The Evidence on Alternative Placement Approaches

Presenters:

- Maxine T. Roberts, Education Commission of the States
- Dan Cullinan, MDRC
- John J. Hetts, Educational Results Partnerships
- Federick Ngo, UNLV

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Assessment & Placement

A National Perspective

Maxine T. Roberts, PhD Education Commission of the States



Agenda

 Overview of Education Commission of the States Shifting from Traditional Assessment & Placement National Data & Early Findings What's Working Differential Outcomes and Concerns Outcomes from Two Institutions What's Next? • Summary



Who we are.

The essential, indispensable member of any team addressing education policy.



What we do.

We believe in the power of learning from experience and we know informed policymakers create better education policy.



How we do it.

We research, report, convene and counsel.





Whinnery, E. & Pompelia, S. (2018). 50-state comparison: Developmental education policies. Denver, CO: Education Commission of the States. Retrieved from http://ecs.force.com/mbdata/MBQuestDEP?Rep=DEP1801.

Assessment & Placement: A National Perspective

Single Score Assessment



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Single Score Assessment Math or English Developmental Education Courses















National Data & Early Findings



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Whinnery, E. & Pompelia, S. (2018). 50-state comparison: Developmental education policies. Denver, CO: Education Commission of the States. Retrieved from http://ecs.force.com/mbdata/MBQuestDEP?Rep=DEP1801.



Ngo, F., & Kwon, W. (2015). Using multiple measures to make math placement decisions: Implications for access and success in community colleges. Research in Higher Education, 56 (5), 442-470.



Barnett, E., Bergman, P, Kopko, E., Reddy, V., Belfield, C., Roy, S., Cullinan, D. (2018). *Multiple Measures Placement Using Data Analytics: An Implementation and Early Impacts Report*. Center for the Analysis of Postsecondary Readiness.

Differential Outcomes & Concerns





Brathwaite, J., & Edgecombe, N. (2018). Developmental Education Reform Outcomes by Subpopulation. New Directions for Community Colleges, 182, 21-29.



■ White ■ Hispanic

Schudde , L. & Meiselman, A. (2019). Early outcomes of Texas Community Collee Students Enrolled in Dana Center Mathematics Pathways Prerequisite Developmental Courses. Research Brief. Center for the Analysis of Postsecondary Readiness.



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- <u>Study focus</u>: How racial beliefs were used as legitimate knowledge by counselors at community college
- <u>Sample</u>: 34 counselors; 2 community colleges
- <u>Findings</u>
 - Counselors' beliefs about racialized groups linked with their perspectives about proper course placements
 - Students from Pacific Palisades tend to be more successful. Usually when they participate in their admitted students day, nearly every one of them places into English 1. But even from Beverly Hills, we're not necessarily getting the best and the brightest so, not every one of those students is placing into English 1 necessarily. (p. 285)
 - Connection between perceptions about students' home lives and "proper" course placement
 - [I]t's the culture and it's the language barrier for most students in that category, the placement of lower levels. Because now they're not only dealing with trying their best in college, trying to get through the process, now they are dealing at home with a whole another series of issues, culturally speaking. So, they are in a whole different kind of—how do I say this, environment than say your Caucasian student." (p. 287)

Maldonado (2019) "Where Your Ethnic Kids Go": How Counselors as First Responders Legitimate Proper Course Placements for Community College Students, Community College Journal of Research and Practice, 43:4, 280-294, DOI: 10.1080/10668926.2018.1463303

Perceptions about Students and their Placement

Outcomes from Two Institutions & Next Steps



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College A: Enrollment into Co-Requisite Math by R/E (after 4 years of implementation)





FY 2018-2019

College A: Enrollment into Co-Requisite Math by R/E (after 4 years of implementation)



EDUCATION COMMISSION

FY 2018-2019

College A: Enrollment into Developmental Math Pre- and Post-redesign by R/E (FY 2013-2014 vs. FY 2018-2019)



EDUCATION COMMISSION

College A: Enrollment into Developmental Math Pre- and Post-redesign by R/E (FY 2013-2014 vs. FY 2018-2019)



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College A: What's Next?



FY 2013-2014 & FY 2018-2019

- Incorporating new forms of assessment
- Training faculty: Equity –focused workshops for leaders
- Focusing efforts on structural changes



College B: Enrollment into College-Level Math by Pell Status



College B: Enrollment into Developmental Math by Pell Status



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College B: What's Next?



- Expanding the use of multiple measures
 - Data-sharing agreements
- Encouraging re-taking placement exam.
- Changing GPA requirement
- Improving student engagement on campus.



Summary



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References

Barnett, E., Bergman, P, Kopko, E., Reddy, V., Belfield, C., Roy, S., Cullinan, D. (2018). *Multiple Measures Placement Using Data Analytics: An Implementation and Early Impacts Report*. Center for the Analysis of Postsecondary Readiness.

Brathwaite, J., & Edgecombe, N. (2018). *Developmental Education Reform Outcomes by Subpopulation*. New Directions for Community Colleges, *182*, 21-29

Maldonado (2019) "Where Your Ethnic Kids Go": How Counselors as First Responders Legitimate Proper Course Placements for Community College Students", Community College Journal of Research and Practice, 43:4, 280-294, DOI: 10.1080/10668926.2018.1463303

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Thank You

Maxine T. Roberts, PhD

Principal, Education Commission of the States mroberts@ecs.org



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Thank you!

Maxine T. Roberts, Education Commission of the States

The Center for the Analysis of Postsecondary Readiness (CAPR) is funded through a grant (R305C140007) from the Institute of Education Sciences, U.S. Department of Education.

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Early Findings from Multiple Measures Assessment in Minnesota

Dan Cullinan, Research Associate MDRC

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About the Study

- Four Minnesota State Colleges and one Wisconsin Technical College:
 - Anoka Ramsey
 - Century
 - MCTC
 - Normandale
 - Madison
- Students randomly assigned to multiple measures assessment (MMA) designed by each college
- Placement data and transcript data collected for both MMA and control group students

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Terms Defined

- Gatekeeper course: First college-level course in a subject
- **Pass rate**: Among those enrolled in a course, the percentage that passed with a C or higher
- **Bump-up zone**: Where students would normally be placed into a developmental course, but through multiple measures (combination of Accuplacer scores, HS GPA, and non-cognitive assessments) are eligible for college-level placement
What rules were tested?

• Colleges set MMA cut-off scores on the following measures:

Pilot Measures	Cut-off Range (depending on College and subject)
Accuplacer Classic	One level below college-level to college-level score (sometimes waived if other measure met)
HS GPA	From 2.5 to 3.0
LASSI non-cognitive assessment: motivation scale	4 or 5 out of 5

The Study Sample

Subject/Level	Students	Percent of subject total
English	3,677	
Developmental Ed	1,389	37.7%
Bump up zone	624	17.2%
College Level	1,664	45.2%

Math	4,487	
Developmental Ed	3,123	69.5%
Bump up zone	703	15.6%
College Level	661	14.8%

Increased Enrollment in the First Semester

- Students randomly assigned to MMA enrolled in the fall at a higher rate than control students
- Students bumped-up into college-level English by MMA were more likely to enroll in college at all than control group members placed into Dev. English



English Impacts

 Students randomly assigned to MMA increased gatekeeper enrollment by 5 percentage points (17%) in the first semester



English Impacts

 Pass rates among enrolled were similar when comparing bump-up students to all students in the control group



 Students bumped up in English were 28 percentage points more likely to have completed the Gatekeeper English course than their control group counterparts in the first semester
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Math Impacts

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• Students randomly assigned to MMA increased Math Gatekeeper enrollment by 4 percentage points (75%) in the first semester

Effect of MMA on Math Gatekeeper Placement and Enrollment (percent)



Math Impacts

 Students bumped up in Math were 12 percentage points more likely to have completed the Gatekeeper English course than their control group counterparts in the first semester

 The large increase in enrollment came with tradeoffs in pass rates among enrolled



Pass Rates in Gatekeeper Math

Effects on Educational Outcomes After the First Semester

- The final report (2021) will show longer term impacts of MMA, cost effective study, and the predictive utility of non-cognitive assessments
- MDRC will analyze transcript outcomes from three semesters of follow-up and add two more student cohorts
 - Compare groups after students complete developmental courses and enroll in college-level courses
- Ultimately, we will know more about which placement system helps students succeed academically

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Thank you!

Dan Cullinan, MDRC dan.cullinan@mdrc.org

Elisabeth Barnett, CCRC eb2231@tc.columbia.edu

The Center for the Analysis of Postsecondary Readiness (CAPR) is funded through a grant (R305C140007) from the Institute of Education Sciences, U.S. Department of Education.

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Let Icarus Fly: Multiple Measures in Assessment, the Re-imagination of Student Capacity, and the Road to College Level for All

November 21, 2019

John J. Hetts, Ph.D. Senior Director of Data Science jhetts@edresults.org

Visiting Executive, Research & Data jhetts@cccco.edu

@jjhetts #LetIcarusFly #CollegeLevelForAll

bit.ly/CAPRHETTS

Assessment's "one" job



Measure student's
capacity/predict student's
performance to get
students into course where
they can thrive

Variance in college level grades explained by Accuplacer, Compass, Asset - NC



Adapted from Bostian (2016), North Carolina Waves GPA Wand, Students Magically College Ready adapted from research of Belfield & Crosta, 2012 – see also Table 1: <u>http://bit.ly/Belfield2012</u> (cf also Scott-Clayton, 2012)

Accuplacer, SAT, ACT - Alaska

Figure 6. Among University of Alaska students who enrolled directly in college English courses, high school grade point average explained more of the variation in college English grades than did exam scores, 2008/09-2011/12

Figure 7. Among University of Alaska students who enrolled directly in college math courses, high school grade point average explained more of the variation in college math grades than did exam scores, 2008/09-2011/12



From Hodara, M., & Cox, M. (2016), Developmental education and college readiness at the University of Alaska: http://bit.ly/HSGPAAK

Percent of variance explained

Multiple Measures Assessment Project

- Collaborative effort of CCCCO, Common Assessment Initiative (CAI), RP Group, Cal-PASS Plus (Educational Results Partnership & San Joaquin Delta College), and >90 CCC pilot colleges
- Identify, analyze, & validate multiple measures data
 - Including HS transcript data, non cognitive variables, & self-report
 - Focus on predictive validity (success in course)
 - using classification and regression tree models (robust to missing data, non-linear effects, and interactions)
 - <u>Conservative approach</u>: target ≥70% success rate
- Engage pilot colleges to conduct local replications, test models and pilot use in placement, and provide feedback

bit.ly/MMAP2019





Multiple Measures Assessment Project: CCC Placement/Support Recommendations: Mathematics

Placement	English	Statistics	Precalculus
Direct placement	HSGPA >=2.6	HSGPA ≥ 3.0 OR	HSGPA ≥ 3.4 & Algebra 2 OR
into college-level		HSGPA ≥ 2.3 and ≥C in	HSGPA ≥ 2.6 and enrolled in
courses		Precalculus	Calculus

For placements throughout the English and Math sequences and classification and regression tree methods used, see <u>bit.ly/RulesMMAP</u> and <u>bit.ly/Bahr2017</u> and <u>bit.ly/MMAP2019</u> for lots of additional resources





Placement into college-level courses



bit.ly/BSIfor2009-2010 and bit.ly/MMAPProjection





Success Rates in Transfer-level English



Success Rates in Transfer-level Math



bit.ly/MMAPSummary2017





College level course-completion by placement & method for pilot colleges



bit.ly/MMAPSummary2017 plus additional data from CCCCO Datamart by college





What about everyone else? What maximizes their completion of gateway English and Math?

Previously identified students were highly likely to successfully complete (~70% or higher)

- Can we identify <u>any</u> students more likely to complete gateway English or Math if they start in developmental education?
 - Let's examine the students least likely to succeed based on their HS performance





What about everyone else? Regions of likelihood of success

Placement	English	Statistics	Precalculus
Highly likely to succeed (Direct placement)	HSGPA >=2.6	HSGPA ≥ 3.0 OR HSGPA ≥ 2.3 and ≥C in Precalculus	HSGPA ≥ 3.4 & Algebra 2 OR HSGPA ≥ 2.6 and enrolled in Calculus
Everyone in between	HSGPA = 1.9 to 2.6	HSGPA 2.3 to 3.0	HSGPA ≥2.6 & Algebra 2 or enrolled in Precalculus
Least Likely to Succeed	HSGPA <=1.9	HSGPA < 2.3	HSGPA ≤ 2.6 and no Precalculus

For classification and regression tree methods used, see <u>bit.ly/RulesMMAP</u> and <u>bit.ly/Bahr2017</u> and bit.ly/MMAP2019 for lots of additional resources





Even lowest performing HS students more likely to complete college level if placed there directly



CA statewide success rates in first attempt at college level (no support) vs. one year throughput for students least likely to succeed in course.(error bars represent ±1 se). For details see: <u>bit.ly/AB705Adjustments</u> and <u>bit.ly/MMAPAB705WEBINAR</u>





The Once and Future of (California) Placement: College Level for All – Tomorrow's Session

- Moderate to high performing high school students placed directly into college-level courses.
- Even lowest performing HS students more likely to complete college-level English & math if placed in college-level work (especially with additional supports)
- Flipped our understanding & responsibility
 - Students no longer have to prove their way into college level
 - We have to demonstrate that pre-college level placement will improve college level completion

Thank you!

Contact Information

- John Hetts
- jhetts@edresults.org
- jhetts@cccco.edu
- Twitter: @jjhetts #LetIcarusFly #CollegeLevelForAll
- bit.ly/MMAP2019
- bit.ly/CAPRHETTS

The Fierce Urgency of Now

- ~Two million new community college students per year
- "We are now faced with the fact that tomorrow is today. We are confronted with the fierce urgency of now. In this unfolding conundrum of life and history, there "is" such a thing as being too late. This is no time for apathy or complacency. This is a time for vigorous and positive action."
 - Dr. Martin Luther King, Jr.

Students are forced to repeat courses <u>successfully completed</u> in HS

Within systems

- Highly reliable progression
- Between systems at CCCs
 - \sim 3/4 repeat ≥ 1 level
 - $-\sim 1/2$ repeat ≥ 2 levels



HS to CCC Math transition

THE IMPORTANCE OF TRANSFER-LEVEL PLACEMENT

Fall 2007 CCC students (by levels below transfer of first attempt)



Percentage completion of transfer-level course by CCC Students in 6

Years (by level of first attempt)



Among transfer-level completers, distribution of completions by F2007 first-time students



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Thank you!

John J. Hetts Educational Results Partnerships jhetts@edresults.org

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Giving Community College Students Choice The Impact of Self-Placement in Math Courses

Holly Kosiewicz, University of Southern California Federick Ngo, University of Nevada Las Vegas

Citation

Kosiewicz, H. & Ngo, F. (Forthcoming). Giving community college students choice: The impact of self-placement in math courses. *American Educational Research Journal*.

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What is Directed Self-Placement (DSP)?

self-placement | guided self-placement

- Students choose, often in consultation with an advisor or counselor, the math and English courses they will enroll in
 - Other info (e.g., grades) may be used to inform decision
- Self-placement being implemented in CA, CT, FL
- One challenge to understanding impact of DSP on improving placement and student outcomes: it may coincide with other reforms to curriculum, instruction, student supports (e.g., FL)

We studied a context where self-placement was sudden and likely the only reform.

A "Natural Experiment" in DSP

- College X, a community college in Southern California, unintentionally failed to renew its placement testing license
 - Students enrolling in Summer and Fall 2008 were allowed to self-place in math courses
 - According to course catalog, students were advised to meet with a counselor before making an enrollment decision (we do not know the nature of these interactions)
 - Other colleges in the district continued with placement testing with multiple measures ("business as usual")

A "Natural Experiment" in DSP

- Therefore we have a "natural experiment" to determine the impact of a DSP relative to a test-based placement policy, on student outcomes.
- Difference-in-differences design with treatment (College X) and control colleges

• Outcomes

- First enrolled math course
- "Course fit" (withdraw, pass, fail)
- Completion of transfer-level math
- Completing 30 degree-applicable units

Findings

How did students place under DSP?

More students chose transfer-level math or lowest level of math after DSP



Female, Latino, and Black students were more likely to enroll in arithmetic under DSP




Findings

What is the impact of DSP on course fit and academic outcomes?







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Bolded values are statistically significant

Withdrawal								
from First	Failed First							
Enrolled	Enrolled	Pass CLM	Pass CLM	Pass CLM	Pass TLM inl	Pass TLM i	nPass TLM in	Completed
Math	Math	in 1yr	in 2yrs	in 4yrs	1yr	2yrs	4yrs	30 Units



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Bolded values are statistically significant

Implications For Decision-makers

- Determine effects of reforms by student subgroup to assess equity in outcomes
- Self-placement may increase counselor influence, so more attention needed towards counselor capacity and the role of implicit bias:
 - Expanding and differentiating approaches to advising
 - Increasing resources to decrease the counselor-tostudent ratio
 - Promoting professional development training focused on equity-mindedness

Citation

Kosiewicz, H. & Ngo, F. (Forthcoming). Giving community college students choice: The impact of self-placement in math courses. *American Educational Research Journal*.

Thank you!

Federick Ngo f<u>ederick.ngo@unlv.edu</u>

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APPENDIX



Difference-in-Difference Approach





Change in student outcomes after DSP (percentage points)

Positive outcomes for the cohort. DSP increased probability of passing college- and transfer-level math

Withdrawal from First Enrolled Math	
	-0.064*
Failed First Enrolled Math	
Math	0.007
Pass CLM in 1yr	0.021*
Pass CLM in 2yrs	0.020
Pass CLM in 4yrs	0.000
Pass TLM in 1yr	0.082***
Pass TLM in 2yrs	0.087***
Pass TLM in 4yrs	0.066**
Completed 30 Units	0.008

Overall treatment effects by subgroup (percentage points)

DSP increased probability of passing college- and transfer-level math and credit completion for male students only.

	Female	Male
Withdrawal from First Enrolled Math	-0.064**	-0.063
Failed First Enrolled Math	0.043**	-0.038*
Pass CLM in 1yr	-0.031	0.087**
Pass CLM in 2yrs	-0.032	0.086*
Pass CLM in 4yrs	-0.054	0.069
Pass TLM in 1yr	0.040	0.133***
Pass TLM in 2yrs	0.036	0.151***
Pass TLM in 4yrs	0.015	0.130**
Completed 30 Units	-0.019	0.042*

Overall t	reatment
effec	ts by
subg	roup
(percenta	ge points)

Positive effects for White and Asian students more than double the effects for Black and Latina/o students

			White or
	Black	Latina/o	Asian
Withdrawal from First Enrolled Math	0 1 1 1 *	0.022	0 100***
	-0.144	-0.033	-0.103
Failed First Enrolled Math	0.057	-0.016	0.015
Pass CLM in 1yr	0.041	-0.001	0.058***
Pass CLM in 2yrs	0.020	-0.018	0.092***
Pass CLM in 4yrs	-0.051	-0.018	0.057*
Pass TLM in 1yr	0.062**	0.063***	0.128***
Pass TLM in 2yrs	0.070**	0.057***	0.144**
Pass TLM in 4yrs	0.036	0.035	0.139**
Completed 30 Units	-0.100*	0.018	0.040

Table 5. Impact of Directed Self-Placement in Mathematics on Short- and Long-Term Outcomes

	Withdrawal from First Enrolled Math	Failed First Enrolled Math	Pass CLM in 1yr	Pass CLM in 2yrs	Pass CLM in 4yrs	Pass TLM in 1yr	Pass TLM in 2yrs	Pass TLM in 4yrs	Completed 30 Units
College X *									
Post-2008	-0.064*	0.007	0.021*	0.020	0.000	0.082***	0.087***	0.066**	0.008
	(0.020)	(0.007)	(0.008)	(0.012)	(0.014)	(0.011)	(0.013)	(0.018)	(0.011)
Post-2008	0.008	0.061***	-0.005	-0.013*	-0.024**	0.028***	0.024***	-0.007	0.060***
	(0.009)	(0.006)	(0.003)	(0.004)	(0.005)	(0.002)	(0.003)	(0.005)	(0.008)
College X	-0.008	0.025	-0.042	-0.03	-0.032	-0.006	-0.006	0.021	0.095**
	(0.011)	(0.013)	(0.023)	(0.021)	(0.024)	(0.009)	(0.015)	(0.016)	(0.019)
N	20096	20096	20096	20096	20096	20096	20096	20096	20096
Notes: Resul	ts from estim	ation using M	lodel (4) [see	e Table 41 are	shown, whic	h include all o	covariates (a	ae, sex, race	, and

Notes: Results from estimation using Model (4) [see Table 4] are shown, which include all covariates (age, sex, race, and language), college and cohort dummies, and standard errors clustered by cohort. College-level math (CLM) is elemetary algebra. Transfer-level math (TLM) is any course for which intermediate algebra is a requisite (e.g., pre-calculus). * p<.05 ** p<.01 *** p<.001

Table 6a. Impact of Directed Self-Placement in Mathematics by Subgroup									
	Withdrawal from First Enrolled Math	Failed First Enrolled Math	Pass CLM in 1yr	Pass CLM in 2yrs	Pass CLM in 4yrs	Pass TLM in 1yr	Pass TLM in 2yrs	Pass TLM in 4yrs	Completed 30 Units
Treatment Effect for Female									
Students	-0.064**	0.043**	-0.031	-0.032	-0.054	0.040	0.036	0.015	-0.019
	(0.013)	(0.009)	(0.019)	(0.026)	(0.027)	(0.019)	(0.018)	(0.020)	(0.015)
Treatment Effect for Male									
Students	-0.063	-0.038*	0.087**	0.086*	0.069	0.133***	0.151***	0.130**	0.042*
	(0.040)	(0.012)	(0.019)	(0.028)	(0.029)	(0.013)	(0.023)	(0.030)	(0.014)

Notes: These heterogeneous effects by subgroup are calculated using coefficients reported in the Appendix. The subgroup categories are drawn from the enrollment application. The reference group is white or Asian for the models estimating heterogeneous effects for Black students and Hispanic/Latino students. Math level is a dichotomous variable splitting the sample by initial math level (those who chose high/advanced math at intermediate algebra and above vs. those who chose lower-level math courses). College-level math (CLM) is elementary algebra. Transfer-level math (TLM) is any course for which intermediate algebra is a requisite (e.g., pre-calculus).

Table 6b. Impact of Directed Self-Placement in Mathematics by Subgroup										
	Withdrawal from First Enrolled Math	Failed First Enrolled Math	Pass CLM in 1yr	Pass CLM in 2yrs	Pass CLM in 4yrs	Pass TLM in 1yr	Pass TLM in 2yrs	Pass TLM in 4yrs	Completed 30 Units	
Treatment Effect for Black Students	-0.144*	0.057	0.041	0.020	-0.051	0.062**	0.070**	0.036	-0.100*	
	(0.060)	(0.065)	(0.023)	(0.041)	(0.051)	(0.015)	(0.014)	(0.035)	(0.035)	
Treatment Effect for Latina/o Students	-0.033	-0.016	-0.001	-0.018	-0.018	0.063***	0.057***	0.035	0.018	
	(0.026)	(0.013)	(0.018)	(0.023)	(0.028)	(0.006)	(0.006)	(0.015)	(0.029)	
Treatment Effect for White/Asian Students	-0 103***	0.015	0 058***	0 092***	0.057*	0 128***	0 144**	0 139**	0.040	
	(0.014)	(0.026)	(0.006)	(0.008)	(0.020)	(0.021)	(0.030)	(0.031)	(0.052)	

Notes: These heterogeneous effects by subgroup are calculated using coefficients reported in the Appendix. The subgroup categories are drawn from the enrollment application. The reference group is white or Asian for the models estimating heterogeneous effects for Black students and Hispanic/Latino students. Math level is a dichotomous variable splitting the sample by initial math level (those who chose high/advanced math at intermediate algebra and above vs. those who chose lower-level math courses). College-level math (CLM) is elementary algebra. Transfer-level math (TLM) is any course for which intermediate algebra is a requisite (e.g., pre-calculus).

* p<.05 ** p<.01 *** p<.001

Table 6c. Impact of Directed Self-Placement in Mathematics by Subgroup									
	Withdrawal from First Enrolled Math	Failed First Enrolled Math	Pass CLM in 1yr	Pass CLM in 2yrs	Pass CLM in 4yrs	Pass TLM in 1yr	Pass TLM in 2yrs	Pass TLM in 4yrs	Completed 30 Units
Treatment Effect for Students Choosing Lower-Level Math	-0.141**	-0.020	-0.031*	-0.034*	-0.060**	0.000	0.007	-0.016	-0.022
	(0.033)	(0.014)	(0.010)	(0.014)	(0.015)	(0.006)	(0.006)	(0.009)	(0.031)
Treatment Effect for Students Choosing Higher-									
Level Math	0.007	0.021**	0.115***	0.118***	0.103***	0.171***	0.182***	0.165***	0.065**
	(0.024)	(0.006)	(0.020)	(0.019)	(0.020)	(0.016)	(0.018)	(0.018)	(0.018)

Notes: These heterogeneous effects by subgroup are calculated using coefficients reported in the Appendix. The subgroup categories are drawn from the enrollment application. The reference group is white or Asian for the models estimating heterogeneous effects for Black students and Hispanic/Latino students. Math level is a dichotomous variable splitting the sample by initial math level (those who chose high/advanced math at intermediate algebra and above vs. those who chose lower-level math courses). College-level math (CLM) is elementary algebra. Transfer-level math (TLM) is any course for which intermediate algebra is a requisite (e.g., pre-calculus).

* p<.05 ** p<.01 *** p<.001