Technical Appendix: Does GAIN increase the self-sufficiency of CalWORKs families in Los Angeles?

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TABLE OF CONTENTS

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A. Data details

Here we describe details of the data received from DPSS for the study.

CalSAWS

The California Statewide Automated Welfare System (CalSAWS) is the system of record for the administration of CalWORKs, GAIN, CalFresh, and other social service programs in the state. Although this is a live system that changes daily, DPSS creates a snapshot of records in a data warehouse on the last day of each month. This allows for changes in case records to be observed over time. These data include demographic and family characteristics of each person on each case; the application history for CalWORKs and CalFresh in Los Angeles; the GAIN activities that participants are referred to and engage with; the issuances they receive from both CalWORKs and CalFresh; GAIN work requirements and exemptions; participants' reported employment and income while enrolled in the program; and sanctions for not completing requirements; amongst other details.[1] The following sections provide more details on the various types of data we relied on to conduct this study.

Demographics. The demographic and family information is self-reported for everyone in the case/family at the time of application and includes race/ethnicity, gender, age, address, marital/relationship status, number and age of children, disability status, and language fluency. The data also contain economic characteristics such as self-reported income and employment before entry, and include other socioeconomic status markers that are used in the study such as whether they have a cell phone, an email address, or a driver's license. There is an indicator of whether the participant listed a DPSS office as their address — which is viewed as a proxy for experiencing homelessness or housing instability. Finally, there are important variables that exist, but we intentionally do not include in our analysis because of variation in data collection. For example, we would like to include the highest-level of education completed at the time of enrollment in the analyses, but it is highly missing for the analysis population. Specifically, the education value is NULL for 48% of first-time CalWORKs + GAIN participants and 72% of first-time CalFresh-only participants.

Program participation and activities. The program and activity data include the administrative documentation of each person's program participation. Specifically, it includes the date a case was opened and the dates when people associated with the case were enrolled. The GAIN activity data documents the activities each person was referred to, whether they engaged with the activity, and whether they completed it. These activities include appraisals, counseling, employment, subsidized employment, education, training, and other services.

Issuances. The issuance data documents all the payments that were either made to the participant or to a vendor on behalf of the participant. The payments made directly to the participants include payments made through CalWORKs and CalFresh. The records also include payments made to vendors for the GAIN program, but do not link payments to individual vendors.

[1] These social service programs are statewide, but are administered by each county. We only have access to records from DPSS in Los Angeles and cannot observe whether an individual participated in any of these programs from another county.

Workforce mandates and exemptions. For GAIN participants, there is also a Work Registration table that identifies which participants are mandated to participate in GAIN workforce activities. The records also include who was exempt, the reason why they were exempt, and how long they were exempt for. Reasons for exemption include caregiving (of children or adults), pregnancy, disability, and age (if they are too young or too old).

Income and employment. While participants are enrolled in the program, GAIN participants are required to report income and the type of employment they have. The types of employment people report can include regular unsubsidized employment, subsidized work, apprenticeships, and self-employment. After participants leave the program they stop reporting employment and income, so we do not use this data for research to measure outcomes, instead we use the employer-reported data.

Sanctions. Sanctions data capture whether a GAIN participant is subject to a reduction in their CalWORKs benefit amounts based on an individual not complying with program rules. These generally occur when participants are not exempt from GAIN workforce participation requirements and they do not complete assigned activities. The data only include whether a person was sanctioned and for how long, but does not include information on why they were sanctioned.

Administrative earnings records from the Employment Development Department
Quarterly employment and earnings records for participants were obtained from the Unemployment Insurance (UI) Base Wage File. These files are maintained by the Employment Development Department (EDD) and include employer-reported earnings for all employees covered by the state's UI system, which is estimated to cover 82% of employment positions (Alamo, 2022). These records were linked to records from CalSAWS at the state level before being delivered to DPSS, who in turn delivered the anonymized data to the study team for analysis. The records include quarterly earnings for each of their reporting employers in any quarter. In addition, EDD provided employer-level details on industry and total wages paid by quarter. The data covers at least 6 quarters before any individual in the study enrolled in a program (either CalFresh or CalWORKs), and at least 4 full years after the enrollment quarter.[2]

Administrative earnings records are frequently used to measure the employment and earnings outcomes of job training programs, but they come with a set of limitations. Because these records are collected as part of California's UI system, they do not include self-employment, "gig" work, informal work, and out-of-state jobs. Although these records are less affected by recall bias relative to survey responses, they can suffer from under-reporting by employers who are engaged in tax evasion (Blakemore et al., 1996; Mathiowetz et al., 2002). There is also evidence that individuals tend to report higher survey earnings relative to administratively-recorded earnings on the lower-end of the earnings distribution, and under-report survey earnings relative to administratively-recorded earnings on the upper-end of the earnings distribution (Abowd & Stinson, 2013; Abraham et al., 2013).

The differences in levels of earnings and employment between administrative and survey records can also translate into different estimates of the impact of workforce programs. Barnow and Greenberg (2015) find that earnings impacts are smaller using administrative records than using survey reports. Moore, Perez-Johnson, and Santillano (2018) replicate their results and find that differences in earnings among the employed is a larger driver of the difference between administrative and survey records than

[2] We identified a data anomaly in 2019Q4 where there was clear under-reporting of earnings for the CalFresh-only population. For this reason, all earnings from that quarter were excluded from all analyses.

differences in who is employed – suggesting that the discrepancies in reporting are mostly coming from differences in amounts received.

Given the limitations of administrative records, it is important to be explicit about the outcome the study is measuring and how the results should be interpreted. Specifically, this study estimates the impact of CalWORKs + GAIN on earnings and employment in UI covered jobs in the state of California. Because of the focus on this outcome, we could over or understate the positive and negative impacts if the types of services participants received made it easier to become self-employed, or if the population was particularly involved in other uncovered positions. However, the measured impacts from employer-reported positions is itself important because these positions tend to be formal positions and workers can access additional protections and benefits (like healthcare) from them.

B. Sample and Exclusion Criteria

There were two sets of sample and exclusion criteria used to identify the study sample. The first set was to identify first-time program participants in either CalWORKs and CalFresh with higher expectations of being in the labor market for at least ten years. We refer to this in the study as the “Focal population.” We focus on first-time enrollees in order to create comparisons that reflect a participants’ full experiences with each program. We also focus on those aged 22 to 49 to identify a population that is expected to be working while making GAIN activity decisions that reflect longer-term benefits. Those under 22 might still be engaged in educational activities, and those older than 49 might have different worker profiles that account for plans to exit the labor market. These exclusion criteria to obtain the focal population are presented in Table B1.

Table B1. Focal Population criteria to identify first-time CalWORKs and CalFresh-only participants

First-time CalWORKs + GAIN	CalFresh-only
Ages between 22 and 49	Ages between 22 and 49
Exclude if enrolled in an office that does not serve both CalWORKs and CalFresh	Exclude if enrolled in an office that does not serve both CalWORKs and CalFresh
Excluded if first CalWORKs status is not “Active”	Excluded if first CalFresh status is not “Active”
Excluded if enrolled in CalWORKs before PY17	Excluded if they had CalFresh before PY17
Excluded if they did not enroll in GAIN in PY17, or had enrolled in GAIN before PY 17	Excluded if they ever participated in CalWORKs
Exclude if first GAIN status was not “Mandatory”	Exclude if not part of CFWR
Exclude if had GAIN before PY17	
Exclude if participant had irregular participation behavior, such as benefit issuances in report months before CalWORKs enrollment, or GAIN enrollment in a report month before CalWORKs enrollment	

Notes: PY is Program Year. PY 17 starts on July 1, 2017 and ends on June 30, 2018. We do not present the share of the population that is excluded with each criterion because they are overlapping. Rather, the changes in the sample sizes from these exclusions can be identified in Table 1 of the report.

The second type of exclusion restriction was based on historic earnings records. The validity of our selected research design relies strongly on our ability to identify comparable individuals based on historic earnings patterns. Therefore, it was important to assess how many participants ever had employer-reported earnings at the time of program enrollment. To assess this, we calculated the percentage of the “focal population” that had earned at least a certain dollar amount in a quarter for up to 6 quarters. These percentages are presented in Table B2. What is clear is that a large percentage of individuals (35%) have no previously reported earnings, and many have earnings in just a few quarters. To proceed with the study, we required that participants in both the GAIN and CalFresh focal populations had received at least $500 in each of at least 2 of the previous 6 quarters. This was intended to reflect a lower bar on having experience with an employer, which we believe reflects a policy relevant group for the GAIN program. Participants with limited employment histories are likely to respond differently to GAIN services compared to those with more employment experience. In the end, this exclusion results in 55% of the focal GAIN population being included in the study. We refer to this as the “in-study” sample.

Table B2: Percentage of first-time CalWORKs + GAIN participants with quarterly earnings of a certain amount

	Number of quarters with at-least the earnings amount					
Earnings amount	**1**	**2**	**3**	**4**	**5**	**6**
More than $0	65	57	50	42	33	23
More than $250	63	56	48	40	31	22
More than $500	62	55	47	39	30	21
More than $1,000	60	52	44	36	28	19

Notes: Authors' calculations using CalSAWS and EDD data. Sample includes 21,320 first-time CalWORKs + GAIN participants considered for the study.

C. Impact Design

This section describes the strategy used to estimate impacts in the study. The primary goal of this study is to estimate the causal effect of participating in the GAIN program on the future labor market outcomes of program participants. However, the program was not administered with an intention of answering that question, so a research design to credibly answer this causal question needed to be identified. This section describes our strategy to do that using available data.

Research design

This study attempts to measure the effectiveness of GAIN using a non-experimental comparison-group design. The specific design relies on available administrative data and an assumption referred to as "selection on observables" to provide causal impact estimates for the program (Imbens, 2004; Rosenbaum & Rubin, 1983). The intuition behind this assumption is that if two groups of individuals are observationally equivalent at the time of benefits enrollment, but only one group enrolls in CalWORKs (and, thus, GAIN), then those enrollments are effectively "as good as random" across individuals in those two groups. If the assumption were true, then any differences in outcomes between the two groups should reflect the impact of the program rather than any underlying differences between the two groups. This is a strong assumption, and its credibility relies on whether we believe that there are people who applied for benefits who should have been enrolled in CalWORKs, but were not for some random reason after taking their characteristics into account. Given how individuals enroll in benefits and the richness of administrative data available, we believe there is a sample of CalFresh participants for whom this is possible. Here we provide details behind this assumption and how we implement the final design.

To create a comparison group for GAIN, we rely on CalFresh participants who did not enroll in CalWORKs. This group offers some obvious benefits as a potential population for creating a comparison group. First, both groups apply for public benefits with DPSS using the same form. Even though they have different eligibility requirements, with income thresholds being higher for CalFresh, there are reasons to believe that some people would opt for just CalFresh since the application process is less onerous. For example, currently, CalWORKs applicants need to have their fingerprints and a digital picture taken as well as have an in-person interview, while CalFresh only requires an interview over the phone. The result is that the CalFresh program has many more participants than CalWORKs, and this increases our chances of identifying participants who are similar to GAIN participants. Second, CalFresh participants often experience labor market instability at the time of program enrollment – which is a similar experience to many GAIN participants. The main limitation of CalFresh participants as a comparison group is that the income threshold for CalWORKs eligibility is lower than that for CalFresh. This means that without purposefully finding a comparable group from CalFresh, we would expect the two groups to be meaningfully different and have different outcomes regardless of which program they participated in. To solve this limitation, we find a comparable group by relying on the selection-on-observables assumption.

A final potential concern with relying on CalFresh participants as a control group is that some participants may enroll in CalFresh Employment and Training (E&T) services. The services provided by CalFresh include supportive employment services, training, or other skill development programs similar to those received by GAIN participants. In other words, the E&T program may be thought of as "contaminating" the control group by providing services similar to the treated CalWORKs + GAIN group. However, this is not contamination. Instead, it represents part of the counterfactual for what the CalWORKs + GAIN participants would have been doing if they were not in CalWORKs and GAIN. If the treated group were not in CalWORKs + GAIN, their behavior would be different and they could take a range of alternative actions including potentially participating in the CalFresh E&T services. This study estimates the effect of CalWORKs + GAIN on participant labor outcomes relative to what they would have been doing if not for CalWORKs + GAIN, as represented by the CalFresh group and all the activities they subsequently participate in.

The selection-on-observables assumption has a long history of being used in research on the effectiveness of labor market interventions (Ashenfelter & Card, 1985; Card & Sullivan, 1988), and continues to be used today (Andersson et al., 2022; Rothstein et al., 2022). When relying on this assumption, some particularly important features of the context have been identified to maintain its validity. This includes making comparisons within similar labor markets and having long-enough work histories to avoid disruptions to employment that tend to occur at the time of program enrollment (Ashenfelter, 1978; Glazerman et al., 2003; Heckman et al., 1997; Heckman & Smith, 1999).

Because of the established history of research relying on the assumption, comparison group strategies that use it are recognized as able to provide causal evidence by the Administration for Children and Families' (ACF) Pathways to Work Evidence Clearinghouse (Rotz et al., 2020). This is the systematic review that is relevant for assessing causal research on the effectiveness of employment programs for low-income populations – including cash-aid recipients. Before a study is classified as being able to provide evidence, however, the systematic review has certain criteria that need to be met when implementing a design. These criteria include:

- **No confounders:** This means that there is some larger shared experience (other than the program) that is experienced by one group that is not experienced by the other group. A prime example would be if all CalWORKs participants applied in a single office or if they all applied at a certain time period that was different from the CalFresh-only participants. Our research strategy does not have such a confounder because we only compare individuals who apply for benefits in an office that offers both programs, and we only make comparisons within the same quarter of enrollment.

- **Satisfy baseline equivalence, and control for potential differences in the outcome:** Baseline equivalence means that the compared groups should not have certain characteristics that are different at a 5% level of confidence when performing a statistical test on a difference in means. The specific characteristics required by the Pathways Clearinghouse are:

- **Earnings at least 1 year before program entry:** Earnings is a primary outcome for this study, and we include each of 6 full quarters before participants enter the program. This allows us to assess equivalence on Quarter -6 and Quarter -5, which are over a year before program entry.
- **Socioeconomic status:** This is tested using participation in public benefits programs, and the comparisons in this study pass this requirement by definition since all are participants in CalFresh (SNAP) or CalWORKs (TANF).
- **Race/ethnicity:** We assess this by including separate indicators for Hispanic, Black, and White participants.
- **Gender:** We assess this by including an indicator for parents self-identifying as Female at program entry.
- **Age:** We assess this by including the age of participants as a count variable.

In addition to the characteristics identified by the Pathways Clearinghouse, the available data allow us to include additional variables that we think are important in this context and reflect either barriers or facilitators for work. These characteristics include being a non-English speaker, being a single parent, the number of children on a case, an indicator for having a child under 5 on a case, having reported income at the time of entry, having a cell phone, having a driver's license, and having a home address that is not a CalWORKs office.[3] These variables are listed in Table C1.

[3] A characteristic that is often included in this list of variables is education level, which has a long history of importance for research on earnings (Mincer, 1958, 1974). However, education level is missing for 48% of the GAIN participants in the study and 72% of CalFresh participants in the study. We exclude that variable for this reason.

Table C1: Variables included in the entropy-balancing procedure

Variable Name	Variable Description	Variable Type
Age	Age on entering the CalWORKs or CalFresh program	Continuous
Female	Binary variable where 1 = Female and 0 = Male	Binary
Non-English Speaker	Person has preferred language other than English	Binary
Single	Does not report having a partner in household (regardless of marital status)	Binary
Number of Children	Number of children under 18 in household	Continuous
Any Children under 5	Binary variable where 1 = Has child under 5, 0 = Does not have child under 5	Binary
Hispanic	Person self-identifies as Hispanic (non-exclusive)	Binary
Black	Person self-identified as Black (non-exclusive)	Binary
White	Person self-identified as White(non-exclusive)	Binary
Has Income	Person reports having income before entering the program	Binary
Has Cell Phone	Person provided cell-phone number on entry	Binary
Has Email Address	Person provided email address on entry	Binary
Has Driver's License	Person had driver's license on entry	Binary
Has Home Address	Person provided a home address on entry	Binary
Pre-Entry Employment	Person had any earnings in each of the 6 pre-entry quarters	Binary
Pre-Entry Earnings	The amount of earnings in each of the 6 pre-entry quarters	Continuous

Note: The demographic and family information from CalSAWS is self-reported for everyone in the case/family at the time of application.

Entropy balancing. The specific strategy we rely on to implement the selection-on-observables assumption is called "entropy balancing" (Hainmueller, 2012). The strategy works as follows: Given two groups — a GAIN group and a CalFresh-only group — and a set of characteristics that are available for both, entropy balancing will produce design weights that make the CalFresh group resemble the GAIN group. For example, if 80% of the GAIN group and 75% of the CalFresh group were employed in the 4th quarter before program entry, applying entropy-balancing weights would result in both groups being employed at 80% in the 4th quarter before program entry. In other words, to the extent the data allow, entropy balancing creates design weights that make the pre-enrollment characteristics across groups the same, or "balanced." Intuitively, this works by creating larger weights for those in the CalFresh group that are observationally similar to those in the GAIN group, and smaller weights (sometimes zero) for those in the CalFresh group that are different from GAIN participants. Throughout, those in the GAIN group receive a weight of one (that is, the weight of one individual). However, for the CalFresh group, the sum of the entropy weights will exactly equal the number of individuals in the GAIN group. One of the strengths of entropy balancing is that it can create weights in a way that simultaneously balances many pre-enrollment characteristics. This provides a distinct advantage over other matching/weighting methods that do not have this feature and require various strategies to balance covariates (see Huber et al. (2013) for a comparison of alternative strategies). The result of entropy balancing is baseline equivalence, as required by the Pathways Clearinghouse, that is presented in Table 7 of the report.

There, the “Weighted” column represents a difference in means between the GAIN and CalFresh group when applying the entropy-balancing weights. The weighted differences are now all essentially 0 with no statistically significant differences at a 1% level of confidence.

As stated above, entropy balancing is done within a GAIN region and entry quarter so that GAIN participants are only compared to CalFresh participants who enrolled in the same region and entry quarter. We do not create comparison groups within offices because the samples would sometimes be too small to create comparable groups, but all participants still had to apply at an office where both programs were offered. We do want to note, however, that there were times when the entropy balancing method could not identify well-balanced groups. This specifically happened when applying the method for the subgroup analysis of Black participants. When doing this, there were some region-quarter combinations where there were too few individuals from one of the programs to identify comparable groups. When this happened, we excluded all participants in that region-quarter pair from the results. We are not concerned about these exclusions because it happened for fewer than 5% of the Black GAIN participants, and this is only relevant for the subgroup analysis – not the overall impacts.

One final note on entropy balancing is that it is a form of propensity-score weighting, which is a common approach when relying on the selection-on-observables assumption. Although entropy balancing is not designed to model the probability of program participation, which is the goal of propensity score modeling, it is effective at achieving that goal (Zhao & Percival, 2017). The distinct advantage of entropy balancing is that, unlike direct estimation of propensity scores, it instead directly addresses the problem of covariate balance. Because of the similarities with direct propensity-score estimation, this study implements entropy balancing using best practices for using the propensity score (Busso et al., 2014; Huber et al., 2013). This includes corrections for estimates of statistical precision that incorporate the fact that entropy weights are themselves estimates when estimating impacts, which we discuss below.

Outcomes. The two main outcomes used for this study are average quarterly employment and quarterly earnings in the fourth year after program entry. These measures are meant to represent stabilized outcomes after the program is completed, and avoid the problems of a “lock-in” effect where training programs have initially shown decreases in earnings due to program participation before earnings gains are realized (Card et al., 2018). This also avoids complications stemming from the beginning of the COVID-19 pandemic. In addition to the average outcomes in the fourth year, the study also calculates quarterly employment and earnings in order to examine dynamic effects over time.

Correcting for statistical precision that uses estimated weights. As mentioned above, statistical tests should correct for estimated impacts that rely on estimated design weights. A valid strategy for this is the bootstrap method (Efron & Tibshirani, 1986; Huber et al., 2013). This is generally implemented by resampling the population with replacement to create alternative samples and then re-estimating the impacts each time so that confidence intervals can be established. The confidence intervals were created by randomly drawing 200 samples of local labor markets for each comparison with replacement. Impacts were then estimated for each draw and the 2.5th centile and 97.5th centile of the resulting impacts are used to create 95% confidence intervals on the impact estimate from the full sample. If this confidence interval does not contain zero, this study considers that impact statistically significant.

D. Assessing Impact Design

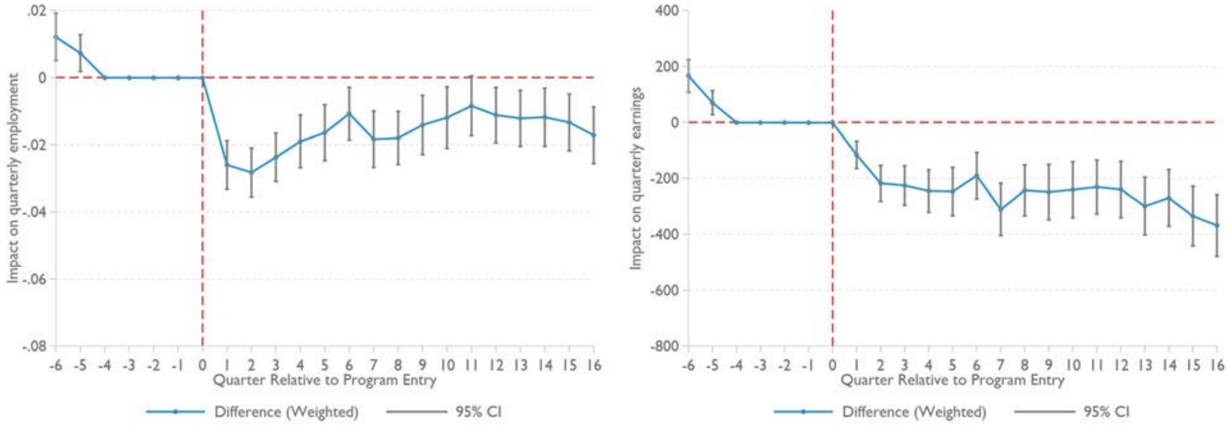
To provide assurances on the validity of the research design, we performed analyses to test if the design was working as intended. These assessments are called “placebo” tests because they identify whether a non-zero impact can be estimated using a research design when an impact is not expected. For example, we would not expect future participation in a program to causally influence an individual’s outcomes from the past. In such a case, if a clear pattern of non-zero placebo impacts can be empirically estimated, it would suggest that the design is likely not removing bias from the focal impact estimates of interest – making those causal impact estimates invalid.

We implemented a placebo test by applying the research design to a partial history of quarterly earnings and estimating the “impact” of CalWORKs + GAIN on the excluded pre-enrollment quarters. Specifically, we have 6 full quarters of pre-enrollment earnings histories for all study participants. We perform the research design as described above in Appendix Section C, but we exclude quarterly employment and earnings information from quarters -5 and -6. We then estimate the “impacts” of CalWORKs + GAIN participation on employment and earnings in these pre-enrollment time periods. If the comparison group is valid, then the difference should be close to zero in those quarters. Note, it is common to assess placebo impacts in time periods just before program entry. However, in the context of social service benefits, there tend to be large labor market drops that immediately precede program entry, and this volatility makes these tests more difficult to implement. To get a clear sense of this, see the left panels of Figures 2 and 3 from the report that show clear dips in wage/salary employment and earnings leading up to program entry. Finally, we performed this test on two samples. We first started with the focal population that includes all first-time CalWORKs + GAIN participants – even if they had no prior earnings histories. We then conducted these tests for the final “in-study” population that had earnings of $500 a quarter for at least 2 quarters before program entry.

The graphical results of the placebo assessment for the full population of first-time CalWORKs + GAIN participants are presented in Figure D1 — employment in the left panel and earnings in the right panel. In this assessment of the model, employment and earnings for quarters -4 to 0 are included in the entropy-balancing process, and this results in differences that are precisely centered at zero. However, the placebo differences in the fifth and sixth quarters before program entry clearly show positive impacts from future CalWORKs + GAIN enrollment relative to the CalFresh-only group. This is evidence that the design – at least when using only four pre-enrollment quarters – is not sufficient to remove bias from the impact estimates. This is a critically important finding because it means that extra precaution needs to be applied before trusting the impact estimates that can be produced using this particular research design — even if it meets the standards set forth by the Pathways to Work Clearinghouse when including all pre-enrollment quarters in the entropy balancing approach. This finding is not particularly surprising given the outcomes are based on employer-report earnings and a large percentage of CalWORKs + GAIN participants do not have strong connections to wage/salary employment before entering the program.

Figure D1: Placebo estimates for first-time CalWORKs + GAIN participants

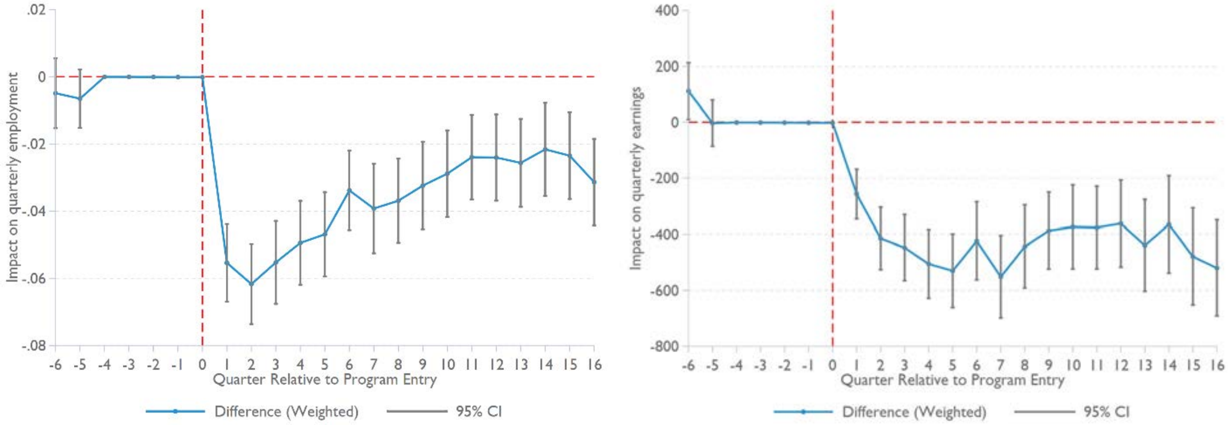
Employment (left) and Earnings (right)



Notes: Authors' calculations using CalSAWS and EDD data when applying the research design described in Appendix C. The CalWORKs (*N* = 21,320) and CalFresh-only (*N* = 92,530) samples are restricted to the focal population of first-time program participants.

In response to these findings, we sought to identify a sample of program participants where the research design would be more in line with the underlying theory. This led us to consider individuals who had more meaningful attachments to employer-reported earnings. As discussed above, this is why the study focuses on individuals who have a minimum attachment to employer-reported earnings based on receiving at least $500 in at least 2 quarters before program entry. Using this "positive-earnings" population, we again performed the placebo assessment. The results are provided in Figure D2. After limiting the sample, we can see that the placebo impacts do not raise significant concern. In the fifth quarter before enrollment, the placebo impacts on employment and earnings cannot be distinguished from zero. In the sixth quarter before enrollment, the placebo impacts on employment cannot be distinguished from zero and the placebo impacts on earnings are marginally positive. Taken as a whole, this increases our confidence that the design is working as intended for this particular population, so we proceed with this population as the main "in-study" population in the report. The impact estimates presented in the body of the report include all pre-enrollment quarters in the entropy-balancing approach, which makes the design even stronger, and ensures that the baseline equivalence requirements of the Pathways Clearinghouse are met.

Figure D2: Placebo estimates for first-time CalWORKs + GAIN participants with positive earnings
Employment (left) and Earnings (right)



Notes: Authors' calculations using CalSAWS and EDD data when applying the research design described in Appendix C. The CalWORKs (*N* = 11,627) and CalFresh-only (*N* = 55,089) samples are restricted to those with at least $500 of earnings in at least 2 of the 6 quarters preceding program enrollment.

E. Supplemental Tables

Table E1. CalFresh benefits for in-study GAIN participants

	CalFresh Payments Received			CalFresh Benefit Amounts	
	Months	For 48 Consecutive Months (%)	With Ever a Month Break (%)	Total Dollars	Monthly Amount
Panel A: In-study GAIN participants					
All	29	14	53	$12,595	$421
Race/Ethnicity					
Black	30	15	54	$11,619	$374
Hispanic	29	15	54	$13,289	$441
White	27	15	50	$12,472	$435
Relationship Status					
Single	29	15	54	$12,399	$403
Partnered	26	13	47	$13,696	$505
Panel B: In-study CalFresh participants (weighted)					
All	23	8	56	$9,116	$353
Race/Ethnicity					
Black	24	8	60	$8,515	$320
Hispanic	22	7	56	$9,535	$369
White	22	7	54	$9,216	$365
Relationship Status					
Single	23	8	58	$9,233	$347
Partnered	20	6	45	$9,706	$418

Notes: Authors' calculations from the Issuance table in CalSAWS for 48 months from the time of enrollment. Demographics are based on the characteristics of the primary applicant for each case. Months is the average total months of CalFresh payments over the 48-month period. The "For 48 Consecutive Months" column is the percentage of individuals that received a payment in all 48 months of the follow-up period. The "With Ever a Month Break" column is the percentage of all participants who stopped receiving payments for at least 1 month, but then began receiving them for any additional time period. Total dollars is the average total amount received over 48 months. The Monthly Amount is the average size of the monthly benefit.

Table E2: Characteristics of GAIN activity engagement, detailed

Activity Group	Associated with activity (%)	For those assigned the activity: Days to first scheduled start (median)	Scheduled Hours/week (median)	Months participating, if engaged (average)	Ever disengaged (%)	Ever completed (%)
Appraisal/Assessment						
Appraisal	100	12	2	2	62	71
Assessment/Other	27	152	4	1	33	79
Employment						
IHSS	2	256	20	11	15	4
Self-employment/Gig	1	230	20	7	21	2
Remaining	37	94	30	8	22	6
Counseling						
Mental Health	10	185	3	10	65	66
Remaining	12	175	2	10	44	45
Labor Force Attachment						
Job Club	36	55	20	2	77	21
Subsidized Employment	8	301	40	7	42	28
Remaining	1	188	16	6	12	26
Human Capital Development						
Remedial Education	5	448	20	7	47	14
Educ/Voc/Skills Training	16	196	21	12	25	27

Notes: Authors' calculations from the Activities table in CalSAWS. The sample is restricted to the 11,627 in-study GAIN sample. Under employment, the individuals identified as "IHSS" or self-employed were obtained using string searches as well as common peer-to-peer services, such as "Lyft", "Uber", and "Postmates". The "Remaining" activities under Labor Force Attachment include all remaining activities not already listed in the table under the WPR activity group.

Table E3: Comparing baseline characteristics of GAIN and CalFresh participants before and after entropy balance weighting – Black Participants

	Group		Difference	
Variable	**GAIN**	**CalFresh**	**Original**	**Weighted**
Age	30.07	32.04	-1.969***	-.002
Female	0.85	0.58	.264***	0
Non-English Speaker	0.00	0.00	0	0
Single	0.89	0.88	.011	0
Number of Children	1.28	0.57	.712***	0
Any Children Under 5	0.41	0.13	.286***	0
Hispanic	0.02	0.02	.001	0
Black	1.00	1.00	0	0
White	0.01	0.02	-.008**	0
Has Income	0.51	0.64	-.121***	0
Has Cell Phone	0.76	0.71	.052***	0
Had Email Address	0.84	0.77	.069***	0
Has Driver's License	0.92	0.86	.06***	0
Has Home Address	0.70	0.75	-.049***	0
Employment				
Quarter -5	0.83	0.82	.013	0
Quarter -6	0.79	0.79	-.002	0
Earnings				
Quarter -5	5,399	5,535	-135	-0.32
Quarter -6	5,189	5,260	-71	-0.03

Notes: Authors' calculations based on CalSAWS and EDD data. The sample is limited to the in-study GAIN sample (*N* = 2,067) and CalFresh-only sample (*N* = 5,099). The Difference columns represent the original/raw differences between the GAIN and CalFresh columns and the entropy-balanced weighted differences between these groups. Demographic and family information is self-reported for everyone in the case/family at the time of application.
***, **, * = 1, 5, and 10% statistically significant differences.

Table E4: Comparing baseline characteristics of GAIN and CalFresh participants before and after entropy balance weighting – Hispanic Participants

	Group		Difference	
Variable	GAIN	CalFresh	Original	Weighted
Age	30.14	32.08	-1.939***	-.001
Female	0.78	0.59	.189***	0
Non-English Speaker	0.10	0.17	-.07***	0
Single	0.70	0.66	.047***	0
Number of Children	1.68	1.14	.54***	0
Any Children Under 5	0.45	0.28	.172***	0
Hispanic	1.00	1.00	0	0
Black	0.01	0.01	.002**	0
White	0.19	0.18	.012**	0
Has Income	0.53	0.70	-.177***	0
Has Cell Phone	0.76	0.71	.047***	0
Had Email Address	0.79	0.70	.088***	0
Has Driver's License	0.90	0.85	.048***	0
Has Home Address	0.91	0.90	.009**	0
Employment				
Quarter -5	0.83	0.84	-.01**	0
Quarter -6	0.80	0.81	-.02***	0
Earnings				
Quarter -5	5,606	5,876	-270***	-0.57
Quarter -6	5,481	5,624	-143**	-0.51

Notes: Authors' calculations based on CalSAWS and EDD data. The sample is limited to the in-study GAIN sample (N = 6,287) and CalFresh-only sample (N = 30,463). The Difference columns represent the original/raw differences between the GAIN and CalFresh columns and the entropy-balanced weighted differences between these groups. Demographic and family information is self-reported for everyone in the case/family at the time of application.
***, **, * = 1, 5, and 10% statistically significant differences.

Table E5: Comparing baseline characteristics of GAIN and CalFresh participants before and after entropy balance weighting – White Participants

	Groups		Difference	
Variable	**GAIN**	**CalFresh**	**Original**	**Weighted**
Age	31.22	32.79	-1.572***	-.001
Female	0.78	0.59	.196***	0
Non-English Speaker	0.06	0.09	-.021***	0
Single	0.61	0.68	-.063***	0
Number of Children	1.63	0.82	.807***	0
Any Children Under 5	0.45	0.20	.25***	0
Hispanic	0.45	0.37	.089***	0
Black	0.01	0.01	.003	0
White	1.00	1.00	0	0
Has Income	0.53	0.67	-.14***	0
Has Cell Phone	0.76	0.69	.075***	0
Had Email Address	0.82	0.75	.067***	0
Has Driver's License	0.89	0.82	.073***	0
Has Home Address	0.91	0.89	.017**	0
Employment				
Quarter -5	0.82	0.82	.007	0
Quarter -6	0.80	0.78	.017*	0
Earnings				
Quarter -5	5,591	5,538	53	-0.116
Quarter -6	5,610	5,304	306**	0.11

Notes: Authors' calculations based on CalSAWS and EDD data. The sample is limited to the in-study GAIN sample (*N* = 2,240) and CalFresh-only sample (*N* = 13,844). The Difference columns represent the original/raw differences between the GAIN and CalFresh columns and the entropy-balanced weighted differences between these groups. Demographic and family information is self-reported for everyone in the case/family at the time of application.
***, **, * = 1, 5, and 10% statistically significant differences.

Table E6: Comparing baseline characteristics of GAIN and CalFresh participants before and after entropy balance weighting – Single Participants

	Groups		Difference	
Variable	**GAIN**	**CalFresh**	**Original**	**Weighted**
Age	29.24	30.67	-1.432***	-.001
Female	0.84	0.57	.266***	0
Non-English Speaker	0.04	0.06	-.022***	0
Single	1.00	1.00	0	0
Number of Children	1.43	0.64	.787***	0
Any Children Under 5	0.45	0.18	.269***	0
Hispanic	0.54	0.54	.007	0
Black	0.31	0.20	.115***	0
White	0.20	0.29	-.087***	0
Has Income	0.51	0.65	-.141***	0
Has Cell Phone	0.76	0.69	.067***	0
Had Email Address	0.82	0.75	.078***	0
Has Driver's License	0.90	0.81	.083***	0
Has Home Address	0.83	0.85	-.016***	0
Employment				
Quarter -5	0.83	0.82	.002	0
Quarter -6	0.79	0.79	.002	0
Earnings				
Quarter -5	5,189	5,345	-156***	-0.32
Quarter -6	5,045	5,103	-57	-0.24

Notes: Authors' calculations based on CalSAWS and EDD data. The sample is limited to the in-study GAIN sample (*N* = 8,426) and CalFresh-only sample (*N* = 37,937). The Difference columns represent the original/raw differences between the GAIN and CalFresh columns and the entropy-balanced weighted differences between these groups. Demographic and family information is self-reported for everyone in the case/family at the time of application.
***, **, * = 1, 5, and 10% statistically significant differences.

Table E7: Comparing baseline characteristics of GAIN and CalFresh participants before and after entropy balance weighting – Partnered Participants

	Groups		Difference	
Variable	**GAIN**	**CalFresh**	**Original**	**Weighted**
Age	33.24	35.48	-2.249***	-.001
Female	0.55	0.51	.039***	0
Non-English Speaker	0.14	0.27	-.124***	0
Single	0.00	0.00	0	0
Number of Children	2.05	1.81	.24***	0
Any Children Under 5	0.50	0.41	.089***	0
Hispanic	0.62	0.64	-.023*	0
Black	0.09	0.05	.041***	0
White	0.32	0.26	.057***	0
Has Income	0.55	0.75	-.205***	0
Has Cell Phone	0.71	0.69	.02	0
Had Email Address	0.74	0.68	.066***	0
Has Driver's License	0.86	0.82	.044***	0
Has Home Address	0.94	0.98	-.048***	0
Employment				
Quarter -5	0.84	0.85	-.01	0
Quarter -6	0.80	0.82	-.022**	0
Earnings				
Quarter -5	6,811	7,153	-342**	-0.42
Quarter -6	6,672	6,816	-144	-0.46

Notes: Authors' calculations based on CalSAWS and EDD data. The sample is limited to the in-study GAIN sample (*N* = 1,528) and CalFresh-only sample (*N* = 9,703). The Difference columns represent the original/raw differences between the GAIN and CalFresh columns and the entropy-balanced weighted differences between these groups. Demographic and family information is self-reported for everyone in the case/family at the time of application.
***, **, * = 1, 5, and 10% statistically significant differences.

Table E8. Labor-market impacts of first-time CalWORKs + GAIN, in-study sample

	Employment		Earnings	
	Impact (level)	Std. Error	Impact (level)	Std. Error
Primary Outcome				
Average Outcome in Year 4	-.026***	0.006	-469***	81
Quarterly Outcomes				
Quarter = 1	-.055***	0.006	-259***	46
Quarter = 2	-.06***	0.006	-419***	57
Quarter = 3	-.055***	0.006	-444***	59
Quarter = 4	-.048***	0.006	-506***	62
Quarter = 5	-.046***	0.006	-525***	68
Quarter = 6	-.033***	0.006	-428***	72
Quarter = 7	-.039***	0.007	-566***	75
Quarter = 8	-.037***	0.006	-459***	77
Quarter = 9	-.033***	0.007	-406***	71
Quarter = 10	-.029***	0.007	-385***	76
Quarter = 11	-.024***	0.006	-384***	75
Quarter = 12	-.024***	0.006	-377***	80
Quarter = 13	-.026***	0.007	-453***	84
Quarter = 14	-.022***	0.007	-381***	89
Quarter = 15	-.023***	0.007	-495***	87
Quarter = 16	-.031***	0.007	-545***	87
GAIN	11,627		11,627	
CalFresh-only	55,089		55,089	
N	66,716		66,716	

Notes: Authors' calculations using CalSAWS and EDD data when applying the research design described in Appendix C. The sample is limited to the in-study GAIN sample (*N* = 11,627) and CalFresh-only sample (*N* = 55,089).
***, **, * = 1, 5, and 10% statistically significant differences.

Table E9. Income impacts of first-time CalWORKs + GAIN, in-study sample

	Earnings + CalWORKs		Earnings + CalWORKs + CalFresh	
	Impact (level)	Std. Error	Impact (level)	Std. Error
Quarterly Outcomes				
Quarter = 1	1,182***	43	1,406***	44
Quarter = 2	604***	51	942***	51
Quarter = 3	429***	56	709***	55
Quarter = 4	221***	62	480***	60
Quarter = 5	177***	66	410***	64
Quarter = 6	264***	71	490***	69
Quarter = 7	159**	63	357***	61
Quarter = 8	264***	74	451***	73
Quarter = 9	314***	70	494***	71
Quarter = 10	251***	75	419***	74
Quarter = 11	246***	76	402***	75
Quarter = 12	178**	78	345***	76
Quarter = 13	113	77	286***	75
Quarter = 14	172**	77	344***	75
Quarter = 15	49	76	230***	75
Quarter = 16	18	78	201***	77
GAIN	11,627		11,627	
CalFresh-only	55,089		55,089	
N	66,716		66,716	

Notes: Authors' calculations using CalSAWS and EDD data when applying the research design described in Appendix C. The sample is limited to the in-study GAIN sample (*N* = 11,627) and CalFresh-only sample (*N* = 55,089).
***, **, * = 1, 5, and 10% statistically significant differences.

Table E10. Labor-market impacts of first-time CalWORKs + GAIN, Black in-study sample

	Employment		Earnings	
	Impact (level)	Std. Error	Impact (level)	Std. Error
Primary Outcome				
Average Outcome in Year 4	-.070***	0.017	-1,159***	234
Quarterly Outcomes				
Quarter = 1	-.078***	0.017	-558***	140
Quarter = 2	-.088***	0.019	-781***	167
Quarter = 3	-.095***	0.019	-822***	189
Quarter = 4	-.089***	0.018	-1,045***	217
Quarter = 5	-.09***	0.018	-1,018***	232
Quarter = 6	-.077***	0.019	-1,126***	230
Quarter = 7	-.068***	0.022	-1,143***	262
Quarter = 8	-.078***	0.022	-1,260***	280
Quarter = 9	-.068***	0.021	-922***	229
Quarter = 10	-.087***	0.021	-1,122***	249
Quarter = 11	-.072***	0.021	-1,192***	272
Quarter = 12	-.083***	0.020	-1,254***	265
Quarter = 13	-.068***	0.021	-1,399***	272
Quarter = 14	-.075***	0.019	-1,037***	264
Quarter = 15	-.058***	0.019	-1,182***	250
Quarter = 16	-.079***	0.019	-1,020***	242
GAIN	2,067		2,067	
CalFresh-only	5,009		5,009	
N	7,076		7,076	

Notes: Authors' calculations using CalSAWS and EDD data when applying the research design described in Appendix C. The sample is limited to the Black in-study GAIN sample (*N* = 2,067) and CalFresh-only sample (*N* = 5,009). ***, **, * = 1, 5, and 10% statistically significant differences.

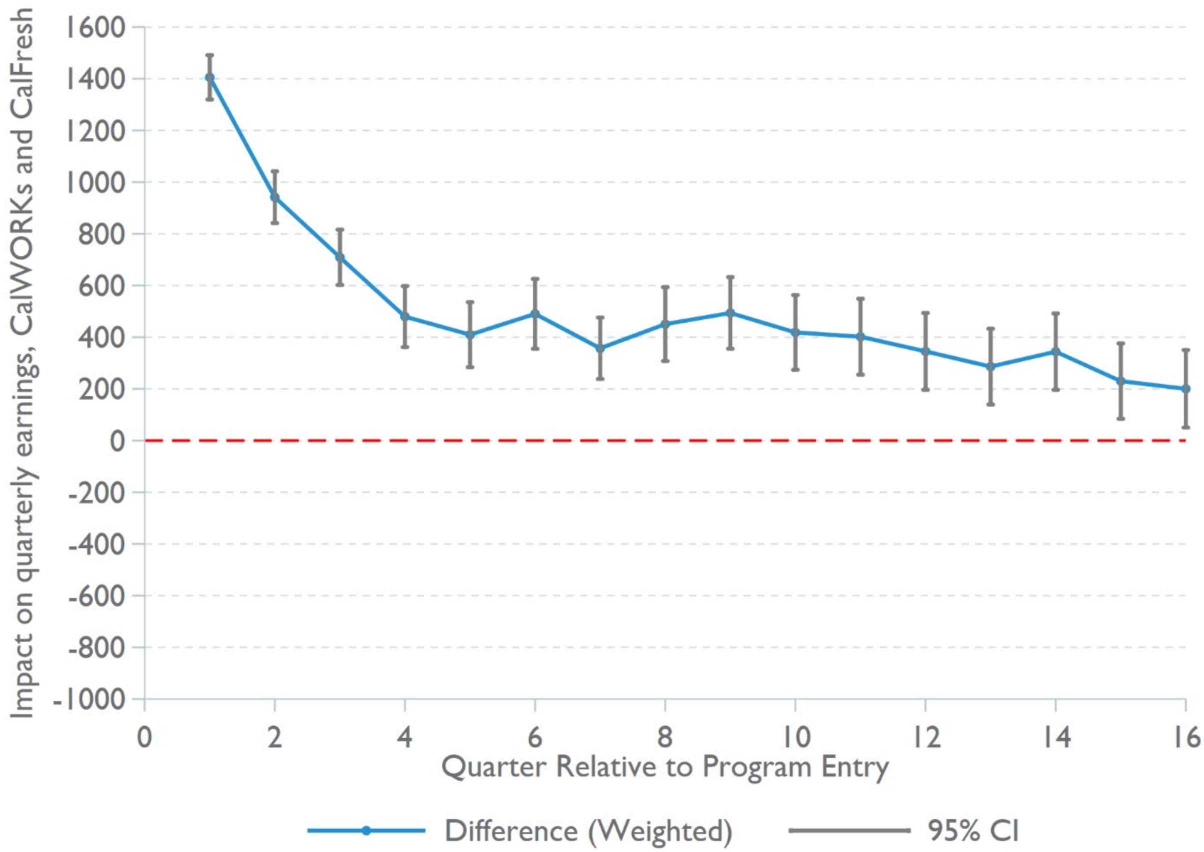
Table E11. Income impacts of first-time CalWORKs + GAIN, Black in-study sample

	Earnings + CalWORKs		Earnings + CalWORKs + CalFresh	
	Impact (level)	Std. Error	Impact (level)	Std. Error
Quarterly Outcomes				
Quarter = 1	746***	160	920***	163
Quarter = 2	207	180	472***	176
Quarter = 3	103	193	325*	188
Quarter = 4	-315	211	-104	205
Quarter = 5	-299	236	-114	230
Quarter = 6	-398*	235	-204	227
Quarter = 7	-559**	254	-416*	251
Quarter = 8	-457*	263	-334	254
Quarter = 9	-159	239	-47	237
Quarter = 10	-460*	251	-340	249
Quarter = 11	-391	244	-290	240
Quarter = 12	-566**	247	-453*	242
Quarter = 13	-670**	272	-494*	268
Quarter = 14	-218	270	-55	262
Quarter = 15	-396	266	-259	260
Quarter = 16	-282	279	-114	270
GAIN	2,067		2,067	
CalFresh-only	5,009		5,009	
N	7,076		7,076	

Notes: Authors' calculations using CalSAWS and EDD data when applying the research design described in Appendix C. The sample is limited to the Black in-study GAIN sample (*N* = 2,067) and CalFresh-only sample (*N* = 5,009).
***, **, * = 1, 5, and 10% statistically significant differences.

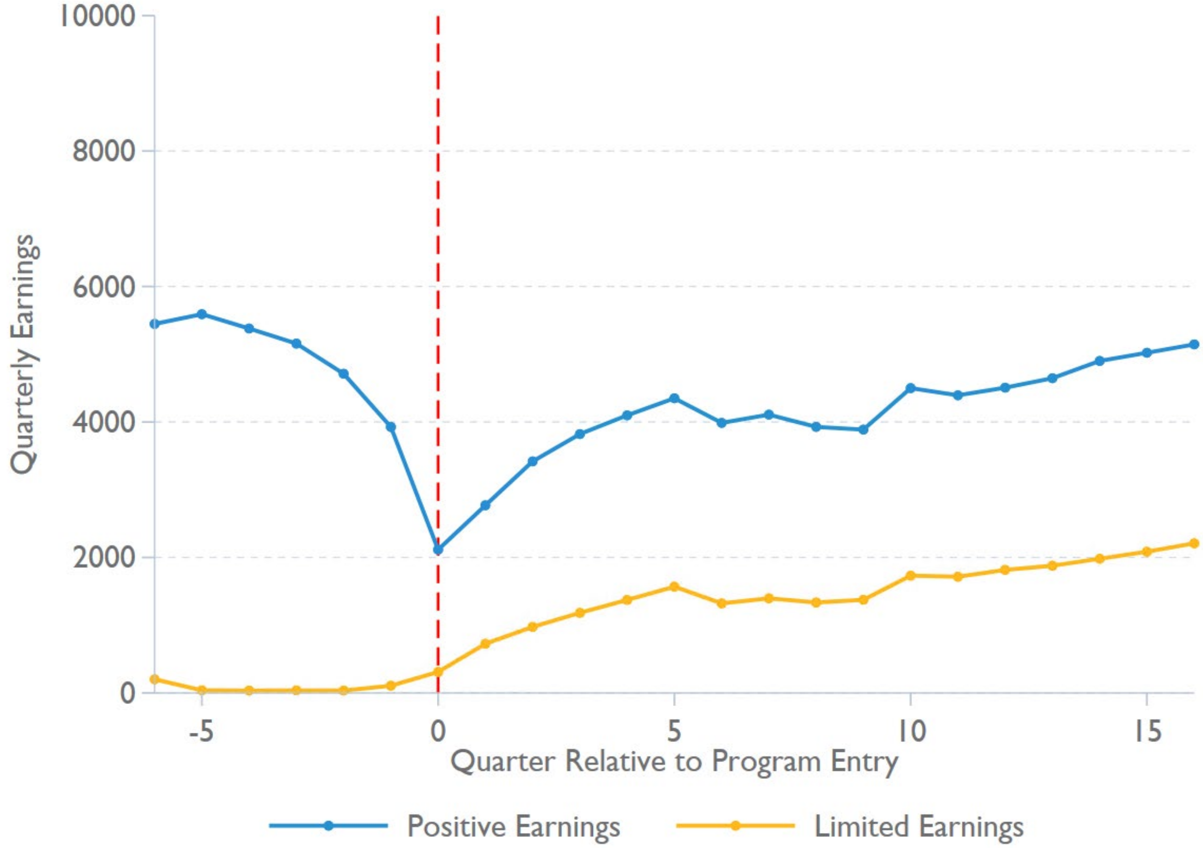
F. Supplemental Figures

Figure F1. Quarterly income (earnings + CalWORKs + CalFresh) impact estimates, by quarter



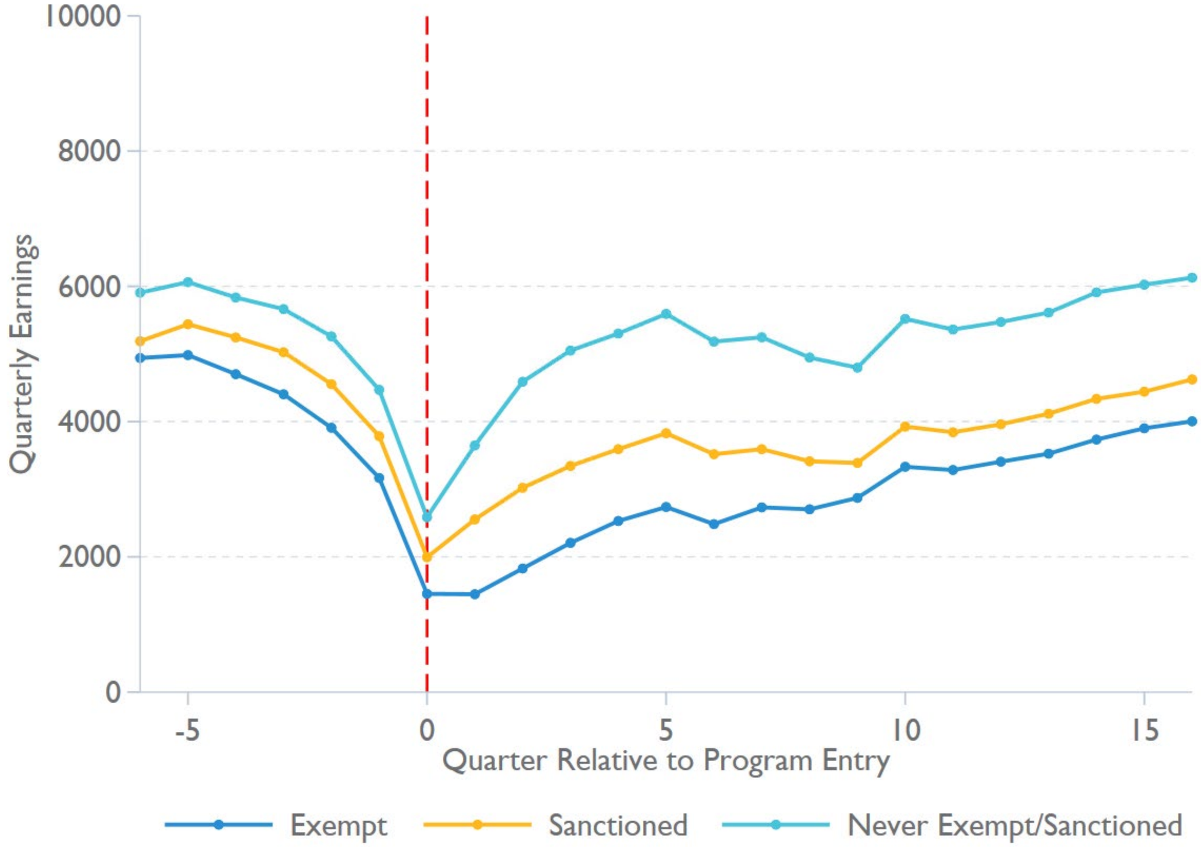
Notes: Authors' calculations using CalSAWS and EDD data when applying the research design described in Appendix C. The sample is limited to the in-study GAIN sample (*N* = 11,627) and CalFresh-only sample (*N* = 55,089). Error bars represent 95% confidence intervals when applying the research design.

Figure F2. Quarterly earnings for first-time CalWORKs + GAIN, by prior earnings groups



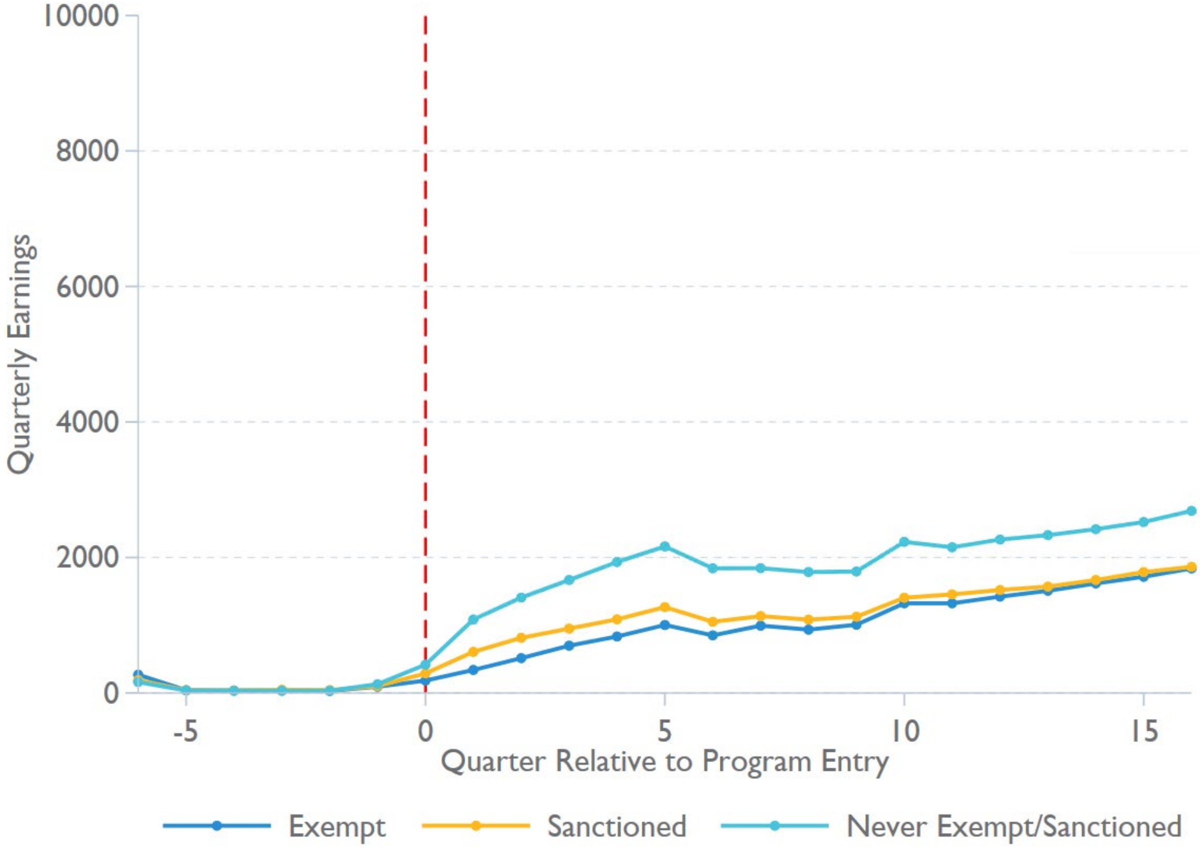
Notes: Authors' calculations of earnings trajectories using employer-reported earnings from EDD. The "Positive Earnings" group received at least $500 in at least 2 of 6 quarters before program entry (*N* = 11,627), and the "Limited Earnings" group did not (*N* = 9,693).

Figure F3: Quarterly earnings for positive-earnings first-time CalWORKs + GAIN participants, by program participation group



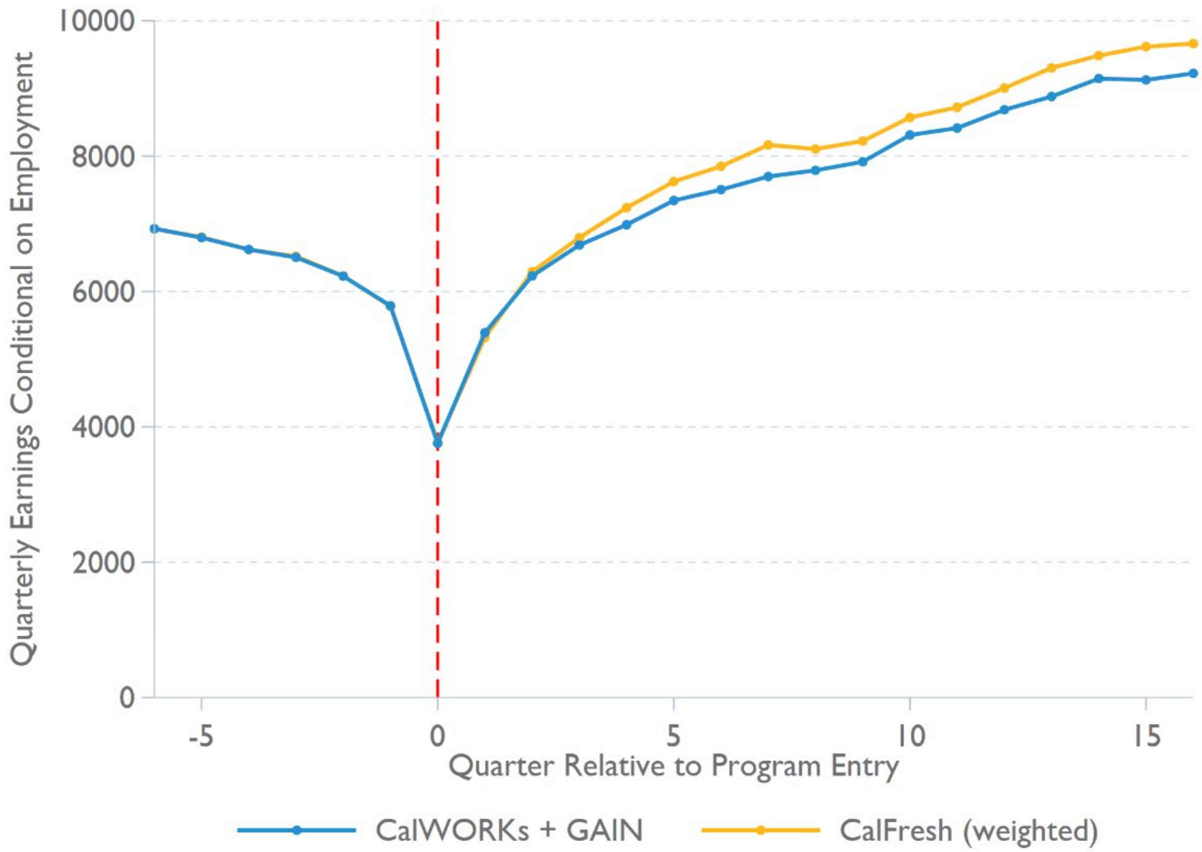
Notes: Authors' calculations of earnings trajectories using employer-reported earnings from EDD. The population is limited to the 11,627 individuals who had received at least $500 in each of at least 2 of 6 quarters before program entry. The "Exempt" group includes those who had ever received an exemption, the "Sanctioned" group includes those who had ever received a sanction, and the "Never Exempt/Sanctioned" group includes those who had never received an exemption or sanction over the 48-month post-enrollment period.

Figure F4: Quarterly earnings for limited-earnings first-time CalWORKs + GAIN participants, by program participation group



Notes: Authors' calculations of earnings trajectories using employer-reported earnings from EDD. The population is limited to the 9,693 individuals who had not received at least $500 in at least 2 of 6 quarters before program entry. The "Exempt" group includes those who had ever received an exemption, the "Sanctioned" group includes those who had ever received a sanction, and the "Never Exempt/Sanctioned" group includes those who had never received an exemption or sanction over the 48-month post-enrollment period.

Figure F5. Quarterly earnings for in-study participants who are employed in the given quarter, by group



Notes: Authors' calculations of earnings trajectories using employer-reported earnings from EDD. The population is limited to the 11,627 individuals who had received at least $500 in at least 2 of 6 quarters before program entry. Earnings are only included in a quarter if they are positive to reflect actual earnings for the employed population.

G. Minimum Detectable Impacts

Table G1. Minimum detectable impacts for select GAIN activities (level), by region

GAIN Region	N	Average Quarterly Employment		Average Quarterly Earnings	
		Year 1	Year 4	Year 1	Year 4
Panel A: Job Readiness					
Region 1	918	0.07	0.08	613	996
Region 2	1,185	0.05	0.07	433	796
Region 3	1,086	0.06	0.07	482	840
Region 4	1,108	0.06	0.07	437	776
Region 5	1,259	0.06	0.07	484	884
Region 6	968	0.07	0.07	563	973
Region 7	878	0.07	0.08	550	990
All Regions	7,402	0.02	0.03	181	338
Panel B: Vocational/Education Training					
Region 1	417	0.10	0.11	770	1,456
Region 2	337	0.09	0.13	566	1,478
Region 3	431	0.10	0.11	645	1,407
Region 4	507	0.09	0.11	657	1,171
Region 5	514	0.09	0.11	653	1,321
Region 6	362	0.11	0.13	817	1,748
Region 7	369	0.08	0.12	600	1,501
All Regions	2,937	0.04	0.04	251	501
Panel C: Paid Work Experience					
Region 1	233	0.13	0.15	895	1,749
Region 2	224	0.12	0.18	822	1,809
Region 3	261	0.12	0.15	680	1,790
Region 4	342	0.10	0.13	660	1,345
Region 5	264	0.11	0.15	650	1,515
Region 6	225	0.13	0.17	1,145	1,806
Region 7	NA	NA	NA	NA	NA
All Regions	1,712	0.04	0.06	296	592

Note: Authors' calculations using CalSAWS and EDD data. Minimum detectable impacts were estimated using 200 simulations of 50-50 random assignment for individuals who were actually assigned to each activity in each region. Within simulations, differences were adjusted using the variables in Appendix Table C1. The standard deviation of impacts from these simulations was multiplied by a factor of 2.8 to reflect a two-sided Type-I error of 5% and a Type-II error of 20%.

Table G2. Minimum detectable impacts for select GAIN activities (percent change)

Area	N	Average Quarterly Employment Year 1	Average Quarterly Employment Year 4	Average Quarterly Earnings Year 1	Average Quarterly Earnings Year 4
Panel A: Job Readiness					
Region 1	918	15	19	25	30
Region 2	1,185	15	18	23	24
Region 3	1,086	13	15	19	21
Region 4	1,108	13	16	20	23
Region 5	1,259	13	15	21	24
Region 6	968	15	14	22	24
Region 7	878	19	18	27	26
All Regions	7,402	5	6	8	9
Panel B: Vocational/Education Training					
Region 1	417	25	26	42	45
Region 2	337	29	28	45	42
Region 3	431	24	22	34	31
Region 4	507	23	24	33	38
Region 5	514	23	23	36	33
Region 6	362	25	26	41	41
Region 7	369	38	35	56	55
All Regions	2,937	10	9	14	14
Panel C: Paid Work Experience					
Region 1	233	34	36	54	54
Region 2	224	48	40	83	57
Region 3	261	37	30	47	46
Region 4	342	33	34	51	52
Region 5	264	29	33	46	50
Region 6	225	36	34	67	49
Region 7	NA	NA	NA	NA	NA
All Regions	1,712	13	12	21	18

Note: Authors' calculations using CalSAWS and EDD data. Minimum detectable impacts were estimated using 200 simulations of 50-50 random assignment for individuals who were actually assigned to each activity in each region. Within simulations, differences were adjusted using the variables in Appendix Table C1. The standard deviation of impacts from these simulations was multiplied by a factor of 2.8 to reflect a two-sided Type-I error of 5% and a Type-II error of 20%.

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