Retraining the Gulf Coast through Information Technology Pathways:

Preliminary Impact Evaluation Report

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September 2015

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This report was prepared with funds provided by The Aspen Institute from the U.S. Department of Labor to the Ray Marshall Center for the Study of Human Resources at the University of Texas at Austin. The views expressed here are those of the authors and do not represent the position of the funding agency or The University.

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INTRODUCTION

The Retraining the Gulf Coast Workforce through Information Technology (IT) Pathways Consortium project is a four-year project funded by the Department of Labor's (DOL) Round Two Trade Adjustment Community College and Career Training (TAACCT) grants program. The grant was awarded in September 2012 to Bossier Parish Community College (BPCC), which is leading a consortium of eight additional colleges across the states of Louisiana and Mississippi. The project's objective is to capitalize on the region's growing IT sector and its increased demand for skilled labor by training almost 2,000 TAA eligible workers, veterans, and other individuals with basic skills needs for jobs. In designing the project, the consortium focused on three IT specialty areas: health information technology, cyber security, and industrial information IT. The project includes five inter-connected strategies to help build career pathways that allow students to earn industry -recognized credentials and access in demand job opportunities.

The Aspen Institute Workforce Strategies Initiative (Aspen WSI), in collaboration with the Ray Marshall Center for the Study of Human Resources at the Lyndon B. Johnson School of Public Affairs at the University of Texas Austin (The Ray Marshall Center), is conducting an implementation study and a quasi-experimental impact analysis to assess the effectiveness of the project. The Ray Marshall Center (RMC) is the lead for the impact analysis and intends to use a difference-in-difference (DID) approach to estimate the impact of the program on student outcomes. The comparison group will be drawn from students who were not enrolled in IT programs, and this methodology is designed to answer the research question: To what extent did the implementation of the IT pathways program improve student outcomes compared to programs/subjects in the same colleges that were not impacted by the TAACCCT initiative?

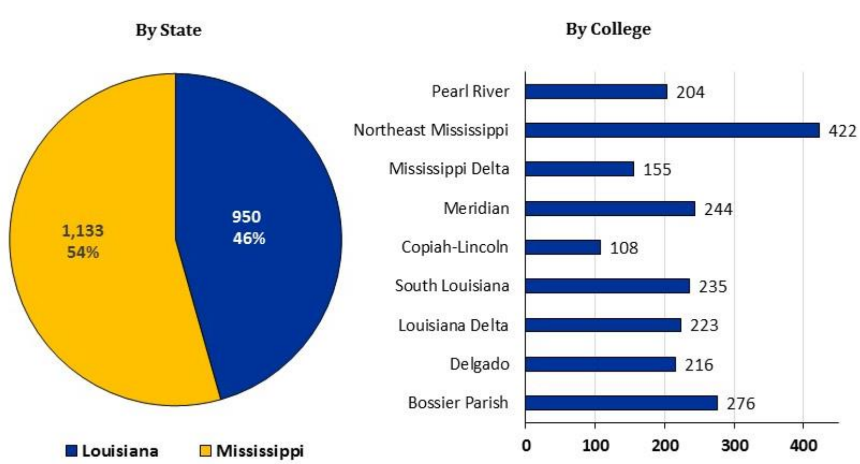
This report begins by describing the characteristics of program participants and then reports the early outcomes of program participants. The report then describes early findings of program impact from the impact analysis. Finally, the report concludes with an overview of challenges that remain and the focus of the impact evaluation in the final year of the grant.

PARTICIPANT CHARACTERISTICS

In this section of the report, we examine participation patterns and describe the population served by the TAACCCT GCIT program. Our primary data source for this discussion is data collected from intake forms. A common intake form to collect information on participants enrolled in the GCIT program was created by the nine colleges in the Consortium, with assistance from the National Strategic Planning & Analysis Research Center (NSPARC). The intake form collects a wealth of data on GCIT participants' academic background, employment history, financial aid status, and other relevant information. Intake forms were administered to all GCIT program participants by student navigators and the data were entered into the NSPARC web portal.

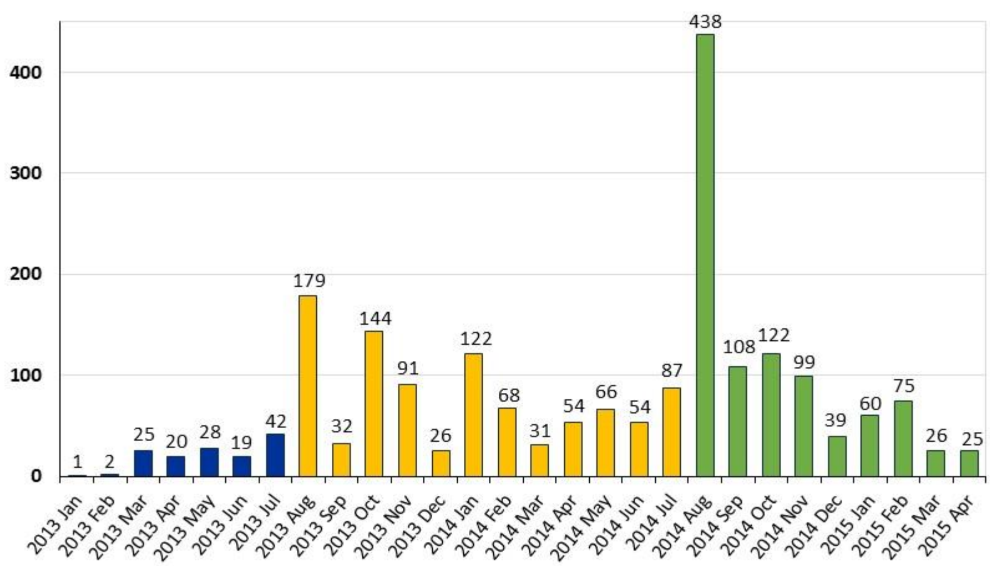
Since the intake data was only collected on GCIT participants, and was not collected on non-participants, the utility of these data is limited for the purposes of the impact evaluation (which compares the treatment group of GCIT participants to a matched comparison group of non-participants). However, the intake data is a rich dataset and is essential for understanding the population served by the TAACCCT GCIT program, for providing context to participant outcomes, and for enhancing the implementation evaluation. The most recent intake dataset provided to the evaluation team includes all students who entered the GCIT program from project start in January 2013 to May 2015. We use this intake data to comprehensively describe GCIT program participants below.

Figure 1. GCIT Participation



By the end of the third year of the grant in May 2015, a total of 2,083 individuals had participated in the TAACCCT GCIT program. Participation was evenly split between the two states in the consortium, with Mississippi having a slightly higher number of participants. Northeast Mississippi Community College has the largest number of participants while Copiah-Lincoln Community College had the smallest number of participants. The Consortium has met and exceeded their original target of serving a total of 1,954 unique participants by the end of the third year of the grant.

Figure 2. Intake over Time



Participant intake over the grant implementation period can be observed in Figure 2. Note that the first official year of the grant was the 2012-2013 academic year, but the majority of that year was dedicated to setting up systems and contracts to implement the grant. With the exception of 2-3 pilots, all colleges officially started program implementation during the 2013-2014 academic year. Students who completed intake prior to 2013 August either enrolled in these pilot programs or waited to enroll in the 2013 Fall semester. The intake patterns show peaks during the start of the fall and spring semesters. The biggest peak is observed in August 2014, indicating that a large number of participants entered the program at the beginning of Year 3.

Figure 3. Characteristics of GCIT Participants

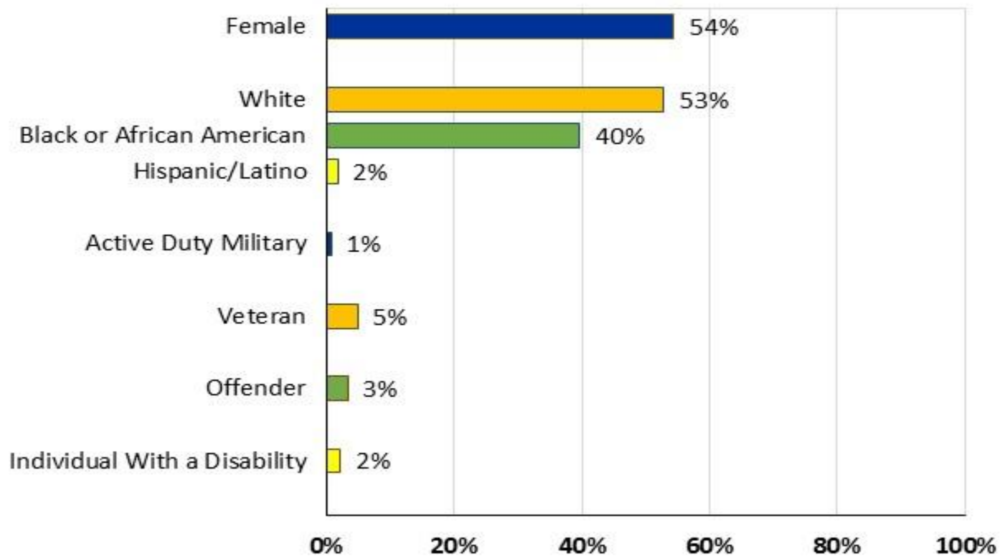


Figure 3 summarizes the demographic characteristics of participants in the TAACCCT GCIT program. A little over half of GCIT participants were female (54%) and participants were mostly White (53%) or African American (40%). Only a very small proportion of participants were veterans (5%) or active duty military (1%).

Figure 4. Employment Background of GCIT Participants

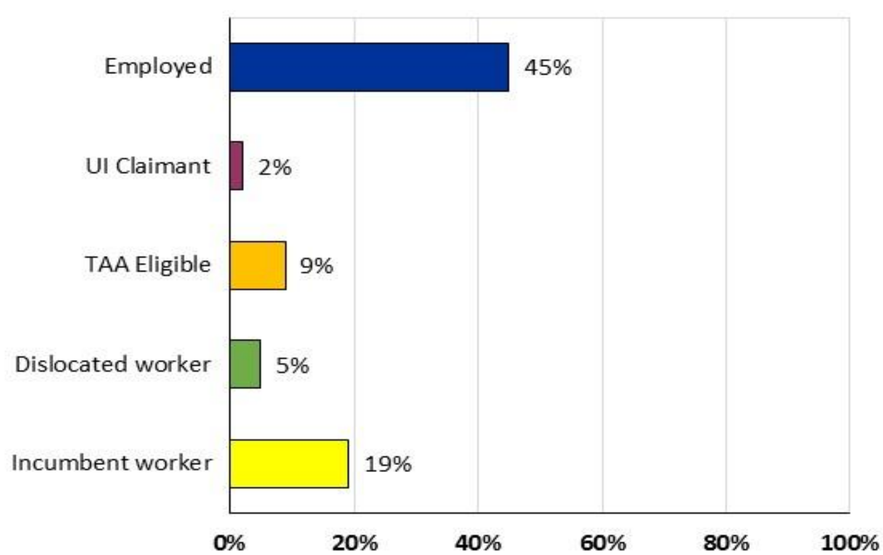


Figure 4 summarizes the employment background of participants in the TAACCCT GCIT program. Nearly half (45%) of all GCIT participants were employed at intake. While about a fifth (19%) of GCIT participants were incumbent workers, only a small proportion were UI claimants (2%), TAA eligible[1] (9%), or dislocated workers (5%).

Figure 5. Education Background of GCIT Participants

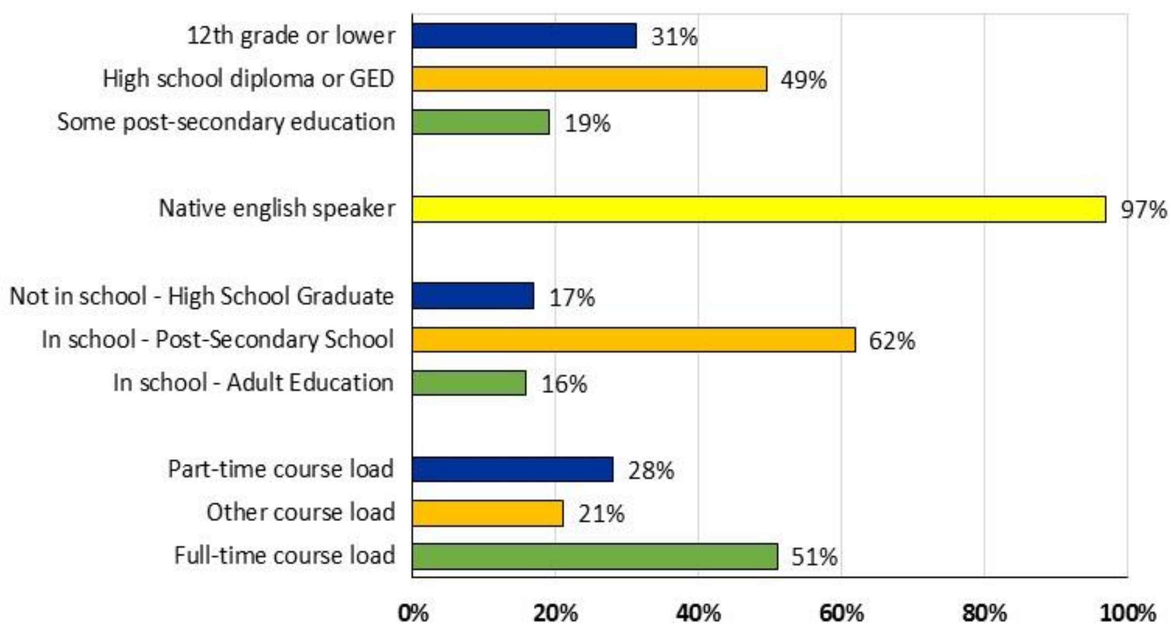


Figure 5 summarizes the education background of participants in the TAACCCT GCIT program. While a fifth (20%) of GCIT participants had some post-secondary education, half of GCIT participants (49%) only had a high school diploma or GED and a third of GCIT participants (31%) had only completed 12th grade or lower. A vast majority of GCIT participants (97%) were native English speakers. The intake form also collects information on participants' enrollment status at the time of intake. A majority of GCIT participants (62%) at intake had a high school diploma or GED and were already enrolled in a post-secondary school; the remaining were either individuals who were enrolled in an adult education program at intake (16%), or individuals who had a high school diploma or GED but were not enrolled in a post-secondary

[1] The "TAA eligible" field in the intake form records if the participant indicates that he/she is eligible for Trade Adjustment Assistance (TAA) services.

school (17%) at intake. Half of GCIT participants (51%) had a full-time course-load, while the remaining half had a part time course load (29%) or other course load (21%).

Information on financial assistance receipt, academic needs, and career and academic goals was also collected through the intake forms. However, these fields were optional and hence data is unavailable for nearly half of the participants. Thus, these data do not give us a full picture of participants. Of the data that is available, working in health informatics, working in industrial technology, and pursuing further education appear to be the most popular goals; improved math skills is the most common academic need, followed closely by improved computer skills, improved writing skills, and improved reading skills; Pell grants and scholarships are the most common types of financial assistance received.

EARLY PROGRAM OUTCOMES

In this section of the report, we summarize certain early outcomes of participants in the TAACCCT GCIT program. However, as a result of the data challenges described in previous reports and the timing of this report, they should be considered preliminary. These results are also based on data from only the first year of program implementation (the 2013-2014 academic year).[2] The evaluation team has not yet received data for the second year of program implementation, and a final full year of program implementation still remains. In addition, key data sources such as Unemployment Insurance data on employment and wages have not been made available to the evaluation team yet.

Our primary data source for the outcomes reporting in this sections is academic data from the colleges' institutional data systems. Data on participants' academic progress and academic outcomes was compiled by each individual college and sent to NSPARC. NSPARC then combined the datasets and performed quality checks before transferring the data to the evaluation team. Data was collected on a number of measures identified by the evaluation team during the first year of the grant (see Appendix A).

It is important to note that data on many academic measures could not be collected for students in non-credit training programs as their information is not systematically recorded in the colleges' institutional data systems. As a result, many outcomes cannot be measured for these students. For the sake of clarity, in the remainder of this section, we present outcomes separately for students in for-credit academic programs and students in non-credit training programs.

OUTCOME DEFINITIONS

In our outcomes analysis, we focus on outcomes similar to the participant outcomes reported by all TAACCCT grantees to DOL through the Annual Performance Report (APR). We begin by reporting the ***total number of participants served***, and we break this number down by

[2] The first official year of the grant was 2012-2013, but the majority of that year was dedicated to setting up systems and contracts to implement the grant. With the exception of 2-3 pilots, all colleges officially started work on the grant during the 2013-2014 academic year.

students in for-credit academic programs vs. students in non-credit training programs. We next report the ***average number of college credits earned per semester***, calculated using the semester credit hours reported for GCIT participants. This measure is calculated and reported for GCIT participants in for-credit academic programs only; a corresponding measure for GCIT participants in non-credit training programs is not available.

We then report persistence measured as the ***percent of students who persisted after their first semester*** in the program. This persistence measure can only be reported for participants who entered the program in the first semester of grant implementation (the 2013 Fall semester), due to insufficient follow-up data. This measure is calculated and reported for GCIT participants in for-credit academic programs only; this measure cannot be reported for students in non-credit training programs as there is no semester recorded for these students. We also report persistence measured as the ***percent of students who persisted after their first year*** in the program. This measure is calculated and reported for participants who entered the program in the first year of grant implementation (the 2013-2014 year) only, due to insufficient follow-up data. This measure is calculated and reported for GCIT participants in non-credit training programs only; this measure cannot be reported for students in for-credit academic programs as there is insufficient follow-up data for these students.

Finally, we focus on credential receipt and report the ***percent of students who earned any credential*** (includes certificates and degrees of all types), the ***percent of students who earned any certificate*** (includes 1-year and 2-year certificates), and the ***percent of students who earned any degree*** (includes diploma, Associate's or Bachelor's degrees). These credential receipt measures are calculated and reported for students in for-credit academic programs only; these measures cannot be reported for students in non-credit training programs as credential receipt data is not available for these students.

When we receive UI wage data in the future, we will report and analyze employment outcomes including the ***percent of students placed in employment*** in the first quarter after program completion, the ***percent of students retained in employment*** two quarters after program completion, and the ***amount of wage increase*** for GCIT participants.

PARTICIPANT OUTCOMES

We begin by looking at overall participant outcomes (see Table 1). A total of 590 students in for-credit academic programs entered the GCIT program in the first year of program implementation.[3] A total of 435 students in non-credit training programs entered the GCIT program: 162 entered in the first year and 273 entered in the second year.

Table 1. Overall Participant Outcomes

Outcomes	For-credit	Non-credit
Number of participants	590	435
First Year	590	162
Second Year	n/a	273
College credits earned per semester (Mean)	12.7	n/a
Persisted after 1st semester (%)	72.0%	n/a
Persisted after 1st year (%)	n/a	24.1%
Earned any credential (%)	9.8%	n/a
Earned any certificate (%)	4.4%	n/a
Earned any degree (%)	4.9%	n/a

Note: "n/a" indicates data was not made available to the evaluation team in order to compute the outcome measure.

We found that GCIT participants in for-credit academic programs earned an average of 13 college credits per semester. Nearly three-quarters of all GCIT participants (72%) in for-credit academic programs persisted beyond their first semester in the program. Nearly a quarter of GCIT participants (24%) in non-credit training programs persisted beyond their first year in the program. Only 10% of GCIT participants in for-credit academic programs had earned a credential at the end of their first year: 4% earned a certificate while 5% earned a degree. This low rate of credential receipt is unsurprising as we are looking at outcomes after only the first year of program implementation; we expect this rate to increase as we receive data on the second and third year of program implementation.

[3] In order to report outcomes consistently, 44 students who participated in pilot programs in spring 2013 are excluded from the analyses reported in this section.

Participant Outcomes by Subgroups

We next examine the same outcomes broken out by demographic groups (see Table 2). We focus on the demographic groups commonly reported by TAACCCT grantees to DOL in the APR: gender, ethnicity/race, age, degree status, and other important characteristics. Due to the extent of missing data for GCIT participants in non-credit training programs, we exclude these students from our sub-group analyses.

GCIT participants in for-credit academic programs were about evenly split across both genders. Male and female participants both earned an average of 13 college credits per semester, and 72% of participants in both groups persisted after their first semester in the program. However, male participants had higher credential receipt rates; 13% of male participants earned a credential after their first year in the program, compared to only 7% of female participants.

The participant group had a very small number of Hispanics, but these few individuals out-performed the other groups. Hispanic participants earned an average of 12 college credits per semester, 86% persisted beyond the first semester, and a fifth (21%) earned a credential after their first year in the program. White and black participants both earned an average of 13 college credits per semester, and about three-quarter of participants in both groups persisted after their first semester in the program. However, black participants had higher credential receipt rates; 10% of black participants earned a credential after their first year in the program, compared to only 8% of white participants.

Among the four age groups we examined, participants aged under 20 and participants aged 20 to 24 both earned an average of 14 college credits per semester, and 70%-75% of participants in both groups persisted after their first semester in the program. However, participants aged 20 to 24 had higher credential receipt rates; 13% of participants aged 20 to 24 earned a credential after their first year in the program, compared to only 6% of participants aged under 20. In contrast to these two younger age groups, the older participants in the 25-34 age group and the 35 & older age group had lower semester credit accumulation rates (12 and 11 respectively) and lower persistence rates (63% and 72% respectively). However, the two older age groups had high credential receipt rates; 11% of participants aged 25-34 and 14% of participants aged 25 and older earned a credential after their first year in the program.

Table 2. Participant Outcomes by Demographic Groups

		Number of participants	College credits earned per semester (Mean)	Persisted after 1st semester (%)	Earned any credential (%)	Earned any certificate (%)	Earned any degree (%)
Gender	Female	288	12.7	72.2%	6.9%	2.8%	4.2%
	Male	302	12.7	71.9%	12.6%	6.0%	5.6%
Ethnicity or Race	Hispanic or Latino	14	12.0	85.7%	21.4%	7.1%	14.3%
	Black or African American	176	13.0	75.6%	10.2%	6.3%	3.4%
	White	352	13.0	74.4%	8.0%	3.7%	5.4%
	Other	9	12.5	41.7%	0.0%	0.0%	0.0%
	More Than One Race	8	12.9	87.5%	12.5%	0.0%	12.5%
	Not reported	31	8.2	19.4%	25.8%	3.2%	3.2%
Age Group	Under 20	141	13.6	74.5%	13.0%	5.6%	8.7%
	20 to 24	231	13.5	70.0%	8.2%	1.8%	3.6%
	25 to 34	110	11.7	63.0%	11.1%	4.6%	4.6%
	35 & older	108	10.8	72.0%	9.8%	4.4%	4.9%
Education Level	12th Grade or Lower	470	12.9	72.3%	10.9%	5.3%	4.7%
	Any post-secondary education	33	10.7	42.4%	3.0%	3.0%	3.0%
	High school degree or GED	87	12.3	81.6%	6.9%	0.0%	6.9%
Enrollment Status	Already enrolled in post-secondary school	470	12.9	72.3%	10.9%	5.3%	4.7%
	Enrolled in adult education	33	10.7	42.4%	3.0%	3.0%	3.0%
	Not enrolled in post-secondary school	87	12.3	81.6%	6.9%	0.0%	6.9%
Course Load	Fulltime Status	415	13.7	79.3%	9.4%	5.8%	4.1%
	Other status	50	13.4	62.0%	8.0%	2.0%	6.0%
	Part-Time Status	125	8.9	52.0%	12.0%	0.8%	7.2%
Other	Incumbent Workers	72	13.9	68.1%	6.9%	0.0%	5.6%
	Eligible Veterans	43	12.6	67.4%	20.9%	16.3%	4.7%
	Persons With A Disability	14	10.5	71.4%	0.0%	0.0%	0.0%
	Pell-Grant Eligible	287	13.9	79.8%	9.8%	4.2%	5.6%
	TAA Eligible	60	12.4	66.7%	13.3%	10.0%	1.7%

Table 3. Participant Outcomes by College

		Number of participants	College credits earned per semester (Mean)	Persisted after first semester (%)	Earned any credential (%)	Earned any certificate (%)	Earned any degree (%)
State	Louisiana	277	10.8	68.6%	14.4%	2.9%	10.5%
	Mississippi	313	14.4	75.1%	5.8%	5.8%	0.0%
College[4]	Bossier Parish Community College	124	11.4	69.4%	11.3%	4.8%	8.1%
	Delgado Community College	69	14.9	82.6%	1.4%	1.4%	0.0%
	Louisiana Delta Community College	22	6.2	0.0%	27.3%	0.0%	0.0%
	South Louisiana Community College	106	11.9	88.7%	18.9%	1.9%	17.9%
	Copiah-Lincoln Community College	86	13.9	70.9%	11.6%	11.6%	0.0%
	Mississippi Delta Community College	50	15.3	75.0%	6.5%	6.5%	0.0%
	Northeast Mississippi Community College	108	13.9	40.0%	0.0%	0.0%	0.0%
	Pearl River Community College	25	7	72.0%	9.8%	4.4%	4.9%

[4] Meridian Community College is not included in this table since the college only served non-credit students through this grant, and education outcome data in not available for non-credit students.

We examined differences in outcomes based on the student's education background. We found that students with a high school degree or GED and students with any post-secondary education earned an average of 12-13 college credits per semester and three-quarters persisted beyond the first semester. In contrast, students with only a 12^{th} grade education or lower earned an average of 11 credits per semester and only 59% persisted beyond their first semester. Interestingly, students with only a 12^{th} grade education or lower had high credential attainment rates; 16% earned a credential at the end of the first year in the program. Students with any post-secondary education also had high credential attainment rates; 18% earned a credential at the end of the first year in the program. In contrast, only 4% of students with a high school degree or GED earned a credential at the end of the first year in the program.

We also examined differences in outcomes based on whether the student was enrolled in school, or not, at intake. We found that students who were already in school when they joined the GCIT program were similar in many aspects to those students who were not in school when they joined the GCIT program; both groups earned an average of about 12-13 college credits per semester and 72%-82% persisted beyond their first semester. However, students who were already in school at intake had higher credential receipt rates; 11% of students who were already in school at intake earned a credential at the end of their first year in the program, compared to only 7% of students who were not in school at intake. This is likely because students who were already in school at intake had already accumulated credits needed to earn a credential at the end of their first year. Compared to these two groups, students who were in adult education programs when they joined the GCIT program earned an average of 11 college credits per semester, fewer than half (42%) persisted beyond their first semester and only 3% earned a credential at the end of their first year in the program (the lowest credential receipt rate of any sub-group).

As expected, there were large differences observed by course-load. Students with a full-time course-load earned an average of 14 college credits per semester and 80% persisted beyond their first semester. In contrast, students with a part-time course load only earned an average of 9 college credits per semester and only half persisted beyond their first semester. Interestingly, in spite of lower college credit accumulation and lower persistence rates, students with part-time course loads had higher credential receipt rates; 12% of students with part-time course loads earned a credential after their first year in the program, compared to only 9% of students with full time course loads.

We also found that veterans in the program did well and had the highest credential receipt rate of any sub group; they earned an average of 13 college credits per semester, 67% persisted beyond the first semester and 21% earned a credential at the end of their first year. GCIT participants who received Pell grants also did well; they earned an average of 14 college credits per semester, 80% persisted beyond the first semester and 10% earned a credential after their first year in the program.

Participant Outcomes by College

Next, we examine the same outcomes broken out by state and college (see Table 3).We found that GCIT participants in for-credit academic programs in Louisiana had a lower credit accumulation rate (an average of 11 college credits per semester), but a higher credential receipt rate (17% earned a credential after their first year in the program), compared to GCIT participants in for-credit academic programs in Mississippi, who earned an average of 14 college credits per semester but only 6% earned a credential after their first year in the program.

Early Program Impact

In the previous section of the report, we examined and reported outcomes for GCIT program participants i.e. the treatment group. In this section of the report, we focus on understanding the impact of the GCIT program using rigorous impact evaluation methods. The impact evaluation is designed to address the research question: what impact did the TAACCCT GCIT program have on student education and employment outcomes?

The main goal of the impact evaluation is attribution – isolating the effect of the TAACCCT GCIT program from other factors. The main challenge of an impact evaluation is to determine what would have happened to the program participants if the program had not existed i.e. the counterfactual. Without information on the counterfactual, the next best alternative is to compare outcomes of program participants with those of a comparison group of non-participants. Successful impact evaluations hinge on finding a good comparison group (Khandker, Koolwal et al. 2010).

Study Design

At the beginning of this grant, RMC selected the **difference-in-differences (DID)** approach for the impact analysis. The key to DID is selecting a comparison group for which data are available over the same time period as the treatment group, and which was likely to have experienced the same exogenous factors but that did not experience the treatment. Although the treatment and comparison groups may differ significantly on both observed and unobserved characteristics, these potentially confounding influences are controlled for by measuring change in the outcome rather than the outcome itself. DID thus allows for unbiased estimates of the treatment effect even if the treatment and comparison groups are not identical.

In our original evaluation plan, we proposed that the comparison group would consist of students from non-Consortium colleges who enrolled in IT programs (see Table 4). But by the end of the first year of the grant, we learned that the evaluation team would not have access to the data of students who attended non-Consortium colleges.

Table 4. Original Cohort Groups for the DID Impact Analysis

Time period	Academic Year	Comparison (IT programs in non-Consortium Colleges)	Treatment (IT programs in Consortium Colleges)
Prior Year	2012-13	Group 1	Group 3
Program Implementation	2013-14 2014-15 2015-16	Group 2	Group 4

We then modified our approach so that the comparison group could be drawn from students who enrolled in Consortium colleges, but did not enroll in one of the IT pathways programs (see Table 5). However, the data we received in November 2014, after the first year of program implementation, only included the treatment group (i.e. GCIT program participants) and a comparison group of students from one year prior to program implementation; the data did not include a comparison group of students from the years after the GCIT program was implemented. This crucial gap in the data was identified and highlighted in our interim report, and was to be addressed in the next data transfer.

Table 5. Revised Cohort Groups for the DID Impact Analysis

Time period	Academic Year	Comparison (Other programs in Consortium Colleges)	Treatment (IT programs in Consortium Colleges)
Prior Year	2012-13	Group 1	Group 3
Program Implementation	2013-14 2014-15 2015-16	Group 2	Group 4

The data that was received by the evaluation team in July 2015, after the second year of program implementation, still only includes comparison students from one year prior to program implementation, and does not include comparison students from the years after the GCIT program was implemented. With the data as it currently stands, it is impossible for the evaluation team to implement the DID approach. For this report, we instead implemented a **retrospective cohort analysis.** In this type of analysis (see Table 6), outcomes for the group that received the intervention during the program implementation period (i.e. the treatment group) are compared to the outcomes for a comparison group that did not receive the intervention from a time period prior to the program implementation period. The difference in the outcome between the two groups can be understood as the effect of the treatment. Although this design is the best approach that we could take with the data as it currently stands, it should be noted that the retrospective cohort design is significantly less rigorous than the original DID approach.

Table 6. Revised Cohort Groups for the Retrospective Impact Analysis

Time period	Academic Year	Group assignment (IT programs in Consortium Colleges)
Prior Year	2012-13	Comparison
Program Implementation	2013-14 2014-15 2015-16	Treatment

We implemented the retrospective cohort analysis using GCIT participants in for-credit academic programs from the 2013-2014 academic year (i.e. the first year of GCIT program implementation) as the treatment group, and students in similar programs from the 2012-2013 academic year (i.e. the year prior to GCIT program implementation) as the comparison group pool. It is important to note that no comparison group is available for GCIT participants in non-credit training programs as their information is not systematically recorded in the colleges' institutional data systems. As a result, these students in non-credit training programs are excluded from the impact analysis.

We also used use **propensity score matching (PSM)** methods to match treatment students to comparison students (Rosenbaum and Rubin 1983) using the observable characteristics included in the data provided to the evaluation team. For every individual in the treatment group, a matching individual was found from among the comparison group pool, using propensity score matching techniques. Thus, this approach allowed us to compare the education outcome of students who participated in the GCIT program to students who did not, taking differences in observable characteristics into account.

SELECTION OF COMPARISON GROUP POOL

The comparison group pool comprises of students in similar IT programs from the year prior to GCIT program implementation. We began by identifying the most common major fields of study[5] (see Table 7), declared by the treatment group (i.e. GCIT participants). We then selected students at the nine consortium colleges from the year prior to program implementation (the 2012-2013 academic year) who had declared the same major fields of study; these students form our comparison group pool. Note that these majors span the three IT specialty areas identified by the consortium in their proposal: health information technology, cyber security, and industrial information IT.

Table 7. Most Common Majors in the Treatment Group

4-digit CIP	Major Field of Study
1101	Computer and Information Sciences, General
1102	Computer Programming
1103	Data Processing
1104	Information Science/Studies
1109	Computer Systems Networking and Telecommunications
1110	Computer/Information Technology Administration and Management
1199	Computer and Information Sciences and Support Services, Other
1506	Industrial Production Technologies/Technicians
4702	Heating, Air Conditioning, Ventilation and Refrigeration Maintenance Technology/ Technician (HAC, HACR, HVAC, HVACR)
4703	Heavy/Industrial Equipment Maintenance Technologies
4805	Precision Metal Working
5107	Health and Medical Administrative Services
5204	Business Operations Support and Assistant Services

Comparison of Observable Characteristics

We began by exploring the differences between the treatment group (i.e. GCIT students) and the comparison group pool (i.e. non-GCIT students in IT programs) on a wide range of observable characteristics. These characteristics are not only potential correlates of participation in the GCIT program, but are also likely to be related to the education and

[5] Major field of study was identified using the program CIP code.

employment outcomes of interest. Table 8 lists these characteristics in detail, documenting the differences between the treatment and comparison group. In some ways, GCIT students appear to be relatively similar to non-GCIT students in IT programs. There are, however, differences worth noting.

Table 8. Comparison of Observable Characteristics

Observable Characteristics	Comparison Group Pool	Treatment Group
Number of participants	5,866	590
State: Louisiana	80.1%	46.9%
State: Mississippi	19.9%	53.1%
Age (median)	25.0	22.0
Female	49.0%	48.8%
Race: Other	10.6%	8.1%
Race: White	41.8%	59.7%
Race: Black	43.0%	29.8%
Race: Hispanic	4.6%	2.4%
U.S. Citizen	98.3%	100.0%
In-State Resident	98.0%	99.0%
Student level: Freshman	50.4%	49.8%
Student level: Sophomore	31.8%	35.9%
Student level: Other Undergraduate	17.8%	14.2%
Pursuing associate's degree	67.2%	84.7%
Pursuing certificate	3.6%	5.6%
Pursuing diploma	28.3%	4.7%
Non-degree seeking student	0.9%	4.9%
Cumulative GPA (median)	2.8	2.7

The treatment group was slightly younger in age, with a median age of 22, compared to the comparison group with a median age of 25. Both the treatment group and comparison group had about an even distribution of gender. However, the two groups did have different racial compositions; the comparison group was about evenly split between black participants (43%) and white participants (42%), while the treatment group had mostly white participants (60%) and less than a third (29%) were black participants. Similar to the treatment group, the comparison group was almost exclusively U.S. citizens and in-state residents.

In both the treatment and comparison groups, about half of the students were freshmen and a third were sophomores. The comparison and treatment group did differ greatly on the degrees pursued; a vast majority of the treatment group (85%) was trying to earn an associate's degree or post-associate certificate, compared to only two-thirds of the comparison group. Over a quarter of the students in the comparison group (28%) were trying to earn a diploma, compared to only 5% of the treatment group.

Comparison of Outcomes

In a direct comparison of the treatment group (i.e. GCIT students) with the comparison group pool (i.e. non-GCIT students), we found large differences in education outcomes (see Table 9).The treatment group earned an average of 13 college credits per semester, compared to an average of 12 college credits per semester for the comparison group. The treatment group had a much higher persistence rate; nearly three-quarters (72%) of the treatment group persisted beyond their first semester, compared to less than half (47%) of the comparison group. However, the treatment group had a much lower credential receipt rate; only 10% of the treatment group earned a credential after their first year in the program, compared to 24% of the comparison group.

Table 9. Comparison of Outcomes

Outcomes	Comparison	Treatment
College credits earned per semester (Mean)	11.5	12.7
Persisted after first semester (%)	47.3%	72.0%
Earned any credential (%)	24.2%	9.8%
Earned any certificate (%)	15.1%	4.4%
Earned any degree (%)	15.2%	4.9%

These results are descriptive in nature and do not control for differences among students in these groups. Given the differences documented in Table 8 between the treatment group and the comparison group pool on the observable characteristics, it is necessary to account for them as well as possible in order to attribute these outcome differences to the treatment (i.e. GCIT program participation).

PROPENSITY SCORE MATCHING

We used the propensity score matching approach to account for differences on the observable characteristics between the treatment group and the comparison group pool. See Appendix B for a detailed description of our application of this method. We matched the students in the treatment group to a subset of students from the comparison group pool. We used the single nearest-neighbor technique which involves finding for each treated individual that non-treated individual with the most similar propensity score and so, the most similar characteristics. We assessed and confirmed that our matching approach achieved satisfactory balance in all observables characteristics. Thus, we can be quite confident that in our estimates of the causal impact of the GCIT program on education outcomes, we are comparing genuinely comparable students.

EARLY FINDINGS OF PROGRAM IMPACTS

Estimated impacts of GCIT participation on education outcomes are documented in Table 10.[6] Overall, the matched comparisons tend to confirm the unmatched comparisons quite closely, despite the differences in observable characteristics discussed earlier. We found that participation in the GCIT program had a significant impact on all three education outcomes of interest: credit hour accumulation, student persistence, and credential attainment.

Table 10. Program Impacts

Outcome	Matched Comparison Group (n=512)	Treatment Group (n=512)	Average treatment effect on the treated(ATT)		
	Mean	Mean	Diff.	Abadie Imbens Robust S.E	P>|z|
College credits earned per semester (Mean)	11.75	12.69	0.95	0.19	0.000
Persisted after first semester (%)	0.48	0.75	0.27	0.03	0.000
Earned any credential (%)	0.16	0.11	-0.05	0.02	0.018
Earned any certificate (%)	0.11	0.05	-0.06	0.02	0.001
Earned any degree (%)	0.10	0.05	-0.05	0.02	0.007

[6] Note that 78 of the 590 students in the treatment group were missing GPA information and were excluded from this impact analysis.

Column 4 of Table 10 indicates the propensity score matching estimates of the differences in education outcomes between the treatment group and the matched comparison group. Our PSM models found that GCIT students had a significantly higher credential accumulation and persistence rates. The average number of credits earned by GCIT students in a semester was 13, compared to an average of 12 for the matched comparison group. GCIT students had a semester persistence rate that was 27 percentage points higher than matched comparison students; GCIT students had a 75 percent persistence rate, compared to 48 percent for the matched students. However, our PSM models also found that GCIT students had significantly lower credential receipt rates. GCIT students had an 11 percent credential receipt rate, compared to 16 percent for the matched comparison group— a 5 percentage point difference.

Limitations

The findings presented above should be considered preliminary as they are based only on a single year of data. As with all PSM approaches, the degree to which unmeasured sources of bias affect the comparability of groups is unknown. PSM does not allow us to correct for selection bias that might be caused by characteristics we do not observe or measure; this remains a limitation of this study.

Since UI wage data was not made available to the evaluation team, the analysis did not include prior labor market experiences for the treatment and matched comparison group. This is an important limitation of the current analysis, since prior labor market experience is an important characteristic in considering section bias; evaluations of job training programs in the US have found the employment histories of individuals to be good predictors of program participation.

Next Steps

In this section of the report, we discuss the impact evaluation team's focus for the final year of program implementation. While much progress related to data quality and data access has been made in this past year, some concerns remain and will need to be addressed during this final year.

Gaps in Data

In our interim impact evaluation report earlier this year, we described the significant data gaps and data delays we experienced during the first two years of program implementation. Since the release of that report, many of these data gaps have been addressed. The most recent data received by the evaluation team in July 2015 contains one of the missing crucial elements we identified in our previous report: educational outcome data (i.e. credential attainment data) for GCIT participants and comparison students. This has allowed us to conduct outcomes analyses and begin preliminary impact analyses, as described in previous sections of this report. However, several elements remain missing including (1) educational outcomes for GCIT participants in non-credit training programs, (2) employment (UI) outcomes for GCIT participants (in for-credit and non-credit programs), and (3) data for comparison students from the time period in which the grant was implemented. NSPARC is currently working on compiling these missing elements, and the evaluation team has set a target date of October 31, 2015 for the next data transfer.

The evaluation team remains concerned about our ability to implement the DID approach since data on the full comparison group has not yet been made available to us. As mentioned previously, comparison students from the time period in which the grant was implemented need to be included in the data sent to the evaluation team in order to implement the DID approach, which compares changes in outcomes in the comparison group to changes in outcomes in the treatment group . The evaluation team has set a target date of December 31, 2015 to receive this data; if data on the full comparison group has not been made available to the evaluation team by that date, we will move forward instead with implementing the retrospective cohort design. The retrospective cohort design is significantly less rigorous than the DID approach, and we will need to discuss its limitations when presenting our results in the final evaluation report.

Final Impact Evaluation Report

The TAACCCT GCIT program received permission from the U.S. Department of Labor to continue program implementation activities for an additional six months into the fourth year of the grant. Thus, program implementation can now end in March 31, 2016, instead of the previous end date of September 30, 2015. Since the March 2016 end date does not align with semester schedule at college, some colleges are wrapping up program implementation by December 2015 while other colleges will continue to enroll students through March 2016. Thus, the Consortium expects that many GCIT participants will be completing their programs of study, receiving college credits, and earning credentials at the end of the Spring 2016 semester. Following DOL requirements, labor market outcomes will need to be tracked for these students for two quarters following their program completion i.e. labor market outcomes will need to be tracked through September 2016.

The evaluation team is contracted to produce the final evaluation report by September 30, 2016 and a request for an extension for evaluation activities by the GCIT consortium to DOL has been denied. In order to have a final report by September 30, 2016, we will need to receive data at least three months prior i.e. by June 30, 2015. It is very likely that we will be unable to access employment outcome data for the students being served in this last year of the grant. Keeping in mind the delays we have experienced over the grant implementation period in receiving academic data and education outcome data, it is also likely that we may be unable to fully access education outcome data for the students being served in this last year of the grant.

We remain concerned that due to these timeline issues, (a) our final impact evaluation report will only be able to report on outcomes for a portion of the students served, and (b) we will be unable to fully conduct our rigorously designed impact analysis due to missing outcomes for a large proportion of the study population. Over the next year, we will work closely with the consortium and data partners to determine what data can be made available to us in a timely manner for the final report.

APPENDIX A. ACADEMIC VARIABLES REQUESTED BY RMC

Academic Date
Academic Year Begin
Academic Term
Institution Code
Student Identification Number
Student Race
Student Ethnicity
Student Gender
Fee Residence
Citizenship
Parish/State/Country
Birth Date
Birth Month
Birth Year
Admission Status
Student Type/Level
Program Classification
CIP Code
Degree Level Code
High School Graduation Year/Date
High School Grade Point Average
High School Class Percentile Rank
Admission Test (type and scores)
Current Term Grade Point Average

Cumulative Overall Grade Point Average
Academic Standing at End of Term
Total Student Credit Hours Scheduled
Total Student Contact Hours Scheduled
Institution Common Identification Number
Cumulative Hours Earned
Attended Summer Session
Student Course Information
Enrolled at Census Date
Developmental Course Flag
Contact Hour Course Flag
Course Abbreviation
Course Classification (CIP)
Course Number
Section Number
Course Credit/Contact Hours
Course Grade
Credential receipt
Level of credential (certificate, associate’s, bachelor’s, etc.)
Subject/major of credential
Date of receipt
FICE or other institution code of granting institution

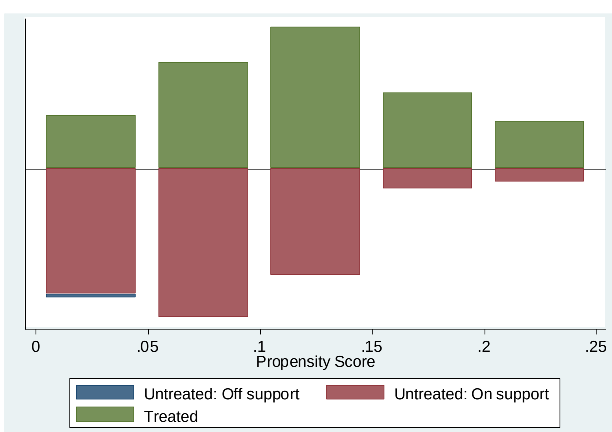
Appendix B. Propensity Score Matching

We used the propensity score matching approach to account for differences on the observable characteristics between the treatment group and the comparison group pool. The aim of propensity score matching is to construct a balanced sample of treatment and comparison students who both participated in IT pathway programs, but are distinct only in their participation in the GCIT program. We utilized the PSCORE, PSMATCH2 and TEFFECTS modules in the Stata statistical software package (Garrido, Kelley et al. 2014).

STEP 1: PROPENSITY SCORE ESTIMATION

First, we constructed a propensity score for each individual (in both the treatment group and the comparison group pool) that estimated the likelihood of participating in the GCIT program using all the observable characteristics. This was done by using the *pscore* procedure in Stata (Becker and Ichino 2002) to perform a probit regression of the treatment dummy variable on all available covariates that, in our judgment, had the potential to influence the chances of being treated. We ensured that there was overlap in the range of propensity scores across the treatment and comparison groups, called "common support." This is important because no inferences about treatment effects can be made for a treated individual for whom there is not a comparison individual with a similar propensity score. Common support was subjectively assessed by examining a graph of propensity scores across treatment and comparison groups (Figure B-1).

Figure B-1. Common Support



STEP 2: MATCHING

Next, we matched the students in the treatment group to a subset of students from the comparison group pool, using the *psmatch2* procedure in Stata (Leuven and Sianesi 2014). We used the single nearest-neighbor technique which involves finding for each treated individual that non-treated individual with the most similar propensity score and so, the most similar characteristics. We also used matching with replacement which allows each comparison unit to be used as a match more than once; matching with replacement produces matches of higher quality than matching with replacement by increasing the set of possible matches (Abadie and Imbens 2006). Also, if two or more observations had the same propensity score and were thus tied for "nearest neighbor", all ties were used for the match; including all the ties provides a more precise estimator (Abadie, Drukker et al. 2004).

Note that one can match each treated individual to one or many comparison group individuals. When matching at the individual level, the first match is always best and will lead to the least biased estimates, but the decrease in bias from fewer matches needs to be weighed against the lower efficiency of the estimate that will occur with fewer observations. A broader one-to-many match will increase sample size and efficiency but can also result in greater bias from matches that are not as close as the initial match (Caliendo and Kopeinig 2008).

Next, we assessed if balance in the observable characteristics had been achieved, using the *pstest* procedure in Stata. Propensity score matching can only lead to viable estimates of the causal effects of treatment, if the desired balancing of observable covariates is achieved. We found that our approach was quite successful in achieving covariate balance. Table B-1 lists overall measures of covariate balance and Table B-2 lists individual measures of covariate balance and.

Table B-1.1 Overall Balance

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.056	204.95	0.000	16.6	12.7	65.2*	0.87	100
Matched	0.001	1.87	0.999	2.1	2.2	8.3	0.98	100

Table B-1.2 Covariate Balance

Observable Characteristics		Mean		% bias	% reduct |bias|	t-test	
		Treatment	Comparison			t	p>|t|
Age Group : 22 to 30	Unmatched	0.29	0.38	-19.70		-4.15	0.000***
	Matched	0.29	0.28	2.90	85.30	0.48	0.628
Age Group : 31 & older	Unmatched	0.28	0.33	-10.80		-2.30	0.022*
	Matched	0.28	0.26	3.00	72.50	0.49	0.623
Gender: Female	Unmatched	0.47	0.50	-5.00		-1.09	0.276
	Matched	0.47	0.48	-2.00	61.20	-0.31	0.755
Race : White	Unmatched	0.58	0.42	33.10		7.17	0.000***
	Matched	0.58	0.57	1.20	96.40	0.19	0.850
Race : Black	Unmatched	0.32	0.43	-22.80		-4.83	0.000***
	Matched	0.32	0.32	-0.80	96.40	-0.13	0.894
Race : Hispanic	Unmatched	0.03	0.05	-11.50		-2.23	0.026*
	Matched	0.03	0.03	-3.10	72.50	-0.56	0.572
Resident: In-state	Unmatched	0.99	0.98	12.30		2.21	0.027*
	Matched	0.99	0.99	5.20	57.40	1.00	0.316
Student Level : Sophomore	Unmatched	0.41	0.34	15.70		3.45	0.001***
	Matched	0.41	0.41	0.80	94.80	0.13	0.899
Student Level: Other	Unmatched	0.16	0.19	-7.60		-1.60	0.109
	Matched	0.16	0.14	4.60	39.10	0.78	0.433
Degree Pursued: Associate’s	Unmatched	0.86	0.67	47.30		9.15	0.000***
	Matched	0.86	0.86	0.90	98.00	0.18	0.857
Cumulative GPA[7]	Unmatched	0.94	0.93	0.60		0.12	0.904
	Matched	0.94	0.91	7.90	-1236.40	1.23	0.221

After matching, the measures indicate good covariate balance: (1) standardized bias[8] for all covariates is less than 5%, (2) t-tests for all covariates are non-significant, (3) the pseudo-R^2 is very low[9], (4) the likelihood-ratio test[10] is non-significant, (5) the mean and median absolute

[7] Logarithmic function of cumulative GPA was used in the analysis.

[8] The standardized bias is the % difference of the sample means in the treated and non-treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups Rosenbaum, P. R. and D. B. Rubin (1985). "Constructing a control group using multivariate matched sampling methods that incorporate the propensity score." The American Statistician **39**(1): 33-38..

[9] The pseudo-R^2 indicates how well the regressors X explain the participation probability.

[10] the likelihood-ratio test of the joint insignificance of all the regressors

bias are less than 5%, (6) Rubin's B[11] is close to 0, and (7) Rubin's R[12] is close to 1. Figure B-2 shows the standardized percentage bias for each covariate using a dot chart. Figure B-3 shows the distribution of the standardized percentage bias across covariates using a histogram.

Figure B-2. Individual Covariate Balance

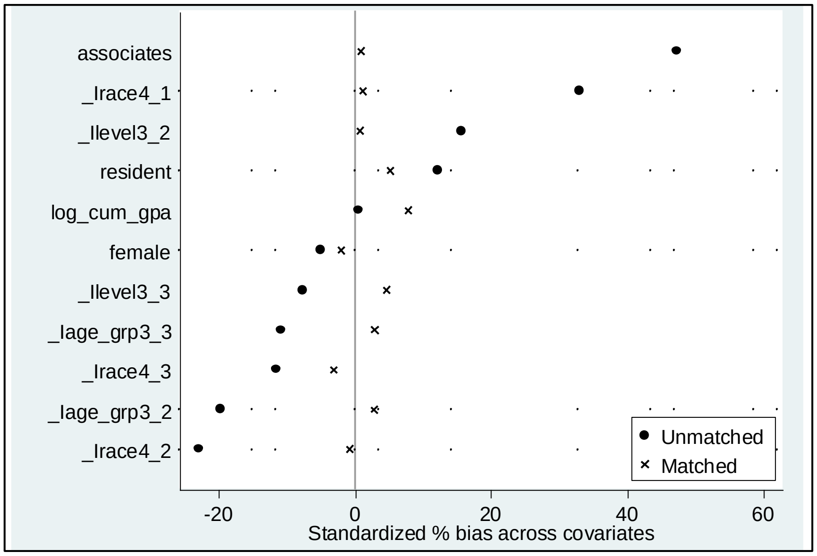
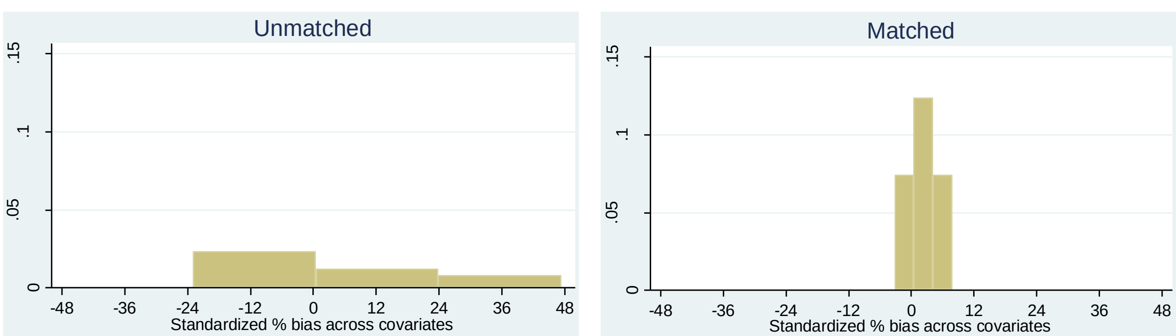


Figure B-3. Overall Covariate Balance



Thus, while the differences between the treatment group and the comparison group pool in observable characteristics were documented in Table 8 to be substantial in the unmatched sample, our matching approach (nearest neighbor matching with replacement)

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[11] Rubin's B is the standardized difference in mean of the linear prediction of the propensity score before and after matching

[12] Rubin's R is the ratio of variance of the treated and comparison group for the linear prediction of the propensity score.

achieved satisfactory balance in all observable characteristics. We can be quite confident that in our estimates of the causal impact of the GCIT program on education outcomes, we are comparing genuinely comparable students.

STEP 3: TREATMENT EFFECT ESTIMATION

Finally, we estimated the average treatment effect on the treated (ATT), which is the average difference on an outcome of interest between the matched treated and untreated observations. The ATT is the average effect of the treatment on the sort of person who participates in the program. The effectiveness of PSM is, in part, a function of having enough relevant information about the cases to accurately estimate the propensity score, and thus accurately estimate the ATT using the matching process that uses this score. The *teffects psmatch* procedure in Stata (StataCorp) calculates the treatment effect along with the Abadie Imbens corrected standard error calculation (Abadie and Imbens 2012).

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