Rising Sun
Employment Trends Data Brief

December, 2024

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Tipping Point Community

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Introduction

What's in This Data Brief?

This brief is the culmination of an employment data project for Rising Sun, funded by Tipping Point Community. The brief shares some topline results from an analysis of employment data provided by California's Employment Development Department (EDD), and is designed to answer key research questions about employment trends for Rising Sun's program participants. All of the research questions addressed as part of this data project take this general form:

> ***What is the trend in employment rate and earnings after program participation, and how does that compare to the trend <u>before</u> program participation?***

In addition to answering that broad question for program participants *overall*, additional research questions dig deeper: they tailor this general question and ask it about subgroups (allowing for comparisons among those subgroups). The comparative questions enable Rising Sun to gain greater insight into the results in two main ways:

- Is successful program completion (and/or "higher dosage") associated with better post-program outcomes, when compared with participants who did *not* complete successfully (or who had "lower dosage")?
- Is program participation associated with better post-program outcomes for some groups than for others (e.g. participants in different racial, gender, or age groups)?

The rest of this introduction shares:

- Background on Tipping Point's employment data project (including a description of the data project *process),*
- Specifics on the metrics that EDD shares,
- An explanation of how data are analyzed and displayed, and
- A discussion of the limitations of the data.

In this introductory section, *all of the data shown are examples* (i.e. none of the charts show Rising Sun data). Following the introduction, the data brief offers a discussion of selected research questions (a subset of the full list of Rising Sun's questions that the EDD data addresses).

Background

Workforce development providers are keen to evaluate the effectiveness of their own programs, and to do this well, it is important to collect data on their employment rates and earnings after participants have exited the program. However, it is essentially impossible for workforce development providers to collect these data on their own. Follow-up data (of any kind) are challenging to collect because participants often don't respond to requests for information after they no longer work with staff. In addition, providers are not asking for something that former participants can easily provide a self-report on (e.g. how they are feeling), and it is common that self-reported data on earnings do not reflect *actual* earnings.

Recognizing the importance of these data, as well as all of the attendant data collection challenges, Tipping Point Community has developed an **Employment Data Project** that enables grantees to:

- Access accurate, longitudinal employment data on their program participants;
- Understand over-time *trends* for employment rates and earnings data – both before and after program participation; and
- View data visualizations designed to answer specific comparative research questions they have about their participants (e.g. how the over-time trends differ for participants in different age groups).

To implement the Employment Data Project, Tipping Point:

- **Established a data-sharing partnership with EDD**, contracting with EDD's Labor Market Information Division (LMID) to extract data from its wage files and share back employment data tables on the participants served by each Tipping Point grantee.
- **Allocates time to the Tipping Point Data Scientist** to upload the EDD data tables to Tableau and develop dashboards showing (with straightforward data visualization) the data trends that address the research questions that the grantees asked.
- **Contracted with Latham Consulting (LC)** to act as an intermediary among the grantees, EDD, and Tipping Point. LC works with grantees to translate their research questions into a data request that goes to EDD, supports grantees to share their datafiles with EDD, facilitates a reflection session based on the Tableau dashboards, and then writes up this data brief based on the reflection session.

Additional information on the specifics of the Employment Data Project *process* is below.

- **Grantees work with LC to translate their research questions into a data request.** Nancy (from LC) facilitates 2-4 meetings with each grantee to learn what they most want to know about their participants. She turns these questions into clear research questions that can be represented in the data request form to be shared with EDD. EDD uses the data request as a guide to extracting the data tables that can address each of the grantees' research questions.
- **Grantees work with LC to develop a datafile to share with EDD.** In order for EDD to share the correct data tables back with the grantees, the datafile must include the variables that form the basis of the research questions. In other words, if the grantee wants to compare participants of different education levels (high school, trade school, college, etc.), the grantee must include an education variable – with each participant tagged with their own education level. In addition, the datafile must include Social Security numbers (SSNs), as well as the participant cohort (the year the participant exited the program). Nancy reviews the grantee datafile *(minus the SSNs)* and provides any feedback necessary to ensure that by the time the file goes to EDD, it is ready for EDD to match to the California employment data.
- **Grantees upload participant data files to a secure site with EDD.** Once Nancy has determined that the datafile is ready to go to EDD, she emails EDD and the grantees, and includes (1) a link to the grantee's data request and (2) a link to the Secure FTP (File Transfer Protocol) site, along file upload credentials. The grantee then uploads the datafile *including SSNs* to EDD's site.
- **EDD develops the grantee data tables.** EDD matches the grantee datafile to their own employment data (using Social Security Numbers as a unique identifier) and returns (de-identified) data tables that answer the specified research questions. EDD emails the tables to Nancy and Tipping Point.
- **Tipping Point develops grantee data dashboards.** Tipping Point's data scientist (Bing Wang) translates the EDD data files into Tableau dashboards that display over-time data trends for program participants in the aggregate. Bing shares the dashboards with grantees and with Nancy. The Tableau dashboards are interactive, so that anyone with access to them can use a range of drop-down menus to explore the data.

- **LC facilitates a reflection session with grantees to review the dashboards.** Nancy gathers with the grantees to reflect on the data, exploring how the dashboard charts address the list of original research questions that grantees identified. The reflection session is designed to interpret results, and consider how specific results might be used for internal learning, for sharing externally with stakeholders, or both.
- **LC develops a data brief.** Nancy records the reflection session Zoom, and then uses the recording as the basis for this data brief that shares key results. The final version of the data brief incorporates any feedback that grantees shared after seeing the first draft.
- **Tipping Point makes the dashboards available to grantees *outside* of the reflection session context.** Tipping Point purchases Tableau licenses for grantees so that they can explore the dashboards on their own at any time.

The Four Metrics Available from EDD

So far this data brief has mostly referred to the data simply as *employment data.* Four metrics are included under the rubric of employment data:

Metric	Definition	Additional Detail
Percent employed	Employed = earning *at least* $1500 in *at least one* quarter during the calendar year The percent of participants in a specific group (specified by the grantee) who are employed during a given calendar year	Only W2 earnings are included; earnings from 1099s are not available
Average earnings	*Of those employed,* the average *annual* earnings in a specific group	No hourly wage data are available – only total earnings for the year
Median earnings	*Of those employed,* the dollar amount at which half the subgroup earns *more* and half of the subgroup earns *less*	
Percent earning above a living wage	*Of those employed,* the percent whose earnings are above a living wage threshold	The threshold is defined as the living wage in Alameda County for one adult and one school-aged child, and calibrated for each calendar year[1]

Because EDD returns data tables that include these four metrics, the basic research question form of *"What is the trend in employment rate and earnings after program participation, and how does that compare to the trend* <u>*before*</u> *program participation?"* gets operationalized in multiple ways:

- How does the post-program trend in percent employed compare to the pre-program trend in percent employed? (Are participants more likely to be employed after the program than before?)
- How does the post-program trend in average and median earnings compare to the pre-program trend in average and median earnings? (Are participants' earnings higher after the program than before?)
- How does the post-program trend in percent above a living wage compare to the pre-program trend in percent above a living wage? (Are participants more likely to be earning enough to put them above a living wage after the program than before?)

[1] For more information on how the yearly amounts are calculated, see Appendix A.

How Data are Analyzed and Displayed

Aggregating Data as a Method of Analyzing Data

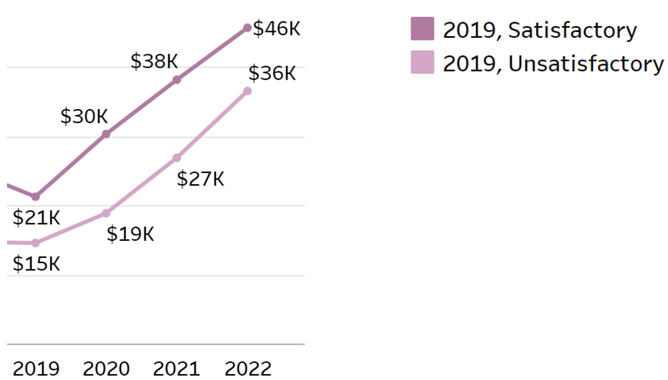
EDD extracts data on the list of participants provided by grantees, *but it does not return data as an individual-level datafile (i.e. a file with each row containing data for a single person).*[2] Instead, EDD returns data tables in which each row contains *aggregate* data for a given group of individuals. For example, say that the data request asks to compare the trend in average earnings between two groups: those who graduated from the program compared with those who dropped out before the program was over. Based on this request, EDD would return a data table, a *portion* of which would look like this:

Cohort (Exit Year)	Program Completion Status	Calendar Year	Average Annual Earnings
2019	Satisfactory	2019	$21,000
2019	Unsatisfactory	2019	$15,000
2019	Satisfactory	2020	$30,000
2019	Unsatisfactory	2020	$19,000
2019	Satisfactory	2021	$38,000
2019	Unsatisfactory	2021	$27,000
2019	Satisfactory	2022	$46,000
2019	Unsatisfactory	2022	$36,000

Each row includes aggregate data for the group exiting in 2019, with a program completion status of either "satisfactory" or "unsatisfactory." The earnings are the average in the calendar year shown. To take the last row as an example, it shows the average annual earnings in 2022 for all program participants exiting in 2019, who did *not* complete the program. ***This data table is one result of the data analysis that addresses the research question:*** *"How do average earnings differ between two groups: those who graduated from the program and those who dropped out before the program was over?"*

Turning Aggregate Data (AKA the Results of Data Analysis) into Data Displays

Once this data table (with aggregate data) is uploaded to and configured in Tableau, the dashboard turns the data analysis results into a data display with this graph:



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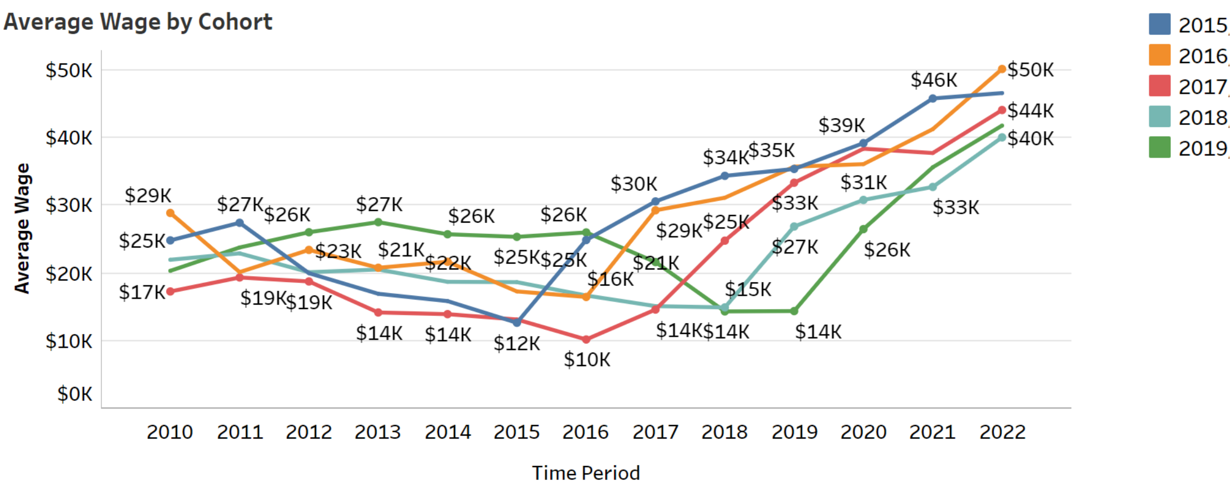
[2] The reason for this is confidentiality: EDD has rules in place so that no third parties would be able to see the employment and earnings data on an individual person (who could be identified by their SSN).

How the Employment Data Project Treats Time in the Analysis: by Cohort v. by "Relative Year"

In the example shown above, data are *aggregated by cohort.* This approach is relatively intuitive. Program participants are grouped by cohort (exit year), and then metrics are calculated for each cohort (or for subgroups within cohorts, such as the subgroups within the 2019 cohort shown above: one subgroup that completed the program satisfactorily; the other subgroup that did *not*).

This chart shows the over-time trend of average earnings for each of five cohorts (2015-2019) on the same chart:



The Employment Data Project treats time in a second way as well: aggregating and displaying data by "relative year." This means that instead of using the *calendar year* in the X-axis (as in the chart above), the displays use the *number of years relative to program exit.* The table below shows how this works. To use the first row as an example, for the 2019 cohort, 2016 is three years before the program (exit) year, and so the relative year is -3. Likewise, 2019 is year 0 (the year of program exit), and 2022 is year 3 (three years after program exit).

Cohort (Exit Year)	Calendar Year	Relative Year	Average Annual Earnings
2019	2016	-3	$15,000
2019	2017	-2	$14,000
2019	2018	-1	$13,000
2019	2019	0	$18,000
2019	2020	1	$20,000
2019	2021	2	$21,000
2019	2022	3	$23,000

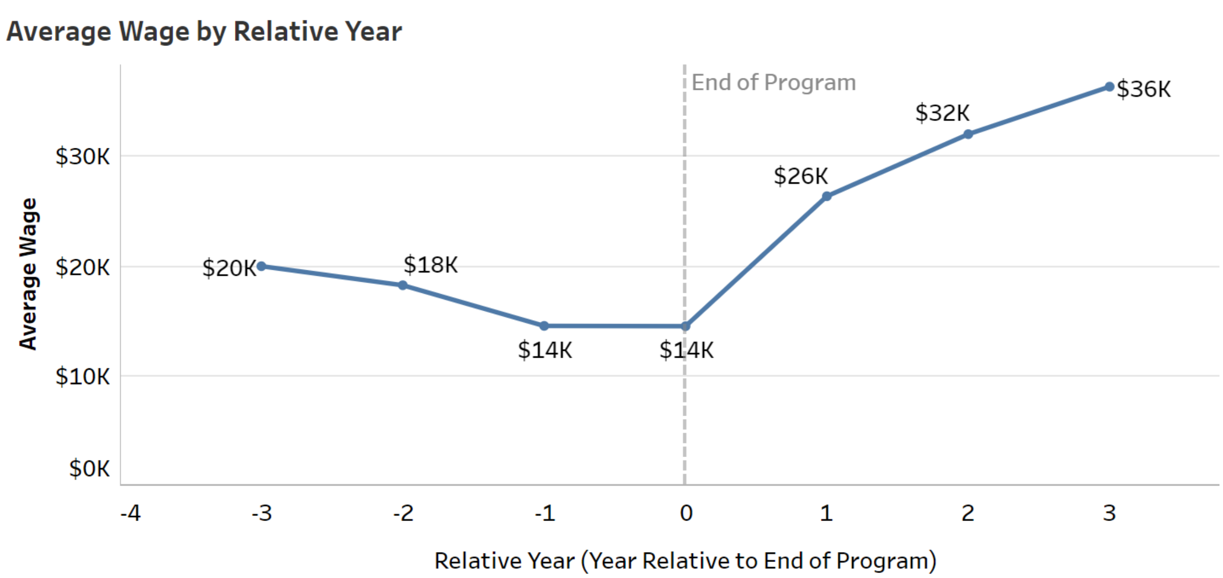
So for everyone who exited the program in 2019, we can see the *average* annual earnings for the *whole cohort* from three years *before* the program (an average of $15,000 in 2016) to three years *after* the program (an average of $23,000 in 2022).

What is the benefit of looking at the data this way? By using relative year, we can aggregate (or "group") the data *across cohorts.* By doing this, we get *larger sample sizes in each relative year* than we would have if we looked at each cohort separately. Aggregating (grouping) the data this way is especially helpful when a grantee wants to "cut" the data multiple ways (using multiple variables). For example: grantees might want to look at the data by race *and* age group *and* gender. For a single cohort, there might be very few Asian-American women, age 18-24; or very few African-American men, age 25-34 (or whatever the case may be). But if we take five cohorts and *group together* all the Asian-American women who are age 18-34, our sample size will be approximately five times the sample size for a single year.

There are additional advantages to using relative year:

- It makes more sense to draw conclusions from larger samples than from very small ones (since larger sample sizes tend to reduce the skewing effect of outliers),
- EDD will not return *any* data if the number of people matched to their wage files is less than five (so with very small numbers, the data disappears altogether), and
- The data displays are *much* easier to visually process.

The chart below shows a relative year data version of the chart shown by cohort above:



Note that the relative year ranges only from -3 to +3. In addition, the cohort years included in the relative year analyses are restricted to the cohorts 2015-2019. There are several reasons for these restrictions:

- The relative year data is meant to show three years of post-program data, and the latest full year of data available from EDD (for this extract) was 2022. Therefore, the *latest* cohort year that can be included is 2019. (If 2020 is included, only two years of post-program would be included in the sample; for 2021, only one year; and for 2022, no years of post-program data would be included.)
- Tipping Point also made the decision to go back no *further* than the 2015 cohort. Background conditions change over the years, so there is some risk in aggregating across too many years. In balancing the desire for larger sample sizes with the desire to avoid the risk of going back too far into the past, Tipping Point decided on the five years from 2015 to 2019.

Limitations of the EDD Data

Having access to EDD data means that workforce development providers gain visibility into post-program trends that would otherwise be impossible. The ability to access these data and use aggregated data and data displays to address research questions is invaluable.

However, EDD data do have some limitations that grantees should take into account as they view their Tableau dashboards. The table below lists the limitations, and their implications for the results that Tableau will show.

Data Limitations	Implications
EDD can return data only for participants with SSNs	Some participants may not share SSNs with providers, or may not have them; where there are missing SSNs, not all participants will appear in the results.
The criterion for what counts as "employed" sets the bar quite low	Because a program participant needs to earn only $1500 during at least one quarter to count as "employed," annual earnings among those employed has the potential to be as low as $1500. This liberal criterion may result in an earnings portrait that shows lower earnings than expected.
EDD data only has earnings *amounts;* it has no information on hourly wages or hours worked	A more nuanced portrait of earnings would include hourly wage. Since EDD does not have data on hours worked or hourly wages, the aggregate data include part-time workers and full-time workers. Like the criterion for what counts as "employed," the mixing in of part-time with full-time workers also results in an earnings portrait that shows lower earnings than expected.
EDD files can't distinguish between "not employed" and "not living in California"	As workers move out of California, they disappear from the EDD wage files. While they may well be employed in another state, they show as "not employed" in the EDD dataset. This will artificially depress the employment rate.
Earnings numbers are not adjusted for inflation	Aggregating across years creates pooled samples for each relative year without adjusting for inflation runs the risks of painting a somewhat misleading picture of the trend from one relative year to another.

Research Questions Addressed

Rising Sun used the EDD data to address research questions about participants in two programs: Opportunity Build and Climate Careers. The Opportunity Build program focuses on supporting participants to enter the building trades, and Rising Sun has goals related to employment rates and earnings. Climate Careers, on the other hand, is focused on youth (with no one in the program older than 24), and so the program not have the same types of workforce goals. Instead, Climate Careers is meant to enrich youth experience by exposing them early on to climate-related careers. Rising Sun decided to include Climate Careers in the EDD data project in a more exploratory way, to see how youth fared in the labor market after leaving the program, but with no expectation that participants would earn family-supporting wages in the three years after the program since they are so young and many of them will be attending school after they leave the Climate Careers program.

This section shares the research questions that Rising Sun developed for each of the two programs included in the EDD data project.

Opportunity Build Research Questions

Overall

- What are the over-time employment trends for Opportunity Build participants as a whole?
- How do employment trends differ for those who graduated v. those who did not graduate?

Program Characteristic

- How do employment trends vary based on time of year, separately by graduation status?

Participant-Level Characteristics: Demographics

- How do employment trends vary for participants of different races, separately by graduation status?
- How do employment trends vary for participants of different genders, separately by graduation status?
- How do employment trends vary for participants in different age groups, separately by graduation status?
- How do employment trends vary for participants with different levels of educational attainment, separately by graduation status?

Other Participant-Level Characteristics[3]

- How do employment trends vary for participants with different types of families, separately by graduation status?
- How do employment trends differ for participants who are system-impacted vs. those who are not, separately by graduation status?
- How do employment trends vary for participants with different types of placement status?

Climate Careers Research Questions

Overall

- What are the over-time employment trends for Climate Careers participants as a whole?
- How do employment trends differ for those who completed v. those who did not complete?[4]

Program Characteristic

- How do employment trends differ for those in the Bay Area v. those in the Central Valley - shown separately by graduation status?

Participation Type

- How do employment trends differ for those who participated in one program vs. those who participated in more than one - shown separately for those who completed v. those who did not complete (from their most recent program)?

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[3] There was one additional research question in the list, but it was not reviewed during the reflection session: "How do employment trends vary for participants when looking at the compound effects of race, gender, and system impact - shown separately by graduation status?"

[4] The Climate Careers program uses the term "completion," rather than the term "graduation" (the term that is used for Opportunity Build).

Participant Characteristics: Demographics

- How do employment trends vary for participants of different races, shown separately by completion status?
- How do employment trends vary for participants of different genders, shown separately by completion status?
- How do employment trends vary for participants in different age groups, shown separately by completion status?
- How do employment trends vary for participants with different levels of educational attainment, shown separately by completion status?

Key Takeaways from the Reflection Session

Rising Sun met with Latham Consulting for a reflection session on Zoom, during which they reviewed the data dashboard in Tableau, with the goal of gaining insight into their research questions. For both programs, the data views exploring the research questions follow this pattern:

1. Employment trends overall (including graduates/completers and non-graduates/non-completers together),
2. Trends for all program graduates/completers compared with all *non*-graduates/*non*-completers, and
3. Remaining trends shown separately for graduates/completers and non-graduates/non-completers.

The data views that compare graduates/completers to non-graduates/non-completers reveal two important findings: (1) there are very few non-graduates/non-completers (i.e. the sample sizes are quite small when broken out further in subsequent data views); and (2) the employment trends for non-graduates/non-completers are quite different from those of graduates/completers. For both these reasons, showing the results for *non*-graduates/*non*-completers is typically not very informative (after looking at the first view that shows all program graduates compared to all non-graduates). While Rising Sun was able to look at most of the non-graduate results during the reflection session, those views are *mostly* not included in this data report.[5]

Opportunity Build

The Opportunity Build data views show positive employment trends outcomes for program graduates. The Rising Sun team was pleased to see that reliable data from the state database showed two things:

1. **Employment rates were higher after the program than before.** The employment rates tended to (mostly) peak in year 1 and then gently decline in years 2 and 3, but the truly positive finding here is that the employment rate was almost always higher during *all* three post-program years than it was during *any* of the pre-program years.
2. **Average earnings rose sharply after the program exit year.** Earnings tended to rise and have high growth rates in each of the out-years. The challenge is that the *absolute* value of earnings is low, with only a small percentage of the graduates earning above a living wage. However, this result is about the structure of the labor market rather than about the program itself. In addition, as was shared above, a limitation of the data is that there is no way to know how many hours participants worked during the year – and working fewer than 2000 hours may go a long way toward explaining low annual earnings.

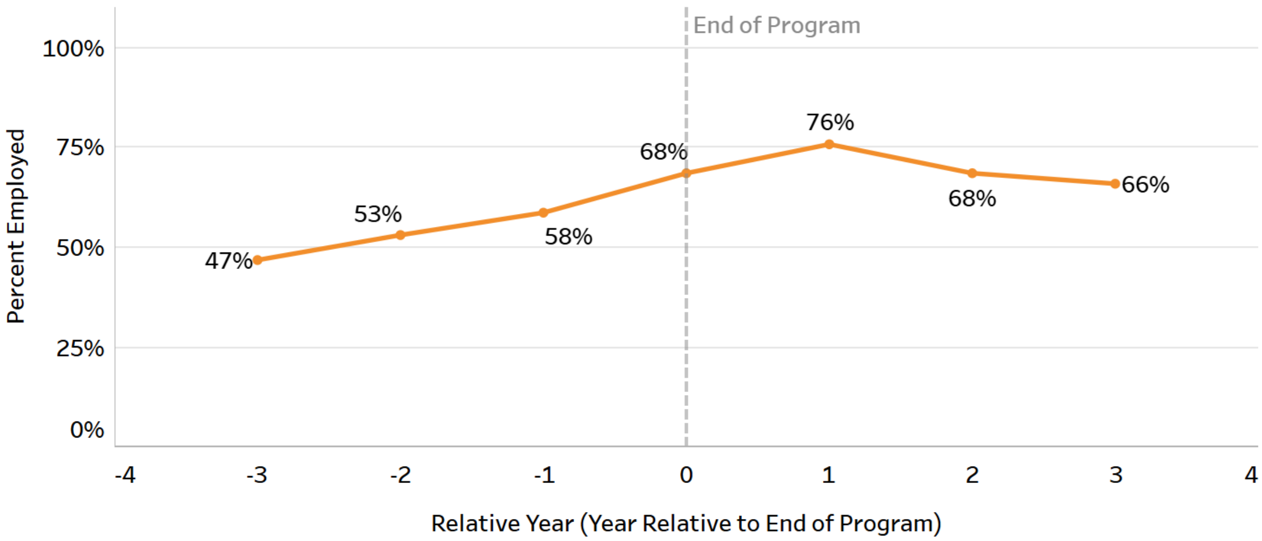
[5] Non-graduates *are* shown for the research question about system impact, since the group differences suggested an extremely interesting pattern worth sharing in this report.

Overall Results: Employment Trends for All Participants

The first results show together in one sample the participants who graduated and those who did *not* graduate as well. When looking at this whole group, we see that the employment rate rose ten percentage points during the exit year (compared with the previous year), and continued to climb in year 1. The highest employment rate was 76% the first year after exiting the program, and the rate then declined in each subsequent year, reaching 66% in year 3.

The Rising Sun team found the decline after year 1 disappointing, but not necessarily surprising; they shared that retention in the trades can be challenging, especially for the participants who participate in Rising Sun programs.

OPPORTUNITY BUILD: EMPLOYMENT RATE for ALL PARTICIPANTS

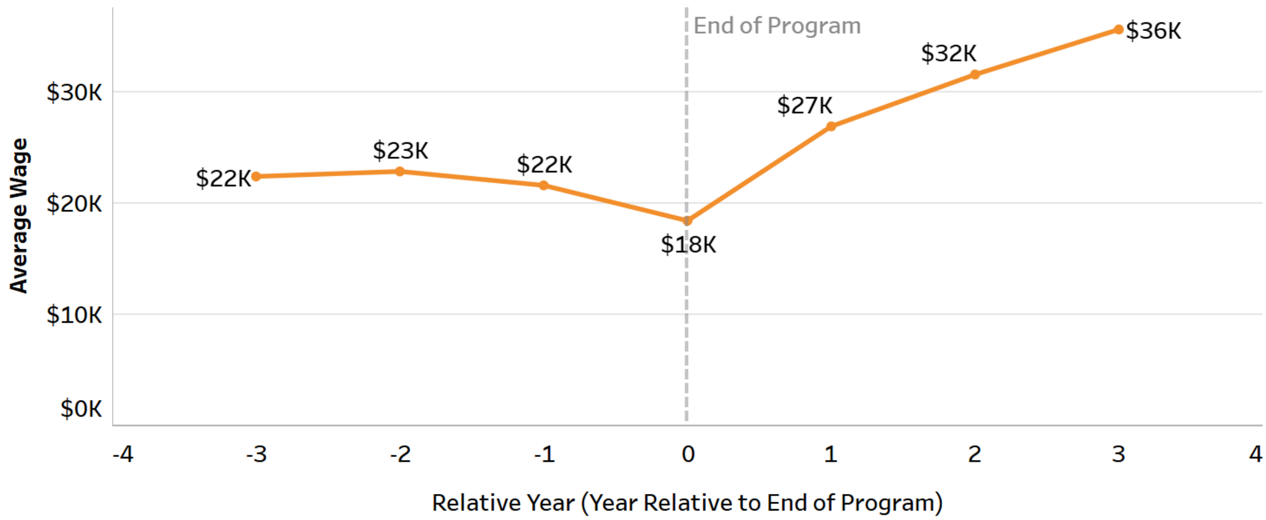


Sample Size for *All* Relative Years
303

When looking at average earnings, we see that they are relatively flat before the program year, and then dip during the program year (from $22,000 to $18,000), before rising sharply in *each year after the program.* Earnings are up a full *50%* from the program year to year 1 (from $18,000 to $27,000), and then top out in year 3 at $36,000: this is *double* the earnings during the program year. The team pointed out that in the trades, the hourly rate typically rises about $2-$3/year (although it's unlikely that all of the people represented in the data were employed full-time year-round). Translating this to a pay raise for a full-time job, this raise comes out to $4,000-$6,000/year. This pay hike no doubt partially explains the rise in average earnings during the post-program period.

It is common for earnings to dip during the program year: an earnings decline is often associated with working fewer hours *because* of program participation. While the absolute value of the average earnings is very low (far below living wages), the *trend* in earnings is extremely encouraging.

OPPORTUNITY BUILD: AVERAGE EARNINGS for ALL PARTICIPANTS



Sample Sizes, by Relative Year	
Relative Year	**People Employed**
-3	141
0	207
+3	199

Graduation Status

This next view of the data separates out those who graduated from the program from those who did not. Several results stand out:

- **An astonishingly high percentage of participants graduate.** Of the 303 total participants represented here, *89% of them completed the program successfully.* This very high graduation rate speaks well of the program's ability to retain those who enroll.
- **The graduates have better outcomes than the non-graduates.** Both the employment rate data and the earnings data show much more positive trends in the post-program years for those who graduated from the program. In addition to the "within-group" difference (the difference between the pre-program and post-program patterns), the "between-group" difference also lends credence to the conclusion that the program has impact on its participants (above and beyond what would have happened to them if they had *not* participated). What is especially impressive about the difference between the pre/post-program patterns for the two groups is that the between-group difference is much larger *after* the program than it was before. If the program had no impact, we would expect to see that the difference in the post-program years was roughly the same as it was in the pre-program years.
- **However, there also seems to be some "self-selection bias" into each group.** While the between-group difference in post-program patterns is impressive, we cannot attribute it to program participation alone. The fact that the non-graduates had poorer outcomes in the *pre*-program period (than did the graduates) suggests that the non-graduates *selected themselves into the non-graduating group* for reasons that went beyond the quality of program delivery. These reasons no doubt included external challenges in their own lives as well as some measure of internal motivation. We can be

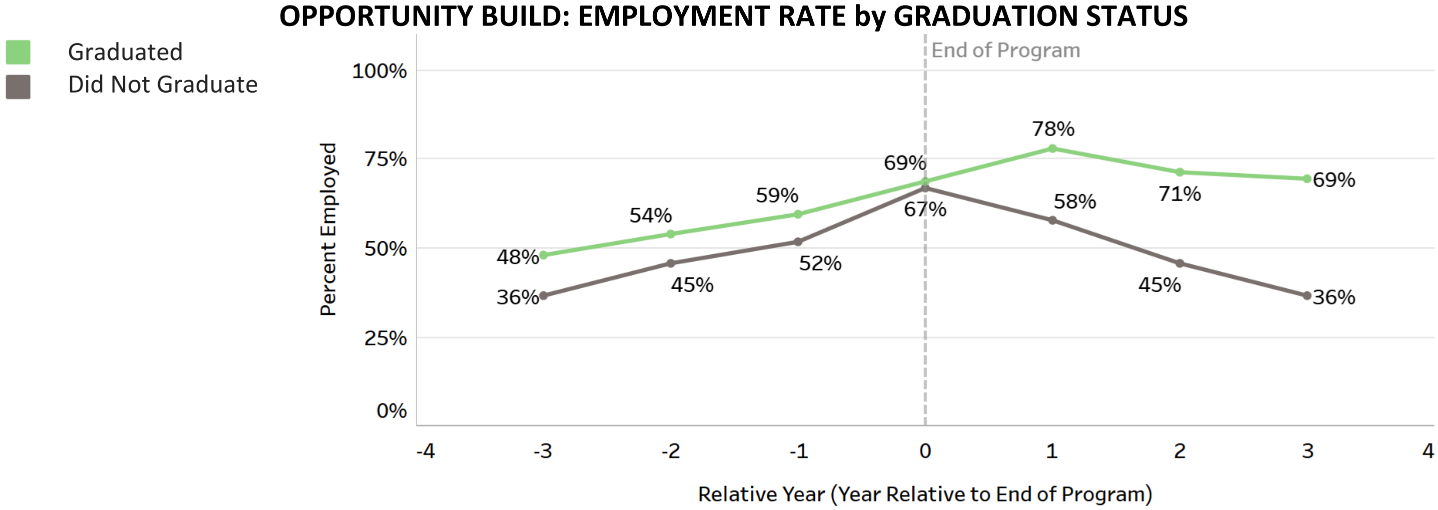
relatively confident that those reasons contributed *both* to the tendency to leave the program before graduating, *and* to their post-program outcomes.

To focus specifically on the specifics of the difference between the two groups, the employment rate shows that those who graduated had higher employment rates that the non-graduate group during the pre-program period – with the difference in each of the three pre-program years ranging from 7 percentage points (year -1) to 12 percentage points (year -3).

The employment rates were practically the same during the program year (with only a 2 percentage point difference), but the pattern in the *post*-program years shows a large advantage for graduates. In year 1, the employment rate for the graduates rose 9 points over the program year (from 69% to 78%), while the employment rate for the *non*-graduates *fell* 9 points (from 67% to 58%). For years 2 and 3, the employment rate for graduates declined each year, but never fell below the program year rate, and so stayed above *all* of the pre-program year rates. In contrast, the employment rate fell sharply for the non-graduates, reaching a low of 36% in year 3 (the same as the low in the pre-program years).

Again it is worth dwelling on how much larger the between-group difference was in the post-program years than it was during the pre-program years. The largest difference before the program was 12 percentage points (year -3), while the largest difference *after* the program was a whopping 33 percentage points (year 3). This "difference-in-difference" suggests that there was a program impact: a difference that program participation made *over and above* what would have happened to the two groups if they had *not* participated in Opportunity Build.

OPPORTUNITY BUILD: EMPLOYMENT RATE by GRADUATION STATUS



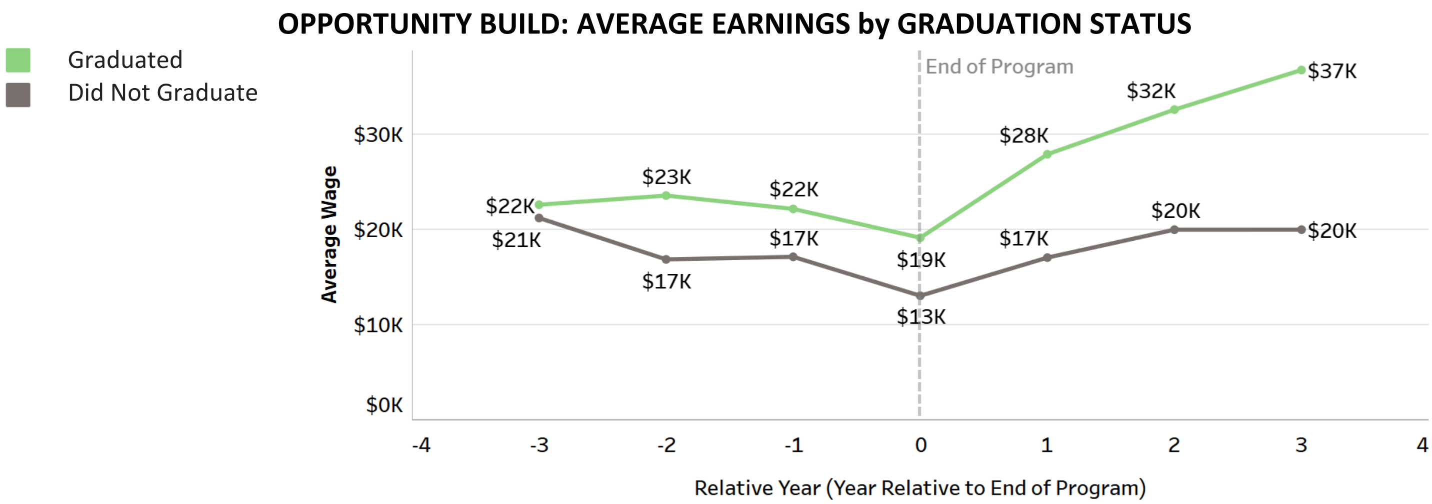
Sample Sizes for *All* Relative Years, by Graduation Status	
Graduated	**Did Not Graduate**
270	33

The pattern we see in average earnings is quite similar to the employment rate pattern. *Among those employed,* the graduates do better than non-graduates, and the between group difference is much larger after program exit than before.

Graduates show a rise in average earnings of $9,000 from the program exit year to year 1 (from $19,000 to $28,000). Average earnings continue to rise, topping out at $37,000 in year 3. This is an almost 100% increase over the program exit year ($18,000 more than the exit year earnings).

The employed non-graduates *also* show a rise in earnings: from $13,000 in the exit year to $20,000 in year 3). This rise is encouraging, since the trend prior to the program year was downward. The shift in the earnings pattern suggests that even *some* engagement with the Opportunity Build program supported participants' wages to increase – this finding again speaks to program effectiveness. However, the rise is not nearly as dramatic as the increase for the graduates, and of course the *level* of earnings is extremely low.

The fact that the between-group difference was so much larger in the post-program years compared to the *pre*-program years also points to program effectiveness: the largest average earnings difference in the pre-program years was $6000 (year -2); the largest average earnings difference in the post-program years was $17,000 (year 3).



Sample Sizes, by Relative Year & Graduation Status		
Relative Year	**Graduated**	**Did Not Graduate**
-3	129	12
0	185	22
+3	187	12

Rising Sun Cohort (Season)

The Rising Sun team was interested in learning if there were systemic differences among the participant groups that attended programs during different seasons (spring, summer, fall) – labeled as RS cohorts.

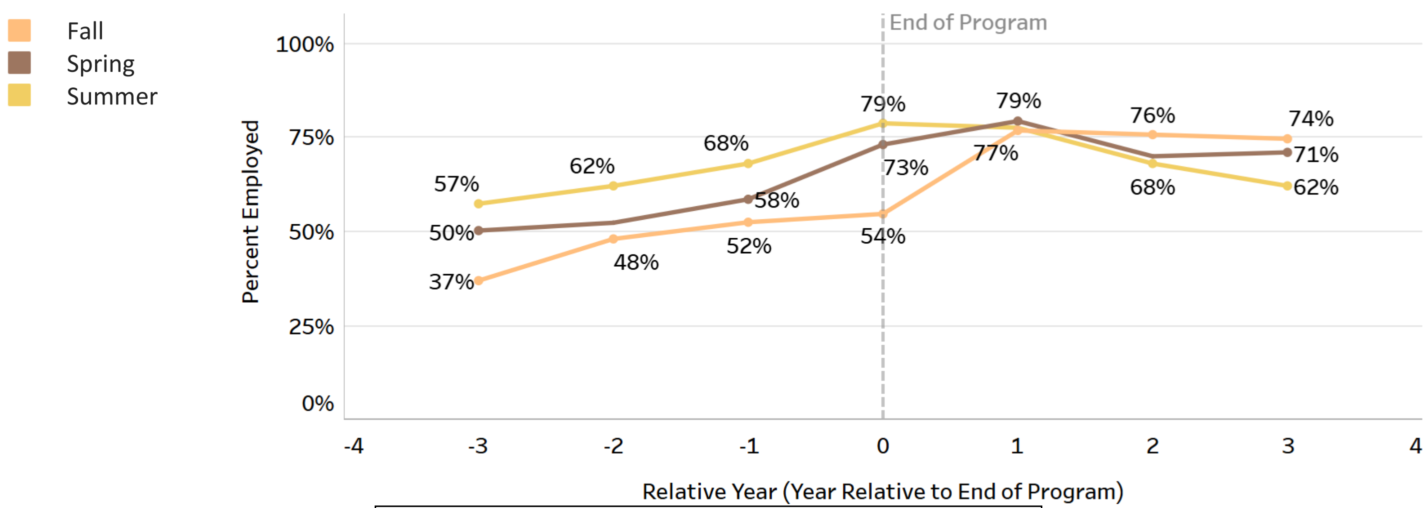
The employment rate data shows a very interesting pattern, in which the three cohorts show some systemic differences *before* the program that *completely reverse after* the program. (The higher employment rate for the summer cohort was not surprising: people in the summer cohorts attend the program on nights and weekends – and this schedule is more attractive to people who are already working.) For all three cohorts, the employment rate rose from year -1 to the program exit year: the summer cohort rose 11 percentage points (from 68% to 79%); the spring cohort rose 15 percentage points (from 58% to 73%); and the fall cohort rose only 2 percentage points (from 52% to 54%).

However, during the *post* program period, the *fall* cohort did the best: in year 1, this group showed an employment rate increase of *23 percentage points* (from 54% to 77%) – during this year roughly matching the employment rates of the other two cohorts. In the subsequent two years, the employment rate declined only very slightly to 76% in year 2 and 74% in year 3. This was the highest employment rate during the final year.

The employment rate for the summer cohort, on the other hand, *declined* slightly in the first post program year (down 2 percentage points from 79% to 77%). The rate continued to trend downward quite a bit – ending at 62% in year 3, a full 15 points lower than it had been in year 1, and 17 points lower than it had been at its highest. The year 3 rate of 62% was also the lowest of the three cohorts in year 3.

The spring cohort was in the middle: in year 1, the rate rose 6 percentage points over the exit year (from 73% to 79%). After that it declined, down to 71% in year 3.

OPPORTUNITY BUILD GRADUATES: EMPLOYMENT RATE by RS COHORT (SEASON)



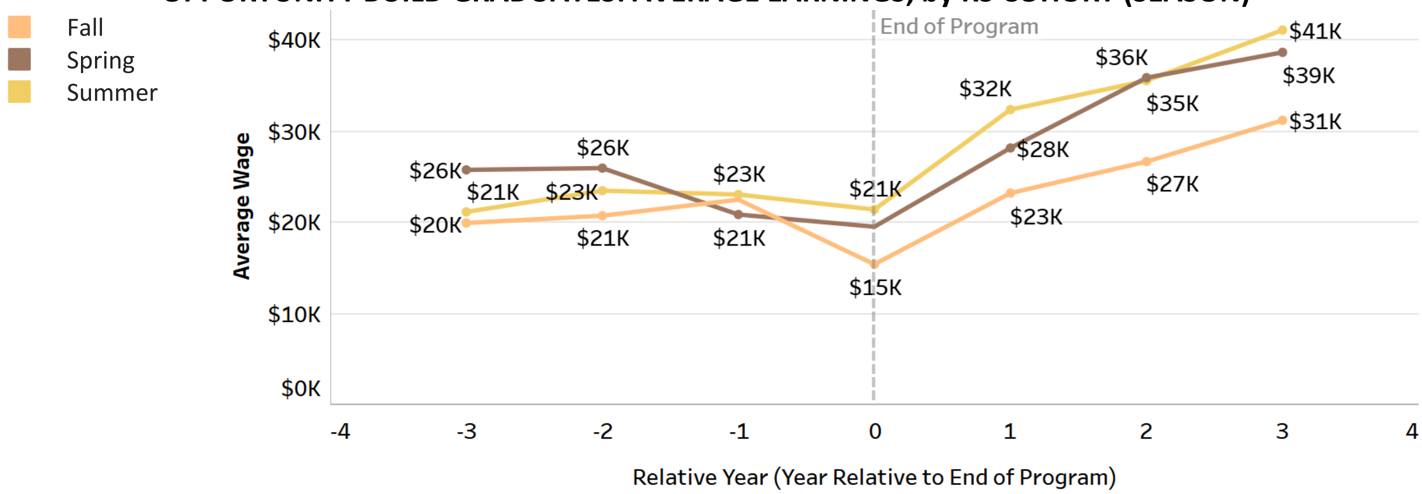
Sample Sizes for *All* Relative Years, by RS Cohort (Season)		
Fall	**Spring**	**Summer**
90	96	84

The average earnings patterns (for those employed) are quite different from the employment rate patterns. While the summer cohort showed the least positive employment rate trend, the average earnings were the highest of the three cohorts: rising to $41,000 in year 3 from $21,000 in the program exit year (reflecting a rise of nearly 100%). The earnings amount was also the highest of the three groups in year 3 (and the earnings had also been the highest in the exit year and year 1, and only slightly behind the highest earnings amount (for the spring cohort) in year 2).

The spring cohort showed average earnings that were quite similar to those of the summer cohort (only a little lower each year from the program year onward, and slightly higher in year 2). The average earnings rose $9,000 in year 1 from the program exit year ($19,000 to $28,000). They rose $20,000 over the three post-program years (up to $39,000).

The fall cohort had the lowest average earnings, but the magnitude of the rise was still impressive. Average earnings rose $8,000 in year 1 from the program exit year (from $15,000 to $23,000), and then more than doubled by year 3 (ending at $31,000).

OPPORTUNITY BUILD GRADUATES: AVERAGE EARNINGS, by RS COHORT (SEASON)



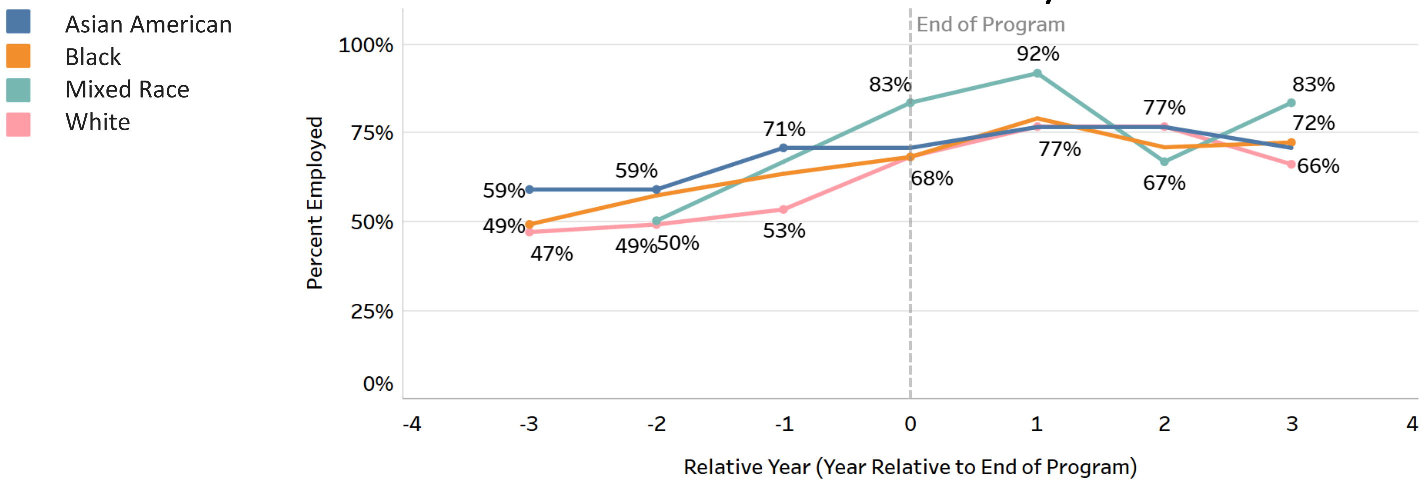
Sample Sizes, by Relative Year & RS Cohort (Season)			
Relative Year	**Fall**	**Spring**	**Summer**
-3	33	48	48
0	49	70	66
+3	67	68	52

Race

For Opportunity Build, the two largest racial groups were Black and white (147 and 47 participants, respectively). There were so few people in the other two groups (17 for Asian American and 12 for mixed race) that it is harder to draw conclusions about those two groups. Therefore, this section will focus on the Black and white groups.

In terms of the employment rates, Black participants did slightly better than white participants in the pre-program period. During the program exit year and later, white participants caught up, and the employment rates are nearly the same. In the exit year they are both at 68%, and they both rise in year 1: the rate for Black participants is up 9 percentage points (to 77%) and the rate for white participants is up 10 percent points. By year 3, the employment rate for Black participants is 72%, and for white participants is 66%. Both groups have employment rates in year 3 that are above *all* of their pre-program rates.

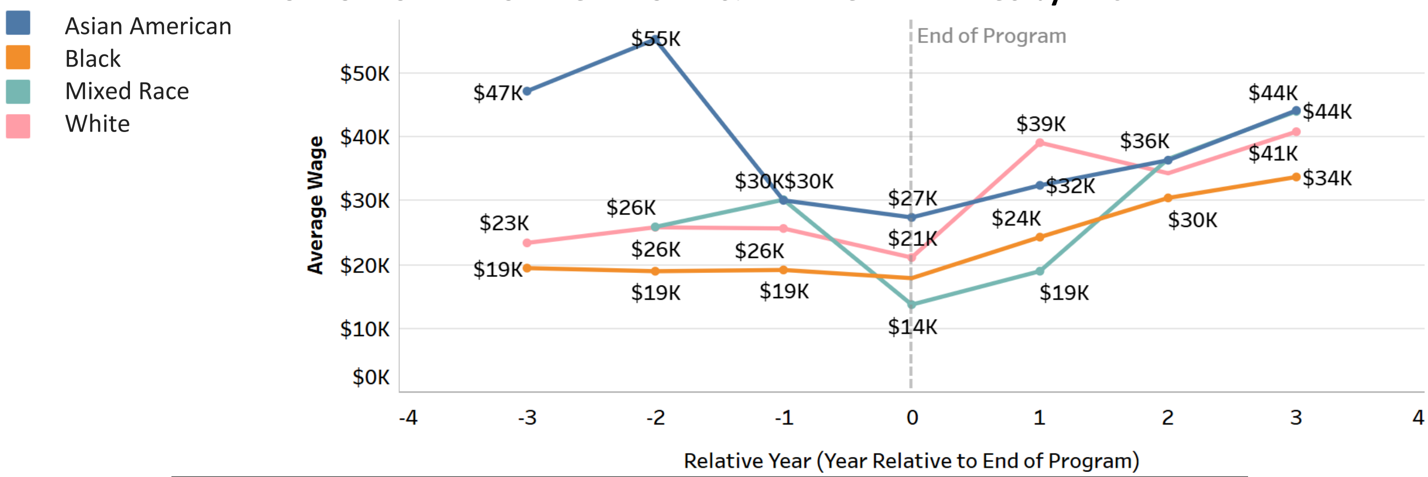
OPPORTUNITY BUILD GRADUATES: EMPLOYMENT RATE by RACE



Sample Sizes for *All* Relative Years, by Race			
Asian American	**Black**	**Mixed Race**	**White**
17	147	12	47

While the Black participants ended in year 3 at an employment rate higher than that for white participants, white participants did better in terms of average earnings. The between-group difference is extremely similar during the periods before *and* after the program (with the exception of year 1, in which there was a spike in earnings for the white participants). This pattern (spike aside) may point to structural racism in the labor market (and is *very* likely to point to structural racism if the two groups are otherwise demographically similar). White participants showed a rise of $20,000 over three years (from $21,000 in the exit year to $41,000 in year 3) and Black participants showed a rise of $16,000 (from $18,000 to $34,000).

OPPORTUNITY BUILD GRADUATES: AVERAGE EARNINGS by RACE

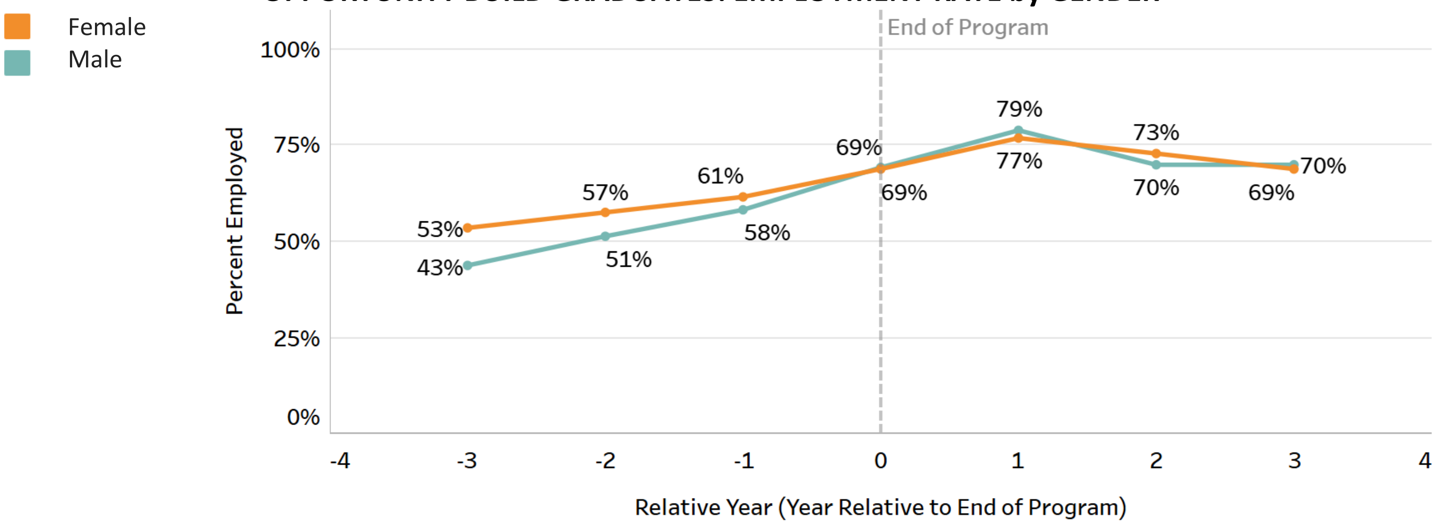


Sample Sizes, by Relative Year & Race				
Relative Year	**Asian American**	**Black**	**Mixed Race**	**White**
-3	10	72	NULL	22
0	12	100	10	32
+3	12	106	10	31

Gender

The results for males and females were quite similar to one another, especially in terms of employment rate. While men had somewhat lower rates during the pre-program period, they were closing the gap with women each year, and the rate was exactly the same during the program exit year (69%). The rates for both rose in year 1 (8 percentage points to 77% for women, and 10 percentage points to 79% for men). The rates then trended downward slightly over the next two years, ending at essentially the same level they had been during the exit year (70% for women and 69% for men). For both groups, the year 3 employment rate was higher than it was during any of the pre-program years.

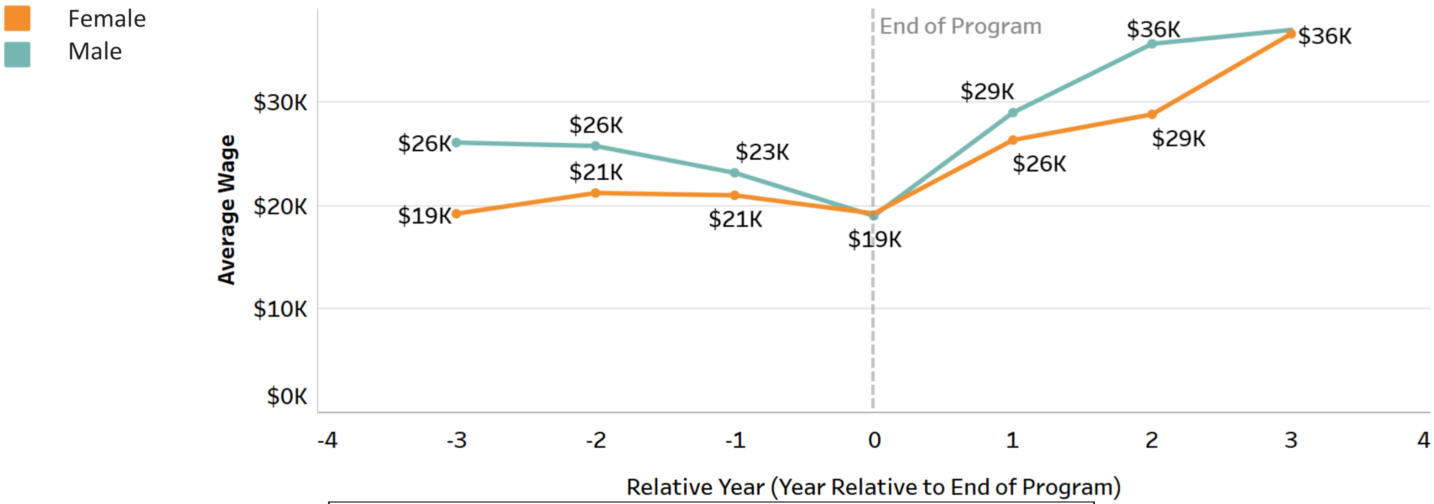
OPPORTUNITY BUILD GRADUATES: EMPLOYMENT RATE by GENDER



Sample Sizes for *All* Relative Years, by Gender	
Female	**Male**
124	145

While there is more of a between-group difference in average earnings than there was in the employment rate, the two groups still look quite similar to one another. Men had higher average earnings during all three pre-program years, but each year (approach the program year), the gap was shrinking. During the program exit year, they had the same average earnings: $19,000. For all three post-program years, earnings rose for both groups. In years 1 and 2, men were earning more than women ($29,000 vs. $26,000 in year 1; $36,000 vs. $29,000 in year 2). In year 3, women caught up with men, and average earnings for both was $36,000.

OPPORTUNITY BUILD GRADUATES: AVERAGE EARNINGS by GENDER



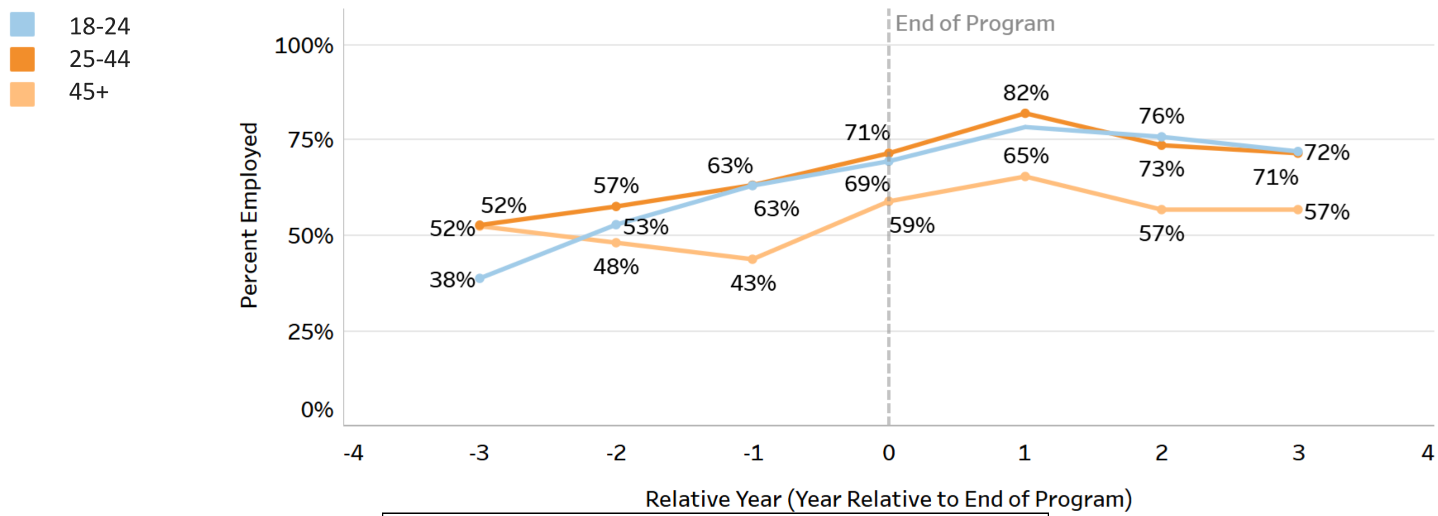
Sample Sizes, by Relative Year & Gender		
Relative Year	**Female**	**Male**
-3	66	63
0	85	100
+3	85	101

Age Group

In terms of age group, the two younger groups (18-24 and 25-44) have almost exactly the same employment rates, starting in year -1. For both, the rates rise during the program exit year compared to the previous year (up 6 percentage points for 18-24, from 63% to 69%; and up 8 percentage points for 25-44, from 63% to 71%). The rates then rise again significantly for both groups (up 9 percentage points for 18-24, from 69% to 78%; and up 11 percentage points for 25-44, from 71% to 82%).

The *shape* of the trend for the 45+ group is the same as it is for the other two age groups (for the five years from year -1 to year 3). Their employment rate rose 16 percentage points from year -1 to the program exit year (from 43% to 59%), and then rose another 6 points (to 65%). The rate then declined in years 2 and 3, to end at 57% in year 3 (a rate higher than any of the pre-program years, however). While the pattern was similar for this age group, the employment *rate* is quite a bit lower at every time period (starting in year -1). This lower rate may reflect the fact that – as one member of Rising Sun team said – “the trades are harder on older workers.”

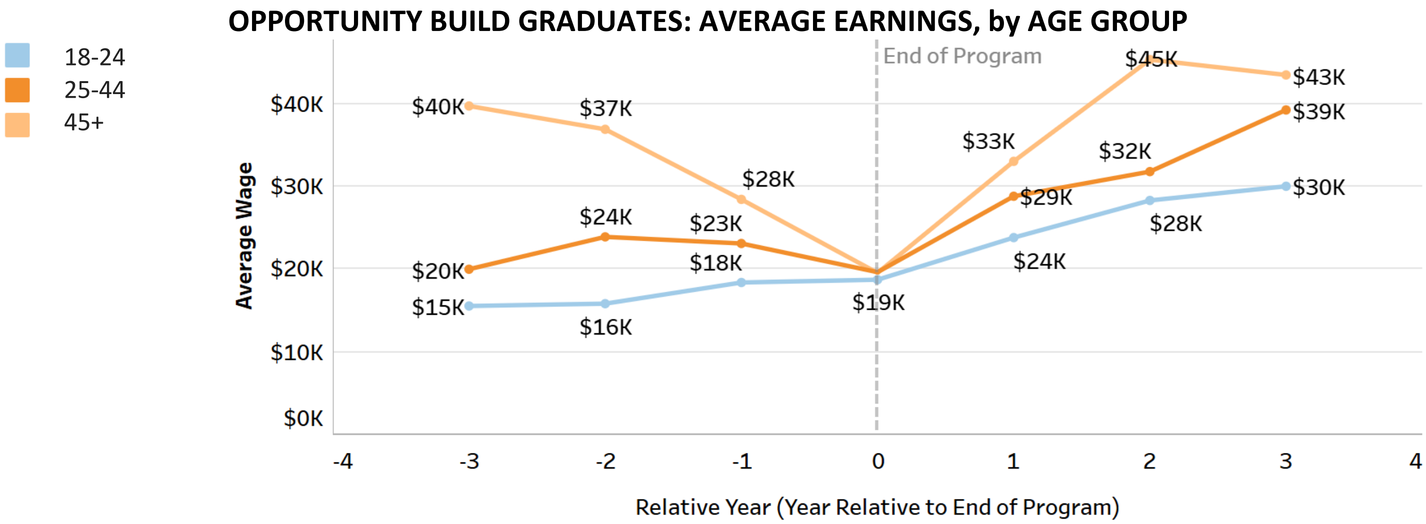
OPPORTUNITY BUILD GRADUATES: EMPLOYMENT RATE by AGE GROUP



Sample Sizes for *All* Relative Years, by Age Group		
18-24	**25-44**	**45+**
78	143	46

For average earnings, the story is quite different. Essentially, the older the workers are, the higher their earnings are (with the exception of the program exit year, when average earnings converge for all three groups). The 45+ group had struggled the most in terms of employment, but *for those employed,* this oldest group has the highest average earnings. The differential is especially large during the pre-program years, although the difference shrinks over time (and disappears during the program year).

The *growth* of average earnings was also correlated with age. Earnings for the 18-24 group rose $11,000 from the program exit year to year 3. During this same time period, earnings for the 25-44 group rose $19,000 (from $20,000 to $39,000); and for the 45+ group, earnings for the 45+ group rose $23,000 (from $20,000 to $43,000). This growth for the 45+ group during the post-program years suggests that once they get trained (and a placement), they are able to capitalize on their experience in the trades.



Sample Sizes, by Age Group			
Relative Year	**18-24**	**25-44**	**45+**
-3	30	75	24
0	54	102	27
+3	56	102	26

Educational Attainment

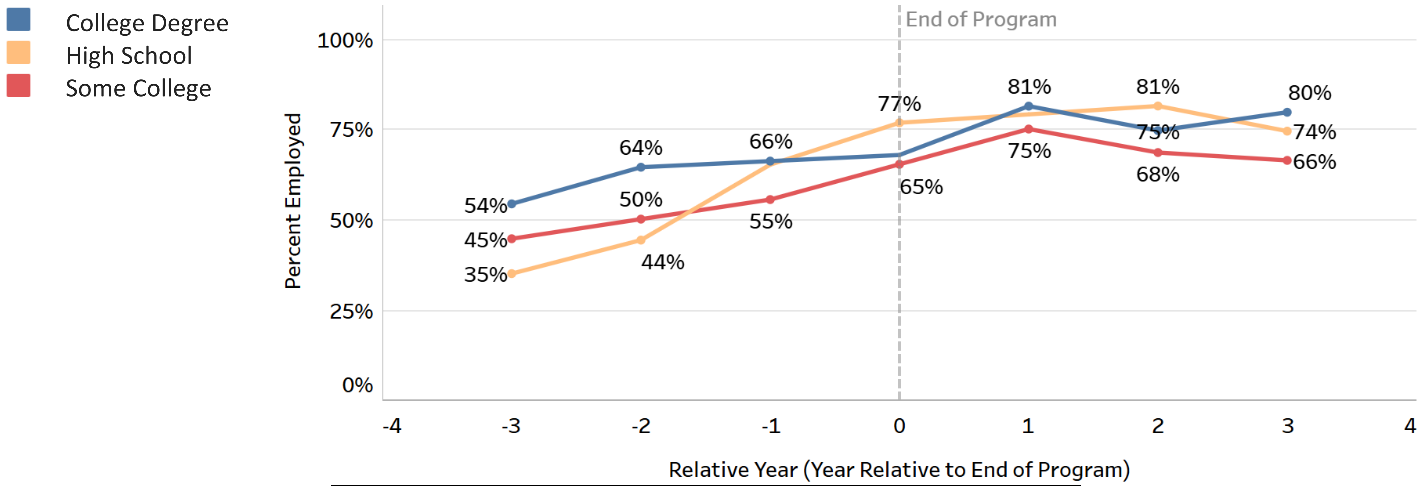
The employment rates show a mysterious pattern that was surprising to the Rising Sun team. Looking at *only* those with a college degree or some college (no degree), employment rates (at every time period) correlate positively with educational attainment. If we look at all *three* levels of educational attainment, though, we can see that the correlation between attainment and employment level doesn't hold, because those with *only* a high school degree do unexpectedly well. They have employment rates higher than those with some college during the exit year *and* in all three post program years, but they also have employment rates higher than those with a college degree during the exit year and year 2 (and only a bit lower in year 1).

First we can look at only those with a college degree and some college. Those with a degree do especially well, with the employment rate ending in year 3 at 80% (only 1 percentage point lower than the highest rate attained (81% in year 1)). This pattern is fairly unusual: for most subgroups, the pattern tends to be a decline in years 2 and 3 after an initial rise in year 1 (compared to the program exit year). In fact, this is the pattern shown for those with some college: the employment rate rose 10 percentage points between the program exit year and year 1 (from 65% to 75%), and then declined over the next two years, to end at 66%.

Turning to the high school group, during year -1, they had the same employment rate as those with a college degree (66%), and during the program exit year, those with a college degree held at 66%, while those with a high school degree rose 11 percentage points (to 77%). The rate continued to rise in year 1 (to 80%), *and* year 2 (to 81%), before declining to 74% in year 3 (a rate that was still higher than those with some college (66%).

There was some speculation that the employment rate was lowest among those with some college because some of those participants may have been returning to school to finish up their degrees during the post-program years.

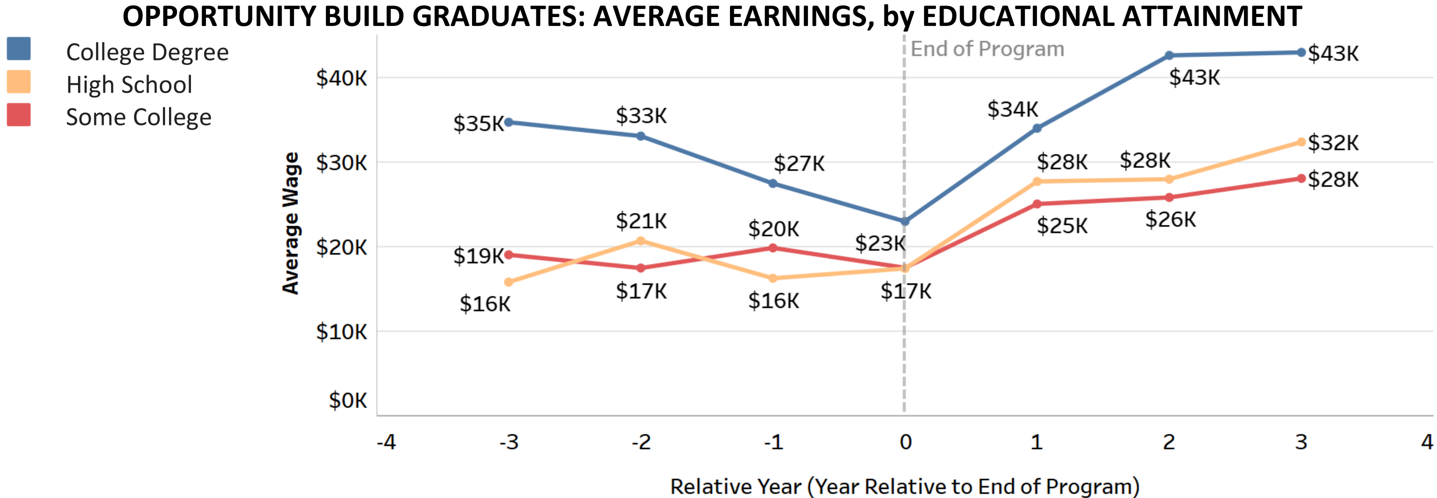
OPPORTUNITY BUILD GRADUATES: EMPLOYMENT RATE by EDUCATIONAL ATTAINMENT



Sample Sizes for *All* Relative Years, by Educational Attainment		
College Degree	**High School Degree**	**Some College**
59	43	92

The results that break average earnings out by educational attainment show that there is a large premium to having a college degree. During every single time period, average earnings for college graduates were *much* higher than the earnings of the other two groups. Earnings for the college graduates were, however, showing a downward trend during the pre-program years that wasn't in evidence for the other two groups, so during the program exit year, the differential had shrunk to $6,000 ($23,000 for college graduates, compared to $17,000 for the other two groups). Average earnings for college graduates rose sharply during the first two post-program years, up $20,000 to $43,000 in year 2 (holding steady at this figure in year 3).

In comparison, the absolute value of average earnings for the other two groups was much lower, *and* the growth much slower. For high school graduates, average earnings rose $15,000 over three years (from $17,000 in the program exit year to $32,000 in year 3). Those with *some* college actually did less well than high school graduates. Over three years, their average incomes rose $11,000 (from $17,000 to $28,000). It's possible that those with some college were earning so little because they were spending time returning to school to finish their college degrees.



Sample Sizes, by Educational Attainment			
Relative Year	**College Degree**	**High School Degree**	**Some College**
-3	32	15	41
0	40	33	60
+3	47	32	61

Family Type

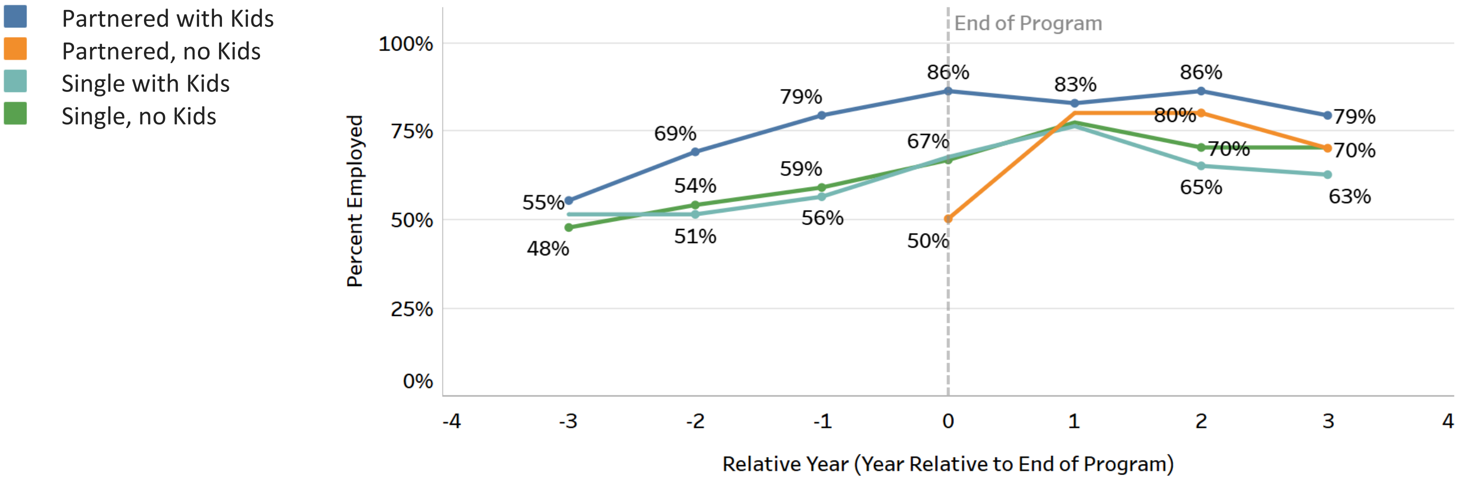
Rising Sun was interested in looking at the employment outcomes for workers in four family types: (1) people with a partner and children; (2) people with a partner but *without* children; (3) single people with children; and (4) single people *without* children. The second type (partnered without kids) is so small (only 10 people), that we focus the discussion of results on the other three family types.

The first group (partnered with children) shows the highest employment rate of all four groups during every time period. During the program exit year, the employment rate is a very high 86% (19 percentage points above the employment rate for the two groups in which the workers are single (67% for the groups with and without children).

The employment rate for the group that is partnered with children remains high during all three post-program years, dipping slightly in year 1 (to 83%) and then recovering to 86% in year 2. The rate then falls to 79% in year 3, its lowest post-program rate but still quite high.

For the two groups with single workers, the employment rates rise from 67% in the program exit year to 76% in year 1. In both groups the rates decline slightly, with the group with children ending at 63% in year 3, and the group, and the group *without* children ending at 70% in year 3.

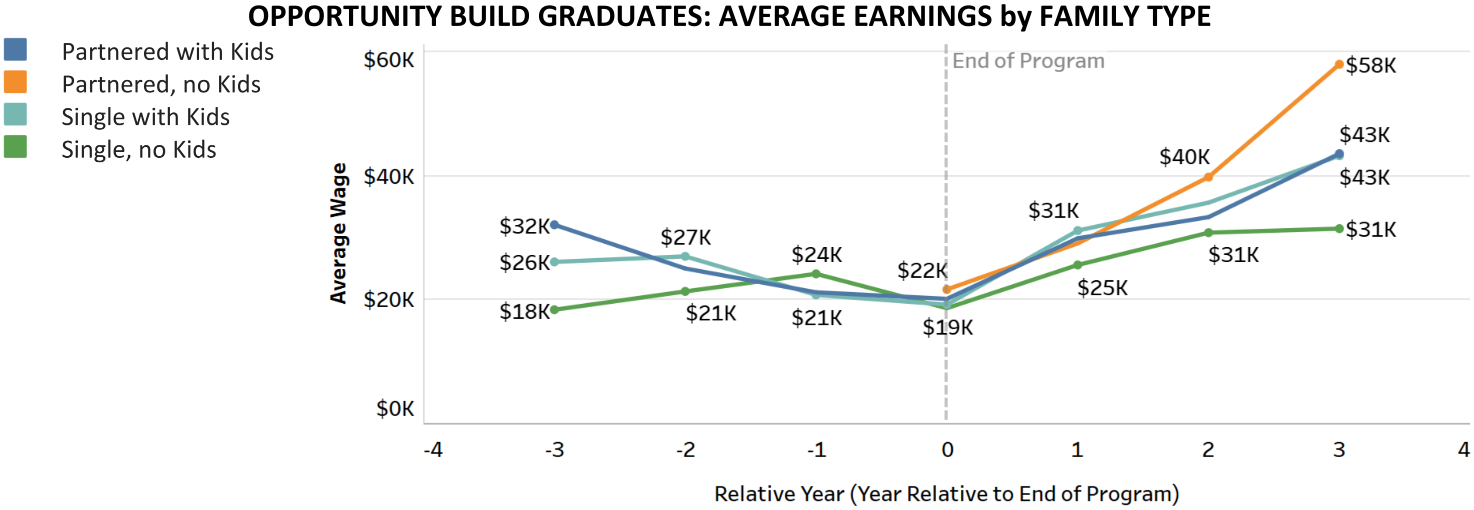
OPPORTUNITY BUILD GRADUATES: EMPLOYMENT RATE by FAMILY TYPE



Sample Sizes for *All* Relative Years, by Family Type			
Partnered		Single	
With Kids	No Kids	With Kids	No Kids
29	10	80	141

All three groups (again, leaving aside the group with a very low sample size) show growth in average earnings after the program exit year. During the exit year, the three groups have average earnings that are essentially the same (ranging from $19,000 to $20,000). Over the next three years, the two groups with children (both partnered and single) more than double, rising to $43,000. The group in which workers are single with no children show a much smaller increase: rising $12,000 from $19,000 to $31,000 in year 3. The Rising Sun team speculated that those who were single without children might tend to be *younger,* and their relative youth could partly explain the lower average earnings.

OPPORTUNITY BUILD GRADUATES: AVERAGE EARNINGS by FAMILY TYPE



Sample Sizes, by Relative Year & Family Type				
Relative Year	Partnered		Single	
	With Kids	No Kids	With Kids	No Kids
-3	16	NULL	41	67
0	25	5	54	94
+3	23	7	50	99

System Impact

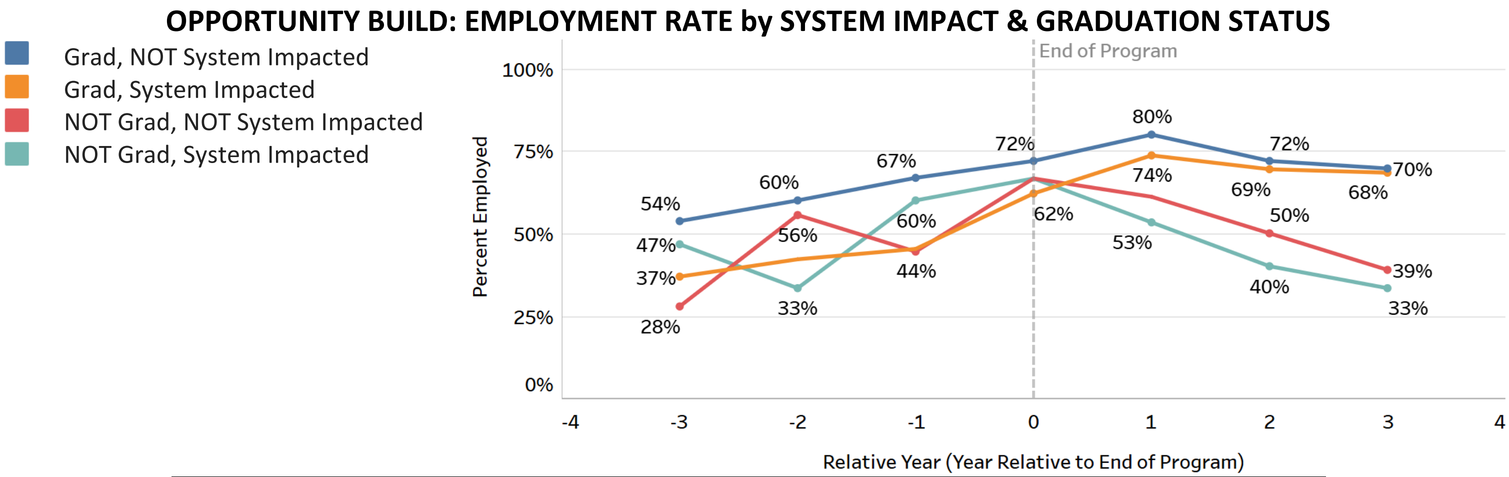
An important question for Rising Sun is how their system-impacted participants do; over one-third of the participants in the 2015-2019 cohorts were system-impacted (110 out of 303). To dig into outcomes for these participants, the charts shown here not only compare system-impacted participants to those who are *not* system-impacted, but also bring in graduation (comparing people who graduated from the program to people who didn't). Even though the *non*-graduates make up a relatively small number of participants, seeing the four groups together in one graph is particularly helpful.

Looking at the employment rate, and first focusing *only* on those who graduated, we see that the positive trend for system-impacted participants is especially pronounced. Those who are *not* system-impacted saw good employment rate outcomes: the rate rose 5 percentage points from year -1 to the program exit year (from 67% to 72%), and then another 8 percentage points from the exit year to year 1 (up to 80%). The rate then declined over the next two years, but still stayed relatively high (ending at 70% in year 3, a rate higher than any of the pre-program employment figures).

The pattern for system-impacted participants, though, is much more dramatic. This group's employment rate rose *18 percentage points* from year -1 to the program exit year (44% to 62%). The rate then rises again from the exit year to year 1, another 12 points to reach 74%. The rate then declines over the next two years, but declines *less* each year than does the rate for the non-system-impacted participants.

As a result, the system-impacted group closes the gap over time with their non-system-impacted counterparts. The year *before* the program, the gap was 23 points; then in each successive year it falls; to 10 points, 6 points, 3 points, and 2 points (in years 0, 1, 2, and 3 respectively). In other words, by 3 years after program exit, there is essentially no difference between the two groups.

We can see another interesting result by looking at all four groups together. During the pre-program years, the graduating non-system-impacted group looks systematically different from the other three groups (and the other three groups look similar to one another). To the extent that the past often does a very good job of predicting the future, we might expect the pre-program trends to partially influence the post-program. However, while the two non-graduate groups did very poorly after the program, the graduating system-impacted group departs from the other two groups dramatically – showing rising employment rates rather than a massive drop-off. The difference in the employment rate patterns here points suggests a strong impact of program participation on those in the system-impacted group who graduated – an impact *that may not be related to a self-selection bias.* Again, conclusions like this must be drawn with extreme caution, given the small sample sizes of the non-graduate groups, and the inability to conduct statistical modeling on the data. However, these results are exciting, and Rising Sun can look for possible replication in future years with larger sample sizes.

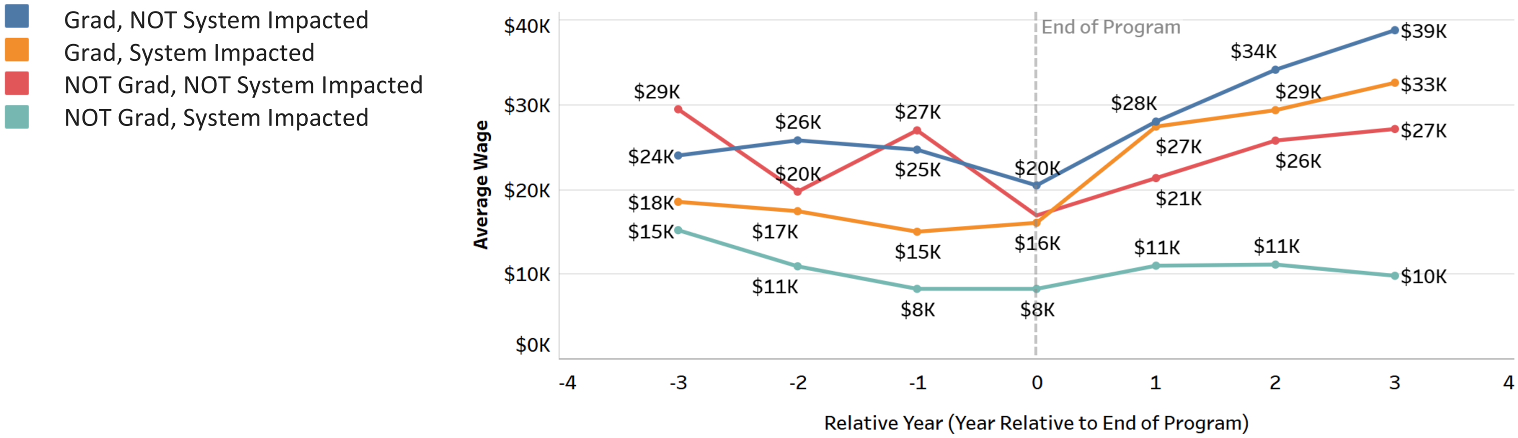


Sample Sizes for *All* Relative Years, by System Impact and Graduation Status			
Graduated		NOT Graduated	
NOT System Impacted	System Impacted	NOT System Impacted	System Impacted
175	95	18	15

Looking at the average earnings of those who are employed, we see results that reinforce the conclusions that we tentatively drew from the employment rate data. First let's look at the two system-impacted groups and compare them to the *non*-system-impacted groups. We can see that *before* the program, the non-system-impacted groups were both doing much better than the system-impacted groups. So again, we might expect that those two groups did better *after* the program as well, but this is not the case. Instead, those who were system-impacted *and who graduated* have virtually the same average earnings during the exit year as the non-system-impacted, non-graduating group (having closed a large pre-program gap).

Then in the post-program years, average earnings for the system-impacted group are *much higher* than average earnings for the *non*-system-impacted *non*-graduates. In year 3, the average earnings of the graduating, system-impacted group is $33,000, $6,000 more than the non-graduating, *non*-system-impacted group. Again, although the sample sizes are small, these results lend some credence to the conclusion that *program graduation matters more to earnings than does system impact.* This conclusion speaks volumes about the quality and effectiveness of the Opportunity Build program.

OPPORTUNITY BUILD: AVERAGE EARNINGS by SYSTEM IMPACT & GRADUATION STATUS



Sample Sizes, by Relative Year, System Impact, and Graduation Status				
Relative Year	Graduated		NOT Graduated	
	NOT System Impacted	System Impacted	NOT System Impacted	System Impacted
-3	94	35	5	7
0	126	59	12	10
+3	122	65	7	5

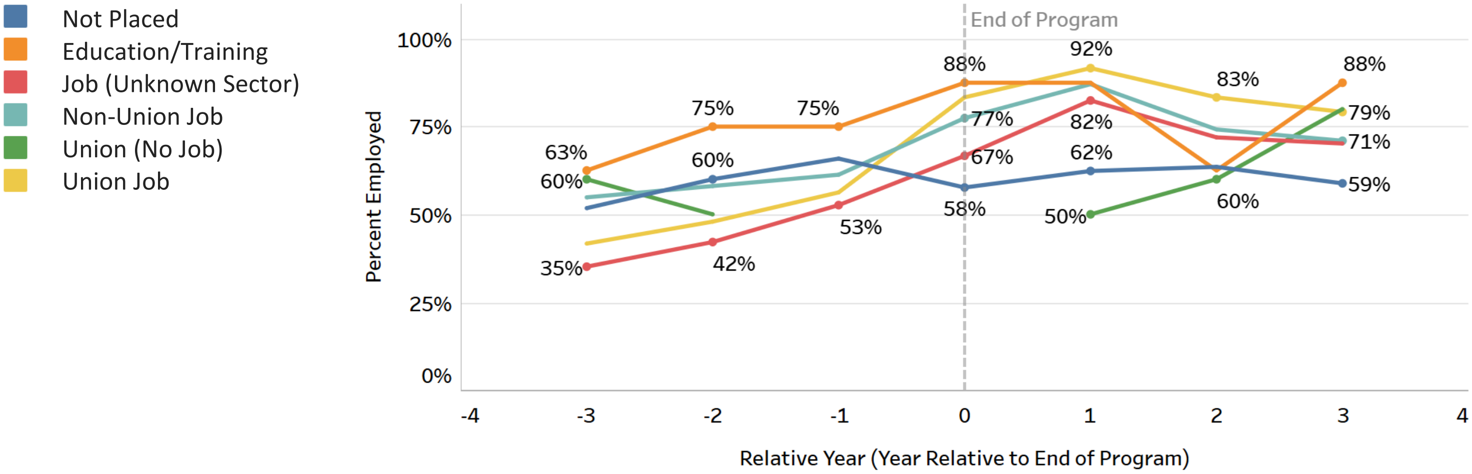
Job Placement Status

An important aspect of the Opportunity Build program is job placement. The charts below show what happens to different sets of participants according to whether, and where, they were placed. Note that there are two groups with extremely small sample sizes: those placed in education and training programs (8 participants), and those placed in a union *but not* in a job (10 participants). For this reason, interpretation of the results will focus on the other four placement types: not placed, placed in a job (but sector unknown), non-union job, and union job.

First, *getting placed in some type of job* appears to make a very large difference to the post-program employment rate. The employment rate of those *not* placed declined from year -1 to the program exit year, while the rate rose for all other groups. During the program exit year, the non-placed group had an employment rate of 58%, while the other three groups (excluding the education/training group) had employment rates ranging from 67% to 83%. This result makes sense on its face, since being employed in any time period will raise the probability of being employed in the next time period. We see, then, that participants who were not placed in any job have essentially a flat employment rate throughout all 7 time periods, and the employment rate is the *lowest* from the program exit year through year 3 (leaving aside the "union, no job" group).

Second, having a union job (compared with a *non*-union job) seems to provide an extra boost to the employment rate. The non-union job group showed a rise in employment rate of 16 percentage points from year -1 to the program exit year (from 61% to 77%), before peaking in year 1 at 87%. In contrast, the union job group showed a larger increase from year -1 to the exit year (*27 percentage points*, from 56% to 83%), and then the employment rate peaked in year 1 at 92% (5 percentage points higher than the peak for the non-union job group (87%).

OPPORTUNITY BUILD GRADUATES: EMPLOYMENT RATE by PLACEMENT STATUS

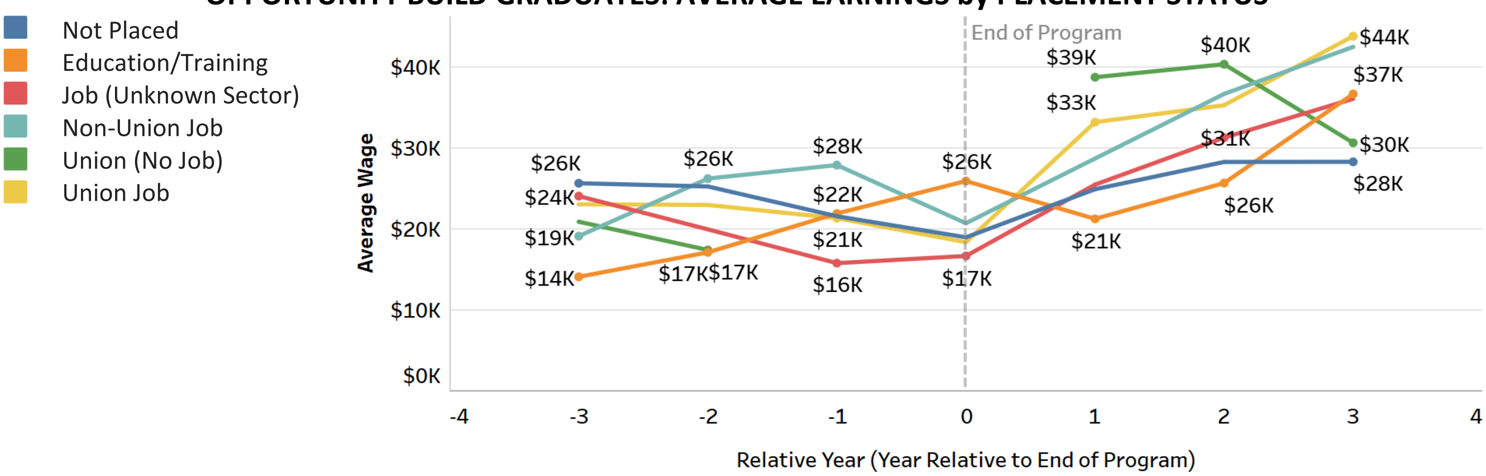


Sample Sizes for *All* Relative Years, by Placement Status					
Not Placed	**Education/Training**	**Job (Unknown Sector)**	**Non-Union Job**	**Union (No Job)**	**Union Job**
85	8	57	62	10	48

The results for average earnings (among those employed) show that all four of the groups that we're focused on have an earnings rise from the program exit year onward (although the group that was not placed shows a leveling off in year 3). The Rising Sun team emphasized that while union job placement is attractive, they seek to place *everyone* in jobs that pay decent wages. So while the union job group shows the steepest upward trend and tops out at the highest wage, the *non*-union job group is not far behind (the unknown sector job group does less well but still shows a decent upward trend).

Specifically, average wages for union jobs rise $26,000 over 3 years (from $18,000 during the exit year to $44,000 in year 3); non-union jobs rise $21,000 during the same time period (from $21,000 to $42,000); and other jobs (sector unknown) rise $19,000 ($17,000 to $36,000). In contrast, average earnings for those who are not placed rise $9,000 over 3 years ($19,000 to $28,000).

OPPORTUNITY BUILD GRADUATES: AVERAGE EARNINGS by PLACEMENT STATUS



Sample Sizes, by Relative Year & Placement Status						
Relative Year	**Not Placed**	**Education/Training**	**Job (Unknown Sector)**	**Non-Union Job**	**Union (No Job)**	**Union Job**
-3	44	5	20	34	6	20
0	49	7	38	48	NULL	40
+3	50	7	40	44	8	38

Climate Careers

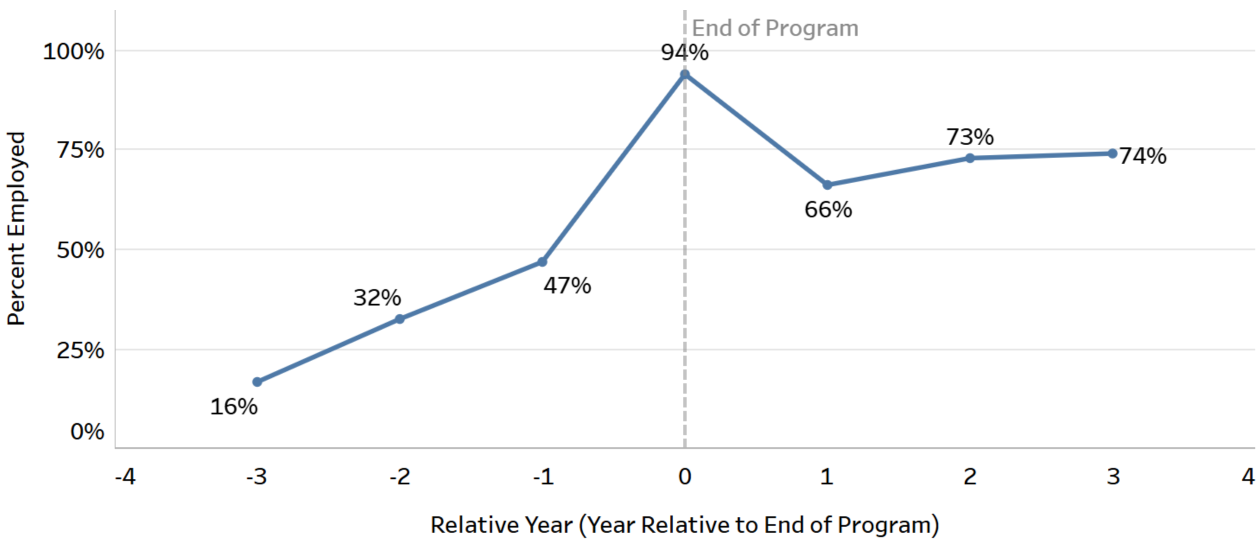
Rising Sun took an exploratory approach to the Climate Careers research questions. Because Climate Careers participants are so young, there is no expectation that they will show high employment rates *or* high average earnings during the post program years. They are especially likely to not be working (because they are in school). In addition, their average earnings will tend to be low because it is likely that they will be working part-time, part of the year, and in entry-level jobs.

With this caveat, the results for Climate Careers graduates are quite positive. The program *includes* employment, so their employment rates are near 100% during the program year. They then dip in year 1 (as is to be expected), but continue to rise from year 1 through year 3. In addition – like the Opportunity Build participants – their average earnings rise sharply, although of course the absolute value of the earnings is much lower than it is for Opportunity Build (for all the reasons stated).

Overall Results

The overall employment rate results (that include graduates *and* non-graduates) show what we would expect to see: a large spike in employment during the program year (since employment is *included* in the program), and then a drop in year 1. In years 2 and 3, the employment rate climbs in a pattern that shows a continuation from the pre-program period.

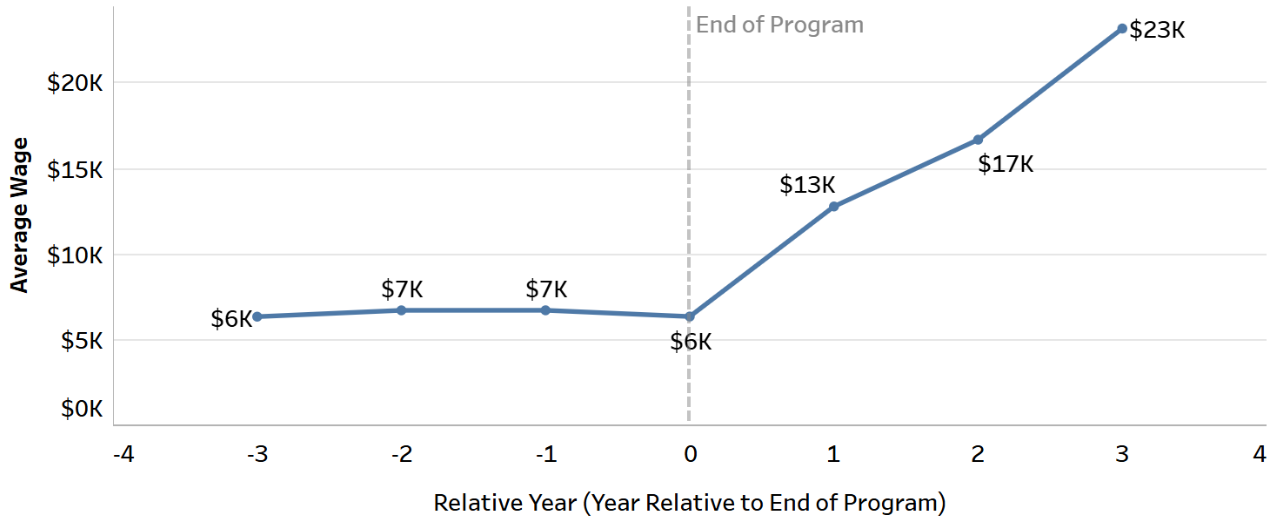
CLIMATE CAREERS: EMPLOYMENT RATE for ALL PARTICIPANTS



Sample Size for *All* Relative Years
341

The data on average earnings among those employed shows a sharp upward trend from the program year through all three post-program years. The earnings are extremely low during all the time periods (between $6,000 and $7,000 in the pre-program years, and then ranging from $6,000 in the program year to a high of $23,000 in year 3). These results are to be expected (*especially* for the pre-program years) because the participants are so young. Most of these jobs will tend to be part-time and entry-level (with low pay).

CLIMATE CAREERS: AVERAGE EARNINGS for ALL PARTICIPANTS



Sample Sizes, by Relative Year	
Relative Year	**People Employed**
-3	56
0	320
+3	232

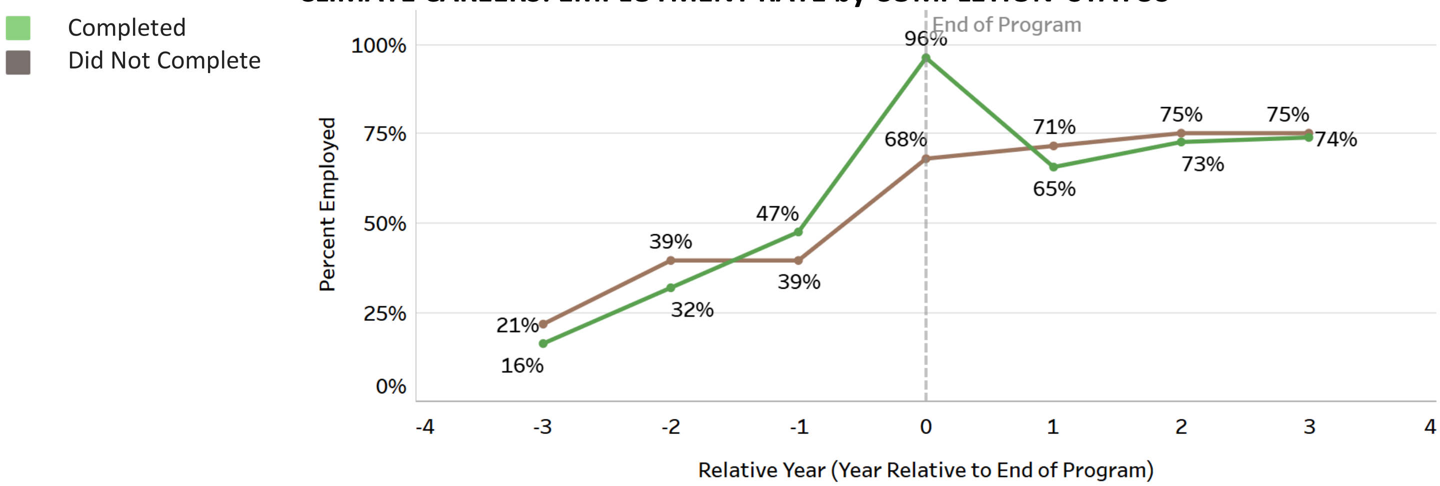
Completion Status

As was the case with Opportunity Build, an incredibly high percentage of the people who enter the program *complete* the program. Of the 341 participants, *92% complete!* The employment outcomes differ between the two groups, with 96% of the completers employed during the program exit year (again, because employment is *part* of the program).[6]

And as was the case when showing the full group, the employment rate for completers fell back down in year 1 to continue a trajectory that had begun during the pre-program years. The pattern looks quite similar for non-completers, with the exception of the program year (since they did not complete, most of all of them did not become employed as *part* of the program).

[6] During the reflection session, the Rising Sun team conjectured about why the employment rate isn't 100% for the graduates (since participants are all in jobs with W2s, they should all show up as employed in the EDD data files). In terms of possible reasons for the slight shortfall, this may be due to some data accuracy challenges that often crop up with large-scale databases such as the one that EDD uses to track employment. It may also be the case that some of the participants did not make the dollar cut-off to "count" as employed (at least $1,500 during at least one quarter).

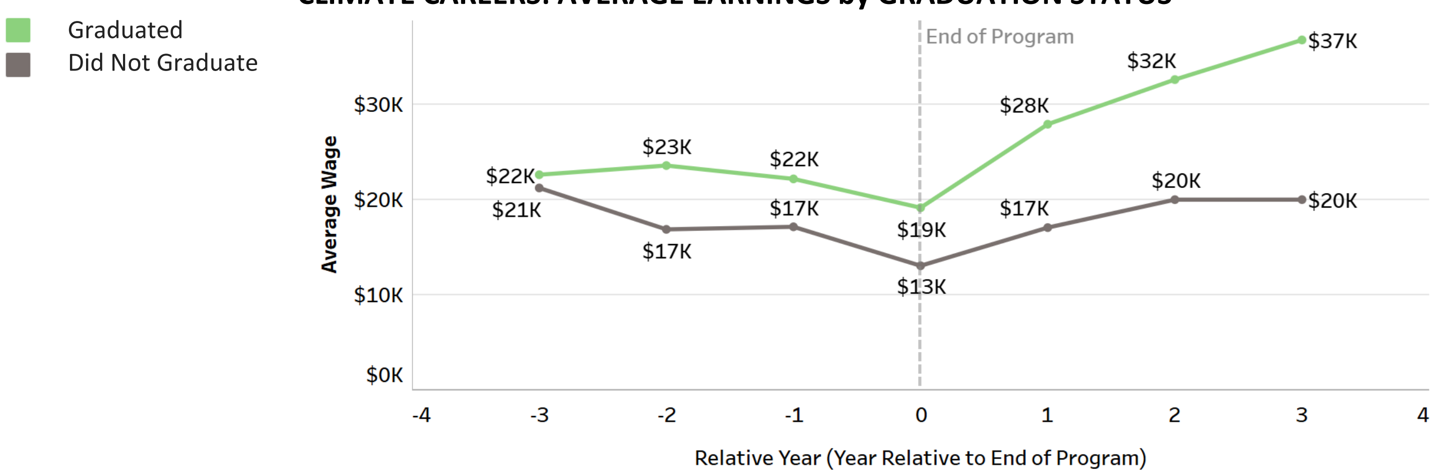
CLIMATE CAREERS: EMPLOYMENT RATE by COMPLETION STATUS



Sample Sizes for *All* Relative Years, by Completion Status	
Completed	**Did Not Complete**
313	28

In terms of average earnings, among employed participants the completers look quite different from non-completers both before *and* after the program. From years -2 through the program year, each year the completers have average earnings that is $5,000-$6,000 higher than average earnings for non-completers. After the program, the "completer advantage" increases, with completers making $11,000 more in year 1 ($28,000 vs. $17,000), $12,000 more in year 2 ($32,000 vs. $20,000) and $17,000 more in year 3 ($37,000 vs. $2000). The over-time increase in this advantage suggests that participation in the Climate Careers program supports growth in human capital as young people start their careers. (Obviously we can't draw any truly strong conclusions here, given all the influences on a young person's life, but the patterns point in a hopeful direction.)

CLIMATE CAREERS: AVERAGE EARNINGS by GRADUATION STATUS

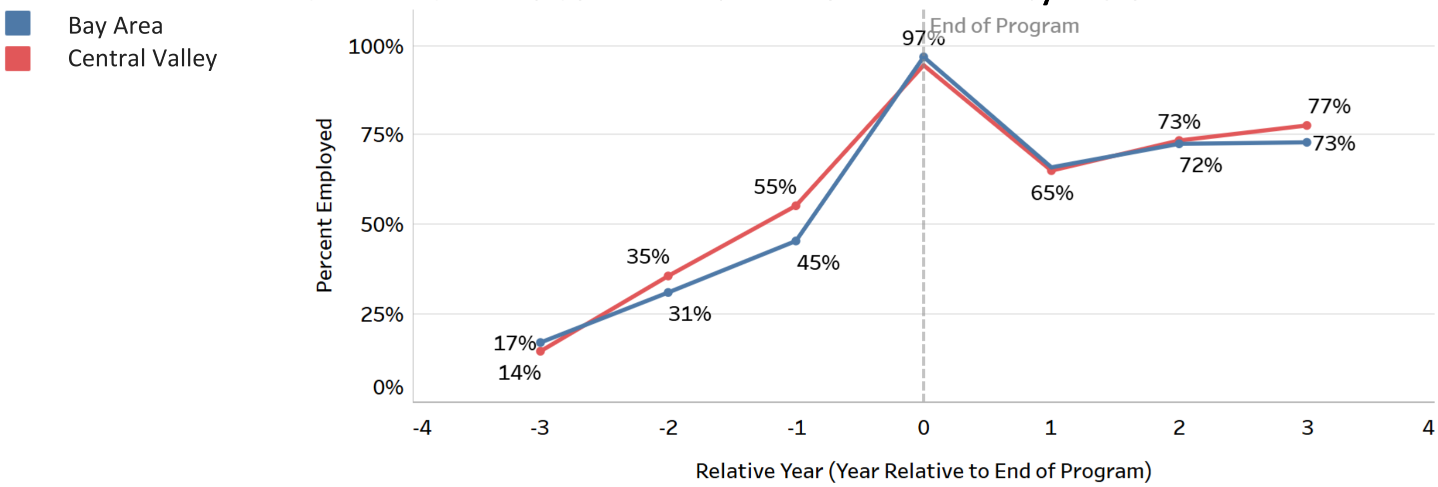


Sample Sizes, by Relative Year & Graduation Status		
Relative Year	**Graduated**	**Did Not Graduate**
-3	50	6
0	301	19
+3	231	21

Region

Rising Sun offers the Climate Career program in two geographic regions: the Bay Area and the Central Valley. The two groups are very similar in terms of both employment rate and average earnings. The two groups show the usual pattern: a peak during the exit year, and then dropping in year 1 and continuing to rise in the out-years. Overall, the findings by region did not yield much of interest to the Rising Sun team.

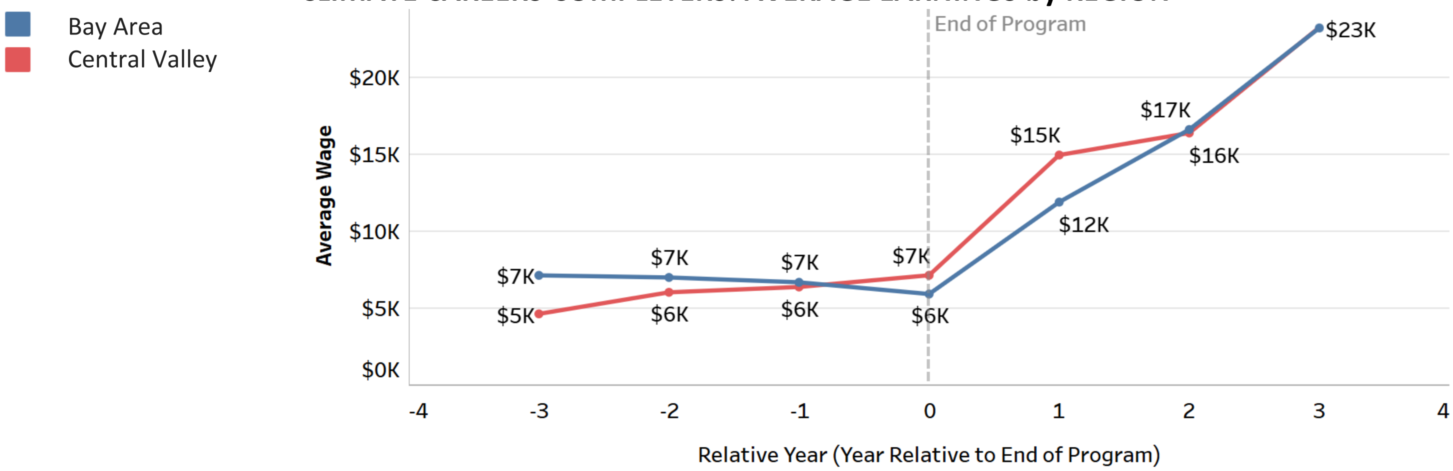
CLIMATE CAREERS COMPLETERS: EMPLOYMENT RATE by REGION



Sample Sizes for *All* Relative Years, by Region	
Bay Area	**Central Valley**
242	71

The average earnings for both groups are quite similar both before and after the program – although in year 1, the average earnings for those who graduated from the Central Valley program had average earnings $3000 higher than the earnings for the Bay Area graduates. The Rising Sun team found two things surprising here: (1) the similar earnings in years 2 and 3, and (2) the higher earnings for Central Valley graduates in year 1. The reason this surprised the team is that Bay Area wages tend to be higher than Central Valley wages (in other words, they expected the Bay Area graduates to have higher average earnings in all the post-program years). However, the pattern could be explained in at least two ways (beyond random chance): (1) the region is about where youth attended the program, not where they live; and (2) there is no information about how many hours participants work, and Central Valley graduates may simply be working more hours (on average) than their Bay Area graduate counterparts.

CLIMATE CAREERS COMPLETERS: AVERAGE EARNINGS by REGION



Sample Sizes, by Relative Year & Region		
Relative Year	**Bay Area**	**Central Valley**
-3	40	10
0	234	67
+3	176	55

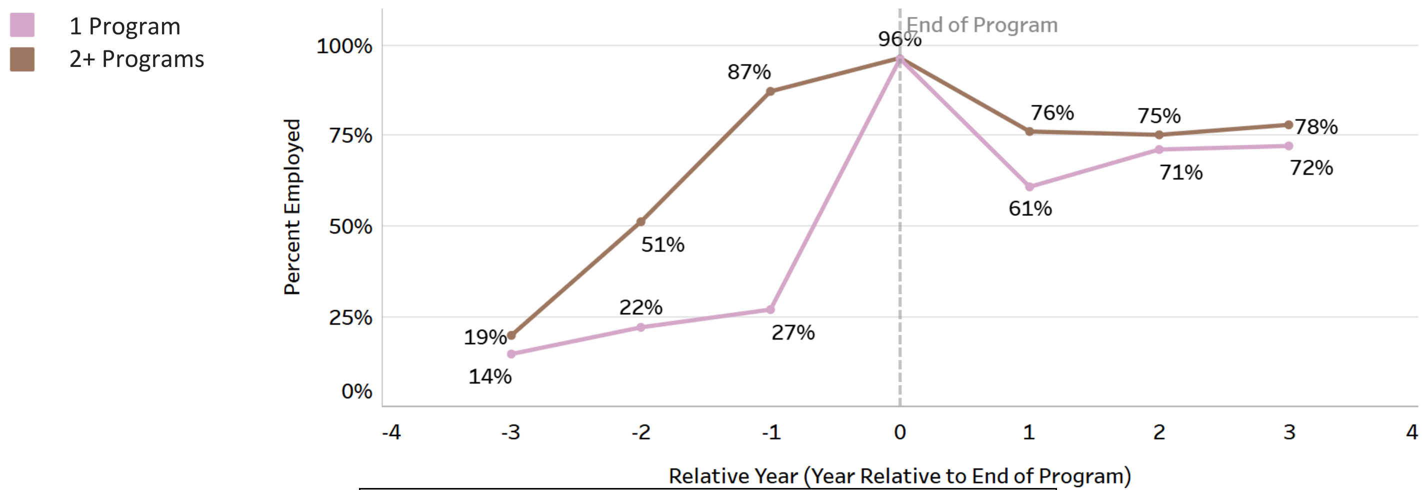
Number of Programs that Participants Participated in

For the Climate Careers program, youth often return to do the program again. Out of the 311 (graduating) participants for whom Rising Sun has data on the number of programs they participated in, *over one-third (35%) returned at least once more!* This figure alone is a testament to the quality of the program.

The employment rate data shows that there is a huge difference during the pre-program years on the employment rate, for obvious reasons: some of the “returners” were employed as part of the program two years earlier than their most recent program year (shown as 51% in year -2); and the same thing is true in year -1 (with 87% employed that year, due to the fact that more returners came back for a second program the very next year).

In addition, the employment rate for returners is higher during the post-program years than it is for youth who participate in the program once: in year 1, the difference is 15 percentage points (76% vs. 61%), and then in years 2 and 3 the gap closes, but the returners still have a slightly higher employment rate (with a 4 percentage point advantage each of those years).

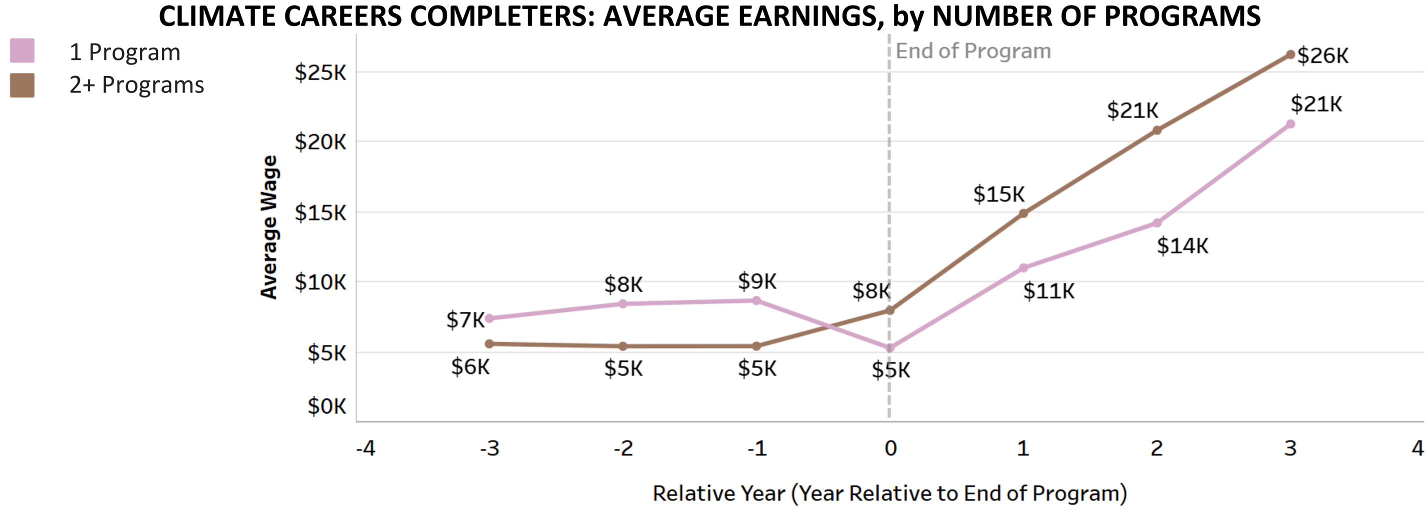
CLIMATE CAREERS COMPLETERS: EMPLOYMENT RATE by NUMBER OF PROGRAMS



Sample Sizes for *All* Relative Years, by Number of Programs	
1 Program	**2+ Programs**
203	108

Earnings data show that there is also a "returner advantage" for average earnings. Even though the returners earned less than those who did the program once during their pre-program years, starting in the program exit year, the two groups switch places (with returners now in the lead). In year 1, returners make $4,000 more than their non-returning counterparts ($15,000 vs. $11,000); in year 2, they make $7,000 more ($21,000 vs. $14,000); and in year 3 they make $5,000 more ($26,000 vs. $21,000).

CLIMATE CAREERS COMPLETERS: AVERAGE EARNINGS, by NUMBER OF PROGRAMS

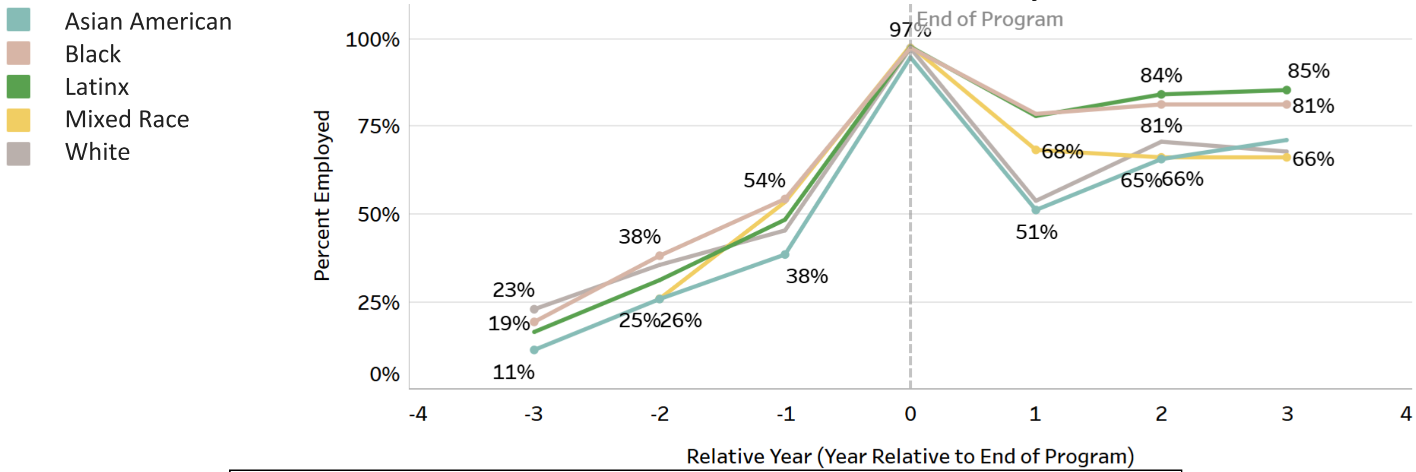


Sample Sizes, by Number of Programs		
Relative Year	**1 Program**	**2+ Programs**
-3	29	21
0	195	104
+3	146	84

Race

Across racial groups the employment rate pattern is similar, although during the post-program years a differential appears that was not present during the pre-rog years. In years 2 and 3, the employment rate was much higher for Latinx and Black youth (85% and 81%, respectively) than it was for the other three groups (71% for Asian American; 68% for white; and 66% for mixed race).

CLIMATE CAREERS COMPLETERS: EMPLOYMENT RATE by RACE

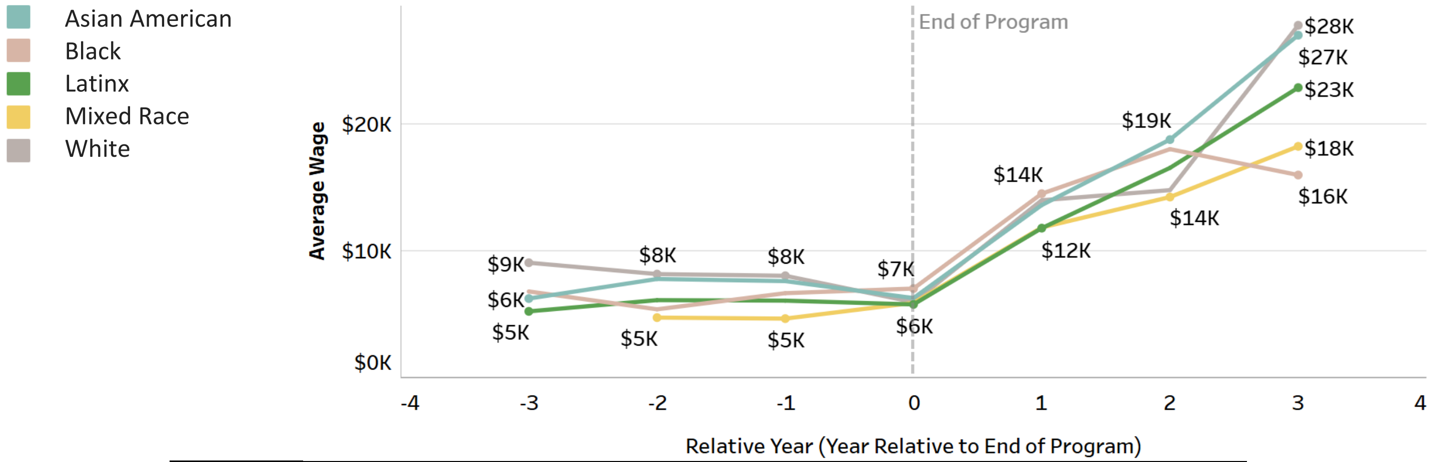


Sample Sizes for *All* Relative Years, by Race				
Asian American	**Black**	**Latinx**	**Mixed Race**	**White**
55	37	81	47	71

The findings on average earnings showed that earnings rose much more over 3 years for Asian Americans and whites than for those who are Black or mixed race (with Latinx showing growth that fell between the two extremes). Earnings for white youth rose $22,000 (from $6,000 in the program exit year to $28,000 in year 3); earnings for Asian American youth rose $21,000 (from $6,000 to $27,000); earnings for Latinx youth rose $17,000 (from $6,000 to $23,000); earnings for mixed race youth rose $12,000 (from $6,000 to $18,000); and earnings for Black youth rose $9,000 (from $7,000 to $16,000). In addition, every racial group *except* Black youth showed a steady rise each year; for Black youth, average earnings peaked in year 2 at $18,000 and then declined $2,000 from year 2 to year 3.

The differential between white and Asian American youth (on the one hand), and Black youth (on the other) is likely to reflect structural racism in the job market. Of course, different earnings levels can also reflect the number of hours worked, but no data on hours worked each year is available.

CLIMATE CAREERS COMPLETERS: AVERAGE EARNINGS by RACE

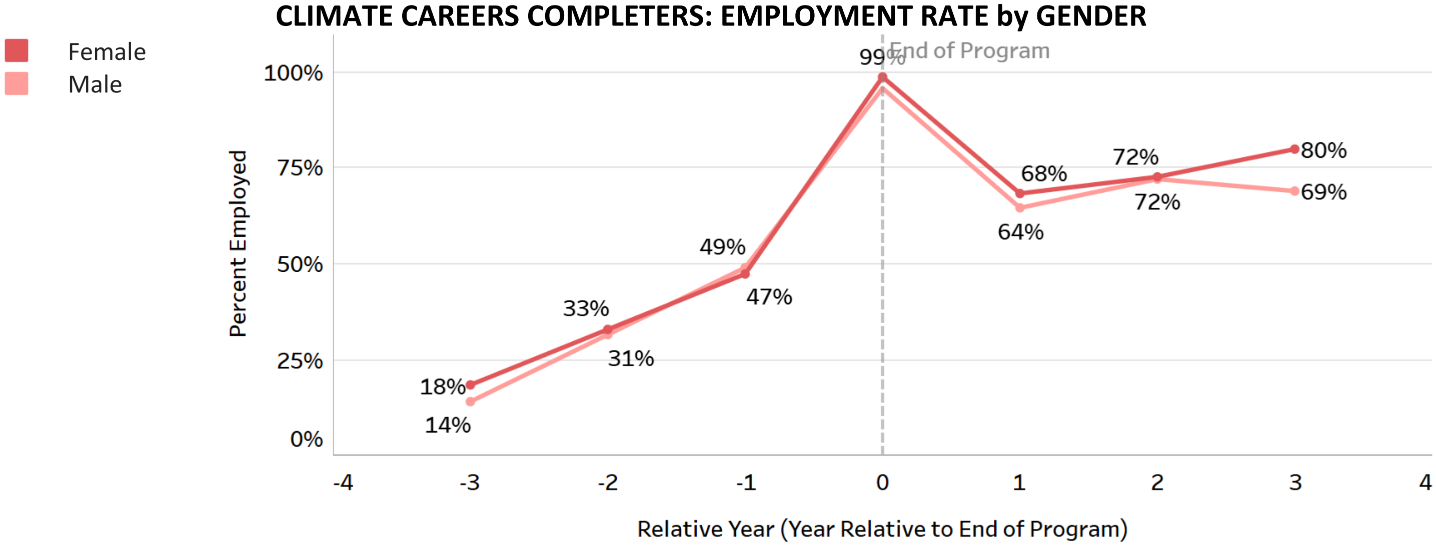


Sample Sizes, by Relative Year & Race					
Relative Year	**Asian American**	**Black**	**Latinx**	**Mixed Race**	**White**
-3	6	6	13	NULL	16
0	52	36	79	46	69
+3	39	30	81	31	48

Gender

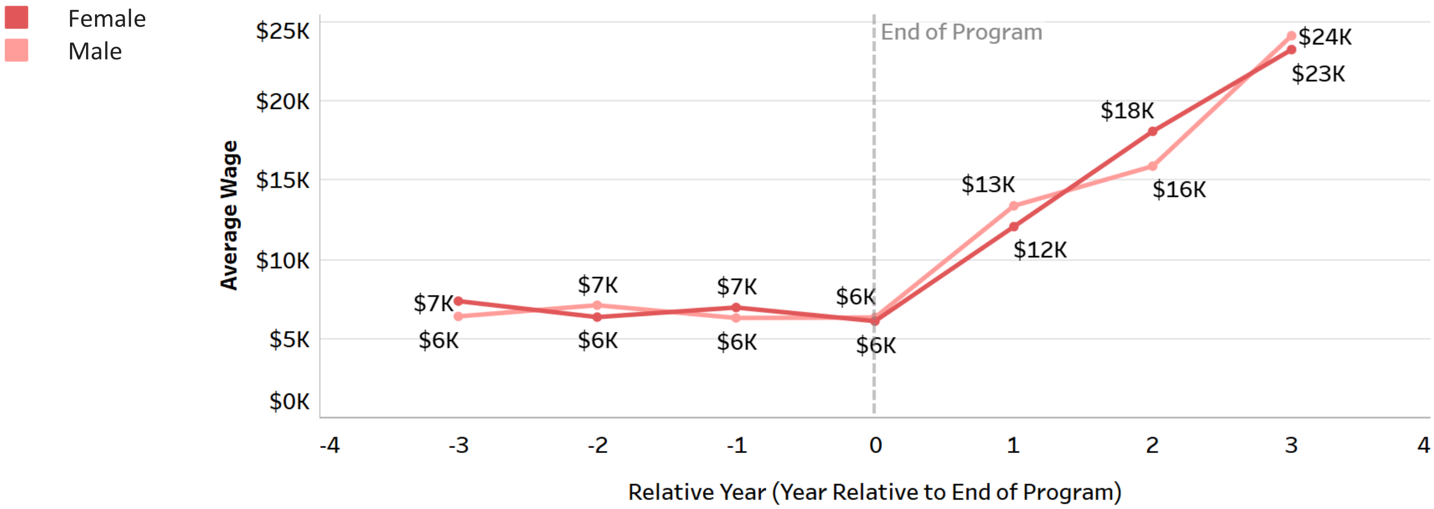
The patterns for *both* employment rate and average earnings is extremely similar for females and males. From one perspective, these results may demonstrate that the gender analysis is not very fruitful, but the Rising Sun team was glad to see that males did not show a systemic advantage for either metric. In other words, the results seem to tell a story of gender equity for Climate Careers graduates.

CLIMATE CAREERS COMPLETERS: EMPLOYMENT RATE by GENDER



Sample Sizes for *All* Relative Years, by Gender	
Female	**Male**
138	160

CLIMATE CAREERS COMPLETERS: AVERAGE EARNINGS by GENDER

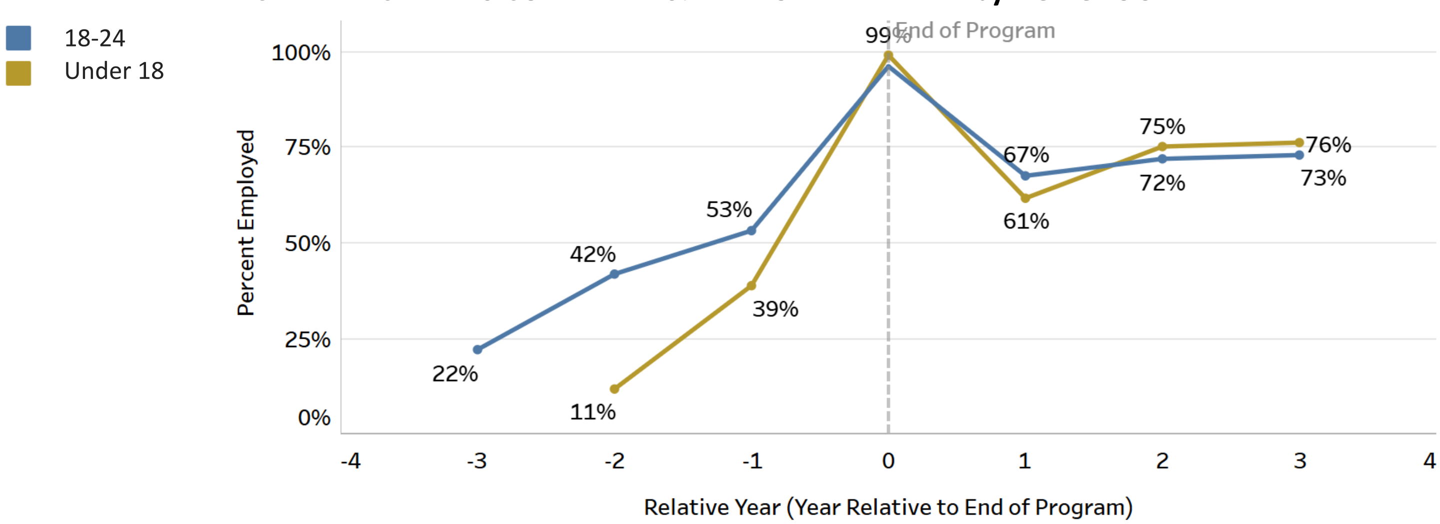


Sample Sizes, by Relative Year & Gender		
Relative Year	**Female**	**Male**
-3	25	22
0	136	153
+3	110	110

Age Group

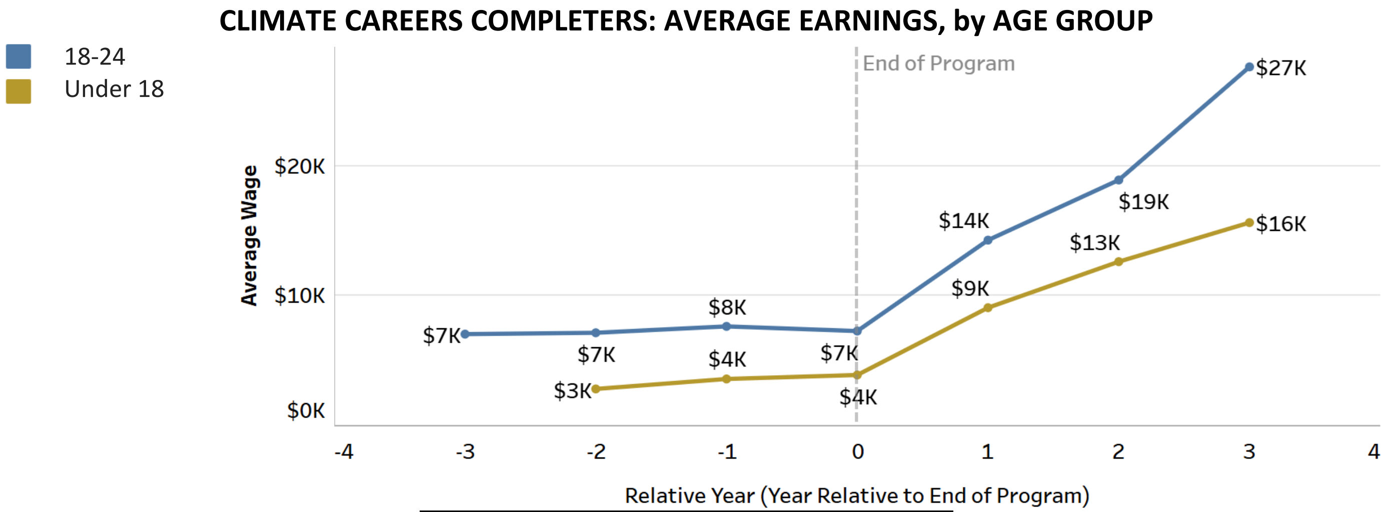
All of the Climate Career participants are very young, with no one older than 24 at the time of their program participation. Because those who are under 18 at the time of program participation are far less likely to have a job during the pre-program years *and* are more likely at any given time period to (1) not be working and (2) to be working for lower wages, we can expect the employment outcomes to show lower employment rates and lower average earnings in general. It's rather surprising, then, to see how *similar* the employment rates are for the two age groups in the *post*-program years.

CLIMATE CAREERS COMPLETERS: EMPLOYMENT RATE by AGE GROUP



Sample Sizes for *All* Relative Years, by Age Group	
18-24	**Under 18**
202	96

The average earnings story, however, is more in line with what the Rising Sun team expected to see: higher earnings at *every* time period for the older participant group. During the program year, the older group has average earnings $3,000 more than the earnings for the younger group ($7,000 vs. $4,000); in year 1, the difference is $5,000 ($14,000 vs. $9,000); in year 2, the difference is $6,000 ($19,000 vs. $13,000); and in year 3 the difference has grown to $11,000 ($27,000 vs. $16,000).



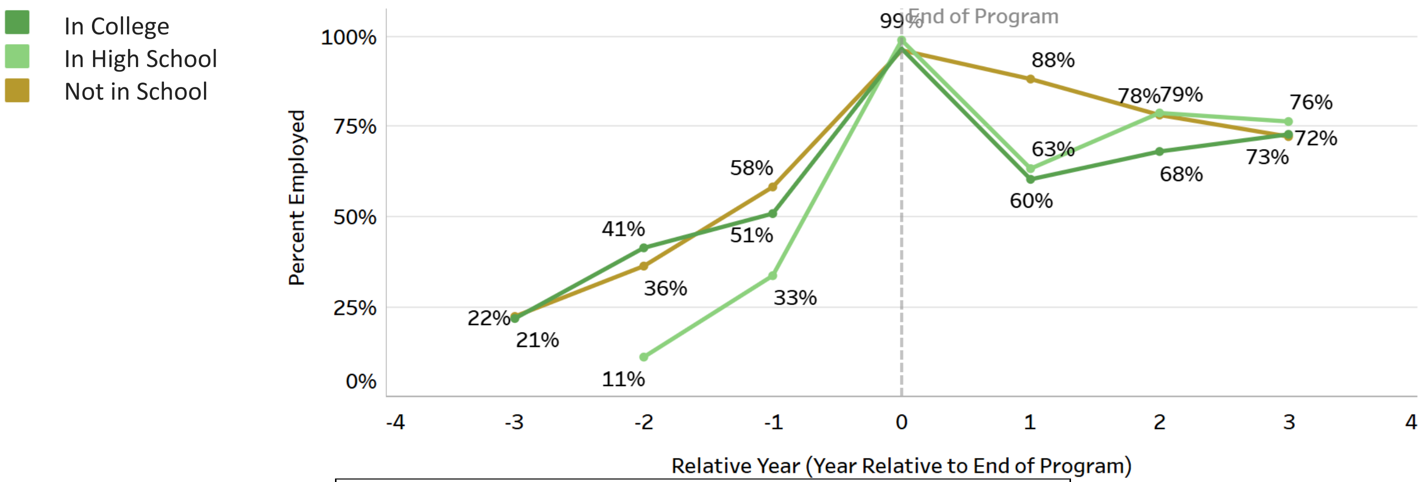
Sample Sizes, by Age Group		
Relative Year	**18-24**	**Under 18**
-3	44	NULL
0	194	95
+3	147	73

Educational Attainment

Rising Sun collects data on the educational attainment of program participants. In addition to the values shown, there is another value: not in school *and* not completed high school (or high school equivalent). However, there were fewer than five youth in this category, so no data are shown.

The results for employment rate are what we would expect to see: those in high at the time of the program have much lower employment rates *before* the program (most likely this is because they are so young). Interestingly, in years 2 and 3 *after* the program, this same group has the highest employment rate (although the differential is small: 1 percentage point in year 2, and 4 percentage points in year 3). The employment rate for those not in school dip much less than anyone else's rate in year 1 (dropping only 11 percentage points from 99% to 88%). This result may be due to this group being less likely to be in school during this year than either of the other two groups.

CLIMATE CAREERS COMPLETERS: EMPLOYMENT RATE by EDUCATIONAL ATTAINMENT

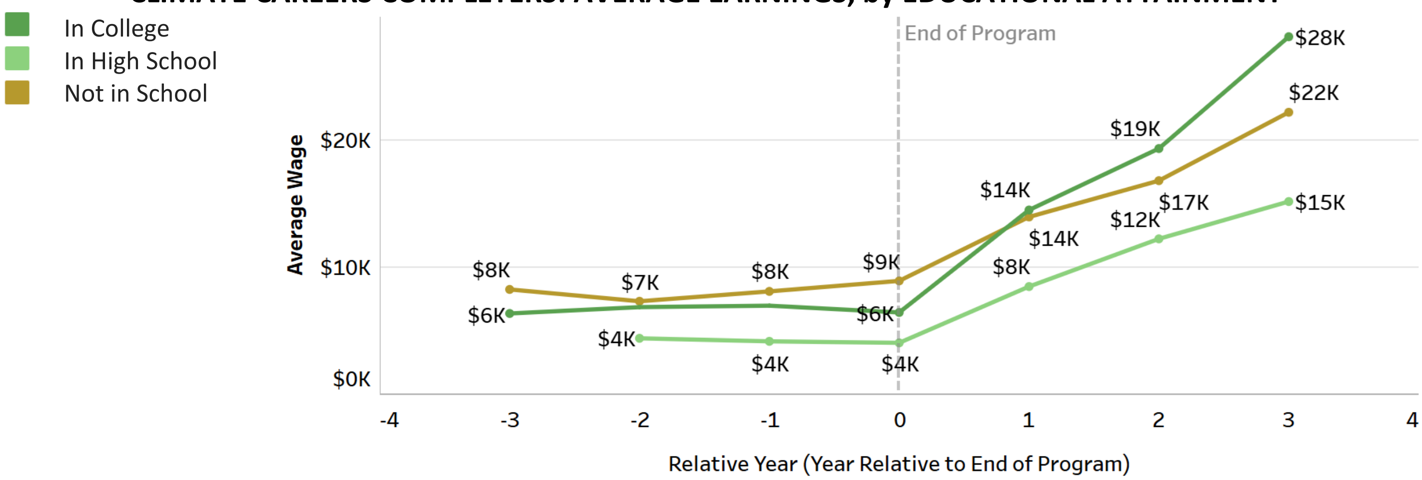


Sample Sizes for *All* Relative Years, by Educational Attainment		
In College	**In High School**	**Not in School (Finished HSE and/or College)**
158	84	50

Data on average earnings show that those who were in college during the program show the largest earnings increase over time after the program: their earnings rise $22,000 over three years (from $6,000 in the program exit year to $28,000 in year 3). Their year 3 earnings are also much higher than earnings for those who were not in school during the program (this group was earning $6,000 less in year 3: $22,000).

The group that was in high school was earning less all the way along; this is to be expected due to their young age *and* the fact that they are highly likely to be in school during the post-program years.

CLIMATE CAREERS COMPLETERS: AVERAGE EARNINGS, by EDUCATIONAL ATTAINMENT



Sample Sizes, by Educational Attainment			
Relative Year	**In College**	**In High School**	**Not in School (Finished HSE and/or College)**
-3	36	NULL	11
0	162	83	48
+3	122	64	36

Appendix A: Living Wage Metric

Data are shared back from the EDD data files from the year 2010 to the year 2022. Tipping Point supplied the living wage threshold for each calendar year. These numbers were based on one adult and one school-aged child living in Alameda County, and were derived using self-sufficiency wage data from the Insight Center, along with some adjustments.

The Insight Center calculates living wages only for selected years in the range used for the data extract: 2011, 2014, 2018, and 2021. Using the living wages from those years *and* the living wage from 2008 ($37,402), the amount for the other years was interpolated, with the exception of 2022. Because the living wage threshold for 2022 could not be interpolated (because no living wage data was available for a later year), and inflation rate was used instead, and applied to 2021 to derive the threshold for 2022. The inflation rate used was 5.1%, a rate that Alameda County included in its economic forecast (see p. 6).

Calendar Year	Living Wage Threshold
2010	$41,271
2011	$43,206
2012	$44,583
2013	$45,960
2014	$47,338
2015	$51,871
2016	$56,403
2017	$60,936
2018	$65,468
2019	$71,142
2020	$76,816
2021	$82,490
2022	$86,697