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Tracking Progress in Community College Access and Success

Technical Appendices

CONTENTS

Appendix A. Data and Methods

Appendix B. Additional Figures and Tables

Appendix C. Case Studies: Methodology & Analysis

Marisol Cuellar Mejia, Cesar Alesi Perez, Sidronio Jacobo, Fernando Garcia, and Olga Rodriguez

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Appendix A. Data and Methods

Longer-Term Analysis

In the second section of the report, “Trends in Longer-Term Outcomes,” we present a descriptive analysis of three-year outcomes among first-time math students from the fall 2015 cohort to the fall 2019 cohort, the latter of which represents the first cohort impacted by the implementation of AB 705. Here, we attempt to move closer toward causal analysis by analyzing longer-term outcomes after controlling for student characteristics, and by utilizing different regression and matching models. It should be noted, however, that our analyses are limited by data availability and the confounding effect of the pandemic which especially impacted the first AB 705 cohort. As such, our results should not be interpreted as causal. Over time, as we move further away from the pandemic, we will continually update these analyses with later cohorts for whom the pandemic had less of an impact.

Our population of interest is first-time math students – students taking their first credit math course in the community college system. We analyze three-year outcomes starting from students’ first term taking math (three-year outcomes for fall 2019 students include outcomes up until the fall 2022 term). Our three-year outcomes of interest are successfully transferring to a four-year institution, reaching “junior standing,” earning an ADT award, earning any AA/AS award, and the total number of transferable units earned over that time period. We define a successful transfer as a student who completed at least 12 units as a non-special admit (non-dual enrollment student) and enrolled in a four-year institution after attending a community college in the academic year prior to transferring. Our proxy for “junior standing” sets a criteria of earning any AA/AS award or earning at least 50 transferable units, obtaining a transfer-level GPA of at least 2.0, and completing a math and English transfer-level course.

In our models, we control for student characteristics (gender; race; age; prior dual enrollment status; CPG/PELL grant recipient; participation in a special program such as Puente, Mesa, or Umoja; first-time student status; transfer goal; education level) and academic characteristics (full-time status and GPA in the first term enrolled in the community college system, excluding math for first-time students). Controlling for early academic characteristics is of critical importance considering our goal to compare outcomes between otherwise similar students who were and were not impacted by the placement reforms brought on by AB 705. A student’s academic preparation before enrolling in their first math course is perhaps the strongest determinant of their future success in the system. Ideally, our models would include high school GPA and course-taking behavior which would provide a clear indication of how students were performing before enrolling in community college. Unfortunately, we are constrained by the limits of community college-level data. This leaves our models underspecified, significantly limiting the causal interpretation of our results. Nevertheless, early course-taking behavior at the community college-level is a strong determinant of future success, validating the utility of our models as, at the very least, improvements over a purely descriptive analysis.

Cohort Comparison using Regression Models

Our first attempt to improve our descriptive analysis is to run multivariate regression models that control for potential confounding factors. Specifically, we run various linear probability and probit models to compare outcomes between the fall 2019 cohort and the fall 2015 to 2018 cohorts after controlling for a linear time trend, student-level characteristics, and college fixed effects.

Results from our linear probability models are presented in Tables A1 and A2 below, where we show coefficients for our “AB 705” variable, which represents the difference in outcomes between pre and post AB 705 cohorts. We

present results for all first-time math students and for transfer-intending first-time math students. Model 1 includes our full list of controls excluding GPA in the first term enrolled in the community college system. Model 2 includes GPA. Model 3 includes college-fixed effects to control for time-invariant characteristics that differ between colleges (e.g., geographic location). Model 4 includes an interaction between college-fixed effects and a time trend, controlling for time-varying characteristics that differ between colleges (e.g., early implementation of placement reforms).

Our results are relatively robust for all outcomes, and differences between cohorts are larger when limiting our population to first-time transfer-intending students. After controlling for student characteristics, we find a decline of about 1 percentage point in the share of students transferring in three years between pre and post AB 705 cohorts. Descriptively, we find a slight increase in transfer attainment, though this share was increasing over time, a trend that is accounted for in our regression analyses (see Figure 13 in report). Additionally, we find that the share of students reaching “junior standing” also declines by 1 percentage point after including controls in our models. ADT and AA/AS award attainment decline by 2 to 3 and 4 to 5 percentage points, respectively. This is in line with the slight descriptive decline we cite in the main report. Lastly, the average number of transferable units earned declines by about 0.2 units after implementing controls. Descriptively, we find a slight increase in units earned over time.

Overall, our regression results vary slightly from our descriptive results, but confirm our general conclusion in the main report that three-year outcomes among first-time math students have not meaningfully improved as a result of AB 705 implementation. However, it is important to note that the pandemic continues to be a confounding factor. From this perspective, small declines in three-year outcomes can be viewed somewhat positively considering the larger effect the pandemic had on enrollment and persistence. Additionally, our population only includes one post-AB 705 cohort, so it may still be too early to detect any significant long-term impacts of reform. Still, our results signal that more work may be needed to support student success along the transfer path in order to truly improve longer-term outcomes.

TABLE A1

Coefficients from linear probability models comparing three-year outcomes between pre- and post-AB 705 cohorts after controlling for student and academic characteristics

First-time math students

	(1)	(2)	(3)	(4)
Outcomes	LPM + Trend	(1) + GPA	(2) + FE	(3) + FE interact
Transfer	-0.00870** (0.00307)	-0.00807** (0.00305)	-0.00935** (0.00297)	-0.00915** (0.00305)
Junior Standing	-0.0120** (0.00436)	-0.0101** (0.00362)	-0.0116** (0.00353)	-0.0112** (0.00358)
Earn ADT	-0.0287*** (0.00238)	-0.0299*** (0.00228)	-0.0295*** (0.00226)	-0.0293*** (0.00224)
Earn AA/AS	-0.0436*** (0.00323)	-0.0450*** (0.00298)	-0.0443*** (0.00306)	-0.0442*** (0.00310)
Transferable Units Earned	-0.238 (0.321)	-0.0473 (0.253)	-0.241 (0.234)	-0.210 (0.236)
N	795642	674912	674912	674912

SOURCE: Author's calculations using MIS data.

NOTES: Presented are coefficients that represent differences in three-year outcomes between pre- and post-AB 705 cohorts, keeping all else equal. The population of interest is first-time math students from fall 2015-2018 (pre-AB 705 cohorts) and fall 2019 (post-AB 705 cohort). All models include controls for student characteristics and full-time status (enrolled in 12 units or more), as well as a linear time trend. Model 2 adds controls for GPA in the student's first term enrolled in the community college system. Model 3 adds college-fixed effects. Model 4 adds an interaction between college-fixed effects and a linear time trend. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01.

TABLE A2

Coefficients from linear probability models comparing three-year outcomes between pre- and post-AB 705 cohorts after controlling for student and academic characteristics

First-time transfer-intending first-time math students

	(1)	(2)	(3)	(4)
Outcomes	LPM + Trend	(1) + GPA	(2) + FE	(3) + FE interact
Transfer	-0.0262*** (0.00388)	-0.0223*** (0.00331)	-0.0220*** (0.00315)	-0.0224*** (0.00317)
Junior Standing	-0.0362*** (0.00563)	-0.0273*** (0.00427)	-0.0276*** (0.00402)	-0.0278*** (0.00408)
Earn ADT	-0.0437*** (0.00337)	-0.0433*** (0.00306)	-0.0434*** (0.00279)	-0.0438*** (0.00275)
Earn AA/AS	-0.0630*** (0.00434)	-0.0609*** (0.00381)	-0.0591*** (0.00348)	-0.0597*** (0.00358)
Transferable Units Earned	-1.945*** (0.390)	-1.202*** (0.266)	-1.289*** (0.231)	-1.258*** (0.230)
N	368357	327735	327735	327735

SOURCE: Author's calculations using MIS data.

NOTES: Presented are coefficients that represent differences in three-year outcomes between pre- and post-AB 705 cohorts, keeping all else equal. The population of interest is first-time, transfer-intending first-time math students from fall 2015-2018 (pre-AB 705 cohorts) and fall 2019 (post-AB 705 cohort). All models include controls for student characteristics and full-time status (enrolled in 12 units or more), as well as a linear time trend. Model 2 adds controls for GPA in the student's first term enrolled in the community college system. Model 3 adds college-fixed effects. Model 4 adds an interaction between college-fixed effects and a linear time trend. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01.

Cohort Comparison using Propensity Score Matching and the Predicted Probability of Starting in Below-Transfer Level Courses

In an effort to better compare similar students, we perform an additional cohort analysis using the predicted probability of starting in a below-transfer-level (BTL) math course as our explanatory variable. First, we run probit models for the pre-AB 705 cohorts (fall 2015 to 2018) using whether a student started in a BTL course as our binary outcome and student characteristics as our explanatory variables. Next, we use the estimated coefficients from these models to predict the probability of starting in a BTL course before AB 705 for all students, including those in the fall 2019 cohort. These predicted probabilities allow us to compare outcomes between students in pre and post AB 705 cohorts who would have had the same predicted probability of starting in BTL courses if new placement reforms were not implemented in fall 2019. To this end, we conduct a one-to-one propensity score matching analysis to compare outcomes only among matched pairs of students, one fall 2019 student (AB 705 cohort) and one fall 2015 to 2018 student (pre-AB 705 cohort) with a similar predicted probability of enrolling in a BTL course under pre-reform conditions – our “propensity score.”

As noted earlier, it is important that we caveat these results given the limitations of our data and models. Our predicted probabilities are only accurate to the extent that our list of student characteristics sufficiently explains the variation in math enrollment outcomes among students. We do not have high school GPA and course-taking data that would provide a better proxy for student skills and potential before enrolling in community college. In lieu of this, we include community college-level academic characteristics in our prediction models (full-time status and GPA in the first term enrolled in the community college system, excluding math for first-time students).

We conduct several robustness checks using different sets of controls and population samples, all of which produced similar results. Here, we present results for all and first-time transfer-intending first-time math students, from our models that include predicted probabilities that take into account all of our student and academic characteristics as well as college fixed effects.

As displayed in Figure A1 below, the distribution of first-time math students, in terms of their predicted probability of enrolling in a below-transfer-level math course under pre-AB 705 placement policies, changed over time from the fall 2017 to fall 2019 cohorts. Specifically, we predict that students in the fall 2019 cohort, the first cohort impacted by AB 705, would have been much less likely to have enrolled in a below-transfer-level-course than previous cohorts, based on their observable characteristics. This motivates the use of a matching method to compare more similar students, as a simple difference in average outcomes between post and pre AB 705 cohorts would likely be biased upward due to selection effects.

Our one-to-one propensity score matching results are presented in Tables A3 and A4 below, where “Unmatched” results represent a simple difference in average outcomes using all students in our sample and “ATT” results represent our estimated average treatment effect on the treated using only matched pairs of students in our sample. Our sample of all first-time math students includes 674,912 total students, 126,522 of which compose our “treatment” group – students in the fall 2019 cohort. Our sample of first-time transfer-intending first-time math students includes 327,285 total students, 60,493 of which compose our “treatment” group. Our ATT results only take into account average outcomes among students in the fall 2019 cohort and their matched pair in the “control” group, students from the fall 2015-2018 cohorts.

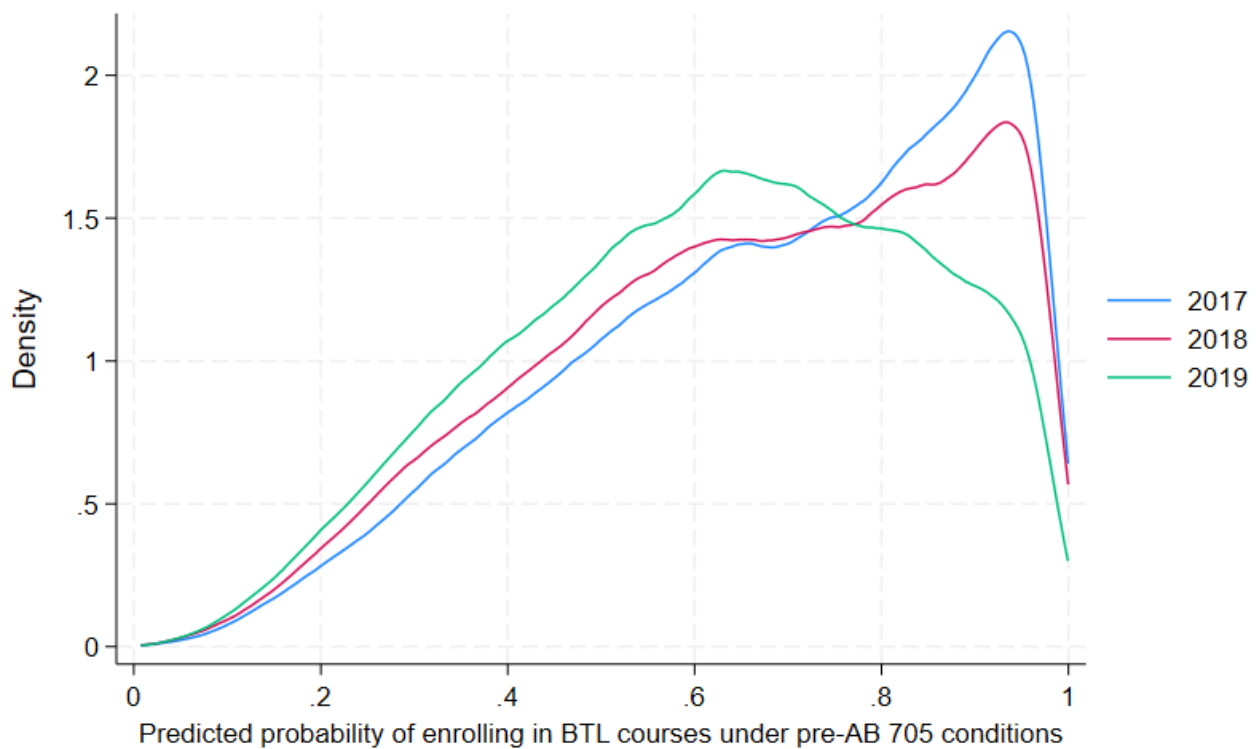
Of primary interest is the average difference in outcomes between groups. As expected, our “Unmatched” results are biased upward given the differences in the distribution of pre and post AB 705 cohorts. Examining our ATT

results, we find a difference in transfer attainment between fall 2019 students and their matched pair, based on their predicted probability of starting in a below-transfer-level course, to be about -1 percentage points. In other words, the AB 705 cohort is 1 percentage point less likely to transfer. This outcome matches up well with our LPM results discussed in the previous section. Our difference in outcomes for achieving “junior standing” is less than one percentage point and statistically insignificant. Similarly, our ATT for earning an ADT is less than one percentage point, while our ATT for earning any award is closer to -3 percentage points. Taken together, these outcomes further suggest that AB 705 has yet to have a meaningful effect on students achieving junior standing or earning an award.

However, it must be noted that the pandemic continues to play a role in impacting these results even when comparing matched students. As such, these results should merely further confirm our initial conclusions that positive longer-term impacts as a result of AB 705 have yet to appear. Additionally, as data from later cohorts becomes available and the confounding effects of the pandemic lessen, more work will be needed to uncover longer-term results, and design models that more effectively identify causal effects.

FIGURE A1.

Distribution of first-time math students by the predicted probability of enrolling in a below-transfer-level course under pre-AB 705 conditions



Source: Author’s calculations using MIS data.

Notes: Graph shows the predicted probability of enrolling in a below-transfer-level math course for first-time math students in the fall 2017, 2018, and 2019 cohorts. Estimates derive from coefficients from probit models of pre-AB 705 cohorts (fall 2015 to 2018) using whether a student started in a BTL course as our binary outcome and student characteristics as our explanatory variables.

TABLE A3

Results from one-to-one propensity score matching comparing three-year outcomes between pre- and post-AB 705 cohorts using predicted probability of enrolling in a below-transfer-level math course

All first-time math students

Outcomes	Sample	Treated	Controls	Difference	S.E.	T-stat
Transfer	Unmatched	0.218	0.189	0.029	0.001	23.480
	ATT	0.218	0.225	-0.007	0.002	-4.050
Junior Standing	Unmatched	0.430	0.381	0.049	0.002	31.990
	ATT	0.430	0.429	0.001	0.002	0.530
Earned an ADT	Unmatched	0.132	0.124	0.008	0.001	8.030
	ATT	0.132	0.140	-0.007	0.001	-5.270
Earned an AA/AS	Unmatched	0.211	0.217	-0.005	0.001	-4.130
	ATT	0.211	0.240	-0.029	0.002	-17.420

SOURCE: Author's calculations using MIS data.

NOTES: See Appendix A for details on calculations.

TABLE A4

Results from one-to-one propensity score matching comparing three-year outcomes between pre- and post-AB 705 cohorts using predicted probability of enrolling in a below-transfer-level math course

First-time transfer-intending first-time math students

Outcomes	Sample	Treated	Controls	Difference	S.E.	T-stat
Transfer	Unmatched	0.234	0.207	0.027	0.002	14.820
	ATT	0.234	0.260	-0.026	0.002	-10.370
Junior Standing	Unmatched	0.439	0.402	0.037	0.002	16.830
	ATT	0.439	0.468	-0.029	0.003	-10.050
Earned an ADT	Unmatched	0.135	0.137	-0.002	0.002	-1.460
	ATT	0.135	0.159	-0.024	0.002	-11.860
Earned an AA/AS	Unmatched	0.200	0.220	-0.020	0.002	-10.610
	ATT	0.200	0.252	-0.052	0.002	-21.720

SOURCE: Author's calculations using MIS data.

NOTES: See Appendix A for details on calculations.

Appendix B. Additional Figures and Tables

TABLE B1

Characteristics of fall cohorts of first-time math students who transferred to a four-year institution within 3 years of taking math

	2015	2016	2017	2018	2019
First-time in college	59.7	61.1	62.3	63.5	59.7
Dual enrollment student	10.8	10.7	13.1	15.4	18.3
CPG or Pell recipient	63.0	62.4	63.7	64.4	64.5
Special program participation	2.3	2.6	2.7	3.0	3.0
Degree-transfer intending students	80.6	86.8	85.5	86.7	86.2
Asian	18.1	17.6	17.7	19.4	19.3
Black	3.7	3.6	3.4	3.4	3.1
Latino	37.7	38.3	40.0	39.6	39.4
White	33.6	33.2	31.4	30.4	28.0
One-term throughput	36.6	38.1	42.2	50.7	69.1
Median GPA	3.3	3.3	3.3	3.4	3.5
Median Transferable units earned	67.0	67.0	67.0	67.0	67.0
ADT (%)	31.6	36.0	38.9	42.0	42.8
AA/AS (%)	50.5	53.9	55.8	57.4	57.8
Junior standing(%)	86.1	86.6	87.9	89.7	90.2

SOURCE: Authors' calculations using MIS data.

TABLE B2

First-time English, first-time math and overall enrollment changes

Annual change, %

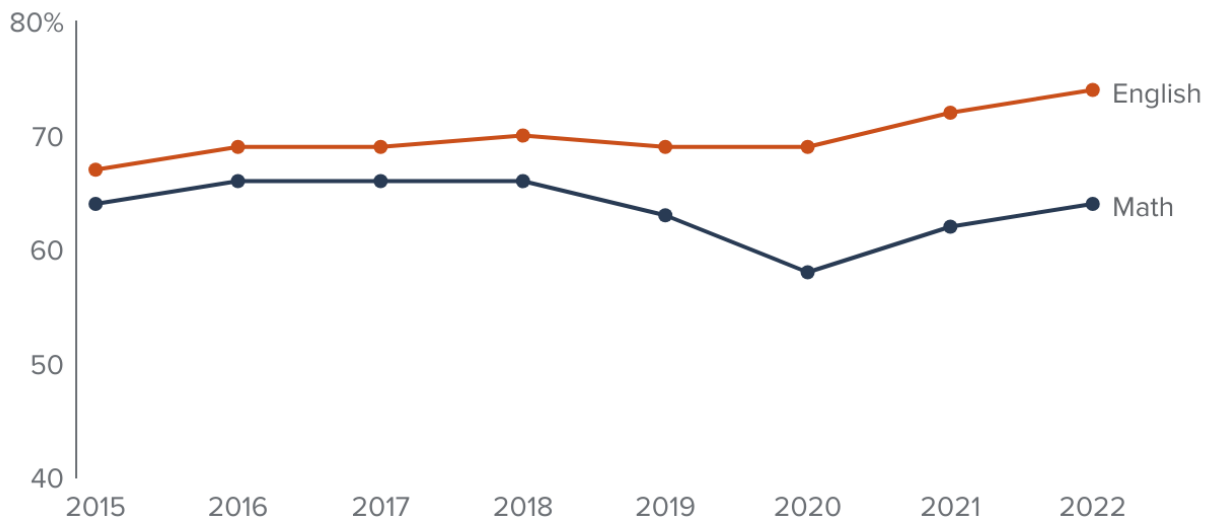
	First-time English students - Continuing	First-time English students - New	First-time English students - All	First-time math students - Continuing	First-time math students - New	First-time math students - All	First-time college students	First-time college students-degree/transfer intending
2016	-6	4	1	-5	2	-1	-2	4
2017	-1	1	0	0	1	1	3	1
2018	-3	1	0	-4	-4	-4	-3	-1
2019	5	-1	1	-2	-15	-11	-1	1
2020	-13	-14	-14	4	-16	-9	-20	-17
2021	-17	-5	-9	-20	-8	-13	0	-1
2022	-2	12	8	-4	4	1	14	14

SOURCE: Authors' calculations using MIS data.

NOTES: 2016 corresponds to the annual change between 2015 and 2016.

FIGURE B1

Share of first-time students in the discipline who are in their first-term in college



SOURCE: Authors' calculations using MIS data.

Table B3

Corequisite enrollment and throughput among first-time English students in fall 2022

College name	Number of first-time English students in corequisites, fall 2022	One-term throughput rate among first-time English students in corequisites, fall 2022 (%)	College name	Number of first-time English students in corequisites, fall 2022	One-term throughput rate among first-time English students in corequisites, fall 2022 (%)
FOOTHILL	167	73	DIABLO VALLEY	290	60
CRAFTON HILLS	81	73	REDWOODS	60	60
IRVINE VALLEY	340	73	CUYAMACA	262	60
OHLONE	190	71	GROSSMONT	409	60
DE ANZA	753	68	SAN DIEGO MESA	361	60
L.A. VALLEY	61	67	WOODLAND	106	59
MERRITT	61	67	SKYLINE	236	59
SADDLEBACK	182	64	FULLERTON	446	59
MT. SAN JACINTO	84	64	GOLDEN WEST	215	59
BUTTE	223	64	CUESTA	65	58
MISSION	129	64	CITRUS	772	58
LOS MEDANOS	642	64	SOLANO	190	57
FOLSOM LAKE	268	63	VICTOR VALLEY	327	57
SACRAMENTO CITY	413	63	MENDOCINO	71	56
SAN DIEGO CITY	323	63	LAS POSITAS	130	56
MARIN	59	63	SAN DIEGO MIRAMAR	93	56
SANTA ROSA	268	63	SAN MATEO	372	56
NORCO	294	61	MONTEREY	142	56
CYPRESS	352	61	COSUMNES RIVER	302	56
PALOMAR	492	60	SOUTHWESTERN	331	56

SOURCE: Author's calculations using MIS data.

Table B3

Corequisite enrollment and throughput among first-time English students in fall 2022 (continued)

College name	Number of first-time English students in corequisites, fall 2022	One-term throughput rate among first-time English students in corequisites, fall 2022 (%)	College name	Number of first-time English students in corequisites, fall 2022	One-term throughput rate among first-time English students in corequisites, fall 2022 (%)
WEST VALLEY	72	56	NAPA VALLEY	200	50
CABRILLO	429	55	EVERGREEN VALLEY	164	49
GAVILAN	121	55	PALO VERDE	147	49
OXNARD	109	55	L.A. PIERCE	45	49
SAN JOAQUIN DELTA	459	54	COALINGA	113	49
SAN FRANCISCO CITY	550	54	BERKELEY CITY	60	48
MIRA COSTA	87	54	EL CAMINO	1,058	48
CONTRA COSTA	236	54	L.A. HARBOR	108	48
LONG BEACH CITY	552	54	EAST L.A.	162	48
COLUMBIA	45	53	LAKE TAHOE	38	47
IMPERIAL VALLEY	184	53	MOORPARK	109	46
CERRITOS	256	52	MADERA	57	46
AMERICAN RIVER	511	52	CLOVIS	240	45
GLENDALE	157	52	PORTERVILLE	109	44
SIERRA	135	52	SAN BERNARDINO	479	43
LEMOORE	136	51	FRESNO CITY	794	42
HARTNELL	217	51	WEST L.A.	38	42
RIO HONDO	470	50	SANTA MONICA	897	41
MT. SAN ANTONIO	540	50	ALAMEDA	46	41
MERCED	345	50	MODESTO	706	41

SOURCE: Author's calculations using MIS data.

Table B3

Corequisite enrollment and throughput among first-time English students in fall 2022 (continued)

College name	Number of first-time English students in corequisites, fall 2022	One-term throughput rate among first-time English students in corequisites, fall 2022 (%)	College name	Number of first-time English students in corequisites, fall 2022	One-term throughput rate among first-time English students in corequisites, fall 2022 (%)
RIVERSIDE	282	41	SANTA ANA	302	36
ALLAN HANCOCK	264	41	REEDLEY	162	34
CERRO COSO	54	41	CANADA	102	32
SANTIAGO CANYON	211	40	L.A. CITY	98	32
SAN JOSE CITY	125	40	BAKERSFIELD	850	26
SEQUOIAS	374	39	YUBA	30	23
			All	24,669	53

SOURCE: Author's calculations using MIS data.

Table B4

Corequisite enrollment and throughput among first-time math students in fall 2022

College name	Number of first-time math students in corequisites, fall 2022	One-term throughput rate among first-time math students in corequisites, fall 2022 (%)	College name	Number of first-time math students in corequisites, fall 2022	One-term throughput rate among first-time math students in corequisites, fall 2022 (%)
OHLONE	31	97	DIABLO VALLEY	580	61
SIERRA	37	86	CANADA	170	61
SOLANO	64	75	IRVINE VALLEY	305	60
MERRITT	87	68	FOOTHILL	62	60
SAN DIEGO MIRAMAR	157	68	GOLDEN WEST	40	58
COASTLINE	51	67	YUBA	35	57
L.A. CITY	42	67	SKYLINE	151	57
CITRUS	606	66	SAN DIEGO MESA	192	57
NORCO	238	66	PORTERVILLE	107	56
LEMOORE	117	65	AMERICAN RIVER	632	56
CONTRA COSTA	131	64	SOUTHWEST L.A.	118	56
MT. SAN JACINTO	542	64	SANTA ROSA	166	55
SAN FRANCISCO CITY	260	64	BERKELEY CITY	84	55
ANTELOPE VALLEY	68	63	IMPERIAL VALLEY	138	54
REDWOODS	75	63	VENTURA	232	53
LOS MEDANOS	376	63	GAVILAN	126	53
DE ANZA	125	62	COALINGA	55	53
HARTNELL	162	62	LANEY	110	52
SANTA BARBARA CITY	125	62	MODESTO	527	52
WEST VALLEY	85	61	SAN MATEO	192	52

SOURCE: Author's calculations using MIS data.

Table B4

Corequisite enrollment and throughput among first-time math students in fall 2022 (continued)

College name	Number of first-time math students in corequisites, fall 2022	One-term throughput rate among first-time math students in corequisites, fall 2022 (%)	College name	Number of first-time math students in corequisites, fall 2022	One-term throughput rate among first-time math students in corequisites, fall 2022 (%)
FRESNO CITY	417	52	PASADENA CITY	413	43
MERCED	428	51	CHAFFEY	279	42
WEST L.A.	56	50	SAN JOAQUIN DELTA	257	42
ORANGE COAST	465	50	ALAMEDA	82	41
EVERGREEN VALLEY	166	49	PALOMAR	298	41
CRAFTON HILLS	196	49	RIO HONDO	169	41
SAN JOSE CITY	158	49	RIVERSIDE	491	40
OXNARD	191	49	EL CAMINO	1,039	40
CUYAMACA	138	49	SADDLEBACK	215	40
GROSSMONT	207	48	MT. SAN ANTONIO	770	39
SAN DIEGO CITY	207	48	SACRAMENTO CITY	282	39
MISSION	69	48	CABRILLO	278	38
FOLSOM LAKE	201	47	MOORPARK	66	38
MONTEREY	133	45	WOODLAND	37	38
SAN BERNARDINO	521	45	MIRA COSTA	85	38
MARIN	129	45	LAS POSITAS	51	37
SOUTHWESTERN	304	44	SHASTA	84	37
VICTOR VALLEY	824	43	CERRITOS	164	37
SEQUOIAS	558	43	FULLERTON	345	36
NAPA VALLEY	107	43	EAST L.A.	1,023	35

SOURCE: Author's calculations using MIS data.

Table B4

Corequisite enrollment and throughput among first-time math students in fall 2022 (cotinued)

College name	Number of first-time math students in corequisites, fall 2022	One-term throughput rate among first-time math students in corequisites, fall 2022 (%)	College name	Number of first-time math students in corequisites, fall 2022	One-term throughput rate among first-time math students in corequisites, fall 2022 (%)
GLENDALE	226	35	CHABOT	169	29
SANTIAGO CANYON	109	34	SANTA MONICA	1,110	29
SANTA ANA	317	33	ALLAN HANCOCK	144	28
BAKERSFIELD	495	33	LONG BEACH CITY	510	27
L.A. HARBOR	159	33	COSUMNES RIVER	131	21
CANYONS	275	32	MORENO VALLEY	118	20
L.A. MISSION	168	32	All	23,397	46

SOURCE: Author's calculations using MIS data.

TABLE B5

Transfer rates of students who started in transfer-level math are lower for the fall 2019 cohort than previous cohorts

Fall 2015-2019 cohorts

Year	Annual change in first-time math students (%)	Annual change first-time math students enrolling directly in TL (%)	Annual change first-time math students who transferred in 3 years (%)	Annual change first-time TL students who transferred in 3 years (%)	Share of first-time math students enrolling directly in TL (%)	3-year transfer rate among all first-time math students (%)	3-year transfer rate among students who started in TL (%)	Share of transfers who started in TL (%)
2015					23.7	15.8	30.2	45
2016	-1	8	2	7	25.7	16.2	29.8	47
2017	1	18	8	23	30.0	17.5	31.2	54
2018	-4	28	3	26	40.1	18.7	30.5	65
2019	-11	75	-3	36	78.6	20.4	23.7	92

SOURCE: Authors' calculations using MIS data.

NOTES: Outcomes measured three years from first math enrollment. TL refers to transfer level.

Appendix C. Case Studies: Methodology & Analysis

Qualitative Research Design:

The findings presented in the last section of the report stem from a qualitative research study that used a case study design to examine AB 705 implementation efforts at ten community colleges in California with relatively strong results among Black or Latino students (Merriam & Tisdell, 2015, Yin & Campbell, 2018; Yazan, 2015). The colleges were selected based on an analysis that looked at one-term throughput of first-time math students for all the community colleges in the state of California. Those colleges with the highest throughput rates in comparison to the state average for each of the populations of interest were then selected. A case study approach allowed us to investigate a “contemporary phenomenon (the ‘case’) in depth and within its real-world context” (Yin & Campbell, 2018). In this research, the phenomenon of interest is AB 705 design and implementation, and the bounded system is each respective community college. Ultimately, the goal was to engage in a deep exploration of existing community colleges that had produced high completion rates and reduced equity gaps in college-level math for Black and Latino students after the implementation of AB 705 (Yin, 2018).

Specifically, the questions that guided this study were:

- How do campus constituents describe the implementation process of AB 705 at each respective campus?
- How did context, including the pandemic, affect the design and implementation process?
- According to campus constituents, what might be contributing to higher levels of throughput rates for Black or Latino students?
- What strategies, if any, helped promote student success for Black and Latino students during the pandemic?

After selecting a total of ten community colleges to serve as our “cases,” we then moved into data collection. As triangulation of varied data sources is a critical component of a case study methodology, we collected 61 documents and conducted a total of 49 semi-structured interviews. The types of documents that were collected included strategic master plans, professional development plans, student equity plans, student support websites, course catalogs, and AB 705 reports and presentations developed by student services staff. These documents were either provided by campus constituents or found online. Interviews were collected with representatives from each of the colleges. Study participants encompass a variety of campus role types including campus administration (Vice President of Instruction, Vice President of Student Services), faculty (mathematics chair, AB 705 coordinators, academic senate presidents, mathematics and English professors), and campus staff (student counselors, student support services, and program coordinators). Each interview lasted between 60-90 minutes and covered topics such as the participant's role in implementing AB 705, their perceptions of what did and did not work for Black and Latino students, and how the campus handled the implementation during the COVID-19 pandemic.

Some of our case study analyses are available upon request. Please contact the authors for more details.



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Public Policy Institute of California
500 Washington Street, Suite 600
San Francisco, CA 94111
T: 415.291.4400
F: 415.291.4401
PPIC.ORG

PPIC Sacramento Center
Senator Office Building
1121 L Street, Suite 801
Sacramento, CA 95814
T: 916.440.1120
F: 916.440.1121