largely excluded from the program. In 2012, the Supreme Court ruled that states could not be compelled to participate in the Medicaid expansion, leading to substantial variation in the extent and timing of Medicaid expansions across states. Many states expanded in January 2014, but some expanded earlier or later, and 14 states have not (as of October 2019) changed their Medicaid eligibility limits.

As noted above, many individuals affected by the Medicaid expansion are potentially eligible for the Earned Income Tax Credit. The federal EITC provides a subsidy to low-income workers, with a subsidy rate of 40 percent on income below the maximum level. The structure of the EITC is shown graphically in Figure 1a for single adults with and without children and in Figure 1b for married couple families. The amount of the credit rises as a family's income rises (the "phase-in") until the maximum credit has been attained, at which point the amount of the credit stays constant as income rises (the "plateau"). Above a cutoff amount of income, the amount of the credit falls as income increases (the "phase-out") until the credit falls to zero. The maximum amount of the credit depends on the number of children in the family (zero, one, two, or three or more), and the earned income limit varies depending on filing status (single/head of household or married filing jointly). In 2014, for example, the maximum credit was $496 for a family with no qualifying children, $3,305 with one qualifying child, $5,460 with two qualifying children, and $6,143 with three or more qualifying children, and the earned income limit ranged from $14,590 for a single individual with no children to $52,427 for a married couple with three or more children (Internal Revenue Service 2013). Participation in the program among eligible taxpayers is relatively high, with overall take-up rates estimated to be between 75 and 79 percent (Nichols and Rothstein 2016), although take-up rates vary according to demographics, family structure, and position on the EITC schedule (Jones 2014), and lack of full take-up of the EITC remains a concern among policymakers (see National Conference of State Legislatures 2018; Internal Revenue Service 2019). Many states also supplement the EITC, generally by providing additional support for those in the Federal EITC eligibility range.

Many of the possible interactions between expanded Medicaid eligibility and EITC receipt arise from interactions between eligibility and labor market decisions of workers. These decisions may be either on the extensive margin (enter or leave the labor market) or on the intensive margin (work more or fewer hours conditional on working at all). The likely impacts also differ by whether the individual is single or married and by the presence or absence of children. In Figures 1a and 1b the dotted vertical lines indicate the typical ACA Medicaid expansion income cutoff of 138 percent of the federal poverty level (FPL) relative to the EITC schedule for each group.

Single and married parents had a route onto Medicaid prior to the ACA, but in most states needed to have very low incomes to qualify. Some parents may have chosen to stay out of the labor force to obtain health insurance; single parents were probably more likely to be on this margin. With higher Medicaid income eligibility threshold post-expansion, parents could enter the labor force without losing Medicaid coverage. As shown for single parents (the top three schedules in Figure 1a) and married parents (the top three schedules in Figure 1b), labor supply entry that allowed Medicaid eligibility in expansion states likely would put parents squarely in the range of EITC receipt.

There is also an incentive for parents earning just above the Medicaid eligibility cutoff of 138 percent of the federal poverty line to reduce their earnings. However, the position of 138 percent of FPL on the EITC schedule for individuals with children indicates that those near the

Medicaid cut-off would be eligible for EITC benefits in any case. Thus, a modest reduction in labor supply would not lead to a change in EITC eligibility for parents. In sum, any EITC response from parents would likely stem from labor force entry increasing EITC participation, and any such effect likely would be concentrated among single parents.

The predicted effect of the ACA on EITC participation for individuals without children is different. Prior to the ACA, non-disabled non-elderly single or married adults without children were typically ineligible for Medicaid at any income. We therefore would not expect the ACA to induce labor force entry for this group. On the other hand, childless individuals who would be earning above 138 percent of FPL in the absence of expanded Medicaid have an incentive to work less to qualify for Medicaid in expansion states. Because EITC benefits for single or married individuals with no children phase out to zero below the Medicaid eligibility cutoff (see Figures 1a and 1b), childless individuals who reduce labor supply to qualify for expanded Medicaid could enter the EITC eligibility range. Individuals without children who would otherwise exceed the Medicaid eligibility limit and choose to exit the labor force altogether would experience no change in EITC eligibility–they would not be eligible in either case. Thus, the most likely response for non-parents, if any, would be an increase in EITC stemming from a reduction in labor supply on the intensive margin.

In addition to labor market-related effects on EITC, there may be information/transaction costs reasons for a change in EITC returns. Workers with low incomes who would not normally file may learn about EITC benefits or be nudged to file taxes when enrolling in Medicaid. In Figures 1a and 1b, dashed vertical lines indicate the tax-filing threshold for the various groups. The threshold at which an individual or family is required to file taxes is in all cases below the expanded Medicaid eligibility cutoff. It is also possible that changes in labor supply induced by the ACA put a low-income worker in a position on the EITC schedule where it is worth the effort to file a return, even if that worker would have been eligible previously.

Unlike the EITC, the structure of SNAP is that of a traditional means-tested transfer program: food benefits (awarded in the form of Electronic Benefit Transfer (EBT) cards that can be used to purchase food from grocery stores) are highest among families with no earnings and are reduced at a 30 percent rate as earnings rise. To be eligible, a household must have gross monthly income below 130 percent of the poverty level and "countable" assets below $2,250 (Hoynes and Schanzenbach 2016). SNAP is one of the few safety net programs that is available to any low-income household and is not limited to certain groups, although nonworking, nondisabled adults up to age 49 without children are limited to three months of benefits within a three-year period (Hoynes and Schanzenbach 2016). Similar to the EITC, overall take-up rates are relatively high for a safety net program—75 percent in 2010—but they vary across states and groups of individuals within states (Cunnyngham 2012).

Some of the potential mechanisms whereby expanded eligibility for Medicaid may affect SNAP participation operate through the labor market. In particular, individuals previously ineligible for Medicaid have an incentive to work less in order to reduce their income below the new Medicaid income limit, which would lead to an increase in SNAP eligibility and participation. Alternatively, individuals who had been eligible for Medicaid previously although at a lower income limit have an incentive to work more, since the higher income limit could allow more earnings while still allowing the individual to qualify for Medicaid. This incentive could reduce SNAP participation if individuals work enough to lose eligibility for SNAP (though this is unlikely given the similar income thresholds for SNAP and Medicaid) or reduce the amount of SNAP benefits such that it is no longer worth the administrative hassle to participate.

In addition, there is the possibility of an information/transaction costs channel connecting Medicaid eligibility and SNAP participation: gaining access to Medicaid may increase individuals' awareness of the possibility of eligibility for SNAP. Often, government offices or non-governmental organizations that assist with Medicaid enrollment offer information about or assistance with applications for SNAP, for example. Finkelstein and Notowidigdo (2018) show that information and assistance can increase SNAP enrollment.

In sum, if expanded Medicaid access has an impact on EITC participation, the predicted direction would be to increase it. For SNAP, predicted effects on eligibility and participation conditional on eligibility are ambiguous, with the most likely impacts being positive. The effect of Medicaid eligibility expansion on safety net participation is ultimately an empirical question. In the next section, we describe our empirical strategy.

III. Empirical Approach

As in most studies of the ACA Medicaid expansion, we use variation in Medicaid eligibility resulting from the June 2012 Supreme Court decision making the Medicaid expansion optional to the states. Unlike most other studies, however, we analyze county-level data and compare changes in EITC receipt and SNAP participation within contiguous county pairs that cross state lines, where one county is in a state that expanded while the other is in a state that did not.[2] This is the same empirical approach laid out in our previous work examining the impact of the ACA Medicaid expansion on SSI and SSDI applications (Schmidt, Shore-Sheppard, and Watson 2019). Relative to a state difference-in-difference approach, the county-border design

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[2] This approach was pioneered in studies of the employment effects of state minimum wages (see Dube, Lester, and Reich 2010, 2016).

has the advantage that counties that border each other are more likely to share similar labor markets, are more likely to be affected by the same local trends, and are more likely to share macroeconomic shocks than are counties that do not share a common border (Allegretto et al. 2013; Dube, Lester, and Reich 2016).[3]

This county border pair approach allows us to focus narrowly on differences arising from the ACA Medicaid expansion choice by comparing changes over time in outcomes from counties on either side of a state border. In this approach, the identifying assumption is that the change in the outcome of interest in the county in the non-expanding state is a reasonable counterfactual estimate for how the outcome of interest would have changed in its neighboring county across the border if the Medicaid expansion had not occurred.

Figure 2 illustrates the variation we use in our empirical approach: the sub-state divisions shown are counties, and contiguous border county pairs that differed in their Medicaid expansion status as of April 2014 are highlighted. In 2014, there were 488 contiguous county pairs in which one county was in a state that had adopted the Medicaid expansion and the other in a state that had not, out of a total of 1195 contiguous county pairs. There are also two sources of variation used in our analysis that are not shown in Figure 2. First, a few states had already expanded eligibility for Medicaid to some nondisabled adults prior to the ACA expansion, so the ACA expansion increased eligibility for Medicaid more in some states than in others.[4] Second, states

[3] One possible concern with this identification strategy is that individuals might migrate across county lines in order to obtain Medicaid. However, evidence to date suggests that any such migration is likely to be minimal. Goodman (2017) finds no evidence of a migration response to the ACA Medicaid expansion at the public-use microdata area (PUMA) level, consistent with findings by Schwartz and Sommers (2014) for earlier health insurance expansions.

[4] California rolled out its early Medicaid expansion on a county-by-county basis. We include this variation, which results in additional discordant pairs on the California state border prior to 2014; beginning in 2014, all states bordering California also expand, so these pairs are no longer discordant at that point.

varied in when, as well as in whether, they expanded Medicaid. The modal expansion date (21 states) was January 1, 2014, but some states began to expand starting in 2010 and other states did not expand until later in 2014 or in later years.[5] Our analysis considers expansions through 2016.

More formally, consider the following specification estimated on a sample of all counties in the continental U.S. for the period 2010-2016:

$$(1) \qquad y_{ct} = \alpha + \delta NoncategoricalLimit_{s(c)t} + X_{ct}\Gamma + \varphi_c + \tau_t + \varepsilon_{ct}$$

where y_{ct} denotes the various outcomes of interest (described in detail in the Data section below) for county c in time t, where t denotes year. $NoncategoricalLimit_{s(c)t}$ denotes the Medicaid noncategorical income limit, that is, the baseline income limit that applies to adults whether or not they have children or disabilities (measured as a percentage of the poverty line) in effect in county c in state s for the majority of year t. Using the actual Medicaid income limit has the advantage that we incorporate information on the generosity of Medicaid eligibility prior to Medicaid expansion, thereby exploiting the fact that some policy changes were larger than others. The vector X_{ct} includes time-varying controls such as demographic characteristics, and φ_c and τ_t are county and time fixed effects, included to account for unmeasured heterogeneity in outcomes across space and time that may be correlated with expansion status. This equation corresponds to the difference-in-differences approach used in the ACA Medicaid expansion literature thus far, although it has typically been estimated at the state level or individual level with state and year fixed effects rather than at the county level.

The identifying assumption implicit in this approach is that after removing county-specific and time-specific fixed effects, outcomes in expansion and non-expansion counties

[5] Of 1195 contiguous county border pairs, 746 have discordant values for the non-categorical income limit at some point between 2010 and 2016. The number of discordant pairs by this definition ranges from 109 in 2010 to 562 in 2014.

would be changing in the same way over time if the expansion had not occurred. We estimate this model using our county-level data, clustering our standard errors at the state level to account for the fact that the variation in expansion status is at the state level. Depending on the outcome, we weight by county working age population or total population to account for the substantial variation in population size across counties.

One empirical challenge in the ACA Medicaid expansion literature is that there is a strong geographic correlation in which states chose to expand, and our outcomes of interest may be trending differently in different parts of the country. To deal with this, we use the discordant state border county approach described above. We limit the sample to contiguous border counties and restructure the data so that each county-county pair-year is one observation. Then we estimate a modified version of equation (1):

$$(2) \qquad y_{ct} = \alpha + \delta NoncategoricalLimit_{s(c)t} + X_{ct}\Gamma + \varphi_c + \tau_{pt} + \varepsilon_{cpt} \; .$$

where the subscript p denotes a county-pair and τ_{pt} is a pair-specific time effect (instead of a national time effect). The use of the pair-specific time effect means that we are using only variation in expansion status within each contiguous border county pair and controlling for local economic shocks that impact both members of the county pair in a given year. The identifying assumption is thus that a difference in expansion status within a contiguous border county pair is not correlated with time-varying unobservables that affect one member of the cross-border pair but not the other. In other words, we implicitly assume that within a pair the outcome in the county with the expansion would have changed in the same way as in the non-expansion county if the expansion had not occurred. Because of the data restructuring, some county-years are observed more than once because they border multiple counties. We re-weight, ensuring that the weights across county-county-pair-year observations within a county-year sum to the county population. We cluster standard errors by state and adjust to account for duplicated observations.

Because model (2) is only relevant to counties on state borders, the models in equations (1) and (2) are estimated on different samples. As a check, we estimate the differences-in-differences model of equation (1) on the restructured subsample of counties used in the estimation of equation (2). This check is useful in determining the effect of a different sample as well as the impact of the loss of statistical power resulting from moving to a smaller number of counties.

IV. Data

We obtain the data for our analysis from a number of different sources, with our primary outcomes of interest coming from administrative data. Recipients claim the EITC via income tax filing, and the Internal Revenue Service reports the number of returns filed in each county in each year with the Earned Income Credit as part of the Statistics of Income administrative records of individual income tax returns (Forms 1040). We use data for the 2010-2016 tax years (filed in 2011-2017). We adjust for county size by denominating the count of returns by estimates of the working age (18-64) population from the Census Bureau, and multiply by 100 to get the number of EITC returns per 100 working age adults. In our EITC regressions, we include controls for the percent non-Hispanic black and the percent Hispanic in the county obtained from the Census Bureau.

For SNAP, we use data on the number of recipients by county from the US Department of Agriculture Food and Nutrition Service National Data Bank. These data are reported biannually, in January and July, and we use the January counts for 2011-2017 to describe participation at the end of the prior year. Some states only report SNAP participation at the state level, so we are unable to use county-level data for the states of Connecticut, Idaho, Maine, Massachusetts, Missouri, Montana, Nebraska, New Hampshire, New York, Oregon, Rhode Island, Utah, Vermont, Washington, West Virginia, and Wyoming. We adjust for county size by denominating the count of SNAP participants with total population estimates in each county from the US Census Bureau, and multiply by 100 to get a SNAP participation rate per 100 residents. We include the same demographic controls as in the EITC regressions. As a robustness check, we control for whether the county had a waiver of the time limits usually applying to able-bodied adults without dependents in the SNAP program (ABAWD waiver).[6]

Health insurance coverage data at the county level are available from the Census Bureau's Small Area Health Insurance Estimates (SAHIE) program, which produces estimates of the fraction with and without health insurance coverage by income group at the county level.[7] The SAHIE estimates are model-based, incorporating information from the American Community Survey, federal tax return data, data on Supplemental Nutrition Assistance Program caseloads, Medicaid and Children's Health Insurance Program caseloads, Census population estimates, County Business Patterns, and the 2010 Census.

We determine the noncategorical Medicaid income eligibility levels applying to all adults following Medicaid expansion from a variety of sources. Prior to the ACA, parents could receive Medicaid if their incomes were below the parental eligibility limit, and a very few states had limited eligibility for non-parents. After the ACA-related Medicaid expansions, income limits

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[6]The ABAWD variables are generated by triangulating data from the U.S. Department of Agriculture, the Center for Budget and Policy Priorities, state websites, and data generously shared by Brian Stacy at the World Bank.
[7] While we would also like to examine Medicaid caseloads, unfortunately such data are not publicly available at the county level.

were raised for adults regardless of parental or disability status in a number of states. In our empirical work, we focus on the maximum noncategorical income limit—the limit facing able-bodied non-parents. Our primary sources for Medicaid income eligibility levels are reports published by the Kaiser Family Foundation (Cohen Ross et al. 2009, Heberlein et al. 2011, Heberlein et al. 2012, Heberlein et al. 2013, Brooks et al. 2015, Brooks et al. 2016, Kaiser Commission on Medicaid and the Uninsured 2013) and the Urban Institute's TRIM3 program rules database supplemented by information from state plan amendments available from the Centers for Medicare and Medicaid Services and state websites.

Our county level control variables include the share of the county population that is non-Hispanic black and Hispanic from the Census Bureau. In robustness checks, we also control for the unemployment rate, which we obtain from the Bureau of Labor Statistics Local Area Unemployment series. We determine which counties are contiguous using two files from the Census Bureau, a 2015 county adjacency file, which lists all adjacent counties, regardless of type of adjacency, and a county adjacency file from 1991 which gives the type of adjacency. We adjust the 2015 county-pair list to keep only counties that share a common land border or that are separated by a body of water but connected by a bridge or boat.[8]

Table 1A presents summary statistics for the overall samples for EITC (top panel) and SNAP (bottom panel). The EITC data (which includes all states) indicate that on average there are just over 14 returns claiming the EITC per 100 working age adults, although counties range from 0 returns to over 51 per 100 adults. Medicaid eligibility expansion to non-parent, non-disabled families was in effect in 32 percent of the county-years in the sample, and the mean

[8] We eliminate counties that meet at a corner only and counties that are separated by a body of water and have no direct bridge or boat connection.

noncategorical income limit (including zeros) was 42 percent of the poverty line. The SNAP sample, which includes only 16,972 county-year observations due to missing data, has similar summary statistics, although county-years in the SNAP sample were somewhat less likely to have a Medicaid expansion and also had somewhat higher fractions of nonwhite populations.

Table 1B shows both the all-county and contiguous-county samples for both the EITC and SNAP data, and in addition shows the first year (2010) and last year (2016) separately. EITC and SNAP participation are similar in the sample of all counties and in the contiguous counties sample. The counties in the border sample have somewhat fewer Hispanic residents although somewhat more non-Hispanic black residents.

Between 2010 and 2016 the number of EITC returns increased while the SNAP participation rate fell, consistent with the improving economy. In both EITC and SNAP data, the border county sample is more likely to have expanded Medicaid, and as a result the average noncategorical income limit is higher in the border county sample. Overall, the samples are fairly similar in their summary statistics, but because there are differences, for all of our regression analyses we estimate the model on the all-county sample and the contiguous county sample without incorporating the within-pair controls to indicate when there are differences that may arise from sample composition rather than specification.

While the county border discontinuity approach has strong intuitive appeal since it narrows the comparison to an arguably more similar counterfactual, it is important to demonstrate that restricting to bordering county pairs improves the comparison between expansion and non-expansion states. Various methods of examining the validity of border-pair models have been suggested in the literature (see Dube, Lester, and Reich (2010, 2016), Allegretto et al. (2013), and Neumark, Salas, and Wascher (2014)). In Table 2, we show that pre-

ACA (2010-11) mean absolute differences in values of our EITC and SNAP outcomes and covariates are smaller for contiguous pairs than they are for pairs formed by matching every other county with each county in the data. This suggests that county pairs that border each other are indeed more similar on observables—and therefore likely more similar on unobservables—than randomly chosen county pairs. We therefore have more confidence in the county-border-pair design than in a standard difference-in-difference design.

As a descriptive exercise to illustrate the county-pair design used in our analysis, we break the counties into two groups: those that ever expanded Medicaid and those that did not, where "ever expanded" is defined as having a Medicaid eligibility limit above zero for non-parents without disabilities at any point between 2010 and 2016. (Most expansions occurred in 2014 in line with the Affordable Care Act, but some states expanded earlier or later; a few had noncategorical Medicaid eligibility before 2010.) We then run regressions of our dependent variables of interest on the interaction of the "ever expanded" dummy with dummies for each year, controlling for the main effects of each year as well as other controls used in the regression analysis below. The resulting coefficients tell us about the mean difference between "ever expanded" counties and "never expanded" counties in each year in an outcome of interest, relative to the year 2010. For example, in the top panel of Figure 3, we show the results of this exercise where the noncategorical Medicaid limit is the dependent variable (bars indicate 95 percent confidence intervals). As expected, the difference between expansion and non-expansion counties starts to emerge in 2012 with early expansion and grows dramatically in 2014 when most counties implemented their Medicaid expansion.

In the bottom panel of Figure 3, we restrict to the border county sample and add controls for border-pair*year fixed effects. In other words, the coefficient reflects the difference in the outcome variable for each “ever expansion” county relative to its adjacent “never expansion” county. Here we again see evidence that income limits changed in “ever” counties relative to their adjacent “never” counties in 2014, as expected.

Figure 4 repeats these two descriptive exercises using the percent low-income uninsured as a dependent variable. In both specifications, we see a substantial relative decline in uninsurance starting in 2014 in “ever expanded” counties. Figure 4 shows no evidence of differential trends between “ever expanded” and “never expanded” counties in uninsurance prior to expansion.

Figure 5 graphs the coefficients from similar regressions using EITC returns per 100 working-age adults as the dependent variable. The top panel indicates somewhat higher numbers of EITC returns in “ever expanded” counties in the pre-period. Once we control for border-pair*year dummies (shown in the bottom panel), this pre-ACA difference is largely eliminated. Focusing on this border-pair specification, it appears that EITC returns increase around 2014 in expansion counties relative to bordering counties, but the effects are not significant in each separate year.

Finally, we show the same graphical illustration for SNAP participation in Figure 6. In the bottom panel of this figure, SNAP participation appears to increase in a relative sense around 2014 in expansion counties relative to their bordering counties, but then the two groups converge. These estimates are noisy, however, and the specification does not account for when a particular county experienced its expansion, nor does it account for differing levels of the noncategorical income limit in effect in different states at different times. We next present our results from analyses that take these differences into account.

V. Results

A. Uninsurance

Table 3 shows the effects of the ACA Medicaid expansions on uninsurance. Column 1 shows the analysis for the all-county sample with county fixed effects and year fixed effects, using the standard differences-in-differences model with a continuous treatment variable shown in equation (1), while column 2 restricts to contiguous county pairs with the same specification. The difference between columns 1 and 2 thus reflects differences in the border counties sample relative to the all counties sample. The results in column 1 suggest that moving from a noncategorical income limit of 0% to 100% of the federal poverty level reduces uninsurance by 0.6 percentage points, while in column 2, the point estimate is larger in magnitude at -1.3. Column 3 incorporates county-pair*year fixed effects as described in equation (2) above. The county-pair approach suggests a reduction of uninsurance of about 1.6 percentage points for an increase in the income limit from 0% to 100%. For context, the typical expansion moved from an income limit of 0% to 138% of the poverty line, and the mean uninsurance rate in 2010 (prior to the ACA) was 18.7 percent. Therefore, a typical expanding county reduced uninsurance by about 2.2 p.p. relative to an adjacent non-expanding county, around 12% of the baseline uninsurance level.

Columns 4 through 6 of Table 3 repeat the exercise examining the percent of the population with family incomes under 250 percent of the federal poverty level that is uninsured as the outcome. The effects of the Medicaid expansion are concentrated in this lower-income group, so it is not surprising that the coefficients are larger in magnitude. The preferred specification in column 6, which includes county-pair*year fixed effects, shows that increasing the Medicaid income limit from 0 to 100% of the poverty line reduced uninsurance 2.8

percentage points. The estimate implies that expansion counties moving from 0 to 138% of the poverty line would have 3.8 p.p. lower uninsurance in the low-income group than bordering counties, again a 12 percent reduction relative to the baseline of 29.5 percent uninsurance in 2010. The findings corroborate the findings of prior research using state differences-in-differences documenting that the ACA Medicaid expansions reduced uninsurance.

B. Earned Income Tax Credit

Our results for estimation of equations (1) and (2) for tax returns with an EITC per 100 working age adults are shown in Table 4. The point estimates are positive and significant in the standard difference-in-differences specifications in columns 1 (all counties) and column 2 (contiguous counties), with estimated coefficients that suggest an increase of 0.17 percentage points. Our preferred estimate in column 3 using the county-pair identification strategy is roughly half the magnitude and is no longer statistically different from zero. The point estimate implies an effect size of 0.09 percentage points, suggesting that an increase in the Medicaid income limit from 0 to 138 percent is associated with an increase of 0.12 EITC returns per 100 working-age adults. Since the mean in 2010 was roughly 14 EITC returns per 100 working-age adults, this point estimate implies that the increase was quite small, approximately 1 percent of the baseline level. For comparison, Kopczuk and Pop-Eleches (2007) estimate that state electronic filing programs increased EITC returns by around 10 percent among the target income group. Overall, our results suggest that the expansion of Medicaid eligibility under the ACA may have led to a small increase in EITC filing, but the preferred specification does not show a statistically significant relationship. The point estimate is about half of the size of that suggested by the standard difference-in-differences approach, which may be biased upward by preexisting differential trends in EITC returns between expansion and nonexpansion counties.

C. Supplemental Nutrition Assistance Program

Next, we turn to our results for SNAP (Table 5). These results rely on a smaller sample because a number of states do not report county-level SNAP data. We find statistically significant and positive estimates for the effect of the Medicaid noncategorical income limit on SNAP participation per 100 population. The coefficient of 0.43 on our preferred specification (column 3) indicates that an increase in the Medicaid noncategorical income limit from 0 to 138% of the poverty level led to a change of 0.6 additional SNAP participants per 100 people, a 4 percent increase relative to the mean rate of 15 percent SNAP participation. The effect is statistically significant. The estimates are about one-quarter of the effect size on uninsurance.

D. State-Level Analyses

For comparison to existing research, we show results for the state-level approach that is more common in the literature. Panel A of Table 6 shows this analysis for the EITC. The first two columns repeat results from Table 4 using a standard county differences-in-differences and county-border pair design. Columns (3) and (4) repeat the analysis at the state level, with column (4) incorporating state border pair controls. The state difference-in-difference estimate in column (3) is statistically significant and is similar to the estimate from the county data using state difference-in-difference variation, as expected. When state border pairs are introduced, there is no longer a statistically significant relationship between ACA Medicaid expansions and EITC.

Panel B of Table 6 contains the results for SNAP. Additional states are available because some states provide state level but not county level information, so results are shown for two different groups of states – those with state level data and those that report SNAP information at the county level. The coefficients are fairly similar in magnitude in all specifications and marginally significant in three of the four state level models.

In sum, the key SNAP results–that Medicaid expansions are associated with an increase in SNAP–are in evidence regardless of whether a county-border pair, a state border-pair, or a state differences-in-differences approach is used. For the EITC, the state border pair approach yields coefficients that are fairly similar to the county border pair approach, and these estimates are substantially smaller in magnitude than the standard differences-in-differences at both the state and the county level. This consistency across specifications may well be sensitive to the particular outcome of interest, however, and we believe the county border-pair approach generally offers a more reliable estimate of the effect of Medicaid expansions.

E. Robustness

Appendix Tables 1 and 2 present results from several robustness tests using our border-pair*year specification. For the EITC (Appendix Table 1), we add controls for the percent of the population that is 65 and older (column 2) and the (potentially endogenous) unemployment rate (column 3). Our main coefficient of interest is reduced slightly with the addition of these controls. In columns 4 through 6, we present the same regressions, but with a binary "expansion" variable instead of our continuous noncategorical Medicaid limit. We consider a county to have expanded in a given year if it has a noncategorical Medicaid limit greater than zero. Results are similar with this alternate specification.

Robustness checks for SNAP are in Appendix Table 2. The models are similar to the EITC regressions in Appendix Table 1, except that columns 2, 3, 5, and 6 also control for the presence of an ABAWD waiver in the county which relaxed work requirements for SNAP. The results consistently point to a positive relationship between Medicaid expansion and SNAP participation.

VI. Mechanisms

Though county-level administrative data has the advantage of completeness and accuracy, it does not allow us to investigate the mechanisms underlying increased safety net participation. It also allows for only basic demographic controls, and does not allow investigation of which demographic groups are particularly affected. We recently received permission from the U.S. Census Bureau to use individual-level data with county identifiers in the American Community Survey (ACS) to investigate heterogeneity in participation responses. Unfortunately, we have not yet been able to access these data pending administrative delays. Instead, we use the public-use IPUMS-ACS data set (Ruggles et al. 2019), focusing on public-use microdata areas (PUMAs) (areas of 100,000 people or more that do not cross state lines) as a preliminary step towards understanding mechanisms. We identify contiguous PUMAs and implement a preliminary set of analyses with PUMA-pair-year fixed effects, analogous to what we did with counties. Unfortunately, EITC receipt is not asked in the ACS, so we are only able to examine mechanisms affecting EITC eligibility using this approach.[9]

Our ACS analysis focuses on adults ages 25 to 64. We run a series of regressions for all adults in border PUMAs, and then split the sample by marital and parental status. Parents are defined as those with a biological, step, or adoptive child under 19 in the home. As in the county

[9] We attempted to use the measure of knowledge about the EITC in the county developed by Chetty, Friedman, and Saez (2013) to examine whether there were differential responses to Medicaid expansion in counties with high versus low levels of knowledge, but the results were statistically inconclusive.

pair analysis, we examine the effect of a change in the noncategorical Medicaid income limit. We include indicator controls for non-Hispanic black, Hispanic, female, presence of children under 19, single parent, education high school, education some college, education college grad, and marital status. We also control for age and age squared.

Results for the individual analysis using PUMA-pairs are shown in Tables 7 and 8. Each coefficient represents the key estimate on the non-categorical income limit from a different regression. As expected, Table 7 shows meaningful increases in health insurance for all demographic groups in expansion PUMAs relative to those in adjacent non-expansion PUMAs. Insurance effects are larger for the sub-sample under 130 percent of the poverty line. These increases in insurance are driven by increases in public health insurance in expansion PUMAs, partially offset by reductions in private insurance (results not shown).

The preliminary ACS results in Table 7 also show impacts on SNAP participation, consistent with the results from the analysis of county administrative data. The SNAP effect is evident across demographic groups, and is somewhat larger under 130 percent of the poverty line (the SNAP income eligibility threshold) for most groups, indicating that changes in income eligibility alone are not driving the results. We also see that Medicaid expansion is associated with an increase in those who participate in both Medicaid and SNAP, and a decline in those who participate in SNAP without Medicaid. The numbers imply that about a quarter of those induced to obtain public insurance as the result of ACA expansions are also induced to participate in SNAP when they otherwise would not have done so.

To investigate whether a change in eligibility (perhaps arising from a Medicaid-induced change in labor supply) could be causing the increased rate of SNAP participation, we examine hours worked, earnings, income under 130 percent of the poverty line and measures of labor force participation in Table 8. These results suggest no overall change in SNAP eligibility due to a labor supply response to Medicaid expansion. This finding is consistent with work that has been done on this question using standard state difference-in-differences methods (Gooptu et al. 2016, Kaestner et al. 2017, Frisvold and Jung 2018, Leung and Mas 2018). However, for single parents, there does appear to be a small reduction in the probability of living below the SNAP eligibility limit of 130 percent FPL, whereas the opposite is true for married parents. The apparent increase in SNAP eligibility for married parents does not seem to be accompanied by changes in basic measures of labor supply such as hours worked or earnings, suggesting it could be a statistical fluke. In any case, it is not large enough to fully explain the change in SNAP participation associated with Medicaid expansion. We also find a reduction in the probability of having business income and a corresponding increase (though not a statistically significant one) in the probability of wage income for single non-parents. Overall, we conclude that take-up factors such as knowledge and lower transaction costs are the most likely explanations for the link between Medicaid and SNAP utilization.

The ACS does not allow us to look at EITC utilization directly. Instead, we impute EITC eligibility based on earnings, income, age, and family structure. There is suggestive evidence that EITC eligibility increases overall, albeit to a very small degree, as shown in Table 7. Again, Table 8 does not suggest overall labor supply responses underlying this change, but does show some entry into the labor market among single parents. These changes, though quite small in magnitude, are consistent with a model of labor supply responses to increased Medicaid income limits among single parents generating spillover effects onto EITC eligibility.

Table 7 also looks at participation in the Temporary Assistance for Needy Families (TANF) cash welfare program, an outcome for which we are unable to obtain county-level administrative data. These preliminary results suggest a higher rate of TANF participation among single parents in expansion PUMAs. In conjunction with the other ACS evidence, one possible explanation is that Medicaid-induced labor market entry allows single parents to meet TANF work requirements..

In sum, the preliminary investigation of mechanisms suggests at most a small labor supply response to Medicaid expansions, with observed effects being largely limited to small increases in labor supply among single parents. Information or transaction costs are likely the primary explanation for increased levels of participation in the SNAP program. In future work we will use restricted access ACS data with county identifiers to better understand the mechanisms underlying our main results.

VII. Conclusion

Our results suggest that the Medicaid expansion does affect safety net participation in counties that expanded relative to nearby counties that did not expand. We find suggestive evidence of small increases in EITC receipt, although these effects are not statistically significant in the preferred specification. As expanding Medicaid eligibility could theoretically have positive or negative impacts on levels of EITC participation, these increases represent a net effect, with the factors leading to greater EITC receipt outweighing the factors leading to lower EITC receipt.[10] Our preliminary results using the ACS suggest a slight boost to single parent labor supply on the extensive margin, which could boost EITC participation.

[10] Note that if Medicaid expansions had general equilibrium impacts on a local area's labor market conditions, those effects would be absorbed by the county-pair*year effects.

We find increases in SNAP participation in counties that expanded relative to neighboring counties that did not, with about a quarter of those gaining public insurance due to the Medicaid expansion also induced to participate in SNAP. Our preliminary analysis using the American Community Survey suggests that information/transaction costs may be the main explanation for the observed association between Medicaid and SNAP. It is likely that the process of enrolling in Medicaid facilitates SNAP enrollment in some way.

Regardless of the mechanism, the finding that Medicaid expansions promote SNAP and perhaps EITC participation suggests the federal costs associated with the ACA may be greater than the direct costs of the program itself. Similarly, states considering Medicaid expansions might want to consider additional inflows of federal SNAP and EITC dollars as a benefit of making Medicaid income eligibility limits more generous.

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Figure 1a

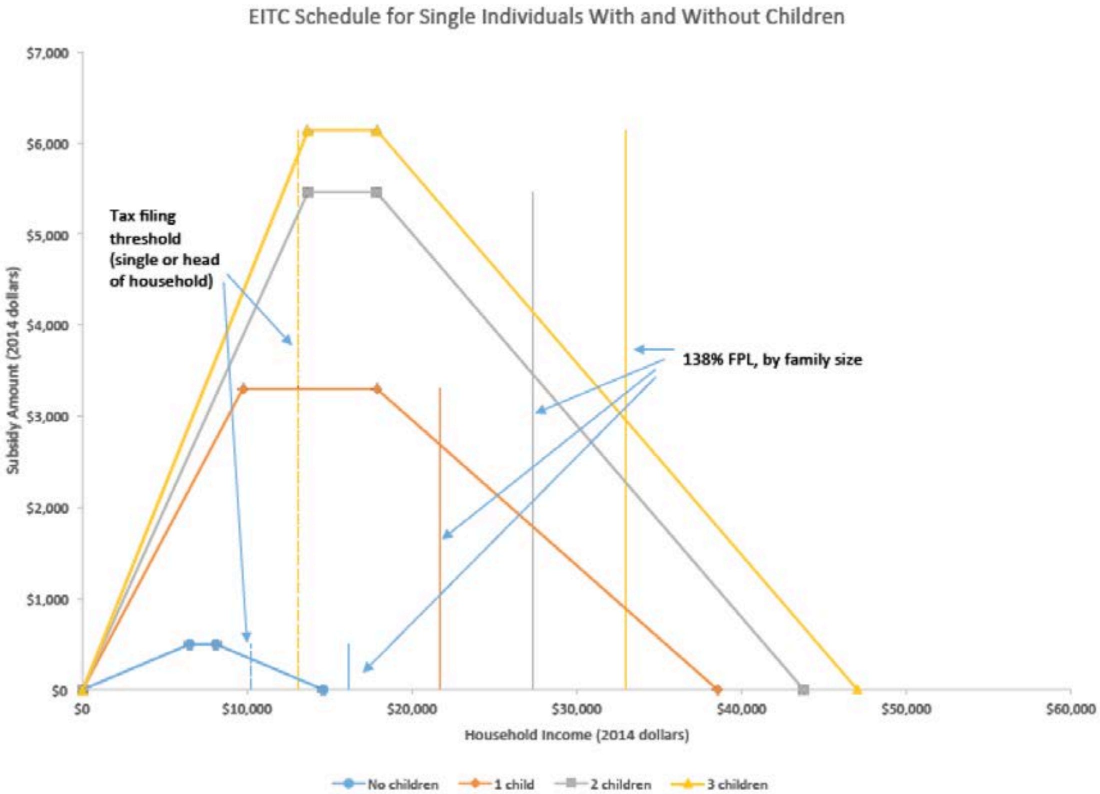
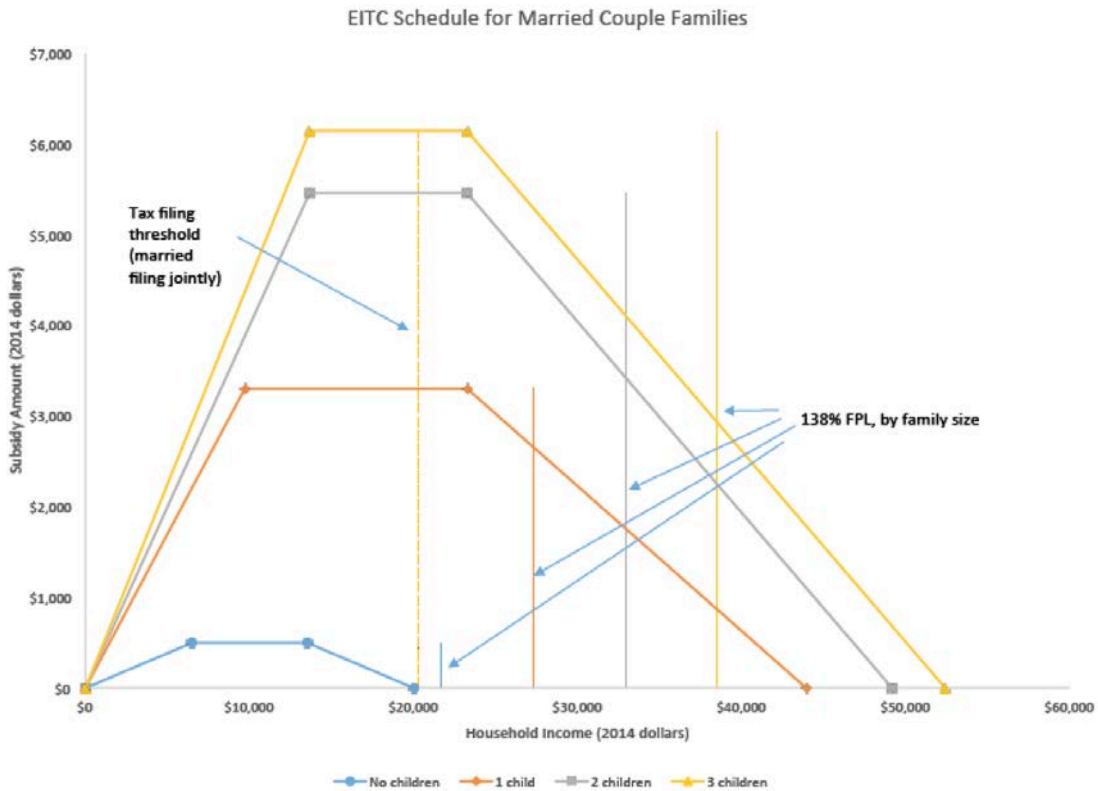
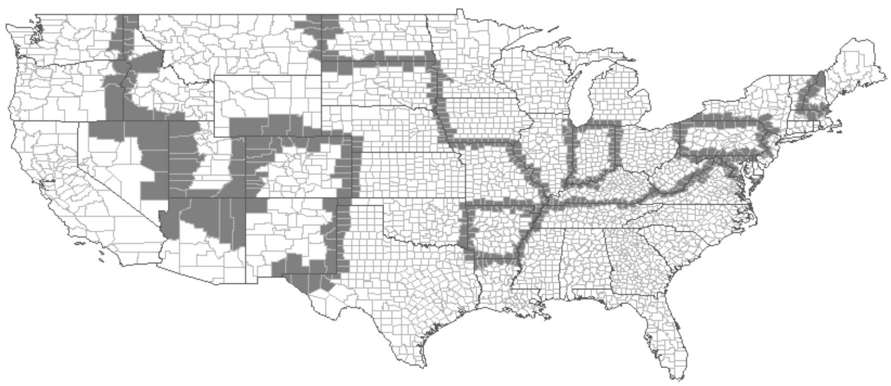

EITC Schedule for Single Individuals With and Without Children
$7,000
$6,000
$5,000
$4,000
$3,000
$2,000
$1,000
$0
Subsidy Amount (2014 dollars)
Tax filing threshold (single or head of household)
138% FPL, by family size
$0
$10,000
$20,000
$30,000
$40,000
$50,000
$60,000
Household Income (2014 dollars)
No children
1 child
2 children
3 children

Figure 1b



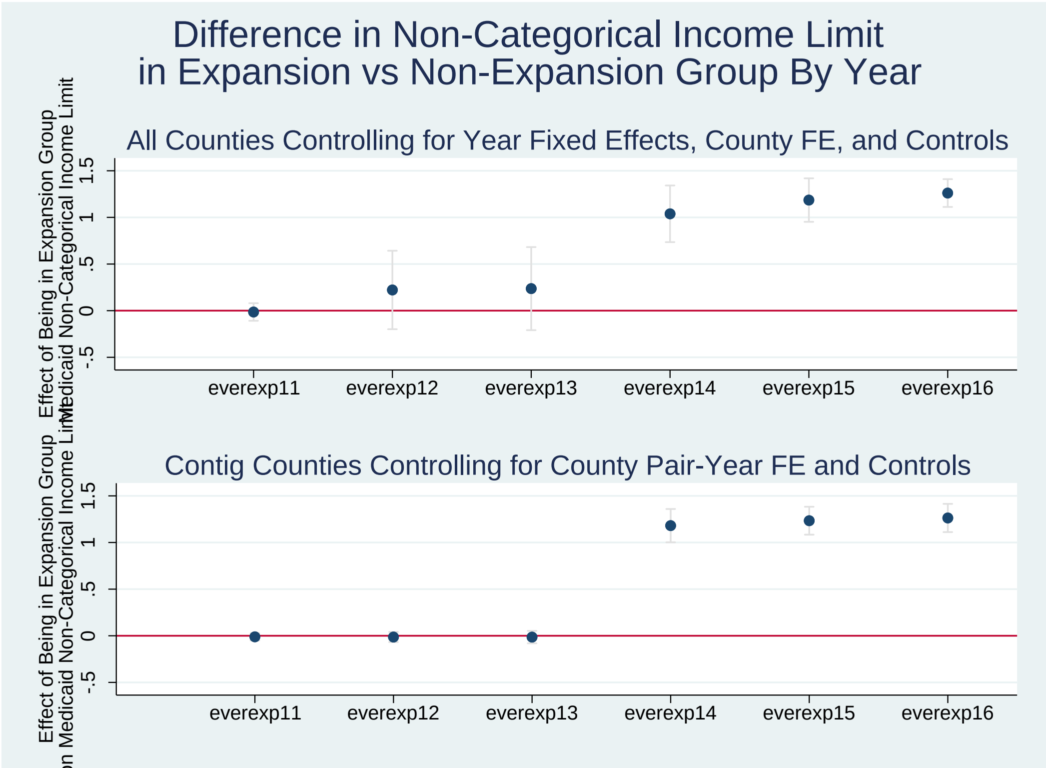
EITC Schedule for Married Couple Families
$7,000
$6,000
$5,000
$4,000
$3,000
$2,000
$1,000
$0
Subsidy Amount (2014 dollars)
Tax filing threshold (married filing jointly)
138% FPL, by family size
$0
$10,000
$20,000
$30,000
$40,000
$50,000
$60,000
Household Income (2014 dollars)
No children
1 child
2 children
3 children

Figure 2: Contiguous Border County Pairs in the US with a Medicaid Expansion Differential, April 2014



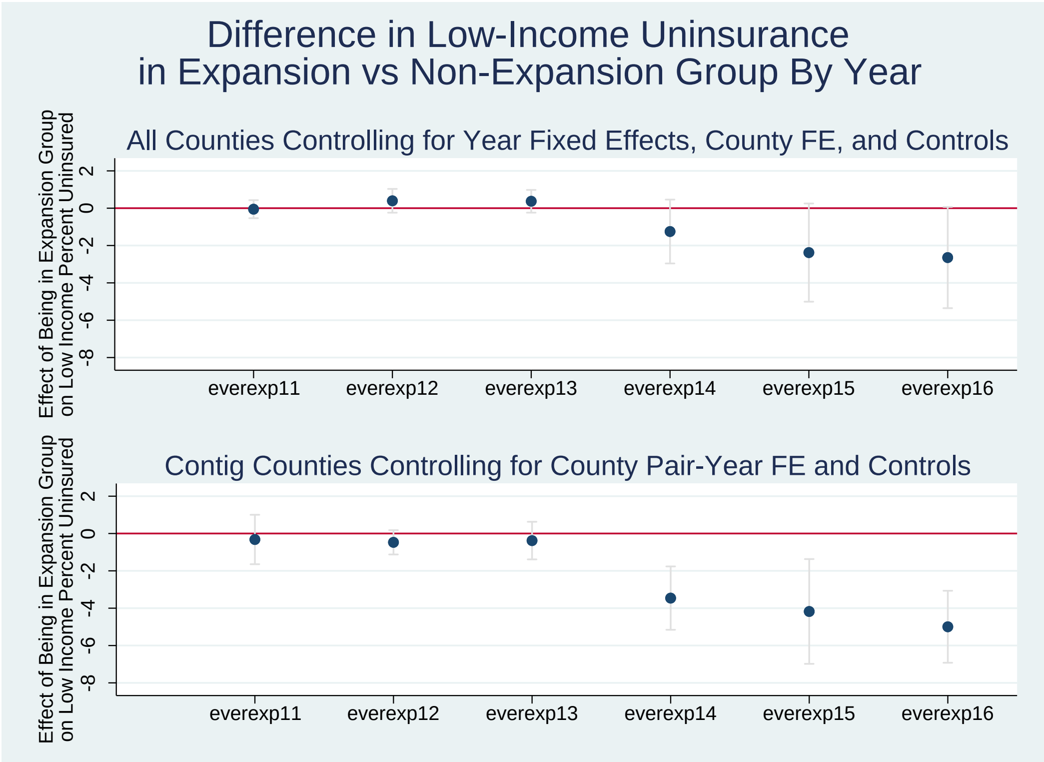
Source: Medicaid expansion status determined from data on state actions collected by the Kaiser Family Foundation.

Figure 3



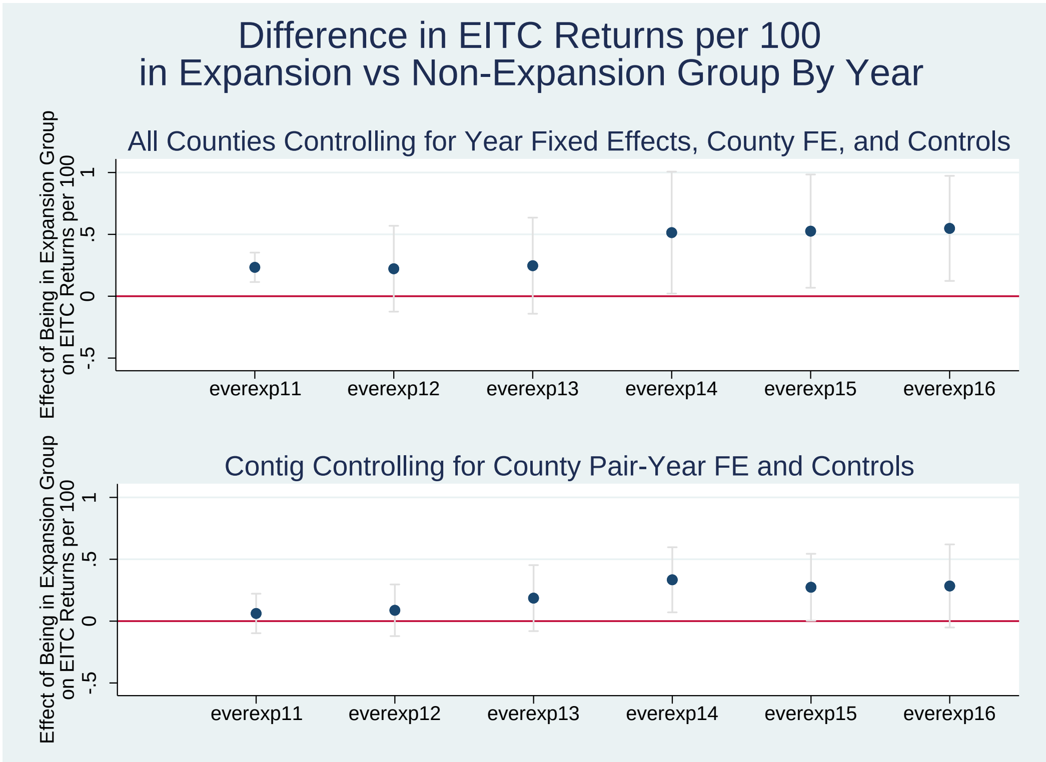
Note: Coefficients from regressions on 2010-2016 data that include county fixed effects and controls for fraction black and fraction Hispanic. The top panel includes year fixed effects and the bottom panel includes county pair by year fixed effects. EverexpYY refers to the coefficient on a dummy for whether county ever expanded interacted with a year indicator for year YY.

Figure 4



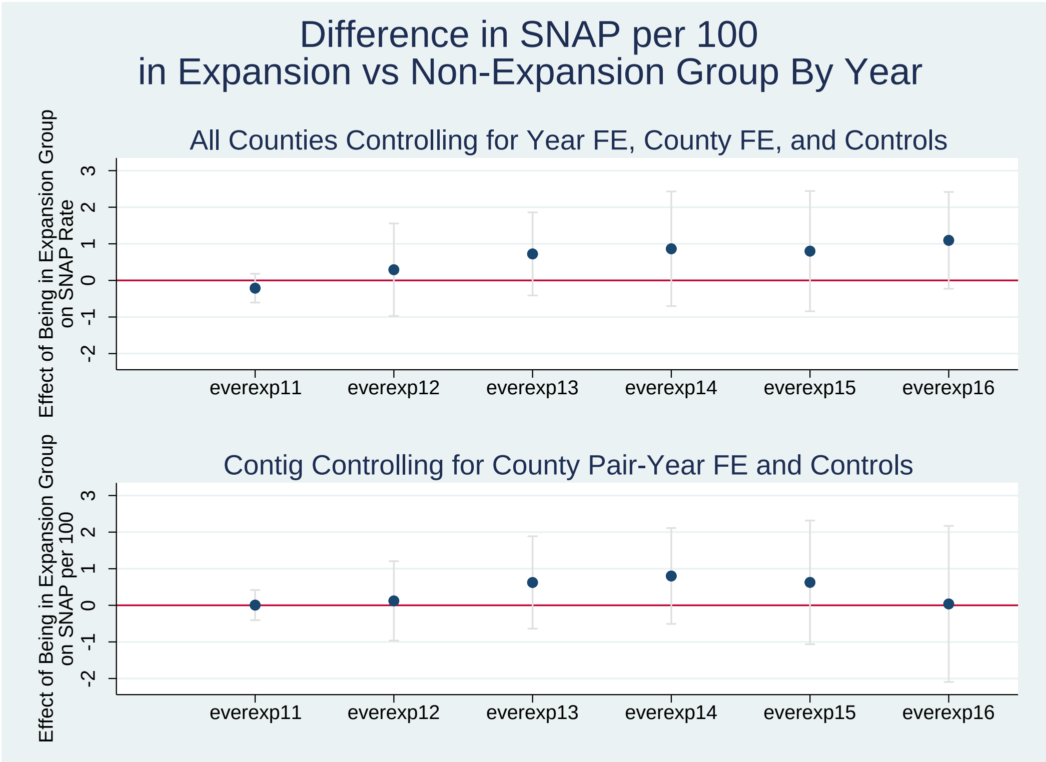
Note: Coefficients from regressions on 2010-2016 data that includes county fixed effects and controls for fraction black and fraction Hispanic. In each graph the top panel includes year fixed effects and the bottom panel includes county pair by year fixed effects. EverexpYY refers to the coefficient on a dummy for whether county ever expanded interacted with a year indicator for year YY.

Figure 5



Note: Coefficients from regressions on 2010-2016 data that includes county fixed effects and controls for fraction black and fraction Hispanic. In each graph the top panel includes year fixed effects and the bottom panel includes county pair by year fixed effects. EverexpYY refers to the coefficient on a dummy for whether county ever expanded interacted with a year indicator for year YY.

Figure 6



Note: Coefficients from regressions on 2010-2016 data that includes county fixed effects and controls for fraction black and fraction Hispanic. In each graph the top panel includes year fixed effects and the bottom panel includes county pair by year fixed effects. EverexpYY refers to the coefficient on a dummy for whether county ever expanded interacted with a year indicator for year YY.

Table 1A: Summary Statistics, All Counties EITC and SNAP Samples 2010-2016

Variable	Mean	Standard Deviation	Min	Max
Panel A: EITC Sample, weighted by working-age population (N=21,623)				
EITC returns per 100 working age adults	14.229	4.591	0.0	51.6
Percent Uninsured	14.686	6.166	2.1	41.4
Percent Low-Income Uninsured	23.350	8.219	4.5	51.2
ACA Medicaid expansion (Y/N)	0.368	0.482	0.0	1.0
Medicaid non-categorical income limit (relative to the poverty line)	0.477	0.655	0.0	2.2
Percent non-Hispanic black	13.455	12.902	0.0	86.0
Percent Hispanic	17.228	16.752	0.0	96.3
Panel B: SNAP Sample, weighted by total population (N=16,965)				
SNAP participation rate	14.374	6.514	0.0	154.6
Percent Uninsured	15.557	6.180	2.9	41.4
Percent Low-Income Uninsured	24.503	8.059	6.2	51.2
ACA Medicaid expansion (Y/N)	0.306	0.461	0.0	1.0
Medicaid non-categorical income limit (relative to the poverty line)	0.404	0.634	0.0	2.2
Percent non-Hispanic black	14.363	13.410	0.0	86.0
Percent Hispanic	18.416	17.870	0.2	96.3

Notes: Observations are county-years. See text for sources.

Table 1B: Weighted Means by Sub-Sample and Year

Sample and Year	All Counties EITC Sample	Border Counties EITC Sample	All Counties SNAP Sample	Border Counties SNAP Sample
Panel A: 2010 data				
EITC returns per 100 working age adult or SNAP participation rate	12.959	12.551	14.170	14.565
Fraction Uninsured	17.685	15.974	18.673	17.268
Fraction Low-Income Uninsured	28.257	26.232	29.528	27.741
ACA Medicaid expansion (Y/N)	0.125	0.157	0.032	0.032
Medicaid non-parent income limit (relat to the poverty line)	0.128	0.62	0.038	0.043
Percent non-Hispanic black	13.278	13.734	14.167	15.649
Percent Hispanic	16.454	12.750	17.640	13.794
Observations	*3089*	*2390*	*2466*	*1781*
Unique counties	*3089*	*1138*	*2466*	*859*
Panel B: 2016 data				
EITC returns per 100 working age adult or SNAP participation rate	14.235	13.919	13.254	13.929
Fraction Uninsured	9.965	8.903	10.675	9.699
Fraction Low-Income Uninsured	15.960	14.613	16.947	15.592
ACA Medicaid expansion (Y/N)	0.618	0.694	0.577	0.673
Medicaid non-parent income limit (relat to the poverty line)	0.902	1.005	0.804	0.944
Percent non-Hispanic black	13.163	14.076	14.535	16.008
Percent Hispanic	18.000	14.249	19.169	15.592
Observations	*3089*	*2390*	*2399*	*1713*
Unique counties	*3089*	*1138*	*2399*	*833*

Table 2: Mean Absolute Difference Between Counties in All Pairs and Contiguous Border Pairs Pre-ACA, EITC Sample

Mean Absolute Difference Between Counties	All Pairs	Contiguous Border Pairs	Difference
EITC returns per 100 Working Age Adults	5.343***	3.124***	-2.219***
	(0.101)	(0.099)	(0.091)
Non-categorical Income Limit	0.100***	0.091***	-0.009
	(0.010)	(0.013)	(0.009)
Unemployment rate	3.465***	1.881***	-1.585***
	(0.046)	(0.048)	(0.058)
Percent in poverty	6.852***	4.287***	-2.566***
	(0.114)	(0.129)	(0.125)
Percent non-Hispanic black	12.770***	4.986***	-7.787***
	(0.367)	(0.252)	(0.287)
Percent Hispanic	9.627***	4.163***	-5.465***
	(0.313)	(0.220)	(0.256)

The first column shows the mean absolute difference between pairs formed by matching each county in the 2010 contiguous county border sample with all possible other counties. The second column shows the mean absolute difference in the values of the variables between counties in a contiguous pair in the 2010 data. The symbol *** indicates that the mean absolute difference within county pairs is different from 0 at $p<0.01$ in columns (1) and (2). The third column represents the difference between columns (1) and (2), and *** indicates the difference between columns (1) and (2) is statistically different from 0 at $p<0.01$.

Table 3: Effects of ACA Medicaid Income Limits on Percent Uninsured and Low Income Uninsured

	(1) All Counties Sample	(2) Contig Counties Sample	(3) Contig Counties Sample	(4) All Counties Sample	(5) Contig Counties Sample	(6) Contig Counties Sample
	Percent Uninsured	Percent Uninsured	Percent Uninsured	Percent Low-Income Uninsured	Percent Low-Income Uninsured	Percent Low-Income Uninsured
Non-categorical	-0.566**	-1.270***	-1.620***	-1.475***	-2.382***	-2.778***
Income Limit	(0.277)	(0.446)	(0.326)	(0.454)	(0.608)	(0.591)
% Non-Hispanic	0.889*	0.631*	0.341***	0.476	0.109	-0.390
black	(0.451)	(0.365)	(0.127)	(0.666)	(0.439)	(0.282)
% Hispanic	-0.441	-0.154	-0.058	-0.319	-0.225	0.317
	(0.378)	(0.748)	(0.269)	(0.522)	(0.861)	(0.507)
Observations	21,623	16,730	16,730	21,623	16,730	16,730
R-squared	0.959	0.952	0.993	0.955	0.952	0.989
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	YES	YES	NO
County Pair*Year FE	NO	NO	YES	NO	NO	YES

Dependent variable is the percent of individuals overall or percent of individuals with family incomes under 250% of poverty uninsured in a county from the Small Area Health Insurance Estimates 2010-2016. EITC analysis sample is used and excludes Republic County, Kansas. Robust standard errors clustered on state in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effects of ACA Medicaid Income Limits on EITC Returns per 100 Working Age Adults

	(1) All Counties Sample	(2) Contig Counties Sample	(3) Contig Counties Sample
Non-categorical	0.168**	0.171***	0.088
Income Limit	(0.081)	(0.051)	(0.053)
% Non-Hispanic	0.088	0.216***	0.266***
black	(0.107)	(0.080)	(0.062)
% Hispanic	0.163***	0.163*	0.154*
	(0.053)	(0.084)	(0.084)
Observations	21,623	16,730	16,730
R-squared	0.990	0.993	0.998
County FE	YES	YES	YES
Year FE	YES	YES	NO
County Pair*Year FE	NO	NO	YES

Dependent variable is the number of EITC returns*100 in a county divided by number of working-age adults (ages 20-64) in the county. Republic County, Kansas does not appear in the Statistics of Income county data. Estimates are weighted by working-age population. Robust standard errors clustered on state in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effects of ACA Medicaid Income Limits on SNAP Participants per 100 People

	(1) All Counties Sample	(2) Contig Counties Sample	(3) Contig Counties Sample
Non-categorical	0.378	0.510*	0.433**
Income Limit	(0.255)	(0.282)	(0.189)
% Non-Hispanic	0.006	0.471**	0.776***
black	(0.216)	(0.204)	(0.230)
% Hispanic	0.665***	1.030***	0.453
	(0.181)	(0.220)	(0.372)
Observations	16,965	12,197	12,197
R-squared	0.948	0.962	0.990
County FE	YES	YES	YES
Year FE	YES	YES	NO
County Pair*Year FE	NO	NO	YES

Dependent variable is the number of SNAP participants*100 in a county divided by county population. A number of states do not report county level SNAP data and are excluded from the sample; see text for details. In columns (4) and (5) sample is split based on the 2010 percentage of low-income individuals that were uninsured. Estimates are weighted by population. Robust standard errors clustered on state in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: State-Level and County-Level Analyses of EITC and SNAP

	(1)	(2)	(3)	(4)	(5)	(6)
	All Counties Sample	Contig Counties Sample	All States Sample	Contig States Sample	SNAP County Reporter All States Sample	SNAP County Reporter Contig States Sample
Panel A. Effect of Non-parent Income Limit on EITC Returns per 100 Working-Age Adults						
Non-categorical Income Limit	0.168**	0.088	0.194**	0.043		
	(0.081)	(0.053)	(0.095)	(0.056)		
Observations	*21,623*	*16,730*	*343*	*1,498*		
Panel B. Effect of Income Limit for Non-parents on SNAP Participants per 100 People						
Non-categorical Income Limit	0.378	0.433**	0.518*	0.380*	0.573*	0.311
	(0.255)	(0.189)	(0.268)	(0.201)	(0.301)	(0.289)
Observations	*16,965*	*12,197*	*342*	*1,496*	*231*	*1,022*
County or State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	NO	YES	NO	YES	NO
Pair*Year FE	NO	YES	NO	YES	NO	YES

Each cell represents the coefficient on the non-categorical Medicaid income limit from a separate regression. Dependent variable is the number of EITC returns*100 divided by working-age adults or SNAP participants*100 divided by population. EITC state regressions include contiguous 48 states plus D.C.; some state-years are missing. SNAP "county reporter" state regressions further exclude 14 states that do not report county-level SNAP data. Race/ethnicity controls included. Estimates are weighted by working-age population or population. Robust standard errors clustered on state in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Individual-Level Analysis using PUMA-pair design
Effect of Non-Categorical Income Limit on Health Insurance, SNAP, Imputed EITC Eligibility, and TANF

	(1) All	(2) Single Non-parents	(3) Married Non-Parents	(4) Single Parents	(5) Married Parents
Number of Obs	*20,745,958*	*6,306,487*	*7,070,177*	*1,452,034*	*5,917,260*
Any Health Ins	0.0199***	0.0329***	0.0087***	0.0284***	0.0127***
	(0.003)	(0.004)	(0.002)	(0.006)	(0.004)
Any Health Ins	0.0644***	0.0705***	0.0778***	0.0383***	0.0616***
Sample <130% Pov	(0.007)	(0.007)	(0.009)	(0.010)	(0.014)
Any SNAP in HH	0.0085***	0.0124***	0.0055***	0.0093**	0.0058**
	(0.002)	(0.003)	(0.001)	(0.005)	(0.002)
Any SNAP in HH	0.0165***	0.0161**	0.0242***	0.0078	0.0198*
Sample < 130% Pov	(0.005)	(0.007)	(0.007)	(0.006)	(0.012)
Public Health Ins and SNAP	0.0161***	0.0224***	0.0081***	0.0277***	0.0131***
	(0.002)	(0.003)	(0.001)	(0.006)	(0.002)
Public Health Ins and No SNAP	0.0135***	0.0221***	0.0045***	0.0175***	0.0114***
	(0.002)	(0.003)	(0.001)	(0.005)	(0.002)
SNAP and No Public Health Ins	-0.0076***	-0.0100***	-0.0025***	-0.0184***	-0.0073***
	(0.002)	(0.002)	(0.001)	(0.006)	(0.003)
Imputed EITC Eligibility	0.0019**	0.0007	0.0020**	0.0014	0.0034
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Any TANF Income	0.0013**	0.0013	0.0005	0.0069**	0.0005
	(0.001)	(0.001)	(0.000)	(0.003)	(0.000)

Sample is individual citizens ages 25 to 64 in contiguous PUMA pairs from 2011-2017 American Community Survey. Each cell is a coefficient on the state non-categorical income limit for the year prior to survey year from a separate regression. Analyses include PUMA fixed effects, PUMA-pair-year fixed effects, and controls for non-Hispanic black, Hispanic, female, presence of children under 19, single parent, education high school, education some college, education college grad, age, age squared, and marital status. Parental status defined by whether a parent reports a child in the household under 19 is their own biological, step, or adoptive child. Robust standard errors clustered on state in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Individual-Level Analysis using PUMA-pair design
Effect of Non-Categorical Income Limit on Income and Labor Supply

	(1) All	(2) Single Non-parents	(3) Married Non-Parents	(4) Single Parents	(5) Married Parents
Number of Obs	*20,745,958*	*6,306,487*	*7,070,177*	*1,452,034*	*5,917,260*
Under 130% Poverty	0.0014	-0.0001	0.0018	-0.0058*	0.0043**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Any Earnings (for couple if married)	0.0005	0.0011	-0.0003	0.0045*	-0.0003
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Any Wage Income (for couple if married)	0.0011	0.0028	-0.0004	0.0081***	-0.0012
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
Any Business Income (for couple if married)	-0.0005	-0.0025***	0.0004	-0.0026	0.0021
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Number Earners (for couple if married)	0.0026	0.0011	0.0047	0.0045*	0.0014
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Log (Couple Real Combined Earnings)	-0.0050	-0.0031	-0.0031	-0.0058	-0.0064
	(0.003)	(0.004)	(0.005)	(0.008)	(0.006)
Any Earnings (for individual)	0.0015	0.0011	0.0020	0.0045*	0.0004
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Any Hours (for individual)	0.0016	0.0013	0.0019	0.0048*	0.0005
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
At Least 35 Hours (for individual)	-0.0003	0.0014	-0.0001	-0.0001	-0.0023
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)

Notes: See notes to Table 7. Robust standard errors clustered on state in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 1: EITC Robustness

	(1) EITC Returns Per 100 Minimal Controls (from Table 4)	(2) EITC Returns Per 100 Expanded Controls	(3) EITC Returns Per 100 Unemp Control	(4) EITC Returns Per 100 Minimal Controls	(5) EITC Returns Per 100 Expanded Controls	(6) EITC Returns Per 100 Unemp Control
Non-categorical	0.088	0.071	0.068			
Income Limit	(0.053)	(0.052)	(0.052)			
Expansion Dummy				0.050	0.035	0.031
				(0.079)	(0.075)	(0.075)
% non-Hispanic	0.266***	0.285***	0.294***	0.271***	0.289***	0.299***
Black	(0.062)	(0.052)	(0.052)	(0.064)	(0.053)	(0.052)
% Hispanic	0.154*	0.248***	0.242***	0.165*	0.260***	0.254***
	(0.084)	(0.074)	(0.074)	(0.086)	(0.076)	(0.077)
% Elderly		0.271***	0.271***		0.275***	0.275***
		(0.055)	(0.056)		(0.055)	(0.056)
Unemployment			-0.044*			-0.045*
Rate			(0.025)			(0.025)
Observations	16,730	16,730	16,730	16,730	16,730	16,730
R-squared	0.998	0.998	0.998	0.998	0.998	0.998
County FE	YES	YES	YES	YES	YES	YES
County Pair*Year FE	YES	YES	YES	YES	YES	YES

Estimates are weighted by working age population or total population. Robust standard errors clustered on state in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2: SNAP Robustness

	(1) SNAP Participation Rate	(2) SNAP Participation Rate	(3) SNAP Participation Rate	(4) SNAP Participation Rate	(5) SNAP Participation Rate	(6) SNAP Participation Rate
	Minimal Controls (from Table 5)	Expanded Controls	Unemp Control	Minimal Controls	Expanded Controls	Unemp Control
Non-categorical	0.433**	0.416**	0.432***			
Income Limit	(0.189)	(0.176)	(0.152)			
Expansion Dummy				0.596***	0.558***	0.573***
				(0.207)	(0.203)	(0.181)
% non-Hispanic	0.776***	0.803***	0.723**	0.782***	0.808***	0.728**
Black	(0.230)	(0.244)	(0.264)	(0.233)	(0.250)	(0.271)
% Hispanic	0.453	0.383	0.352	0.459	0.396	0.367
	(0.372)	(0.354)	(0.293)	(0.378)	(0.366)	(0.300)
% Elderly		-0.193	-0.204		-0.190	-0.200
		(0.364)	(0.379)		(0.366)	(0.380)
ABAWD Waiver		0.463	0.438		0.433	0.409
		(0.374)	(0.377)		(0.375)	(0.380)
Unemployment			0.367**			0.366**
Rate			(0.173)			(0.175)
Observations	12,197	12,197	12,197	12,197	12,197	12,197
R-squared	0.990	0.990	0.990	0.990	0.990	0.990
County FE	YES	YES	YES	YES	YES	YES
County Pair*Year FE	YES	YES	YES	YES	YES	YES

Estimates are weighted by working age population or total population. Robust standard errors clustered on state in parentheses. *** p<0.01, ** p<0.05, * p<0.1