



Washington State's Integrated Basic Education and Skills Training Program (I-BEST): New Evidence of Effectiveness

Matthew Zeidenberg
Sung-Woo Cho
Davis Jenkins

September 2010

CCRC Working Paper No. 20

Address correspondence to:

Matthew Zeidenberg
Senior Research Associate, Community College Research Center
Teachers College, Columbia University
525 West 120th Street, Box 174
New York, NY 10027
212-678-3091
Email: zeidenberg@tc.edu

Funding for this research was generously provided by the Bill & Melinda Gates Foundation. We would like to thank Tina Bloomer, David Prince, and their colleagues at the Washington State Board for Community and Technical Colleges for providing the data used in this study and for their helpful insights on our preliminary findings. We would also like to thank Michelle Van Noy, Shanna Smith Jaggars, and Judith Scott-Clayton of CCRC and Amanda Richards and Laura Horn of MPR Associates for helpful comments and suggestions on earlier drafts. We thank Amy Mazzariello of CCRC for her excellent work in editing the document. All errors are our own.

Table of Contents

Executive Summary	1
1. Introduction and Background	3
2. Data and Methods.....	6
3. Findings from Multivariate Analyses.....	8
3.1 Descriptive Characteristics and Outcomes.....	9
3.2 Estimates of the Probability of Earning College Credit.....	11
3.3 Estimates of the Probability of Earning CTE College Credit	15
3.4 Estimates of the Number of Credits Earned.....	15
3.5 Estimates of the Probability of Persisting into the Next Year	17
3.6 Estimates of the Probability of Earning an Award	19
3.7 Estimates of the Probability of Achieving Point Gains on Basic Skills Tests.....	19
3.8 Employment Outcomes.....	20
4. Difference-in-Differences Analysis	22
4.1 Sample.....	22
4.2 Methodology	25
4.3 Results	26
4.4 Enrollment as a Measure of Take-Up	27
5. Conclusion	28
Appendix A: Tables	31
Appendix B: A Brief Description of Propensity Score Matching.....	38
References.....	40

Executive Summary

Many community colleges are faced with the problem of educating basic skills students—students who have very low levels of academic skill. Nationally, over 2.5 million students take adult basic skills courses through community colleges, high schools, or community organizations. Often, these students hold low-skill jobs or are not working, and few of them successfully transition from basic skills courses to college-level coursework that would help them earn credentials that would increase their chances of securing jobs paying family-supporting wages.

To increase the rate at which adult basic skills students advance to and succeed in college-level occupational programs, the Washington State Board for Community and Technical Colleges (SBCTC) developed the Integrated Basic Education and Skills Training, or I-BEST. In the I-BEST model, a basic skills instructor and an occupational instructor team teach occupational courses with integrated basic skills content, and students receive college-level credit for the occupational coursework. The goal of this instructional model is to increase the rate at which basic skills students are able to succeed in college-level coursework leading to certificates and associate degrees in high-demand fields. I-BEST programs cover a wide range of occupations, with courses in such areas of study as nursing and allied health, computer technology, and automotive technology.

We examined students who enrolled in I-BEST in 2006–07 and 2007–08. We examined the effect of the program on seven educational outcome variables: (1) whether a student earned any college credit (of any kind), (2) whether a student earned any occupational college credit, (3) the number of college credits a student earned, (4) the number of occupational college credits a student earned, (5) whether or not a student persisted to the following year after initial enrollment, (6) whether a student earned a certificate or degree, and (7) whether a student achieved point gains on basic skills tests. We also examined the following two labor market outcomes: the change in wages for those who were employed both before and after program enrollment, and the change in the number of hours worked after leaving the program.

We used three methods in this study: multivariate regression analysis (both OLS and logistic), propensity score matching (PSM), and differences-in-differences. The same

control variables were used for all three methods: basic skills test scores, whether or not basic skills students were native English speakers, age, sex, race, disability status, single parent status, married parent status, a proxy for socioeconomic status based on students' residence, academic or occupational intent, financial aid receipt, the type of aid received, quarter of initial enrollment, level of previous schooling, whether the student was on welfare, and whether the student worked while enrolled.

We selected as our comparison group for the regressions those basic skills students who during the study period took an occupational course on their own, outside of I-BEST. Considering I-BEST students alongside those in the control group—who exhibited motivation to pursue college-level occupational education by enrolling in at least one such course on their own—creates a fair and probably conservative comparison. In the PSM analyses, we allowed the PSM algorithm to select comparison students from the full sample of basic skills students.

Both the multivariate regressions and the PSM analyses produced similar results, which add robustness to the study. We found that enrollment in I-BEST had positive impacts on all but one of the educational outcomes (persistence was not affected), but no impact on the two labor market outcomes. However, it is likely that I-BEST students did not fare better than the comparison group in the labor market because they were entering the market just as the economy was entering the recent major recession. Perhaps a future evaluation will reveal better labor market outcomes.

The difference-in-differences (DID) analysis found that students who attended colleges with I-BEST after the program was implemented were 7.5 percentage points more likely to earn a certificate within three years and almost 10 percentage points more likely to earn some college credits, relative to students who were not exposed to I-BEST. Unlike the regression and PSM analyses, the DID approach allows us to make causal inferences about the effectiveness of I-BEST. The DID findings are especially impressive given that they are based on the effects of I-BEST during their first year of implementation at the subset of colleges offering the “treatment” examined. We assume that the effectiveness of the I-BEST model will improve as colleges have more experience with it.

1. Introduction and Background

Many adults in the United States have a very low level of basic academic skills in reading, writing, or math. Of the nearly 200 million adults over the age of 25, about 26 million, or 13%, lack a high school diploma, and about 11 million, or 5%, have less than a ninth grade education.¹ In addition, the U.S. is home to many immigrants who do not understand or speak English well and may have had limited opportunities for education in their home countries.²

The lack of basic skills is a barrier to the acquisition of occupational skills because programs that teach such skills often assume at least a certain minimum level of basic academic skills. This is particularly the case for career and technical education (CTE) offered by community colleges and other postsecondary institutions, which research suggests often enables individuals to obtain higher wages compared to those with at most a high school education (Belfield & Bailey, 2010; Grubb; 2002; Jacobson & Mokher, 2009). Community colleges often require students to score above a certain threshold on a test of basic skills before they will be admitted to college-level vocational programs.

Community and technical colleges, school districts, and community organizations offer adult basic education (ABE), GED preparation, and English-as-a-second-language (ESL) programs to help individuals seeking to improve their basic skills. The conventional assumption in these programs, which enroll over 2.5 million students per year (U.S. Department of Education, 2007, p. 4), is that students with basic skills deficiencies often need to complete such programs before enrolling in postsecondary education and training.

Perhaps as a result of the time it takes to progress through a linear sequence of basic skills courses, relatively few adult basic skills students advance to college-level coursework. Of students in federally funded adult basic skills programs, only about a

¹ These figures were calculated from Current Population Survey statistics posted at <http://www.census.gov/population/www/socdemo/education/cps2008.html>.

² The Census Bureau's American Community Survey found that that 8.6% of those 5 years or older surveyed between 2006 and 2008 spoke English less than "very well." See http://factfinder.census.gov/servlet/STTable?_bm=y&-geo_id=01000US&-qr_name=ACS_2008_3YR_G00_S1601&-ds_name=ACS_2008_3YR_G00

third of those who had indicated that they intended to pursue postsecondary education actually did so (U.S. Department of Education, 2007, p. 2). A study of enrollment patterns of adult basic skills students in the Washington State community and technical colleges found that a small fraction of basic skills students also do college-level work, and even fewer complete programs—even though basic skills students who fail to take college-level coursework and earn at least a one-year occupational certificate earn substantially less than those who succeed in doing so (Prince & Jenkins, 2005).

To increase the rate at which adult basic skills students advance to college-level occupational programs that lead to career-path employment, Washington State’s community and technical college system developed the Integrated Basic Education and Skills Training program, or I-BEST. In the I-BEST model, basic skills instructors and professional-technical faculty jointly teach college-level occupational classes that admit basic skills students. By integrating instruction in basic skills with instruction in college-level professional-technical skills, I-BEST seeks to enable basic skills students seeking occupational training to enroll directly in college-level coursework. Details on how I-BEST programs work in practice are provided in a companion report (Wachen, Jenkins, & Van Noy, 2010).

The Washington State Board for Community and Technical Colleges (SBCTC) funds I-BEST programs at 1.75 times the normal rate per full-time-equivalent (FTE) student to compensate for the cost of using two faculty members in each CTE class (instructors are expected to spend at least 50% of class time together in the class) and the high costs of planning and coordination typically associated with I-BEST programs.³ Colleges in the Washington community and technical college system must apply to the SBCTC for I-BEST program approval. To be approved by the SBCTC, every proposed I-BEST program must be part of a “career pathway;” that is, a course of study that leads to postsecondary credentials and career-path employment in a given field for which colleges must document demand. Thus, I-BEST provides a structured pathway to college credentials and employment so that students do not have to find their way on their own. Table 1 lists the I-BEST programs with the highest number of course enrollments (among

³ In all I-BEST courses, both a CTE instructor and a basic skills instructor participate, and there is CTE content. In many programs, the basic skills instructor also offers supplemental instruction to I-BEST students, although this, if offered in a classroom format, is not considered an I-BEST course.

first-time students) during the two academic years examined in this analysis, in rank order. The fields that dominate are health care, education, the skilled trades, office work, computers, and law enforcement.

Table 1
Top I-BEST Programs by Enrollment,
2006–07 and 2007–08

1	Medical Assistant
2	Nurse's Aide
3	Office Manager
4	Microcomputer Applications Specialist
5	Early Childhood Teacher
6	Auto Mechanic
7	Welder
8	Criminal Justice/Law Enforcement
9	Office/Clerical
10	Home Health Aide

I-BEST started in academic year 2004–05 with pilots at five colleges. In 2005–06, five more colleges were added to the pilot, for a total of ten. In 2006–07 (the first non-pilot year), another 14 colleges began offering I-BEST programs. In 2007–08, I-BEST was expanded to all 34 colleges in the system, and all colleges continue to offer I-BEST programs. I-BEST has generated much excitement within Washington's community college system and elsewhere. Other states are looking at it as a model for constructing similar programs, and major foundations such as the Gates Foundation and the Annie E. Casey Foundation have expressed interest in replicating it.

This is the second CCRC quantitative study of I-BEST. In the first study (Jenkins, Zeidenberg, & Kienzl, 2009), we studied the outcomes of the 2006–07 cohort. At the time of that study, we did not yet have data on the 2007–08 cohort. We now have these data, so we examined the educational outcomes of both cohorts in this study along with those of the 2005–06 cohort. We also lacked information on the wages of students before, during, and after school; now that we have that information, we are able to study the impact (if any) of I-BEST on employment.

With any program developed by practitioners and not designed as an experiment, we are confronted with the problem of selection bias. There may be systematic differences between students who enrolled in I-BEST and those who did not that are not captured in the characteristics that we can observe about them. In the earlier study, we used propensity score matching (PSM) to compare I-BEST students with students matched based on observed characteristics. We use PSM in this study as well, but while PSM may provide a better estimate of program effects than can linear regression, it still cannot control for unmeasured characteristics. (See Appendix B for a brief description of PSM.) In the present study, we also use a difference-in-differences methodology—which, under certain assumptions, can address selection bias—to estimate the causal effects of exposure to the I-BEST program on student outcomes.

2. Data and Methods

We obtained the data used in this study through a cooperative arrangement with the Washington State Board for Community and Technical Colleges (SBCTC). The data contain information on all basic skills students, including I-BEST students, enrolled in any Washington community or technical college during the 2005–06, 2006–07, and 2007–08 academic years. We confined our analysis to basic skills students, that is, students who took at least one (non-credit) basic skills course during the period of study. These students may also have taken credit-bearing, college-level courses. We looked in particular at the students who enrolled in I-BEST in 2006–07 and 2007–08, comparing them to other basic skills students who enrolled in the same years. We focused on these two years because the SBCTC staff indicated to us that 2006–07 was the first year that the program had moved beyond the pilot phase and was being implemented in its current form.

The data contain information on the socioeconomic and demographic characteristics of the students in our sample as well as transcript information, which was used to determine the number of credits (both total and vocational) that each student earned. We also had data on all awards earned by each student in each year, if any. In addition, we had students' basic skills test scores. To assess the initial skill levels and

progress of its basic skills students, the Washington State community and technical colleges use the Comprehensive Adult Student Assessment System (CASAS) test, which has three components: reading, listening, and math.⁴

Like the current study, our earlier study looked at the effects of participation in I-BEST on the following seven outcome variables:

- whether the student earned any college credit,
- whether the student earned any CTE college credit,⁵
- the number of total college credits the student earned,
- the number of CTE college credits the student earned,
- whether the student persisted to the following year (for students who did not complete a degree, certificate, or credential),
- whether the student earned an award, and
- whether the student achieved point gains on basic skills tests.

In the first study, we found that, on all of these measures, I-BEST students performed moderately or substantially better than non-I-BEST basic skills students who enrolled at the same time. They also performed better than a group of basic skills students who we believe provide a better comparison to I-BEST students than basic skills students generally: those who took at least one CTE course on their own, outside of I-BEST. (We refer to these as “Non-IB Workforce students.”) In the first study, we also used propensity score matching to match the I-BEST students to a set of students who were similar on measured characteristics. We found that the I-BEST students also did better than the matched students on all of the above measures. For instance, 55% of I-BEST students earned an occupational certificate, compared to only 15% for the matched group.

This study differs from the previous one in two principal ways. First, we have more data. We now have data on the 2007–08 cohort of I-BEST students as well as the 2005–06 cohort and the 2006–07 cohort we studied in the earlier report. We have data on all students through spring 2009, as well as employment data consisting of quarterly hours worked, earnings, and wages from the first quarter of 1998 through the second quarter of 2009. Thus in this report we can study more I-BEST students over a longer

⁴ For more information on the CASAS, see www.casas.org.

⁵ CTE college credit is a subset of college credit.

span of time, using the same outcomes that we used in the first report. In addition, we examine two employment outcomes, namely whether or not there was any change in students' wages after participation in I-BEST and average hours worked after leaving the program. The second difference is that in this study we use a difference-in-differences methodology to examine the effects of I-BEST on student outcomes to account for the fact that I-BEST students may differ in unobserved ways from other basic skills students. The differences between the previous study and this study are summarized in Table 2.

Table 2
Comparison Between the Previous I-BEST Study
(Jenkins, Zeidenberg, & Kienzl, 2009) and the Current Study

	Previous Study	Current Study
Cohorts Studied	2006–07	2006–07 and 2007–08
Cohorts Studied Through	2007–08	2007–08 and 2008–09
Number of Students in Sample	31,078	77,147
Number of I-BEST Students	896	1,390
CASAS Score Included as a Control	No	Yes
Logistic Regression Analysis	Yes	Yes
Propensity Score Matching Analysis	Yes	Yes
College Credit Outcomes	Yes	Yes
Persistence Outcome	Yes	Yes
Award Outcome	Yes	Yes
Basic Skills Test Gain Outcome	Yes	Yes
Labor Market Outcomes	Yes	Yes
Causal (Difference-in-Differences) Analysis	No	Yes ^a

^aThe causal analysis also uses the 2005–06 cohort.

3. Findings from Multivariate Analyses

We first present the descriptive statistics comparing I-BEST students to two other groups: Non-IB Workforce students (basic skills students who took at least one CTE course, but not I-BEST), and Non-IB Non-Workforce students (basic skills students who took no college-level CTE courses during their first year).⁶ We then describe the results of multivariate analyses estimating the effect of I-BEST for each outcome examined here.

⁶ Note that Non-I-BEST Non-Workforce students could have taken a non-CTE college course.

3.1 Descriptive Characteristics and Outcomes

For this analysis, we obtained data on 89,062 students who took a basic skills course in a Washington State community or technical college in 2006–07 or 2007–08. To compare outcomes for students who entered college at the same time, we excluded students who had prior college education (including those with any prior college credits, degrees, or credit from dual high school-college enrollment courses). This reduced the sample size to 77,147. Of these, 1,390 were I-BEST students. The 2006–07 entering cohort had 38,305 students, and the 2007–08 entering cohort had 38,842 students. There were 608 first-time students who enrolled in I-BEST in 2006–07 and 782 first-timers enrolled in I-BEST in 2007–08.

In 2006–07, there were 3,583 first-time Non-IB Workforce students, basic skills students who did not enroll in I-BEST but took a CTE college course on their own, and 2,619 such students in 2007–08. As mentioned, we believe that this subgroup of basic skills students is most comparable to the I-BEST students because they, like the I-BEST students, indicated a desire to pursue at least some occupational training by enrolling in a CTE course. Unlike the I-BEST students, however, the Non-IB Workforce students did not take the CTE course as part of an integrated program that incorporates basic skills instruction. The third group of students took no CTE course, either through I-BEST or on their own. This group, referred to as the Non-IB Non-Workforce students, includes by far the largest number of basic skills students, since taking a CTE course, whether through I-BEST or otherwise, is relatively rare.

Table 3 shows that the Non-IB Workforce students have CASAS scores that are similar to those of the I-BEST students (with a notable difference in the listening score) and somewhat higher than the average for the entire basic skills student population (especially on reading and listening). This reinforces our belief that the Non-IB Workforce students provide a good comparison group for the I-BEST students.

Table A.1 (see Appendix A) shows the mean values of the student characteristics used as control variables in the regressions and the propensity score matching for each

outcome. We also included CASAS scores (means shown in Table 3) as controls.⁷ As Table 3 shows, in many ways, the I-BEST students in our sample were similar to other basic skills students. Some differences, however, are worth noting. I-BEST students were more likely to be ABE-GED students (as opposed to ESL)—over three quarters of them are. Significantly more of them received financial aid (we have one general measure of this and three measures of participation in particular programs). This is partially because I-BEST program administrators are encouraged to help their students apply for financial aid, since many of them have low incomes and are not accustomed to paying college tuition and fees, as they must do for the credit portion of I-BEST.⁸ I-BEST students were more likely to be welfare (TANF) participants. They were more likely to be female, less likely to be Hispanic, and somewhat more likely to be Black. They were much more likely to enroll full-time. (Higher rates of financial aid may make this possible.) They were also more likely to be single parents.

Table 3
Means of Earliest CASAS Scores: First Time Basic Skills Students,
2006–07 and 2007–08

	I-BEST		Non-IB Workforce Students		Non-IB Non-Workforce Students	
	<i>n</i>	Median Score	<i>n</i>	Median Score	<i>n</i>	Median Score
	1,390		6,202		69,555	
CASAS Math	1,014	225	2,708	224	22,073	222
CASAS Reading	1,239	235	3,151	233	49,946	217
CASAS Listening	314	218	691	211	25,060	204

Note: Scores are the earliest on each test, when the test is taken multiple times.

⁷ Where CASAS scores are missing, we set the score to missing and set an associated dummy variable to one to indicate the missing value. This is a technique commonly used in econometrics when there are missing test scores (Puma et al., 2009).

⁸ Basic skills courses in Washington State and the basic skills portion of I-BEST programs are offered for a modest fee of \$25 per quarter, but this fee is waived when a student is enrolled in I-BEST. In contrast, students have to pay tuition for college-level CTE courses and the CTE part of I-BEST courses.

There were also some noteworthy similarities and differences between the I-BEST students and the Non-IB Workforce students. We have already noted that they had similar CASAS scores, higher than those of the basic skills population at large. Both groups were dominated by ABE-GED students, as opposed to ESL students; the overall population has more ESL students. Both groups were also much more likely to indicate an intent to enroll in CTE courses when they registered for college, a goal which they are working to fulfill. Both groups had similar rates of participation in TANF, higher than the basic skills population at large. And students in both groups were more likely to be single parents. One notable difference is that the I-BEST students were about the same age as their Non-IB Non-Workforce peers and about four years older than the Non-IB Workforce students.

3.2 Estimates of the Probability of Earning College Credit

Table 4 shows the estimates, from logistic regression, of the differences in the probabilities of earning college credit of I-BEST and Non-IB Workforce students relative to the baseline group, Non-IB Non-Workforce students.⁹ (This baseline group was used for all of the regressions described here.) Overall, I-BEST students were 56 percentage points more likely to earn college credit than the baseline group. I-BEST ABE-GED students were 65 percentage points more likely, and I-BEST ESL students 39 percentage points more likely, to earn college credit.

Table 4 also shows that Non-IB Workforce students had a probability of earning college credit that was 17 percentage points higher than the baseline group. The figures for the ABE-GED and ESL subgroups of the Non-IB Workforce students exceeded the baseline average by 27 and 13 percentage points, respectively. Thus, Non-IB Workforce students did significantly better than the baseline group, but not as well as I-BEST students.

⁹ These probability estimates are marginal effects from the logistic regression estimated at the means of the control variables (see Kennedy, 2003). They can be thought of as the changes in probability associated with changing from one group to another, when the other covariates are at their means.

Table 4
Logistic Regression Estimates of Differences in Probabilities of Selected Outcomes of
First-Time I-BEST Students and First-Time Non-IB Workforce Students
Relative to First-Time Non-IB Non-Workforce Students

Outcome	Group	First-Time I-BEST Students			First-Time Non-IB Workforce Students			Pseudo-R ²	N
		Diff.	S.E.	Sig. Level	Diff.	S.E.	Sig. Level		
Received College Credit	All	0.56	0.03	***	0.17	0.01	***	0.51	51,149
	ABE-GED	0.65	0.03	***	0.27	0.01	***	0.47	23,570
	ESL	0.39	0.07	***	0.13	0.02	***	0.57	27,552
Received CTE College Credit	All	0.54	0.03	***	0.19	0.01	***	0.53	51,149
	ABE-GED	0.66	0.03	***	0.27	0.01	***	0.50	23,570
	ESL	0.34	0.06	***	0.15	0.02	***	0.58	27,055
Persisted to Next Year	All	0.13	0.02	***	0.21	0.01	***	0.16	51,149
	ABE-GED	0.12	0.02	***	0.16	0.01	***	0.18	23,570
	ESL	0.02	0.05	not significant	0.25	0.02	***	0.15	27,555
Received Award	All	0.26	0.03	***	0.03	0.00	***	0.56	47,213
	ABE-GED	0.26	0.03	***	0.04	0.01	***	0.52	21,320
	ESL	0.21	0.05	***	0.02	0.01	***	0.63	24,179
Achieved Basic Skills Point Gain	All	0.19	0.02	***	0.07	0.01	***	0.10	51,149
	ABE-GED	0.17	0.02	***	0.06	0.01	***	0.06	23,570
	ESL	0.21	0.05	***	0.09	0.02	***	0.13	27,552

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Using the regression results and holding the values of the other variables in the regression at their means for the full sample of basic skills students, we obtained adjusted estimates for the probabilities of earning college credit, as shown in Table 5. These estimates were 57% for I-BEST students, 18% for Non-IB Workforce Students, and 1% for the Non-IB Non-Workforce students. This method allows us to compare the three groups while adjusting for differences in characteristics between the groups.

Table 5
**Regression-Adjusted Estimates of Probabilities of Outcomes for First-Time I-BEST,
 Non-I-BEST Workforce, and Non-I-BEST Non-Workforce Students**

Outcome	I-BEST	Non-IB Workforce	Non-IB Non-Workforce
Received College Credit	0.57	0.18	0.01
Received CTE College Credit	0.55	0.18	0.01
College Credits Earned	18.2	9.1	1.1
CTE College Credits Earned	17.2	7.6	0.5
Persisted to Next Year	0.40	0.48	0.28
Received Award	0.26	0.03	0.00
Achieved Basic Skills Point Gain	0.53	0.40	0.33
Difference in Log Wages (Post-Prior)	-0.03	-0.02	-0.04
Difference in Adjusted Quarterly Hours Worked (Post-Prior)	-17.54	-24.06	-20.83

Table 6 shows the estimates of the difference in the probability of earning college credit between I-BEST students and matched “control” students selected by the PSM method.¹⁰ By this method, the difference in probability was 33 percentage points. As shown in Figure 1, the mean probability was 84% for the I-BEST students and 51% for the matched students. We cannot directly compare the PSM results to the regression results because they use different methods, but the fact that both methods produce highly significant and positive results adds robustness to our study. As we indicate in Appendix B, there are reasons to have more confidence in the PSM results. As noted above, the characteristics used to generate the propensity score for each student are the same characteristics that were used in the regressions, and their means are shown in Table A.1.

The difference in probability of earning college credit between the I-BEST students and Non-IB workforce students was 40 percentage points, close to the PSM result of 33%. This value of 40 percentage points represents the difference between the 57 percentage points and the 18 percentage points given above, when rounding is accounted for. Since this value is similar to the 33% difference found by PSM, this suggests that the PSM method is selecting from the entire population of basic skills students a comparison group similar to the Non-IB Workforce students.

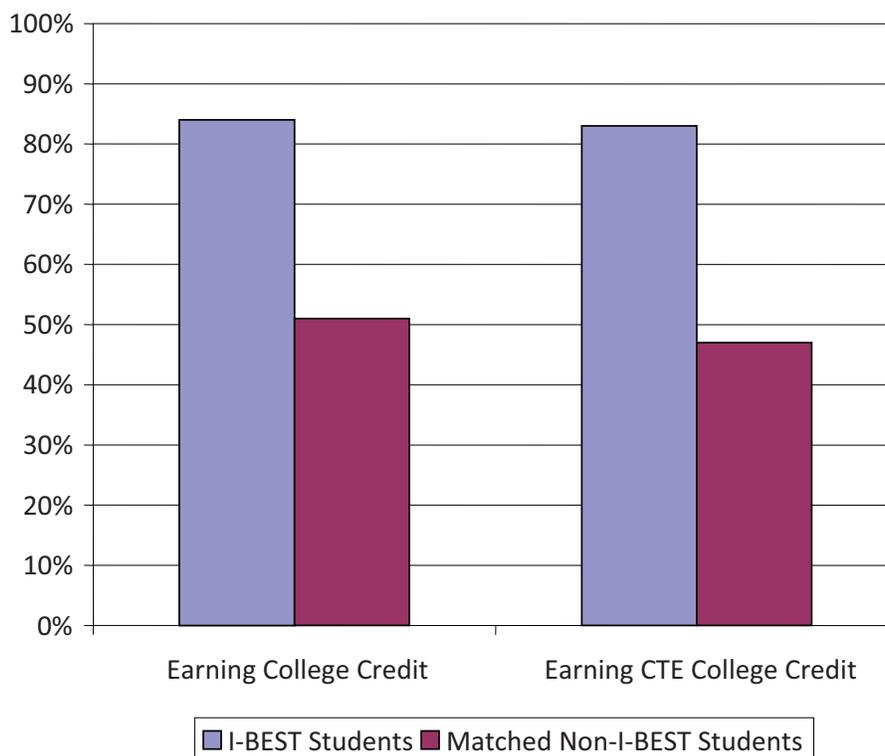
¹⁰ The quality of a particular PSM is often measured by the degree of “balance,” that is, the extent to which the means of the treated and matched “controls” are close on the means of known covariates. In this case, there were 65 covariates, and 51 of them showed improved balance as a result of the matching; the remaining 14 showed worsened balance.

Table 6
Results of Propensity Score Matching—Means of Outcomes of
Matched First-Time I-BEST students and First-Time Control Basic Skills Students,
Estimate of Average Treatment Effect on the Treated (ATT), and Difference With Unmatched Students

	Mean: I-BEST	Mean: Controls	ATT	S.E.	Sig. Level	Difference With Unmatched	S.E.	Sig. Level
Received College Credit	0.84	0.51	0.33	0.02	***	0.78	0.01	***
Received CTE College Credit	0.83	0.47	0.36	0.02	***	0.78	0.01	***
College Credits Earned	24.89	17.29	7.61	0.86	***	23.85	0.26	***
CTE College Credits Earned	21.40	13.09	8.31	0.74	***	20.87	0.20	***
Persisted to Next Year	0.55	0.56	-0.01	0.03	not significant	0.18	0.02	***
Received Award	0.51	0.14	0.36	0.02	***	0.50	0.00	***
Achieved Basic Skills Point Gain	0.58	0.39	0.19	0.03	***	0.22	0.02	***
Difference in Log Wages (Post-Prior)	-0.03	0.00	-0.03	0.03	not significant	0.01	0.02	not significant
Difference in Average Hours Worked (Post-Prior)	-18.06	-29.05	10.45	13.71	not significant	2.36	6.47	not significant

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Figure 1
Estimated Probabilities of Earning College Credit or CTE College Credit,
I-BEST Students and Matched Non-I-BEST Students, From Propensity Score Matching



3.3 Estimates of the Probability of Earning CTE College Credit

Table 4 shows the logistic regression estimates of earning CTE college credit. Note that all students earn as many or fewer CTE college credits than college credits because CTE credit is a type of college credit. I-BEST students had a probability of earning CTE college credit that was 54 percentage points higher than the probability for the baseline group. The two subgroups of I-BEST students, ABE-GED and ESL students, were respectively 66 and 34 percentage points more likely than the baseline group to earn CTE credit.

As was the case for earning college credit, the Non-IB Workforce students performed better than the baseline group but worse than the I-BEST students. They had a probability of earning CTE college credit that was 19 percentage points higher than the probability for the baseline group. The ABE-GED subgroup did 27 percentage points better than the corresponding subgroup in the baseline group, while the ESL subgroup did 15 percentage points better.

Holding the other variables at their means, we used the regression to calculate adjusted point estimates of the probabilities for each group. The results are shown in Table 5. We estimated that 55% of I-BEST students would earn CTE college credit, as opposed to 18% of Non-IB Workforce students and 1% of Non-IB Non-Workforce students.

The PSM results are shown in Table 6. Using this method, we found a difference of 36 percentage points between I-BEST students and matched controls. As shown in Figure 1, the mean probability of earning CTE credit was 83% for the I-BEST students and 47% for the matched students. This 36 percentage point difference is very similar to the 37 percentage point difference between I-BEST students and Non-IB Workforce students estimated by regression, indicating that our results are robust.

3.4 Estimates of the Number of Credits Earned

As shown in Table 6, ordinary least squares (OLS) regression finds that I-BEST students earned 17.1 more college credits and 16.6 more CTE credits than the baseline group. ABE-GED I-BEST students earned 18.1 more college credits and 17.8 more CTE

college credits than the corresponding baseline group. For the ESL I-BEST subgroup, the corresponding figures were 12.2 and 12.0.

Table 6
OLS Regression Estimates of Differences in Selected Outcomes for First-Time I-BEST and First-Time Non-IB Workforce Students Relative to First-Time Non-IB Non-Workforce Students

Outcome	Group	First-Time I-BEST Students			First-Time Non-IB Workforce Students			R2	N
		Diff.	S.E.	Sig. Level	Diff.	S.E.	Sig. Level		
College Credits Earned	All	17.1	0.8	***	8.0	0.3	***	0.4	51,149
	ABE-GED	18.1	1.0	***	7.9	0.4	***	0.4	23,573
	ESL	12.2	1.2	***	6.8	0.6	***	0.4	27,555
CTE College Credits Earned	All	16.6	0.7	***	7.0	0.3	***	0.3	51,149
	ABE-GED	17.8	0.9	***	7.0	0.3	***	0.3	23,573
	ESL	12.0	1.0	***	6.0	0.5	***	0.3	27,555
Difference in Log Wages (Post-Prior)	All	0.01	0.02	not significant	0.01	0.01	not significant	0.0	15,146
	ABE-GED	0.01	0.02	not significant	0.01	0.01	not significant	0.0	9,877
	ESL	-0.01	0.03	not significant	0.02	0.03	not significant	0.0	5,262
Difference in Average Quarterly Hours Worked (Post-Prior)	All	3.1	8.1	not significant	-3.2	4.5	not significant	0.0	15,144
	ABE-GED	7.5	9.6	not significant	-5.6	5.2	not significant	0.0	9,875
	ESL	-4.0	16.5	not significant	-2.3	10.4	not significant	0.0	5,262

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

The Non-IB Workforce students earned eight more college credits and seven more CTE credits than the baseline group. The ABE-GED subgroup also earned eight more college credits and seven more CTE credits than the corresponding subgroup of the baseline group. The corresponding figures for the ESL subgroup were seven and six.

Using our regression model and setting the values of the control variables at their means, we calculated regression-adjusted point estimates for the mean number of college credits and CTE credits earned, as shown in Table 5. On average, I-BEST students earned 18 college credits and 17 CTE credits; Non-IB Workforce students earned 9 college credits and 8 CTE credits. Non-IB Non-Workforce students earned 11 college credits and about half of one CTE college credit.

The PSM method, as shown in Table 6, found that the I-BEST students earned 8 college credits and 8 CTE college credits more than the matched group. As shown in Figure 2, the I-BEST students earned 25 college credits and 21 CTE college credits on

average; for the matched group, the corresponding figures are 17 and 13. Note that the differences found by PSM are very similar to the corresponding differences of 9 and 10 credits found using OLS to compare the I-BEST and Non-IB Workforce students, indicating that the result is robust.

3.5 Estimates of the Probability of Persisting into the Next Year

For students in each cohort (2006–07 or 2007–08), we determined whether or not they persisted as a student in the following year. Persistence was defined as either enrolling in a course or obtaining an award. Those who received an award are considered persisting to avoid penalizing programs whose students leave because they receive an award.

As shown in Table 4, logistic regression found that I-BEST students were 13 percentage points more likely than the baseline group to persist. The ABE-GED subgroup was 12 percentage points more likely to persist. There was no significant difference in persistence from the baseline for the ESL group.

This was the only outcome variable on which the Non-IB Workforce students performed better than their I-BEST peers. They were 21 percentage points more likely to persist than the baseline group. Their ABE-GED subgroup was 16 percentage points more likely to persist than the corresponding subgroup of the baseline group; the figure for the ESL subgroup was 25 points.

We used our logistic regression model with the controls held at their means to estimate regression-adjusted means for each of the three groups, as shown in Table 5. I-BEST students had a 40% probability of persisting, Non-IB Workforce students had a 48% probability, and Non-IB Non-Workforce students had a 28% probability.

As shown in Table 6 and Figure 3, the PSM model did not find a statistically significant difference in persistence between the I-BEST and matched students. (The I-BEST students had a higher rate, but the difference was not significant.) Thus we have not found any relationship between participation in I-BEST and persistence.

Figure 2
Number of College Credits and CTE College Credits Earned, I-BEST Students and Matched Non-I-BEST Students, From Propensity Score Matching

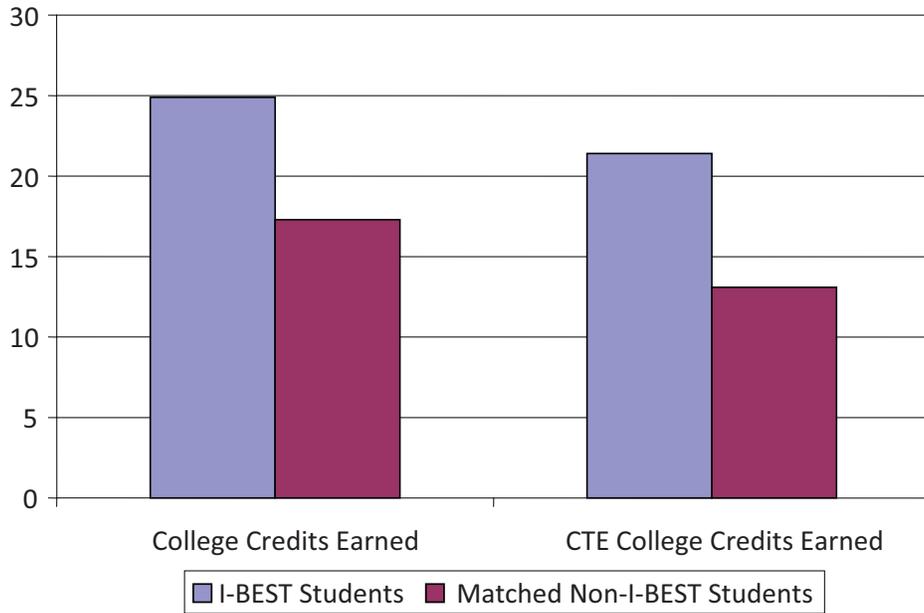
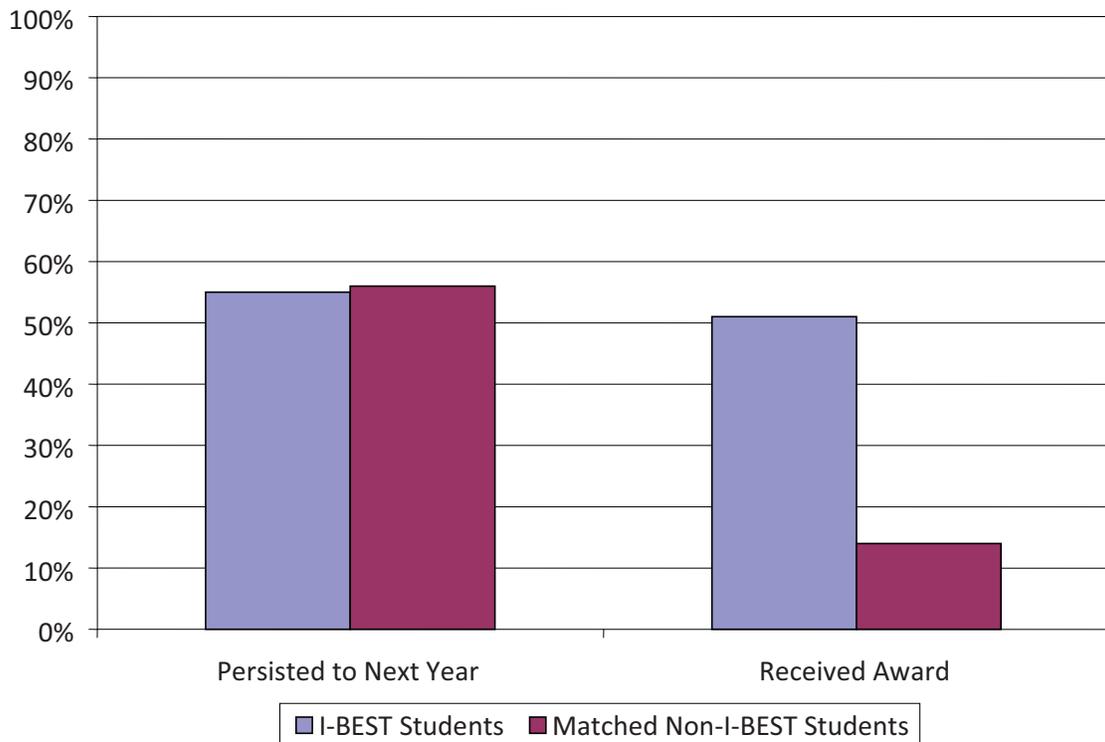


Figure 3
Rates of Persistence and of Award Receipt, I-BEST Students and Matched Non-I-BEST Students, From Propensity Score Matching



3.6 Estimates of the Probability of Earning an Award

Table 4 shows the logistic regression estimates of the probability of earning an award, relative to the baseline group. (As we have seen, the vast majority of awards earned by basic skills students are certificates, not degrees.)

I-BEST students were 26 percentage points more likely to earn an award than the baseline group. The ABE-GED subgroup was 26 percentage points more likely to earn an award; the ESL subgroup, 21 percentage points more likely.

Non-IB Workforce students were 3% more likely to earn an award than the baseline group. Among them, the ABE-GED subgroup was 4% more likely, and the ESL subgroup 2% more likely, to earn an award.

We used the logistic regression model to estimate adjusted means for the three groups by setting the controls at their means to eliminate measured differences between the groups. As shown in Table 5, using this method, the I-BEST students were estimated to have a 26% chance of getting an award; the Non-IB Workforce students had a 3% chance, and the Non-IB Non-Workforce students had a negligible chance.

Table A.2 (see Appendix A) shows the marginal effects from the regression. While quite a few variables in the specification were statistically significant, only the I-BEST and non-I-BEST-workforce dummies had any substantial relationship with the outcome.

The PSM model (shown in Table 6) found that I-BEST students were 36 percentage points more likely than the matched group to obtain an award. Figure 3 shows that the I-BEST students had a 50% chance of getting an award, whereas the matched students had a 14% chance. The 36 point difference is larger than the 23 point difference between the I-BEST and the Non-IB-Workforce students estimated by regression, but they are both highly significant and in the same direction.

3.7 Estimates of the Probability of Achieving Point Gains on Basic Skills Tests

The fact that students in I-BEST learn basic skills in the context of instruction on technical subject matter raises the question of whether I-BEST helps students improve their basic skills. Table 4 shows the logistic regression estimates of the differences in the probability of achieving point gains on the CASAS basic skills tests used throughout the

Washington community college system. As shown in the table, I-BEST students were 19 percentage points more likely to make such gains than the baseline group. This figure was 17 percentage points for the ABE-GED subgroup and 21 percentage points for the ESL subgroup. Non-IB Workforce students were 7 percentage points more likely to make gains than the baseline group. For the ABE-GED subgroup of this group, the figure was 6 percentage points, and for the ESL subgroup, it was 9 percentage points.

Table 5 shows the results of using the logistic regression to estimate the adjusted means, setting the controls at their means in order to control for systematic differences between the groups. Following this method, 53% of I-BEST students were found to make gains, as were 40% of Non-IB Workforce students and 33% of Non-IB Non-Workforce students.

The PSM results in Table 6 show that I-BEST students were 19 percentage points more likely than matched students to achieve point gains. Of the matched I-BEST students, 58% achieved a gain, as opposed to 39% of the matched controls. The 19 percentage point difference is greater than the 13 percentage point difference that was found between the I-BEST students and the Non-IB-workforce students using logistic regression; however, both results are highly significant and in the same direction.

3.8 Employment Outcomes

We examined two employment outcomes, the change in the logarithm of real wages and the change in the average number of hours worked per quarter.

Estimates of the change in the logarithm of real wages. To examine the relationship between I-BEST enrollment and wages, we used data on real (inflation-adjusted) wages for the students in the sample. We looked at two periods: a period three to eight quarters prior to their enrollment in school, and a period three to eight quarters after.¹¹ We determined the average real wages for each of these periods. For students to be included in this analysis, they needed to have at least one wage record in each of these periods. Only 28% of students in our sample had wage records both before and after enrollment. Note that this was partially due to the fact that about a third of the students

¹¹ Note that we excluded the quarters immediately before and after schooling because there is a well-known effect, known as Ashenfelter's dip, which is a dip in earnings that begins soon before entering a training program and does not generally start to increase until several quarters after training (Heckman & Smith, 1999).

did not provide a social security number (perhaps for privacy reasons, or perhaps because they lacked one), and without a social security number, a student's wage records cannot be identified.

Table A.3 (see Appendix A) shows the differences in observed characteristics between those students who worked both before and after, and those who did not. Note that those who worked before and after were more likely to be ABE or GED students (as opposed to ESL) and less likely to be Hispanic.

We used OLS regression to predict the effect of enrollment in I-BEST on an outcome that was defined as the change in the logarithm of the wage (the log wage after minus the log wage before). It is conventional practice in labor economics to use the log wage as an outcome because wages tend to be not uniformly distributed (Card, 1999). We found no significant effect of I-BEST on wages. A PSM model also found no significant effect.

Descriptively, there was actually a small decline in wages for all of the basic skills students. Their mean wages before entering school were \$12.26. After leaving school, they were \$12.16. We believe this decline in wages is due to the unusually deep recession—the deepest since the Great Depression—that started as these two cohorts of students were leaving school (Barkley & Davis, 2009). Unemployment in Washington State started to rise sharply in early 2008.¹²

Estimates of the change in quarterly hours worked. Basic skills students who were employed before and after school experienced a decline in average hours worked during the periods examined to calculate the wage outcome—another probable effect of the deep recession. Prior to school, these workers worked a mean of 340 hours per quarter, and after leaving school, they worked a mean of 318 hours per quarter. OLS regression found no significant effect of I-BEST on this decline in hours worked. Neither did a PSM model.

We also tested to see if enrollment in I-BEST had any effect on the chances of employment for those workers that were not employed prior to entering school. We found no statistically significant effect.

¹² The unemployment rate in the state was between 4.4 and 4.6% for all of 2007. In March of 2008, it began to trend upward, to 4.7 percent. By December of 2008, it had reached 6.9 percent, and by December of 2009, 9.2 percent. These figures were obtained from the Bureau of Labor Statistics' website.

4. Difference-in-Differences Analysis

The regression and propensity score matching methods used in the analyses so far produced similar results. However, although both methods accounted for observed differences between the treated (I-BEST) and comparison groups, neither could control for selection bias that may be due to unobserved differences between the groups. Some unobserved differences could have been related to the process by which students are selected into I-BEST programs. Thus, while the results of the above analyses, as well as our previous study, indicate that participation in I-BEST is *correlated* with better educational outcomes over the two-year tracking period, they do not provide definitive evidence that the I-BEST program *caused* the superior outcomes.

To address the issue of selection bias, we conducted a difference-in-differences (DID) analysis. We compared the overall change in outcomes at schools that implemented I-BEST to the overall change in outcomes at schools that had not yet implemented the program during the same time, thus effectively “differencing out” the pre-intervention student characteristics. Any time-invariant individual characteristics are removed when we find the difference between post- and pre-intervention outcomes.

4.1 Sample

In this analysis, we exploited the fact that 14 new Washington State colleges started offering the I-BEST initiative in the 2006–07 academic year and used information from the students who were in these new institutions to compare with new students who did not have I-BEST in these same institutions in the 2005–06 academic year.¹³ We limited our sample to students who were considered to be “basic skills” students, that is, students who initially enrolled in adult basic education, English-as-a-second-language, or GED courses at their initial college of enrollment. We further limited the sample to those students who enrolled in I-BEST or a non-I-BEST workforce course in 2005–06 or 2006–07, since both groups indicated a desire to pursue college-level CTE education by taking a CTE course and because, as discussed, these two groups are more similar to one another in their average CASAS scores and other key respects than to basic skills

¹³ Note that we did not use the 2005–06 data for the regression and PSM analyses, because 2005–06 was still a pilot year for I-BEST. Here, we use 2005–06 data for only those 24 colleges that did not have I-BEST in that year because it is important for the difference-in-differences analysis.

students who do not take a CTE course. Thus, these students were more likely to be affected by the change in I-BEST policies than the rest of the basic skills student population. We defined treatment exposure by cohort, or the year of first-time entry into a Washington State community or technical college. As a control group, we used data from the 10 colleges that did not have I-BEST in their institutions until the 2007–08 academic year. By observing students in the control group institutions in the 2005–06 and 2006–07 academic years, we have an entirely untreated group that we can measure against using data on students in the 14 colleges that started I-BEST in 2006–07.

In the 2005–06 academic year, only 10 two-year colleges in Washington State implemented I-BEST programs. In the 2006–07 year, 14 new colleges offered I-BEST programs, bringing the total to 24 colleges. By the year 2007–08, all 34 Washington State community and technical colleges offered I-BEST programs. The four outlined boxes in Table 7 represent the colleges (Group B and Group C) and cohorts (2005–06 and 2006–07) that are of interest in this difference-in-differences analysis:

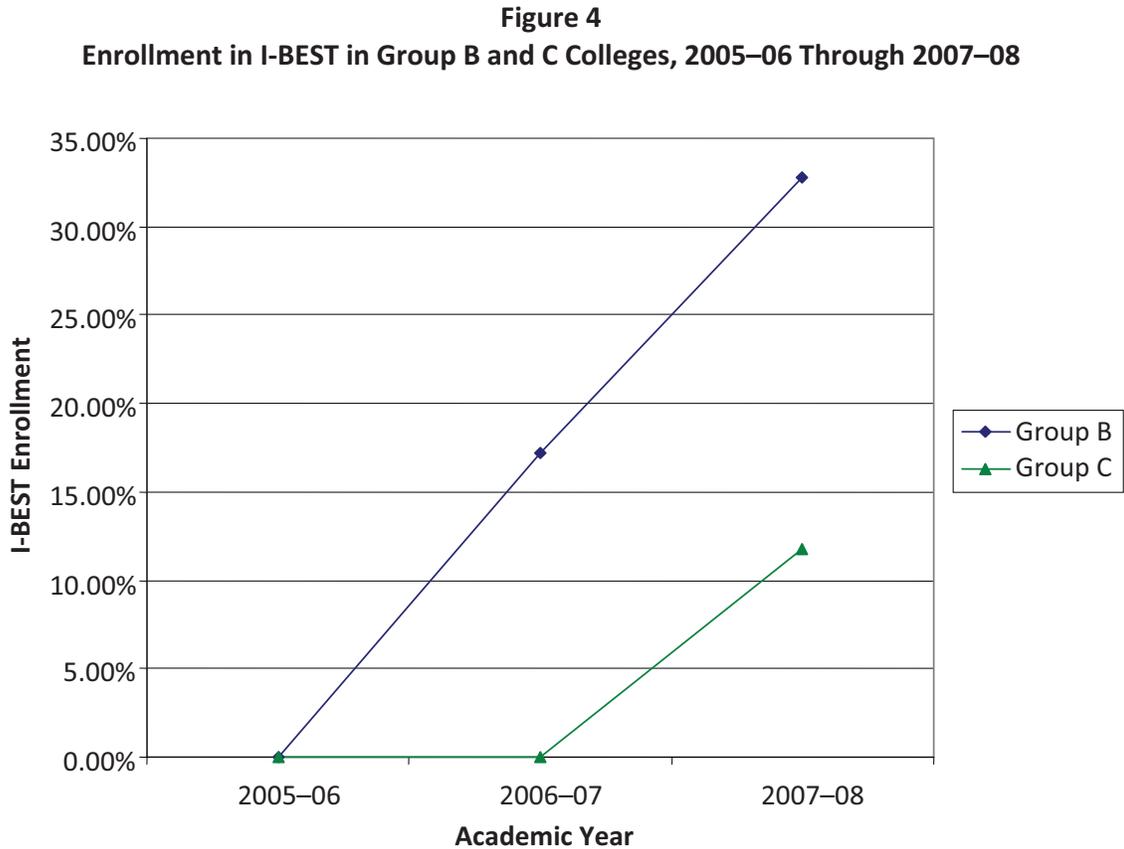
Table 7
Timing of Introduction of I-BEST in Washington State’s
34 Community and Technical Colleges

	2005-06	2006-07	2007-08
Group A Colleges	10	10	10
Group B Colleges		14	14
Group C Colleges			10

The group B and C comparison is relevant because it is the only place in the grid in which the policy (I-BEST) was introduced in one group of colleges (B) while it had not yet been introduced in another (C). A situation like this is necessary to carry out a difference-in-differences analysis, because one is assuming for the purposes of the

analysis that any variation over time not due to the policy is the same in both groups, and that the only difference between the groups was due to the policy.

Enrollment in I-BEST in each academic year, separated by college group, is illustrated here, in Figure 4:¹⁴



Among students enrolled in a Group B college, enrollment increased to 424 students by the 2006–07 academic year, with 17% of basic skills students taking at least one CTE course. By the 2007–08 academic year, 701 students in a Group B college enrolled in I-BEST, compared to 187 students in a Group C college.

¹⁴ Students with spurious enrollments in I-BEST were dropped from the sample. A total of 83 students were listed as being enrolled in I-BEST in 2005–06 in a Group B college, and 44 students were listed as being enrolled in I-BEST in 2006–07 in a Group C college. The denominator of each percentage calculation was the number of I-BEST and Non-IB Workforce students in each box (e.g., Group B, cohort 2006–07).

4.2 Methodology

Any statistically significant “differences in differences”—that is, changes in pre- and post intervention outcomes in the 14 “Group B” colleges (which began to formally offer I-BEST in 2006–07) compared with changes in student outcomes in the 10 “Group C” colleges (which did not offer I-BEST until 2007–08)—can be attributed to the I-BEST interventions under the assumption that the changes in student outcomes the Group B colleges would have exhibited a similar trend as the changes observed during that time period in the Group C colleges, had the Group B colleges not implemented I-BEST. With this assumption, the difference-in-differences method addresses the selection bias limitations of the regression and propensity score matching methods used in the analyses of I-BEST outcomes presented in the previous section.¹⁵ As we have information on both the intent to treat (the fact that the students are in the 14 new colleges in 2006–07) and the actual receipt of treatment (the fact that some of these students actually enrolled in I-BEST of their own accord), we are able to run separate regressions using these two groups.

In the first regression, we modeled our intent-to-treat framework much like Dynarski did with her HOPE study (2000) by comparing outcomes before and after I-BEST was introduced, both within colleges that implemented I-BEST and those that did not. We first indicated basic skills students who were in one of the 14 new colleges ($GroupB_i$) as those who were newly eligible for participation in I-BEST. We also added a dummy variable for students in the 2006–07 cohort ($2006-07_i$) to indicate those in the 14 new colleges who were newly eligible for I-BEST strictly due to timing. We then added an interaction term for which the coefficient will indicate the effect of being in a school and year in which I-BEST was offered on student outcomes for basic skills students seeking CTE. We also added a vector of student and institutional characteristics (X_i):

$$1) y_i = \beta_0 + \beta_1 GroupB_i + \beta_2 2006-07_i + \beta_3 (GroupB_i * 2006-07_i) + X_i \beta_4 + v_i$$

¹⁵ There are, however, some alternative hypotheses that could potentially violate this assumption, including the recruitment of high-achieving students into I-BEST programs and the implementation of other reforms concurrent with I-BEST implementation, among others.

Outcomes (y_i) included certificate and associate degree completion as well as college credits earned. The coefficient β_3 captures the impact estimate of the colleges' intent to treat. β_1 controls for pre-existing differences between schools that did or did not implement I-BEST, and β_2 controls for cohort differences that are observed for all institutions in the Washington State community and technical college system.

We used information on only the 2005–06 and 2006–07 cohorts, limiting the sample to only the students in the 14 colleges that began to implement I-BEST in 2006–07 (the 2005–06 and 2006–07 cohorts in Group B colleges) and the students in the 10 colleges that did not have I-BEST in 2005–06 and 2006–07 (the 2005–06 and 2006–07 cohorts in Group C colleges). The 10 colleges comprise a “clean” control group against which we can measure the effects of I-BEST, as the students in these colleges were not subject to I-BEST within this time frame. The coefficient β_3 will identify the effect of the colleges' intent to offer I-BEST on student outcomes.

4.3 Results

The results shown in Table A.4 (see Appendix A) capture the intention to treat our target sample of basic skills students seeking CTE through eligibility to participate in I-BEST. Using difference-in-differences, we measure the difference between being in a Group B college and being in a Group C college, both before and after I-BEST eligibility as measured by the 2005–06 cohort (when neither Group B nor Group C colleges offered I-BEST) versus the 2006–07 cohort (when Group B colleges began offering I-BEST). We used ordinary least squares (OLS) estimates to measure the effect of I-BEST on certificate and degree attainment as well as on college credits received. We checked these results with marginal probit estimates for robustness.¹⁶

Our results indicate that students who were eligible for I-BEST (i.e., those who were in Group B colleges in 2006–07) were about 10 percentage points more likely to obtain college credits than to those who were not (i.e., those who were in Group C colleges), and the results were statistically significant at the five-percent level. I-BEST eligibility had a positive effect on earning an occupational certificate by 7.4 percentage

¹⁶ OLS and marginal probit outcomes were similar in nearly all cases. The probit results are given in Table A.5 (see Appendix A).

points, a result that was statistically significant at the ten-percent level. There were no indications, however, that I-BEST had an effect on associate degree attainment.

We also performed the difference-in-differences analysis on the same two employment outcomes that we looked at earlier, the difference between log wages earned after leaving school and before entering school and the corresponding difference in the average quarterly hours worked. We did not find any indications that I-BEST had an effect on these, which is the same result we found with the regression and propensity score models.

4.4 Enrollment as a Measure of Take-Up

We conducted a second set of regressions using the same sample used to produce the results in Table A.4 and exploiting data on which students actually enrolled in I-BEST and thus received the treatment. This allowed us to measure the effect of treatment by enrollment, given that these students voluntarily accepted the offer to join I-BEST. The variables used are the same as for the DID analysis, save for a dummy dependent variable indicating that the student actually enrolled in I-BEST within two years in one of the 14 new colleges through enrollment (E_i). The resulting first-stage equation predicts I-BEST enrollment:

$$2) E_i = \beta_0 + \beta_1 GroupB_i + \beta_2 2006-07_i + \beta_3 (GroupB_i * 2006-07_i) + X_i \beta_4 + v_i$$

The results are shown in Table A.6 (see Appendix A).

Among the students in our targeted sample, our results indicate that attending a school that offered I-BEST increased enrollment in I-BEST by 17 percentage points. This indicates that simply being eligible for I-BEST is a good predictor for actually enrolling in it. From a policy perspective, this is a promising indication that the intent to treat these students through I-BEST actually leads to treatment, by way of student enrollment.

5. Conclusion

As in our earlier quantitative study of I-BEST (Jenkins, Zeidenberg, & Kienzl, 2009), the regression and propensity score analyses conducted with a larger sample of students over a longer time period showed positive relationships between participation in I-BEST and various desirable outcomes. Many of the relationships are striking: I-BEST students earned substantially more college credits (both total and CTE) than their peers, were much more likely to earn an award, and were moderately more likely to achieve a basic skills gain. The only outcome under study on which I-BEST students did not do better than the Non-IB Workforce students was persistence, and even on that outcome, I-BEST did better than the Non-IB Non-Workforce students. These results are robust with respect to the two methodologies of regression and propensity score matching. Although there is reason to believe that the latter method does a better job in accounting for selection bias, neither of these techniques can eliminate it in the presence of unobserved (and perhaps unobservable) factors, such as student motivation, that may be influencing the outcomes and are not controlled for.

As we have seen, the I-BEST students in our sample received financial aid at significantly higher rates than other basic skills students, which is not surprising because we found through qualitative work reported in a companion study that colleges have actively sought to help I-BEST students get financial aid. Over half (58%) of I-BEST students received some form of financial aid, as opposed to 21% of Non-IB Workforce students and only 2% of Non-IB Non-Workforce students (this last group probably received little aid because they did not take college-level courses at all and therefore did not need and were not eligible for aid). Thus, it is possible that the positive effects of I-BEST are due not to the program content or structure but to the improved access to financial aid that allows students to progress. Washington State's Opportunity Grants, in particular, were targeted at I-BEST students. Unfortunately, we are unable to disentangle the effects of financial aid and the program itself because improving access to financial aid is part of the design of I-BEST.

To measure the causal effects of the intention to treat basic skills students with the I-BEST program, we employed a difference-in-differences strategy, taking advantage of

the fact that different colleges in the Washington community and technical college system began implementing the program at different times. That analysis revealed a 10 percentage point increase in the likelihood that targeted students would earn at least one college credit if they were eligible for the program. Simply being in a cohort enrolled in a group of colleges that offered I-BEST also increased the likelihood of earning an occupational certificate within three years by over seven percentage points. When students were exposed to this program, there was a direct and statistically significant relationship to their actual enrollment in it, which further supports our finding of a causal relationship between I-BEST and positive student outcomes. This finding is especially impressive because it represents an estimate of the effect on student outcomes of I-BEST programs during their first year of implementation at the colleges that provided the treatment in our analysis. It is likely that these colleges have been able to improve their delivery of the I-BEST model as they have gained experience with it over time.

We were not able to find any relationship between I-BEST and positive wage changes or average hours worked after leaving the program. However, the students in our sample exited the program just as a major recession was starting, which might explain the lack of labor market benefits of I-BEST in the period under study. Given that I-BEST students are more likely than similar students to earn postsecondary credentials and that workers with such credentials have historically had an advantage in the labor market, we expect that I-BEST students will fare better than students in the comparison groups as the Washington State labor market recovers.

In a parallel study to this quantitative analysis of I-BEST outcomes, we interviewed faculty, staff, and administrators involved with I-BEST at all 34 Washington State community and technical colleges to find out how I-BEST programs operate and to learn about common challenges and promising practices in implementing programs based on the I-BEST model. The findings from that study are presented in a companion report (Wachen, Jenkins, Van Noy, et al., 2010).

In the next phase of research on I-BEST (to be carried out in 2011), CCRC will conduct field research to examine the practices of I-BEST programs that are found through quantitative analysis to have superior outcomes (controlling for student and institutional characteristics). This planned research should provide further insight into

what makes I-BEST programs effective in helping basic skills students enter and succeed in postsecondary CTE programs.

Appendix A: Tables

Table A.1
Characteristics of First Time Basic Skills Students, 2006–07 and 2007–08

	I-BEST	Non-IB Workforce	Non-IB Non-Workforce
Number of Students in Program	1,390	6,202	69,555
<i>Program Classification</i>			
ABE/GED Student	76.28%	80.18%	47.24%
ESL Student	23.72%	19.82%	52.76%
<i>Social and Economic Characteristics</i>			
Mean Age	30.73	26.42	30.24
Female	62.52%	60.21%	53.17%
Hispanic	20.72%	17.72%	37.40%
Black, Non-Hispanic	11.08%	11.59%	7.58%
Asian/Pacific Islander	9.86%	8.16%	10.87%
Single w/ Dependent	21.22%	20.24%	13.24%
Married w/ Dependent	22.45%	13.59%	22.75%
Disabled	6.62%	7.30%	3.59%
Percent of Students in the Lowest Two Quintiles of Socioeconomic Status [1]	61.56%	55.91%	58.18%
<i>Current Schooling Characteristics</i>			
CTE Intent[2]	71.29%	48.02%	18.02%
Intent Is Academic	7.12%	8.71%	6.88%
Received Aid	25.68%	13.96%	1.55%
Enrolled Full Time	66.83%	57.85%	27.84%
First Enrolled in 1st Quarter	13.74%	17.35%	14.57%
First Enrolled in 2nd Quarter	38.35%	46.66%	31.46%
First Enrolled in 3rd Quarter	27.63%	23.52%	29.06%
First Enrolled in 4th Quarter	20.29%	12.46%	24.91%
<i>Previous Schooling Characteristics</i>			
GED	15.11%	11.38%	4.47%
High School Graduate	37.12%	21.72%	16.59%
WorkFirst (WA TANF) Participant	40.58%	38.55%	20.95%
<i>Financial Aid</i>			
Received a Pell Grant	26.40%	15.21%	0.78%
Received an Opportunity Grant	34.32%	2.08%	0.05%
Received a State Need Grant	21.87%	13.12%	0.58%
Received Any Aid	58.13%	21.33%	2.01%
Worked While Enrolled	9.06%	5.13%	12.14%

Note: [1] This is based on the quintile of the average socioeconomic status of the Census block group in which the student's residence is found. For details, see Crosta, Leinbach, and Jenkins (2006) and Washington State Board for Community and Technical Colleges (2006). [2] CTE and academic intent indicate the type of college program the student means to pursue. If CTE, the student intends to pursue workforce training; if academic, the student intends to pursue a program that leads to a degree and/or transfer to a four-year institution. Students do not always follow their stated intent (see Bailey, Jenkins, & Leinbach, 2006).

Table A.2
Marginal Effects Coefficients for Logistic Regression
Outcome Variable: Award Within Two Years

	Coefficient	Robust Standard Error	P-value
I-BEST Student	0.2625	0.0273	***
Non-I-BEST Workforce Student	0.0342	0.0041	***
Age	0.0000	0.0000	***
Estimated SES	0.0000	0.0001	
Received Need-Based Financial Aid	-0.0002	0.0002	
Received Pell Grant	0.0002	0.0004	
Received State Need Grant	0.0003	0.0004	
Received Opportunity Grant	0.0012	0.0005	**
Disabled	-0.0002	0.0003	
In 06–07 Cohort	0.0000	0.0001	
Single Parent	0.0000	0.0002	
Married Parent	0.0002	0.0002	
Full-Time Student	0.0009	0.0002	***
Female	-0.0004	0.0002	***
Hispanic	-0.0006	0.0002	***
Black, Non-Hispanic	-0.0002	0.0002	
Asian/Pacific Islander, Non-Hispanic	0.0003	0.0003	
CTE Intent	0.0010	0.0003	***
Academic Intent	0.0004	0.0004	
GED is Highest Educ.	0.0000	0.0002	
HS Graduate	0.0002	0.0002	
First Enrolled in Quarter 1	0.0002	0.0003	
First Enrolled in Quarter 2	-0.0001	0.0002	
First Enrolled in Quarter 3	-0.0004	0.0002	
CASAS Math Score	0.0000	0.0000	
CASAS Math Score Missing	0.0013	0.0016	
CASAS Reading Score	0.0000	0.0000	***
CASAS Reading Score Missing	0.0117	0.0112	
CASAS Listening Score	0.0000	0.0000	***
CASAS Listening Score Missing	0.0094	0.0069	
TANF (Welfare) Recipient	0.0003	0.0002	
Worked While Enrolled	-0.0010	0.0002	***
College 1	-0.0007	0.0008	
College 2	-0.0011	0.0005	
College 3	-0.0007	0.0009	
College 4	-0.0012	0.0004	***
College 5	-0.0012	0.0005	**
College 6	-0.0014	0.0003	***
College 7	0.0001	0.0017	
College 8	-0.0010	0.0006	*
College 9	0.0083	0.0104	
College 10	-0.0007	0.0009	

College 11	0.0011	0.0027	
College 12	0.0023	0.0036	
College 13	0.0012	0.0028	
College 15	0.0211	0.0277	
College 16	0.0002	0.0018	
College 17	-0.0006	0.0010	
College 18	-0.0005	0.0011	
College 19	0.0005	0.0022	
College 20	-0.0005	0.0011	
College 22	-0.0011	0.0007	
College 23	0.0005	0.0020	
College 25	0.0013	0.0029	
College 26	-0.0013	0.0003	***
College 27	-0.0002	0.0013	
College 28	0.0000	0.0016	
College 30	-0.0011	0.0004	***
College 31	-0.0004	0.0011	
College 32	0.0019	0.0033	
College 33	0.0002	0.0018	
College 34	0.0044	0.0061	
College 35	-0.0003	0.0014	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3
Comparison Between Students Who Worked Both
Before and After Schooling and Those Who Did Not Do So

	Worked Both Before and After	Did Not Do So
Number of Students	21,967	55,180
<i>Program Classification</i>		
ABE/GED Student	67.64%	42.77%
ESL Student	32.36%	57.23%
<i>Social and Economic Characteristics</i>		
Mean Age	29.13	30.27
Female	54.75%	53.57%
Hispanic	25.57%	39.48%
Black, Non-Hispanic	10.65%	6.89%
Asian/Pacific Islander	11.12%	10.44%
Single w/ Dependent	16.97%	12.75%
Married w/ Dependent	19.92%	22.84%
Disabled	3.96%	3.94%
Percent of Students in the Lowest Two Quintiles of Socioeconomic Status [1]	57.45%	58.33%
<i>Current Schooling Characteristics</i>		
CTE Intent[2]	24.73%	20.06%
Intent Is Academic	8.75%	6.34%
Received Aid	5.46%	2.00%
Enrolled Full Time	35.71%	29.06%
First Enrolled in 1st Quarter	16.85%	13.96%
First Enrolled in 2nd Quarter	35.10%	31.89%
First Enrolled in 3rd Quarter	27.56%	29.00%
First Enrolled in 4th Quarter	20.49%	25.15%
<i>Previous Schooling Characteristics</i>		
GED	6.76%	4.61%
High School Graduate	17.99%	17.13%
WorkFirst (WA TANF) Participant	34.45%	18.05%
Financial Aid		
Received a Pell Grant	4.72%	1.46%
Received an Opportunity Grant	1.71%	0.48%
Received a State Need Grant	4.10%	1.11%
Received Any Aid	8.59%	2.97%
Worked While Enrolled	26.59%	5.53%

Note: See Note for Table A.1.

Table A.4
Results of Difference-in-Differences Analysis on Three Outcome Variables

OLS Coefficients	Dependent Variables		
	Certificate Within Three Years (0.152)	Degree Within Three Years (0.007)	Any College Credits Within Three Years (0.521)
In a Group B College	0.061 [0.054]	0.003 [0.003]	0.070 [0.062]
Cohort 2006–07	-0.026 [0.025]	0.002 [0.002]	-0.050 [0.035]
<i>In a Group B College * Cohort 2006–07</i>	0.074* [0.041]	-0.002 [0.003]	0.097** [0.046]
Age	0.002* [0.001]	-0.000 [0.000]	0.000 [0.001]
Highest SES	0.028 [0.026]	-0.003* [0.002]	0.156*** [0.046]
High SES	-0.007 [0.034]	0.006 [0.005]	0.087* [0.048]
Mid SES	0.043 [0.029]	0.003 [0.003]	0.076 [0.048]
Low SES	0.016 [0.017]	0.001 [0.002]	0.018 [0.027]
Full-Time Student	0.078** [0.028]	0.006** [0.002]	0.017 [0.039]
Female	-0.005 [0.027]	-0.001 [0.002]	-0.055 [0.033]
Hispanic	-0.076* [0.041]	-0.004 [0.004]	-0.150*** [0.041]
Black, Non-Hispanic	0.028 [0.044]	-0.005 [0.003]	-0.035 [0.040]
White, Non-Hispanic	-0.027 [0.027]	-0.007** [0.003]	-0.031 [0.037]
ABE or GED Basic Skills Student	-0.082 [0.071]	-0.008 [0.014]	-0.105 [0.069]
Received Need-Based Financial Aid	0.055* [0.032]	0.004 [0.005]	0.248*** [0.059]
Intent is CTE	0.074** [0.030]	-0.004 [0.003]	0.065 [0.041]
Earliest CASAS Math Score	0.000 [0.000]	0.000 [0.000]	0.000* [0.000]
Earliest CASAS Reading Score	0.000 [0.000]	-0.000 [0.000]	-0.001** [0.000]
Constant	-0.002 [0.049]	0.014 [0.009]	0.575*** [0.088]
Observations	4,276	4,276	4,276
R-squared	0.063	0.009	0.094

Note: Robust standard errors in parentheses, clustered by institution.

*significant at 10%; **significant at 5%; ***significant at 1%.

Table A.5
Probit Results for Comparison with Difference-in-Differences Result

	Dependent Variables					
	Certificate Within Three Years		Degree Within Three Years		Any College Credits Within Three Years	
	<i>OLS</i>	<i>Probit</i>	<i>OLS</i>	<i>Probit</i>	<i>OLS</i>	<i>Probit</i>
In a Group B College	0.061 [0.054]	0.066 [0.056]	0.003 [0.003]	0.002 [0.001]	0.070 [0.062]	0.072 [0.066]
Cohort 2006–07	-0.026 [0.025]	-0.031 [0.031]	0.002 [0.002]	0.001 [0.001]	-0.050 [0.035]	-0.053 [0.038]
<i>In a Group B College * Cohort 2006–07</i>	<i>0.074*</i> <i>[0.041]</i>	<i>0.073*</i> <i>[0.046]</i>	<i>-0.002</i> <i>[0.003]</i>	<i>-0.001</i> <i>[0.001]</i>	<i>0.097**</i> <i>[0.046]</i>	<i>0.104**</i> <i>[0.049]</i>
Age	0.002* [0.001]	0.002** [0.001]	-0.000 [0.000]	-0.000 [0.000]	0.000 [0.001]	0.000 [0.001]
Highest SES ^a	0.028 [0.026]	0.036 [0.028]	-0.003* [0.002]	-0.001 [0.001]	0.156*** [0.046]	0.162*** [0.047]
High SES	-0.007 [0.034]	-0.004 [0.035]	0.006 [0.005]	0.004** [0.003]	0.087* [0.048]	0.094* [0.050]
Mid SES	0.043 [0.029]	0.045* [0.030]	0.003 [0.003]	0.001 [0.001]	0.076 [0.048]	0.082 [0.050]
Low SES	0.016 [0.017]	0.017 [0.018]	0.001 [0.002]	0.001 [0.001]	0.018 [0.027]	0.019 [0.028]
Full-Time Student	0.078** [0.028]	0.077*** [0.027]	0.006** [0.002]	0.003*** [0.002]	0.017 [0.039]	0.017 [0.041]
Female	-0.005 [0.027]	-0.006 [0.026]	-0.001 [0.002]	-0.001 [0.001]	-0.055 [0.033]	-0.058 [0.036]
Hispanic	-0.076* [0.041]	-0.071** [0.035]	-0.004 [0.004]	-0.001 [0.001]	-0.150*** [0.041]	-0.154*** [0.042]
Black, Non-Hispanic	0.028 [0.044]	0.024 [0.041]	-0.005 [0.003]	-0.001* [0.001]	-0.035 [0.040]	-0.035 [0.043]
White, Non-Hispanic	-0.027 [0.027]	-0.029 [0.026]	-0.007** [0.003]	-0.003*** [0.001]	-0.031 [0.037]	-0.030 [0.040]
ABE or GED Basic Skills Student	-0.082 [0.071]	-0.091 [0.077]	-0.008 [0.014]	-0.004 [0.006]	-0.105 [0.069]	-0.110 [0.072]
Received Need-Based Financial Aid	0.055* [0.032]	0.049 [0.031]	0.004 [0.005]	0.002 [0.002]	0.248*** [0.059]	0.261*** [0.060]
Intent is CTE	0.074** [0.030]	0.076*** [0.029]	-0.004 [0.003]	-0.002* [0.001]	0.065 [0.041]	0.070 [0.043]
Earliest CASAS Math Score	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000* [0.000]	0.000** [0.000]
Earliest CASAS Reading Score	0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	-0.001** [0.000]	-0.001** [0.000]
Constant	-0.002 [0.049]		0.014 [0.009]		0.575*** [0.088]	
Observations	4,276	4,276	4,276	4,276	4,276	4,276
R-squared ^a	0.063	0.067	0.009	0.158	0.094	0.072

Note: Marginal probit estimates. Robust standard errors in parentheses, clustered by institution.

^aPseudo R-squared for probit regressions.

*significant at 10%; **significant at 5%; ***significant at 1%.

Table A.6
Result of First-Stage Difference-in-Differences—
Analysis of Enrollment in I-BEST

Marginal Effects Coefficients (OLS)	Dependent Variable: I-BEST Enrollment Within Two Years (0.088)
In a Group B College	0.090*** [0.022]
Cohort 2006–07	0.035** [0.014]
<i>In a Group B College * Cohort 2006–07</i>	0.168** [0.062]
Age	0.001 [0.001]
Highest SES	0.016 [0.032]
High SES	-0.008 [0.033]
Mid SES	0.002 [0.030]
Low SES	-0.006 [0.022]
Full-Time Student	0.043** [0.020]
Female	-0.028 [0.024]
Hispanic	-0.045* [0.025]
Black, Non-Hispanic	0.059 [0.042]
White, Non-Hispanic	-0.001 [0.017]
ABE or GED Basic Skills Student	-0.102* [0.052]
Received Need-Based Financial Aid	0.023 [0.027]
Intent is CTE	0.025 [0.016]
Earliest CASAS Math Score	0.000* [0.000]
Earliest CASAS Reading Score	0.000** [0.000]
Constant	-0.100 [0.077]
Observations	4,276
R-squared	0.162

Appendix B: A Brief Description of Propensity Score Matching

Propensity score matching (PSM) matches “treated” subjects—in this case, students served by I-BEST programs—to selected untreated “control” subjects—in this case, basic skills students who did not enroll in I-BEST—who have similar background characteristics (Rosenbaum & Rubin, 1983; Winship & Morgan, 1999). PSM conducts comparisons between similar pairs of students who differ on whether or not they received the treatment but have similar other observed characteristics.

PSM first estimates the “propensity score,” an assessment of the propensity to be treated, by performing a logit or probit regression of the treatment dummy variable on all available covariates that, in the researcher’s judgment, have the potential to influence the chances of being treated. Treated and untreated observations with similar propensity scores are then matched, and then the average treatment effect on the treated (ATT) can be estimated; the ATT is the average difference on an outcome of interest between the matched treated and untreated observations.¹⁷ 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 in order to accurately estimate the ATT using the matching process that uses this score.

The matching process selects from those observations for which there is “common support”, that is, whose distribution of propensity scores are deemed by the algorithm to be sufficiently close to the propensity scores of the treated observations. The fact that PSM draws its comparison group from only the observations that give common support rather than all observations, as is typically done when regression is employed, is one reason why PSM estimates may be more accurate.

In addition, unlike regression, PSM does not assume a particular functional relationship between an outcome of interest and the available relevant covariates, including treatment status. In contrast, if we estimated a linear regression model of an outcome, such as college credits earned, on a treatment status dummy variable (here I-

¹⁷ There are many variants of PSM, many of which match each treated observation to a weighted set of matched untreated observations rather than a single observation. Herein, we have used probit to estimate the propensity score and a local linear regression estimator, which is one method of conducting such a match (Todd, 1999).

BEST participation) and a number of controls (such as demographics, etc.), we would obtain an estimate of a fixed effect of treatment across all of the cases (assuming that we did not interact the treatment status dummy variable with any other covariates). PSM does not do this; the treatment effect varies with each matched pair of treated and untreated cases, and is the difference in the outcome between the two cases.

References

- Bailey, T., Jenkins, D., & Leinbach, D. T. (2006, September). *Is student success labeled institutional failure? Student goals and graduation rates in the accountability debate at community colleges* (CCRC Working Paper No.1). New York, NY: Columbia University, Teachers College, Community College Research Center.
- Barkley, T., & Davis, B. (2009, April 23). IMF says global recession is deepest since Great Depression. *Wall Street Journal*. Retrieved from <http://online.wsj.com>
- Belfield, C. & Bailey, T. The Returns and Benefits to Community College: A Review of the Evidence. Working Paper. New York, NY: Columbia University, Teachers College, Community College Research Center.
- Card, D. (1999). The causal effect of education on earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics* (Vol. 3, pp. 1802–1863). Amsterdam, Netherlands: Elsevier.
- Crosta, P. M., Leinbach, T., & Jenkins, D. (with Prince, D., & Whittaker, D.) (2006, July). *Using census data to classify community college students by socioeconomic status and community characteristics* (CCRC Research Tools No. 1). New York, NY: Columbia University, Teachers College, Community College Research Center.
- Dynarski, S. M. (2000). Hope for whom? Financial aid for the middle class and its impact on college attendance. *National Tax Journal*, 53(3), 629–662.
- Grubb, W.N. (2002). Learning and earning in the middle, Part II: state and local studies of pre-baccalaureate education. *Economics of Education Review*, 21, 401-414.
- Heckman, J. J., & Smith, J. A. (1999, July). The pre-programme earnings dip and the determinants of participant in a social programme: Implications for simple programme evaluation strategies. *The Economic Journal*, 109(457), 313–348.
- Jacobson, L., & Mokher, C. (2009, January). *Pathways to boosting the earnings of low-income students by increasing their educational attainment*. The Hudson Institute and CNA.
- Jenkins, D., Zeidenberg, M., & Kienzl, G. S. (2009). *Educational outcomes of I-BEST, Washington State Community and Technical College System's Integrated Basic Education and Skills Training Program: Findings from a multivariate analysis* (CCRC Working Paper No.16). New York, NY: Columbia University, Teachers College, Community College Research Center.
- Kennedy, P. (2003). *A guide to econometrics*. Cambridge, MA: MIT Press.

- Prince, D., & Jenkins, D. (2005, April). *Building pathways to success for low-skill adult students: Lessons for community college policy and practice from a longitudinal student tracking study* (CCRC Brief No. 25). New York, NY: Columbia University, Teachers College, Community College Research Center.
- Puma, M. J., Olsen, R. B., Bell, S. H., & Price, C. (2009, October). *What to do when data are missing in group randomized controlled trials* (NCEE Report No. 2009-0049). Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance. Retrieved from <http://ies.ed.gov/ncee/pdf/20090049.pdf>
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41–55.
- Todd, P. E. (1999). *A practical guide to implementing matching estimators*. Philadelphia, PA: Department of Economics, University of Pennsylvania. Retrieved from <http://athena.sas.upenn.edu/~petra/papers/prac.pdf>
- U.S. Department of Education, Office of Vocational and Adult Education. (2007). *Adult Education Annual Report to Congress Year 2004–05*, Washington, DC: Author. Retrieved from www.ed.gov/offices/OVAE
- Wachen, J., Jenkins, D., and Van Noy, M. (with Kulongoski, K., Kurien, K., Richards, A., Sipes, L., Weiss, M., and Zeidenberg, M.) (2010). *How I-BEST works: Findings from a field study*. New York, NY: Columbia University, Teachers College, Community College Research Center.
- Washington State Board for Community and Technical Colleges (2006). *The socioeconomic well-being of Washington State: Who attends community and technical college*. Olympia, WA: Author. Retrieved from http://www.sbctc.ctc.edu/docs/data/research_reports/resh_06-4_socioeconstudy.pdf
- Winship, C., & Morgan, S. L. (1999). The estimation of causal effects from observational data. *Annual Review of Sociology*, 25, 659–707.