Does the Economy Explain the Explosion in the SNAP Caseload?

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013

DRAFT – not for citation or distribution
6/3/2013

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Latest revision: June 2013

Abstract

The Supplemental Nutrition Assistance Program (SNAP), which provides a monthly benefit to low-income families to help ensure an adequate and nutritious diet, has grown rapidly in recent years—by 50 percent in the seven years between 2000 and 2007 and by another 50 percent in the four years between 2007 and 2011—today serving 14 percent of the U.S. population. This paper makes three contributions to our understanding of the causes of this very rapid increase in the caseload: (i) extend the time period of analysis through and past the official end of the Great Recession, the most severe economic downturn since the Great Depression of the 1930s; (ii) analyze more geographically disaggregated caseloads and the impact of sub-state economic conditions; and (iii) relax the difference-in-differences assumption of common national year-to-year shifts allowing more robust estimates of the impact of the economy. Surprisingly, while one might have expected more geographically disaggregated data to improve the alignment of the measurement with the concept of interest (i.e., the labor market opportunities of an individual) and therefore lead to larger estimates of the impact of the economy, in fact estimates fall—perhaps due to measurement error. Indeed, in models that exploit sub-state level data, we find significant impacts of both the sub-state level and statewide economy on local area SNAP caseloads.

1. Introduction

The Supplemental Nutrition Assistance Program (SNAP), which provides a monthly benefit to low-income families to help ensure an adequate and nutritious diet, is now the largest U.S. safety net programs apart from means-tested health insurance—both in program expenditures and in caseload size.[1] In fiscal year 2011, the program supplemented the incomes of an average of 14 percent of U.S. residents at an annual cost of $75.7 billion.

This has not always been the case: In 2000, the program served only 6 percent of the population, the lowest fraction since its nationwide rollout in 1974. While the SNAP caseload did grow strongly after the December 2007 start of the Great Recession, it also grew by nearly 50 percent—from 6 to 9 percent of the population—between 2000 and 2006, years of relatively robust labor markets (Figure 1). Previous research has concluded that both policies and the economy played a role in the SNAP caseload increase of the 2000s, but that roughly half of the increase remains unexplained (Klerman and Danielson, 2011; Mabli, Martin, and Castner, 2009; Ratcliffe, McKernan, and Finegold, 2008).

Towards explaining this unexplained component of the increase, this paper incorporates three advances over the previous literature. First, the paper extends the time period of analysis through and past the official end of the Great Recession, the most severe economic downturn since the Great Depression of the 1930s. Such extreme events are often valuable for understanding causal relationships, and impacts adverse economic events typically continue to be felt for several years after the economy has started to improve. This longer time period also gives us more years since the policy changes of the early 2000s, increasing the precision of those estimates. In addition, given the sharp recent interest in the caseload, estimates for the most recent period are of substantial intrinsic interest.

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[1] Until October 2008 the program was known nationally as the Food Stamp Program.

Second, compared to earlier papers that analyze the impact of state level proxies for the economy on state level caseloads, this paper analyzes the impact on more geographically disaggregated caseloads of more geographically disaggregated measures of the economy. Since labor market conditions vary widely within a state, it is conceivable that specification error—using statewide proxies for the economy, when the appropriate economic measure is more local—has resulted in underestimates of the true impact of the local economy on local caseloads.

Third, our strategy of sub-state analysis also enables us to relax the difference-in-differences (DiD) assumption that common national year-to-year shifts and linear state trends capture the unobserved, time-varying factors that drive caseloads.[2] The resulting estimates should be more robust to unobserved state policies.

Contrary to expectation, we find that empirical estimates produced from data aggregated to the state level are larger in magnitude than estimates produced from data aggregated to the sub-state level. Thus, the conjecture that using state-level proxies for the economic opportunities available to potential SNAP participants induces specification error that causes attenuation bias and underestimates of the impact of the economy on the caseload appears to be incorrect; or at least that measurement error from attempting to measure the condition of the economy for small areas swamps measurement error due to aggregation. In addition, relaxing the DiD assumption of common year-to-year shifts reduces the estimates of the impact of the economy on caseloads (aggregated to the sub-state level) by roughly a third. Third, measuring the state of the economy by the unemployment rate or the employment to population ratio produces roughly equivalent estimates of economic impacts. Finally, we are able to identify both state-level and sub-state level impacts of the economy.

[2] Our identification strategy does not permit us to estimate the effects of national-level events—for example, the benefit increase included in the American Recovery and Reinvestment Act of 2009.

The next section discusses the findings of the previous research about the sources of the caseload increase. The third and fourth sections describe our methodology and data sources, the fifth section presents our estimation results, and the sixth section concludes.

2. Previous literature

The existing literature considers the dual questions of the impact of a unit change in policy or the economy on the SNAP caseload; and the factors that explain the observed wide swings in the size of the caseload (Currie and Grogger, 2001; Kornfeld, 2002; Kabbani and Wilde, 2003; Hanratty, 2006; Ratcliffe, McKernan, and Finegold, 2008; Mabli, Martin, and Castner, 2009; Klerman and Danielson, 2011). With respect to the effects of SNAP policies on caseloads, the evidence is mixed. These policy changes, largely implemented at state option in the 2000s, reduced the frequency of paperwork and shrank the number of tests of eligibility that applicants needed to demonstrate. On balance, several of these changes do appear to have had the intended effect of reducing the burden of applying and keeping one's SNAP eligibility current; the most recent of these papers finds that SNAP policy changes accounted for roughly one sixth of the caseload increase that occurred between 2000 and 2009 and the economy accounted for about a quarter of the increase (Klerman and Danielson, 2011). However, crucially, existing studies—using data through at most 2009—have few observations with the new policies in place. These studies, therefore, have trouble estimating the impact of these new policies with any precision.

With respect to the economy, the findings are uniform. All studies find a strong relationship between the economy (usually proxied by the state unemployment rate) and the SNAP caseload. Klerman and Danielson (2011) found that the economy explained about a quarter of the increase between 2000 and 2009; i.e. the increase was explained equally by the economy and by policy changes, but about half of the increase was left unexplained. However, crucially, existing studies—using data through at most 2009—do not include the sharp worsening of the economy during the Great Recession and the sharp increase in the caseload. It seems plausible that such large variation in the economy would be illuminating about the impact of the economy on the caseload.

3. Methodology

Most recent studies of the determinants of the SNAP caseload have used a difference-in-differences (DiD) specification with state by year, or state by month data. For our purposes a standard DiD model can be written as:

$$y_{s,t} = \log\left[\frac{M_{s,t}}{N_{s,t}}\right] = \alpha + X_{s,t}\beta + Z_{s,t}\gamma + \mu_s + f(s,t,\tau) + \varepsilon_{s,t} \qquad (1)$$

In equation (1), y is the ratio of SNAP program participants[3] (M) to the population (N) in state s at time t.[4] The vector X represents state-level, time-varying proxies for the economy, the vector Z represents state-level, time-varying proxies for policies, μ is a vector of 51 state fixed effects, and ε is the residual. The specification of time effects, f(s,t,τ), includes a dummy for each year in the analysis, a vector of month dummies to absorb seasonal effects, and 50 linear, state-specific time trends.[5] In equation (1), the parameters of interest, β, are identified from variation within states over time.

This specification implicitly makes two assumptions:

1. That state-level proxies for the economy apply uniformly across the state. Inasmuch as there is intra-state variation in the economy and the local economy is what affects the

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[3] Note that the unit of analysis—for both the numerator and denominator of this rate—are individuals. Thus, while we use the term "caseload", we analyze persons on the SNAP case. This is slightly different than members of households received SNAP, since we do not count individuals in such households who are not "on the case" and who do not affect the size of the benefit); e.g., undocumented immigrants.
[4] Because SNAP eligibility is not conditioned on age or family structure, we use the entire population in the denominator.
[5] In principle, with data measured at monthly or semi-annual frequency, we could specify the national time effects as a vector of month dummies. The SNAP counts we use are measured at semi-annual or monthly frequency although annual data are used in much of the previous literature.

SNAP participation decision, using state-level proxies for the economy will induce specification error. The resulting attenuation bias will lead to an under-estimate (in absolute value) of the impact of the economy. At the same time, if sub-state estimates of the economy have more measurement error than state-level measures, this measurement error will also lead to larger under-estimates of the impact of the economy in estimates at the sub-state level. Thus, the choice of level is not obvious.

2. That there are no unobserved aspects of state policy that are correlated with the economy. Instead unobserved, time-varying factors that drive SNAP caseloads are either national in scope or trend smoothly within a state over time.

Neither of these assumptions is attractive. Both are testable. We return to the interpretation of the findings relative to these two assumptions in the conclusion to the paper.

The first assumption is testable by reestimating Equation (1) using, sub-state caseload data as the outcome variable and not state-level proxies for the economy, but sub-state proxies for the economy. (We discuss data sources for such sub-state proxies below.) Equation (2) provides a representative specification:

$$(2) \qquad y_{c,s,t} = \log\left[\frac{M_{c,s,t}}{N_{c,s,t}}\right] = \alpha + X_{c,s,t}\beta + Z_{s,t}\gamma + \mu_c + f(s,t,\tau) + \varepsilon_{c,s,t}$$

Where the *c* term subscript some sub-state geography (“c’ for county). The dependent variable and the economic variables include a *c* subscript. The policy variables *Z* are only measured at the state level. We include county level dummy variables (but not state *x* year dummy variables; see Equation 3 below).

Standard measurement error (in this case specification error) arguments—and an assumption of independence across sub-state units—imply that the larger is intra-state variation in the economy, the larger would be the expected bias in estimates of the impact of the economy. Counteracting this aggregation bias argument is a simple measurement error bias. In the SNAP determinants literature, the conventional proxy for the economy is the unemployment rate. The conventional unemployment rate is based on the Monthly Current Population Survey (CPS) (BLS, 2012). With a sample size of about 60,000 households, CPS-based state-level estimates of the unemployment have moderate pure sampling variability; more in smaller states. CPS-based sub-state estimates would have much more sampling variability. To address this concern, the DOL/BLS LAUS/Local Area Unemployment Statistics program) that we use rely on use synthetic estimation methods exploiting other local level information (e.g., Unemployment Insurance claims). Such synthetic estimation methods induce other forms of measurement error and modeling bias Both simple sampling variability and modeling bias will lead to measurement error and therefore underestimates of the effect of the economy—and the bias will be larger at lower levels of geography (i.e., sub-state vs. state).

Second, intra-state variation in the economy allows the estimation of Difference-in-Difference-in-Difference (DiDiD) models that control non-parametrically (i.e., with dummy variables) for policy and any other statewide variables, observed or unobserved. Specifically, for forcing variables that vary at the sub-state level—i.e., the economy—a more flexible specification of time effects is possible if we exploit intra-state variation in caseloads:

$$y_{c,s,t} = \log\left[\frac{M_{c,s,t}}{N_{c,s,t}}\right] = \alpha + X_{c,s,t}\beta + \eta_c + f(c,s,t,\tau) + \varepsilon_{c,s,t} \tag{3}$$

In equation (3), the addition of the *c* subscript (“c” for county) indicates variation at the sub-state level, so that each value of the dependent variable, *y*, is the log of the fraction of the population in county or (Labor Market Area) *c* and state *s* at time *t* that is receiving SNAP. On the right hand side of equation (2) is the vector *X*, now varying at the county level. State-level policy variables, Z, drop out of this equation.

Crucially, the specification of the dummy variables is more robust. Where the DiD specification (Equation 1, but not Equation 2) included state-specific dummy variables, the DiDiD specification includes county specific dummy variables. Where the DiD specification included year dummy variables and state-specific linear time trends (Equation 1 and Equation 2), the DiDiD specification includes a full set of state x year dummy variables. In essence, this specification of the model allows us to move the unrestricted, year-to-year changes to the state, rather than national, level. Note, however, that this approach absorbs state policies into the specification of time effects, so that *X* contains only proxies for the economy.

In what follows, we estimate three sets of models:

(i) **The Conventional Model**. We estimate Equation 1 at the state level, generating estimates of the impact of state policies and the economy at the state level on the caseload—for a more recent period.

(ii) **Sub-State Model**: We again estimate Equation 2 (i.e., Equation 1 now at the sub-state level), generating new estimates of the impact of the impact of state policies and of the economy at the sub-state level on the caseload. By using sub-state proxies for the economy, this analysis adjusts for potential mis-specification of sub-state economic conditions (i.e., aggregation bias) when using state-level proxies.

(iii) **DiDiD Model**: We estimate Equation 3, also at the sub-state level, generating new estimates of the impact of the economy at the sub-state level on the caseload. Because these models include state x year dummy variables, they are robust to any correlation between state policies and the economy at the state level. Such biases (e.g., states pass some policies when the economy is good) would bias estimates that do not include such state *x* year dummy variables. However, since we include state *x* year dummy variables, we cannot estimate the impact of state policies that are constant throughout the state.

4. Data

To estimate the models discussed in the previous section, we require counts of SNAP participants, population estimates, proxies for the economy and measures of SNAP policy. For Model 1, we need each of these concepts at the state level. For Model 2 and Model 3, we need all but the state policy proxies at the sub-state level.

This paper's basic data strategy follows the previous literature (in particular Danielson and Klerman, 2012). However, this study requires sub-state level estimates for the caseload, population, and the economy. (For our purposes, there is no sub-state level variation in policies.) As we discuss in detail in Appendix A, we define sub-state variables at the Labor Market Area (LMA) level, where LMAs are aggregates of counties defined by the Census Bureau for release of sub-state data. For some purposes, we aggregate simply to counties. Appendix Table A.1 provides summary statistics at each of the three levels of aggregation.

Specifically, we measure SNAP caseloads using reports that states file with USDA: form FNS-388 and form FNS-388A. These reports record state-level and "project area" —usually county— caseloads, respectively.[6] We measure population data with Census Bureau estimates. Finally, we measure the economy using Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) estimates and Quarterly Census of Employment and Wages (QCEW) estimates. Table 1 summarizes the data we assembled.

<Table 1 about here.>

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[6] Nine states do not file county-level caseloads in form FNS-388A, and several other states did so for only part of our analysis period. We do not interpolate for these missing observations. See Appendix A for further details.

5. Estimation results

Beginning with data aggregated to the level of the state-month as previous research has done, we first discuss estimates of SNAP policy effects that update the overall caseloads estimates presented in Klerman and Danielson (2011) by adding data from federal fiscal years 2010 and 2011 (Table). These are years in which the U.S. was not technically in recession, but in which unemployment remained high, and state SNAP caseloads continued to increase rapidly (Figure 1). These additional years may be particularly valuable because data only through 2009 includes few state-year observations with the new policies were put in place.

SNAP policies can be categorized into two types: those aimed at easing *access* to the program and those intended to ease *use* of the program. Vehicle and expanded categorical eligibility policies ease access to SNAP by reducing the number and types of eligibility tests for applicants. Simplified reporting, longer certification periods, and EBT ease use of the program by reducing paperwork required to maintain eligibility. We find mixed effects of both types of policies across the models presented in Table 4. In particular, we find no effects of eliminating vehicle asset tests for some or all cars or of more restricted expansions of categorical eligibility. However, we do find a roughly 5-6 percent increase in SNAP participation attributable to the introduction of broad expansions of categorical eligibility. For policies that ease use of the program, we find no significant effects of the introduction of ATM-like EBT cards, but a large negative effect of short certification periods and a 4-5 percent increase in SNAP caseloads in the wake of simplifying interim reporting requirements for households with earned income. At the same time we estimate no effect of expanding simplified reporting to all, or nearly all, SNAP households.

The pattern of significance across the models in Table 4 is quite similar to the SNAP caseload estimates presented in Klerman and Danielson (2011). The main change is that, unlike the earlier paper, with the two additional years of post-implementation observations we find some evidence of policy impacts of simplified reporting.

Proxies for the economy (unemployment rate and employment)

Looking next at the estimates of the effects of the economy on per capita SNAP caseloads, across the columns of Table 2 we provide a comparison of two proxies for the state of the economy: the unemployment rate and the employment to population ratio. They measure somewhat different concepts. The unemployment rate is a measure of success among those who are currently active labor market participants, while the employment to population ratio is a measure of the reach of the labor market. The unemployment rate is sensitive to macroeconomic conditions that draw marginal workers into the labor force or drive them out. This implies that the employment to population ratio is potentially a more stable measure of economic conditions when macroeconomic conditions are fluctuating widely.

In terms of measurement, counts of employment is based on the universe of employers' reports for employees covered by state unemployment insurance systems, while the unemployment rate is in part based on responses to a household survey (BLS, 2012). This implies that measurement error, especially for geographically disaggregated estimates, may be (more of) a concern for the unemployment rate than for employment. At the same time, employment covered by unemployment insurance does exclude some categories of workers. In general, state unemployment insurance laws imply that employment covers approximately 98 percent of non-agricultural employment, but only 47 percent of agricultural employment (BLS, 2012).

Furthermore, employment to population data is based on place of work, while the unemployment rate is based on place of residence. (Synthetic estimation muddies that distinction.) SNAP caseloads are measured based on place of residence. Thus, this consideration would suggest preferring the unemployment rate.

On balance, then, the different measures both have strengths and weaknesses, and it is not a priori obvious which should be preferred. Table 2 presents estimates using the current unemployment rate, the employment to population ratio, and two sectoral measures of employment—retail trade and accommodation/food services. The estimates across the top rows of columns 1-4 of the table indicate that all four proxies for the economy are statistically significant and have the expected signs.

<Table 2 about here>

The estimate in column 1 of Table 2 imply that a one percentage point increase in the unemployment rate results in a 3.7 percent increase in per capita SNAP recipients, while an equivalent 1.4 percentage point decrease in the total employment to population ratio implies a 5.1 percent increase in the SNAP caseload (column 2).[7] These results are consistent with a conjecture that measurement error is more severe in the unemployment rate measure. The results are also consistent with an inference that, compared to the more conventional unemployment rate, the employment-to-population ratio is a better proxy for the economy.

We turn next to a discussion of these estimates at the three different levels of aggregation: counties, LMAs, and states. In a later section we return to the inclusion of multiple proxies for the economy in our specifications using a sub-state level of aggregation.

Level of aggregation

The estimates just discussed in Table 2 represent caseload and economic data aggregated to the state level. The notion that the economy drives both eligibility and enrollment conditional upon eligibility rests on the idea that we are measuring the economy at the level that workers face it. State-level research necessarily relies on state-level measurement of the economy, but clearly the macroeconomy can vary widely between, for example, urban and rural areas. At the same time workers commute to employment, even across state lines. Thus, even if state-level measures are ill-targeted in larger, diverse states, it is also not clear that county-level measures are appropriate:

[7] We calculated equivalence across changes in the unemployment rate and the employment to population ratio by taking the ratio of the standard deviations of the residuals from two auxiliary regressions of each economic proxy on a full set of year and geography indicators.

They may be too local. In this section we provide comparisons of the employment to population ratio using state-level, county-level, and LMA-level aggregations of the measure.

Table 3 presents estimation results for the unemployment rate at these three levels of aggregation. Columns 3 and 5 of the table also introduce the more flexible specification of time effects from equation (2). The models shown are estimated on a homogeneous set of observations across the columns, representing data from between 39 and 44 states, depending on the year; i.e., the counties for which we have consistent data.[8]

<Table 3 about here>

The estimates imply that measuring caseloads and the economy at the sub-state level reduces the estimated effects of the economy by 50 percent or more, but that there is little difference between county- and LMA-levels of aggregation.[9] In particular, in models that include proxies for major state-level SNAP and TANF policy changes over the period, a one percentage point increase in the unemployment rate is associated with a 3.2 percent increase in SNAP caseloads at the state level, but a 2.0 percent increase at the county level and a 2.2 percent increase at the LMA level. When we also introduce interactions between year and state fixed effects (i.e., Equation 2), these estimated effects drop to 1.2 percent at the county level (from 2.0 percent when measured at the state level) and 1.4 percent at the LMA level (from 2.2 percent when measured at the state level).

We turn next to an exploration of estimates of the different proxies for the economy at the sub-state level. Table 4 replicates Table 2 at the LMA level in place of the state level (the unemployment rate, the total employment to population ratio, the retail employment to population ratio, and the food and accommodation employment to population ratio).[10] Table 4

[8] Five states provide only partial series at the county level, six states report only state-level caseloads to USDA. Appendix A provides further details.
[9] Lindo (2013) provides similar evidence of smaller estimated impacts of the economy on health outcomes using local-level vs. statel-level data.
[10] Empirical results estimated at the county level are qualitatively similar (not shown).

also includes the comparison across specifications that model major statewide SNAP and TANF policies and ones that include instead a vector of state-by-year indicators.

<Table 4 about here>

The results are consistent with Tables 2 and 3. First, the more targeted (i.e., sectoral) measures of the economy have larger estimated impacts on caseloads. In particular, the coefficients on food/accommodation employment are four to five times larger than the estimates of total employment. Second, including state x year fixed effects reduces the estimated impacts of the economy by roughly a quarter to a third. Recall that, descriptively, SNAP caseloads trend strongly and follow the unemployment rate and so we might expect overestimates of the effects of the economy if we do not control adequately for time trends. The estimates presented in Tables 4 and 5 suggest that this may be the case.

However, we have so far modeled the SNAP caseload as a function of the current economy. There is ample theoretical and empirical reason to believe that caseload stocks do not adjust immediately to factors that drive them up or down, implying that modeling lagged effects of the economy is critical. We turn next to an examination of such lagged effects.

Specification of the economy

Panel B of Table 5 begins with our baseline estimates, then compares the addition of five lagged values for the economy (similar to the specification in Klerman and Danielson, 2011).

<Table 5 about here>

Estimated lagged effects are generally significant and of the same sign as the coefficients on the current measure. The exception is the longest one or two lags that change sign. To ease interpretation of the lagged models in comparison to the baseline models and across the two proxies for the economy, in Figure 2 we present a set of graphical comparisons. Each line in the figure represents the cumulative effect of a one-unit deterioration in the economy over the period of five years. We use the same approach described earlier to put changes in the unemployment rate and the employment to population ratio on the same scale. The flat lines represent the baseline models while the curved lines describe the evolution of the estimated lagged impacts over time.

<Figure 2 about here>

The figure implies that the inclusion of lags increases estimated impacts of the economy on SNAP caseloads by 50 percent or more (with the exception of the state-level unemployment rate model, where the difference is modest). The estimates summarized in Figure 2 also suggest that economic impacts grow for at least 3 years after the change.

Table 5 also explores functional form. The starting point for this exploration is the hypothesis that the caseload response is not independent of the level of the economy. Specifically, we explore non-linear responses to large changes, considering a quadratic function, a piecewise linear function, and the inclusion of dummy variables to allow for permanent shifts in the responsiveness of the SNAP caseload to the economy after the two recessionary periods in our data. The estimates in Table 6 imply *smaller* impacts of the economy on SNAP caseloads when the economy is weaker (e.g., during the Great Recession). For example, the estimates in the first column of Panel C (quadratic specification) imply a 5.1 percent increase in SNAP caseloads if the unemployment rate increases from 5 to 6 percent, but a 2.7 percent increase in SNAP caseloads if it increases from 9 to 10 percent.

Multiple proxies for the economy

Table 6 presents estimates at the LMA level using our DDD specification. Columns 1 and 2 of the table add the total and retail employment measures to the unemployment rate specification presented in Table 4. In both columns, the additional proxies are significant at the 0.05 level or better, although the unemployment rate and retail employment estimates are roughly 50 to 60 percent smaller in magnitude. Columns 3 and 4 add lags of these measures, and we continue to find a pattern, although mixed, of statistically significant and substantially large (compared to the current measure estimates) lagged effects. Taken together, these estimates imply that the different measures of the economy contribute to our ability to explain SNAP caseloads with the economy.

<Table 6 about here>

Finally, columns 5 through 7 add state-level, current proxies for the economy to the LMA-level proxies considered thus far. The LMA-level proxies remain significant and are similar in magnitude across these specifications. However, the state-level proxies are also significant (with the exception of state-level retail employment). In particular, the state-level employment rate is of similar magnitude to the estimates show in Tables 2 and 3 (3.5 percent). Taken together, these estimates suggest that both the local area and statewide state of the economy can be separately identified in models that include a set of flexible controls for other factors that also drive SNAP caseloads. Substantively speaking, they suggest that both local area and statewide economic conditions drive SNAP caseloads.

6. Conclusion

With the exception of health insurance programs, the SNAP program is the largest U.S. means-tested program; and this is a recent development. This paper has largely foregone a consideration of policy changes—which were substantial in the 2000s—and instead has focused on the economy. We take advantage of more variation in the economy, more fine-grained economic variables, and more months of post-recession observations.

Clearly, SNAP is a countercyclical program. However, the extent to which the state of the economy drives the SNAP caseload is unclear. Research to date has ascribed well under half of the increase to the economy (Klerman and Danielson, 2011; Mabli, et al., 2009).

Using data aggregated to the level of the state, we find apparently larger effects of the standard proxies for the economy. However, when we disaggregate to sub-state levels and include multiple proxies for the economy and both state-level and sub-state level proxies, we find a strong pattern of significant effects. .

Immediate next steps for this research are to simulate the impact of the economy on the SNAP caseload across the state-level and LMA-level specifications. Preliminary estimates to date indicate that, consistent with previous research, simulations using lagged specifications the amount explained substantially.

The finding that estimated impacts are much smaller at the sub-state level is consistent with substantially more measurement error there. In the absence of measurement error, including fixed effects is a test for endogeneity. However, in presence of measurement error (but the absence of endogeneity), the fixed effects soak up some of the “signal”; the “noise” remains. In net, the share of measurement error in the observed variance increases, and therefore so does the bias due to measurement error (Griliches and Hausman, 1986; Wansbeek, 2001).

Also consistent with this inference is the pattern of impacts of lagged values of the economy. When there is (i) serial correlation in the economy (as there certainly is) and (ii) measurement error that is (at least in part) independent across periods, lagged values will have explanatory power, even when there is no true dependence of the caseload on lagged values of the economy (above and beyond the contemporaneous effect). In fact, we find minimal evidence of lag patterns using state-level measures of the economy, but considerable evidence for lag patterns using sub-state level measures of the economy.

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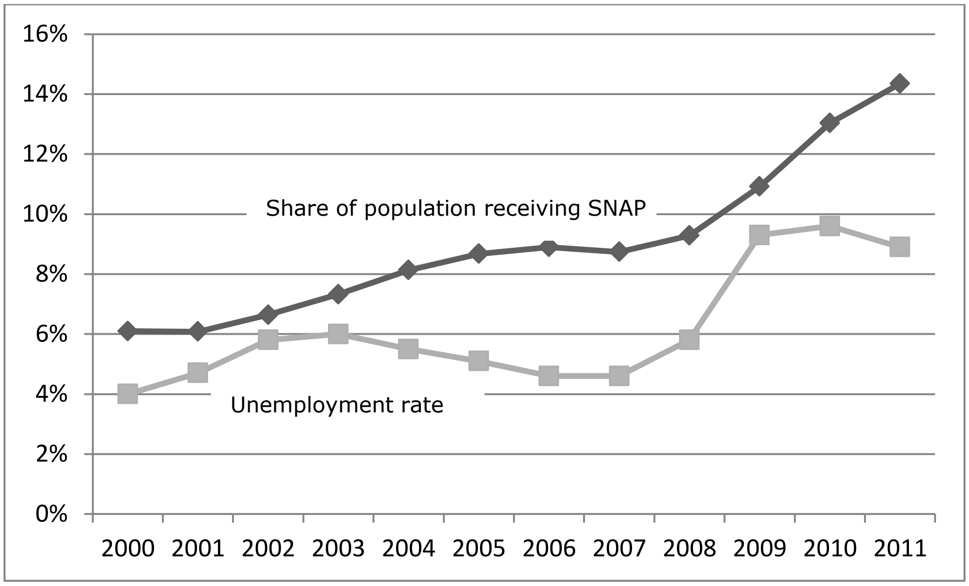
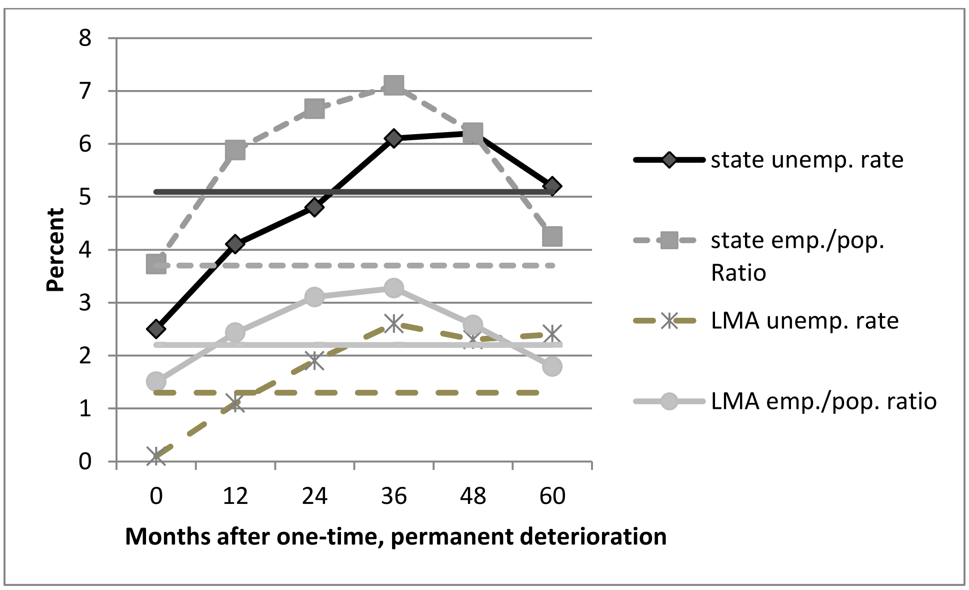
Figures

Figure 1. Recent trends in the U.S economy and SNAP caseload



Sources: Food and Nutrition Service, U.S. Department of Agriculture; Bureau of Labor Statistics.

Figure 2. Equivalent effects of the economy



Notes: Based on estimates from Panels A and B of Table 5. LMA estimates are from models that include state by year fixed effects.

Tables

Table 1. Data sources

Name	Time period	Frequency	Level(s) of aggregation	Gaps	Source
SNAP participant counts					
FNS-388 reports;	1990-2011	monthly	state	N/A	USDA, Food and Nutrition Service
FNS-388A reports;	1990-2011	semi-annual (January, July)	county	9 states do not report county-level data	USDA, Food and Nutrition Service
Population	1990-2011	annual	county, LMA, state	N/A	Census
Proxies for the economy					
Unemployment rates	1990-2011	monthly	county, LMA, state	N/A	BLS, Local Area Unemployment Statistics
Total employment and employment by 2-digit NAICS sectors	1990-2011	monthly	county, LMA, state	N/A	BLS, Quarterly Census of Employment and Wages
SNAP policies	1990-2011		state	N/A	Danielson, Klerman, Andrews, and Krimm (2011)
TANF policies	1990-2011		state	N/A	Urban Institute, Welfare Rules Database

Table 2. State-level estimates across four proxies for the economy

	Unemployment Rate (1)	Employment to Population Ratio (2)	Retail Employment to Population Ratio (3)	Food/Accommodation Employment to Population Ratio (4)
Proxy for the economy	0.037 (0.004)***	-3.461 (0.408)***	-19.838 (4.381)***	-8.834 (2.288)***
Introduction of EBT	0.006 (0.021)	0.009 (0.020)	0.013 (0.019)	0.005 (0.024)
Some vehicles excluded	0.012 (0.029)	0.018 (0.027)	0.005 (0.030)	0.004 (0.033)
All vehicles excluded	-0.014 (0.024)	-0.007 (0.024)	0.006 (0.022)	0.001 (0.026)
Expanded cat. elig. – participation based	0.006 (0.021)	0.017 (0.022)	0.011 (0.022)	0.011 (0.021)
Expanded cat. elig. – information based	0.047 (0.025)*	0.054 (0.025)**	0.053 (0.025)**	0.058 (0.024)**
Simplified reporting –earned income HHs	0.053 (0.028)*	0.045 (0.027)*	0.044 (0.026)*	0.057 (0.029)*
Expanded simplified reporting	-0.051 (0.018)***	-0.045 (0.016)***	-0.053 (0.016)***	-0.061 (0.017)***
Short certification periods	-0.361 (0.071)***	-0.325 (0.072)***	-0.328 (0.082)***	-0.347 (0.071)***
TANF implemented	-0.070 (0.026)***	-0.057 (0.026)**	-0.078 (0.024)***	-0.087 (0.027)***
Diversion	-0.049 (0.026)*	-0.048 (0.024)**	-0.056 (0.023)**	-0.054 (0.025)**
Gradual full family sanction	-0.010 (0.025)	-0.005 (0.026)	-0.006 (0.027)	-0.013 (0.028)
Immediate fully family sanction	-0.040 (0.040)	-0.035 (0.037)	-0.030 (0.039)	-0.051 (0.040)
Time limits implemented	0.031 (0.025)	0.025 (0.024)	0.038 (0.026)	0.053 (0.027)*
Earnings at which TANF benefit is $0	-0.002	-0.002	-0.003	-0.003

	(0.003)	(0.003)	(0.003)	(0.003)
Maximum TANF benefit for a family of 3	-0.048 (0.020)**	-0.044 (0.020)**	-0.040 (0.021)*	-0.059 (0.024)**
Minimum wage, 30 hours of work	-0.011 (0.010)	-0.015 (0.009)	-0.010 (0.009)	-0.014 (0.009)
Observations	13,050	13,050	13,050	13,050
R-squared	0.957	0.959	0.957	0.954

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

Notes: Dependent variable is the natural log of per capita SNAP program participants. Robust standard errors, clustered on state, shown in parentheses. SNAP policies and TANF policies are described in more detail in Appendix A. All models include population controls, state, month and year indicators and state-specific linear trends. District of Columbia excluded. Models estimated on all available state-level observations.

Table 3. Unemployment rate estimates at three levels of geographic aggregation

	State Level	County level		Labor Market Area Level	
	(1)	(2)	(3)	(4)	(5)
Unemployment_Rate	0.032	0.020	0.012	0.022	0.014
	(0.004)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Observations	1,525	111,474	111,474	81,674	81,674
R-squared	0.966	0.834	0.871	0.819	0.876
County Fixed effects		X	X		
State Fixed effects	X				
County-specific linear trends		X	X		
LMA-specific linear trends				X	X
State-specific linear trends	X				
SNAP and TANF controls	X	X		X	
State x year interactions			X		X

Robust standard errors clustered on geographic unit of analysis in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variable is the natural log of per capita SNAP program participants. Homogeneous sample across columns. See data description in Appendix A for additional details. All models include year and month dummy variables.

Table 4. LMA-level estimates across four proxies for the economy

	Unemployment Rate		**Employment to Population Ratio**		**Retail Employment to Population Ratio**		**Food/Accommodation Employment to Population Ratio**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proxy for the Economy	0.020	0.013	-1.643	-1.270	-8.151	-5.492	-1.931	-1.166
	(0.003)***	(0.002)***	(0.308)***	(0.238)***	(1.345)***	(0.868)***	(0.491)***	(0.251)***
SNAP and TANF policies	X		X		X		X	
State x year indicators		X		X		X		X
Observations	83,601	83,601	83,601	83,601	83,601	83,601	83,601	83,601
R-squared	0.826	0.887	0.826	0.887	0.826	0.887	0.825	0.887

Robust standard errors clustered on LMA in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variable is the natural log of per capita SNAP program participants. Models estimated on all available LMA-level observations. All models include year, month, and LMA indicators, LMA-level linear trends, and population controls. Where LMAs cross state lines, “state” designation (for state policies and state x year indicators) made using majority of population. Appendix A provides a detailed discussion.

Table 5. State-level and LMA-level estimated effects of the economy

	Level of aggregation:	State		LMA			
Specification		**Unemployment rate**	**Employment to population ratio**	**Unemployment rate**	**Employment to population ratio**	**Unemployment rate**	**Employment to population ratio**
A. Baseline	Current measure	0.037	-3.461	0.020	-1.643	0.013	-1.270
		(0.004)***	(0.408)***	(0.003)***	(0.308)***	(0.002)***	(0.238)***
B. Lags	Current measure	0.025	-2.534	0.009	-1.202	0.001	-0.868
		(0.005)***	(0.469)***	(0.004)***	(0.215)***	(0.003)	(0.247)***
	Lag (1 year)	0.016	-1.460	0.008	-0.550	0.010	-0.541
		(0.004)***	(0.310)***	(0.003)***	(0.160)***	(0.002)***	(0.125)***
	Lag (2 years)	0.007	-0.532	0.011	-0.582	0.008	-0.392
		(0.003)**	(0.262)**	(0.003)***	(0.116)***	(0.003)***	(0.084)***
	Lag (3 years)	0.013	-0.290	0.005	-0.135	0.007	-0.095
		(0.004)***	(0.393)	(0.003)*	(0.117)	(0.003)**	(0.068)
	Lag (4 years)	0.001	0.588	0.002	0.662	-0.003	0.400
		(0.005)	(0.281)**	(0.003)	(0.164)***	(0.003)	(0.125)***
	Lag (5 years)	-0.010	1.302	-0.008	0.895	0.001	0.460
		(0.005)**	(0.351)***	(0.003)***	(0.181)***	(0.003)	(0.134)***
C. Quadratic	Linear term	0.084	0.196	0.054	-2.406	0.041	-2.062
		(0.013)***	(3.687)	(0.007)***	(0.563)***	(0.006)***	(0.582)***
	Quadratic term	-0.003	-3.257	-0.002	0.615	-0.001	0.634
		(0.001)***	(3.370)	(0.000)***	(0.518)	(0.000)***	(0.498)
D. Piecewise linear	Current measure	0.060	-3.030	0.103	-1.435	0.100	-0.839
		(0.011)***	(0.415)***	(0.020)***	(0.263)***	(0.012)***	(0.228)***
	Spline at 25th percentile	-0.005	-0.276	-0.055	2.329	-0.082	0.643
		(0.019)	(0.949)	(0.033)	(1.094)**	(0.019)***	(1.007)
	Spline at 50th percentile	-0.007	0.315	-0.019	-4.854	0.018	-3.077
		(0.017)	(1.206)	(0.027)	(2.537)*	(0.016)	(1.844)*
	Spline at 75th percentile	-0.024	-0.986	-0.020	2.113	-0.032	1.709

		(0.012)*	(1.230)	(0.015)	(2.111)	(0.009)***	(1.413)
E. Period effects (linear)	Proxy for the Economy	0.045	-3.469	0.024	-1.643	0.015	-1.264
		(0.004)***	(0.412)***	(0.003)***	(0.304)***	(0.002)***	(0.238)***
	Interaction: Post July 2001	-0.005	-0.023	0.003	0.072	0.005	0.049
		(0.004)	(0.019)	(0.003)	(0.030)**	(0.002)**	(0.015)***
	Interaction: Post January 2008	-0.012	0.024	-0.016	0.171	-0.014	0.250
		(0.004)***	(0.025)	(0.005)***	(0.175)	(0.004)***	(0.118)**
	N (without lags)	13,311	13,050	83,596	83,596	83,596	83,596
	Labor Market Area fixed effects			X	X	X	X
	State fixed effects	X	X				
	LMA-specific linear trends			X	X	X	X
	State-specific linear trends	X	X				
	SNAP and TANF policies	X	X	X	X		
	State x year indicators					X	X

Robust standard errors clustered on geographic unit of analysis in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variable is the natural log of per capita SNAP program participants. Models estimated on all available observations at each level of aggregation. For LMA-level, data are for January and July of 1990-2011 and exclude Alaska, Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, and Vermont. For state-level, data are monthly for 1990-2011 and exclude the District of Columbia. All models include year and month dummy variables. For splines, percentiles computed within series.

Table 6. LMA-level estimated effects of the economy including multiple proxies

	Current proxies		Lagged proxies		LMA-level and State-level current proxies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemployment rate	0.005	0.005	-0.000	-0.000	0.008	0.004	0.004
	(0.002)**	(0.002)**	(0.003)	(0.003)	(0.002)***	(0.002)*	(0.002)*
Employment to pop. ratio	-1.162	-1.009	-0.749	-0.729		-1.093	-0.931
	(0.257)***	(0.258)***	(0.253)***	(0.258)***		(0.260)***	(0.262)***
Retail emp. to pop. ratio		-2.787		-0.745			-2.843
		(0.884)***		(0.839)			(0.877)***
Unemp. rate (lagged 1 year)			0.007	0.007			
			(0.002)***	(0.002)***			
Unemp. rate (lagged 2 years)			0.005	0.005			
			(0.003)*	(0.003)*			
Unemp. rate (lagged 3 years)			0.004	0.004			
			(0.003)	(0.003)			
Unemp. rate (lagged 4 years)			-0.002	-0.002			
			(0.003)	(0.003)			
Unemp. rate (lagged 5 years)			0.003	0.003			
			(0.003)	(0.003)			
Emp. to pop. ratio (lagged 1 year)			-0.386	-0.379			
			(0.125)***	(0.127)***			
Emp. to pop. ratio (lagged 2 years)			-0.285	-0.261			
			(0.086)***	(0.087)***			
Emp. to pop. ratio (lagged 3 years)			-0.047	-0.015			
			(0.076)	(0.074)			
Emp. to pop. ratio (lagged 4 years)			0.388	0.364			
			(0.107)***	(0.106)***			
Emp. to pop. ratio (lagged 5 years)			0.494	0.409			

			(0.142)***	(0.131)***			
Retail emp. to pop. ratio (lagged 1 yr)				0.409			
				(0.695)			
Retail emp. to pop. ratio (lagged 2 yrs)				-0.547			
				(0.579)			
Retail emp. to pop. ratio (lagged 3 yrs)				-1.268			
				(0.646)*			
Retail emp. to pop. ratio (lagged 4 yrs)				0.526			
				(0.768)			
Retail emp. to pop. ratio (lagged 5 yrs)				1.963			
				(0.711)***			
State-level unemp. rate					0.035		
					(0.006)***		
State-level emp. to pop. ratio						-0.649	-0.724
						(0.323)**	(0.333)**
State-level retail emp. to pop. ratio							0.712
							(1.120)
Observations	83,596	83,596	83,596	83,596	83,552	83,552	83,552
R-squared	0.888	0.888	0.886	0.887	0.885	0.886	0.886
Joint significance test	F(2, 2040) = 27.71	F(3, 2040) = 24.85	F(12, 1951) = 7.44	F(18, 1951) = 5.39	F(2, 2039) = 46.15	F(3, 2039) = 21.71	F(5, 2039) = 16.72
	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000

Robust standard errors clustered on geographic unit of analysis in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variable is the natural log of per capita SNAP program participants. Data are for January and July of 1990-2011 and exclude Alaska, Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, and Vermont. All models include year and month dummy variables, LMA fixed effects, and state by year fixed effects.

Appendix A. Data

In the analyses presented in the body of this paper, we make use of time series of cross-sections. These data are aggregated to the level of the state, to the Labor Market Area, and to the county. In this appendix we describe our data sources, the procedures we used to aggregate and disaggregate the available data to the appropriate level for each state of the analysis, and our handling of missing observations. Table A.1 provides summary statistics at each level of aggregation.

Table A.1. Descriptive statistics, 1990-2011

	Obs.	**Mean**	**Std. Dev.**	**Min.**	**Max.**
A. State					
SNAP Caseloads	13,050	507,752	579,377	10,210	4,147,489
Population	13,050	5,627,062	6,176,502	453,690	37,700,000
Working Age Population	13,050	4,443,260	4,844,413	338,889	30,100,000
Total Employment	13,050	2,454,479	2,616,367	178,587	15,800,000
Retail Trade Employment	13,050	288,812	292,222	23,334	1,782,528
Food & Accommodation Services Employment	13,050	196,356	203,666	15,533	1,332,322
Unemployment Rate	13,050	5.53	1.94	1.5	14.8
Employment-to-Population Ratio (Total Employment)	13,050	0.559	0.046	0.405	0.738
Employment-to-Population Ratio (Retail Trade Employment)	13,050	0.068	0.008	0.050	0.200
Employment-to-Population Ratio (Food & Accommodation Services Employment)	13,050	0.048	0.019	0.025	0.185
Percent of population under age 5	13,050	0.069	0.008	0.050	0.103
Percent of population under ages 5-14	13,050	0.142	0.012	0.113	0.210

Percent of population 65 and over	13,050	0.127	0.019	0.040	0.184
Employment Growth	12,450	0.010	0.023	-0.2	0.2
SNAP Caseloads Growth	12,450	0.030	0.113	-1.5	1.4
B. County					
SNAP Caseloads	115,700	7,904	29,130	1	1,767,720
Population	115,700	88,457	298,087	72	9,889,056
Working Age Population	115,700	69,698	232,560	60	7,946,215
Total Employment	115,700	37,381	137,538	0	4,229,496
Retail Trade Employment	114,466	4,497	14,707	0	455,632
Food & Accommodation Services Employment	91,387	3,799	12,590	0	333,398
Unemployment Rate	115,700	6.61	3.32	0.0	59.4
Employment-to-Population Ratio (Total Employment)	115,700	0.421	0.169	0.000	5.366
Employment-to-Population Ratio (Retail Trade Employment)	114,466	0.051	0.024	0.000	0.336
Employment-to-Population Ratio (Food & Accommodation Services Employment)	91,387	0.033	0.031	0.000	1.133
Percent of population under age 5	115,700	0.065	0.011	0.023	0.144
Percent of population under ages 5-14	115,700	0.142	0.020	0.036	0.270
Percent of population 65 and over	115,700	0.151	0.042	0.013	0.455
Employment Growth	82,834	0.058	0.146	-1.7	2.2
SNAP Caseloads Growth	82,306	0.051	0.592	-11.0	10.9
C. Labor Market Areas					
SNAP Caseloads	83,596	10,939	45,148	1	1,915,539

Population	83,596	125,239	576,792	72	12,900,000
Working Age Population	83,596	98,687	452,345	60	10,400,000
Total Employment	83,596	52,958	255,635	0	5,675,566
Retail Trade Employment	83,596	6,314	28,777	0	600,562
Food & Accommodation Services Employment	83,596	4,235	19,639	0	474,976
Unemployment Rate	83,596	6.92	3.58	0	59.4
Employment-to-Population Ratio (Total Employment)	83,596	0.425	0.127	0.0	2.2
Employment-to-Population Ratio (Retail Trade Employment)	83,596	0.041	0.016	0.0	0.2
Employment-to-Population Ratio (Food & Accommodation Services Employment)	83,596	0.021	0.025	0.0	0.7
Percent of population under age 5	83,596	0.065	0.011	0.0	0.1
Percent of population ages 5-14	83,596	0.142	0.020	0.0	0.3
Percent of population 65 and over	83,596	0.158	0.041	0.0	0.5
Employment Growth	79,528	0.007	0.053	-1.7	1.7
SNAP Caseloads Growth	79,364	0.024	0.312	-10.2	9.8

1. SNAP participant counts

We obtained monthly counts of SNAP participants from the forms FNS-388 that states report to the USDA's Food and Nutrition Service (FNS), which oversees the SNAP program. County-level caseloads are available on a semi-annual basis from forms FNS-388A, and we also obtained these counts from FNS.

Form FNS-388A is a project area report of issuance and participation in the Food Stamp Program. Each state or local agency submits the Form FNS-388A data to the FNS regional office twice a year only for the report months of January and July. In most states the project area is a county, but in few states it is a regional district. Some states report as a single statewide project area. The participation data reported on the 388A reports are not estimates, but are actual participation. We obtained data for January 1990 to July 2011 (44 months).

Nine states reported as a single statewide project area during the entire sample period: Connecticut, Maine, Massachusetts, New Hampshire, Oregon, Rhode Island, Vermont, West Virginia and Wyoming. Another group of 15 states reported as a single statewide project area in one or more months. We excluded Alaska because of changes to county equivalents during our sample period made over time comparisons difficult. Further, caseloads for every county in every state are not always available. Most states reported data for all or a majority of their counties.

Table A.2. Number of months that states reported as a single statewide project area

Maine	44	Nebraska	25
Massachusetts	44	Minnesota	19
New Hampshire	44	Missouri	17
Oregon	44	Washington	17
Vermont	44	Wisconsin	11
West Virginia	44	South Dakota	10
Wyoming	44	Utah	9
Connecticut	44	North Dakota	7

Rhode Island	44	Colorado	6
Idaho	40	Alabama	2
New York	39	Georgia	2
Connecticut	28	North Carolina	2

Finally, 34 states reported caseloads in every January and July over our analysis time period while seven states only reported caseloads for part of our period of analysis. Therefore, we are using unbalanced panels in our regressions. We did not interpolate missing caseloads. Table A.3 reports the number of observations for each analysis year across the three levels of aggregation.

Table A.3. Number of Counties, States, and Labor Market Areas with non-missing SNAP caseloads

Year	Counties	Labor Market Areas	States (LMAs)	States (counties)
1990	2,803	2,033	44	41
1991	2,805	2,034	44	41
1992	2,805	2,034	44	41
1993	2,705	1,966	43	39
1994	2,685	1,949	43	39
1995	2,684	1,948	43	39
1996	2,685	1,949	43	39
1997	2,685	1,949	43	39
1998	2,671	1,937	43	39
1999	2,670	1,937	43	39
2000	2,668	1,935	43	38
2001	2,666	1,933	43	38
2002	2,681	1,945	43	38
2003	2,627	1,894	42	37
2004	2,590	1,862	40	36
2005	2,600	1,862	40	36
2006	2,600	1,862	40	36
2007	2,600	1,862	40	36
2008	2,486	1,785	40	35
2009	2,486	1,785	40	35
2010	2,481	1,780	39	34
2011	2,481	1,780	39	34

2. Labor Market Areas

A Labor Market Area (LMA) is an economically integrated geographic area within which individuals reside and can find employment within a reasonable distance or can readily change employment without changing their place of residence. LMAs are non-overlapping and geographically exhaust the Nation. LMAs include both the metropolitan and micropolitan areas defined by the U.S. Office of Management and Budget and the small labor market areas defined by the Bureau of Labor Statistics. Also, LMAs are required to be contiguous but can be single or multi-county. Since these designations are based on the degree of economic integration determined primarily by commutation flows without regard to state boundaries, some interstate LMAs exist. LMAs in New England are based on cities and towns rather than counties.

According to the LAUS Labor Market Area Directory, there are 380 metropolitan areas, of which 50 are interstate; 590 micropolitan areas, of which 16 are interstate; and 1,365 small areas, of which 5 are interstate.

Table A.4. LMA areas

	Total	Analysis sample	Share (%)
Micropolitan Area	590	535	90.7
Metropolitan Area	380	340	89.5
Small Labor Market Area	1,365	1,167	85.5
Total	2,335	2,042	87.5
Interstate LMAs	71	56	78.9

Aggregating counties to Labor Market Areas. Unemployment Rates are available at the Labor Market Area level, but employment, population and SNAP caseloads are not. We aggregated counties into Labor Market Areas using the Labor Market Area Directory available at the BLS-LAUS website. This directory lists all LMAs alphabetically by state and area title. Included with each area title are the type of area, the LAUS area code, and the definition of the area. Definitions are in terms of full counties or county equivalents. Labor market area definitions are updated on an annual basis, and changes to area definitions and titles are introduced with the labor force estimates for the following January. In order to maintain a consistent time series, data for labor market areas generally are reconstructed back to January 1990.

In the case of interstate LMAs, each LMA was assigned to the state with the largest population share among the parts of the area. It is worth noting that in few interstate LMAs, the state with the largest population is a state that is not part of our sample. For example, we do not have county caseloads data for Oregon. However, once we collapse caseloads by LMA we get data for Oregon because there are two interstate LMAs - Portland-Vancouver-Hillsboro, OR-WA Metropolitan Statistical Area, and the Ontario, OR-ID Micropolitan Statistical Area - in which Oregon's part constitutes the largest population share. The same is true for West Virginia and Wyoming.

3. Population estimates

We use Census population estimates for states, age groups, and counties. Total population at the appropriate level of aggregation forms the denominator for the dependent variables across the models. Working age populations (18-64) are the denominators for employment ratios. Finally, we use fraction of population in several age categories to adjust for changing population shares that may be correlated with risk of SNAP receipt.

We use intercensal population estimates from the U.S. Census Bureau to produce SNAP caseloads per-capita for each state and county by year. Estimates are as of July of each year. We used population estimates by 5-year age groups to calculate the percent of population under 5 years, ages 5 to 14, and 65 and older.

Intercensal estimates are produced each decade by adjusting the existing time series of postcensal estimates for a decade to smooth the transition from one decennial census count to the next. They differ from the postcensal estimates that are released annually because they rely on a formula that redistributes the difference between the April 1 postcensal estimate and April 1 census count for the end of the decade across the estimates for that decade.

4. Unemployment rate

Unemployment rates are model-based estimates of those currently employed, about to begin employment, and actively looking for employment. The two main inputs to these models are the Current Population Survey and state unemployment insurance system data on employment and new claims for unemployment (BLS, 2012).

We use monthly unemployment rates available from the Local Area Unemployment Statistics (LAUS) program available for states, counties and Labor Market Areas.

Estimates for seven large areas and their respective balances of State are developed using bivariate signal-plus-noise models. These area models are based on the classical decomposition of a time series into trend, seasonal, and irregular components. A component to identify and remove the CPS sampling error is also included. Area and balance of State models are controlled directly to the State totals, which are themselves controlled to the national CPS via the Census division models. Estimates for the remainder of the substate labor market areas are produced through a building-block approach known as the "Handbook method." This procedure also uses data from several sources, including the CPS, the CES program, State UI systems, and the decennial census, to create estimates that are adjusted to the statewide measures of employment and unemployment. Below the labor market area level (that is for many counties and virtually all cities), estimates are prepared using disaggregation techniques based on inputs from the decennial census, annual population estimates, and current UI data.

5. Employment

These data are provided by state employment security agencies and represent employment of those covered by state unemployment insurance laws and civilian workers covered by federal unemployment insurance. These programs cover nearly all non-agricultural employment and roughly half of agricultural employment (BLS, 2012). They represent counts rather than estimates, and are therefore less subject to measurement error.

Data on monthly total employment, employment in retail trade (44-45) and employment in accommodation and food services (72) come from the Quarterly Census of Employment and Wages (QCEW) available at the state and county levels.

The QCEW program produces a comprehensive tabulation of employment and wage information for workers. Employment data under the QCEW program represent the number of covered workers covered by State unemployment insurance (UI) laws who worked during, or received pay for, the pay period including the 12th of the month. Excluded are members of the armed forces, the self-employed, proprietors, domestic workers, unpaid family workers, and railroad workers covered by the railroad unemployment insurance system. Employment covered by these UI programs represents about 99.7% of all wage and salary civilian employment in the country.

We used the QCEW program as opposed to the Current Employment Statistics (CES) Survey, because QCEW provides information by industry for counties, while CES provides it only for major metropolitan areas. We adjusted employment figures by the size of the civilian population age 15 years old and older[11].

Table A.5 presents correlations across the four proxies for the economy included in the models presented in the paper.

[11] Strictly speaking civilian population refers to people 16 years of age and older but because we only have county population by 5 year age groups we are using people 15 years of age and older.

Table A.5. Correlations, Proxies for the Economy

	Unemployment Rate	Employment to Population Ratio	Retail Emp. to Population Ratio	Food and Accommodation Emp. to Population Ratio
Unemployment Rate	1			
Employment to Population Ratio	-0.4164*	1		
Retail Emp. to Population Ratio	-0.2066*	0.4207*	1	
Food and Accommodation Emp. to Population Ratio	-0.1797*	0.3253*	0.2236*	1

Note: Shown are weighted correlations using population weights for all LMAs. Correlations are for residuals from a weighted regression of each variable on year, month, and LMA indicators.

6. Policies

In the analyses presented in the body of the paper we consider state-level SNAP and TANF policy changes over the 1990s and 2000s. While the SNAP program has strong federal oversight, our DiD identification strategy precludes an analysis of nationwide policy changes. Both the SNAP and the TANF programs allow states substantial flexibility in policy choice. In principle, some of this flexibility can be devolved to more local levels. However, the policies we consider are by and large driven by state-level decisionmaking. This implies that we have at most 50 degrees of freedom for each policy we consider, regardless of the level of aggregation of the caseload, population and economic variables.

SNAP policy changes: We update the policies dataset reported in Danielson, Klerman, Andrews and Krimm (2012) through FY 2011. This dataset includes major, state-level SNAP policy changes that focused applicant eligibility determinations on current income rather than on both income and assets. In particular, over the 2000s most states reduced or eliminated ceilings on the value of personal vehicles and of liquid assets like bank accounts. The dataset also includes major SNAP policy changes aimed at easing use of SNAP among current recipients. These changes included semi-annual reports of income changes for many recipients, and full redetermination of eligibility at semi-annual or annual frequency. They also included the introduction of ATM-like Electronic Benefit Transfer (EBT) cards to replace paper coupons ("food stamps").

Welfare policy changes: As earlier research has done, we include measures of welfare policy changes that accompanied states' shift from Aid to Dependent Families with Children (AFDC) programs to Temporary Assistance for Needy Families (TANF) programs in the mid-1990s. One consequence of the introduction of TANF was the partial decoupling of welfare assistance from food assistance in the sense that policies that discouraged TANF participation also dampened SNAP participation (Klerman and Danielson, 2011). These TANF policy changes included time limits on welfare receipt, more stringent sanction policies for non-compliance with welfare program requirements, and increased ability to combine a welfare payment with earnings. We draw these variables from Urban Institute's Welfare Rules Database for various years and follow the coding developed in Danielson and Klerman (2008).