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THE EFFECT OF MEANS-TESTED TRANSFERS ON WORK: EVIDENCE FROM QUASI-RANDOMLY ASSIGNED SNAP CASEWORKERS

Jason B. Cook
Chloe N. East

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ABSTRACT

We comprehensively evaluate the effect of the Supplemental Nutrition Assistance Program (SNAP) on labor supply using newly linked data on SNAP applicants to administrative earnings records. Prior to applying for SNAP, earnings are trending down, but this trend is more severe for those granted SNAP than those denied. This motivates our novel IV approach based on assignment of applicants to caseworkers. Most applicants do not work before applying, and do not change work if granted SNAP. Those who work before applying appear to treat SNAP as insurance against negative shocks; they decrease work temporarily but work more in the longer-run.

Jason B. Cook
University of Utah
GARFF 3412
1731 E Campus Center Dr
Salt Lake City, UT 84112
jason.cook@eccles.utah.edu

Chloe N. East
Department of Economics
University of Colorado, Denver
1380 Lawrence Street
Denver, CO 80217
and NBER
chloe.east@ucdenver.edu

1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) is a key part of the safety net in the United States. It serves 41 million recipients monthly and is the only nearly universal means-tested transfer program (Moffitt, 2002). Proponents of SNAP argue it provides crucial resources to those in need, while critics claim it disincentivizes work and leads to long-term "dependency" on government benefits. The canonical static labor supply model where individuals trade off consumption and leisure predicts that access to SNAP will reduce work (Hoynes and Schanzenbach, 2015) but past empirical research has mixed findings. Due to the lack of exploitable variation in SNAP, these papers either study the program in the 1960-70s (Hoynes and Schanzenbach, 2012), or study the effects on very specific sub-populations– immigrants or those subject to work requirements, who are 12% and 5% of SNAP recipients respectively (e.g. East, 2016; Stacy et al., 2018; Gray et al., 2022).

In this paper, we provide a comprehensive evaluation of the dynamic effects of modern SNAP for a large, generalizable group. SNAP has undergone many changes since it began in the 1960s, when it was called "Food Stamps." The modern program has eliminated the purchase requirement that meant households must buy their benefits. Additionally, the program is now distributed on a debit card instead of paper coupons and many recipients now face explicit work requirements. Moreover, the economic environment and typical household structure are significantly different than in the 1960s. We study the modern program using newly-linked SNAP and earnings administrative data from a single mountain-plains state (hereafter "the mountain-plains state"). Our main sample is new SNAP applicants, most of whom are non-disabled and working-aged, between 2012-2016. While our data is limited to a single state, we show the applicants in our analysis sample are very similar to all applicants in the mountain-plains state, and that the labor supply behavior of SNAP recipients in the mountain-plains state is similar to SNAP recipients in the entire country.

Importantly, we see applicants' earnings whether or not they receive SNAP, and these data allow us to observe work behavior *prior* to SNAP application, which was not possible in earlier studies. With these longitudinal data, we first examine trends in labor supply for those accepted and denied SNAP. We find that earnings were trending downwards in the quarters immediately before SNAP application, however these downward trends are slightly steeper for those accepted compared to those denied. Following SNAP application, there is little difference in employment between those accepted and denied, and those accepted have somewhat lower earnings especially in the first year after application. Importantly, however, there is a decline in earnings after SNAP application even for those denied SNAP, suggesting that other factors besides SNAP receipt (e.g. a layoff) are partly driving the decline in earnings we observe among those who do receive SNAP.

The fact that those accepted are on a slightly different trajectory than those denied *prior to application* motivates our instrumental variables strategy using an examiner design. This design has been used in other contexts where quasi-experimental variation is hard to find, such as the criminal justice system, Disability Insurance receipt, and foster care placement (e.g. Dobbie et al., 2018; Norris et al., 2021; Agan et al., 2023; Maestas et al., 2013; Autor et al., 2019; Doyle Jr, 2007) and we are the first to use it in the literature on means-tested transfer program receipt in the U.S.[1] Specifically, we take advantage of quasi-random assignment of new SNAP applicants to caseworkers and variation in caseworkers' application acceptance rate. Beyond allowing us to look at how SNAP affects labor supply, studying how caseworkers impact take-up of SNAP is important in its own right and contributes to the literature investigating causes of incomplete take-up of transfer programs and the ability of programs to target the neediest recipients (Nichols and Zeckhauser, 1982; Currie, 2006; Herd and Moynihan, 2019; Finkelstein and Notowidigdo, 2019).

Caseworkers are randomly assigned to applicants conditional on the timing and certain observable characteristics of the application. Following the examiner design approach in Kolesár (2013), we construct the Conditional Caseworker Approval Rate (CCAR), which measures the likelihood of each caseworker to accept a random application. We verify conditional random assignment by showing that the CCAR is unrelated to applicant observable characteristics, including pre-application labor supply, conditional on fixed effects. Then, we document a strong effect of the CCAR on SNAP receipt–a one standard deviation increase in the CCAR increases the likelihood of approval at application by 1 percentage point, which is a 2% effect of the overall rate of acceptance of 52%. We provide evidence that caseworkers impact applicant outcomes through differential helpfulness throughout the application process. Importantly, applicants who marginally receive SNAP because of their caseworker are similar to all SNAP applicants in the mountain-plains state, so caseworkers do not impact program targeting and the results can be plausibly generalized. Finally, we verify the CCAR satisfies the average monotonicity assumption needed to use it as an instrument for SNAP receipt (Frandsen et al., 2023)–that for each applicant there is a positive correlation between their potential treatment status and caseworkers' CCAR across all caseworkers.

The results using the IV model are similar to those in the OLS approach described above, comparing those accepted to those denied. First, there is no significant effect of

[1] Other papers have used safety net caseworker assignment to look at placement into different types of benefits among recipients (e.g., Bolhaar et al., 2020; Jonassen, 2013; Autor and Houseman, 2010; Cohen, 2024).

SNAP on employment. The 95% confidence intervals on the IV estimate allow us to rule out *cumulative* changes in employment over the *three years* following SNAP application of less than -0.8 quarters or more than 2 quarters. Second, there is a significant 1 quarter increase over three years in the likelihood of having positive earnings below $2,000 per quarter (our proxy for part-time work). Finally, the IV estimates on earnings are noisily estimated but indicate a different dynamic pattern than OLS–specifically, while there is suggestive evidence of a short-run decline in earnings, the coefficients become large and positive, but insignificant, by the third year after SNAP application. Taken together, the results indicate that SNAP has no large effects on labor supply.

We next investigate the mechanisms behind these findings. Crucially for thinking about labor supply effects, we document that only 25% of all SNAP working-aged applicants had strong attachment to the labor market *prior* to applying, and we take advantage of the richness of our data to split the analyses by pre-application labor market attachment. We show that, for the SNAP applicants who did not work before applying for SNAP, there are no significant or quantitatively large impacts on their labor supply in the three years following SNAP application. This suggests other barriers to entering the labor market exist among this population. Other research has found barriers to work in low-income populations include transportation costs, dependent care costs (Keith-Jennings and Chaudhry, 2018), discrimination (Turner et al., 1991; Lang and Spitzer, 2020), and the fact that SNAP recipients work in occupations that are very volatile (Butcher and Schanzenbach, 2018).

On the other hand, an interesting dynamic pattern of effects is revealed for those working before they applied for SNAP. In the first year after SNAP application, there is a small, marginally significant decline in the likelihood of having earnings above $2,000 per quarter, and a small, marginally significant increase in the likelihood of having earnings between $1-2,000 per quarter. In the third year after application, the coefficients on all measures of labor supply are positive and there is a significant and meaningful increase in employment, earnings, and part-time work. Our data and approach allow us to show that applicants who were working before applying experience a negative shock around the time of application regardless of whether they receive SNAP.[2] Thus, the income (liquidity) effect–that allows recipients to maintain higher consumption and reduces the pressure to, for example, find a new job after layoff–likely plays an important role in the effect of SNAP on labor supply for this subgroup, in addition to any substitution effects (Chetty, 2008). This is particularly important for these households, who have very little private savings and are unlikely to face perfect credit and insurance markets.

[2]This is consistent with prior evidence on disruptive events prior to SNAP receipt (Leftin et al., 2014).

Taken together, our analyses give a much more complete picture of SNAP's labor supply effects and mechanisms than has been possible before. Additionally, our results shed light on what labor supply model best explains individuals' response to SNAP. We find that accounting for external barriers to work faced by SNAP recipients is important. Additionally, among SNAP recipients who are able to work, we find that a model with labor market frictions and credit constraints best fits the results. These models are common in the literature on Unemployment Insurance (e.g. Nekoei and Weber, 2017), but have been mostly absent from the discussion of means-tested transfer programs. From a policy perspective, our estimates suggest no lasting, large impact of SNAP on labor supply, or government revenues due to changes in labor supply, which has important implications for cost-benefit analyses of SNAP.

The rest of the paper proceeds as follows. Section 2 provides background on SNAP policy and our setting. Section 3 describes our data. Section 4 explores trends in labor supply around SNAP application. Section 5 presents the results on the role of caseworkers and Section 6 examines the impact of SNAP on labor supply using the IV approach.

2 Policy Background

2.1 SNAP and Labor Supply

SNAP (formerly the Food Stamps Program) is a means-tested federal entitlement program, and states are responsible for determining eligibility and paying out benefits. In general, to qualify for SNAP, applicants must have gross income below 130 percent of the federal poverty level and net income after deductions below 100 percent of the federal poverty level. Households with zero and near-zero income receive maximum SNAP benefits, which are a function of household size. By providing this benefit guarantee for low-income households, the canonical labor supply model predicts a decrease in labor supply due to the income effect. As a household's income increases, benefits are decreased by the benefit reduction rate.[3] This lowers the return to work for SNAP recipients, so the model predicts a decrease in labor supply due to the substitution effect. Benefits are paid out automatically each month on electronic benefits transfer (EBT) cards, which are used like a debit card for qualifying food

[3]SNAP's benefit reduction rate is 30%; however, the actual benefit reduction rate as income increases varies by the types of deductions the household has and is very close to zero at low income levels (Bitler et al., 2021; Han, 2022). SNAP-allowable deductions include a 20 percent deduction for every dollar of earned income, as well as deductions for certain types of expenditures including costs for shelter, child care, and medical care. Households participating in multiple programs may have a more complicated benefit reduction rate. There are also asset tests and residency tests for non-citizens that vary by state and time.

purchases at SNAP-accepting stores. Within our sample of recipients, the average monthly benefit is $226 in 2012 dollars.

Since the Personal Responsibility and Work Opportunity Reconciliation Act of 1996, SNAP includes work requirements for able-bodied adults without dependents (ABAWDs). Generally, ABAWDs are between the ages of 18-49, report having no disabilities, are not pregnant, and do not take care of any dependents (e.g., children, people with disabilities, or the elderly). In the mountain-plains state, 4% of all recipients are subject to ABAWD work requirements.[4] Unfortunately, we cannot identify who is subject to work requirements at the time of application in our sample. However, previous research using high-quality administrative data has found that these work requirements do not affect work (Stacy et al., 2018; Gray et al., 2022).

To understand what we expect to see in terms of labor supply responses, it is useful to know the characteristics of SNAP recipients and the labor market they work in. First, many SNAP recipients are in demographic groups that have low labor force attachment generally, making them unlikely to work regardless of whether they receive SNAP (Keith-Jennings and Chaudhry, 2018). Children and the elderly make up about half of SNAP recipients. Our sample is restricted to be mostly working-aged heads of household, who are not flagged as having a disability at the time of application (this does not mean they do not have a disability, only that they did not submit sufficient proof of disability at the time of application). Among working-aged SNAP recipients in SNAP Quality Control Data, 61% have children and 39% have children of pre-school-age, and 20% are flagged as living in a household with someone who has a disability, though at least some of these disabled households will be excluded based on our sample restrictions.

In surveys of households in low-income areas, working-aged adults reported that child-care and transportation present the largest barriers to work, following lack of labor demand and job mismatch (Edmiston, 2019). Households in these low-income areas are less likely to own a vehicle and are also less able to work close to home compared to households in high-income areas. Similarly, households in low-income areas spend a much larger fraction of their income on childcare and are more likely to be headed by a single female, making

[4]SNAP also includes General Work Requirements that focus more on tasks related to becoming employed. In the mountain-plains state, 16% of all recipients are subject to these work requirements and not subject to additional ABAWD requirements. Additionally, it is worth noting the historical context of work requirements. These requirements were often selectively placed on Black recipients and were sometimes motivated by the idea that Black people were less likely to work than white people (Nunn et al., 2019), when in fact the desire to work more has been consistently higher among Black Americans than white Americans (Minoff, 2020). Finally, our state operates a mandatory E&T program that applies to a small fraction of working-aged participants.

child care responsibilities even more salient for work decisions. Finally, a study of mothers receiving welfare in the 1990s (similar to the SNAP population) found that half had no vehicle or driver's license, half reported depression, PTSD, or anxiety (which do not qualify as a disability under SNAP), 14% commonly were discriminated against and, finally, 14% experienced severe domestic violence in the past year (Danziger et al., 2000). The incidence of all of these barriers to work was much higher than among all women in the U.S. We find 46% of working-aged adults who are income-eligible for SNAP report the reason they do not currently work is caregiving responsibilities, another 27% report disability, and 22% report that their schooling limits their ability to work.[5]

The labor markets that potential SNAP recipients work in also present challenges to finding and maintaining stable work. Butcher and Schanzenbach (2018) document that the most common occupations among SNAP recipients not only pay less than middle class occupations but are more volatile. In particular, workers in these occupations (whether or not they receive SNAP) have a 1 percentage point higher unemployment rate and face a 5 percentage point higher job displacement rate than workers in middle class occupations.

2.2 SNAP Application Process and Caseworker Behavior

The application process must balance the goals of providing support for qualifying individuals and screening out ineligible individuals. In the U.S., the burden of proving eligibility is generally placed on the applicants (Herd and Moynihan, 2019). Applying for SNAP is complicated and time consuming. Individuals must first submit an application and supporting documentation before completing a required screening interview and then any missing information must be provided.[6] Two-thirds of SNAP administrative costs–which is about 5% of total SNAP spending–are spent on caseworkers and case management.

SNAP applications require information on household composition, income sources, and financial and property assets. An example of the application form is in Appendix Figure A1. These applications can be submitted online, in person, or via mail, but in the mountain-plains state almost all are submitted online. Some of the fields on the application form are verified automatically against administrative records (e.g. earnings are verified against UI earnings data and vehicle ownership is verified against DMV records for asset tests). However, applicants must provide supporting documentation for many other components

[5] Authors' calculation from the Current Population Survey.

[6] Many other programs require similar interviews though some require in-person visits, e.g., the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), Temporary Assistance for Needy Families (TANF), and Social Security Disability Insurance (SSDI). Giannella et al. (2023) find that moving from pre-scheduled interviews to on-demand interviews increases participation in SNAP.

of their application such as rent or mortgage payments, letters from their employers, bank statements, utility bills, child or elder care bills, and child support payments. It is common for applicants to not fill in all the fields on the application form and/or to not submit all the required supporting documentation on initial application submissions. Applicants have 30 days to submit all the necessary information, or their application is automatically denied. However, they have 60 days after the initial submission to go back and finish the application process without having to start from the beginning with a new application. Additionally, after individuals submit their initial application, they must complete a mandatory interview within 30 days to have a caseworker verify their information. During this interview, caseworkers can collect any missing information from the initial application. Caseworkers can also choose to do extra follow-up work with applicants, for example, notify them via email if a form or supporting document is missing.

A USDA-commissioned survey of applicants confirms that the application process is complex and costly (Bartlett et al., 2004). In 2000, applicants spent an average of 3.9 hours in Food Stamp offices completing the application process. They took an average of 2.4 trips to the office as well as 1.2 trips to additional locations to acquire necessary documentation. 39% of working households said they had to miss work to complete the application.[7] 10% of applicants who did not complete the process said they dropped out because of some aspect of the process and another 46% cited they thought they were ineligible, possibly because of information they received during the process. This study also found that applicants were more likely to complete their application if they were at an office with a more "pro-participation" supervisor.

The institutional structure surrounding applications and case management in the mountain-plains state provides an ideal setting to explore the impact of caseworkers on SNAP receipt. First, case management is almost exclusively handled over the phone through a statewide system. Caseworkers are organized within tracks based on their specialization to ensure that caseworkers have the relevant skills, such as language or knowledge of special program rules to handle applications. In our analysis we focus only on the General track where assignment to caseworkers is the most random and which handles the majority of applications. And, we show below that the demographics and labor supply patterns of those in the General track are very similar to those of the overall sample of SNAP applicants, so this is unlikely to impact the generalizability of our results. Each caseworker works in one of multiple call centers located around the state and caseworkers handle cases from all over the state, rather

[7] Administrative changes to the program since 2000 have streamlined this process somewhat (e.g. creating online applications and replacing in-person interviews with over-the-phone ones).

than just those nearest to them.[8]

The second useful institutional feature is that the mandatory interviews with caseworkers are on-demand from the perspective of the applicants. Unlike some states (see for example, Homonoff and Somerville, 2021), applicants in the mountain-plains state can call into the statewide phone system at any time Monday through Friday, 8am to 5pm to complete their interview. During the interview, caseworkers do not have a set script to follow and have flexibility in the type and number of questions that they ask. Interviews last about 20 minutes on average. Caseworkers then enter the information into a computer system and the software ultimately determines eligibility.

Third, and crucial to our empirical strategy, caseworkers take calls in the order they are received, and the case is officially assigned to that worker when they take the call for the interview. For initial applications, the caseworker does not see any information about the case until they answer the phone and have no control over which cases they receive. So, conditional on the timing of application, caseworkers are effectively randomly assigned to applicants within the General track.

By and large, caseworkers are motivated by two factors: 1) they want to give benefits to those who qualify and 2) they want to avoid errors in their decisions.[9] In our setting, the second factor is in part motivated by the several layers of review that exist to monitor caseworker decisions. First, the USDA has its Quality Control system that audits decisions of caseworkers in all states each year. To do this, they select a random sample of SNAP recipients and do a follow-up survey with them to decide if they are indeed eligible or not. States are then ranked based on the percentage of incorrect decisions and states with lower rankings are fined. In our sample period, over-payment rates (Type II Errors, as defined by Kleven and Kopczuk, 2011) are 3-6% across states. The mountain-plains state is not fined in our sample period and has relatively low error rates in general. In addition to this federal monitoring, the mountain-plains state chose to have an Editing Team, which is not required by the federal government. Editors from the Editing Team review the decisions of caseworkers every month by examining the case file information (they do not collect any additional information beyond what the caseworker initially collected). Newer caseworkers–who we exclude from this analysis–have more cases reviewed per month than seasoned caseworkers, who have about 10 cases reviewed per month. Caseworkers who fall below a rate of 90%

[8]Prior to 2012, teams were also organized around physical locations and the applications were automatically sorted to the closest office. In 2012, the mountain-plains state moved to a state-wide model where caseworkers serviced applications from across the state. Nationwide in 2000, only 1 state operated a statewide call center for SNAP, but by 2016, 32 states were operating them.

[9]In 2000, 80% of a national sample of supervisors had "pro-participation" attitudes (Bartlett et al., 2004).

accuracy are subject to consequences including additional individual mentoring and coaching, a written warning, or further disciplinary action.

Given that caseworker decisions are closely monitored and that a computer decides eligibility, what are the mechanisms through which caseworker behavior can affect SNAP receipt? We hypothesize and provide supporting evidence below that the biggest source of variation in caseworker behavior is how helpful they are at guiding applicants through the complicated application process. This is also consistent with prior work that found when a state automated assistance for means-tested transfer applications, rather than having caseworkers assist, there was a reduction in means-tested transfer program receipt (Wu and Meyer, 2021). Though, this change was accompanied by increases in wait times and backlogs in processing applications, so the exact mechanism is unclear. Additionally, Finkelstein and Notowidigdo (2019) and Schanzenbach (2009) found that connecting likely SNAP-eligible nonparticipants to application assistance significantly increased their program receipt.[10]

We construct a one-dimension measure of the Conditional Caseworker Approval Rate (CCAR) discussed in more detail below, which captures all caseworker behavior that leads to applicants being more likely to receive SNAP when assigned to a particular caseworker.

3 Data

Our data come from a single state in the mountain-plains region, which remains unidentified for anonymity, and include all SNAP applicants from 2011 through early 2022. For applicants, we observe basic demographic information along with application dates. Unique to our setting, we can also see the caseworker assigned to the application and the track in which the caseworker works. For those who receive SNAP, we observe benefit amounts and more detailed demographics as well as recertification information. For those who do not receive SNAP, we observe the reason for denial.

Application information is linked to quarterly labor supply information from the state's Unemployment Insurance (UI) database. This type of linked data has been used in the past

[10]Work in Economics on other programs shows that streamlining the application process increases take-up (e.g. Rossin-Slater, 2013; Bhargava and Manoli, 2015; Deshpande and Li, 2019). There is also a large literature in Public Administration that studies the determinants of decision-making for "street-level bureaucrats" including caseworkers in programs such as SNAP (Meyers and Nielsen, 2012). This research has suggested that several factors may play a role: 1) political control such as the goals of politicians, 2) organizational factors including the tasks assigned, resources available and oversight from managers, and 3) worker ideology and professional norms. The strong oversight of caseworker decisions in our context limits the potential discretion quite a bit relative to many of these studies. However, Kogan (2017) hypothesizes that caseworker behavior may be a reason that local public support for redistribution is positively correlated with local SNAP caseloads even though it is a federal program.

to evaluate the labor supply effects of other means-tested programs like Medicaid, public housing, and SNAP work requirements (Baicker et al., 2014; Chyn, 2018; Gray et al., 2022). The state only matched the head of the household for each application as a data security measure. However, 52% of all applicants in our sample are single-adult-headed households and we show the results are similar among this subsample. Moreover, in the mountain-plains state, only 2% of all SNAP recipients are in dual-income households in the SNAP Quality Control (QC) Data (a nationally representative sample of SNAP recipients), and among a sample of SNAP-income-eligible households in the Current Population Survey (CPS) only 10% are dual-income households. The UI records contain the earnings and industry for each individual and job by quarter from 2011-2021. Importantly, we can observe these outcomes even for SNAP applicants who are denied, and, for all applicants, we observe outcomes before SNAP application. A limitation of any study using UI earnings data to measure labor supply is that a small group of workers are excluded from the data because they work in jobs not covered by UI. We show in the Appendix that this is unlikely to impact our results and below we confirm that the earnings measured in the UI data are very similar to total earnings that SNAP recipients report when they apply for SNAP. We describe further details of these data in Appendix A.

3.1 Sample Construction

To construct a sample that allows us to cleanly identify the effects of caseworker behavior on labor supply dynamics, we begin with the 196,435 new applications that were submitted between 2012-2016. New applications are important in our context because it abstracts away from possible dynamic labor supply effects that could occur from prior SNAP receipt. Also, new applicants have less program knowledge and therefore may be more reliant on the caseworker to navigate the application process. To identify this group, we remove any applicants for whom we observe SNAP receipt within one year prior to their first-observed application in our sample.[11] We focus on applications after the implementation of the state-wide call center model in 2012 that generates the quasi-random caseworker assignment to applicants. We limit to those who applied before 2017 so we can examine quarterly labor supply outcomes 3 years after application and exclude the COVID-19 pandemic. Next, we limit the sample to applications handled within General tracks (123,975 observations). Assignment of caseworkers in these tracks is the most plausibly random given the many applicants and many caseworkers. Note, that we do not restrict our main analysis sample

[11]We use a rolling one-year period instead of all observable prior SNAP receipt so that observations at the beginning and end of our sample are treated similarly. Results are similar if we instead condition on not having any SNAP receipt prior to the application.

on age or disability explicitly, but because we drop tracks that handle applications for the elderly and disabled applicants, this effectively restricts our sample to non-disabled working-aged applicants and the results are nearly identical if we drop the few applicants in our sample outside working age.

We further drop applications assigned to workers who handled relatively few cases in a given year to ensure that there are enough observations to get an accurate estimate of caseworker decision making and also exclude new caseworkers who are given fewer and nonrandom sets of applications. Specifically, we drop the bottom 20% of the caseload distribution, which is 126 cases per year. This leaves us with 99,410 observations. Finally, we keep applications assigned to caseworkers with Conditional Caseworker Approval Rate (CCAR) values between the 1st and 99th percentiles of the CCAR distribution and to a balanced sample over time. These restrictions leave us with our final regression sample of 88,543 application decisions. We show below that this final analysis sample looks very similar to *all* working-age SNAP applicants in the mountain-plains state, and, we demonstrate robustness to these sample restriction decisions in the Appendix.

3.2 Descriptive Statistics

To understand the external validity of our findings, we explore how working-age SNAP recipients in the mountain-plains state differ from working-age SNAP recipients in the whole country using the SNAP QC Data in the first two columns of Table 1. On most dimensions the mountain-plains state is similar to the national sample, except there are fewer recipients who identify as Black. This includes, importantly, that the labor supply–in terms of the rate of employment and quarterly earnings–is similar in the mountain-plains state to the national sample.

In column (3) of this table, we show equivalent statistics for all working-age SNAP recipients using our data and this group is very similar to the sample from the QC data (column (2)) as expected. Especially important is that the likelihood of working and the value of real earnings among SNAP recipients is very similar in the QC data (measured as reported to the SNAP office) and our data (measured with the UI data). This supports the idea that the UI earnings data do a good job of fully capturing employment and earnings among our relevant population.

In the fourth column we include all working-age *applicants* using our data. Applicants are similar to recipients (comparing columns (3) and (4)), though not identical; in particular, applicants are less likely to be female, are slightly younger, are slightly less racially diverse, and have smaller households. These differences are the result of two things: 1) that not all applicants receive benefits, and that the beneficiaries who receive SNAP for longer, and are thus weighted more heavily in column (3), may be different than those who receive SNAP for shorter periods of time.

Finally, columns (5)-(7) implement our sample restrictions and include applicants, recipients, and those denied in our main analysis sample, respectively. Our analysis sample of applicants is very similar to the full sample of all working-aged SNAP applicants in the mountain-plains state, suggesting our results can be plausibly generalized. Additionally, we show below that the labor supply trends, both before and after SNAP application, of applicants in our analysis sample are almost identical to the labor supply trends of all, new applicants in the mountain plains state in our sample period.

Several other statistics are worth noting for the interpretation of results in the following sections. First, only 52% of new applicants receive benefits in the quarter of application. The probability of receipt in the entire year after the application is very similar. This is slightly higher, but similar to the 44% acceptance rates found in Los Angeles during this same time period (Giannella et al., 2023). Additionally, only 32% of applicants in our sample are working in the quarter before application, and applicants have only $1,583 in real quarterly earnings (2012$s) before application on average. Even among those working, earnings are relatively low before application–$4,964 quarterly. To give a frame of reference for this, one person working full time at minimum wage for a full quarter would earn $3,770, which is almost the same as the quarterly household income that puts a household of two just at the poverty line – $3,782 in 2012.

We compare this to a sample of working-age adults who are income-eligible for SNAP in our state in the CPS and find for that sample roughly 50% report working at all. So, SNAP applicants are less attached to the labor force than a sample of those likely income-eligible for SNAP. This highlights a strength of our data–because our sample is *applicants* to SNAP, those that receive and are denied SNAP are more similar than if we compared outcomes within a sample that is all *income-eligible* for SNAP but some receive SNAP and some do not.

Finally comparing SNAP recipients (column (6)) to those denied (column (7)), recipients are slightly less likely to be working pre-application (30% compared to 34%) and have lower earnings ($1,373 compared to $1,806). On the demographic variables, those granted and denied SNAP are relatively similar. However, since we see that there are some differences in observables between those granted and those denied, we might worry there are differences in unobservables, and this is why, in addition to estimating OLS models, we implement our IV approach.

4 Descriptive Results

Our data allow us to observe labor supply before SNAP application, so we begin by comparing trends in labor supply before *and* after application for those granted and denied SNAP benefits. While we saw evidence of differences in pre-period levels between those granted and denied SNAP above, of more concern for estimating the casual impact of SNAP using a panel design is whether there were differential pre-trends in labor supply. Figure 1 plots the labor supply outcomes across each quarter relative to SNAP application date. Those granted SNAP in the quarter of application have outcomes plotted in solid black lines and those denied SNAP have outcomes plotted in dashed blue lines. These figures control only for application-date fixed effects. In this analysis, we simply plot the coefficients, and below we estimate formal OLS models to assess statistical significance.

Focusing first on quarterly employment shown in panel (a), SNAP recipients are about 0.03 percentage points less likely to work at all one year before applying than those denied. Additionally, in the quarters leading up to SNAP application, the gap in the employment rate slightly widens due to differential trends across the two groups. These differential pre-trends, which we also see on the other outcomes discussed next, motivate the IV strategy described below. Interestingly, in the quarter of SNAP application, employment rates for both groups are very similar to the quarter before application. Over time, the gap in the employment rate narrows, so that three years after SNAP application, those granted SNAP are only 0.015 percentage points less likely to work at all compared to those denied, suggesting that SNAP may actually have a small positive effect on employment.

Next, we look at earnings, inclusive of zeros, in panel (b) and again see the same pattern before application–the level of earnings is about $400 lower and is trending slightly more negatively for those approved for SNAP. In the quarter of application, there is a large decrease relative to the pre-period for *both* groups. The fact that we see a decline for those denied as well as those accepted means there are other factors at least partially causing a reduction in earnings besides SNAP receipt–e.g. a layoff. These other factors may be the precipitating events leading to the initial SNAP application.[12] The gap in earnings between SNAP recipients and those denied becomes slightly larger in the period of application, but

[12]This is consistent with prior descriptive evidence using the Survey of Income and Program Participation that found 47% of SNAP recipients experience a decrease in work or unemployment before receiving SNAP (Leftin et al., 2014).

then this gap shrinks, though remains wider than during the pre-period.

Panel (c) shows the change in the likelihood of having earnings above $0 and below $2,000 per quarter. We use this as a proxy for part-time work because $2,000 per quarter is below the earnings level of a full-time full-quarter minimum wage job. The threshold of $2,000 earnings per month is not particularly notable for SNAP recipients, and the results are similar using other cutoffs, such as $1,500 or $2,500. We contrast this with panel (d), which shows the share of workers who have quarterly earnings at or above $2,000. We see the same pattern in the pre-period as with the above outcomes–recipients are more likely to work part-time and are trending towards higher rates of part-time work in the pre-period, and we see the opposite pattern with the likelihood of earning above $2,000 in panel (d). In the quarter of SNAP application, the likelihood of part-time work increases for both SNAP recipients and those denied, at the same time the likelihood of earning above $2,000 declines, again suggesting some other factor impacts labor supply besides SNAP receipt. The gap in the rates of part-time work is largest in the quarter of application (0.04 percentage points) and then shrinks somewhat, but remains larger than in the pre-period, even after three years. The gap for earnings above $2,000 follows the same pattern of dynamics but with the opposite sign, and these opposing changes explain why we observe a decline in earnings, but no change in employment in panels (a) and (b) of this figure.

We also use these OLS figures to further assess generalizability of our analysis sample. Specifically, in Appendix Figure A2, we show the baseline plots of employment and earnings for our analysis sample in panels (a) and (c), and we show analogous plots for a broader sample in panels (b) and (d). For the broader sample, we include applications *regardless* of the track they are assigned (so not only the General track), and we also include applicants regardless of the number of decisions their assigned caseworker makes, or the CCAR value of their assigned caseworker. The only sample restriction we keep for the broader sample is that the application be new–meaning that the applicant hasn't received SNAP in the year prior to the focal application. We do this because receipt of SNAP prior to the focal application could impact the labor supply decisions of the applicant in the pre-period, and we want to be able to cleanly compare across samples. The figures indicate that the labor supply trends, both before and after SNAP application, for those accepted and denied SNAP, are nearly identical in our analysis sample and this broader sample. This provides further evidence that our results can be plausibly generalized.

Taken together, these trends highlight that SNAP applicants face negative shocks regardless of whether they eventually receive benefits. They also suggest that SNAP is associated with no large change in employment, a short-term negative change in earnings, and a modest, persistent positive change in the likelihood of working part-time. Of course, we cannot rule out that other factors correlated with SNAP receipt are driving these changes, so we next turn to our instrumental variables approach.

5 The Role of Caseworkers

5.1 Estimating Caseworker Behavior

We build on the analysis above by using the assigned caseworker's application acceptance rate as an instrument for SNAP receipt. Caseworkers are randomly assigned to applicants in our sample, conditional on the timing of the application. Because of this, caseworkers' applicants have the same baseline likelihood of being approved, so differences in average caseworker approval rates must be driven by caseworker behavior. The Conditional Caseworker Approval Rate (CCAR) quantifies and aggregates caseworker behaviors that impact application acceptance.

We follow the newer examiner-effects literature to create the CCAR using the UJIVE approach ("unbiased jackknife instrumental variables estimator"). Kolesár (2013) proposed the UJIVE and it has been used in other recent papers including Norris et al. (2021) and Agan et al. (2023). It is also recommended as best practices by Chyn et al. (2024).[13] Bringing this examiner-effects methodology into the setting of safety net program receipt to demonstrate the importance of caseworkers is an important contribution of our paper. To implement this, we estimate two equations for each application i:

$$Approved_{-i} = \lambda_a + \epsilon_{-i} \tag{1}$$

$$Approved_{-i} = \phi_a + \rho_c + \nu_{-i} \tag{2}$$

where $Approved_{-i}$ indicates whether each application, besides the focal application i, is approved. In each equation, we include a set of application-date fixed effects (respectively λ_a and ϕ_a), which determines the set of caseworkers the applicant may be assigned to and is the level of randomization. Note, we do not observe the date that each applicant calls to conduct their interview, which is the true level of randomization, so we use the application start date to proxy for this. Equation (2) adds caseworker fixed effects (ρ_c). We then calculate $CCAR_i$ – the predicted approval likelihood for applicant i – by subtracting the

[13] The UJIVE approach is robust to weak-instrument issues caused by small numbers of observations per examiner, which is potentially important in our setting. It has other advantages in terms of better accounting for covariates and being relatively easy to compute (Norris et al., 2021). We have experimented with alternative estimators, which are highly correlated with our primary measure, but they provide us with less precision, likely because of the relatively small numbers of application decisions per caseworker.

predicted value of equation (1) from the predicted value from equation (2). Intuitively, this gives us each applicant's predicted likelihood of approval based solely on the caseworker they are assigned, netting out any heterogeneity due to application timing, and the caseworker's decision on the focal application.[14] Thus, our instrument for SNAP receipt is unique to each application, though for simplicity we still sometimes refer to it as "the CCAR" or "caseworker's CCAR".

There is considerable variation in the CCAR as shown in panel (a) of Figure 2. The standard deviation in our sample of the CCAR is 0.03. We collapse the data to the caseworker level and show that a 10 percentage point increase in the average CCAR across caseworkers is associated with a 14 percentage point increase in their approval rate (panel (b)). This is a 27% increase of the overall approval rate in our sample of 52% (Table 1). We demonstrate below that the CCAR is strongly *causally* related to SNAP receipt (the first stage). As a test of the exogeneity of caseworker assignment, we regress the assigned caseworker's caseload, months of experience, and applicant-specific CCAR onto baseline applicant demographics and pre-application labor supply—conditional on application-timing fixed effects. We contrast this with the relationship between whether an application is approved and these applicant characteristics. In column (1) of Table 2, there is a strong relationship between the set of observable applicant characteristics and the likelihood of SNAP approval. The F-statistic on this model is 50. On the other hand, in columns (2)-(4), the caseworker characteristics and CCAR are largely unrelated to applicant characteristics and the F-statistics are very small– from 0.82 to 1.12. This provides evidence that caseworker assignment is indeed random, conditional on the fixed effects, supporting the independence assumption that the CCAR is unrelated to determinants of labor supply.

5.2 The Effect of Caseworkers on SNAP Receipt

Table 3 examines the effect of the CCAR on receipt of SNAP (panel (a)) and benefit amount received including zeros (panel (b)) by quarter or year following an initial application. In the quarter of application, there is a large and statistically significant effect of the CCAR on benefit receipt. The coefficients indicate the effect of a unit increase in the CCAR, however the CCAR in our sample ranges from -0.12 to 0.11. So, to interpret this coefficient, we scale it by a one standard deviation increase in the CCAR (0.03). A one standard deviation change increases the likelihood of receiving SNAP in the quarter of application for the full sample

[14] We use whether the application was *approved* in this calculation of the CCAR, which is slightly different from our measure of benefit receipt used for the IV analysis below. See Appendix A. The CCAR is very similar when using benefit receipt instead.

by 1 percentage point, which is a 2% effect of the overall rate of acceptance of 52%. The F-statistic for the estimate on benefit receipt in the quarter of application is 79. Turning to the amount of benefits received in the quarter of application, a one standard deviation increase in the CCAR increases the amount received by about $6. To get a sense of the magnitude of this increase, informational interventions aimed at increasing SNAP enrollment among likely eligible elderly non-participants increased participation by 5 percentage points (Finkelstein and Notowidigdo, 2019); the same intervention when accompanied by application assistance increased participation by 12 percentage points.

The largest effect on SNAP receipt is in the quarter of application, which motivates our choice to use this as the endogenous variable in Equation (3). The effects fade out in subsequent years, as shown in the second to fourth columns of the table, which indicate the likelihood of receiving SNAP at all and total annual benefit amounts received in the year denoted by the column heading. The decline in the effect of the CCAR over time could be due to those denied reapplying and being accepted for SNAP, or those who initially receive SNAP not receiving it for very long. We investigate this and show re-approval rates are relatively low, so the latter mechanism drives these dynamic effects. These results are discussed in more detail in Appendix B.

5.2.1 Mechanisms Behind the Effect of Caseworkers

We hypothesize that the main way caseworkers can impact applicants' outcomes is through assistance during the application process. To test this, we examine the relationship between the CCAR and the likelihood an applicant does not complete their application. Incomplete applications are those that are auto-denied for administrative reasons, withdrawn by the applicant, or those that failed to include all the required documentation. An incomplete application is the most common reason for denial–77% of applicants who are denied are denied for this reason (the overall denial rate is 48%). In Table 4, we regress onto the CCAR whether the given application was incomplete, conditional on application date fixed effects. We find that a one standard deviation increase in the CCAR decreases the likelihood of having an incomplete application by 1 percentage point, 3% of the sample mean. This suggests that caseworkers with a higher CCAR are more helpful in ensuring the applicant submits all the necessary information and completes the application process. This is in contrast to the findings in Finkelstein and Notowidigdo (2019), who show that likely-SNAP-eligible individuals who are pushed to apply are *more* likely to be rejected due to incomplete applications. However, their study is on a different population and on a different margin–elderly SNAP non-participants enrolled in Medicaid who have not applied for SNAP benefits.

The difference is likely because in our setting all individuals have taken the first step to apply, whereas in their setting people are marginally pushed to apply and may be less likely to follow through with their application as a result.

We also explore what observable characteristics of caseworkers are correlated with their average CCAR in Appendix Table A3. While we do not see caseworker demographics, we do know information about their workload, how long they have worked as a caseworker, and the team of other caseworkers and the manager they work with. These teams are not always located in the same geographic place, but meet together and message each other virtually with regularity. In panel (a), we show the relationship between the CCAR and the caseworker characteristics listed in the column, conditional on application-date fixed effects. In panel (b), we report the adjusted R-squared from regressions where the CCAR is the dependent variable and the variables listed in the columns are the independent variables, along with application-date fixed effects. Panel (a), column (1), suggests that caseworkers with a higher CCAR also have a higher monthly caseload, which makes sense as more of the applicants they interact with will end up receiving SNAP. The second column indicates that caseworkers who have been at the job longer have a lower CCAR. Though both these relationships are quantitatively small for a one standard deviation increase in the CCAR. Panel (b) indicates that the caseworker's team has the most explanatory power. This suggests peers or managers may impact the CCAR.

6 Instrumental Variables Approach

In order to identify the effect of SNAP on labor supply using our instrumental variables approach, we estimate the following:

$$y_i = \beta ReceiveSNAP_i + \theta_a + \rho X_i + \zeta_i \tag{3}$$

where y_i is the labor supply outcome of individual i. We instrument for the receipt of SNAP benefits in the quarter of application ($ReceiveSNAP_i$) in Equation (3) with the caseworker-and-applicant-specific CCAR:

$$ReceiveSNAP_i = \alpha CCAR_i + \mu_a + \pi X_i + \eta_i \tag{4}$$

We include fixed effects for the application date (θ_a and μ_a) to ensure that we compare applicants who are exposed to the same set of potential caseworkers. We include a vector of baseline controls X to improve statistical precision.[15] Results in the Appendix confirm that estimates are stable to the exclusion of these controls. This design estimates the Local Average Treatment Effect (LATE) of SNAP applicants who are accepted, compared to those who are denied, because of the caseworker they are assigned.[16] Following best practices from recent design-based approaches to inference, we use heteroskedasticity-robust standard errors, but do not adjust for clustering because each applicant is randomly assigned to their own caseworker (Abadie et al., 2022; Chyn et al., 2024).

In our main analysis, we estimate this model by year after SNAP application. We also estimate the OLS version of this model as given by Equation (3) to compare to the IV results. Finally, we decompose the LATE into the potential outcomes under two alternative states of the world (Frandsen et al., 2023): 1) applicants receive SNAP due to their caseworker's CCAR ("treated compliers"), and 2) applicants are denied due to their caseworker's CCAR ("untreated compliers"). This is useful because it allows us to visualize levels of the outcomes of interest in both states of the world for the compliers before and after application. Specifically, we run the following regression to recover the outcomes for treated compliers: $y_i * ReceiveSNAP_i = \beta ReceiveSNAP_i + \theta_a + \zeta_i$, using $CCAR_i$ as an instrument for the endogenous right-hand-side variable–$ReceiveSNAP_i$. And, we run the following regression to recover the outcomes for untreated compliers: $y_i * (1 - ReceiveSNAP_i) = \beta(1 - ReceiveSNAP_i) + \theta_a + \zeta_i$, using $CCAR_i$ as an instrument for the endogenous right-hand-side variable–$(1 - ReceiveSNAP_i)$. Intuitively, this gives us the average outcome if all marginal applicants received benefits, or were denied benefits, respectively, because of their caseworker's CCAR.

6.1 Validity of CCAR as Instrument for SNAP Receipt

6.1.1 Monotinicity

A key assumption underlying our research design is monotonicity of the instrument. Until recently, papers using examiner designs often invoked the strong assumption of pairwise monotonicity in order to ensure that IV estimates are properly weighted aggregates of complier treatment effects. Intuitively, the assumption requires that if a caseworker with a higher CCAR is assigned to an application, this caseworker will be more likely to accept

[15] The vector X includes the following head-of-household information: gender, race/ethnicity, citizenship, age, and Spanish speaking status. It also includes baseline labor supply information for each of the four quarter preceding the initial SNAP application, including: quarterly employment, earnings, indicators for quarterly earnings within $\$1 - \$1999$, arc percent of earnings, and industry experience.

[16] Our estimates are a compliance-weighted average of treatment effects, so they are "local" to the affected population.

that application than a caseworker with a lower CCAR, regardless of case characteristics. A growing literature has emphasized the importance of this assumption and suggested tests that researchers can use to support its validity; Frandsen et al. (2023) propose a joint test for violations of either exclusion or pairwise monotonicity assumptions. In our empirical design, we reject the null hypothesis that both conditions are satisfied. Fortunately, Frandsen et al. (2023) also show that under a relaxed "average monotonicity" assumption, IV still estimates a convex combination of treatment effects. Average monotonicity requires that for each individual, the covariances between that individual's caseworker-specific treatment status and caseworker overall CCAR are positive. Two testable implications of this assumption are: 1) the first stage estimates for all sub-samples should yield positive estimates, and, 2) there should be a positive relationship between the CCAR for the full sample and the CCAR for various subgroups. In Appendix Table A4 and Appendix Figure A3, we show that our instrument passes both of these tests. Thus, the CCAR is plausibly a valid instrument for SNAP receipt under the weaker average monotonicity assumption.[17]

6.1.2 Exclusion Restriction

The exclusion restriction requires that caseworkers only impact applicant outcomes through the proposed causal channel: whether the applicant is approved for SNAP. In the state we study, caseworkers have a limited scope for affecting applicants outside of the SNAP determination. Caseworkers interact with applicants during a short mandatory phone interview, the purpose of which is to simply verify the information on the application form. Caseworkers can also message applicants via the online system or use snail mail correspondence to notify applicants if there are any issues with their application. The mountain-plains state administers joint applications for SNAP, Medicaid, and TANF. However, specialized teams focus on applicants jointly applying to multiple programs and the caseworkers we study mostly handle SNAP-only applications and thus have limited scope to impact participation in Medicaid and TANF. Caseworkers are instructed to focus on the given application and not to direct applicants to other sources of government support or provide any sort of labor market advice or resources. If the applicant did decide to apply to other programs, they would need to start a brand new application for the given program, which would be han-

[17]Other prominent papers fail pairwise monotonicity and instead rely on average monotonicity like we do here (e.g., Norris et al., 2021). Recent research has pointed out that if there are multiple dimensions, such as skill and preferences, that both contribute to variation in actor's decision-making this can lead to a violation of the strict or average monotonicity assumptions (Chan et al., 2022). We do not observe false positives or false negatives, making it hard to use the suggested methods that explicitly test for this. However, we argue that the "pro-participation" attitude of the caseworker is the primary determinant of the CCAR and provide evidence to support this above.

dled by a different caseworker from the other tracks. Indeed, when we regress whether the applicant receives TANF onto the CCAR, we estimate a precise zero. Unfortunately, we do not currently have data on Medicaid enrollment. Finally, we also investigated changes in cross-program participation at SNAP participation initiation using the Survey of Income and Program Participation, and these results are discussed in Appendix C, which also suggest that other programs are unlikely to drive our main results.

6.1.3 Targeting Effects of Caseworkers

To understand who is pushed into receiving SNAP because of their caseworker, we explore the characteristics of compliers following the method outlined in Frandsen et al. (2023). While the IV estimates are internally valid regardless of impacts on targeting, this analysis helps us interpret the LATE we estimate with the IV approach. To do so, we estimate Equation (3) instrumenting with the CCAR, but replace the labor supply outcome with various applicant characteristics interacted with an indicator for whether the applicant received SNAP during the quarter of application.[18] The first row in Table 5 shows the characteristics of the compliers calculated using this method. The second and third rows show the average of the same characteristics for the full analysis sample of applicants and the sample of applicants who receive benefits in the quarter of application, respectively. The fourth and fifth rows provides the ratio of the complier characteristics to the full sample characteristics to test if the compliers differ significantly from all applicants and beneficiaries, respectively. The statistical test is whether this ratio is significantly different from one.

In general, compliers seem slightly more attached to the labor market, however, only one of these differences is marginally statistically significantly different from the full samples of beneficiaries. Compliers are about 30 percent more likely to be female than all applicants and beneficiaries, and this difference is statistically significant. Compliers are also a few years younger and more likely, though not significantly so, to be Black or Hispanic. We also explore whether compliers are those closer to the income eligibility cutoff; we use the observed earnings in the UI data relative to the eligibility threshold based on their household size. This is a coarse measure of eligibility, but we see no evidence compliers are closer to the eligibility margin.

There is no conclusive evidence that caseworkers affect targeting. Given these find-

[18] Specifically, we estimate: $y_i * ReceiveSNAP_i = \beta ReceiveSNAP_i + \theta_a + \zeta_i$ using $CCAR_i$ as an instrument for the endogenous right-hand-side variable–$ReceiveSNAP_i$. This gives the average of the characteristic y among those that receive SNAP and because we instrument for SNAP receipt, this is the characteristic among those who were pushed onto receiving SNAP because of their caseworker's CCAR.

ings, it is plausible that the LATE we estimate can apply to the population of beneficiaries more generally. It is also informative to compare our findings to that of Finkelstein and Notowidigdo (2019), who show assistance and informational interventions for likely-SNAP-eligible populations that push more people to apply for SNAP reduce targeting. In contrast, everyone in our sample has already chosen to apply for SNAP and overcome the initial costs of doing so. The evidence indicates that caseworkers with higher CCARs are providing help to all applicants they interact with, regardless of the applicants' characteristics, which is why they have little impact on targeting. Our findings highlight the importance of studying the impacts of different interventions within the same program to fully understand the targeting impacts of changing administrative burdens.

6.2 Labor Supply Results

In Table 6 we show the OLS and IV results on our main measures of labor supply. To increase precision, we include controls for demographics of the applicants and pre-application work history, however, the results are nearly identical when we exclude these controls as shown in Appendix Table A5. Additionally, we show the results from a weighted-least-squares model where we weight the OLS results to mimic compliers from the IV analysis (Dobbie et al., 2018)–this is labelled "WLS" in the table. Across the columns, we examine the effect of SNAP over time since application, and in the final set of columns we estimate the effect on the *cumulative* value of the outcome of interest over the three years following application.

Looking first at employment shown in panel (a), there is little evidence of large or statistically-significant effects from either OLS or IV models. The cumulative IV results indicate that those who receive SNAP work 0.65 quarters more than those denied on average, which is small in magnitude and not statistically significant. The 95% confidence intervals on our IV estimate allow us to rule out *cumulative* changes in employment of less than -0.8 or more than 2 quarters over the three years following application. Similarly, the cumulative OLS estimate is an insignificant 0.03 additional quarters of work, and we can rule out changes in employment of more than -0.02 to 0.07 quarters. As a point of comparison, the full sample worked on average 10.5 quarters over the three year period before applying for SNAP.

In Figure 3, we decompose the LATE from the IV model into the potential outcomes at the quarterly level for the compliers under two alternative states of the world: 1) applicants receive SNAP due to their caseworker's CCAR ("treated compliers", shown in orange) and 2) applicants are denied due to their caseworker's CCAR ("untreated compliers", shown in blue). The gap between the potential outcomes are the IV estimates for a given quarter, but exploring the underlying levels of the potential outcomes provides additional information about mechanisms. The results for employment are shown in panel (a) of Figure 3. The potential outcomes are nearly identical both in the pre period and in the post period, following the null results documented above.

Next, we examine earnings in panel (b) of Table 6. In the first year after application, the results point to a small decline in annual earnings of a significant \$925-1,122 with OLS models, and an insignificant \$978 decline with the IV model. Over time, the OLS and IV estimates diverge, with the OLS remaining consistently significantly negative, while the IV coefficients become positive and insignificant. In panel (b) of Figure 3, we plot the corresponding potential outcomes from the IV model. We mechanically see the same pattern as in the table–a small negative and temporary effect of SNAP on earnings right after application, due to a larger drop if compliers are accepted than if they are denied in the quarter of application. Though, again, importantly we see a drop in earnings for both states of the world suggesting some external factor is also causing a reduction in labor supply. And, if anything, there is a small positive effect in the longer-run, due to a slower but similarly sized decline in earnings in the state of the world where all compliers are denied SNAP.

Finally, we explore earnings above and below the \$2,000-per-quarter threshold. Recall that we chose this threshold because those who have positive earnings, but earn below \$2,000 per quarter, are unlikely to be working full-time for the full quarter. And, since we do not observe hours worked directly in the data, this can help shed light on potential margins of adjustment not evident from employment or average earnings. Panel (c) of Table 6 looks at the likelihood of having positive earnings less than \$2,000, and the results consistently point to a positive effect of SNAP on this proxy for the likelihood of working part-time. The cumulative IV estimate indicates an additional 0.9 quarters worked part-time over three years, which is statistically significant; OLS results are also positive and significant, though smaller in magnitude than the IV estimates. This positive effect on part-time work is confirmed when looking at the potential outcomes in panel (c) of Figure 3–there is an immediate and persistent increase in the likelihood of working part-time.

Panel (d) of Table 6 looks at the likelihood of earning greater than \$2,000 a quarter. Here the estimates point towards a small, negative effect that diminishes over time. While the point estimates are very similar across the OLS and IV models, the estimates are not statistically significant in the IV model. Again, there is a similar pattern when looking at the potential outcomes in panel (d) of Figure 3 driven by an immediate drop in the potential outcomes if compliers are treated and a slower and slightly smaller drop if they are not treated.

Taken together, this analysis shows no evidence of meaningful effects of SNAP on the extensive margin of work. The analysis on earnings is more mixed but indicates at most a modest decline in earnings that is short-lived. This short-run change in earnings is in part driven by a significant increase in part-time work (quarterly earnings of $1-1,999) though this effect is also quantitatively small.

6.2.1 Mechanisms

A strength of our data is the ability to split the sample into subgroups based on *pre-application* labor supply to understand potential mechanisms. Recall that 61% of SNAP applicants did not work at all in the year before applying for SNAP. Thus, labor supply decisions for this group are unlikely to be greatly impacted by SNAP receipt.

In Table 7 panel (a), we investigate the effects on this group that was unattached to the labor market in the year prior to applying for SNAP using the IV model. Across all outcomes, there are no quantitatively large or statistically significant effects. The point estimate on the cumulative effect on employment is -0.01 quarters and we can rule out changes in the number of quarters employed of more than 1.6 quarters and less than -1.6 quarters over the three-year time period after applying for SNAP. Similarly, for the number of quarters the applicant worked while earning less than $2,000, we can rule out cumulative three-year increases or reductions of more than 0.6 quarters. Finally, for the number of quarters with earnings of at least $2,000, we can rule out cumulative three-year increases or reductions of more than 1.3 quarters. We also show in Appendix Figure A4 there are no large divergences in potential outcomes between the treated and untreated states of the world at the quarterly level. This null result is consistent with the hypothesis that many SNAP recipients face barriers to work regardless of whether they receive SNAP benefits.

Next in panel (b) of Table 7, we examine the subgroup that *was* working the entire year prior to receiving SNAP. Several distinct patterns emerge. First, there is a decline in labor supply in the first year after application. There is a marginally significant decline in the likelihood of earning above $2,000 per quarter of 0.8 quarters ($p = 0.13$) and a marginally significant increase of 0.6 quarters ($p = 0.11$) in our proxy for part-time work. There are also negative, but imprecisely estimated effects on employment and average earnings in this first year. Then, in the third year after application, we estimate significant, *positive* effects on employment, average earnings and part-time work. SNAP beneficiaries work an additional 1.4 quarters and earn $11,991 more than those denied in the third year. There is also a positive effect on earnings above $2,000, though it is not significant.

Figure 4 decomposes these results into quarterly potential outcomes. This decomposition sheds additional light on why SNAP recipients are working more than those denied in the longer-run. In both states of the world, there is a large drop in employment and earnings at the time of application–again providing evidence that these SNAP applicants experience a shock that negatively impacts their labor supply *whether or not they receive SNAP* (as in Figure 1 and 3). Further, in the state of the world where compliers are all denied SNAP, they experience a sharp downward trajectory in their earnings and employment in the longer-run. Three years after application, the likelihood of quarterly employment in this state of the world is less than 0.50, which is striking given that this entire group worked for a full year before applying for SNAP. Average earnings also fall by 55% after three years, relative to pre-application. On the other hand, in the state of the world where compliers receive SNAP, they instead experience long-run increases in earnings and employment relative to the quarter after application.

This is consistent with the receipt of SNAP helping people buffer against a negative shock. For example, SNAP could help people who lost a job search for a higher-quality job or allow recipients to pay for goods and services necessary to prevent cascading events creating a downward trajectory, such as an eviction (Collinson et al., 2022). This consumption-smoothing benefit is likely important among this population because they live hand to mouth and are credit constrained. Only 62% of SNAP recipients have bank accounts before receiving SNAP, and, among those with accounts, the median balance is only $389 (2012 dollars).[19] Moreover, 17% of SNAP recipients paid their rent late, 11% paid utility bills late, many reported having to decide between spending money on food or on rent and utilities, and are in danger of eviction (Propel, 2023). Among SNAP recipients with children, the majority have expenses that exceed their income in a given month and they report SNAP benefits help alleviate this deficit, though not entirely.

6.2.2 Specification Checks

We test the sensitivity of the IV results to our sample construction and model choices in Appendix Tables A5 through A7 (for the full sample and pre-application employment subsamples, respectively). The estimates in panel (a) use the baseline specification. Panel (b) removes all demographic and baseline labor supply controls that we included to enhance statistical precision. In our baseline sample we omit applications with a CCAR below the

[19] Authors' calculation with the Survey of Income and Program Participation.

1st and above the 99th percentiles. We show the robustness to further restricting extreme CCAR values, and not restricting the sample based on CCAR values, shown in panels (c) and (d), respectively. Additionally, in our baseline sample we drop applications assigned to caseworkers with fewer than the 20th percentile number of decisions. The estimates in panels (e) and (f) show results with alternative cutoffs–the 10th percentile and 30th percentile, respectively. The results are very similar across all these choices, so none of these decisions drive our key findings.

Next, in Appendix Table A8, we reproduce our main results and then limit the sample to only households with one working-aged adult to ensure our results are similar for households where we observe all potential earners in the earnings data. The results are nearly the same for this subgroup as for the full sample, so having the UI earnings information only for heads of households is not important for the broader conclusions.

6.2.3 Comparison to Prior Literature

The past literature studies specific subgroups or the effect of the program decades ago. Overall, existing work suggests modest negative-to-null effects of SNAP *access* on the labor supply of likely impacted groups. Studying Food Stamps in the 1960-70s–the precursor to SNAP–Hoynes and Schanzenbach (2012) find mixed evidence of effects on labor supply. For all low-educated households, the effects are not significant and not of consistent sign. There is, however, a significant decline in annual earnings and work hours for single female-headed households. The implied treatment-on-the-treated effect for this group is a 58% decline in annual earnings and 60% decline in annual hours worked. East (2016) estimates effects of a similar magnitude for some immigrants likely affected by the changes in non-citizen's eligibility for Food Stamps. The treatment-on-the-treated estimates imply a reduction in employment and hours among single females of 43% and 51%, respectively, and a reduction in hours among married men of 75%. There is no consistent effect on married women's labor supply.

There are a handful of studies on the impact of SNAP *work requirements* for ABAWDs–who make up about 5% of all SNAP participants. These studies have mixed findings with some finding no effects of imposing work requirements on labor supply (Stacy et al., 2018; Vericker et al., 2023) and some finding small positive effects (Cuffey et al., 2022). Recent analysis by Gray et al. (2022) uses high-quality administrative data and a regression discontinuity design based on the maximum age of people subject to the requirement (49), and finds no effect on employment but a large negative effect on SNAP receipt. The authors hypothesize that the null effect on employment is potentially due to other barriers to work that SNAP recipients face, which is complementary to our findings on a broader group of SNAP applicants.

Finally, Bitler et al. (2021) study the effect of kinks in the budget constraint created by SNAP on labor supply. Among SNAP participants who might be affected, there is little evidence of a response.

In contrast to the existing literature, our paper studies the effect of modern SNAP *receipt* on a large, policy-relevant and generalizable group. Additionally, the ability to observe heterogeneity in the effects over time and by pre-application labor supply allow us to shed more light on the full labor supply response and its mechanisms than has been possible before. Our results illuminate one potential reason why the prior literature has mixed findings, as those estimates often combine both the short-run and long-run response, and responses among those who do and do not face barriers to work, whereas we are able to separate out these differential effects.

6.2.4 Welfare Effects

We quantify the results in a social welfare framework using the Marginal Value of Public Funds (MVPF) approach in Hendren and Sprung-Keyser (2020). Though, these results should be taken with a grain of salt given the large standard errors on the earnings estimates we use for this calculation. Specifically, we calculate the MVPF of the CCAR being one standard deviation higher.[20] The MVPF is the ratio of benefits to net government costs of the policy change, defined as:

$$MVPF = \frac{WTP}{C + FE} \tag{5}$$

The numerator is the willingness to pay to get SNAP benefits for SNAP applicants, which we assume to be equivalent to the change in the benefit amount paid due to a one standard deviation increase in the CCAR. The denominator is the direct cost of operating the program (C) for marginal recipients, including benefits paid out, administrative costs, and any fiscal externalities (FE) due to changes in behavior for marginal recipients. However, the fiscal externalities of a program like SNAP are complex and include effects beyond just the labor supply response of adult recipients that we identify here.

We estimate an MVPF of SNAP due to a one standard deviation increase in caseworker CCAR of 1.3, indicating the value to beneficiaries is larger than the net cost to the

[20]We estimate the MVPF within the first three years of SNAP receipt, which assumes effects after three years on both SNAP participation and labor supply are zero.

government.[21] In fact, we find that the effect of SNAP on government revenue due only to changes in labor supply over three years is *positive* because the longer-run positive effects outweigh the short-term negative ones.

Prior estimates of the MVPF of increasing access to SNAP range from 0.89 to 56.25. However, it is important to note that the study that produces estimates close to 1 are unable to examine any benefits to SNAP recipients beyond the direct value of the transfers themselves (Finkelstein and Notowidigdo, 2019), whereas the study that produces a higher MVPF is able to quantify many other benefits because of the richness of the data and the fact that the policy changes analyzed happened many decades ago (Bailey et al., 2020). This highlights a perennial challenge with analyzing the costs and benefits of safety net programs– the costs are often borne out in the short-run, whereas many of the benefits, including improvements in health and labor market outcomes (Bailey et al., 2020) and reductions in crime (Barr and Smith, 2023), only appear much later.

7 Conclusion

This paper examines the effect of SNAP on labor supply decisions using an examiner design. We are the first to bring the examiner design to the setting of means-tested transfer program receipt in the United States. We show that caseworker behavior matters for determining whether SNAP applicants receive benefits and provide evidence that this operates through caseworkers helping applicants navigate the complex application process.

We find no evidence of large effects of SNAP on labor supply for the full sample of working-aged applicants. The richness of data allow us to understand why our findings are counter to the canonical static labor supply model predictions. We document that most applicants do not work the year before applying for SNAP, and the receipt of SNAP has no impact on their labor supply decisions. We posit these applicants likely face other, larger barriers to work that dominate any potential effect of SNAP. Among the 25% of our sample that worked in the year leading up to their SNAP application, SNAP appears to act as insurance against negative shocks and reduces earnings temporarily, but increases earnings and the likelihood of work in the longer-run.

While our analysis is for a single state, we show a variety of evidence that suggests our results are generalizable. First, our analysis sample looks very similar to the full sample of working-aged applicants in the mountain-plains state, on both demographics as well as levels and trends in labor supply. Second, the labor supply of SNAP recipients in our state is very

[21] Appendix D provides the details of the MVPF calculation.

similar to the labor supply of a national sample of SNAP recipients. And, finally, we show the compliers in our IV approach are similar to the full sample of SNAP applicants.

Recently, lawmakers have raised concerns about work disincentives from SNAP and other means-tested transfer programs; work requirements were expanded under the Trump administration, changed as a result of the 2023 debt ceiling negotiations, and are again being debated as part of the Farm Bill reauthorization. Our findings inform this debate; we find no evidence that receiving SNAP leads to long-term reductions in labor supply or dependency on government benefits. If anything, our results suggest the opposite–SNAP provides support for those who are unable to work and provides important insurance for workers experiencing a negative shock.

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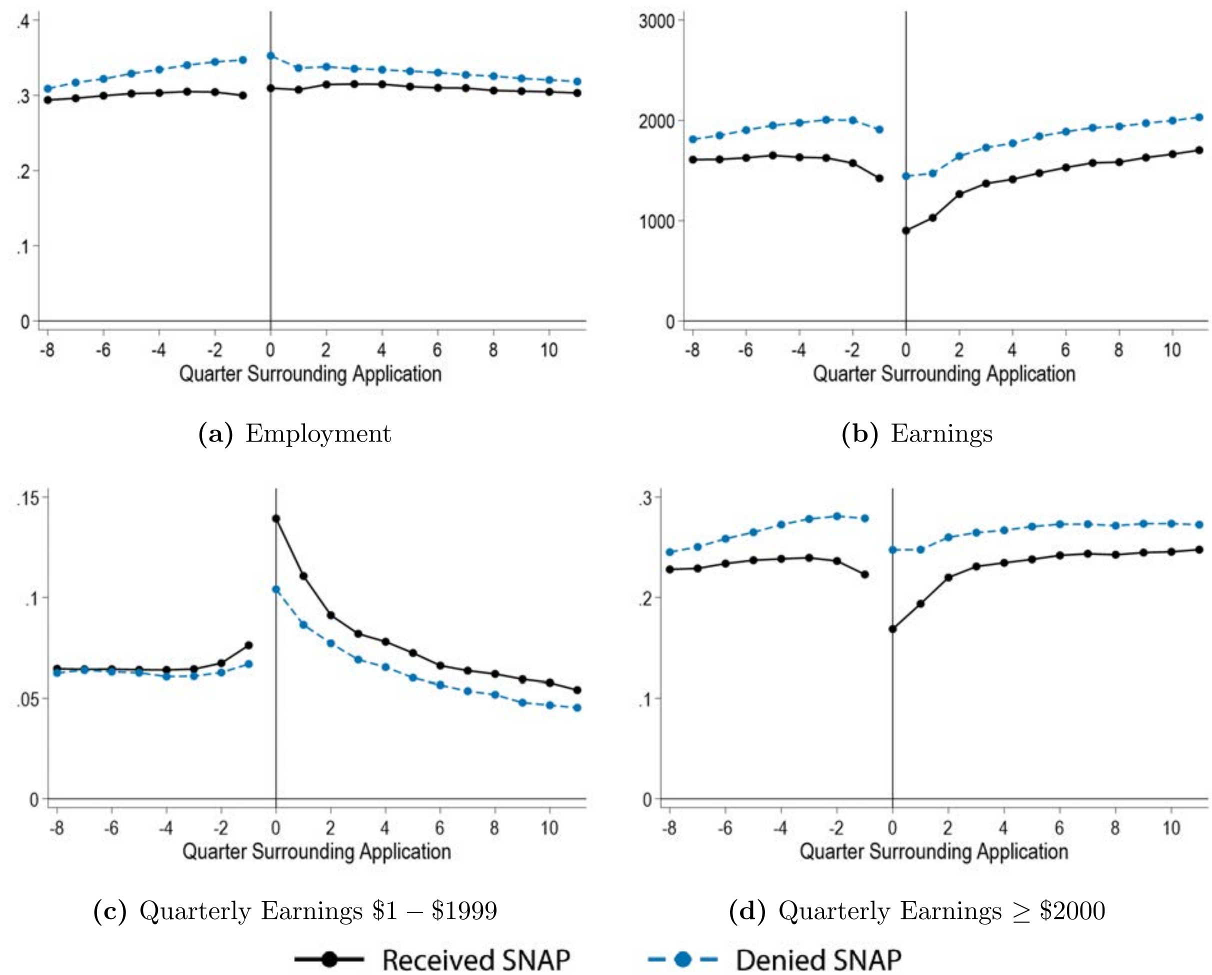
Figure 1: Differences in Quarterly Labor Supply by SNAP Receipt at $t = 0$



(a) Employment

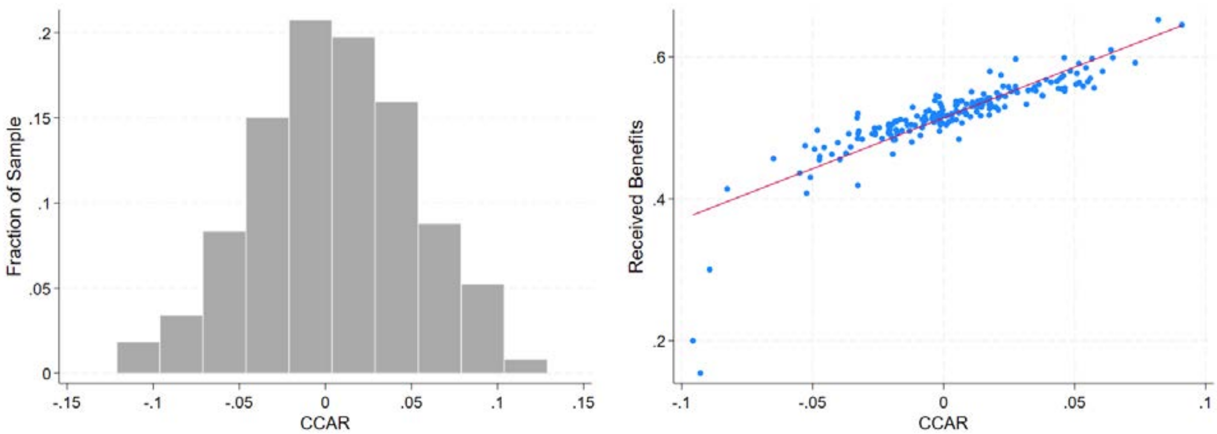
(b) Earnings

(c) Quarterly Earnings \$1 – \$1999

(d) Quarterly Earnings $\geq$ \$2000

Notes: These figures show the results from running separate regressions for the given event time of the outcome. We regress the given outcome in the given period on whether the applicant received SNAP during period 0 along with application date fixed effects. The blue dashed line is the coefficient on the constant from those regressions and the black solid line is the coefficient on the SNAP indicator added to the constant coefficient. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application.

Figure 2: Distribution of the CCAR and its Relationship with Benefit Receipt

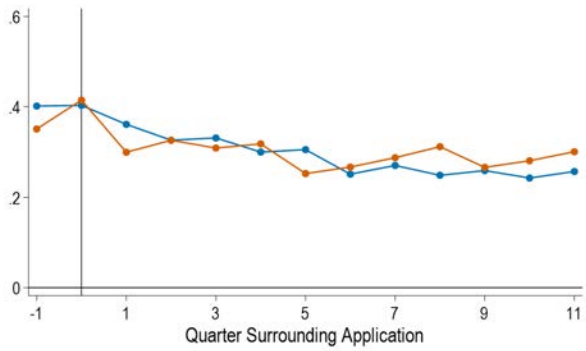


(a) Histogram of CCAR

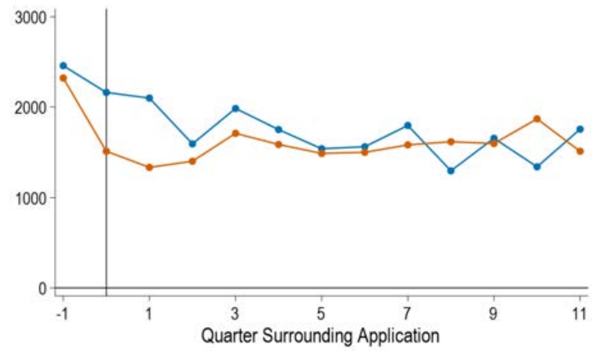
(b) Scatterplot of CCAR and Benefit Receipt

Notes: Panel (a) plots the histogram of our calculated CCAR for the main sample. Panel (b) is at the caseworker level and plots the relationship between the caseworker-level average CCAR and the SNAP acceptance rate of applicants for each caseworker. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application.

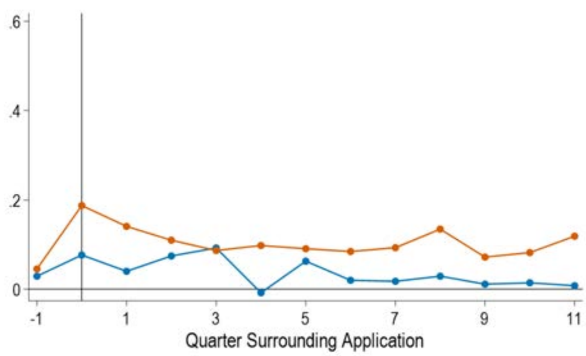
Figure 3: Decomposing IV Estimates into Potential Outcomes, Full Sample



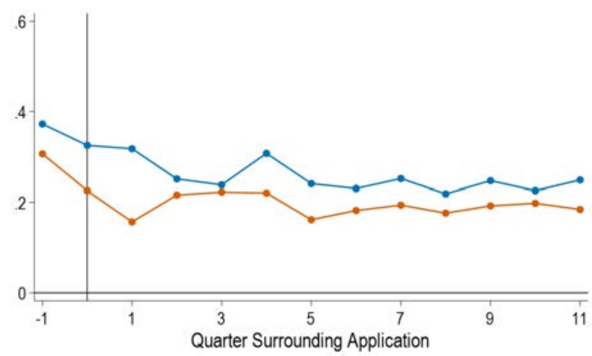
(a) Employment



(b) Earnings



(c) Quarterly Earnings $1 – $1999

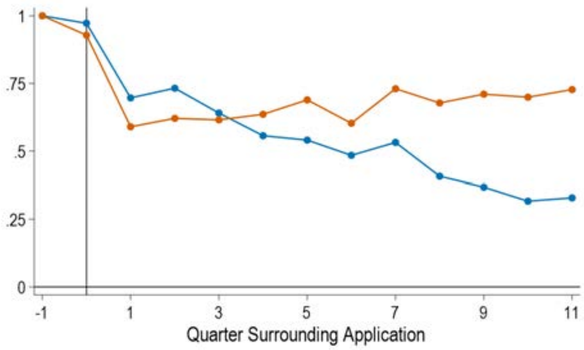


(d) Quarterly Earnings ≥ $2000

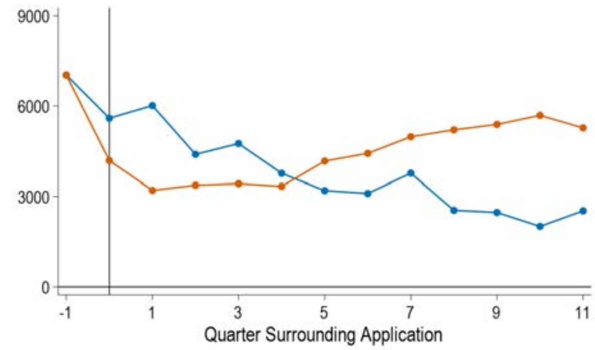
Untreated Compliers   Treated Compliers

Notes: These figures depict the potential outcomes in the state of the world that complier applicants are either approved or denied SNAP due to their caseworker's CCAR. Section 6 details the method. These regressions include demographic controls and application-date fixed effects, but exclude baseline labor supply controls to assess pre-application balance. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. The blue line plots the potential outcomes for untreated compliers (i.e., the state of the world where compliers are denied SNAP) and the orange line plots the potential outcomes for treated compliers (i.e., the state of the world where compliers receive SNAP).

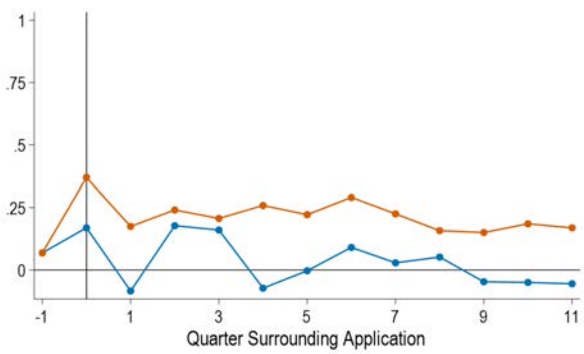
Figure 4: Decomposing IV Estimates into Potential Outcomes, Employed Year Before Application



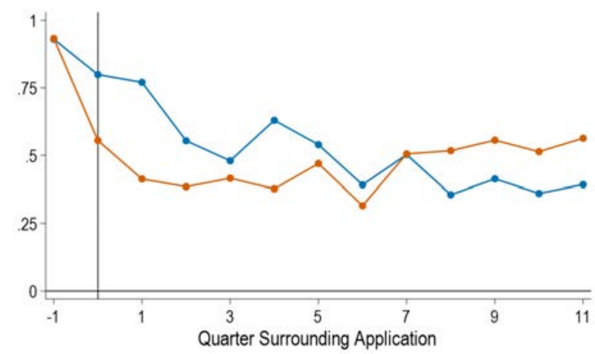
(a) Employment



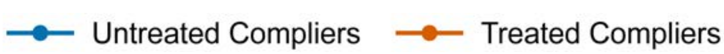
(b) Earnings



(c) Quarterly Earnings \$1 – \$1999



(d) Quarterly Earnings ≥ \$2000



Notes: These figures depict the potential outcomes in the state of the world that complier applicants are either approved or denied SNAP due to their caseworker's CCAR. Section 6 details the method. We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. The blue line plots the potential outcomes for untreated compliers (i.e., the state of the world where compliers are denied SNAP) and the orange line plots the potential outcomes for treated compliers (i.e., the state of the world where compliers receive SNAP).

Table 1: Summary Statistics

	All SNAP Recipients (QC Data)		Mountain Plains Administrative Data				
					Analysis Sample		
	National	Our State	All Recipients	All Applicants	New Applicants	New Recipients	New Denials
Quarterly Receipt of Benefits	1	1	1	0.52	0.52	1	0
Female	0.70	0.69	0.70	0.55	0.55	0.54	0.56
Age	39.55	37.86	37.66	32.88	33.77	34.64	32.88
Hispanic	-	-	0.11	0.08	0.07	0.08	0.07
Black	0.26	0.03	0.04	0.02	0.02	0.02	0.02
Pacific Islander	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Asian	0.02	0.01	0.02	0.01	0.01	0.01	0.01
Any Kids under Age 5	0.25	0.33	-	-	-	-	-
Number of Kids	1.02	1.38	1.44	0.72	0.70	0.71	0.69
Number of People in Hhold	2.34	2.71	2.75	1.91	1.87	1.86	1.90
Any Member w Disability	0.22	0.20	-	-	-	-	-
Real Earnings before Application (2012$)	-	-	-	1624.66	1583.05	1372.57	1806.44
Percent Employed before Application	-	-	-	0.33	0.32	0.30	0.34
Real Earnings after Application (2012$)	758.24	919.92	793.71	1261.23	1222.10	1015.54	1449.37
Percent Employed after Application	0.25	0.28	0.26	0.33	0.32	0.31	0.33

Notes: The first two columns use data from the SNAP Quality Control Data Set for years 2012-2016. Columns (3)-(7) present summary statistics from the mountain plains state using our administrative data. Columns (5)-(7) are for only those in our main analysis sample. We present the demographics of the head of household only from both data sets. For pre-application labor supply information, we use 1 quarter *before* application in our data. For post-application labor supply information, we use 1 quarter *after* application in our data for new applicants and new recipients, and quarterly wage information during all periods of SNAP receipt in the Quality Control data and for all recipients in our data. In the Quality Control data, and the mountain-plains data that is not our analysis sample, the head of household must be aged 18 - 64. We use the weights provided by the Quality Control data. Statistics are for 2012-2016.

Table 2: Balance Test

	Received Benefits	Monthly Caseworker Caseload	# Months of Caseworker Experience	CCAR
Female (0.55, 0.50)	-0.023***	-0.832***	-0.072	0.000
	(0.003)	(0.316)	(0.084)	(0.000)
Hispanic (0.07, 0.26)	0.036***	0.844	0.027	0.000
	(0.007)	(0.577)	(0.167)	(0.001)
Black (0.02, 0.14)	0.028**	-2.154*	-0.240	-0.000
	(0.012)	(1.117)	(0.318)	(0.001)
Asian (0.01, 0.10)	-0.061***	-1.014	0.356	-0.002
	(0.017)	(1.439)	(0.430)	(0.002)
Other Race (0.54, 0.50)	-0.017***	-0.118	-0.022	-0.001
	(0.003)	(0.319)	(0.086)	(0.000)
Citizen (0.96, 0.20)	0.116***	-0.375	0.185	0.000
	(0.010)	(0.902)	(0.248)	(0.001)
Age (33.86, 13.73)	0.005***	0.018	0.003	-0.000
	(0.000)	(0.013)	(0.003)	(0.000)
Spanish-Speaking (0.01, 0.10)	-0.052***	0.803	0.017 -0.002	
	(0.017)	(1.540)	(0.409)	(0.002)
Pre-Appl. Labor Supply Outcomes	X	X	X	X
Mean Y	0.52	247.09	34.63	0.00
F	49.86	1.09	0.82	1.12
N	88,543	88,457	88,543	88,543

Notes: This table regresses benefit receipt (column (1)), the monthly caseload of the assigned caseworker (column (2)), the months of experience of the assigned caseworker (column (3)), and the CCAR (column (4)) onto the pre-application characteristics of the head of household. "One-year Employment History" includes quarterly employment, earnings, indicators for Quarterly Earnings within $1 – $1999, arc percent of earnings, and industry experience. We include application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01

Table 3: First-Stage Estimates: Any Benefit Receipt and Total Benefit Amounts Received within the Given Period

	Quarter of Application	1st Year	2nd Year	3rd Year
a) Any Benefit Receipt				
Caseworker CCAR	0.340***	0.270***	0.109***	0.115***
	(0.036)	(0.036)	(0.033)	(0.030)
F	78.5			
N	88,543			
b) Total Real Benefit Amount				
Caseworker CCAR	212.8***	693.5***	367.6***	277.3***
	(27.3)	(99.6)	(94.7)	(84.4)
F	71.3			
N	88,543			

Notes: This table presents estimates of the effect of the CCAR on an indicator that equals one if the applicant receives SNAP during any of the months during the window of time specified in the column header (panel (a)) or the total real SNAP benefit dollars received over the given period (panel (b)). We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Relationship of the CCAR with Incomplete Application

	Incomplete Application
Caseworker CCAR	-0.346***
	(0.035)
Mean Y	0.37
N	88543

Notes: We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01

Table 5: Complier Characteristics

	Employed t−1 (1)	Earnings t−1 (2)	Number of Jobs t−1 (3)	Industry Experience (Quarters) t−1 (4)	Arc Percent t−1 (5)	Female (6)	Age (7)	Black or Hispanic (8)	Within $250 of GI Limit (9)
Complier-weighted char	0.35	2251.86	0.53	3.04	0.13	0.73	27.85	0.15	0.18
Full-sample average char	0.32	1654.96	0.40	2.45	0.22	0.55	33.77	0.09	0.17
Beneficiary average char	0.30	1418.81	0.37	2.27	0.22	0.54	34.64	0.09	0.17
Complier-weighted char relative to overall	1.09	1.36	1.31	1.24	0.59	1.33**	0.82***	1.68	1.04
	(0.22)	(0.30)	(0.25)	(0.33)	(0.36)	(0.15)	(0.06)	(0.50)	(0.63)
Complier-weighted char relative to beneficiaries	1.17	1.59	1.44	1.34	0.57	1.37***	0.80***	1.63	1.09
	(0.24)	(0.36)	(0.27)	(0.36)	(0.36)	(0.15)	(0.06)	(0.49)	(0.66)
Observations	88,543	88,543	88,543	88,543	88,543	88,543	88,543	88,543	88,543

Notes: Row 1 presents the results of our main IV specification from Equation (3) instrumenting with the CCAR, where the outcome variable is the given column characteristic interacted with a indicator equal to one if the case received SNAP during the quarter of application. This can be interpreted as the average value of the characteristic among compliers. Row 2 provides the average characteristics among the full regression sample (compliers, always-, and never-takers). Row 3 provides the average characteristics among the SNAP beneficiaries in the regression sample. Row 4 provides (Row 1)/(Row 2) and standard errors (calculated by the delta method) are in parentheses. Row 5 is a similar calculation but comparing compliers to the beneficiary average, i.e., (Row 1)/(Row 3). Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Effect of SNAP Receipt on Labor Supply – Full Sample

	1st Year		2nd Year		3rd Year		Three-Year Cumulative	
Full Sample (N=$88,543$)								
a) Employment (Baseline Avg.=0.322)								
OLS	-0.010	(0.008)	0.014	(0.009)	0.023***	(0.009)	0.027	(0.023)
WLS	-0.029***	(0.008)	-0.005	(0.009)	0.007	(0.010)	-0.028	(0.024)
IV	0.133	(0.236)	0.184	(0.282)	0.328	(0.291)	0.645	(0.715)
b) Earnings (Baseline Avg.=$1,655$)								
OLS	-925***	(48)	-604***	(68)	-481***	(77)	-2,010***	(172)
WLS	-1,122***	(57)	-789***	(79)	-653***	(89)	-2,564***	(200)
IV	-978	(1,559)	507	(2,171)	1,534	(2,418)	1,064	(5,457)
c) Quarterly Earnings \$1 – \$1999 (Baseline Avg.=0.073)								
OLS	0.092***	(0.005)	0.049***	(0.004)	0.045***	(0.004)	0.186***	(0.010)
WLS	0.094***	(0.005)	0.050***	(0.005)	0.046***	(0.004)	0.191***	(0.011)
IV	0.258*	(0.149)	0.288**	(0.140)	0.361***	(0.133)	0.906***	(0.318)
d) Quarterly Earnings $\geq$ \$2000 (Baseline Avg.=0.250)								
OLS	-0.103***	(0.007)	-0.035***	(0.009)	-0.022***	(0.009)	-0.160***	(0.021)
WLS	-0.124***	(0.008)	-0.056***	(0.009)	-0.039***	(0.010)	-0.219***	(0.023)
IV	-0.121	(0.220)	-0.100	(0.271)	-0.030	(0.279)	-0.251	(0.670)

Notes: This table presents estimates from OLS, complier-weighted OLS (WLS), and IV analogs of Equation (3). Outcomes are calculated as totals over the post-SNAP-application time period specified in the column headers. Specifically, the number of quarters employed (panel (a)), total earnings (b), total number of quarters with earnings between \$1-1999 (c), and number of quarters with earnings above \$1999 (d). Estimates in the "Three-Year Cumulative" column use as the outcome the total over the entire three-year-post-application window. We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01

Table 7: IV Estimates of SNAP Receipt on Labor Supply – Baseline-Employment Subgroups

	1st Year		2nd Year		3rd Year		Three-Year Cumulative	
a) Not Employed Four Quarters Before App. (N=54,218)								
Employment (Baseline Avg.=0.000)	0.239	(0.271)	-0.136	(0.312)	-0.114	(0.311)	-0.012	(0.820)
Earnings (Baseline Avg.=0)	1,237	(1,172)	-1,252	(1,818)	-1,013	(2,014)	-1,028	(4,577)
Quarterly Earnings \$1 – \$1999 (Baseline Avg.=0.000)	0.010	(0.139)	-0.028	(0.127)	-0.009	(0.120)	-0.027	(0.306)
Quarterly Earnings ≥ \$2000 (Baseline Avg.=0.000)	0.224	(0.199)	-0.109	(0.265)	-0.103	(0.270)	0.012	(0.662)
b) Employed Four Quarters Before App. (N=21,817)								
Employment (Baseline Avg.=1.000)	-0.288	(0.460)	0.545	(0.604)	1.393**	(0.694)	1.650	(1.500)
Earnings (Baseline Avg.=5,776)	-6,561	(4,355)	3,076	(5,878)	11,991*	(6,973)	8,506	(14,906)
Quarterly Earnings \$1 – \$1999 (Baseline Avg.=0.152)	0.569	(0.352)	0.954***	(0.361)	0.764**	(0.330)	2.286***	(0.791)
Quarterly Earnings ≥ \$2000 (Baseline Avg.=0.848)	-0.835	(0.546)	-0.396	(0.635)	0.628	(0.680)	-0.603	(1.565)

Notes: This table presents estimates from the IV version of Equation (3). Outcomes are calculated as totals over the post-SNAP-application time period specified in the column headers. Specifically, the number of quarters employed, total earnings, total number of quarters with earnings between $1-1999, and number of quarters with earnings above $1999. Estimates in the "Three-Year Cumulative" column use as the outcome the total over the entire three-year-post-application window. We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application.
* p<0.10, ** p<0.05, *** p<0.01

A Further Data Details

A.1 Caseworker and Decision Assignment

For a given applicant and application date, there can be multiple decisions made. For example, if an applicant is automatically denied because of lack of documentation, but then reapplies within 60 days with the required documentation. In our analysis sample, roughly 10 percent of initial applications are associated with multiple decisions. Additionally, multiple caseworkers can work a single case and this happens to about 4% of applicants in our sample.[22] We address these complications by keeping the final decision related to an initial application, but attribute this decision to the *first-assigned* caseworker. We prefer to use the last decision since it reflects the final outcome. Results are nearly identical if we instead use the first decision on the application or include all decisions.

We use a combination of information to determine whether an application is ultimately approved, which is a key variable in calculating the CCAR. We define an application as being approved if the ending date for the case is later than the starting date, or if the applicant has an accompanying recertification record corresponding with the given initial application date. We also consider applications approved if the applicant receives benefits during either the month of or the month after the initial application date. Otherwise, we consider the application denied.

A.2 UI Earnings Data Details

The UI earnings records only include workers living in the mountain-plains state, but we estimate that 97% of households with SNAP-eligible income don't move across states in a given year in the Current Population Survey, so out-of-state migration is unlikely to be an issue. Additionally, as with all studies that use this type of administrative earnings data, we do not observe workers who are self-employed, federal employees, or independent contractors. While some states further exclude agricultural workers, domestic workers, and workers without sufficient wages and credit weeks from the UI administrative earnings data, the mountain-plains state *includes* these workers in their data. Further, using the Current

[22]This occurs because cases are randomly reassigned due to regular equalizations of work load across caseworkers. Also, when an applicant calls in, the phone system makes *no* attempt to route their call to their original caseworker. As a result, if an applicant calls back after their interview and speaks with a new caseworker, the worker may opt to assign themselves the case. Caseworkers are trained to only assign themselves to the case if they made substantive changes to the case and are willing to take ownership. Caseworkers are often hesitant to do so because the caseworker who submits the case is the one who is penalized if errors are found–even if the errors originated from a previous caseworker.

Population Survey, we tabulate that only 6% of heads of household who are income-eligible for SNAP are self-employed, and among those receiving SNAP, in the QC data, only 1% are self-employed.[23] We assume that individuals who are not observed in the UI data are not working and assign them a value of 0 for their earnings. We do not know whether the applicant was searching for work or was out of the labor force.

B Dynamics of SNAP Receipt

The decrease in the magnitude of the impact of the CCAR over time is consistent with two hypotheses: 1) SNAP benefit spells are on average shorter than three years, so the effect of the CCAR fades out as people stop receiving benefits, or 2) denied applicants re-apply and receive benefits later. We explore whether those who are denied SNAP because of their assigned caseworker re-apply after the initial quarter of application. Overall, rates of reapplication are low among compliers, and we find only a slight (5 percentage point in the first year after application) increase in rates of reapplication for those who are denied SNAP because of their caseworker (Appendix Table A1).[24] So, reapplication and re-timing of benefit receipt is not a primary driver of the dynamics we observe. Note, we cannot look at the effect of the CCAR on the likelihood of reapplying *among those denied* because this would condition on the endogenous variable. Similarly, we do not look at recertification length as an outcome because this is only observed for those who receive SNAP.

Next, we compare the dynamics of benefit receipt for marginal recipients in our analysis, as in Table 3, to the dynamics of benefit receipt for all applicants and those who receive benefits in the quarter of application, regardless of whether they receive benefits due to their assigned caseworker (Appendix Table A2). The levels in these comparison groups will be different than the results we found in Table 3, because they are conditional means rather than the effect of the CCAR, but we are interested in whether the *dynamics* in benefit receipt are the same. We find the pattern of benefit receipt over time is nearly identical across these groups. Many recipients–whether they are pushed to receive SNAP because of their caseworker or not–stop receiving SNAP by the second year, and there are only about 16.5% of applicants that continue to receive SNAP during the third year after initially applying. This pattern is consistent with prior evidence that the median length of SNAP participation

[23] Gig work has become increasingly important since the end of our sample period, especially in and after the COVID-19 pandemic (Maneely and Roth-Eisenberg, 2020). Gig work is also poorly measured in many data sets (Abraham et al., 2023). Additionally, the complex nature of the application process may be particularly costly for those with self-employment income (Moynihan et al., 2022). Future work with more recent data that measures self-employment would help to shed light on this issue.

[24] We explain the layout of this table below at the beginning of section 6.2.

among new entrants is about 12 months, with 26% exiting after 4 months (Leftin et al., 2014). This also suggests the reason the effects of the CCAR fade out over time is that recipients reduce their SNAP participation over time.

C Cross-Program Participation

Other data sources point to a high degree of cross-program participation among SNAP recipients. However, of greatest concern is that *changes* in program participation occur at the same time; that when individuals begin to receive SNAP, they also start receiving benefits from other programs. If this were the case, our IV estimates might be the effects of multiple programs and not just SNAP. We use the Survey of Income and Program Participation (SIPP) to investigate this directly. The SIPP is a panel study that asks individuals about their demographics and receipt of many safety net and social insurance programs.[25] In Appendix Figure A3, we plot the rates of safety net program receipt around SNAP spell initiation. It is clear that households that start receiving SNAP are already receiving benefits from other programs–most commonly Medicaid (short dashed blue line), Free and Reduced Price Lunch (long dashed maroon line) and Breakfast (dotted purple line). Notably, the *change* in program receipt of these other programs in the period the household starts receiving SNAP is relatively small and much smaller than the change in receipt of SNAP. The programs with the most meaningful changes at SNAP initiation are Medicaid and WIC. Medicaid increases by 18 percentage points and WIC increases by 7 percentage points. To understand if changes in these other programs impact labor supply decisions we turn to the prior literature. Recent evidence find mixed evidence of whether Medicaid impacts adult labor supply decisions, with some finding it reduces labor supply and some finding no effects (Baicker et al., 2014; Garthwaite et al., 2014; Kaestner et al., 2017). The literature on the impact of WIC on labor supply is very limited but does suggest that WIC may increase work leave among mothers with newborns (Bullinger and Gurley-Calvez, 2016), but this is a very small fraction of our sample.

D Details of MVPF Calculation

To calculate the change in SNAP benefit amount (WTP) due to a one standard deviation increase in the CCAR, we calculate a version of the model in Table 3 over the entire three year

[25] One drawback of the SIPP is that, as with most major surveys, program receipt is under-reported. As a check, we have adjusted for this under-reporting as suggested by Meyer et al. (2022) and Meyer et al. (2009) and the results are very similar.

period following application. Total additional benefits received are $1,341, so a one standard deviation increase in the CCAR increases benefit amount over three years by $40.

Using statistics from the USDA, the administrative costs of operating SNAP are $261 per year and case in 2012$s.[26] We assume the administrative costs include the costs of certifying and recertifying SNAP recipients. This likely overstates the costs somewhat because part of the initial certification costs have already been paid by the time the caseworker interacts with each application. Our first stage effects on SNAP receipt indicate a total increase of 1.63 quarters of benefit receipt over three years, or 0.05 quarters per one standard deviation in the CCAR (1.63*0.03). Thus, administrative costs increase by $3 for a one standard deviation increase in the CCAR (($261/4)*0.05). Total direct costs are thus $40 + 3 = 43$ for both the increase in benefits paid out and administrative costs.

Finally, turning to fiscal externalities, we take the IV cumulative three-year estimate on quarterly earnings as the outcome variable. The total change in earnings for the full sample over three years is an increase of $1,064. So, a one standard deviation increase in the CCAR increases earnings by $31.92 over the following three years.

We then calculate the tax rate on earnings for this group. The average working SNAP recipient is a single adult earning $23,104 in the year before applying for SNAP (from Table 1). Applying the 2012 tax rules, the standard deduction is $5,950, so taxable income is $17,154. Head of households are taxed 10% on the first $12,400 of income and then 15% on the remaining $4,754. Additionally, they are subject to a payroll tax of 4.2% and the SNAP benefit amount is reduced by 24% as earnings increase. Thus, the average tax rate for this group is $24 + 4.2 + (10 * (12400/17154) + (15 * 4754/17154) = 40\%$. Multiplying the change in earnings due to a one standard deviation increase in the CCAR by this tax rate, the increase in government revenue is $13.

Combining all these estimates, the MVPF is 1.3 $(40/(43 - 13))$.

[26] https://fns-prod.azureedge.us/sites/default/files/media/file/SNAP-State-Variation-Admin-Costs-FullRe
pdf

Figure A1: SNAP Application Form

HOUSEHOLD AND GENERAL INFORMATION

4. List everyone who is living in your household and applying for benefits:

First and Last Name	Social Security #[1]	Birth Date	U.S. Citizen/ Eligible Non-Citizen Yes/No	Gender M / F	Relationship	[redacted] Resident Yes/No	Resident Since[2] (ex: 07/14/13)	Race[3, 6]	Ethnicity[4, 6]	Marital Status[5]
					Self					

22. Does anyone in your household receive any of the following types of income? .... ☐ Yes ☐ No
If yes, complete all columns:

	Type	Recipient's Name	Gross (before deductions) Amount Received	How Often Paid? (ex: weekly, monthly)	Date Income Started
☐	Social Security		$		
☐	SSI		$		
☐	Child Support received directly from parent or another state		$		
☐	Child Support received through ORS		$		
☐	Unemployment State:		$		
☐	Money received from family, friends or church From who?		$		
☐	Retirement		$		
☐	Pension		$		
☐	Alimony		$		
☐	Veteran's Benefits		$		
☐	Workers Compensation		$		
☐	Tribal Income		$		
☐	Lump Sum Payments		$		
☐	Other income (ex: Adoption, Mineral Rights, Rental, Royalty, Child and Adult Care Food Program payments etc.): ____________		$		

Other than taxes, are any deductions being withheld from anyone's income listed? .... ☐ Yes ☐ No
If yes, complete the following information:

Name: ____________________ Type of Deduction: ____________ Deduction amount: $ ________

Name: ____________________ Type of Deduction: ____________ Deduction amount: $ ________

24. Does anyone in your household have financial accounts? .... ☐ Yes ☐ No
If yes, list all accounts owned by you or anyone applying with you. Some examples of financial accounts are Checking, Savings, 401K*, IRA*, Annuities, Money Market, Stocks/Bonds/Mutual Funds, etc.
** Not Required for SNAP*

Type	Account Owner(s)	Bank Name	Account Balance	Date Opened
			$	
			$	
			$	
			$	

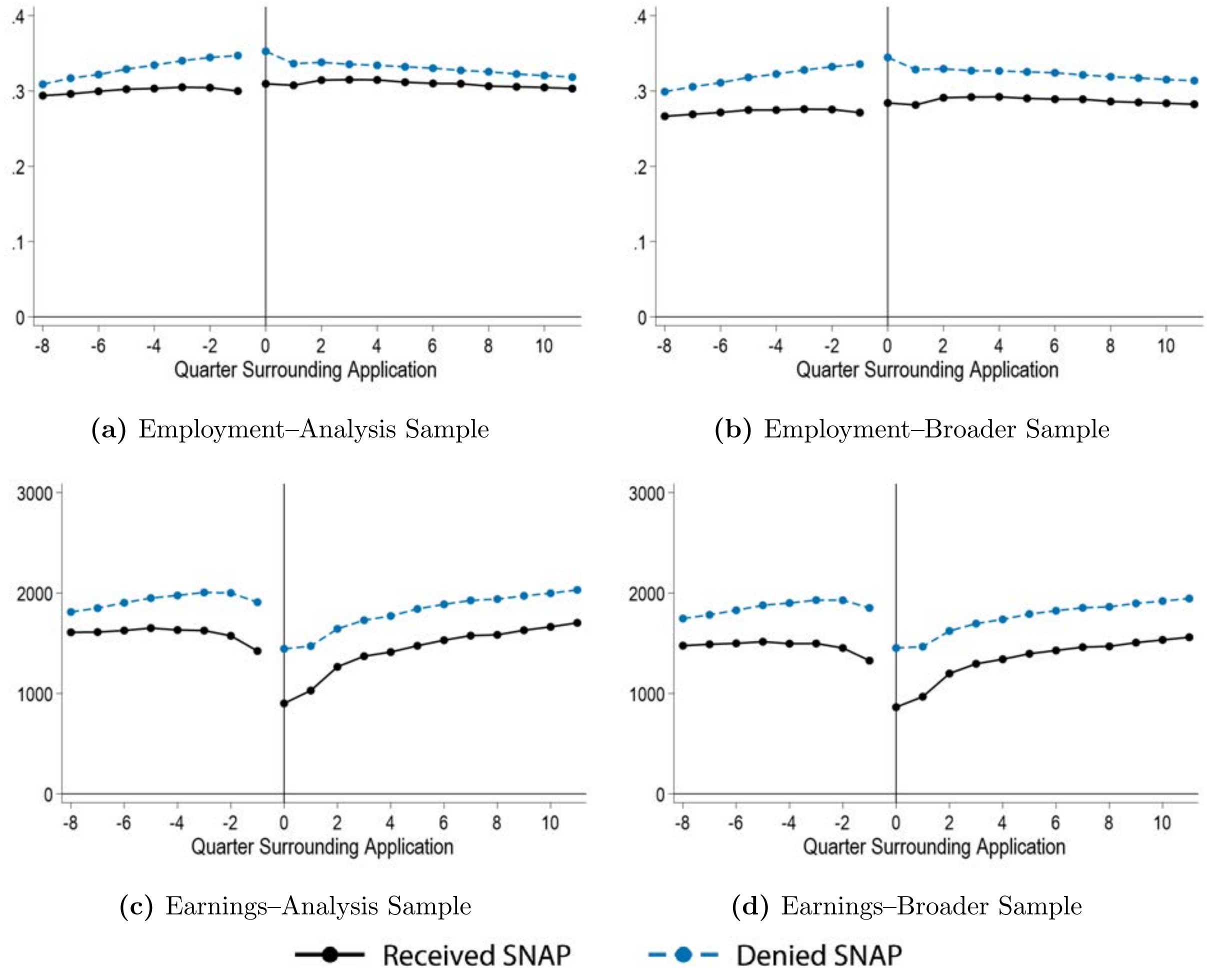
25. Does anyone in your household have any vehicles? .... ☐ Yes ☐ No
If yes, complete all columns. Some examples of vehicles are cars, trucks, boats or water craft, motorcycles, snowmobiles, motor homes, ATV's, etc.

Registered Owner(s)	Make	Model	Year	Licensed	State	Amount Owed	Vehicle Use	Date of Purchase
				☐ Yes ☐ No		$		
				☐ Yes ☐ No		$		
				☐ Yes ☐ No		$		

26. Does anyone in your household have any of the following property assets? .... ☐ Yes ☐ No
If yes, complete all columns:

	Type	Who Owns This?	Fair Market Value	Amount Owed	Date Acquired
☐	Home		$	$	
☐	Other property (ex: Land, rental home, vacation home/time share, mineral/other rights, etc.): ____________		$	$	
☐	Trailers		$	$	
☐	Other (ex: equipment/tools, machinery, livestock, etc.): ____________		$	$	

Figure A2: Differences in Quarterly Labor Supply by SNAP Receipt at $t = 0$ – Analysis Sample and Broader Sample Comparisons



(a) Employment–Analysis Sample

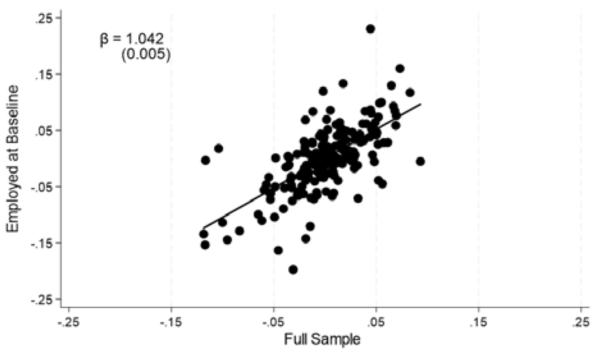
(b) Employment–Broader Sample

(c) Earnings–Analysis Sample

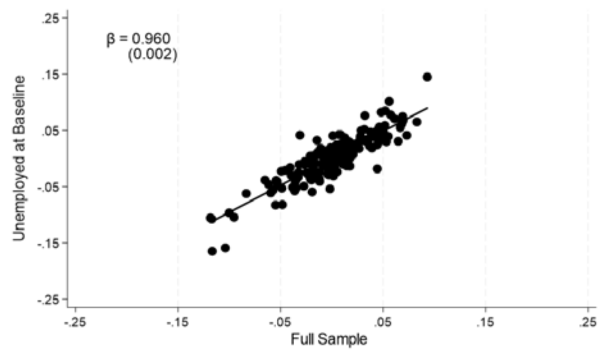
(d) Earnings–Broader Sample

Notes: These figures show the results from running separate regressions for the given event time of the outcome. We regress the given outcome in the given period on whether the applicant received SNAP during period 0 along with application date fixed effects. The blue dashed line is the coefficient on the constant from those regressions and the black solid line is the coefficient on the SNAP indicator added to the constant coefficient. The left column presents results from the main analysis sample, while the right column presents results from the broader sample, described in detail in the text.

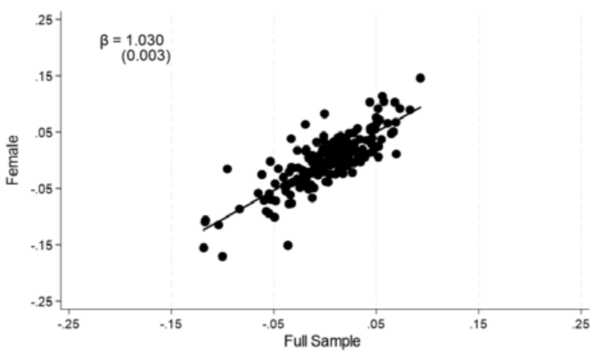
Figure A3: Group-Specific CCAR vs General CCAR



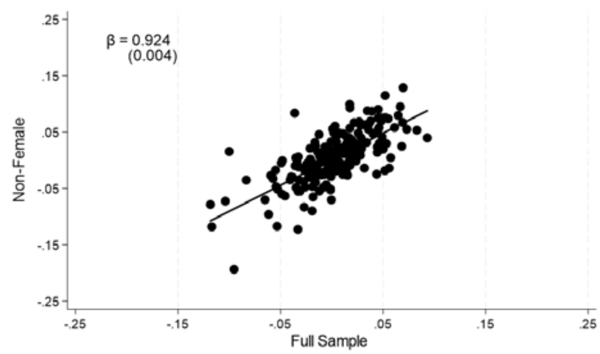
(a) Employed at Baseline



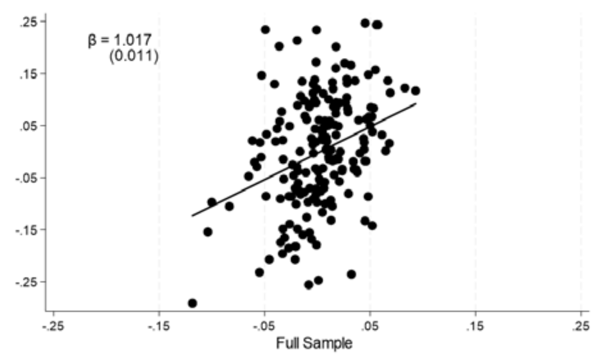
(b) Not Employed at Baseline



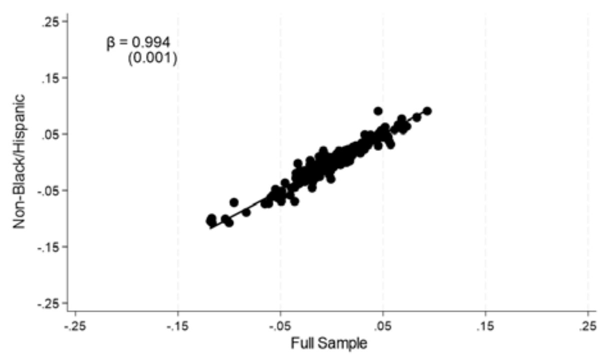
(c) Female



(d) Non-Female



(e) Black/Hispanic



(f) Non-Black/Hispanic

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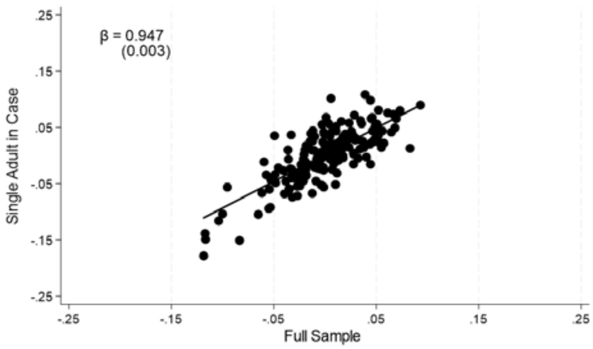
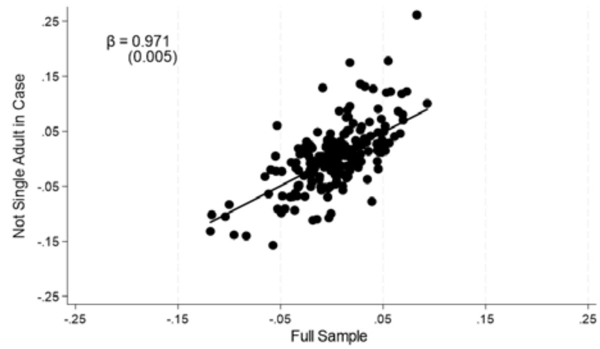
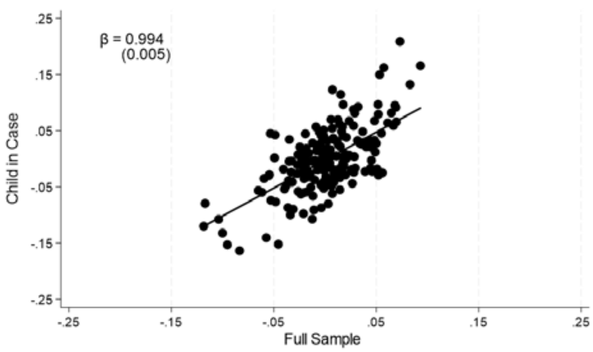
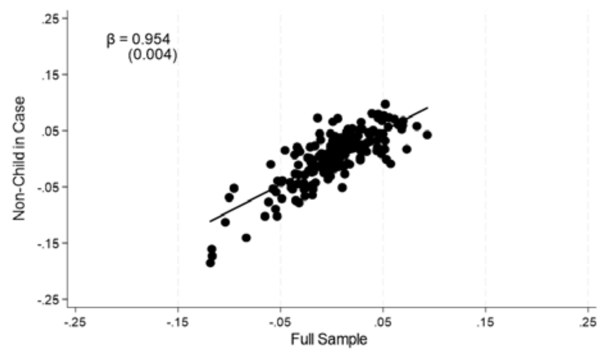




(d) One Adult in Case

(e) Non-One Adult in Case



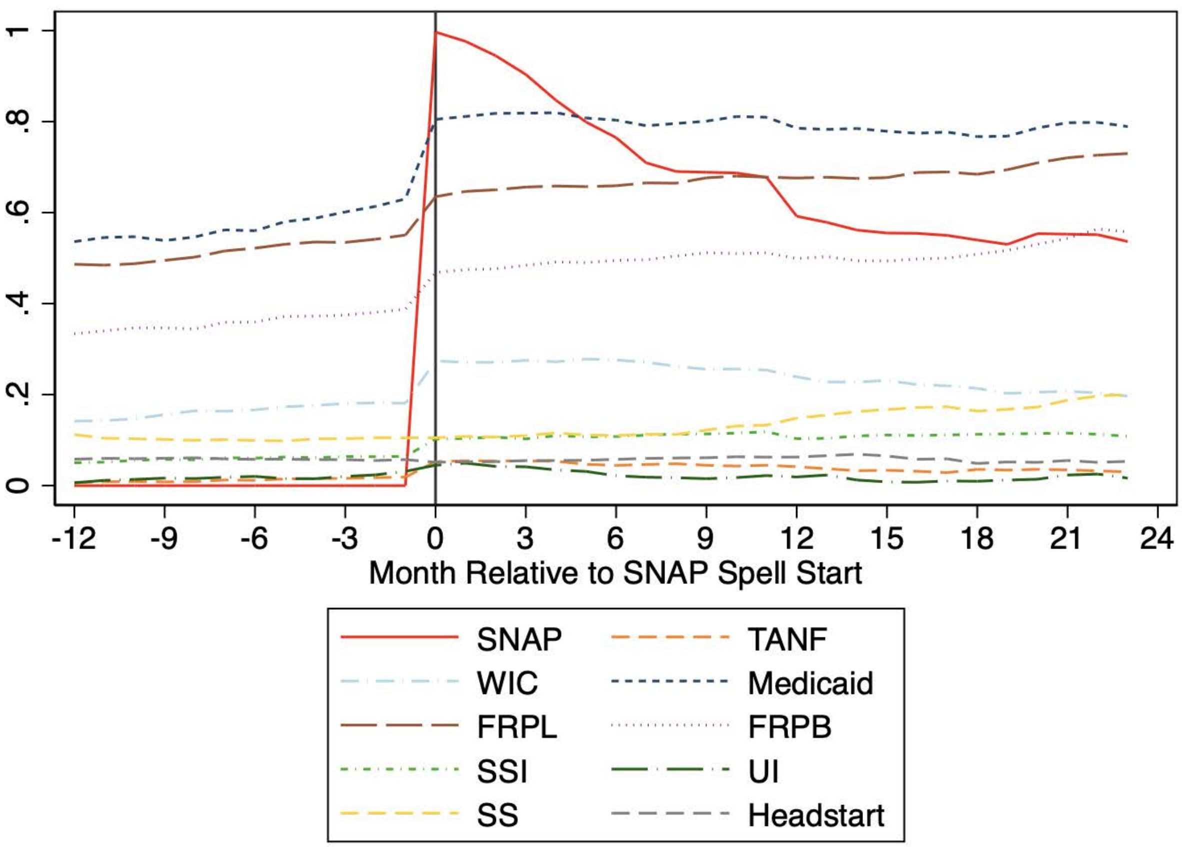


(f) Child in Case

(g) Childless Case

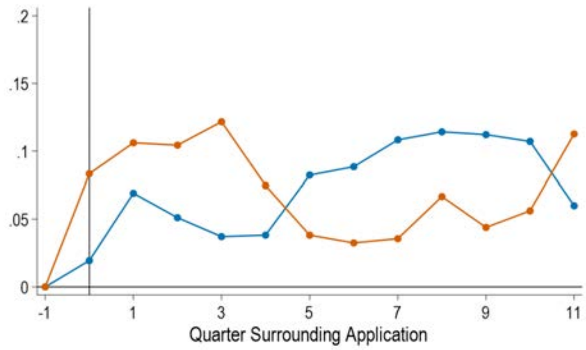
Notes: Each figure plots the CCAR for the specified subgroup (vertical axis) against the full-sample CCAR (horizontal axis). OLS estimates of the relationship between the two are displayed in the figure. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. Code adapted from Dobbie et al. (2018).

Figure A3: Cross-Program Participation Around First SNAP Spell

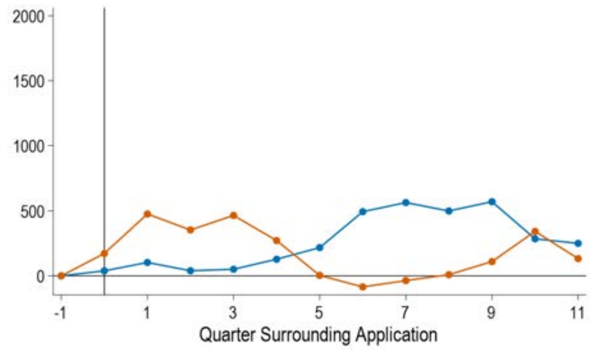


Notes: This figure plots the average household-level program receipt in the 2014 Survey of Income and Program Participation. We focus on households with heads who are ages 18-64 and who we observe transitioning from not receiving SNAP to receiving SNAP for the first time in the survey period. We weight observations using the SIPP-provided person weight in the month of SNAP participation initiation.

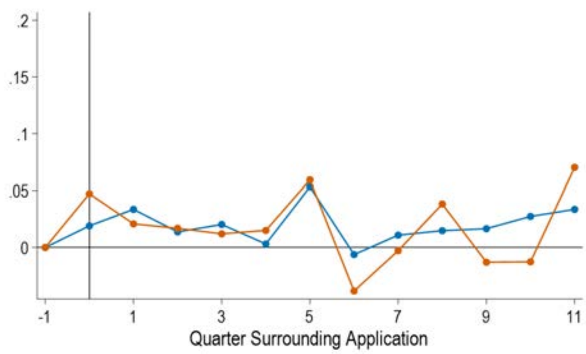
Figure A4: Decomposing IV Estimates into Potential Outcomes, Not Employed Year Before Application



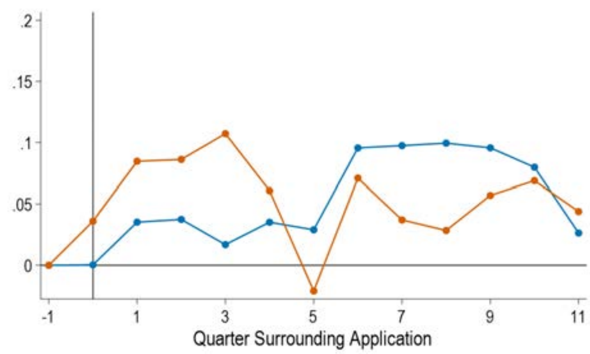
(a) Employment



(b) Earnings



(c) Quarterly Earnings \$1 – \$1999



(d) Quarterly Earnings ≥ \$2000

Notes: These figures depict the potential outcomes in the state of the world that complier applicants are either approved or denied SNAP due to their caseworker's CCAR. Section 6 details the method. We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. The blue line plots the potential outcomes for untreated compliers (i.e., the state of the world where compliers are denied SNAP) and the orange line plots the potential outcomes for treated compliers (i.e., the state of the world where compliers receive SNAP).

Table A1: Effect of SNAP Receipt on (Re)Application – Full Sample

	1st Year	2nd Year	3rd Year	Three-Year Cumulative
Full Sample (N=88,543)				
Whether Submitted (Re)Application (Baseline Avg.=0.000)				
OLS	-0.026*** (0.001)	0.028*** (0.001)	0.021*** (0.001)	0.008*** (0.001)
WLS	-0.026*** (0.001)	0.028*** (0.001)	0.021*** (0.001)	0.008*** (0.001)
IV	-0.051** (0.026)	0.028 (0.027)	0.083*** (0.024)	0.020 (0.017)

Notes: This table presents estimates from OLS, complier-weighted OLS (WLS), and IV analogs of equation (3). Outcomes are whether the any re-applications were submitted during the year specified in the column headers. Estimates in the "Three-Year Cumulative" column use as the outcome whether the case reapplied any time over the three-year-post-application window. We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01

Table A2: Average Benefit Receipt for All Applicants and Initial Recipients

	Quarter of Application	1st Year	2nd Year	3rd Year
Any Benefit Receipt				
All Applicants ($N = 88,543$)	0.298***	0.387***	0.122***	0.075***
	(0.012)	(0.012)	(0.011)	(0.010)
Recipients at Quarter 0 ($N = 46,241$)	1.000***	1.000***	0.255***	0.165***
	(0.000)	(0.000)	(0.018)	(0.016)

Notes: The outcome for this table is an indicator that equals one if the applicant receives SNAP during the time period specified in the column header. Each cell in this table presents, for the given time period, the average benefit receipt among all applicants (row 1) or among all applicants who initially receive SNAP (row 2). Each average is the coefficient on the constant term of a regression of any benefit receipt on the full set of controls from equation (3) and application-date fixed effects for the given sample. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01

Table A3: Explanatory Power of Caseworker Demographics and Caseworker Teams for the CCAR

	Monthly Caseworker Caseload	# Months of Caseworker Experience	Team FE	Caseload, # Months & Team FE
Panel a) Correlation Between CCAR and Column Outcome				
CCAR	164***	-13.981***		
	(3)	(0.908)		
Mean Y	247	34.628		
Panel b) Variation of CCAR Explainied by Column Outcome				
Adjusted R^2	0.029	0.004	0.082	0.098

Notes: Panel (a) shows the results from regressing the given caseworker characteristics in the column header onto the CCAR and application-date fixed effects. Panel (b) provides the Adjusted R^2 from regressing the CCAR onto the given caseworker characteristic listed in the column header. The "Combined" column regresses the CCAR on to all the caseworker characteristics from columns (1)-(3).

Table A4: Effect of CCAR on SNAP Receipt – Various Sub-Groups

	Quarter of App.	1st Year	2nd Year	3rd Year
a) Any Benefit Receipt				
Employed Four Quarters Before App.	0.393*** (0.075)	0.290*** (0.075)	0.134** (0.068)	0.124** (0.061)
Not Employed Four Quarters Before App.	0.320*** (0.047)	0.279*** (0.046)	0.120*** (0.043)	0.123*** (0.039)
Female Head	0.401*** (0.049)	0.311*** (0.048)	0.105** (0.048)	0.107*** (0.044)
Male Head	0.241*** (0.054)	0.189*** (0.054)	0.104** (0.047)	0.106*** (0.040)
One Adult in HH	0.247*** (0.050)	0.201*** (0.049)	0.052 (0.046)	0.114*** (0.042)
Not One Adult in HH	0.441*** (0.072)	0.317*** (0.071)	0.163*** (0.067)	0.054 (0.061)
ABAWD	0.286*** (0.059)	0.218*** (0.058)	-0.023 (0.052)	0.044 (0.047)
Non-ABAWD	0.362*** (0.046)	0.292*** (0.045)	0.169*** (0.044)	0.152*** (0.040)
Children	0.453*** (0.068)	0.336*** (0.067)	0.185*** (0.065)	0.125** (0.060)
No Children	0.241*** (0.052)	0.190*** (0.051)	0.033 (0.046)	0.076* (0.042)
Black/Hispanic	0.381*** (0.132)	0.283** (0.128)	0.130 (0.124)	0.339*** (0.114)
Non-Black/Hispanic	0.331*** (0.038)	0.266*** (0.037)	0.111*** (0.035)	0.098*** (0.031)
b) Total Real Benefit Amount				
Employed Four Quarters Before App.	219.8*** (53.3)	640.5*** (186.1)	529.3*** (179.7)	409.4*** (160.8)
Not Employed Four Quarters Before App.	198.4*** (36.6)	720.5*** (136.0)	349.2*** (128.4)	259.3** (113.5)
Female Head	235.6*** (41.0)	861.4*** (153.7)	415.2*** (150.1)	442.1*** (136.6)
Male Head	168.0*** (35.4)	404.6*** (120.0)	265.0*** (106.0)	21.9 (87.8)
One Adult in HH	145.4*** (35.4)	530.9*** (126.8)	210.8* (120.0)	300.5*** (107.3)
Not One Adult in HH	321.3*** (65.1)	927.1*** (240.9)	503.9** (229.4)	203.7 (199.2)
ABAWD	156.3*** (36.5)	442.7*** (124.1)	-88.6 (120.5)	65.9 (110.3)
Non-ABAWD	220.1*** (37.7)	706.2*** (138.8)	558.8*** (133.4)	355.5*** (118.7)
Children	350.2*** (66.1)	1,148.2*** (244.3)	746.5*** (235.9)	486.9*** (206.3)
No Children	127.7*** (31.3)	390.1*** (107.6)	5.4 (102.5)	135.5 (93.2)
Black/Hispanic	171.5* (100.0)	605.8* (366.5)	406.6 (357.6)	385.5 (330.1)
Non-Black/Hispanic	209.4*** (28.7)	684.1*** (104.6)	360.1*** (99.1)	249.8*** (87.9)

Notes: This tables shows the results from the first stage of the IV model from Equation (4) for the subgroups listed in the row headers. Outcomes include an indicator that equals one if the applicant receives SNAP during any of the months during the window of time specified in the column header (panel (a)) or the total real SNAP benefit dollars received over the given period (panel (b)).

Table A5: Specification Sensitivity Checks for Full Sample

	1st Year		2nd Year		3rd Year		Three-Year Cumulative	
a) Main Specification (N=88,543)								
Employment	0.133	(0.236)	0.184	(0.282)	0.328	(0.291)	0.645	(0.715)
Earnings	-978	(1,559)	507	(2,171)	1,534	(2,418)	1,064	(5,457)
Quarterly Earnings \$1 – \$1999	0.258*	(0.149)	0.288**	(0.140)	0.361***	(0.133)	0.906***	(0.318)
Quarterly Earnings $\geq$ \$2000	-0.121	(0.220)	-0.100	(0.271)	-0.030	(0.279)	-0.251	(0.670)
b) No Demog./Labor Supply Controls (N=88,543)								
Employment	-0.048	(0.364)	0.036	(0.380)	0.209	(0.382)	0.197	(1.055)
Earnings	-2,180	(2,175)	-813	(2,752)	343	(3,001)	-2,650	(7,378)
Quarterly Earnings \$1 – \$1999	0.268	(0.171)	0.304**	(0.150)	0.376***	(0.140)	0.949***	(0.365)
Quarterly Earnings $\geq$ \$2000	-0.313	(0.311)	-0.264	(0.348)	-0.164	(0.353)	-0.741	(0.934)
c) 5th/95th ptile IV Trimming (N=79,687)								
Employment	0.273	(0.302)	0.253	(0.358)	0.417	(0.373)	0.944	(0.911)
Earnings	1,128	(1,990)	2,417	(2,786)	2,255	(3,105)	5,800	(6,993)
Quarterly Earnings \$1 – \$1999	0.240	(0.189)	0.176	(0.176)	0.391**	(0.169)	0.807**	(0.401)
Quarterly Earnings $\geq$ \$2000	0.037	(0.282)	0.082	(0.344)	0.032	(0.356)	0.152	(0.853)
d) No IV Trimming (N=90,347)								
Employment	0.099	(0.212)	0.094	(0.253)	0.169	(0.261)	0.362	(0.640)
Earnings	-1,599	(1,406)	-1,342	(1,954)	-1,154	(2,174)	-4,095	(4,916)
Quarterly Earnings \$1 – \$1999	0.293**	(0.135)	0.343***	(0.127)	0.398***	(0.118)	1.034***	(0.287)
Quarterly Earnings $\geq$ \$2000	-0.194	(0.198)	-0.246	(0.244)	-0.227	(0.253)	-0.667	(0.603)
e) 10 ptile # Decisions Trimming (N=94,690)								
Employment	0.230	(0.191)	0.267	(0.227)	0.363	(0.234)	0.860	(0.576)
Earnings	-1,217	(1,255)	-314	(1,756)	-130	(1,957)	-1,660	(4,418)
Quarterly Earnings \$1 – \$1999	0.344***	(0.121)	0.323***	(0.113)	0.388***	(0.107)	1.055***	(0.260)
Quarterly Earnings $\geq$ \$2000	-0.110	(0.177)	-0.053	(0.218)	-0.024	(0.224)	-0.187	(0.539)
f) 30 ptile # Decisions Trimming (N=80,677)								
Employment	0.186	(0.286)	0.202	(0.340)	0.351	(0.351)	0.738	(0.863)
Earnings	-5	(1,886)	1,455	(2,626)	2,009	(2,918)	3,458	(6,596)
Quarterly Earnings \$1 – \$1999	0.202	(0.179)	0.174	(0.168)	0.333**	(0.159)	0.709*	(0.379)
Quarterly Earnings $\geq$ \$2000	-0.010	(0.266)	0.031	(0.326)	0.023	(0.336)	0.044	(0.805)

Notes: This table shows the results from the IV model in Equation (3) instrumenting with the CCAR. The "Main Specification" uses our primary sample and controls. "No Demog./Labor Supply Controls" drop the baseline demographic and labor supply controls. "5th/95th ptile IV Trimming" includes applications that were assigned CCAR values within the 5th to 95th percetile. "No IV Trimming" does not restrict the sample based on the CCAR values. "XX ptile # Decisions Trimming" changes the percentile cutoff for the minimum number of caseworker decisions per year in order for us to keep the caseworker and associated decisions in the sample.

Table A6: Specification Sensitivity Checks for Baseline-Not-Employed Sample

	1st Year	2nd Year	3rd Year	Three-Year Cumulative
a) Main Specification (N=54,218)				
Employment	0.239 (0.271)	-0.136 (0.312)	-0.114 (0.311)	-0.012 (0.820)
Earnings	1,237 (1,172)	-1,252 (1,818)	-1,013 (2,014)	-1,028 (4,577)
Quarterly Earnings \$1 – \$1999	0.010 (0.139)	-0.028 (0.127)	-0.009 (0.120)	-0.027 (0.306)
Quarterly Earnings $\geq$ \$2000	0.224 (0.199)	-0.109 (0.265)	-0.103 (0.270)	0.012 (0.662)
b) No Demog./Labor Supply Controls (N=54,218)				
Employment	0.242 (0.276)	-0.119 (0.318)	-0.087 (0.316)	0.036 (0.835)
Earnings	1,141 (1,182)	-1,347 (1,848)	-1,060 (2,042)	-1,266 (4,651)
Quarterly Earnings \$1 – \$1999	0.026 (0.141)	-0.011 (0.128)	0.007 (0.121)	0.022 (0.310)
Quarterly Earnings $\geq$ \$2000	0.212 (0.200)	-0.109 (0.269)	-0.093 (0.274)	0.010 (0.672)
c) 5th/95th ptile IV Trimming (N=48,775)				
Employment	0.259 (0.342)	0.061 (0.389)	-0.097 (0.393)	0.223 (1.027)
Earnings	1,233 (1,465)	-1,339 (2,313)	-2,576 (2,624)	-2,683 (5,834)
Quarterly Earnings \$1 – \$1999	0.068 (0.174)	0.143 (0.159)	0.099 (0.148)	0.310 (0.380)
Quarterly Earnings $\geq$ \$2000	0.188 (0.251)	-0.080 (0.334)	-0.194 (0.345)	-0.085 (0.838)
d) No IV Trimming (N=55,325)				
Employment	0.189 (0.247)	-0.145 (0.283)	-0.138 (0.285)	-0.094 (0.746)
Earnings	623 (1,071)	-2,125 (1,715)	-2,058 (1,899)	-3,560 (4,278)
Quarterly Earnings \$1 – \$1999	0.049 (0.128)	0.058 (0.116)	0.029 (0.110)	0.136 (0.278)
Quarterly Earnings $\geq$ \$2000	0.133 (0.179)	-0.204 (0.241)	-0.166 (0.249)	-0.237 (0.602)
e) 10 ptile # Decisions Trimming (N=58,092)				
Employment	0.408* (0.211)	0.182 (0.237)	0.240 (0.238)	0.830 (0.629)
Earnings	1,681* (915)	318 (1,382)	811 (1,546)	2,810 (3,515)
Quarterly Earnings \$1 – \$1999	0.125 (0.106)	0.061 (0.097)	0.096 (0.091)	0.282 (0.233)
Quarterly Earnings $\geq$ \$2000	0.281* (0.154)	0.120 (0.202)	0.144 (0.207)	0.545 (0.508)
f) 30 ptile # Decisions Trimming (N=49,334)				
Employment	0.186 (0.341)	-0.299 (0.397)	-0.333 (0.397)	-0.446 (1.037)
Earnings	1,321 (1,474)	-1,479 (2,285)	-1,584 (2,535)	-1,742 (5,740)
Quarterly Earnings \$1 – \$1999	-0.044 (0.176)	-0.157 (0.164)	-0.090 (0.153)	-0.291 (0.394)
Quarterly Earnings $\geq$ \$2000	0.226 (0.250)	-0.146 (0.333)	-0.240 (0.343)	-0.160 (0.830)

Notes: This table shows the results from the IV model in Equation (3) instrumenting with the CCAR. The "Main Specification" uses our primary sample and controls. "No Demog./Labor Supply Controls" drop the baseline demographic and labor supply controls. "5th/95th ptile IV Trimming" includes applications that were assigned CCAR values within the 5th to 95th percetile. "No IV Trimming" does not restrict the sample based on the CCAR values. "XX ptile # Decisions Trimming" changes the percentile cutoff for the minimum number of caseworker decisions per year in order for us to keep the caseworker and associated decisions in the sample.

Table A7: Specification Sensitivity Checks for Baseline-Employed Sample

	1st Year		2nd Year		3rd Year		Three-Year Cumulative	
a) Main Specification (N=21,817)								
Employment	-0.288	(0.460)	0.545	(0.604)	1.393**	(0.694)	1.650	(1.500)
Earnings	-6,561	(4,355)	3,076	(5,878)	11,991*	(6,973)	8,506	(14,906)
Quarterly Earnings \$1 – \$1999	0.569	(0.352)	0.954***	(0.361)	0.764**	(0.330)	2.286***	(0.791)
Quarterly Earnings $\geq$ \$2000	-0.835	(0.546)	-0.396	(0.635)	0.628	(0.680)	-0.603	(1.565)
b) No Demog./Labor Supply Controls (N=21,817)								
Employment	-0.244	(0.459)	0.568	(0.597)	1.367**	(0.681)	1.692	(1.493)
Earnings	-6,236	(4,854)	3,003	(6,309)	11,566	(7,354)	8,334	(16,534)
Quarterly Earnings \$1 – \$1999	0.606*	(0.367)	0.937***	(0.358)	0.729**	(0.323)	2.272***	(0.814)
Quarterly Earnings $\geq$ \$2000	-0.829	(0.556)	-0.356	(0.627)	0.636	(0.672)	-0.549	(1.574)
c) 5th/95th ptile IV Trimming (N=19,637)								
Employment	-0.071	(0.645)	0.662	(0.851)	2.377**	(1.114)	2.969	(2.221)
Earnings	605	(6,177)	12,707	(9,004)	25,355**	(11,642)	38,667	(23,895)
Quarterly Earnings \$1 – \$1999	0.274	(0.481)	0.457	(0.463)	0.920*	(0.486)	1.652	(1.052)
Quarterly Earnings $\geq$ \$2000	-0.319	(0.761)	0.217	(0.895)	1.458	(1.027)	1.357	(2.272)
d) No IV Trimming (N=22,271)								
Employment	-0.262	(0.402)	0.412	(0.529)	0.896	(0.580)	1.047	(1.290)
Earnings	-6,660*	(3,831)	1,915	(5,111)	6,560	(5,785)	1,815	(12,850)
Quarterly Earnings \$1 – \$1999	0.507*	(0.307)	0.735***	(0.301)	0.723***	(0.283)	1.966***	(0.665)
Quarterly Earnings $\geq$ \$2000	-0.758	(0.478)	-0.313	(0.558)	0.173	(0.583)	-0.899	(1.371)
e) 10 ptile # Decisions Trimming (N=23,334)								
Employment	-0.543	(0.394)	0.019	(0.503)	0.663	(0.552)	0.139	(1.229)
Earnings	-9,788***	(3,832)	-4,106	(4,974)	994	(5,553)	-12,900	(12,530)
Quarterly Earnings \$1 – \$1999	0.646**	(0.307)	0.939***	(0.311)	0.788***	(0.287)	2.374***	(0.695)
Quarterly Earnings $\geq$ \$2000	-1.174***	(0.478)	-0.911*	(0.552)	-0.128	(0.565)	-2.213	(1.355)
f) 30 ptile # Decisions Trimming (N=19,840)								
Employment	0.103	(0.540)	0.954	(0.723)	2.100***	(0.878)	3.157*	(1.855)
Earnings	-1,862	(4,998)	8,116	(7,093)	18,657**	(8,714)	24,911	(18,367)
Quarterly Earnings \$1 – \$1999	0.283	(0.394)	0.820**	(0.403)	0.657*	(0.371)	1.760**	(0.860)
Quarterly Earnings $\geq$ \$2000	-0.149	(0.626)	0.145	(0.736)	1.442*	(0.844)	1.438	(1.876)

Notes: This table shows the results from the IV model in Equation (3) instrumenting with the CCAR. The "Main Specification" uses our primary sample and controls. "No Demog./Labor Supply Controls" drop the baseline demographic and labor supply controls. "5th/95th ptile IV Trimming" includes applications that were assigned CCAR values within the 5th to 95th percetile. "No IV Trimming" does not restrict the sample based on the CCAR values. "XX ptile # Decisions Trimming" changes the percentile cutoff for the minimum number of caseworker decisions per year in order for us to keep the caseworker and associated decisions in the sample.

Table A8: IV Estimates of Effect of SNAP Receipt on Employment and Earnings– Single Adult Households

	1st Year		2nd Year		3rd Year		Three-Year Cumulative	
a) Quarterly Employment								
Full Sample	0.133	(0.236)	0.184	(0.282)	0.328	(0.291)	0.645	(0.715)
One Adult in HH	0.024	(0.466)	-0.301	(0.553)	0.492	(0.572)	0.214	(1.394)
b) Quarterly Earnings								
Full Sample	-978	(1,559)	507	(2,171)	1,534	(2,418)	1,064	(5,457)
One Adult in HH	-1,104	(2,873)	1,694	(4,051)	3,251	(4,540)	3,841	(10,204)
c) Quarterly Earnings \$1 – \$1999								
Full Sample	0.258*	(0.149)	0.288**	(0.140)	0.361***	(0.133)	0.906***	(0.318)
One Adult in HH	0.218	(0.291)	0.116	(0.268)	0.471*	(0.267)	0.805	(0.613)
d) Quarterly Earnings $\geq$ \$2000								
Full Sample	-0.121	(0.220)	-0.100	(0.271)	-0.030	(0.279)	-0.251	(0.670)
One Adult in HH	-0.199	(0.435)	-0.405	(0.536)	0.038	(0.544)	-0.566	(1.312)

Notes: This table presents IV estimates from Equation (3). Outcomes are calculated as totals over the post-SNAP-application time period specified in the column headers. Specifically, the number of quarters employed (panel (a)), total earnings (b), total number of quarters with earnings between \$1-1999 (c), and number of quarters with earnings above \$1999 (d). Estimates in the "Three-Year Cumulative" column use as the outcome the total over the entire three-year-post-application window. We include the baseline employment and demographic controls specified in equation (3) as well as application-date fixed effects. Our sample includes new applications between 2012-2016 who apply in the General track. We exclude applicants assigned to caseworkers who handled fewer than the 20th percentile of applications that year as well as applicants who have extreme CCAR values. We further restrict to applications for whom we observe outcomes for at least one year prior and three years following the given SNAP application. * p<0.10, ** p<0.05, *** p<0.01