Local Labor Demand and Program Participation Dynamics: Evidence from New York SNAP Administrative Records

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Abstract

This study uses SNAP administrative records from New York State, 2007–2012, linked to county-level labor market indicators to estimate the effect of local labor demand on individuals' likelihood of transitioning out of the program. We disaggregate county-level monthly demand factors by industry to isolate local demand conditions in the industries most likely to be relevant for SNAP participants, and we then estimate the effects of these labor demand conditions on the probability of exiting SNAP. We find that local labor markets matter for the length of time individuals spend on SNAP. Growth in local food service and retail employment significantly increases the likelihood of a recipient leaving the program in a given month. Wage growth in the same industries has similar, but more modest, estimated effects. Our models include county fixed effects and time-trends, and our results are identified by detrended within-county variation in local labor market conditions. We confirm that our results are not driven by endogenous inter-county mobility or New York City labor markets.

Keywords: Administrative Records, Duration Models, Local Labor Markets, Program Participation
JEL Codes: C23, I32, I38, J23

1 Introduction

The link between labor market conditions and participation in the Supplemental Nutrition Assistance Program (SNAP) has long been of interest to policy makers and program administrators. Employment is a a key factor in moving individuals off SNAP and other public assistance programs. The sharp rise in the SNAP caseload during the Great Recession brought renewed attention to the relationship between SNAP and the labor market. More recently, attention has shifted to understanding why the caseload has not been as responsive to the modest recovery in the labor market.

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The link between labor demand conditions and SNAP participation is also reflected in SNAP regulations. Although federal regulations limit receipt of SNAP benefits by able-bodied adults without dependents (ABAWDS) who do not meet the program's work requirements to no more than three months in a three year period, states may request a waiver of this provision in areas of high unemployment. Some recent proposals, such as the Southerland amendment to the most recent farm bill, have called for eliminating these waivers, and for permitting states to extend work requirements to adults with dependents and those with disabilities. This amendment was ultimately not included in the 2013 Farm Bill; however, the policy debate surrounding it highlights the need for more quantitative evidence on how local labor demand conditions affect SNAP participation. Such evidence could shed further light on the potential consequences of measures, like the Southerland amendment, that would further decouple SNAP eligibility determination from local labor market conditions.

Most of the evidence on the link between SNAP use and labor demand has come from caseload studies. However, caseload studies have a number of drawbacks. First, they are not informative about individuals' behavioral response to labor market conditions. Estimating behavioral responses requires microdata on individuals. Second, these studies tend to rely on measures of labor demand at high levels of geographic aggregation, so they are not measuring the conditions relevant to SNAP recipients or potential SNAP recipients. Individuals are likely not responding to the national, or even state, unemployment rate, but rather to demand conditions in a much more local labor market, and conditions in these labor markets may differ substantially from conditions at the state level.

Household survey data are also not well suited to estimating the effect of local labor conditions on SNAP participation. Although they provide rich information on individuals, survey data typically do not disclose sub-state geographic identifiers, so that labor markets smaller than the state cannot be identified. Sample sizes in survey data may also be too small to detect labor market effects for important subgroups within the SNAP recipient population and too small to employ labor market fixed effects. Most studies that use survey data, therefore, rely on measures of labor market conditions that obscure potentially important within-state heterogeneity. Another concern with survey data is the well-documented measurement error in the SNAP participation itself (Meyer and Goerge, 2011). Studies have shown that SNAP participation is measured with substantial error in the cross-section, and that survey measures of participation spells may be even less reliable (Bollinger and David, 2005).

This study uses SNAP administrative records from New York State linked to county-level labor market indicators to obtain more accurate estimates of the effect of demand factors on individuals' decision to transition off the program. Using administrative records addresses a number of the shortcomings of caseload studies and studies using household survey data. First, the administrative data provides microdata on the universe of SNAP participants in the state, so that even when using a subsample of the data, sample sizes are large enough to support subgroup analysis at the county level. The large sample size also makes it possible to implement a county fixed effects approach to control for the other local, time-invariant characteristics.

Second, our data have very granular geographic identifiers, down to the Census block and tract level. In this study, however, we demarcate the local labor market as the recipient's county of residence and merge monthly and quarterly labor market indicators from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics and the Census Bureau's Quarterly Census of Employment and Wages (QCEW). These data sources allow us to address two potential sources of measurement error. One source stems from defining the labor market too broadly. The second is that even when measuring overall labor demand conditions at the county level, there may still be important heterogeneity across industries and occupations within these local labor markets that affect SNAP recipients' labor market outcomes. We therefore disaggregate demand factors by industry to isolate local demand conditions in the industries most likely to be relevant for SNAP participants. Specifically, we consider county- and industry-specific measures of monthly employment and average weekly wages by quarter.

A third advantage of using administrative records over most survey data is that they cover a relatively long period of time: a total of six years spanning 2007 to 2012. This enables us to observe recipients for a longer period of time than is possible using the Survey of Income and Program Participation (SIPP), the survey most commonly used to analyze dynamic aspects of SNAP participation. The longer time frame allows us to observe more spells in their entirety, obviating to a greater degree the difficulties that arise with left-censored observations.

This work builds primarily on previous research by Hoynes (2000) and Herbst and Stevens (2010), who examine the effect of local labor market conditions on entries into and exits from Assistance for Familes with Needy Children (AFDC) and, later, Temporary Assistance for Needy Families (TANF). Like them, our main approach is to estimate exits from SNAP using discrete time hazard models that include monthly and quarterly county-level employment and earnings information by industry, individual and case characteristics, county fixed effects, year effects, and county-level time trends. This paper extends the literature in several important ways. First, our administrative data provide many empirical contributions. To this point, the literature has focused on how local labor markets influence participation in AFDC/TANF; to the best of our knowledge, this is the first study to examine the effect of local labor market conditions on participation in SNAP. Furthermore, our data allow us to explore these effects in a new setting; while Hoynes (2000) uses data from California and Herbst and Stevens (2010) use data from Maryland, our data derive from New York State. Our data are also much more recent than in the previous studies and span one of the U.S.'s most important economic events: the Great Recession. A final methodological contribution is that we estimate local labor market effects on spell duration seperately by first and second observed spells. Over 30 percent of the recipients in our data experience two or more SNAP spells during our observation period.[1] Examining participants' second spells informs us about how local labor market conditions differentially effect spell duration for the most persistant SNAP participants.

We find that local labor market conditions matter for the length of time individuals

[1]We smooth over 1 month gaps in enrollment to avoid treating temporary lapses in certification as actual spell breaks.

spend on SNAP. In particular, employment in the local food service and retail industries—two important destination industries for SNAP leavers—significantly increases the likelihood of a recipient leaving the program in a given month. We also find evidence that a higer wage in the retail industry (and, to a lesser extent, in the construction industry) hastens exits from SNAP. These results are fairly robust to a variety of specification checks, which include accounting for higher order spells, potential endogeneity of the labor market measures, potential endogenous mobility among SNAP recipients, and a lack of demographic information on recipients in the SNAP administrative records. Our results indicate that modest improvements in employment in the food service and retail industries—controlling for the size of the overall county population and labor force—can significantly increase the hazard of exit from SNAP. For instance, raising county-level employment in retail by one percent leads to a more than threefold increase in the likelihood of SNAP recipient in that county leaving the program in that month. Simiarly, a rise in county-level employment in the food service industry is associated with a 45 percent increase in the hazard of program exit.

These results are quite robust. For example, unobserved differences may exist between single-spell participants and multiple-spell participants, yet our estimates are very similar for participants in their first spells and second spells. We also show that our main findings do not change when using lagged local labor market variables or when we exclude New York City residents from our models.

We also rule out concerns that residential mobility may bias our results. For example, if more motivated SNAP participants endogenously relocate within-state to counties with favorable labor market conditions, then our estimates of local labor market effects on the hazard of exiting SNAP would be biased upward. We find, however, that our results are very similar when estimating our models over the subsample of individuals whose county of residence does not change during our observation period.[2]

The administrative records used in our analysis have, however, some important shortcomings. First, our records do not contain very detailed demographic information on individuals, so our analysis is more likely to be subject to omitted variables bias. To address this issue, we extend our analysis by linking persons in the administrative records to their responses about race and ethicity in the 2010 Census and reestimate over the linked sample. We find that our main results are robust to the inclusion of these demographic variables. Nevertheless, because additional information on individuals (e.g., educational attainment) in these data is sparse, the pervasive problem of unobserved individual heterogeneity in duration analysis is likely still to figure in our analysis. Addressing this problem with models that account for unobserved individual heterogeneity under different distributional assumptions is a topic for future work. Finally, using data from a single state is that it raises concerns about the generalizability of our findings to other states and the U.S. as a whole.

[2]Out-of-state mobility presents other hurdles. Since the data do not allow us to observe individuals when they are not receiving program benefits in New York State, we are unable to distinguish apparent program exits from migration to another state where SNAP receipt continues. Two factors mitigate this potential issues. One is that in some case out-of-state moves are identified in the administrative records. The other mitigating factor is that estimates from the American Community Survey (ACS) indicate the incidence of out-of-state moves in a given year is quite low, on the order of one to two percent.

The remainder of the paper is as follows. Section 2 describes the literature on factors influencing individuals' entry into and exit from SNAP. Section 3 describes the data and sample construction, Section 4 details our estimation strategy, and Section 5 presents our results and sensitivity analysis. Section 6 offers concluding remarks.

2 Prior Research on SNAP Dynamics

A number of studies have investigated the dynamics of SNAP participation using household microdata. The USDA Food and Nutrition Service (FNS) has commissioned an ongoing series of reports, produced by Mathematica Policy Research (MPR), that uses the most recent panel of the Survey of Income and Program Participation (SIPP) to analyze the determinants of program entry and exit (Gleason et al., 1998; Cody et al., 2005, 2007; Mabli et al., 2011). These reports have focused on State policy variables and household-level trigger events and have consistently identified adverse income shocks as the most common trigger for program entry. Along the same lines, Mabli and Ohls (2012) used SIPP data from 2001 to 2003 to focus on the relationship between SNAP dynamics and changes in employment status. Their results suggest that employment changes are more strongly associated with entry to (and exit from) SNAP for individuals with more stable employment histories.

These reports employ longitudinal data that follow respondents for a period of about 2-3 years. But this rather brief window of observation gives rise to two shortcomings. One is that many of the program spells observed in the data are left-censored and therefore the beginning of the spell, as well as other events contemporaneous with the start of the spell, cannot be identified. Omitting left-censored spells, which tend to be longer than average, results in a biased sample. Another shortcoming is that researchers often cannot determine if the spell observed in the data is in fact an individual's first, or subsequent, spell on the program. Atasoy et al. (2010) pursue a somewhat different approach to the study of SNAP receipt dynamics. Rather than estimating a duration model, they employ lagged-dependent variable models, which control for individual unobserved heterogeneity and estimate one-period state dependence in SNAP. Their sample is drawn from the Panel Study of Income Dynamics (PSID) which allows them to examine SNAP dynamics over a longer time frame than the studies using the SIPP. They found that welfare reform measures also had the effect of reducing long-term dependence (i.e., estimated state-dependence) in SNAP participation. Moreover, SNAP policies that discourage program entry, through either changes in benefit levels or certification requirements, also have the effect of reducing state dependence in SNAP participation.

Schroeder (2007), Cadena et al. (2006), and Ribar et al. (2005) each study dynamics using administrative records from a single state. Ribar et al. (2005), however, is the only one of these studies to model unobserved heterogeneity. Using the NLSY79, Baum (2008) examines the role of SNAP in transitions off cash welfare and into employment. He finds some evidence that SNAP may discourage employment and transitions off welfare. Although with Atasoy et al. (2010), this is one of the few studies to explicitly account for individual unobserved heterogeneity. In this case, discrete mass points are used to approximate the distribution of unobserved heterogeneity. However, this study does not directly model SNAP dynamics, but rather is interested in the dynamics of (cash) welfare and work (e.g., on welfare without work, off welfare with work, etc.).

3 Data and Descriptive Statistics

3.1 Data Sources

We use administrative records from New York State linked to a number of other data sources that provide information on county characteristics. The main benefit of the administrative files is that they accurately record spells of participation over time, not only for SNAP but also for Temporary Assistance for Needy Families (TANF) and New York general assistance (GA) programs. The administrative records also enable us to determine the age and gender of individuals in the SNAP unit. Since we are able to identify the case unit in the administrative records, we construct variables characterizing case composition, such as the unit size, the number of elderly and non-elderly individuals, and children. We are not, however, able to characterize the household when other members not belonging to the SNAP unit are present. The files also contain the benefit amount received by the SNAP unit.

The files also contain very detailed geographic information on recipients' place of residence. When applying for SNAP benefits, recipients must provide a valid address (or indicate that they or homeless, or "undomiciled"). The Census Bureau geocodes the address information to enable identification of the Census tract and block in which recipients resides. We do not make use of this level of geographic detail. Rather, we define local labor markets according to county boundaries.

We use the county identifiers to merge to administrative records four other sources of data: the BLS LAUS, the Census Bureau QCEW, and the ERS county urban-rural continuum codes. From the BLS LAUS data we obtain monthly county-level unemployment rates. From the QCEW, we obtain county-level monthly employment counts, overall and by industry. The QCEW also provide quarterly wage data. In this study, we use the average weekly wage in a quarter, both across all industries within a county and disaggregated by industries. Finally, the ERS urban-rural continuum codes characterize the urban-rural status of the county. Since this status tends not to change over time, they are omitted from empirical specifications that employ county fixed effects.

The administrative records are a longitudinal file, composed of person-month records. We identify individuals over time on the longitudinal identifier known as the Protected Identification Key (PIK), which is a unique identifier used within the Census Bureau's Center for Administrative Records Research and Applications (CARRA) to link individual person records across data sets. These PIKs are assigned through the Person Identification Validation System (PVS), which employs probability record linkage techniques (see Wagner and Layne (2014) for more information). CARRA uses Personally Identifiable Information (PII) such as name, date of birth, and address to assign a PIK. CARRA then removes the PII from the data file to anonymize the data and preserve confidentiality so it can be used for statistical purposes and research. Encouragingly, there is a very high degree of correspondence between New York OTDA recipient identifiers, used to follow peole over time and programs, and the Census Bureau PIKs.

Identifying individuals via PIK also permits us to augment demographic information in the administrative records. As part of our sensitivity analysis, we use the PIK to link individuals to their responses about race and Hispanic origin in the 2010 Census. A discussion of the data linkage, including match rates and limitations of this approach, follows in Section 3.3.

3.2 Sample Construction

We start with the universe of SNAP participants in New York from 2007 to 2012. We drop individuals without a valid PIK. The PIK rate for the administrative records is very high, so this results in a loss of only a few percent of the total observations sample. We drop children (under 18 years of age) because children belong to adults' benefit units and do not make the decision about whether to participate. We also drop very elderly individuals—those over 90 years of age—primarily out of concern that date of birth information for some of these individuals may be incorrect. Individuals of this age are also more likely to be a dependent in a SNAP unit and thus may not be making the participation decision on their own.

As is typically done with survey data, we smooth one month gaps in spells, as these are likely the result of administrative churning that does not truly reflect an interruption in the spell. After smoothing one-month gaps, we drop one-month spells. We suspect that many one-month spells are administrative artifice. Even with these cuts, our data set contains 3.17 million individuals and over 100 million person-months.

Even with the restrictions imposed on the universe of SNAP administrative records described in the data section, our full analysis sample is still quite large. In the six years of our analysis period, we observe 2.4 million exits, 1.86 million non-left-censored spells, and 22.3 million person months.

We next present descriptive statistics on the complete data set, subject to the restrictions discussed above. To estimate our multivariate hazard models, however, we take a 2 percent flow sample of our data since estimation, particularly the fixed effects estimation, on the full data set become very cumbersome.

3.3 Descriptive Statistics

We begin by discussing censoring, individual spell counts, and spell lengths in our data. We are able to observe roughly half of the spells in their entirety. Left-censored spells—i.e., spells in progress as of January 2007— account for about 22 percent of all spells, of which 9.3 percent are also right-censored. A further 30 percent of spells are right-censored only, so that right-censored spells account in total for nearly 40 percent of spells.[3] The high incidence of right-censored spells is a product of the large number of spells that started during the recession, and the "jobless" recovery, but did not end as of December 2012. Fortunately, right-censoring does not pose a problem for the hazard models we estimate below.

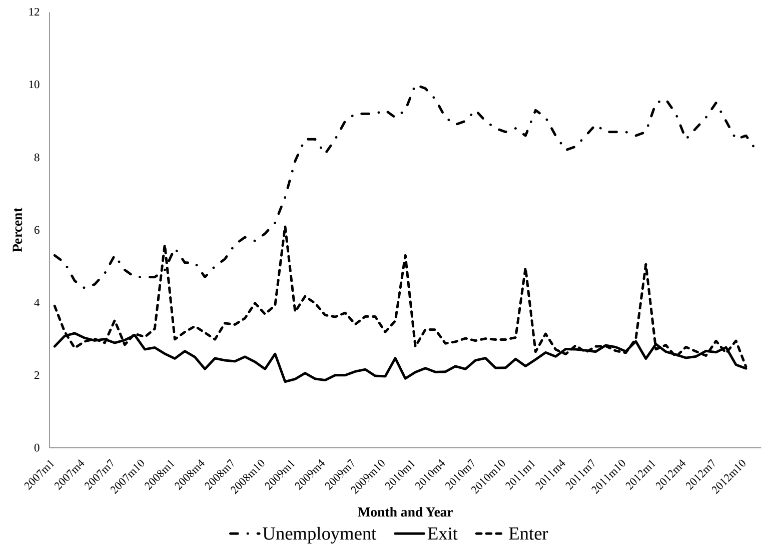
The majority of individuals in our data–68.7 percent–have only one spell between 2007 and 2012. Over 30 percent of the recipients during this period, however, have multiple

[3]In some cases temporary out-of-state residency is recorded in the administrative records, typically the last month of an observed spell. We treat these spells as censored; in fact, these constitute the only spells that are censored prior to the last month in our data—December 2012—, at which point all ongoing spells are considered censored.

spells of SNAP receipt, even when one-month gaps are smoothed. Specifically, 21.2 percent have two spells, 6.9 percent have 3 spells, and 3.2 percent have 4 or more spells. Among all spells in the administrative records, the median spell was 11 months, with a mean of 15.1. Restricting attention to only complete (i.e.,non- censored spells), the median length is 10 months, with a mean of 13.0 months. As expected, excluding censored spells biases the mean and median spell lengths downward. Given the degree of right-censoring, however, this bias is perhaps not as large as one might have expected.

At most, a person can spend a total of 72 months on SNAP in our data. The 10th percentile of the distribution of total months on the program was 4 months, and the 25th percentile was 11 months. The median amount of time that a recipient spent on the program, was 26 months, with a slighty higher mean of 32.1 months.

Figure 1
SNAP Entry and Exit Rates in New York



Source: 2007-2012 New York SNAP Administrative Records and BLS Local Area Unemployment Statistics

Figure 1 plots the monthly SNAP entry and exit rates, along with the (seasonally unadjusted) unemployment rate in New York. The figure illustrates the divergence of entry and exit rates, starting early in 2008, that drove the large increase in the SNAP caseload over this period, and the convergence of the two rates early in 2011. Again, it is notable that the caseload changes were driven by substantial changes in both entry and exit rates, although entry rates appeared to adjust more quickly to their pre-recession level. This convergence occurs despite a very modest decline in the state unemployment rate.

What is also striking about this figure are the pronounced spikes in the entry rate in January of each year. This is likely the result of a program in New York State under which Supplemental Security Income (SSI) recipients who live alone are automatically enrolled in SNAP under the New York State Nutrition Improvement Project (NYSNIP) at the beginning of the calendar year. These new case openings will be closed if the benefits are not used in given amount of time, thus many of these case openings are in fact spurious spells. More work will need to be done to try to identify these NYSNIP-related spells.

Figure 2
New York SNAP Caseload and State Unemployment Rate

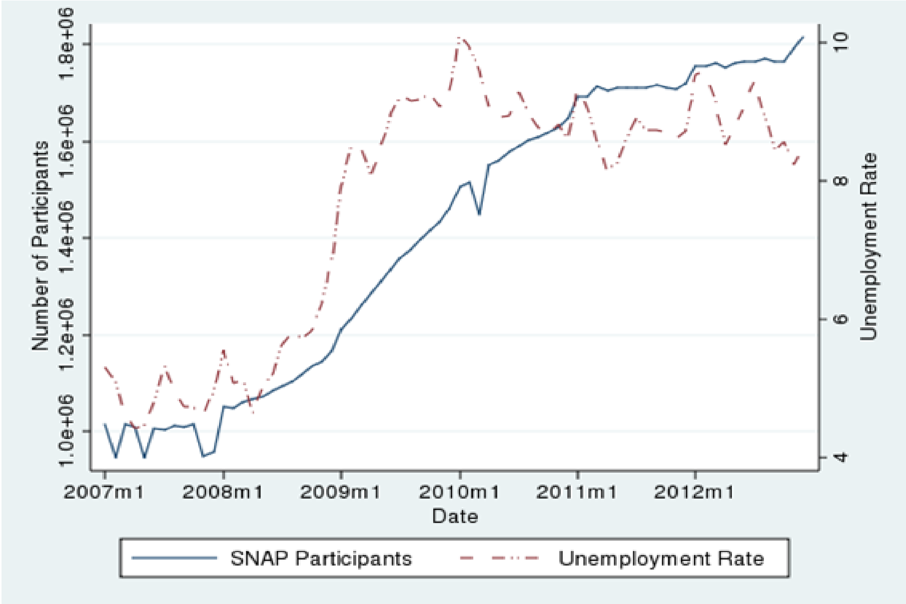


Figure 2 displays time series plot of the SNAP caseload (measured in persons) and the (unadjusted) unemployment rate in New York.[4] Prior to the recession, there was interesting co-movement between the unadjusted unemployment rate and the SNAP caseload. We observe the rate of growth in the SNAP caseload leveling off starting in 2011, but the overall caseload continued to grow, which may indicate that the January "spikes" observed in Figure 1 may not entirely reflect spurious spells.

Table 1 displays descriptive statistics for the 2 percent estimation sample. The unit of analysis is the individual in the first month we observe that person in the administative records. More than half of the sample is female (55 percent), and the average age is 40.8 years old. The average case unit size is 2.2 members, with 21 percent of cases having a child four years old or younger and another 18 percent having child between the ages of five and 17. An elderly member is a member of 15 percent of case units, while another 65 percent of units contain at least one other nonelderly individual. A non-elderly male belongs to 33 percent of case units. The average log monthly benefit amount for a case was 5.43, or $228.15, 2 percent of cases were on TANF at some point in the observation period, and 4 percent were on another form of public assistance.

Only 8 percent of the sample relocated from one county in New York State to another during the sample period. Most participants in our data lived in more metropolitan areas. The average participant resided in a county with population of just over 806 thousand individuals and a labor force of just over 388 thousand. Furthermore, 78 percent of the sample lived in counties that were themselves part of a metropolitan area with at least 1 million people, most likely reflecting the fact that many of the SNAP participants in our sample reside in New York City.

Finally, the last six rows of Table 1 show the distribution of first-years we observe a person in our data. As we saw in Figure 1, entry rates increase leading into the recession

[4]Note that, due to our prior cuts to the data, these numbers represent the number of adults on the programs, also excluding those over age 90.

but begin to decline in the later years of the data. The difference between Figure 1 and the results in Table 1 is that the former includes re-entries of previous SNAP cases, while the latter does not. We see that 16 percent of all new cases appeare in 2007, 21 percent of all new cases appear in 2009 (the year the recession officially ended), but only 12 percent of all new cases appeared in 2012.

Table 1
Summary Statistics

	Mean	SD	Min	Max
Female	0.55	0.50	0.00	1.00
Age (in years)	40.78	16.64	18.00	90.00
Number of members in case	2.24	1.68	1.00	19.00
Presence of children under 5	0.21	0.40	0.00	1.00
Presence of children 5–17	0.18	0.38	0.00	1.00
Presence of non-elderly members	0.65	0.48	0.00	1.00
Presence of on-elderly males	0.33	0.47	0.00	1.00
Presence of elderly members	0.15	0.36	0.00	1.00
Log benefit amount	5.43	0.89	0.69	9.57
TANF	0.02	0.13	0.00	1.00
Other public assistance	0.04	0.20	0.00	1.00
Metro area	0.78	0.42	0.00	1.00
Log county population	13.60	1.21	8.47	14.76
Log county labor force	12.87	1.20	7.91	13.96
Ever changed county	0.08	0.27	0.00	1.00
Year = 2007	0.16	0.37	0.00	1.00
Year = 2008	0.17	0.37	0.00	1.00
Year = 2009	0.21	0.41	0.00	1.00
Year = 2010	0.18	0.39	0.00	1.00
Year = 2011	0.15	0.36	0.00	1.00
Year = 2012	0.12	0.32	0.00	1.00
Individuals	35,456			

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to BLS Local Area Unemployment Statistics and Census Quarterly Census of Employment and Wages (QCEW).

One of our sensitivity tests will be to link the observations in Table 1 to their responses on race and Hispanic origin in the 2010 Census. As we mentioned above, matching is based on the PIK, which affords us the chance to control for potentially important demographic factors that could influence the relationship between local labor market conditions and SNAP exit. However, it is important be aware that PIK assignment, while quite high in both files, is not non-random, particularly in the case of the Census data.[5] In particular, young children, minorities, residents of group quarters, immigrants, recent movers, low-income individuals, and non-employed individuals are less likely to receive a PIK (Bond et al., 2014; Rastogi et al., 2012).

In light of this, it is not surprising if either the match rate between the SNAP adminis-

[5]The PIK assignment rate is 90.81 percent in the 2010 Census and 99.2 percent in the administrative files. The relatively high match rate in the administrative files is due to the requirement that individuals provide valid Social Security Numbers in order to qualify for SNAP benefits.

trative records and the 2010 Census is somewhat low or if the matched sample differs in its measureable characteristics from the unmatched sample. Indeed, 75.21 percent of the individuals in our administrative files were also identified in the 2010 Census, and there are differences between the matched and unmatched samples that must be considered when we later interpret the results using the linked sample. In general, those whose records were not found in the Census are more likely to be males who live in smaller households with fewer children and fewer elderly members. They are also more likely to live in metropolitan areas and more likely to have moved during the observation period. There do not appear to be meaningful differences, however, in age, participation in other programs like TANF and state public assistance, or the year they first appear in the data. Appendix Table 9 provides a detailed analysis of the differences between the matched and non-matched samples. While these differences are mostly statistically significant, many of them are practically small. Furthermore, as we will see, our main findings are not sensitive to the exclusion of non-matched individuals.

4 Methodology

In this section, we use hazard models to examine the determinants of exit from SNAP. Specifically, we estimate discrete-time hazard models of program exit using the complementary log-log link function. This functional form approximates in discrete-time the proportional hazard model in continuous time. However, when the hazard is low, there is little difference between the choice of logit and complementary log-log link function. We also model the baseline hazard flexibly, using a step for each month at risk.

In this section, we estimate discrete-time hazard models in which individuals are "at risk" for exiting SNAP as soon as they are first observed to enter the program. Thus for individual i the probability of exiting a SNAP spell at time t is given by

$$\lambda_i(t) = Pr(T_i|T_i \geq t, x_i) = F(\alpha_0 + \alpha_1(t)x_i(t) + \gamma_i(t)), \tag{1}$$

where $F(\cdot)$ denotes the complementary log-log function. The vector $x_i(t)$ contains the explanatory variables of the model and $\gamma_i(t)$ represents duration dependence, or the effect on the SNAP exit probability of time "at risk." The discrete-time hazard model estimates the probability of an individual exiting SNAP in a given month conditional on that individual not having left the program prior to that month.

The log likelihood function takes the following form:

$$log\, L = \sum_{i=1}^{N}\sum_{t=1}^{\bar{t}}[(1-y_{it})log(1-\lambda_i(t)) + y_{it}log\lambda_i(t)] \tag{2}$$

where $\bar{t}$ is the longest observed duration, N is the number of individuals in the sample, and y_{it} is equal to one if individual i is observed to exit SNAP in period t and is equal to zero otherwise. With the data arranged in person-period format, individuals who do not exit SNAP during the sample period will have a y_{it} sequence equal to zero for every period, t. Individuals observed to exit SNAP during the period will have a y_{it} sequence equal to zero for every period except for the period in which they exit SNAP, their last period in the sample.

Following Hoynes (2000), our preferred specification includes county fixed effects and county time trends, so that x_{ict}'s in equation 1 becomes:

$$x_{ict} = X'\beta + \phi Labor_{ct} + \alpha_0 County_c + \alpha_1 Time_t + \alpha_2 County_c \cdot Trend_t. \tag{3}$$

Our interest variables are the covariates in the vector $Labor_{ct}$, which reflect alternative measures of time-varying county-level labor market conditions. In the results that follow, we model $Labor_{ct}$ in two basic ways: in the first case, we estimate the effects of time-varying county- and industry-specific log employment on exit hazard, while controlling for monthly county-wide average wage levels. In the second approach, we estimate the effects of time-varying county- and industry-specific wage levels on exit hazard, controlling for log county-level employment levels for that month. In both sets of models, we focus on industries that are likely to be important for SNAP recipients. Specifically, we estimate the effects of within-county changes in employment and wages for construction, food service, manufacturing, and retail. In all models, we also control for the log of the county labor force

Our parameters of interest, ϕ, are identified by within-county variation in labor market conditions, differencing out county-specific trends in the labor market. Identification of the these county-level labor market variables requires sufficient variation in these measures both across counties and over time. Figures 4 and 5 in the appendix provide a sense of the degree of variation in county-level unemployment rates and average weekly wages over the sample period. The maps measure the difference between the maximum and minimum value of the county-level unemployment rate and the county-level average weekly wage, respectively, in each county between 2007 and 2012. Indeed, they reveal substantial temporal differences in each labor market variable over time. We ensure that ϕ is identified by within-county variation by including the vectors, $County_c$, which represents county fixed effects (time invariant unobserved county characteristics) and $County_c \cdot Trend_t$, which captures county time trends. We also estimate base models that do not include the county fixed effects or time trends as well as models that include county fixed effects but not time trends.

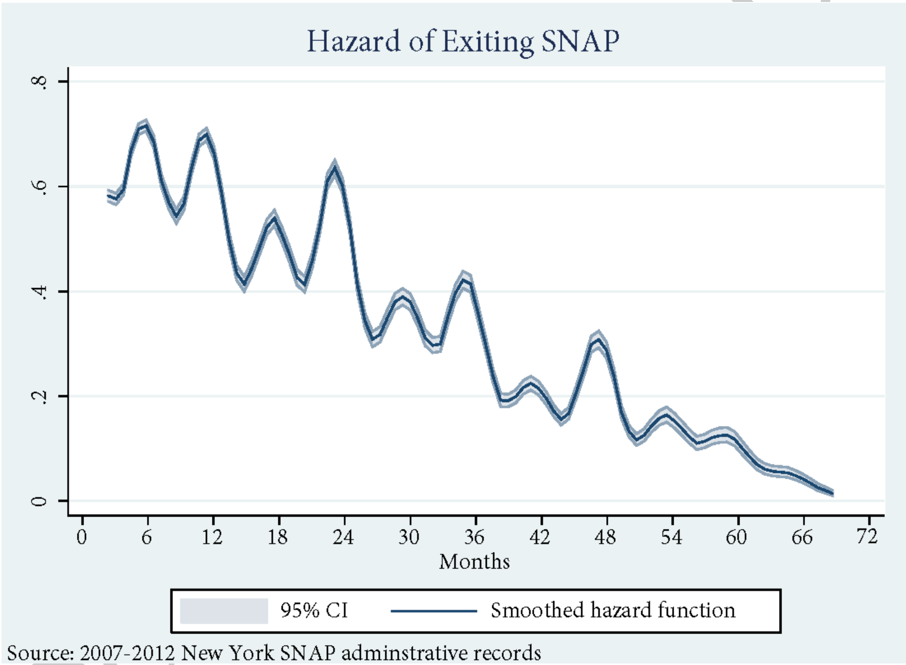
In the vector X we include covariates for recipient age, age squared, gender, several variables characterizing SNAP unit composition (presence of children under 5, presence of children 5–17, presence of elderly members, presence of non-elderly members, and presence of non- elderly adults, and an indicator for monthly inter-county mobility). As a robusntess check, we restrict to the sample that could be linked to the 2010 Census and include variables on race (White alone, Black or African American alone, and neither White alone nor Black alone) and Hispanic origin. In all models we control for the natural log of the montly SNAP benefit amount, the percent change in benefit amount from the previous month, receipt of TANF and state general assistance benefits by members of the unit. To capture other time- varying environmental factors that may affect the SNAP exit probability, we also include year indicators, and we model the baseline hazard, $\gamma_i(t)$, as the number of months on SNAP, plus its square and its cube. Finally, we control for the natural log of the county's population size and the urban-rural status of the county.

Without adequate pre-sample information on recipients, we are not able to address left-censoring by modeling initial conditions(Wooldridge, 2010). We therefore follow much of the literature and eliminate left-censored spells from the main analysis sample,and analyze them separately. In doing so, we are likely disproportionately eliminating longer than average spells. And as previously noted, we also eliminate one-month spells.

In this study, we also do not address the issue of multiple spells of participation, even though a substantial proportion of our sample (about 30 percent) had more than one spell of SNAP participation during the period of observation. Instead, we also follow much of the literature on hazard modeling and restrict our estimation sample to first spells of participation. More work on incorporating higher order spells of particiaption into our analysis will be done in future, including models that allow for individual unobserved heterogeneity to be correlated across across spells for a given recipient.[6]

5 Results

Figure 3
SNAP Exit Model: Unconditional Hazard



In figure 3, we plot the unconditional hazard of SNAP exit. Two features should be noted in this figure. One is that the hazard of exit is decreasing with spell duration, suggesting negative duration dependence. Negative duration dependence implies that the longer someone is on SNAP, the less likely they are to exit. It is important to note, however, that we are not controlling for unobserved heterogeneity. And given the sparse individual-level characteristics in our model, neglecting this unobserved heterogeneity may well be important, despite not imposing any assumptions on the form of the duration dependence. By ignoring unobserved heterogeneity we may confounding the hazards

[6]Attempts to estimate single spell models that incorporated unobserved individual heterogeneity as a discrete mass point distribution (with two mass points) had difficulty converging. As noted in the text, it is often argued that flexibly controlling for the baseline hazard function ameliorates much of the bias that can arise from ignoring individual unobserved heterogeneity in discrete-time duration models. And in a similar study using AFDC/TANF administrative records from California, Hoynes (2000) reports that specifications that accounted for individual unobserved heterogeneity did not appreciably alter her results.

of two (or more) very heterogeneous groups of SNAP participants: one group we might term "fast exiters," and another, "slow exiters". That is, we might have one group that is on SNAP for a short spell in the face of some negative shock. They contribute to the high exit rates we observed for early durations. At longer durations, however, as more of these "fast exiters" leave the program, only slow exiters will remain in the at-risk pool. Disability may be one source of unobserved heterogeneity that could lead to such a scenario. In our results that follow, we control for several person and case-level characteristics to attain estimates of conditional discrete time hazard models.

5.1 Main Results

Table 2

Hazard Model of SNAP Exit with County Fixed Effects and Time Trends, First Spells

	(1)	(2)	(3)	(4)	(5)
Panel A. County Employment Variables					
Log of Industry Employment:					
Construction	1.02				1.01
	(0.02)				(0.02)
Food		1.45**			1.25
		(0.17)			(0.15)
Manufacturing			1.02*		1.02*
			(0.01)		(0.01)
Retail				3.35***	2.88***
				(0.82)	(0.74)
ln(County Labor Force)	3.18	1.20	3.41	1.85	1.08
	(2.04)	(0.86)	(2.18)	(1.20)	(0.77)
Average Weekly Wages (100s)	0.99	0.99	0.99	0.99	0.99
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log-Likelihood	-90408.75	-90404.09	-90406.70	-90397.22	-90392.78
Panel B. County Wage Variables					
Average Weekly Wages (100s):					
Construction	1.01*				1.01
	(0.01)				(0.01)
Food		1.02			0.97
		(0.03)			(0.04)
Manufacturing			1.01		1.01
			(0.01)		(0.01)
Retail				1.06*	1.04
				(0.03)	(0.05)
ln(County Labor Force)	3.11	2.96	3.38	3.18	3.43
	(2.00)	(1.91)	(2.19)	(2.04)	(2.22)
ln(County Employment)	1.62	1.94	1.92	1.56	1.58
	(0.63)	(0.73)	(0.71)	(0.62)	(0.63)
Log-Likelihood	-90405.99	-90407.74	-90406.31	-90405.84	-90404.88
Observations	701,395	701,395	701,395	701,395	701,395

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to BLS Local Area Unemployment Statistics and Census Quarterly Census of Employment and Wages (QCEW).

Notes: Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2 shows results of estimating the discrete time hazard model described by equation 3. The sample includes first spells only. Columns 1–4 focus in turn on construction, the food industry, manufacturing, and retail. Estimates from a fully-saturated model appear in column 5. The top panel (Panel A) shows estimates of the effects of industry- and county-specific employment levels, and the bottom panel (Panel B) shows estimates for industry- and county-specific average wages. All regressions include the demographic (age and sex) and case-composition controls listed in Section 4, year effects, duration controls (spell duration, its square, and its cube), county characteristics, county fixed effects, and county time trends. We present estimates of our parameter of interest, ϕ, but full regression results are available upon request.

Panel A of Table 2 shows positive and statistically significant relationships between the SNAP exit hazard and several of employment measures included in the regressions. For example, column 2 indicates that a 1 percent increase at the mean in employment in a county's food industry is associated with a 45 percent increase in the probabiliyt of exiting SNAP. Column 3 shows a positive though modest statistically significant estimated effect of employment in manufacturing, but the most pronounced effect is from retail employment. Column 4 suggests a 1 percent increase at the mean in retail employment in a person's local labor market more than triples the hazard of exiting SNAP. This relatively large and precise point estimate is still evident in column 5, which estimates the four industry-specific effects simultaneously. In column 5, the estimate of the food industry employment effect becomes smaller in magnitude and statistically insignificant; the point estimate on manufacturing employment remains relatively small but statistically significant. Interestingly, the strength of the local construction industustry does not have a descernable effect on the likelihood of SNAP exit. However, it may be the case that once county fixed effects and time trends are accounted for, there is little independent variation in the time-varying county labor market measures. Indeed, Table 8, in the Appendix, shows much more precision in column 1, where county fixed effects and time trends are both excluded from the model. However, this restricted model also attains opposite conclusions about, for example, the role of local growth in retail employment for SNAP exits, underscoring the importance of including the county fixed effects and time trends despite loss in precision. With that in mind, it is noteworthy how precise many of the point estimates are even while including the county fixed effects and time trends.

Panel B presents results of estimating conditional wage effects on SNAP exit hazard. In general, changes in wages appear to have a weaker relationship with the likelihood that a person exits SNAP. However, this may be due to the fact that our measures of average industry wage vary by quarter, while the industry variables in Panel A vary by month. By definition, there will be less variation that can be used to identify effects of changes in industry wages on SNAP exit. Nevertheless, as in the Panel A, we do observe the strongest effect coming from the retail sector. Column 4 shows a \$100 increase from the mean in the average weekly wage in the retail sector is associated with a 6 percent increase in the probability of exiting SNAP. Unlike Panel A, however, we also see a positive and statistically significant relationship between wages in the construction sector and SNAP exit hazard, although the point estimate is quite small. None of the industry effects are statistically significant in the fully saturated model in column 5, however this is likely due to the county fixed effects and time-trends absorbing too much county-level variation in average wages. As was the case with the models in Panel A, excluding the county effects and county time-trends yields more precise estimates on the wage variables, but in some cases the direction of the estimated effects differs. (See Appendix Table 8.)

As a whole, Table 2 suggests that even in the presence of controls for county fixed effects and time trends, local labor market conditions—employment levels, in particular—are positively related to the likelihood that SNAP particpants exit the program. SNAP exits appear to be most sensitive to changes in the strength of the retail sector, although the food service sector also shows strong (albeit somewhat imprecise) employment effects. In the follow section, we extend the results in Table 2 and also conduct several robustness checks. In particular, we extend the analysis by estimating the models using second spells. The results in Table 2 are based on first observed spells in our data; but over 30 percent of the sample exhibits multiple spells, and examining second spells only allows us to learn more about those whose attachment to the program is more persistent. We also estimate our models using lagged labor market variables to examine how protracted SNAP participants' responses are to changes in their local labor market. Next, we address concerns that our estimates are driven by endogenous mobility, concerns that our results are dominated by conditions specific to New York City, and concerns that limited demographic variables in the administrative records comprimises our main results.

5.2 Extensions and robustness checks

5.2.1 Second spells

As we noted in Section 3, roughly 30 percent of adult recipients in New York experienced more than one SNAP spell between 2007 and 2012, even when one-month gaps in participation are smoothed. The models in Table 2, however, were estimated only for first spells observed during the sample period. Our results may therefore be biased by ignoring higher order spells. There are a number of ways to address multiple spells in duration analysis. One is to simply pool all spells and include model controls indicating higher order spells (and, potentially, other characteristics of prior spells, such as spell length). Another straigthforward approach—and the one that we adopt here—is to estimate separate models for each spell number, allowing all covariates in the model to vary by spell number. A final approach employed in the literature is to estimate an individual random-effects model on all spells, allowing for correlated individual unobserved heterogeneity across spells. These models can prove difficult to estimate, however. We postpone estimation of these more complex models for future work. [7]

Table 3 replicates the analysis in table 2 for second-order spells. [8] The effects of local labor market conditions on the hazard of SNAP exit are largely unchanged relative to effects obtained for first spells. Strong and statistically significant positive effects on SNAP exit persist for county-level retail and food service industry employment, although the

[7] As previously noted, Wooldridge (2010) and Meyer (1990) indicate that individual unobserved heterogeneity may be less of a concern in models that control flexibly for duration dependence. Although we do not control in a completely flexible manner for duration dependence (i.e., a monthly step function in spell length), our cubic function in spell length does avoid strong parametric assumptions).

[8] We do not analyze spells of order three or higher, since these sample sizes become rather small.

Table 3
Hazard Model of SNAP Exit with County Fixed Effects and Time Trends, Second Spells

	(1)	(2)	(3)	(4)	(5)
Panel A. County Employment Variables					
Log of Industry Employment:					
Construction	0.97				0.96
	(0.04)				(0.04)
Food		1.72**			1.50
		(0.36)			(0.33)
Manufacturing			1.03*		1.03*
			(0.01)		(0.01)
Retail				4.00**	3.01*
				(1.89)	(1.52)
ln(County Labor Force)	18.49*	3.49	18.44*	10.12	3.73
	(21.70)	(4.72)	(21.58)	(11.96)	(5.03)
Average Weekly Wages (100s)	0.99	0.99	0.99	0.99	0.99
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log-Likelihood	-25011.34	-25008.19	-25008.86	-25007.28	-25002.54
Panel B. County Wage Variables					
Average Weekly Wages (100s):					
Construction	1.01				1.00
	(0.01)				(0.02)
Food		1.01			0.96
		(0.06)			(0.07)
Manufacturing			1.01		1.01
			(0.01)		(0.01)
Retail				1.06	1.06
				(0.06)	(0.09)
ln(County Labor Force)	15.48*	14.81*	18.22*	15.96*	18.61*
	(18.35)	(17.53)	(21.67)	(18.91)	(22.15)
ln(County Employment)	2.43	2.69	2.54	2.16	2.39
	(1.73)	(1.87)	(1.73)	(1.56)	(1.73)
Log-Likelihood	-25010.47	-25010.62	-25009.38	-25010.12	-25009.11
Observations	156,586	156,586	156,586	156,586	156,586

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to BLS Local Area Unemployment Statistics and Census Quarterly Census of Employment and Wages (QCEW). Second spells only.
Notes: Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

effect for retail employment is somewhat less precisely measured in the full model in column 5 when attention is restricted to second spells. Looking at second spells does, however, substantially increase the magnitude of the effect of the county-level labor force on the hazard of exit. It is not clear why the magnitude of this effect should change so dramatically for second spells. Clearly, the population of SNAP "recidivists" may be quite different from the population who are included in the analysis of first spells only. The analysis of second spells is more likely to include spells that started later in the sample period, either in the midst of the recession or during the “jobless” recovery. While either of these reasons may explain why the size of the county labor force (controlling for county population) may have a differential effect on the hazard of exit from second spells, the change in the magnitude of this effect is nevertheless rather curious and and may merit further investigation.

Similar results obtain for the analysis of industry-specific wages in panel B of table 3. In fact, the direction and magnitude of the wage effects are nearly identical to those that obtain for first spells. Some precision is lost, however, in the effects of retail and food service wages. The unusually large effects for county labor force also appear in the wage analysis of second spells.

5.2.2 Lagged labor market effects

As another sensitivity check, we re-estimate our models in table 2 but replace the contemporaneous measures of the labor market variables with one-period lagged measures. This is meant to address concerns over the potential endogeneity of the labor market variables and over the timing of individuals’ behavioral response to changes in local labor market conditions. It is possbile, for example, that changes in aggregate rate of exit from SNAP in a given month might well have an independent effect on county-level employment and wages in common destination industries for SNAP leavers. If there is substantial feedback from SNAP exit rates in a given month to employment in these industries, we would expect that the models in panel A of table 2 would overstate the (positive) effect of industry-specific employment on the hazard of SNAP exit. Moreover, it may be, for administrative and other reasons, labor demand conditions operate with a lag on the decision of individuals to exit SNAP, so that the behavioral response of SNAP recipients is better captured by a one-period lag of local labor market variables.

The results in panel A of table 4 are qualitatively similar to those in panel A of table 2, although the effects of employment in the county-level food service and retail industries are attenuated (and less precise) relative to our primary specification. The same is true for the wage effects in panel B. Recall that these effects were smaller and less precise than the employment effects in our primary specification, so that when lagged measures are employed the estimates are rendered not significantly different than unity. And once again, changes in model specification induce unusually large changes in the labor force variable.

5.2.3 Endogenous mobility

We saw in Table 1 that only 8 percent of our sample changed counties during our observation period. A concern is that SNAP participants who are especially motivated or relatively

Table 4

Lagged Hazard Model of SNAP Exit with County Fixed Effects and Time Trends, First Spells

	(1)	(2)	(3)	(4)	(5)
Panel A. County Employment Variables					
Lagged Log of Industry Employment:					
Construction	1.03				1.03
	(0.02)				(0.02)
Food		1.24*			1.06
		(0.13)			(0.13)
Manufacturing			1.01		1.01
			(0.01)		(0.01)
Retail				1.63*	1.50
				(0.31)	(0.34)
Lagged ln(County Labor Force)	1.13	0.45	1.22	0.38	0.32
	(0.51)	(0.30)	(0.55)	(0.24)	(0.22)
Lagged Average Weekly Wages (100s)	0.99	0.99*	0.99	0.99*	0.99*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log-Likelihood	-87326.58	-87325.31	-87326.96	-87322.90	-87320.63
Panel B. County Wage Variables					
Lagged Average Weekly Wages (100s):					
Construction	1.00				1.00
	(0.01)				(0.01)
Food		0.98			0.98
		(0.03)			(0.04)
Manufacturing			1.00		1.00
			(0.01)		(0.01)
Retail				0.99	1.01
				(0.03)	(0.05)
Lagged ln(County Labor Force)	0.71	0.72	0.69	0.71	0.70
	(0.45)	(0.46)	(0.44)	(0.45)	(0.45)
Lagged ln(County Employment)	1.14	1.16	1.16	1.15	1.17
	(0.16)	(0.17)	(0.16)	(0.17)	(0.18)
Log-Likelihood	-87329.00	-87328.88	-87328.80	-87329.01	-87328.68
Observations	649,334	649,334	649,334	649,334	649,334

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to BLS Local Area Unemployment Statistics and Census Quarterly Census of Employment and Wages (QCEW).
Notes: Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5
Hazard Model of SNAP Exit with County Fixed Effects and Time Trends, First Spells, Non-Movers

	(1)	(2)	(3)	(4)	(5)
Panel A. County Employment Variables					
Log of Industry Employment:					
Construction	1.01				1.01
	(0.02)				(0.02)
Food		1.41**			1.21
		(0.17)			(0.16)
Manufacturing			1.02*		1.02*
			(0.01)		(0.01)
Retail				3.44***	3.04***
				(0.88)	(0.82)
ln(County Labor Force)	2.83	1.16	3.01	1.64	1.06
	(1.91)	(0.87)	(2.02)	(1.11)	(0.79)
Average Weekly Wages (100s)	0.99	0.99	0.99	0.99*	0.99
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log-Likelihood	-82349.16	-82345.54	-82346.47	-82338.07	-82333.94
Panel B. County Wage Variables					
Average Weekly Wages (100s):					
Construction	1.01				1.01
	(0.01)				(0.01)
Food		1.03			0.99
		(0.03)			(0.04)
Manufacturing			1.01		1.01
			(0.01)		(0.01)
Retail				1.05	1.02
				(0.03)	(0.05)
ln(County Labor Force)	2.83	2.71	3.06	2.86	3.07
	(1.92)	(1.83)	(2.08)	(1.93)	(2.09)
ln(County Employment)	1.55	1.79	1.81	1.53	1.53
	(0.63)	(0.71)	(0.71)	(0.64)	(0.64)
Log-Likelihood	-82349.16	-82345.54	-82346.47	-82338.07	-82333.94
Observations	636,746	636,746	636,746	636,746	636,746

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to BLS Local Area Unemployment Statistics and Census Quarterly Census of Employment and Wages (QCEW).
Notes: Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

high-skilled may relocate to counties with more favorable labor market conditions. Under this scenario, our estimates of ϕ will combine the effect of local labor market conditions with the effect of this omitted variable. To rule out the possibility that our main results in Table 2 are driven by this type of endogenous mobility, we estimate equation 3 over the subsample of individuals who are never observed to change counties.

Table 5 shows the results from using only those for whom we observe no inter-county mobility. The point estimates on log employment variables in Panel A are remarkably similar to those in Table 2. Column 2 shows a 1 percent increase at the mean in food service employment is associated with a 41 percent increase in the hazard of exiting SNAP, and column 4 shows a 1 percent increase from the mean in retail employment is associated with a 3.4-fold increase in the likelihood of exiting SNAP. As before, manufacturing employment shows a modest but statistically significant point estimate, and construction shows no detectable effect on SNAP exit. As was the case with our main estimates, the fully saturated model in column 5 also shows strong retail sector effects, small but precise manufacturing effects, and no descernable food or construction effects. Point estimates for the wage effects in Panel B are all statistically insignificant, but they are nevertheless similar in magnitude to the results in Table 2. In general, the results in Table 5 suggest endogenous mobility is not a factor that drives our main findings.

5.2.4 New York City

Table 1 showed that 78 percent of our sample resides in a county that is part of a metropolitan area with at least 1 million residents, and New York City residents account for 54 percent of the sample. In order to verify that our main results hold for residents of counties that are not part of New York City, we attain estimates that exclude residents of Bronx, Kings, New York, Queens, and Richmond Counties from the sample. Table 6 shows the results of this exercise.

Despite the reduction in observations (person-months) from just over 700 thousand in Table 2 to just over 291 thousand, Table 6 shows that our main findings are remarkably robust across the entire state. In fact, the point estimates on food service and retail employment in Panel A are substantially larger across counties that are not part of New York City than they are when estimated over all counties in the state. Furthermore, the fully-saturated model in column 5 yields statistically significant results for food service employment as well as retail when estimated over counties outside of New York City. As we saw before, estimated wage effects are not detectably different than unity. Together, these results suggest that our estimates in Table 2 hold across the entire state, and, if anything, are stronger outside New York City than within it.

5.2.5 Race and Hispanic origin

Finally, we wish to address one of the main limitations of the administrative data, namely the lack of demographic measures of race and Hispanic origin. Table 7 presents the results of estimating equation 3 over the sample of individuals in the administrative files that we were able to link to the 2010 Census. As before, Panel A shows results for our estimates of employment effects on SNAP exit hazard, and Panel B shows results for estimates of wage effects.

Table 6
Hazard Model of SNAP Exit with County Fixed Effects and Time Trends, First Spells, Non-NYC Residents

	(1)	(2)	(3)	(4)	(5)
Panel A. County Employment Variables					
Log of Industry Employment:					
Construction	1.02				1.02
	(0.02)				(0.02)
Food		1.81***			1.49*
		(0.29)			(0.25)
Manufacturing			0.89		0.89
			(0.28)		(0.28)
Retail				5.87***	4.20***
				(2.31)	(1.77)
ln(County Labor Force)	4.34	0.63	4.80*	1.49	0.48
	(3.29)	(0.58)	(3.69)	(1.18)	(0.45)
Average Weekly Wages (100s)	1.04	1.03	1.04	0.99	0.99
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Log-Likelihood	-40797.28	-40791.13	-40797.83	-40788.03	-40784.82
Panel B. County Wage Variables					
Average Weekly Wages (100s):					
Construction	1.02				1.02
	(0.01)				(0.01)
Food		1.00			0.97
		(0.04)			(0.04)
Manufacturing			1.01		1.00
			(0.01)		(0.01)
Retail				1.09	1.05
				(0.06)	(0.07)
ln(County Labor Force)	2.95	2.43	2.66	2.77	3.23
	(2.19)	(1.79)	(2.01)	(2.05)	(2.45)
ln(County Employment)	3.03*	3.55**	3.44**	3.07*	2.84*
	(1.42)	(1.65)	(1.60)	(1.46)	(1.37)
Log-Likelihood	-40793.00	-40794.95	-40794.81	-40793.95	-40792.55
Observations	291,369	291,369	291,369	291,369	291,369

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to BLS Local Area Unemployment Statistics and Census Quarterly Census of Employment and Wages (QCEW). Non-NYC residents only.
Notes: Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7
Hazard Model of SNAP Exit with County Fixed Effects and Time Trends, First Spells, with 2010 Census Controls

	(1)	(2)	(3)	(4)	(5)
Panel A. County Employment Variables					
Log of Industry Employment:					
Construction	1.03				1.02
	(0.02)				(0.02)
Food		1.50**			1.25
		(0.20)			(0.18)
Manufacturing			1.02*		1.02*
			(0.01)		(0.01)
Retail				4.36***	3.73***
				(1.24)	(1.12)
ln(County Labor Force)	4.87*	1.70	5.37*	2.59	1.49
	(3.63)	(1.40)	(3.99)	(1.94)	(1.22)
Average Weekly Wages (100s)	0.99	0.99	0.99	0.99	0.99
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log-Likelihood	-66801.92	-66798.26	-66800.16	-66789.87	-66785.45
Panel B. County Wage Variables					
Average Weekly Wages (100s):					
Construction	1.02**				1.01
	(0.01)				(0.01)
Food		1.05			0.99
		(0.04)			(0.04)
Manufacturing			1.01		1.00
			(0.01)		(0.01)
Retail				1.08*	1.02
				(0.04)	(0.05)
ln(County Labor Force)	4.66*	4.28	4.92*	4.66*	4.98*
	(3.48)	(3.19)	(3.69)	(3.47)	(3.74)
ln(County Employment)	2.06	2.57*	2.69*	2.09	2.03
	(0.92)	(1.13)	(1.16)	(0.95)	(0.93)
Log-Likelihood	-66796.84	-66799.35	-66798.69	-66797.78	-66796.45
Observations	553,171	553,171	553,171	553,171	553,171

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to 2010 Census, BLS Local Area Unemployment Statistics, and Census Quarterly Census of Employment and Wages (QCEW).
Notes: Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel A of Table 7 shows point estimates for industry-specific employment effects, conditional on race and Hispanic origin, that are broadly similar to the main results in Panel A of Table 2. As before, we observe positive and statistically significant estimates of local employment effects on SNAP exits within the food service and retail sectors. Results in Panel B are also very close to those in Panel B of Table 2, both in terms of which industry effects are statistically significant, but also in terms of the magnitude of the estimated effects. Taken as a whole, Table 7 suggests that the limited information on race and Hispanic origin does not comprimise the validity of our main findings. Favorable local labor market conditions, especially in industries that are likely to be important for SNAP participants, are associated with substantial increases in the likelihood of exiting the program.[9]

6 Conclusion

This study offers a preliminary investigation of an issue of central importance for SNAP policy and administration: how do labor market conditions affect the probability that recipients leave the program? The key contribution has been to focus on much more granular measures of local labor demand than has previously be done in studies of SNAP dynamics, at both the county and the county and industry level. We find, even when including county fixed effects and county time trends, that increases in employment in certain industries that are likely to be important to SNAP recipients significantly increase the probability that SNAP recipients exit the program. In particular, the food service and retail industries showed robust positive effects on the hazard of exit for SNAP recipients. Manufacturing, and in some specifications construction, had more modest positive effects on the likelihood of exit. The effect of average wages on the hazard of exiting SNAP was more muted—we suspect this due in part to a lack of variation in our industry wage measures, which are measured quarterly instead of monthly. Neverthess, point estimates on wage effects are also more stable across specifications. Wages in the construction industry, and to a greater extent the retail industry, were associated with an increased hazard of exit, an effect that may reflect the general health of the housing and retail markets in the recipient's local labor market.

Our main findings are robust to a series of sensitivity analyses and robustness checks. Although our main analysis is based on first spells and contemporaneous measures of county-level industry-specific labor market variables, we find that the results hold when looking at second spells and when using lagged measures of the local labor market variables. We also rule out the possibility that our estimates are driven by endogenous mobility or unobserved characteristics specific to the residents and labor markets of New York City. Finally, by linking the administrative records to individual responses in the 2010 Census, we show that limited demographic information in the administrative files does not pose a threat to the accuracy of our results.

Our findings point to the important role of local and industry-specific labor demand factors on the duration SNAP participation. It is notable that we found strong effects for these variables without controlling for many of those individual, or household, character-

[9] We also estimate the same specification as in Table 2 (i.e., without the race and Hispanic origin controls) over the linked sample. The results are almost identical to those in Table 7 and are available upon request.

istics, such as health issues and disability, that would likely signal a need for long-term SNAP receipt irrespective of local labor demand. Looking too broadly at labor demand, at, say, the national or even state level, may provide a misleading picture about the strength of the link between labor demand and SNAP, especially in time of uneven economic recovery. Policies that ignore this local link and seek to reduce the regulatory flexibility currently given to states to extend eligibility in areas where labor markets are slower to recover (or faster to decline) may have undesirable consequences.

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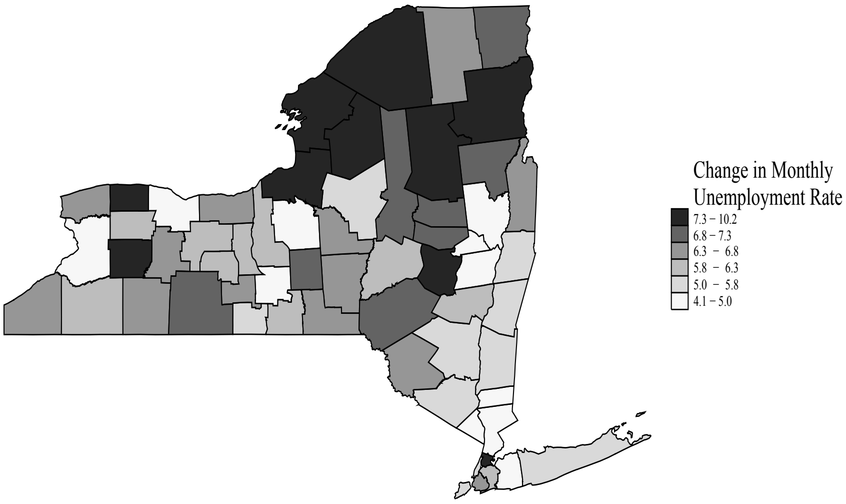
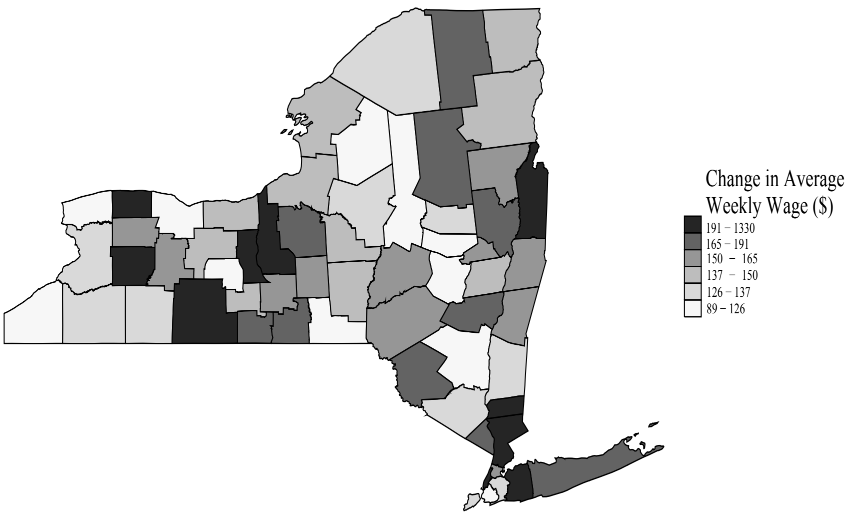
7 Appendix Figures and Tables

Figure 4
Maximum Change in County Unemployment Rate, 2007–2012



Source: 2007-2012 BLS Local Area Unemployment Statistics

Figure 5
Maximum Change in Average Weekly Wage, 2007–2012



Source: 2007-2012 Census Bureau Quarterly Census of Employment and Wages

Table 8

Hazard Model of SNAP Exit with and without County Effects and Time Trends, First Spells

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. County Employment Variables						
Log of Industry Employment:						
Construction	1.04**		1.01		1.01	
	(0.01)		(0.02)		(0.02)	
Food	1.17***		1.17		1.25	
	(0.05)		(0.13)		(0.15)	
Manufacturing	1.00		1.01		1.02*	
	(0.00)		(0.01)		(0.01)	
Retail	0.78***		3.02***		2.88***	
	(0.04)		(0.69)		(0.74)	
Lagged Construction		1.04***		1.02		1.03
		(0.01)		(0.02)		(0.02)
Lagged Food		1.17***		1.01		1.06
		(0.05)		(0.11)		(0.13)
Lagged Manufacturing		1.00		1.00		1.01
		(0.00)		(0.01)		(0.01)
Lagged Retail		0.77***		1.62*		1.50
		(0.04)		(0.34)		(0.34)
ln(County Labor Force)	1.23		1.84		1.08	
	(0.15)		(1.07)		(0.77)	
Lagged ln(County Labor Force)		1.21		0.63		0.32
		(0.15)		(0.38)		(0.22)
Average Weekly Wages (100s)	0.99		0.99		0.99	
	(0.00)		(0.01)		(0.01)	
Lagged Average Weekly Wages (100s)		1.00		0.98**		0.99*
		(0.00)		(0.01)		(0.01)
Log-Likelihood	-90569.07	-87487.50	-90432.52	-87383.95	-90392.78	-87320.63
Observations	701,395	649,334	701,395	649,334	701,395	649,334
Panel B. County Wage Variables						
Average Weekly Wages (100s):						
Construction	1.03***		1.01		1.01	
	(0.00)		(0.01)		(0.01)	
Food	0.95**		0.97		0.97	
	(0.01)		(0.03)		(0.04)	
Manufacturing	0.99**		1.00		1.01	
	(0.00)		(0.01)		(0.01)	
Retail	1.01		1.04		1.04	
	(0.02)		(0.04)		(0.05)	
Lagged Construction		1.02***		1.01		1.00
		(0.00)		(0.01)		(0.01)
Lagged Food		0.96**		0.98		0.98
		(0.01)		(0.03)		(0.04)
Lagged Manufacturing		0.99***		0.98*		1.00
		(0.00)		(0.01)		(0.01)
Lagged Retail		1.02		0.99		1.01
		(0.02)		(0.04)		(0.05)
ln(County Labor Force)	1.45***		4.60**		3.43	
	(0.15)		(2.52)		(2.22)	
Lagged ln(County Labor Force)		1.36**		1.48		0.70
		(0.14)		(0.81)		(0.45)
ln(County Employment)	0.98		1.77		1.58	
	(0.03)		(0.63)		(0.63)	
Lagged ln(County Employment)		0.99		1.12		1.17
		(0.03)		(0.17)		(0.18)
Log-Likelihood	-90554.08	-87478.71	-90444.01	-87389.47	-90404.88	-87328.68
Observations	701,395	649,334	701,395	649,334	701,395	649,334
Lags	No	Yes	No	Yes	No	Yes
County Fixed Effects	No	No	Yes	Yes	Yes	Yes
County Time Trends	No	No	No	No	Yes	Yes
Duration Effects	Yes	Yes	Yes	Yes	Yes	Yes

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to BLS Local Area Unemployment Statistics and Census Quarterly Census of Employment and Wages (QCEW).

Notes: Exponentiated coefficients; Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9
Matched and Non-Matched Individuals in Administrative Records and the 2010 Census

	Not Matched to 2010 Census		Matched to 2010 Census		
	Mean	SD	Mean	SD	Difference
Female	0.46	0.5	0.58	0.49	-0.12***
Age	39.12	15.76	41.33	16.89	-2.20***
Number of case members	1.92	1.48	2.34	1.73	-0.42***
Presence of children under 4	0.17	0.38	0.22	0.41	-0.05***
Presence of children 5–17	0.13	0.34	0.2	0.4	-0.07***
Presence of nonelderly	0.72	0.45	0.63	0.48	0.10***
Presence of nonelderly males	0.42	0.49	0.29	0.46	0.13***
Presence of elderly	0.12	0.33	0.16	0.37	-0.04***
Ln(Benefit Amount)	5.41	0.79	5.44	0.92	-0.03**
TANF	0.02	0.13	0.02	0.13	0.00
Other Public Assistance	0.06	0.24	0.04	0.19	0.02***
Metro Area	0.83	0.37	0.76	0.43	0.07***
Ln(Population)	13.79	1.11	13.53	1.24	0.26***
Ln(Labor Force)	13.06	1.1	12.8	1.23	0.25***
Ever changed county of residence	0.11	0.31	0.07	0.25	0.05***
Year = 2007	0.17	0.37	0.16	0.37	0.00
Year = 2008	0.17	0.37	0.17	0.37	0.00
Year = 2009	0.2	0.4	0.22	0.41	-0.02***
Year = 2010	0.19	0.39	0.18	0.39	0.00
Year = 2011	0.15	0.36	0.15	0.36	-0.00
Year = 2012	0.12	0.33	0.11	0.32	0.01**
Individuals	8,785		26,655		
Match Rate	75.21%				

Source: 2007–2012 New York SNAP Administrative Records, 2 percent sample, linked to 2010 Census, BLS Local Area Unemployment Statistics, and Census Quarterly Census of Employment and Wages (QCEW).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$