Multilevel Issues in the Application of Propensity Score Matching

Simulations and Results for Evaluation of the Advanced Placement Program

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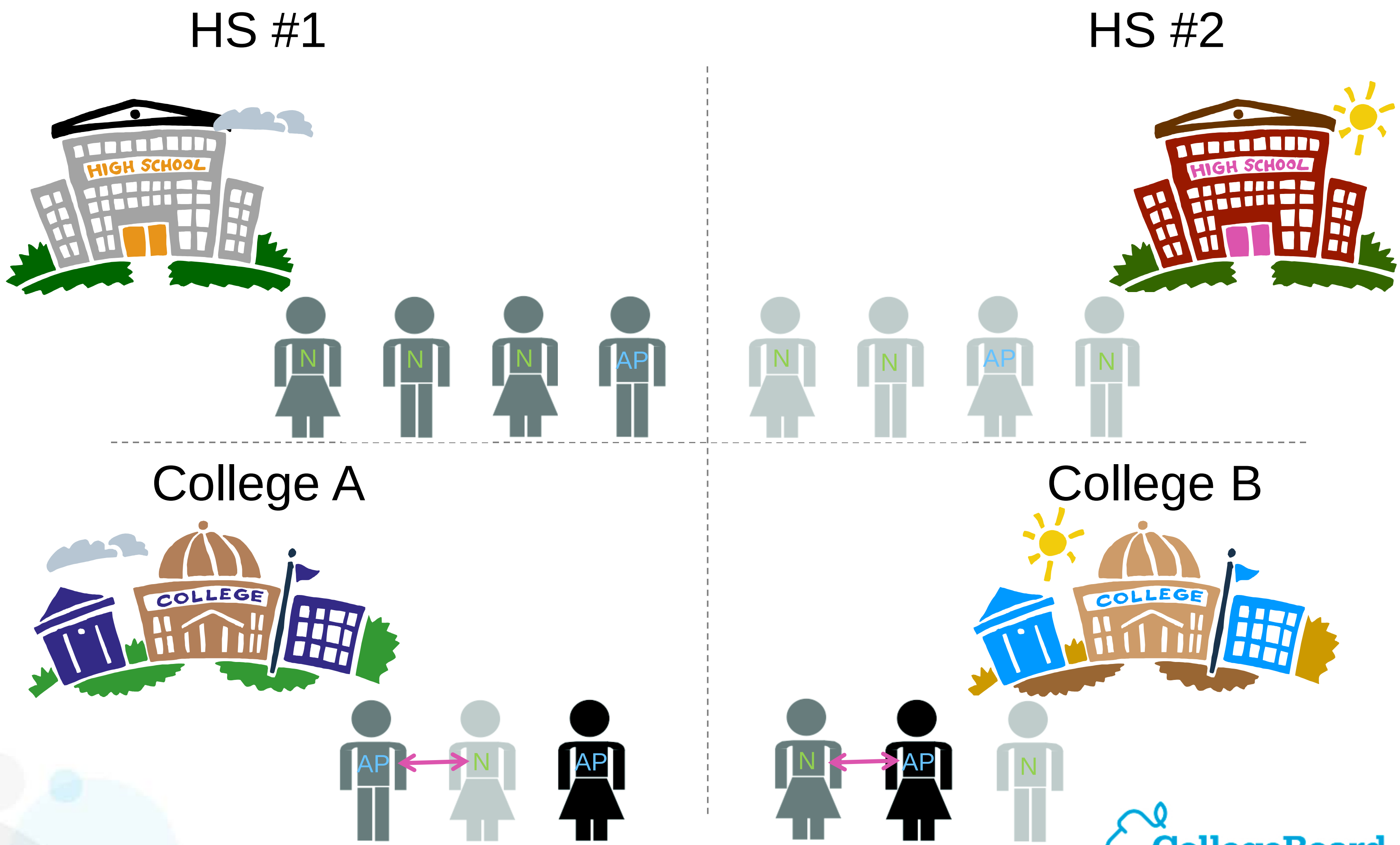
Outline

1. Context for the Empirical Study
2. Simulation to Inform the Empirical Study
3. Some Preliminary Results from the Empirical Study

1.1 Current Empirical Study

- Goal: Estimate unbiased effect of Advanced Placement (AP) on related college grades
  - Propensity score methods may reduce bias
- Problem: Propensity for taking AP varies across high schools, even after conditioning on student characteristics
  - We are unsure of the consequences on our conclusions of ignoring such dependence within high schools
- Solution: Estimate multilevel propensity score model with random high school effects

1.2 Picturing the Empirical Study



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1.3 If we could design the perfect experiment…

- We might:
  - take a cluster sampling approach to selecting a representative set of high schools;
  - randomly assign students of a variety of ability levels to take the Advanced Placement (AP) course;
  - follow all students to their college of choice and:
    - assign non-AP to take intro and subsequent course; and
    - assign AP to skip the intro and take the sequent.
- We hope to find that the AP group tended to perform at least as well as the non-AP

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1.4 Choosing to Participate in AP

- Construct a model of propensity for AP participation
- Potentially important predictors of AP participation
  - Academic achievement
  - Subject area interest
  - Achievement motivation
  - Opportunities for participation
  - High school atmosphere (e.g., college-focused; pro-AP)

2.1 Existing Research

- Griswold, Localio, and Mulrow (2010)
  - Compared: ignoring clusters; within-cluster; and multilevel match
- Arpino and Mealli (2011)
  - Fixed cluster effects superior to either random or no effects
  - No normality assumption for cluster effects
- Vanderweele (2008)
  - Ignorability & stable unit assumptions for cluster-level treatment
- Outside the multilevel context, see:
  - Rosenbaum & Rubin — foundational propensity score theory
  - Peter Austin — recent simulations & best practice

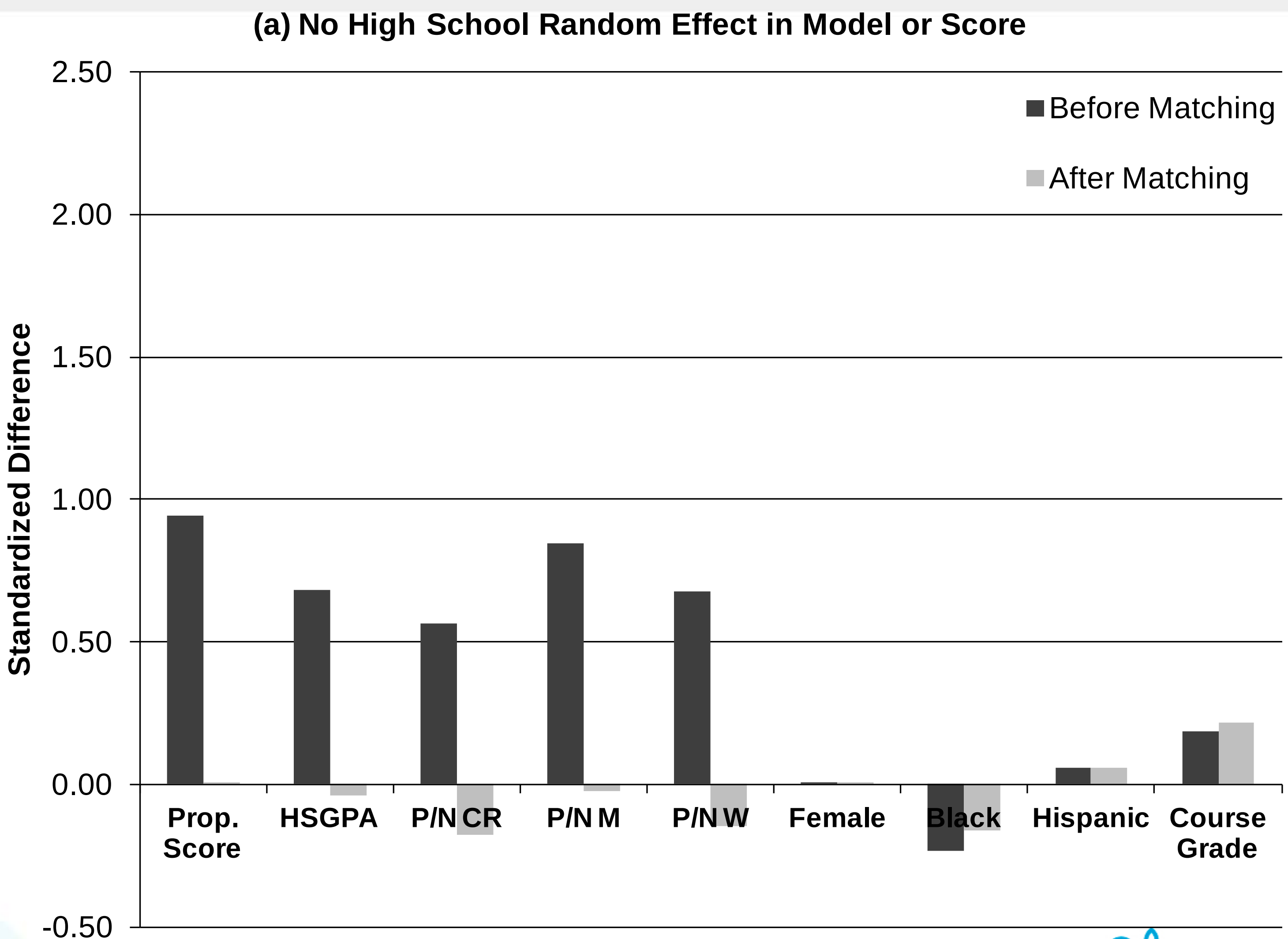
2.2 What about College Effects?

- Ignore college effects in estimating prop. scores
  - Data not cross-classified until students enter college
- Since the outcome is at the college level…
  - Only match AP- and non-AP-examinees:
    - at the same college; and
    - who took the same subsequent course.
  - Referred to as exact matching on these variables
  - Do not require that students attended the same high school

2.3 Some Notes on Propensity Score Matching Procedure

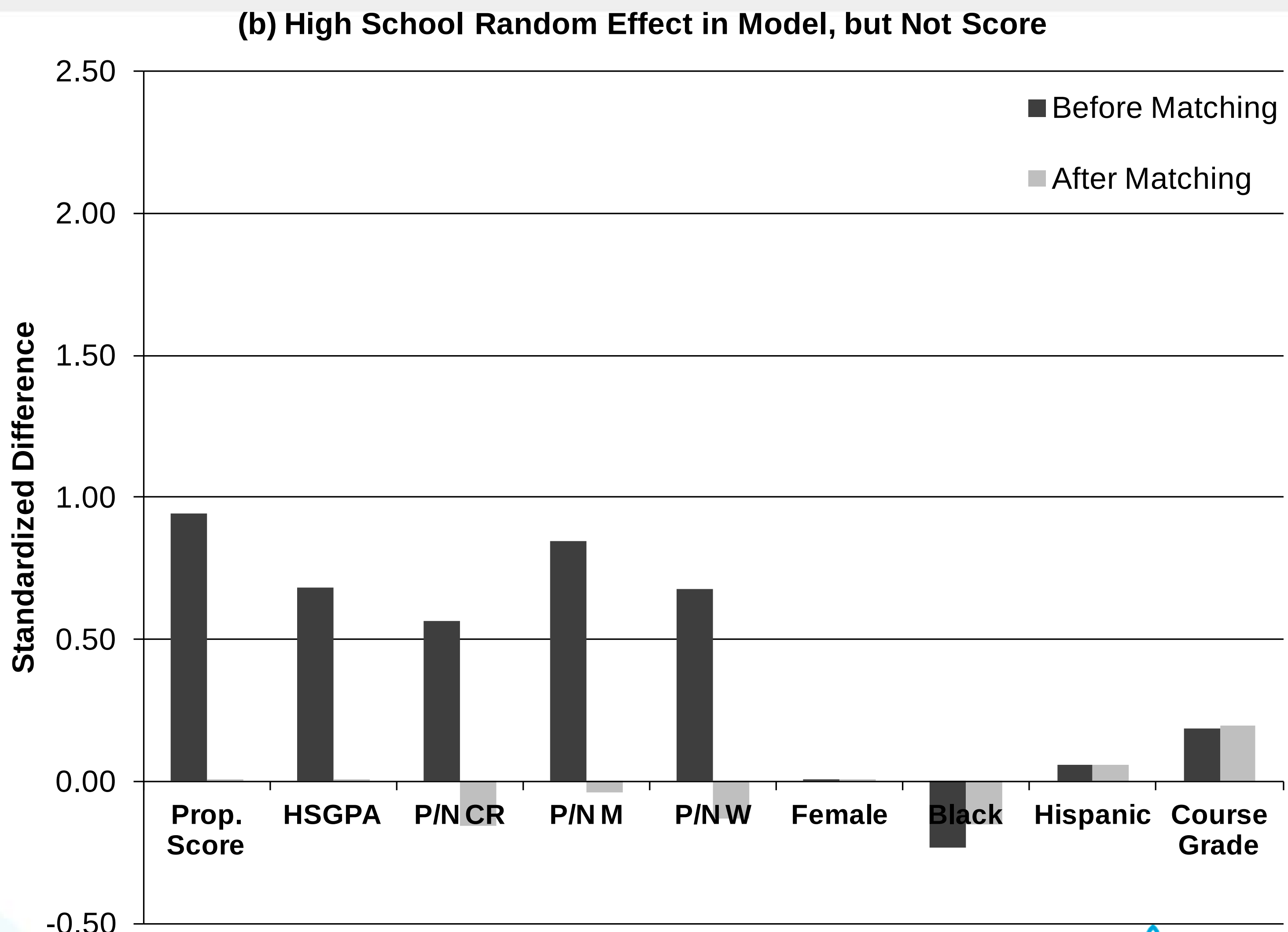
- Greedy matching
  - As opposed to optimal matching
- Within calipers
  - Caliper size = 0.2 * Population SD(propensity score)
- On logistic scale
  - As opposed to probability scale; avoids scale issues
- Use BLUP predicted propensity score?
  - Simulations will examine effects of either including or excluding predicted random intercept effect

2.4 Example w/ $\tau = 6$, No RE



Replicate #59 from condition 4 simulated on 2012-03-13

2.5 Example w/ $\tau = 6$, Model RE, Not in PS



Replicate #59 from condition 4 simulated on 2012-03-13

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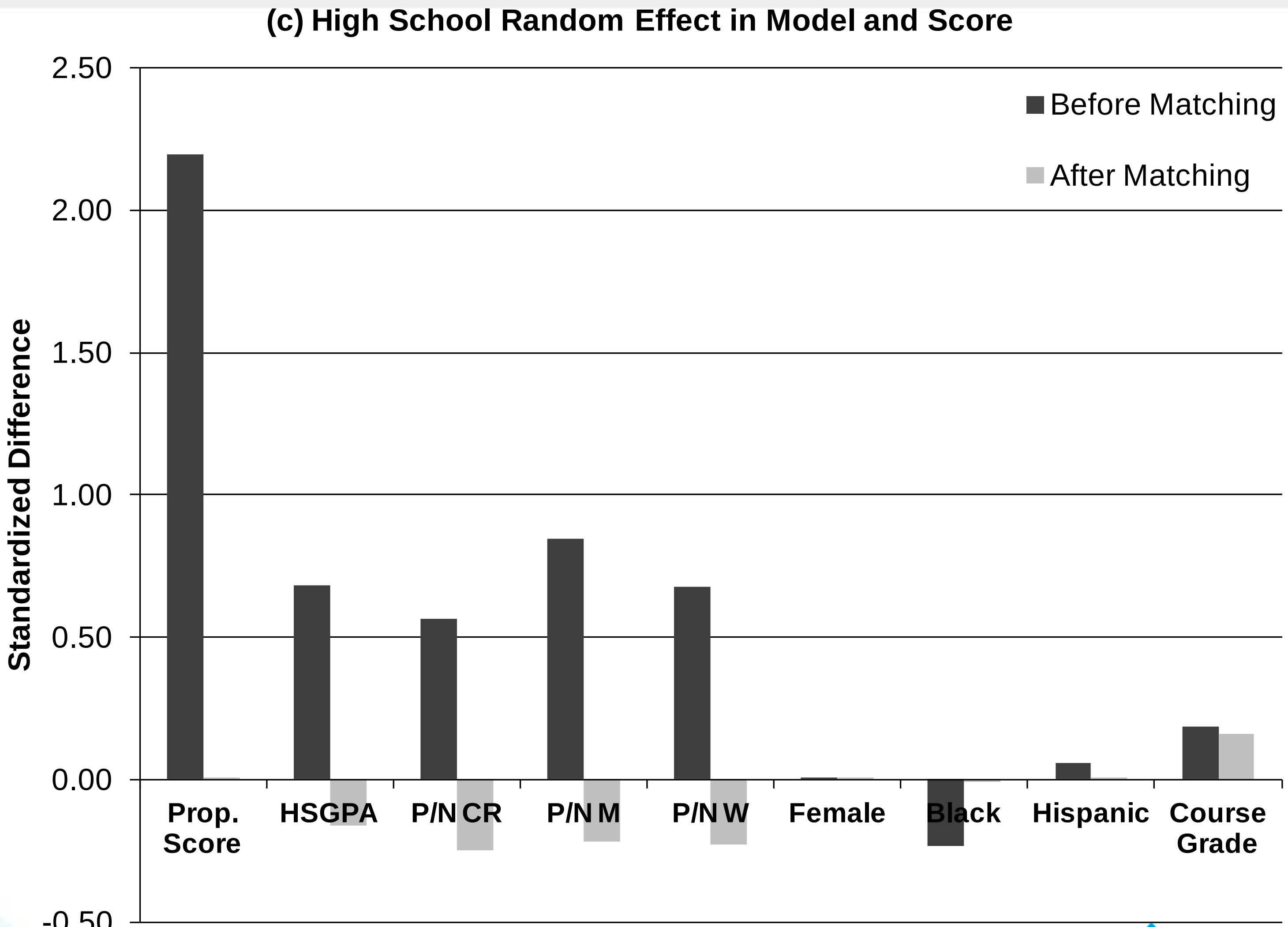
2.6 Example w/ τ = 6, Model RE, Inc. in PS

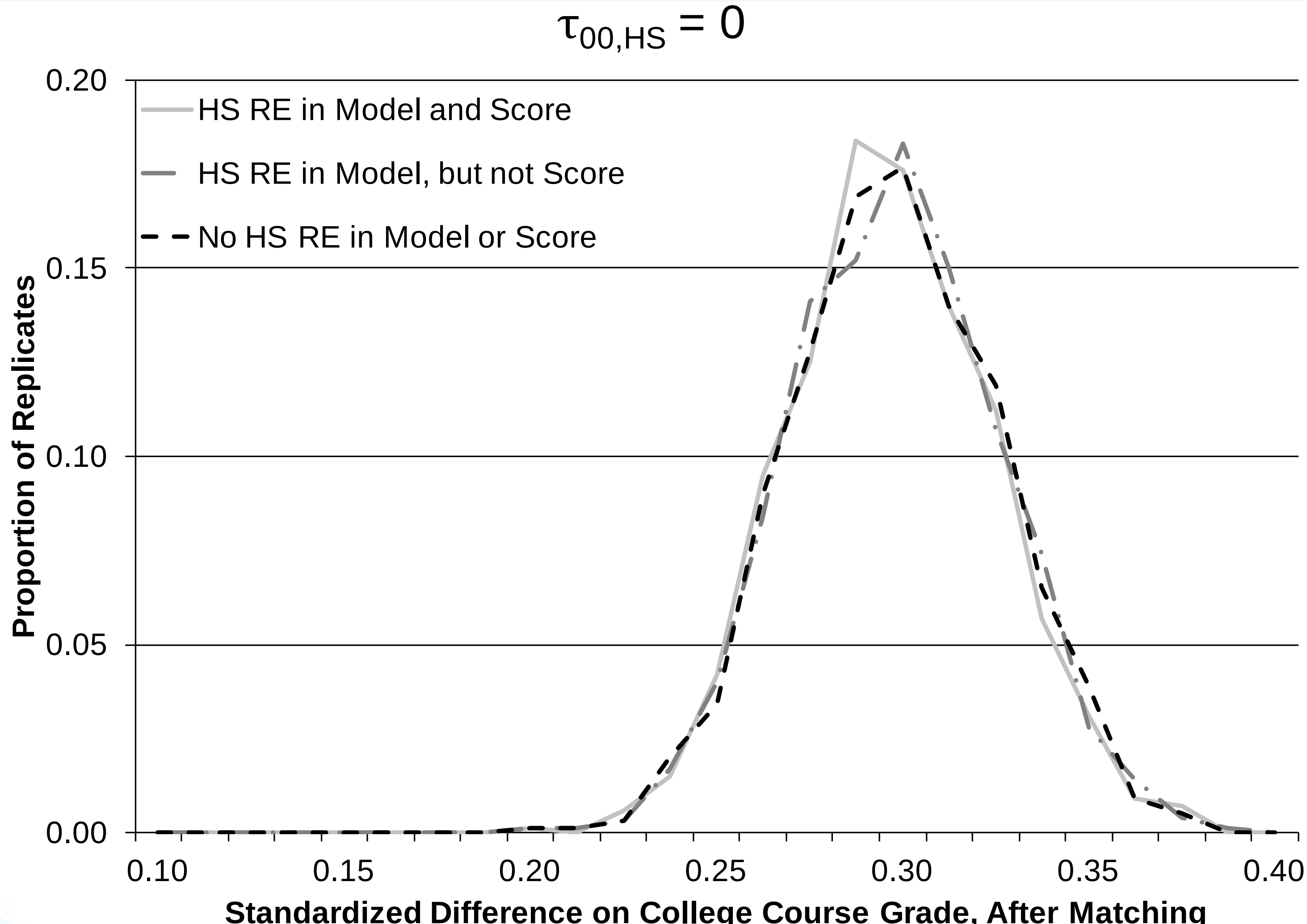


Replicate #59 from condition 4 simulated on 2012-03-13

2.7 Comments on Example Replicate

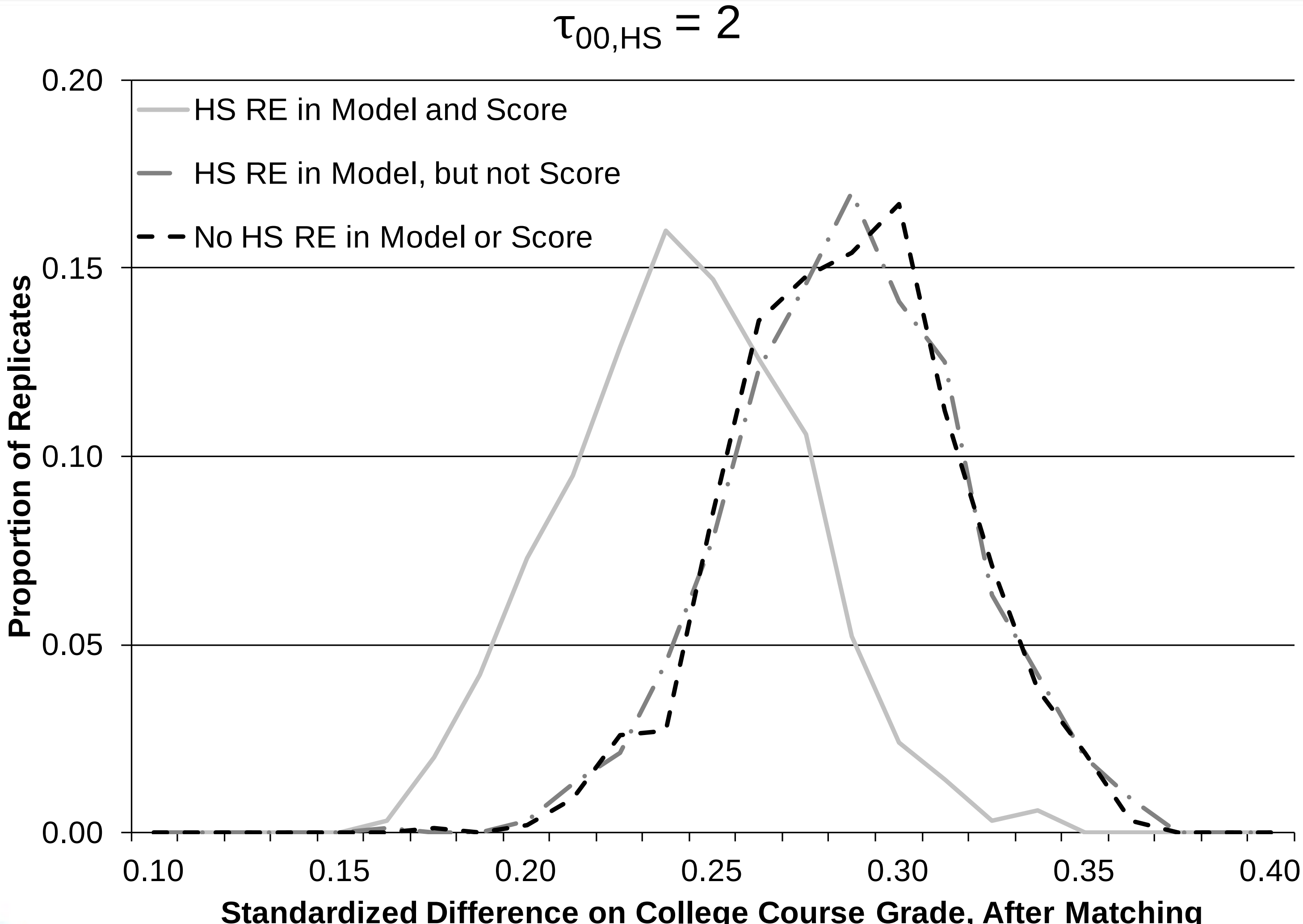
- When including HS random effects:
  - Propensity score *d* much larger, before matching
  - Better balance on gender & race after matching
- Aside from that, either picture looks pretty good:
  - Approximate balance after matching.
  - Non-negative course grade *d*.
- The problem with ignoring random effects is a violation of ignorability
  - Without HS, AP Participation is not MAR.

2.9 Course Grade *d*'s after Matching



1,000 replicates from condition 1 simulated on 2012-03-13

2.10 Course Grade *d*'s after Matching



1,000 replicates from condition 2 simulated on 2012-03-13

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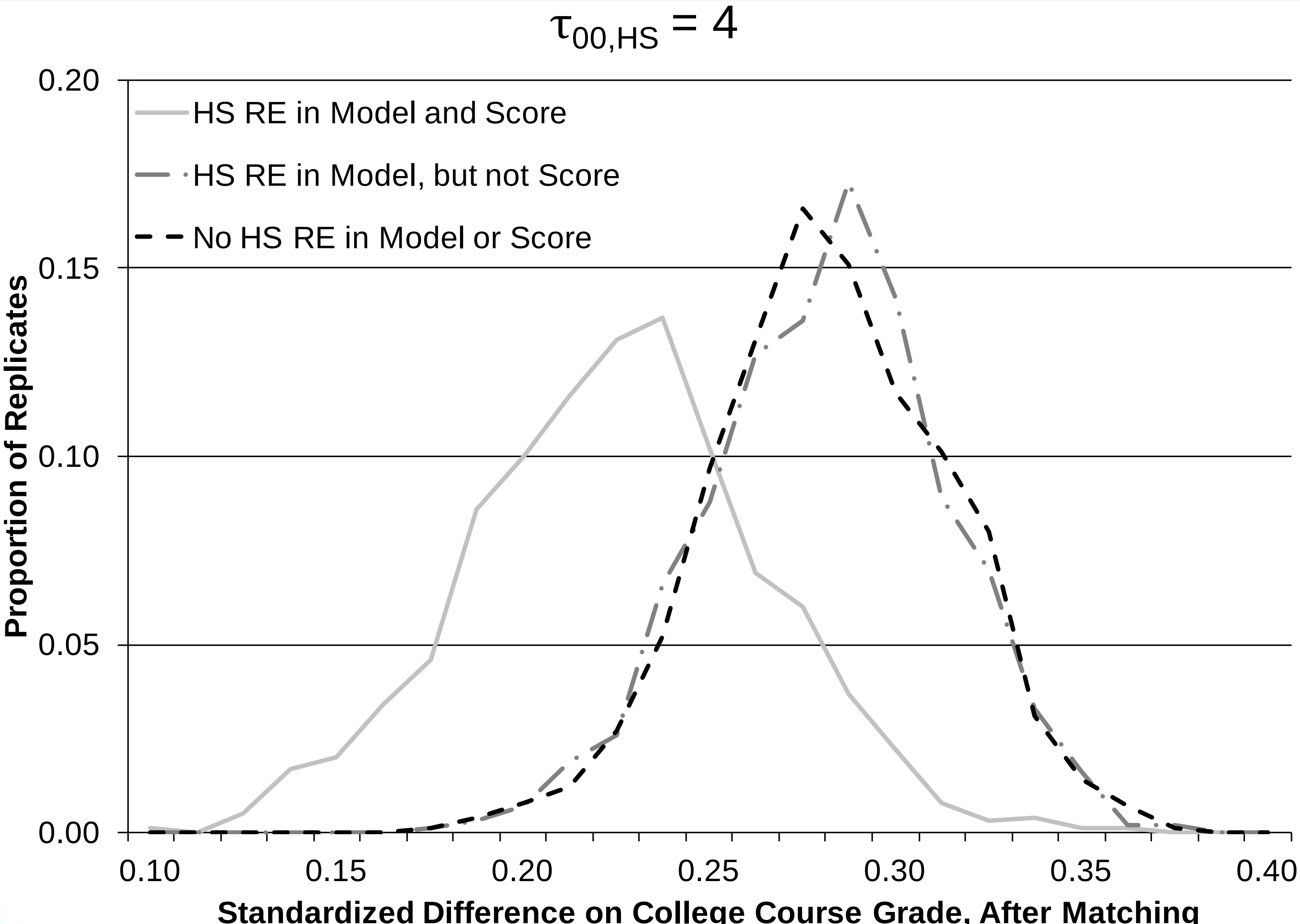
2.11 Course Grade *d*'s after Matching



1,000 replicates from condition 3 simulated on 2012-03-13

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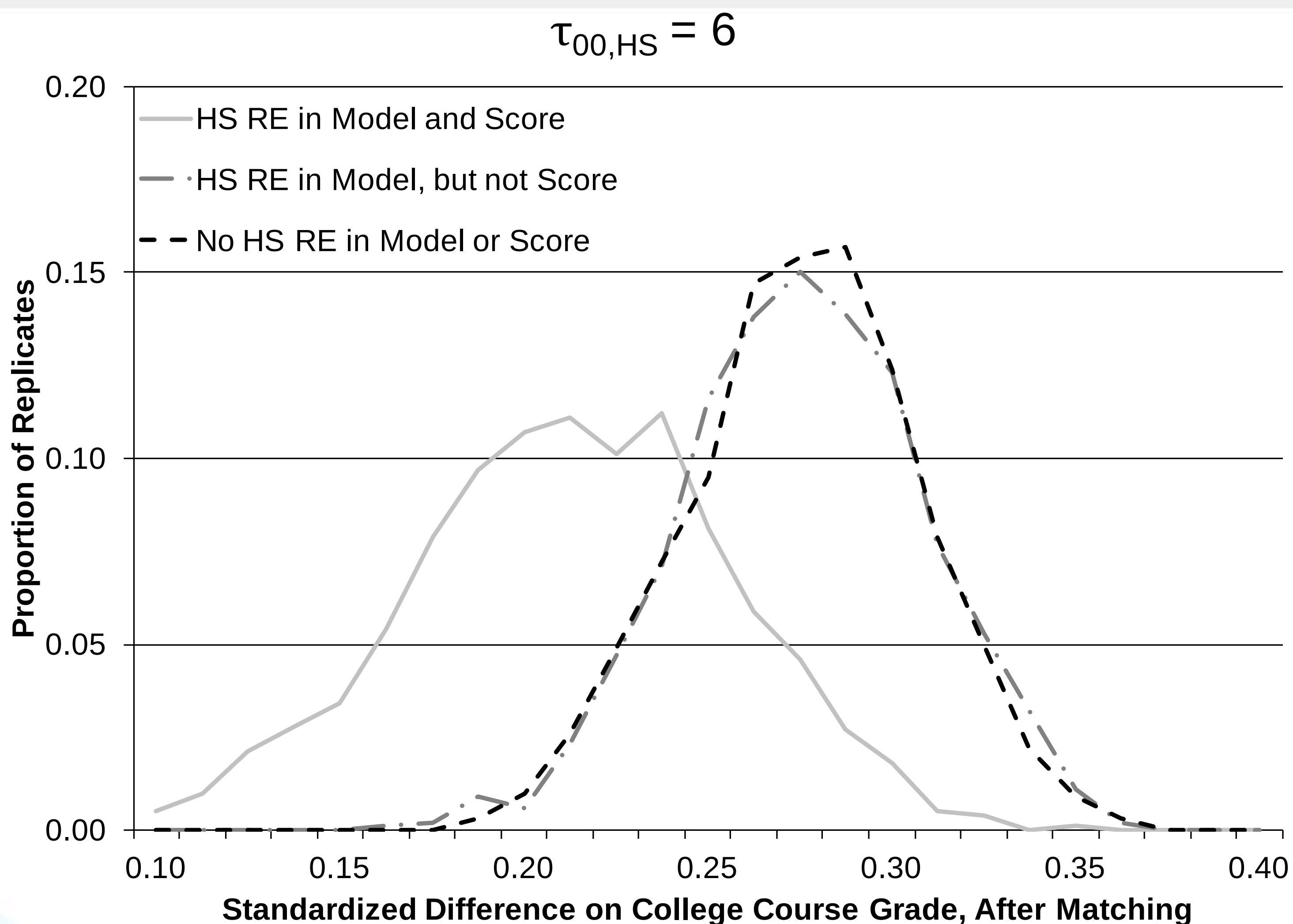
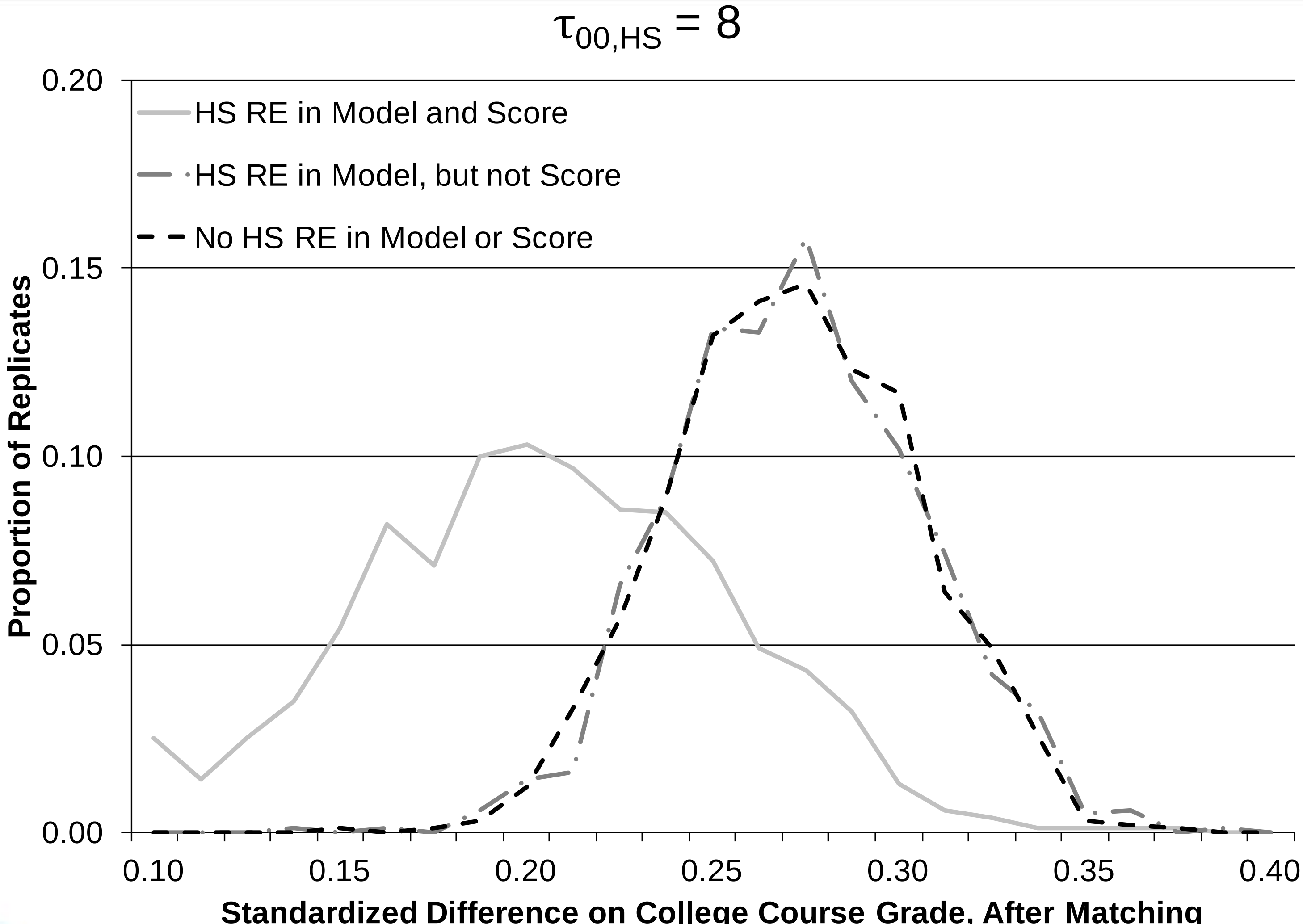
2.12 Course Grade *d*'s after Matching



1,000 replicates from condition 4 simulated on 2012-03-13

2.13 Course Grade *d*'s after Matching



1,000 replicates from condition 5 simulated on 2012-03-13

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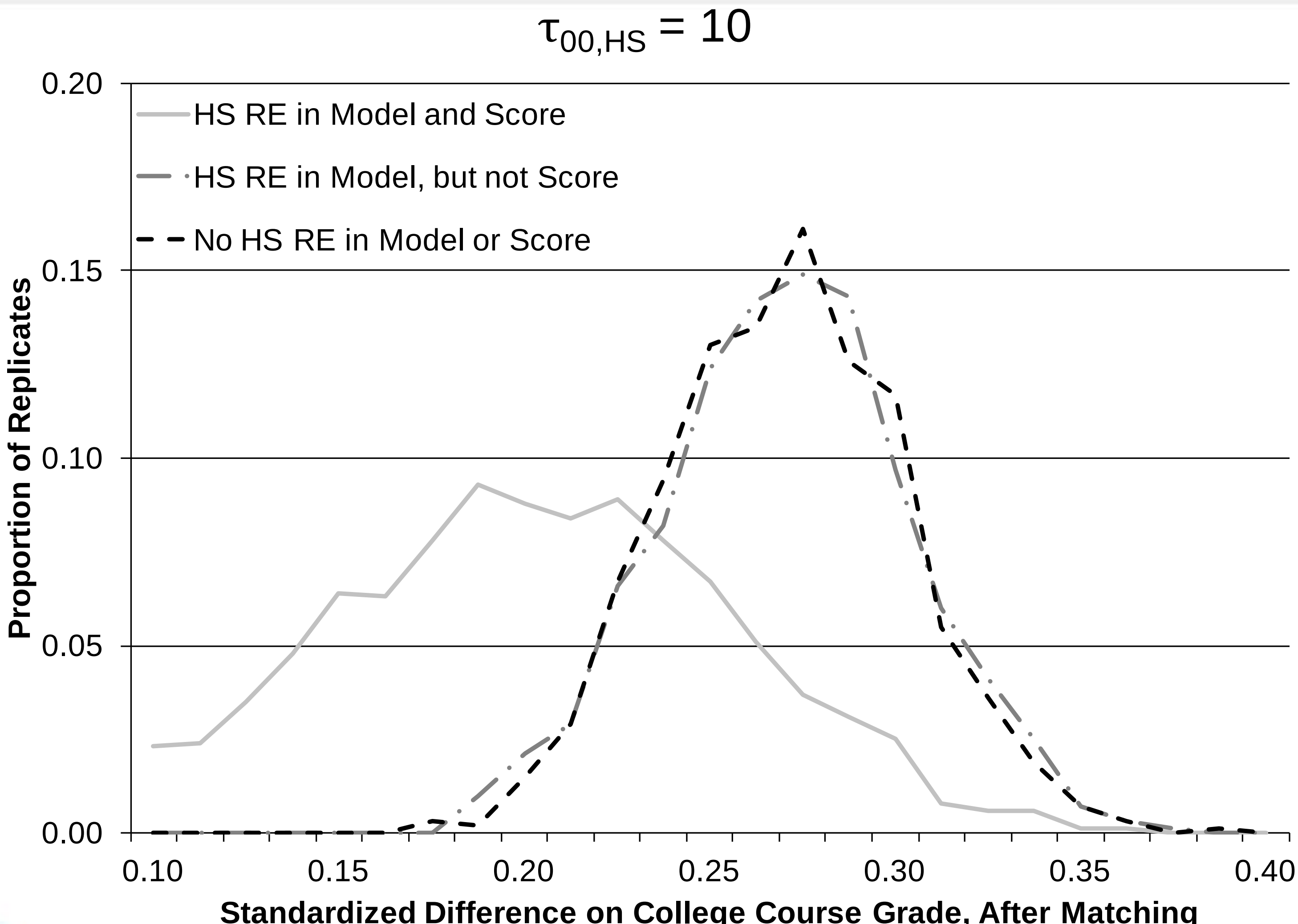
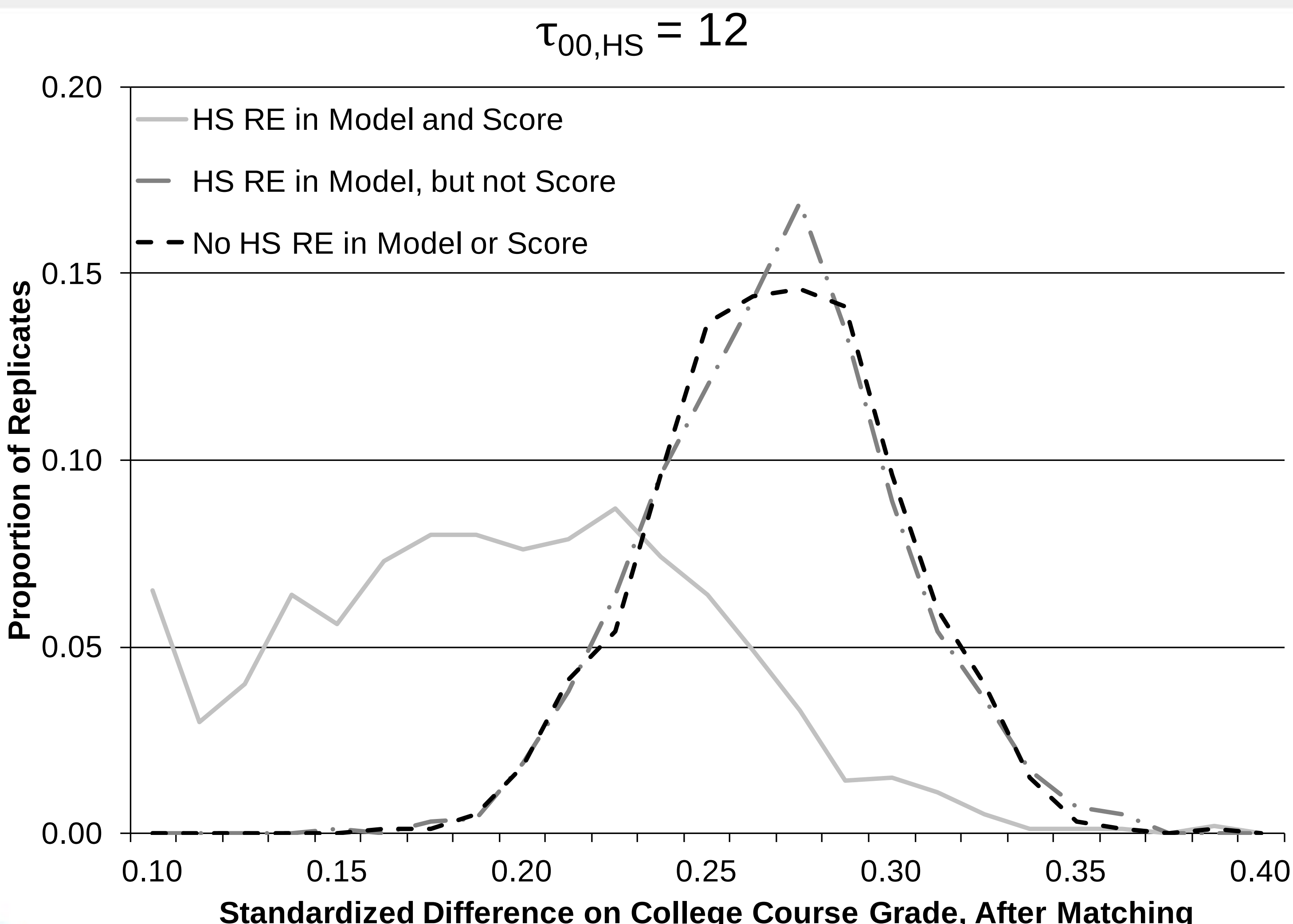
2.14 Course Grade *d*'s after Matching



1,000 replicates from condition 6 simulated on 2012-03-13

2.15 Course Grade *d*'s after Matching



1,000 replicates from condition 7 simulated on 2012-03-13

2.16 Average Course Grade Stats After Matching by Condition & PS Model

	HS RE in…			AP		Non-AP		*d*	
τ_{00}, HS	Model?	Prop Score?	Matched Pairs	M	SD	M	SD	SD bef Match	SD aft Match
0	No	n/a	4,392	3.11	0.67	2.89	0.80	0.29	0.21
	Yes	No	4,392	3.11	0.67	2.89	0.80	0.29	0.21
	Yes	Yes	4,392	3.11	0.67	2.90	0.80	0.29	0.21
4	No	n/a	6,487	3.07	0.67	2.87	0.80	0.28	0.19
	Yes	No	6,487	3.07	0.67	2.87	0.80	0.28	0.19
	Yes	Yes	6,270	3.07	0.67	2.91	0.79	0.22	0.15
8	No	n/a	7,817	3.06	0.67	2.87	0.80	0.27	0.19
	Yes	No	7,817	3.06	0.67	2.87	0.80	0.27	0.19
	Yes	Yes	7,201	3.06	0.67	2.91	0.79	0.20	0.14
12	No	n/a	8,743	3.06	0.67	2.87	0.80	0.26	0.19
	Yes	No	8,743	3.06	0.67	2.87	0.80	0.26	0.19
	Yes	Yes	7,667	3.05	0.67	2.91	0.79	0.19	0.13

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2.17 Simulation Results w/ respect to τ

- As random HS intercept variance (τ) increases…
  - number of within-caliper matches made increases;
  - ignoring HS RE → mean recovered *d* is stable;
  - modeling HS random effects:
    - PS excludes HS RE → similar to ignoring HS; and
    - PS includes HS RE →
      - mean recovered *d* decreases; and
      - variance in recovered course grade *d* increases.

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2.18 Other Simulation Results

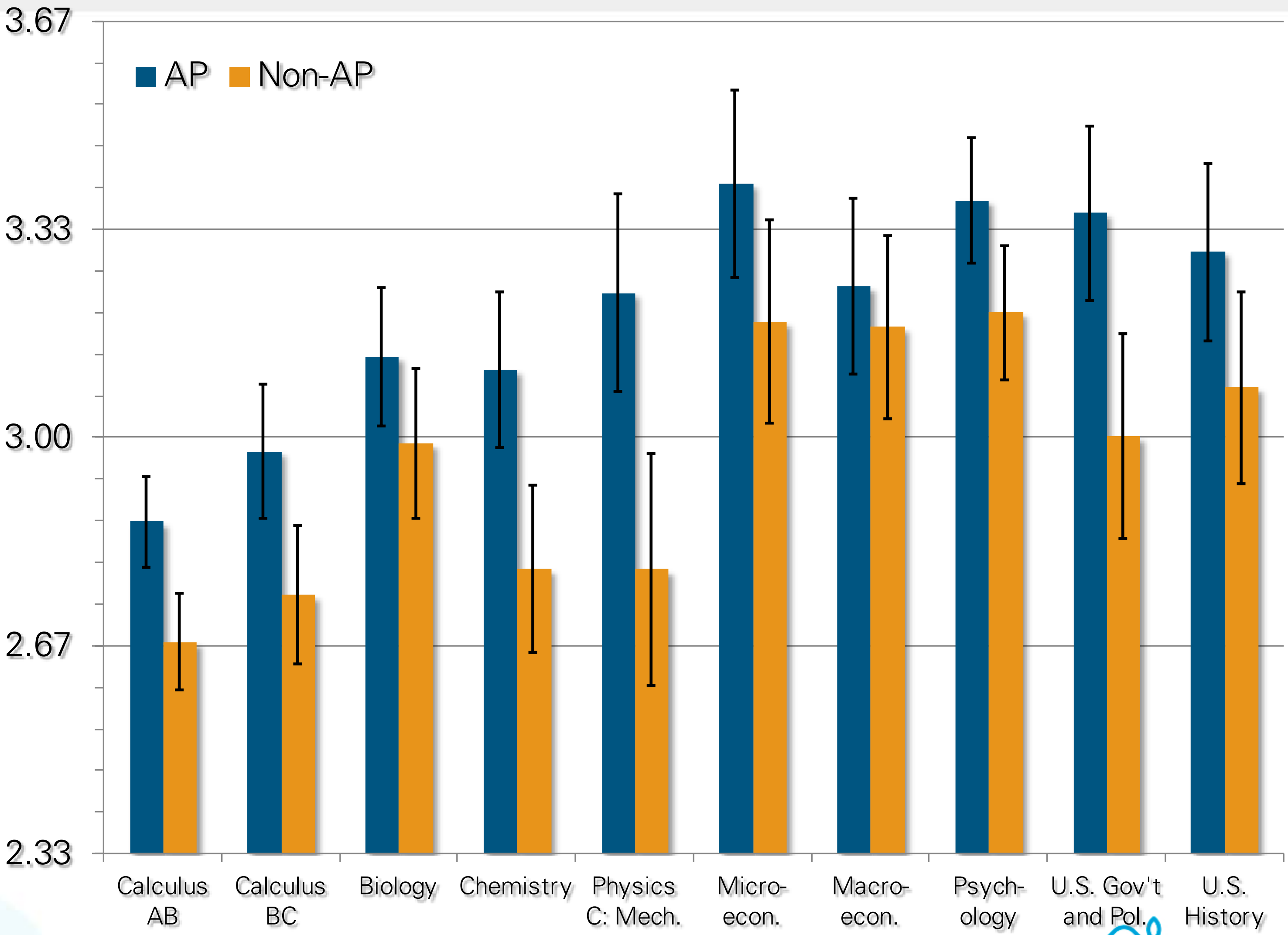
- When ignoring HS or excluding from prop. score:
  - Prop. score SD and therefore caliper size is smaller
  - More matches result
  - Are these better matches, than when modeling and including in the prop. score the HS random effect?

- How to optimize both the quality of matches and sample size

3.1 Tying Simulations back to Application

- A Placement Validity Study for Advanced Placement® Exam Scores
  - Forthcoming study with my colleague Maureen Ewing
  - 2006 cohort of first-time, first-year college students
  - Used official AP credit / placement granting policies
  - Needed sufficient number of AP examinees taking subsequent courses
  - Needed a good propensity score model and to achieve balance
  - Final sample: 10 exams; ≤ 53 colleges

3.2 Mean Course Grades, after Matching



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3.3 Summary of Results

- AP participation differs across high schools
- AP examinees significantly outperformed matched non-AP counterparts in five AP exams
  - Calculus AB, Calculus BC, Chemistry, Physics C: Mechanics, and United States Government and Politics
- In the remaining five exams, no significant differences existed for course grades
  - Biology, Microeconomics, Macroeconomics, Psychology, and U.S. History
  - Criterion differences? Differential selection?

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3.4 Questions, Comments, Suggestions?

- Researchers are encouraged to freely express their professional judgment. Therefore, points of view or opinions stated in College Board presentations do not necessarily represent official College Board position or policy.

- Please forward any questions, comments, and suggestions to:
  - bpatterson@collegeboard.org
- And check out Research & Development's site:
  - http://www.collegeboard.com/research

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3.5 References

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