Economic Impacts of Supplemental Nutrition Assistance Program Payments in Nonmetro vs. Metro Counties*

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Abstract

The Supplemental Nutrition Assistance Program (SNAP) is the largest Federal food and nutrition program and the second largest Federal means-tested transfer program. Participation in the program and real average monthly payments grew rapidly in the past decade. We investigate the impacts of changes in SNAP benefit payments on earnings in nonmetro and metro counties during the 2000 to 2010 period using three econometric methods: i) ordinary least squares fixed effects (OLS-FE) regressions, ii) instrumental variables fixed effects (IV-FE) regressions, and iii) spatial discontinuity OLS and IV first difference (SD-OLS-FD and SD-IV-FD) regressions. The estimated impacts vary considerably across the estimation methods, and all methods suffer significant weaknesses. The OLS-FE regressions appear to be affected by unobserved heterogeneity and endogeneity biases. The instrumental variables used in the IV regressions (state-level SNAP policy variables) are found not to be exogenous in most cases, and are weak in the SD-IV-FD regressions. The most plausible results are found using the SD-OLS-FD model, but large standard errors in this model limit the statistical power to draw confident conclusions. The most interesting finding is of a more positive (or less negative) association of SNAP payments with earnings during the Great Recession. This difference supports our hypothesis that the positive impacts of SNAP payments are likely to be larger during a recession. Several avenues for further research are suggested.

Keywords: Supplemental Nutrition Assistance Program, Food Stamp Program, economic impacts, spatial discontinuity model

JEL Codes: R11, R15, H53

Introduction

The Supplemental Nutrition Assistance Program (SNAP), formerly called the Food Stamp Program (FSP), is the largest Federal food and nutrition program, the largest program operated by the U.S. Department of Agriculture, and the second largest Federal means-tested program after Medicaid. Participation in the program in recent years has grown dramatically, with SNAP participants increasing from 6 percent of the U.S. population in 2000 to 15 percent in 2013 (Figure 1), while the average real monthly benefit paid to recipients increased from about $73 in 2000 to $98 (in 2000$) in 2013. SNAP participation has been higher in rural areas throughout this period.

A substantial body of literature has investigated the factors affecting SNAP participation (e.g., Danielson and Klerman 2013; Ganong and Liebman 2013; Goetz et al. 2004; Hanratty 2006; Klerman and Danielson 2011). Important factors found in this literature include changes in macroeconomic conditions, policies related to SNAP and welfare programs, demographic characteristics, and other factors. Another body of literature investigates the impacts of SNAP participation on food consumption and other expenditures of SNAP recipient households (e.g, Fraker 1990; Wilde and Ranney 1996; Wilde et al. 2009). However, very little research has investigated the economic impacts of SNAP participation beyond impacts on SNAP-recipient households. A few studies have investigated impacts at a national scale using computable general equilibrium models (e.g., Hanson et al. 2002; Reimer and West, forthcoming) or input-output models (Hanson 2010). We are aware of no econometric studies of the economic impacts of SNAP participation at the county level.

In this paper we investigate the impacts of SNAP program payments on earnings in nonmetro vs. metro counties during 2000 to 2010. We focus on earnings as one of the primary outcomes that we would expect to be affected by SNAP payments.[1] For example, the demand generated by SNAP payments can affect local earnings by affecting business sales and income, even if employment is unaffected. Hence impacts of SNAP payments may be more evident for earnings than for employment measures. We focus on the period 2000 to 2010 because this includes an interesting contrast of growth and recessionary periods. We hypothesize that the economic impacts of SNAP payments will differ between such periods, and test this hypothesis. We find evidence that the impact of SNAP payments on earnings was more positive (or less negative) during the Great Recession.

This paper contributes to the literature on the SNAP program in particular, and to literature on Federal anti-poverty programs in general, by using the best available econometric methods and data to assess the local economic impacts of this program, and compare the impacts in metro vs. nonmetro areas. This has not been done for the SNAP program, and has rarely been done for other Federal anti-poverty programs. We apply three econometric methods – ordinary least squares fixed effects regressions, instrumental variables fixed effects regressions, and spatial discontinuity first difference regressions. The spatial discontinuity approach has been used in several papers in recent years to assess the economic impacts of changes in state level policies, such as branch banking deregulation (Huang 2008), changes in minimum wages (Dube et al. 2010), corporate taxes (Heider and Ljungqvist 2015; Lungqvist and Smolyansky 2014), and unemployment benefits (Hagedorn et al. 2013). No papers have used this approach to investigate the impacts of SNAP. In contrast to previous studies using this approach, we combine the spatial discontinuity approach, which compares contiguous counties across state borders, with use of commuting zones to better ensure comparability of the counties being compared. We

[1] We don't investigate impacts of SNAP payments on total personal income because this includes SNAP payments (and other transfer payments), which would induce an automatic relationship.

also combine the approach with instrumental variables estimation; although as we will show, this approach faces problems of weak instruments in this case.

The next section discusses our hypotheses about how SNAP program payments may affect regional economies. The third section discusses the econometric methods used in the study. The fourth section explains the variables and data sources used. The fifth section presents the results, and the sixth section concludes.

Expected Impacts of SNAP Benefits on County Economies

SNAP participation and benefits may affect regional economies in many ways. These benefits may increase effective demand for all goods and services, leading to increases in employment, earnings, profits, and multiplier impacts in the regional economy. Since SNAP benefits have been shown to increase food consumption by more than a comparable increase in cash income (Fraker 1990; Wilde and Ranney 1996; Wilde et al. 2009), the impacts of SNAP may be particularly strong where agricultural production or food processing and distribution account for a relatively large portion of the economy. This fact, together with the fact that SNAP participation is generally greater in rural areas, suggests that many rural regions may experience relatively larger economic impacts of SNAP than urban regions. On the other hand, the multiplier effects of SNAP transfers may be smaller in smaller, less economically diverse rural economies. Differences across communities in the extent to which residents are net payers of Federal taxes or net recipients of SNAP benefits may also cause differences in the impacts of increases in SNAP participation.

SNAP impacts also likely depend on the state of the local economy, with greater impacts expected in situations where there is substantial poverty and unemployment. When there are more unemployed resources, such as during a recession, the increase in demand resulting from SNAP benefits is likely to generate greater economic impacts than when the economy is closer to full employment, by enabling some of these slack resources to be more fully utilized. Furthermore, since the program provides income to poorer households who have a higher marginal propensity to consume than wealthier ones, the potential economic short-term stimulus during a recession from the SNAP program is likely to be greater than would result from a program targeting wealthier beneficiaries. For example, using a national economic model, Zandi (2009) estimated that the increases in SNAP benefits in the American Recovery and Reinvestment Act would have the largest impact on GDP per dollar spent of any of the program increases in the Act.

Although SNAP payments can yield positive impacts on regional economies through income transfer and multiplier effects, they may also have negative impacts. If taxes rise to finance an increase in SNAP benefits, this can have negative income effects, with net impacts depending on changes in the distribution of income in a region (as well as net changes in aggregate regional income) and how income distribution affects the demand for local goods and services. Impacts can be complex and differ by sector. For example, Hanson et al. (2002), using a national CGE model, predicted that a large cut in the Food Stamp Program (FSP) would have negative employment effects in nonmetro areas specializing in livestock and feed crops. Nevertheless, the aggregate predicted impact of a FSP cut on employment was positive in both nonmetro and metro regions (though larger in metro regions), due to the assumed reduction in tax receipts that would result. No studies have investigated such impacts econometrically, however.

SNAP payments also may reduce employment and earnings by reducing the incentive of people to work. Since the benefits offered under the program decline as income increases, this acts as an effective tax on increased earnings. Although the marginal tax rate resulting from the SNAP program can be quite high for particular individuals (especially those close to the income threshold for program eligibility) (Kotlikoff and Rapson 2006), average marginal tax rates across entire populations of social safety net programs as a whole were fairly modest in the 2000 to 2010 period. Moffitt (2015) estimated that the effective marginal tax rate (MTR) from all transfer programs facing households with income less than 50 percent of the poverty line increased from 14 percent in 2000 to 18 percent in 2010, while the MTR increased from 3 percent in 2000 to 7 percent in 2010 for households with incomes from 50 to 100 percent of the poverty line, and from 5 percent in 2000 to 15 percent in 2010 for households with incomes from 100 percent to 150 percent of the poverty line. Moffitt (2015) concluded, based upon this evidence and earlier studies of the labor supply impacts of the FSP (e.g., Fraker and Moffitt 1988; Hagstrom 1996; Currie 2003; Hoynes and Schanzenbach 2012), that the SNAP program has had a minimal impact on labor supply overall, although impacts on particular groups such as single mothers is significant.

SNAP payments may also have short and long term economic impacts to the extent that they affect households' incentives and ability to save and invest. On one hand, as an implicit income transfer, SNAP payments can increase the ability of recipient households to save. On the other hand, asset limits in the program (which have been largely reduced or eliminated through policy changes since 2000) may undermine recipients' incentive to save and invest. The net impact of these factors is not clear, and to our knowledge no studies have investigated these impacts to date. If such impacts are present, they may be reflected to some extent in near term impacts on earnings and other sources of income, by affecting savings vs. consumption decisions.

Econometric Approach

We estimate the impacts of changes in SNAP participation or benefits per capita on earnings per capita in metro vs. nonmetro counties using econometric methods.[2] Three methods are used, their assumptions tested, and the results compared to assess the robustness of the conclusions.

Ordinary Least Squares Fixed Effects (OLS-FE) Regression Model

The OLS-FE models estimate the regression equation:

1) $Y_{ct} = \alpha_c + \alpha_t + \beta S_{ct} + \gamma X_{ct} + \varepsilon_{ct}$

Y_{ct} represents real earnings per capita in county c during year t; S_{ct} represents real SNAP benefits per capita; X_{ct} is a set of control variables that may be correlated with SNAP benefits per capita and with real earnings per capita (economic conditions; demographic characteristics of the population, state policy environment); α_c are county fixed effects; α_t are year fixed effects; ε_{ct} is an error term assumed to be uncorrelated with S_{ct} and $X_{ct;}$ and β is the parameter of interest, reflecting the effect of SNAP benefits per capita on earnings per capita at the county level.

In one version of the OLS-FE model, we account for all time-varying state-level factors (such as state policies and state-level economic trends) by including state by year fixed effects (α_{st}):

1') $Y_{ct} = \alpha_c + \alpha_{st} + \beta S_{ct} + \gamma X_{ct} + \varepsilon_{ct}$

[2] In this paper we report only the results using the value of SNAP benefits per capita as the key explanatory variable. The results were qualitatively similar using SNAP participants per capita instead. Full regression results are available upon request.

Instrumental Variables Fixed Effects (IV-FE) Regression Model

The IV-FE model addresses the potential endogeneity of S_{ct} in equation 1) by using instrumental variables to predict S_{ct}:

2) $S_{ct} = \delta_c + \delta_t + \theta P_{st} + \lambda X_{ct} + \nu_{ct}$

Candidate instrumental variables include state-level SNAP policies (P_{st}). These policies have varied substantially over time and across states, are arguably exogenous to county-level economic outcomes, and have been shown in several studies to predict differences in SNAP participation.

Equation 2) is combined with equation 1) to estimate the IV-FE model.[3] We test the strength and validity of the instrumental variables using weak identification and overidentification tests.

Spatial Discontinuity (SD) Regression Model

If there is unobserved heterogeneity in the factors affecting SNAP participation and economic outcomes, the FE and IV models may yield biased estimates of the impacts of SNAP. One approach to this problem that has recently been used to estimate impacts of other policies (Dube et al. 2010; Hagedorn et al. 2013; Heider and Ljungqvist 2015; Huang 2008; Ljungqvist and Smolyansky 2014) is to estimate a fixed effects or first difference model for contiguous pairs of counties across state borders that experienced differential changes in the policy variable.

In our version of the SD model, we estimate differences in impacts of SNAP benefits per

[3] Equation 1') cannot be estimated using instrumental variables estimation because the instrumental variables used are state level SNAP policies, which are perfectly correlated with the state by year fixed effects in equation 1').

capita within commuting zones across state borders.[4] This method differs from that used by other authors by focusing on border counties within commuting zones, rather than all border county pairs. Our assumption is that border counties within commuting zones are more likely to reflect the same economic environment than all border county pairs. With this assumption, we revise equation 1) slightly, including a commuting zone by year fixed effect (α_{zt}) rather than a common year fixed effect (α_t):

1'') $Y_{ct} = \alpha_c + \alpha_{zt} + \beta S_{ct} + \gamma X_{ct} + \varepsilon_{ct}$

We estimate this equation in first differences, eliminating the county fixed effect (α_c):

3) $\Delta Y_{ct} = \Delta\alpha_{zt} + \beta\Delta S_{ct} + \gamma\Delta X_{ct} + \Delta\varepsilon_{ct}$

The $\Delta\alpha_{zt}$ term is accounted for in the estimation using commuting zone by year fixed effects, while ΔS_{ct} and ΔX_{ct} are observed changes in the SNAP variable and in the control variables. We estimate two versions of the SD first difference model in equation 3): one using an OLS first difference fixed effects model (SD-OLS-FD) and one using an IV first difference fixed effects model (SD-IV-FD). To our knowledge, ours is the first paper to combine a spatial discontinuity estimator with instrumental variables estimation.

Besides the inclusion of commuting zones by year fixed effects, the main difference between the SD and other models is the sample of counties included in the estimation. All counties in the 48 states of the continental United States were included in the estimation of the OLS-FE and IV-FE models. For the SD model, we first identified states that had similar SNAP policies in 2000, the beginning of our study period. In 2000, 27 states did not use any of the following nine participation-promoting policies: i) broad-based categorical eligibility eliminating

[4] Commuting zones are groups of counties that have strong commuting ties, identified using hierarchical cluster analysis (see http://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas.aspx for an explanation of the method of classifying commuting zones and data on the zones). The method of classification is explained in more detail by Tolbert and Sizer (1996).

the asset test for SNAP, [5] ii) operation of call centers statewide, iii) operation of a Combined Application Project for SNAP and SSI recipients, iv) provision of a waiver allowing use of telephone interviews instead of face-to-face interviews at the time of the initial eligibility certification, v) provision of a waiver allowing telephone interviews at the time of recertification, vi) eligibility of all legal noncitizen children that otherwise satisfy eligibility requirements, vii) allowing households to submit an online application for SNAP, viii) one or more vehicles are excluded from the asset test, and ix) a simplified reporting option to reduce beneficiaries' requirements for reporting changes in their status.[6] Use of these policies has since expanded throughout most states, contributing to the expansion of SNAP participation in recent years (Figure 2) (Ganong and Liebman 2013; Klerman and Danielson 2011).

For the SD regressions for nonmetro counties, we identified all nonmetro counties on the borders between pairs of these 27 states, and then identified which of these counties were within commuting zones that straddled state borders.[7] In many cases, commuting zones did not cross state lines. Excluding state borders with no nonmetro counties within commuting zones that cross the border, and further restricting our sample to state border pairs with sufficient numbers of counties within the commuting zones to estimate differences in outcomes between the states within the commuting zones, we are left with 23 state border pairs among 24 states, including 266 nonmetro counties and 65 metro counties in our initial SD sample (Figure 3).

As a check on the comparability of the counties across state lines within commuting zones at the beginning of the study period, we estimated mean differences in the growth rate of

[5] USDA defines broad-based categorical eligibility as a household's eligibility for SNAP because they qualify for or are already receiving Temporary Assistance for Needy Families (TANF) or other State-specified low-income assistance program. (http://www.fns.usda.gov/broad-based-categorical-eligibility-chart)

[6] The states in which none of these policies were operational in 2000 included Alabama, Arkansas, Arizona, Colorado, Florida, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Mississippi, Missouri, Nevada, New Hampshire, New Mexico, New York, North Carolina, Oklahoma, Pennsylvania, South Dakota, Tennessee, Texas, Vermont, Virginia, and Wyoming.

[7] A similar procedure was used to identify metro counties within commuting zones that straddled state borders.

real earnings per capita from 2000 to 2001 across state lines within each state border pair and within commuting zones. The mean difference in this growth rate was less than 5 percent for 16 of the 23 state border pairs and larger than 5 percent for the other 7 state border pairs (Table 1). In a second version of the SD models, we dropped the 7 state border pairs with large mean differences in the growth rate in real earnings per capita from 2000 to 2001, to better assure comparability of the counties in the sample. This left 172 nonmetro counties and 58 metro counties in 16 state border pairs among 19 states in the second SD sample.

Estimates for Different Macroeconomic Periods

As indicated above, we expect that the potential for positive economic impacts of SNAP payments on local economies depends on the macroeconomic context. When unemployment is high, as during the recession/slow growth period of 2008 to 2010, SNAP payments may have a more stimulative impact on local economies than during non-recessionary years. Hence, for one set of analyses we split the sample into two periods: 2000 to 2007 and 2008 to 2010.[8]

Variables and Data

The dependent variable in the analysis is county-level real earnings per capita. The data for earnings per capita are from the Regional Economic Information System of the Bureau of Economic Analysis (http://bea.gov/regional/index.htm). Nominal values are converted to real 2010 values using the Consumer Price Index (CPI-U), from the Bureau of Labor Statistics (BLS) (http://www.bls.gov/cpi/tables.htm).

The key explanatory variable is the county-level real value of SNAP benefits per capita.

[8] Because of the recession in 2001, in one set of analyses we focused on 2002 to 2007 rather than 2000 to 2007 for the earlier period. The results were similar.

The value of SNAP benefits per capita is from the USDA Economic Research Service's (ERS's) SNAP Data System (http://www.ers.usda.gov/data-products/supplemental-nutrition-assistance-program-(snap)-data-system.aspx). SNAP benefits per capita are converted to real 2010 values using the CPI-U.

The state-level SNAP policy variables used as instrumental variables to predict SNAP participation are from ERS's SNAP Policy Database (http://www.ers.usda.gov/data-products/snap-policy-database.aspx). In addition to the nine variables used in this analysis, several other state-level SNAP policies are included in the ERS SNAP Policy Database. The nine policy variables included in this analysis were those that had the largest statistically significant positive impacts on SNAP participation in initial regressions examining the determinants of SNAP participation during the 2000 to 2010 period. Use of all of these policies increased substantially during this period, whereas other SNAP policies were more stable or declined.

The other state policies used as control variables in the analysis include the real value of the state minimum wage[9] and three indexes developed by the Fraser Institute and used in estimating the economic freedom index of states and provinces in the United States, Canada, and Mexico (http://www.freetheworld.com/efna.html). These indexes include an index reflecting the size of government (based on general consumption expenditures by all government levels as a percentage of GDP, transfers and subsidies as a percentage of GDP, and social security payments as a percentage of GDP), taxation (based on total tax revenue as a percentage of GDP, the top marginal income tax rate and the income threshold at which it applies, indirect tax revenue as a percentage of GDP, and sales tax collected as a percentage of GDP), and "labor market freedom" (based on the annual full-time equivalent value of the federal minimum wage as a percentage of

[9] The Federal minimum wage was used for states not having a minimum wage or where the state minimum wage was less than the Federal minimum wage. Nominal minimum wages were converted to real 2010 values using the CPI-U.

GDP, government employment as a percentage of total nonmilitary state/provincial employment, and union density).

The demographic control variables included the population of the county, the child (under age 15) share of the population, the elderly (over age 64) share of the population, the black or African American share of the population, the American Indian share of the population, the Asian or Pacific Islander share of the population, and the Hispanic share of the population. The source of these data was the Census Bureau County Intercensal Estimates (https://www.census.gov/popest/data/intercensal/county/county2010.html).

The economic control variables included the county-level unemployment rate and poverty rate. Because of the potential endogeneity of these variables in the regressions, we ran three versions of all models – one version using current values (or concurrent changes in the first difference regressions), one using lagged values (or lagged changes in the first difference regressions), and one dropping these variables. All results for the impacts of SNAP benefits on earnings were qualitatively similar across the three versions for different models. In the results section, we report the versions using current or lagged values of economic conditions in the OLS-FE models.[10] In all other cases, we report only the version using lagged economic conditions. The data for the county-level unemployment rate are from the BLS's Local Area Unemployment Statistics (http://www.bls.gov/lau/). The data for county-level poverty are from the Census Bureau's Small Area Income and Poverty Estimates (http://www.census.gov/did/www/saipe/data/statecounty/).

The data on commuting zones in the United States are from the ERS website (http://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas.aspx).

[10] All regression results are available from the authors upon request.

Results

Descriptive statistics of the data, shown separately for metro and nonmetro counties, are reported in Table 2. On average, real earnings per capita were greater in metro than nonmetro counties during 2000 to 2010, while the mean real SNAP benefits per capita and poverty rate were greater in nonmetro counties. The mean adoption of state SNAP policies and other state policy indexes were similar between metro and nonmetro counties; differences in these reflect which states have more metro or nonmetro counties. The most common SNAP policies were exemptions to asset tests for vehicles, allowing all legal noncitizen children to be eligible for SNAP (if otherwise eligible), and allowing a simplified reporting option to SNAP beneficiaries for reporting changes in their situation. The mean unemployment rate was similar between metro and nonmetro counties. Mean population size was much larger in metro counties, while many of the other demographic indicators for age, race, and ethnicity were fairly similar. Nonmetro counties have somewhat larger mean proportions of elderly people and American Indians, and somewhat smaller mean proportions of black/African American, Asian/Pacific Islander, and Hispanics. There is substantial variation across counties and years in all of these variables.

Regression Results for Nonmetro Counties

The regression models for nonmetro areas are presented in Table 3. Eight models are presented. Three versions of the OLS-FE model are presented; one using concurrent values of the county level economic variables (unemployment rate and poverty rate) and two using lagged values. One of the versions with lagged values estimates equation 1), including measured indicators of state policies and year fixed effects; the second version estimates equation 1'), including state by year fixed effects instead of state policy indicators and year fixed effects. Two versions of the IV-FE model are presented; one using all nine state SNAP policy variables as instrumental variables, and one using only two instruments – broad-based categorical eligibility and allowing eligibility of all legal noncitizen children that otherwise meet eligibility requirements. This restricted model was selected because it was the model with more than one instrumental variable that achieved the highest P value of the overidentification test (i.e., the model for which a false rejection of the null hypothesis of valid instrumental variables was most likely). Two versions of the SD-OLS-FD model are presented; one using the full set of 23 state border pairs shown in Table 1 for which the model was estimable, and the second one using the 16 state border pairs which had smaller differences in growth of real earnings per capita from 2000 to 2001 across state lines within commuting zones (also shown in Table 1). Two comparable versions of the SD-IV-FD model are also presented; one using the 23 state border pairs and one using the 16 state border pairs. Many other versions of these models were run using different combinations of the control variables and the instrumental variables (regression results available upon request). The qualitative results in Table 3 are robust to these variations.

The main finding in Table 3 is that the estimated impact of SNAP benefits on county-level earnings in nonmetro counties depends heavily on the estimation method and sample. The OLS-FE models all (including variations in the specification not reported) find a statistically significant negative effect of SNAP benefits on earnings. The magnitude of these effects is larger than one would plausibly expect to result from work disincentives caused by SNAP, with a $1 increase in SNAP benefits associated with up to $9 of reduced earnings.[11] This could be a spurious effect resulting from endogeneity of SNAP benefits, and may reflect reverse causality;

[11] As noted earlier, Moffitt (2015) argues that the aggregate labor supply impact of SNAP is minimal, even though it is significant for single mothers.

i.e., reductions in earnings not explained by the other control variables could be causing an increase in SNAP payments. Inclusion of the local poverty rate and unemployment rates as control variables in the regression helps to address this potential for reverse causality, but likely doesn't perfectly control for the effects of earnings changes on SNAP payments. Furthermore, poverty and unemployment are also potentially endogenous in these regressions. Using lagged values of those variables or omitting them may help to address the endogeneity concern, but possibly at the expense of contributing to an omitted variable bias. Including state by year fixed effects reduces the magnitude of the negative impact of SNAP benefits (to about $4.50 in reduced earnings per $1 of additional SNAP benefits). This model controls for any unobserved heterogeneity at the state level, but still could be subject to endogeneity bias.

The IV-FE models yield estimates of the impact of SNAP benefits that are surprisingly even larger in the negative direction, with $1 of additional SNAP benefits associated with as much as $45 in reduced earnings. These impact levels are even more implausible than the OLS-FE results. The instrumental variables used in both IV models pass the weak instruments test by a large margin, so it is unlikely that a bias caused by weak instruments is the explanation. However, the full set of instrumental variables fails the overidentification test, indicating that some of the instrumental variables and/or the control variables are not truly exogenous. Using the restricted set of instruments in the second IV-FE model produces a less clear violation of exogeneity, given that the J statistic in this case (2.60) is only marginally statistically significant at the 0.1068 probability level. But this weak passage of the overidentification test was based on a search among all subsets of the instrumental variables and is based on only two instruments. Essentially, this test simply shows that the estimated results are similar when either of these two instrumental variables is used; and does not provide great confidence in the validity of the estimated result. The lack of clear validity of the instrumental variables undermines confidence in the IV-FE results.

The rationale for using a spatial discontinuity approach, as opposed to a traditional OLS-FE or IV-FE approach, is that unobserved heterogeneity across counties may be biasing the results of these estimators (Dube et al. 2010). Implicitly, any county is allowed to be used as a comparator to any other county by these estimators, as long as they are similar in terms of the control variables used, even though such counties may have greatly different earnings per capita as a result of unobserved differences. The SD models address this concern by focusing on differences in growth of earnings per capita within commuting zones and years in selected state border pairs. As shown in Table 1, the growth in earnings per capita between 2000 and 2001 was fairly similar across state lines within most of these state border pairs and commuting zones, and in the second version of the SD models we have excluded state border pairs where the differences across state lines in earnings growth from 2000 to 2001 was relatively large. These methods of sample selection were used to help ensure that the counties being compared in the regression were as similar as possible in terms of the dependent variable prior to the major changes in SNAP policies that occurred in these sample states during the study period.

The coefficient of SNAP benefits per capita is statistically insignificant in all four versions of the SD models presented in Table 3. In the SD-OLS-FD models, the coefficients of SNAP benefits are smaller in magnitude than in the OLS-FE models, and vary in sign depending on which sample is used. A similar result is evident for the SD-IV-FD models. The standard errors are very large in the SD-IV-FD models, reflecting the weakness of the instrumental variables in these models. Both of these models fail to pass the weak instruments test at the 10% level. We thus do not have confidence in the SD-IV-FD model results.

Of all the models presented in Table 3, our preferred specification is the SD-OLS-FD model for the set of 16 state border pairs in which earnings per capita growth rates from 2000 to 2001 were most similar. That model suffers the least from unobserved heterogeneity, and does not depend on suspect instrumental variables. It still may be subject to endogeneity and omitted variable bias, but arguably less so than the other models presented. Our conclusion from these results is that SNAP benefits per capita did not have a measurable effect on nonmetro county-level earnings per capita during the study period.

Regression Results for Metro Counties

A slightly different story emerges from the results for metro counties, reported in Table 4. As in nonmetro counties, the OLS-FE model estimates statistically significant negative effects of SNAP benefits on earnings; although the magnitude of these negative effects are smaller in metro counties in two of the three versions of the OLS-FE model. The exception is the model including state by year fixed effects; that model predicts that $1 in additional SNAP benefits is associated with nearly $6 in reduced earnings; which again seems implausibly large. The IV-FE model yields a large positive coefficient for SNAP benefits when all of the instrumental variables are used ($9 in additional earnings per $1 of additional SNAP benefits), but this model fails the overidentification test and is thus not reliable. A more restrictive model using four of the nine SNAP policy variables as instruments passes both the weak instruments test and the overidentification test. This model yields a smaller (than estimated by other models) negative estimate of the SNAP benefits coefficient (about $1.50 reduction in earnings associated with $1 of additional SNAP benefits), but this coefficient is statistically insignificant.

As for nonmetro counties, the SD models are preferred in terms of addressing unobserved heterogeneity. Both of the SD-IV-FD models fail the weak instruments test, so these estimates are unreliable. Both of the SD-OLS-FD model produce similar estimates for the impact of SNAP benefits (about $4 reduction in earnings for each $1 of additional SNAP benefits), and both of these estimates are weakly statistically significant at the 10% level. These estimates suggest that there may be a negative impact of SNAP benefits on metro county earnings, although the confidence bounds on this estimated impact are quite large and include zero at the 5% level.

Regression Results for Different Time Periods

Regression results using the OLS-FE and SD-OLS-FD models for different time periods are reported in Table 5. Because of the problems with the instrumental variables models reported in Tables 3 and 4, we did not use those models in this extension of the analysis.

We find substantial differences in the OLS-FE results across time periods for both nonmetro and metro counties. For the pre-recession period of 2000 to 2007, we again find a statistically significant negative coefficient for SNAP benefits per capita in the nonmetro county regression, of similar magnitude to that found in the models reported in Table 3 (about $8 of reduced earnings associated with an additional $1 of SNAP benefits). By contrast, for the recession/slow growth period of 2008 to 2010, we find a statistically significant positive coefficient for SNAP benefits per capita in the nonmetro county regression (nearly $3 of increased earnings associated with an additional $1 of SNAP benefits). In metro counties, we also find a statistically significant negative coefficient for SNAP benefits during 2000 to 2007 (about $7 of reduced earnings associated with an additional $1 of SNAP benefits), but a much smaller and statistically insignificant negative coefficient for SNAP benefits during 2008 to

2010.

The general pattern of these results is for the associations between SNAP payments and earnings to be less negative or even positive during the recessionary period. The qualitative direction of this difference – i.e., more positive (or less negative) association of SNAP benefits with earnings – is consistent with our hypothesis that SNAP payments are expected to have more positive economic impacts on local economies during a recession.

We find a similar qualitative pattern in the results of the SD-OLS-FD models reported in Table 5, although the coefficient of SNAP benefits per capita is statistically insignificant in all of those models. Hence those results are suggestive but do not provide clear support of our hypothesis.

Conclusions

In this paper we sought to estimate the economic impact of SNAP payments on nonmetro and metro counties, as measured by earnings, using several different estimators. We found that our estimates depend greatly on the method and sample of counties and years used. The OLS-FE estimates indicated implausibly large and statistically significant negative associations of SNAP benefits with earnings in all regressions focused on the entire study period of 2000 to 2010; the magnitude of these associations ranged from about $3 to $9 in reduced earnings per $1 of additional SNAP benefits. Although many factors were accounted for in these OLS regressions – including state by year fixed effects in one version – the results still may reflect biases resulting from endogeneity of the SNAP benefits and unobserved heterogeneity of the factors affecting earnings.

We sought to address the endogeneity of SNAP benefits using IV-FE models, but the results showed even larger negative associations between predicted SNAP benefits per capita and earnings per capita in nonmetro counties, and a nonrobust large positive association in one version of the IV-FE regression (the version that failed the overidentification test) for metro counties. Tests of the SNAP policy indicators used as instrumental variables indicated violations of the validity of these variables for the analysis of nonmetro counties. One version of the IV-FE regressions for metro counties passed the overidentification and weak instruments tests, and in this model the coefficient of SNAP benefits was statistically insignificant (with a very large standard error). These instrumental variable results are thus inconclusive.

We sought to address unobserved heterogeneity (beyond what could be accomplished with full sample fixed effects models) by selecting a subsample of arguably comparable counties across state borders within commuting zones using SD models. The results of these models for the association between SNAP benefits and earnings per capita in nonmetro counties were generally smaller in magnitude than the estimates of the corresponding OLS-FE or OLS-IV model, and were statistically insignificant in all cases. We thus do not have robust evidence of any impact of SNAP benefits on earnings in nonmetro counties. In metro counties, the SD-OLS-FD models yielded weakly statistically significant (at 10 percent level) estimates of a negative association between SNAP benefits and earnings, and the magnitude of these estimates (about $4 in reduced earnings per $1 of additional SNAP benefits) was similar to the magnitudes of estimates of the OLS-FE model. We thus have somewhat more robust estimates of negative impacts of SNAP benefits on earnings in metro counties. However, the unexpectedly large magnitude of these effects, and our inability to confirm these results with strong and valid instrumental variables estimates limits our confidence in these results, as they may be subject to bias due to endogeneity of the SNAP benefits.

One interesting finding from the OLS-FE models is that the association between SNAP benefits and earnings is more positive (or less negative) for the recession period of 2008 to 2010 than for the expansion period from 2000 to 2007 in both nonmetro and metro counties. Results from the SD-OLS-FD models are consistent with this finding, though are statistically insignificant. This result is hard to explain as a result of reverse causality or other estimation bias, and is consistent with our hypothesis that the positive economic impacts of SNAP payments (per $ spent) are likely to be greater during a recession. Further research on this issue would be valuable.

Overall, these findings reflect the difficulty of reliably measuring the economic impacts of a program such as SNAP using non-experimental econometric methods. Although instrumental variables methods can in principle address the endogeneity problem, finding exogenous instruments that strongly predict the program variable is always a challenge. In this case, state SNAP policies appeared to be strong candidates as instrumental variables; but these are not necessarily exogenous to earnings outcomes, since state policy makers may adjust SNAP policies in response to economic cycles. Furthermore, although we controlled for some other state policies that could be correlated with SNAP policies, benefits and earnings, other state policies that weren't accounted for may have caused the SNAP policies to not be exogenous (i.e., the SNAP policies could be correlated with other policies that affect earnings). We were able to use state by year fixed effects in the OLS models to reflect the effects of all state policies, but this approach could not be used with the IV models.

The SD approach helps to address biases caused by unobserved heterogeneity, but at a cost of increasing standard errors and reducing estimation efficiency. Detecting the county-level economic impacts of SNAP payments may simply not be feasible using this method, given the size of the standard errors of this coefficient using SD models (in almost all cases larger than $2 per $1 of additional SNAP benefits) relative to the plausible magnitude of SNAP impacts on earnings (arguably less than $2 per $1 of additional SNAP benefits).

Further work on this issue could pursue several possible avenues to improve the analysis. County-level time-varying instrumental variables for SNAP participation and benefits could be sought. For example, indicators of access to SNAP offices (if available or if could be constructed at a county level and if they vary over time) may be suitable as instrumental variables. Additional state policy indicators could be included in the analysis, helping to address the non-exogeneity of state SNAP policies. The efficiency of the SD estimators could be improved by including more state border pairs and more years in the analysis. Impacts of SNAP payments on other dependent variables that are more directly affected by SNAP payments could be investigated. For example, earnings in the grocery industry are most directly affected by increased SNAP payments. Alternative indicators of financial flows from the SNAP program could also be investigated. For example, data on SNAP redemptions, which track where SNAP benefits are used, could be used rather than data on the value of SNAP benefits or SNAP participation, both of which are based on the county of residence of SNAP recipients. If SNAP recipients buy groceries in a different county from their residence, the impacts will likely be greater in the county where they purchase groceries than where they live. Using data on SNAP redemptions would help to address this issue.

To sum up, this paper is only a first attempt to estimate the economic impacts of SNAP in nonmetro and metro counties. Given the problems evident in the preceding results and discussion (nonrobustness, implausibly large coefficient values, potential for biases, large standard errors), we wish to emphasize that these findings are not conclusive and call for further research on this topic.

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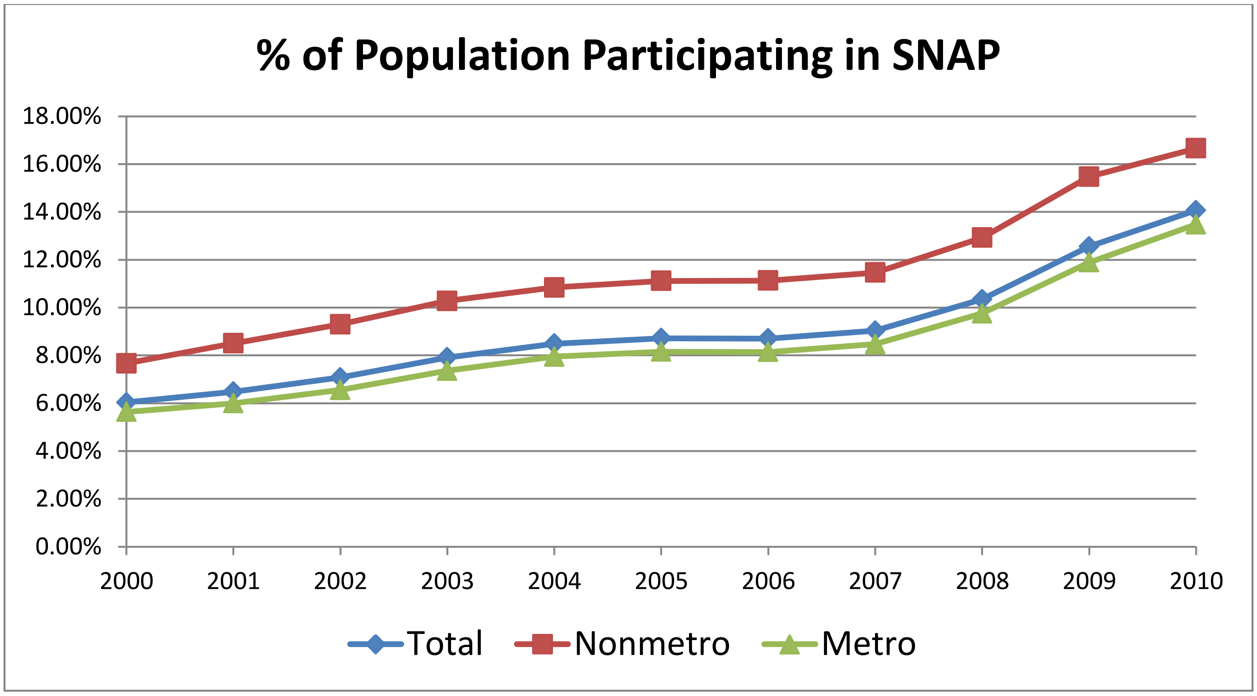
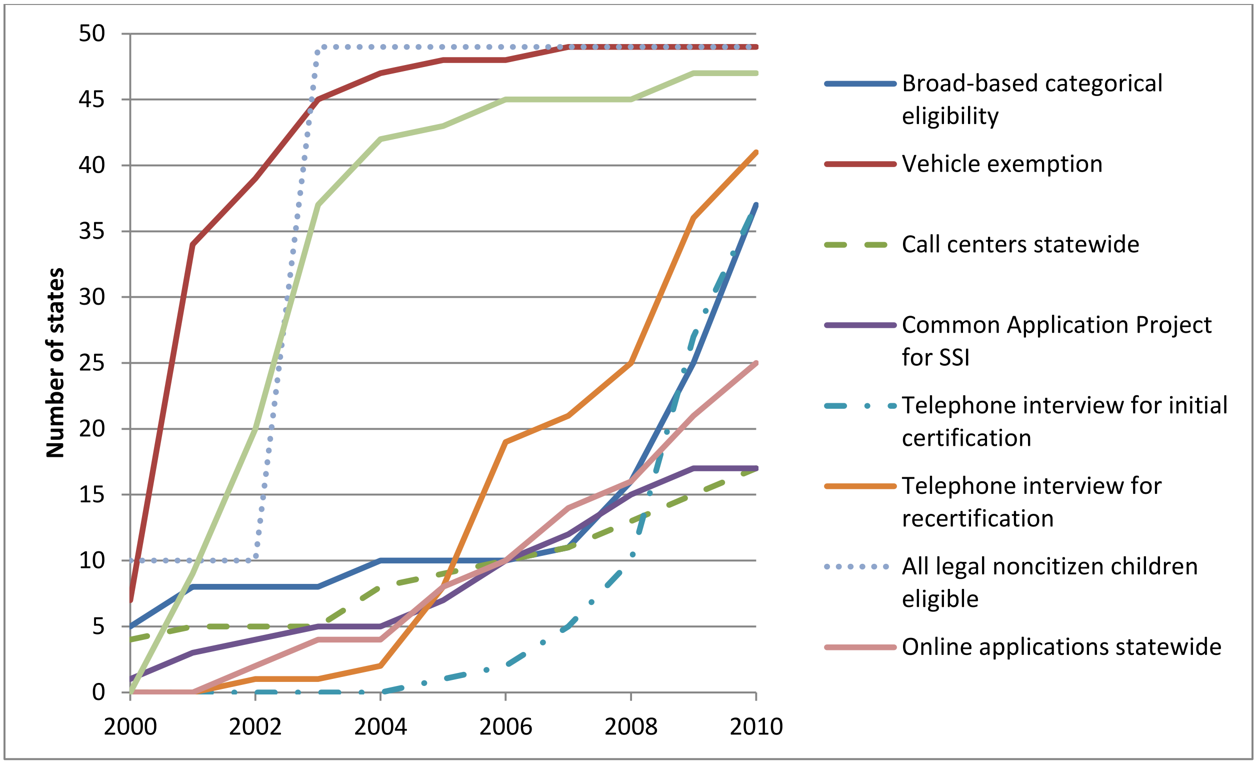
Figure 1. SNAP participation in metro and nonmetro counties, 2000 to 2010



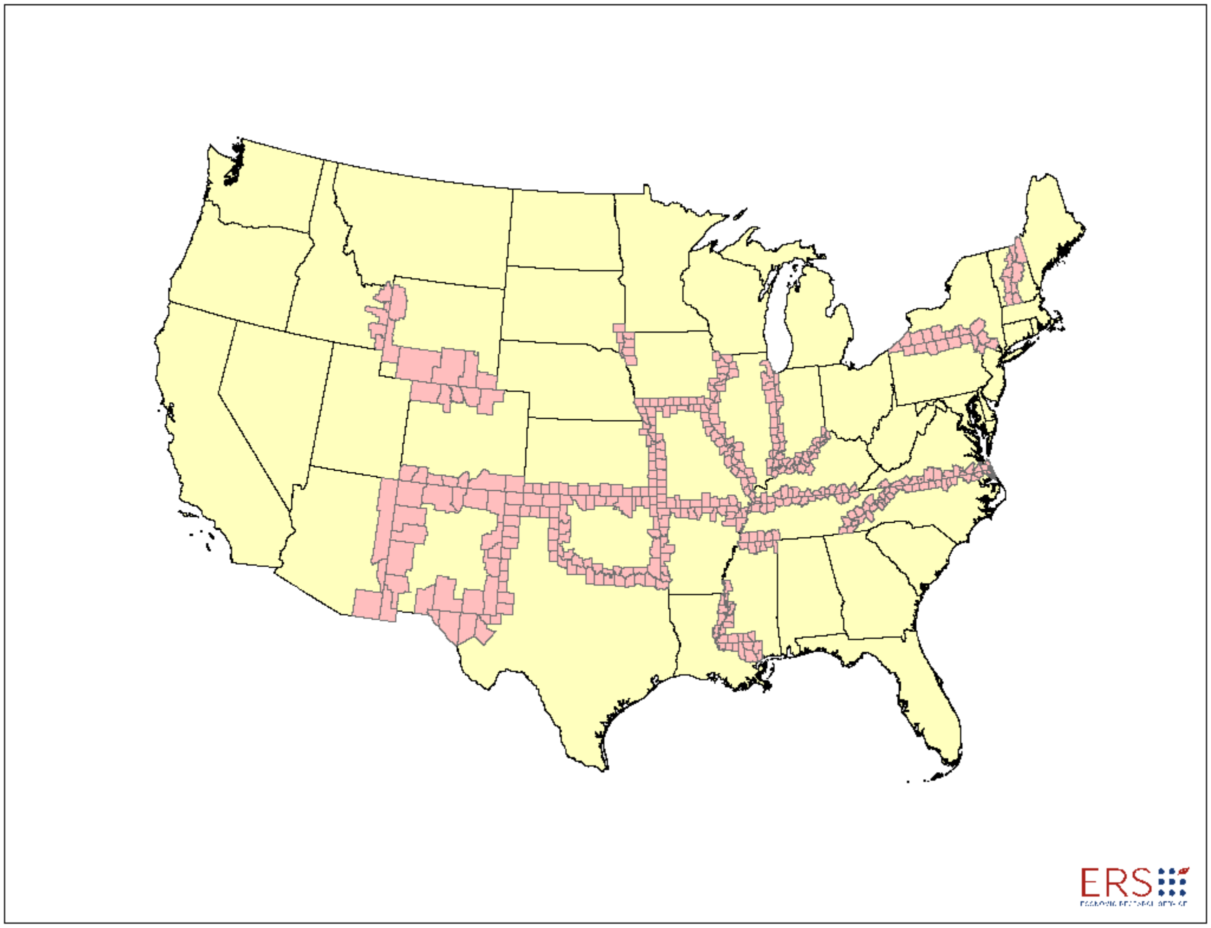
Source: Estimates based on ERS SNAP Data System

Figure 2. Changes in state-level SNAP policies (number of states adopting each policy by year)



Source: ERS SNAP Policy Database

Figure 3. Map of contiguous state border counties used in the spatial discontinuity (SD) analysis



Source: ERS

Table 1. Differences in mean change in ln(real earnings per capita) from 2000 to 2001 across selected state borders within commuting zones (standard errors in parentheses)

Base State	AL	AR	AZ	CO	FL	IA	ID	IL	IN	KS	KY	LA	MO	MS	NC	NH	NM	NV	NY	OK	PA	SD	TN	TX	VA	VT	WY
AL					NE									NE									NE				
AR												NE	-.001 (.031)	NE						.040 (.064)			NE	NE			
AZ																	-.101 (.075)	NE									
CO										NE							.110 (.040)			NE							.164 (.027)
FL																											
IA								-.011 (.022)					.002 (.041)									-.035 (.012)					
ID																		NE									-.007 (.046)
IL									.015 (.030)		NE		-.005 (.022)														
IN											.012 (.019)																
KS													.026 (.076)							.071 (.070)							
KY													NE										-.046 (.023)		NE		
LA														-.005 (.109)										NE			
MO																				NE			NE				
MS																							-.022 (.045)				
NC																							-.009 (.068)		.077 (.022)		
NH																										.036 (.025)	
NM																				NE				-.060 (.025)			
NV																											
NY																					.024 (.042)					NE	
OK																								-.089 (.059)			

Base State	AL	AR	AZ	CO	FL	IA	ID	IL	IN	KS	KY	LA	MO	MS	NC	NH	NM	NV	NY	OK	PA	SD	TN	TX	VA	VT	WY
PA																											
SD																											NE
TN																									NE		
TX																											
VA																											
VT																											
WY																											

NE = within commuting zone effects not estimable because no commuting zones cross this state border, or insufficient number of counties

Border pairs dropped in second version of SD model due to large mean difference in earnings growth within commuting zones from 2000 to 2001

Table 2. Descriptive statistics

Variable	Nonmetro Counties (N = 24,569)				Metro Counties (N = 8,800)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Real per capita earnings (2010 $)	18078	4743	2463	91306	25135	7106	11212	79332
Real per capita SNAP benefits (2010 $)	134.0	98.3	0	952.6	107.7	74.0	0.9	605.8
SNAP state policies (dummy variables)								
Broad-based categorical eligibility	0.1830	0.3867	0	1	0.2264	0.4185	0	1
Call centers statewide	0.1705	0.3760	0	1	0.2239	0.4169	0	1
Common Application Project for SSI	0.2104	0.4076	0	1	0.2661	0.4420	0	1
Telephone interview allowed for certification	0.1346	0.3413	0	1	0.1609	0.3675	0	1
Telephone interview allowed for recertification	0.2766	0.4473	0	1	0.3073	0.4614	0	1
All legal noncitizen children are eligible	0.7611	0.4264	0	1	0.7689	0.4216	0	1
Online applications statewide	0.1926	0.3944	0	1	0.2244	0.4172	0	1
Simplified reporting option for changes	0.7068	0.4552	0	1	0.7265	0.4458	0	1
Exemption to asset test for 1 or more vehicles	0.8437	0.3631	0	1	0.8508	0.3563	0	1
Other state policies								
Real minimum wage (2010 $)	6.359	0.656	5.417	8.690	6.507	0.730	5.417	8.690
Size of government index	6.833	1.000	3.177	8.804	6.692	1.018	3.177	8.804
Taxation index	6.823	0.725	4.225	8.703	6.744	0.776	4.225	8.703
"Labor market freedom" index	6.863	0.612	5.241	8.337	6.893	0.629	5.241	8.337
County economic conditions								
Unemployment rate	0.0604	0.0264	0.0130	0.2900	0.0570	0.0233	0.014	0.261
Poverty rate	0.1577	0.0609	0.0400	0.6200	0.1193	0.0472	0.017	0.407
County demographic characteristics								
Population	24829	24794	40	215686	291657	554767	5623	9848011
Share of pop. under age 15	0.1962	0.0286	0.0744	0.3754	0.2060	0.0251	0.1116	0.3083
Share of pop. over age 64	0.1622	0.0396	0.0301	0.4339	0.1255	0.0323	0.0168	0.3463
Share of pop. black or African American	0.0820	0.1506	0	0.8645	0.1082	0.1266	0.0005	0.6931
Share of pop. American Indian	0.0215	0.0757	0	0.9648	0.0081	0.0153	0.0008	0.2104
Share of pop. Asian or Pacific Islander	0.0049	0.0057	0	0.0875	0.0226	0.0317	0.0005	0.3388
Share of pop. Hispanic	0.0699	0.1303	0	0.9754	0.0860	0.1211	0.0038	0.9571

Table 3. Regression results for impacts on real earnings per capita in nonmetro counties (robust standard errors in parentheses)

Item	OLS-FE			IV-FE		SD-OLS-FD		SD-IV-FD	
SNAP real benefits per capita	-7.445*** (0.842)	-9.306*** (0.904)	-4.475*** (1.073)	-28.94*** (2.222)	-44.83*** (3.517)	2.053 (1.976)	-0.175 (1.256)	-14.097 (9.703)	4.881 (5.416)
Control variables:									
State policy variables	X	X		X	X	X	X	X	X
Demographic variables	X	X	X	X	X	X	X	X	X
Current economic variables	X								
Lagged economic variables		X	X	X	X	X	X	X	X
Year fixed effects	X	X		X	X				
County fixed effects	X	X	X	X	X				
State x year fixed effects			X						
Commuting zone x year fixed effects						X	X	X	X
Instrumental variables:									
All SNAP policies considered				X				X	X
Broad-based categorical eligibility					X				
All legal noncitizen children are eligible					X				
Sample	All counties	All counties	All counties	All counties	All counties	Border counties in 23 state border pairs	Border counties in 16 state border pairs	Border counties in 23 state border pairs	Border counties in 16 state border pairs
Number of observations	24,569	22,326	22,464	22,326	22,326	2,366	1,520	2,366	1,520
Number of counties	2,248	2,248	2,248	2,248	2,248	266	172	266	172
Number of commuting zones x years						876	543	876	543
R^2 (within) (OLS) or centered R^2 (IV)	0.2695	0.2435	0.4103	0.1817	0.0410	0.0959	0.0257	0.0336	0.0092
Weak identification test (Kleibergen-Paap rk Wald F statistic)				104.53	257.48			5.02	7.30
Stock-Yogo weak ID test critical value for 10% maximal IV relative bias				11.46	19.93			11.39	11.39
Overidentification test - Hansen's J statistic (P-value)				121.05 (0.0000)	2.60 (0.1068)			8.36 (0.3020)	13.55 (0.0599)

***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4. Regression results for impacts on real earnings per capita in metro counties (robust standard errors in parentheses)

Item	OLS-FE			IV-FE		SD-OLS-FD		SD-IV-FD	
SNAP real benefits per capita	-2.904** (1.214)	-4.956*** (1.222)	-5.938*** (1.498)	9.170*** (3.323)	-1.460 (3.910)	-4.143* (2.354)	-4.355* (2.444)	-4.884 (8.800)	-8.080 (10.091)
Control variables:									
State policy variables	X	X		X	X	X	X	X	X
Demographic variables	X	X	X	X	X	X	X	X	X
Current economic variables	X								
Lagged economic variables		X	X	X	X	X	X	X	X
Year fixed effects	X	X		X	X				
County fixed effects	X	X	X	X	X				
State x year fixed effects			X						
Commuting zone x year fixed effects						X	X	X	X
Instrumental variables:									
All SNAP policies considered				X				X	X
Broad-based categorical eligibility					X				
All legal noncitizen children are eligible					X				
Call centers operated statewide					X				
State operates a Combined Application Project for SSI recipients					X				
Sample	All counties	All counties	All counties	All counties	All counties	Border counties in 23 state border pairs	Border counties in 16 state border pairs	Border counties in 23 state border pairs	Border counties in 16 state border pairs
Number of observations	8,800	7,994	8,056	7,994	7,994	567	504	567	504
Number of counties	806	806	807	806	806	65	58	65	58
Number of commuting zones x years						208	181	208	181
R^2 (within) (OLS) or centered R^2 (IV)	0.4289	0.4272	0.5401	0.3797	0.4243	0.0953	0.1085	0.0950	0.1015
Weak identification test (Kleibergen-Paap rk Wald F statistic)				26.59	41.51			4.16	3.33
Stock-Yogo weak ID test critical value for 10% maximal IV relative bias				11.46	10.27			11.39	11.39
Overidentification test - Hansen's J statistic (P-value)				49.45 (0.0000)	0.542 (0.9096)			7.469 (0.3818)	9.092 (0.2461)

***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5. Regression results for impacts on real earnings per capita in different periods (robust standard errors in parentheses)

Item	OLS-FE				SD-OLS-FD			
	Nonmetro		Metro		Nonmetro		Metro	
	2000-2007	2008-2010	2000-2007	2008-2010	2000-2007	2008-2010	2000-2007	2008-2010
SNAP real benefits per capita	-8.239*** (1.009)	2.865*** (1.086)	-7.175*** (1.362)	-1.000 (1.059)	-0.952 (1.748)	2.128 (2.139)	-5.971 (3.659)	-1.972 (3.260)
Control variables:								
State policy variables	X	X	X	X	X	X	X	X
Demographic variables	X	X	X	X	X	X	X	X
Lagged economic variables	X	X	X	X	X	X	X	X
Year fixed effects	X	X	X	X				
County fixed effects	X	X	X	X				
Commuting zone x year fixed effects					X	X	X	X
Sample	All counties	All counties	All counties	All counties	Border counties in 16 state border pairs	Border counties in 16 state border pairs	Border counties in 16 state border pairs	Border counties in 16 state border pairs
Number of observations	15,727	6,599	5,628	2,366	1,296	610	436	200
Number of counties	2,248	2,247	806	806				
Number of commuting zones x years					630	299	214	99
R^2 (within)	0.2606	0.1318	0.3957	0.4521	0.0250	0.0863	0.1339	0.3086

***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.