Education
Centre for Education
Statistics & Evaluation

Big data, big possibilities, big challenges: Lessons from using quasi-experimental designs in evaluation of educational reforms

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About CESE

Provide data analysis, information and evaluation that improve effectiveness, efficiency and accountability

Collect essential education data and provide a one-stop shop for information needs

Build capacity across the whole education sector so that everyone can make better use of data and evidence

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Overview

- Theory of causal attribution
  - Randomised controlled trials just a special case for causal inference
- Planning, conducting and presenting a quantitative evaluation
- Local Schools, Local Decisions (LSLD) evaluation case example
  - Using regression methods to test predictions based on program logic
- Reading Recovery (RR) evaluation case example
  - Using regression and propensity score methods to estimate average treatment effects
- Literacy and Numeracy Action Plan (LNAP) Phase 2 evaluation case example
  - Using propensity score methods to influence research design
- Final thoughts

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Theory of causal attribution

- Rubin Causal Model
  - Unified perspective of causal inference
- Causal effects defined by within-unit differences
  - Potential outcomes defined as outcome value after application of treatment **and** non-application of treatment
  - Fundamental problem of causal inference
- Randomised trials just a special case
  - Assignment mechanism allows within-unit differences to be easily inferred from between-unit observations
  - Often not possible based on ethical and/or political grounds
- Causal effect estimation is possible with observational data, but not necessarily the goal of a quantitative outcome evaluation
  - Regression based methods
  - Propensity score methods

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Planning, conducting and presenting a quantitative evaluation

- Influencing the research design stage
- Scoping and operationalising research questions
  - Features of the policy/initiative
  - Data availability
  - Mapping data to appropriate outcomes
  - Formalising analysis approach
- Conducting the analysis
  - Skills assessment
- Presenting the results
  - Graphical and verbal methods
  - Quantify uncertainty
- Influencing policy and decision-making

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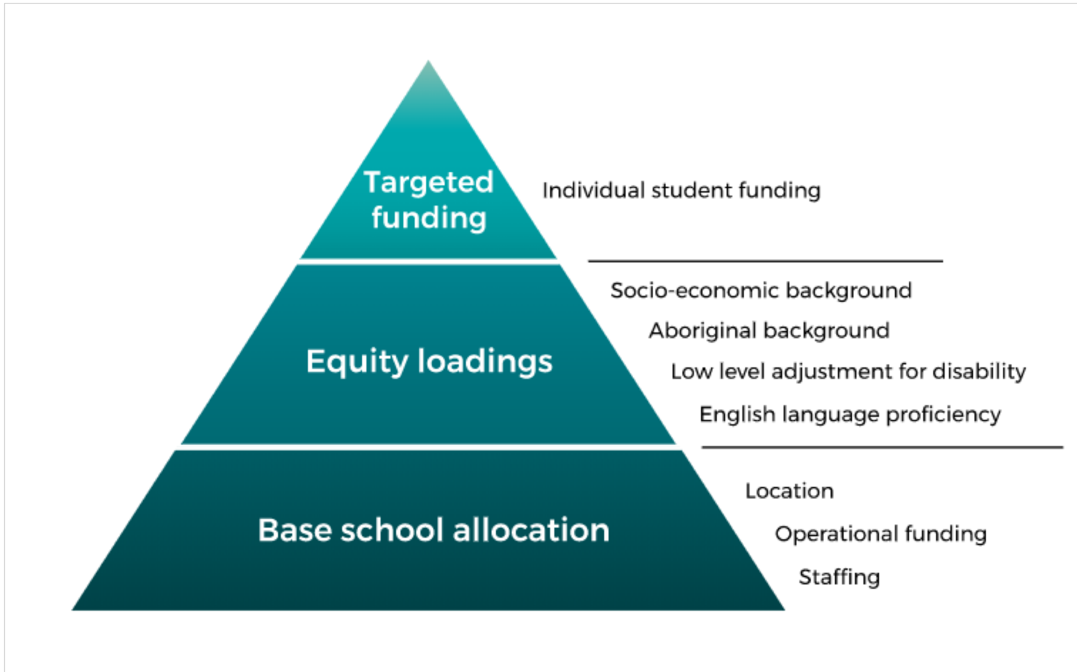
Scoping and operationalising research questions

Local Schools, Local Decisions (LSLD) evaluation

- Progressively implemented since 2012, LSLD includes 37 different initiatives
  - Almost all initiatives in place by the end of 2016
- Includes a phased transition to a needs-based funding model for NSW schools
  - Resource Allocation Model (RAM) - $667M



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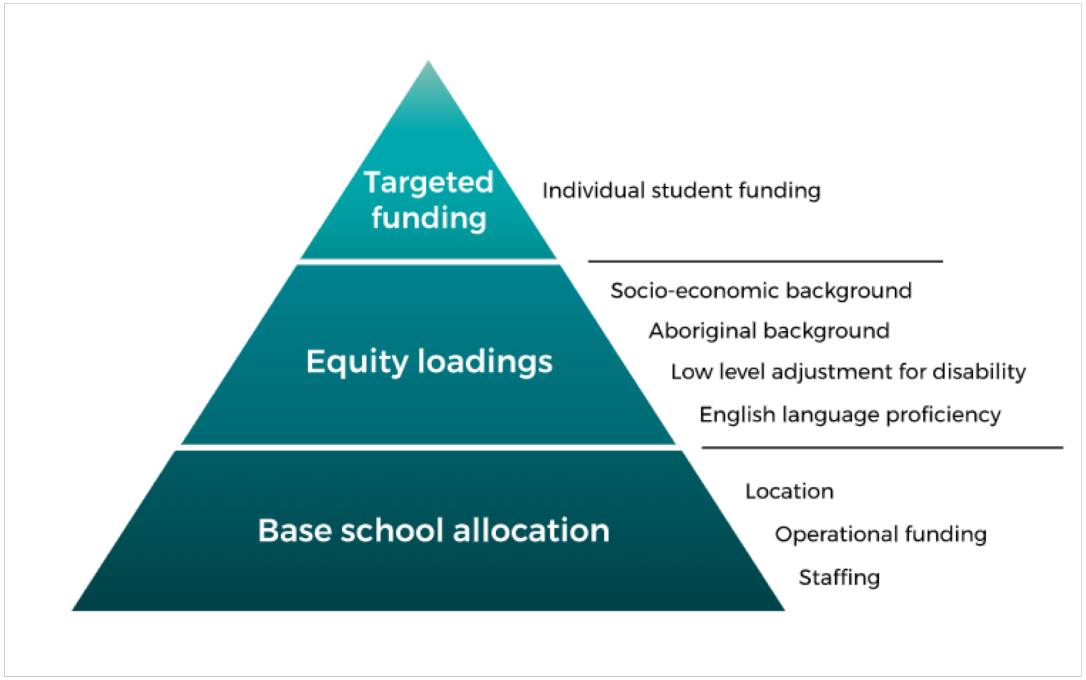

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What has been the impact of LSLD and RAM funding on school and student outcomes?

- Could not identify counterfactual potential outcomes due to the systemic nature of the policy
- Formulate predictions based on program logic
  - We predicted that schools with higher levels-of-need would show greater changes across time than those with lower levels-of-need

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- Map data to outcomes
  - Use attendance data from 2011 through 2016
  - Use *Tell Them From Me* (TTFM) data from 2013 and 2016
  - Others…

- Formalise analysis approach
  - Use latent variable growth curve models to estimate school-specific changes in outcomes across time
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$$\text{level of need}_s = \ln\left(\frac{\sum_{i=1}^{4} \text{RAM equity loading}_{si}}{\left(\left(\sum_{p=1}^{6}\sum_{c=1}^{4} \text{enrolment count}_{spc}\right)/4\right)}\right)$$

- Map data to outcomes

$$n_{st} = \text{number of enrolment days}_{st} = \sum_{p=1}^{6}\sum_{c=1}^{4} \text{enrolment count}_{stpc} \cdot \text{school days}_{stpc}$$

$$y_{st} = \text{number of attended days}_{st} = n_{jt} - \sum_{p=1}^{6}\sum_{c=1}^{4} \text{absent days}_{stpc}$$

- Formalise analysis approach

$$y_{st} \sim \text{Binomial}(n_{st}, \pi_{st}),$$

$$g(\pi_{st}) = (\beta_{00} + \beta_{01} \cdot \text{need GMC}_s + \beta_{02} \cdot \text{need GMC}_s^2 + e_{st} + u_{0s}) + (\beta_{10} + \beta_{11} \cdot \text{need GMC}_s + \beta_{12} \cdot \text{need GMC}_s^2 + u_{1s}) \cdot \text{time}_{st} + \beta_{20} \cdot \text{time}_{st}^2 + \beta_{30} \cdot \text{ICSEA CMC}_{st},$$

$$\text{for } t = 0,1,\ldots,T \text{ calendar years and } s = 1,2,\ldots,n_t \text{ schools, and } e_{st} \sim N(0,\sigma_e^2) \text{ and } \mathbf{u}_s \sim MN\left[\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma_{u0}^2 & \sigma_{01}\\ \sigma_{10} & \sigma_{u1}^2\end{pmatrix}\right].$$

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Presenting the results

Local Schools, Local Decisions (LSLD) evaluation

Table G3
Parameter estimates obtained from the final attendance model – primary schools

				Wald based 95% confidence intervals	
Model parameter	Point estimate	Standard error	*p* value	Lower limit	Upper limit
$\boldsymbol{\beta_{00}}$	2.69	0.01	<.005	2.67	2.70
$\boldsymbol{\beta_{01}}$	-0.20	0.01	<.005	-0.22	-0.19
$\boldsymbol{\beta_{02}}$	-0.03	0.01	<.005	-0.04	-0.01
$\boldsymbol{\beta_{10}}$	0.04	0.00	<.005	0.04	0.04
$\boldsymbol{\beta_{11}}$	-0.00	0.00	0.30	-0.00	0.00
$\boldsymbol{\beta_{12}}$	--	--	--	--	--
$\boldsymbol{\beta_{20}}$	-0.01	0.00	<.005	-0.01	-0.01
$\boldsymbol{\beta_{30}}$	0.00	0.00	<.005	0.00	0.00
$\boldsymbol{\sigma_{e}}$	0.11	--	--	--	--
$\boldsymbol{\sigma_{u0}}$	0.21	--	--	--	--
$\boldsymbol{\sigma_{u1}}$	0.03	--	--	--	--
$\mathbf{Corr}(\boldsymbol{\sigma_{u0}}, \boldsymbol{\sigma_{u1}})$	-0.54	--	--	--	--

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β_{12}	--	--	--	--	--
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β_{30}	0.00	0.00	<.005	0.00	0.00
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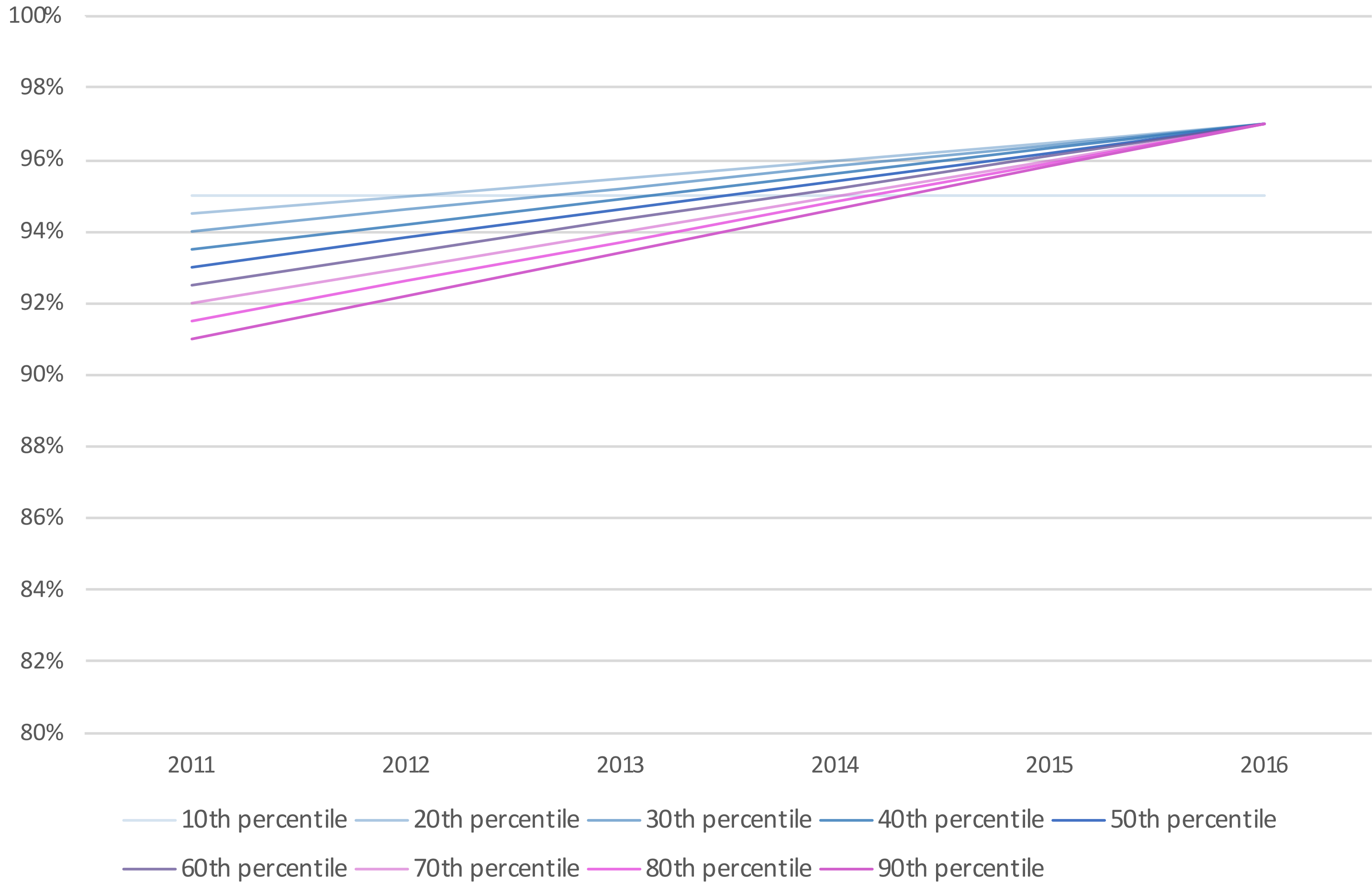
Local Schools, Local Decisions (LSLD) evaluation

- Hypothesised attendance rates for primary schools with different levels-of-need



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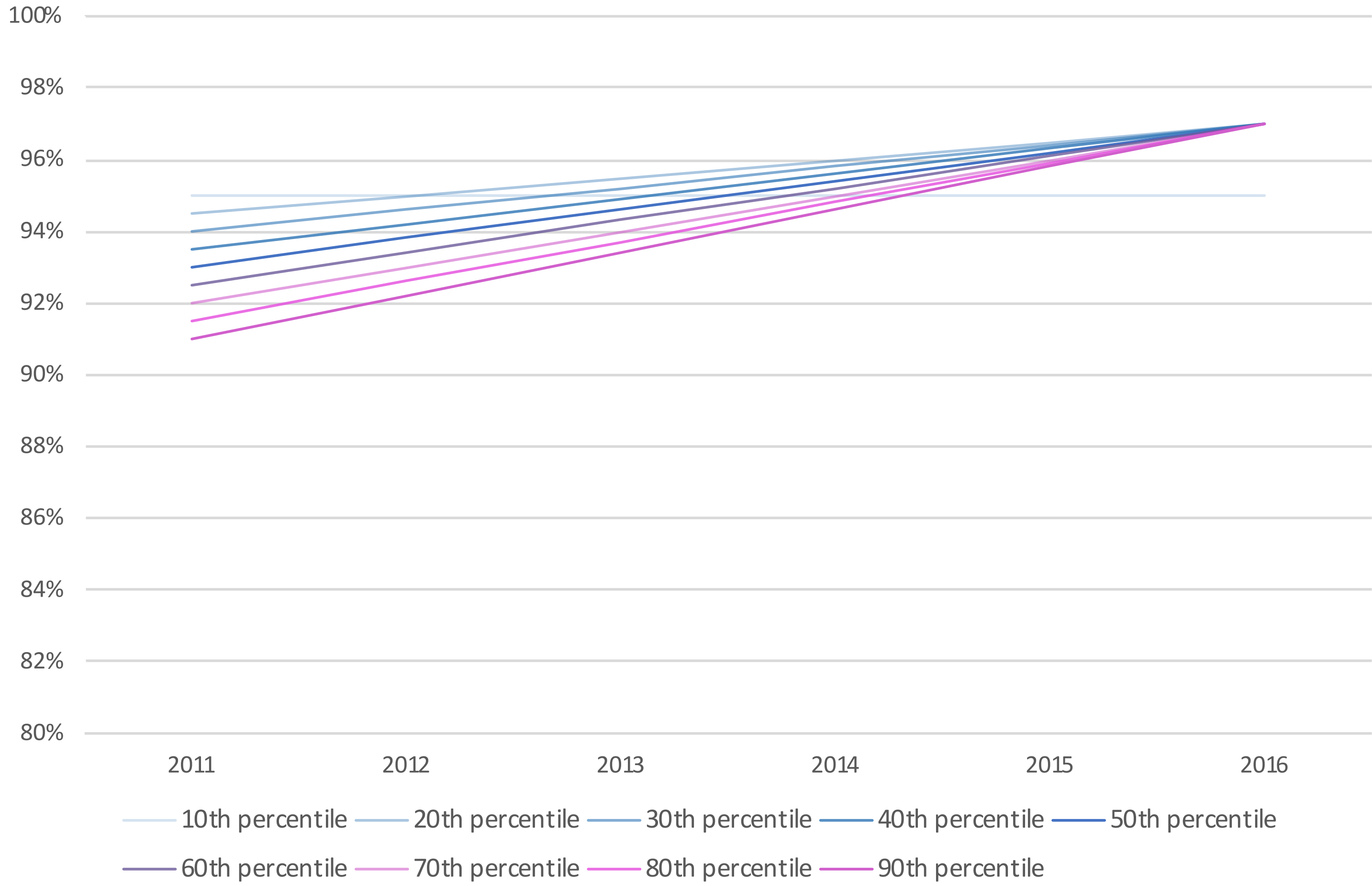

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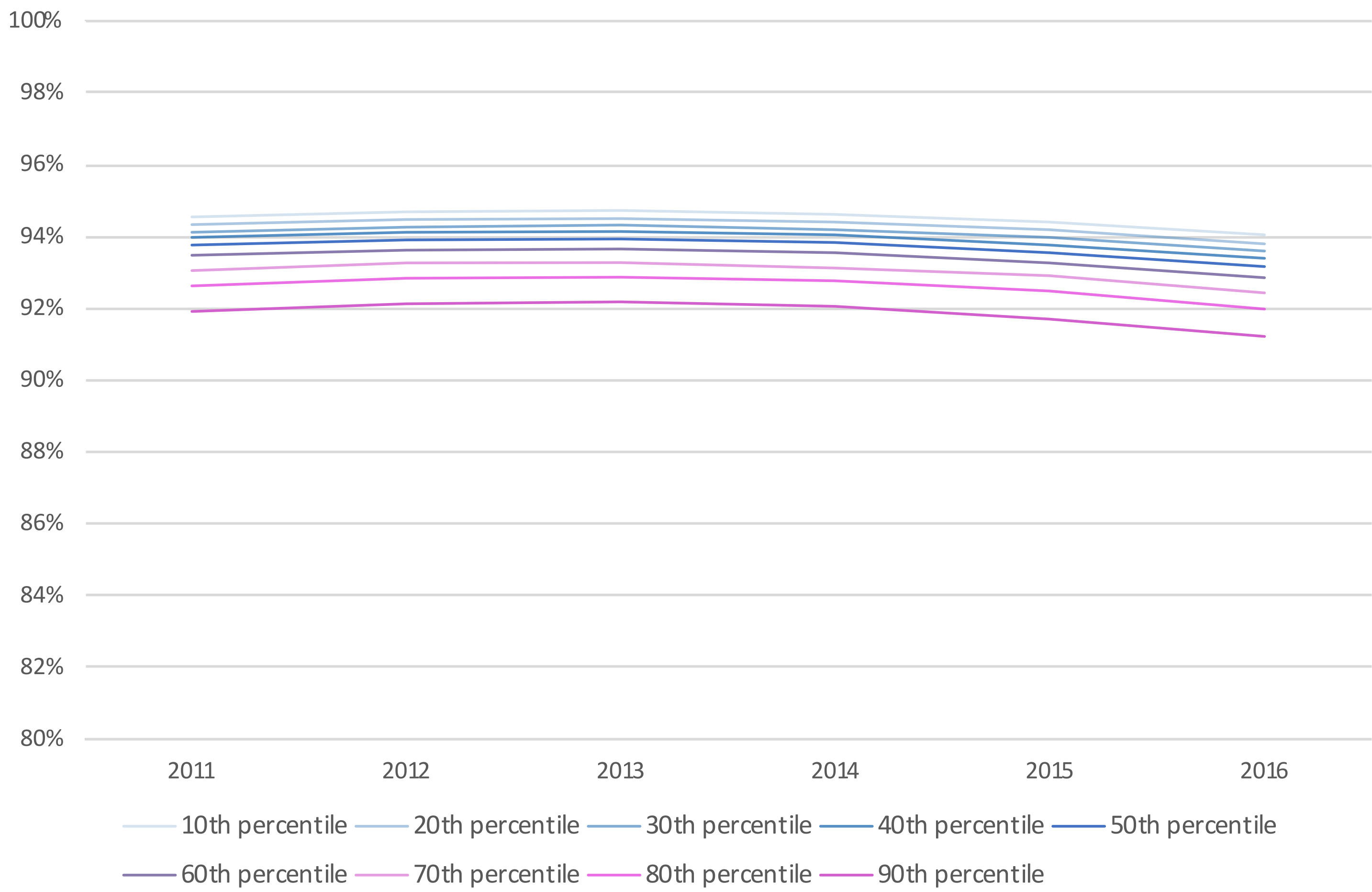
- Predicted attendance rates for **primary schools** with different levels-of-need



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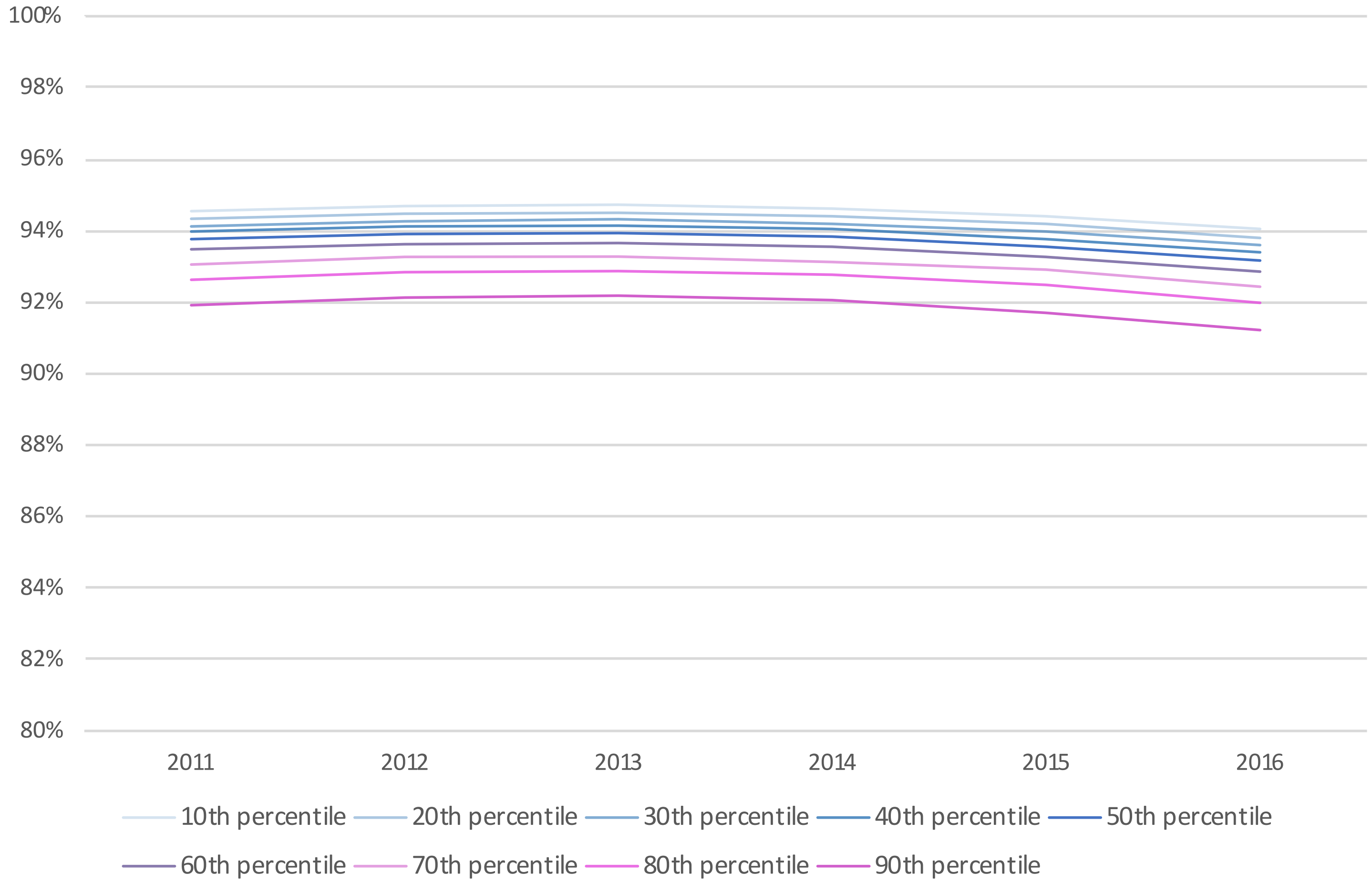

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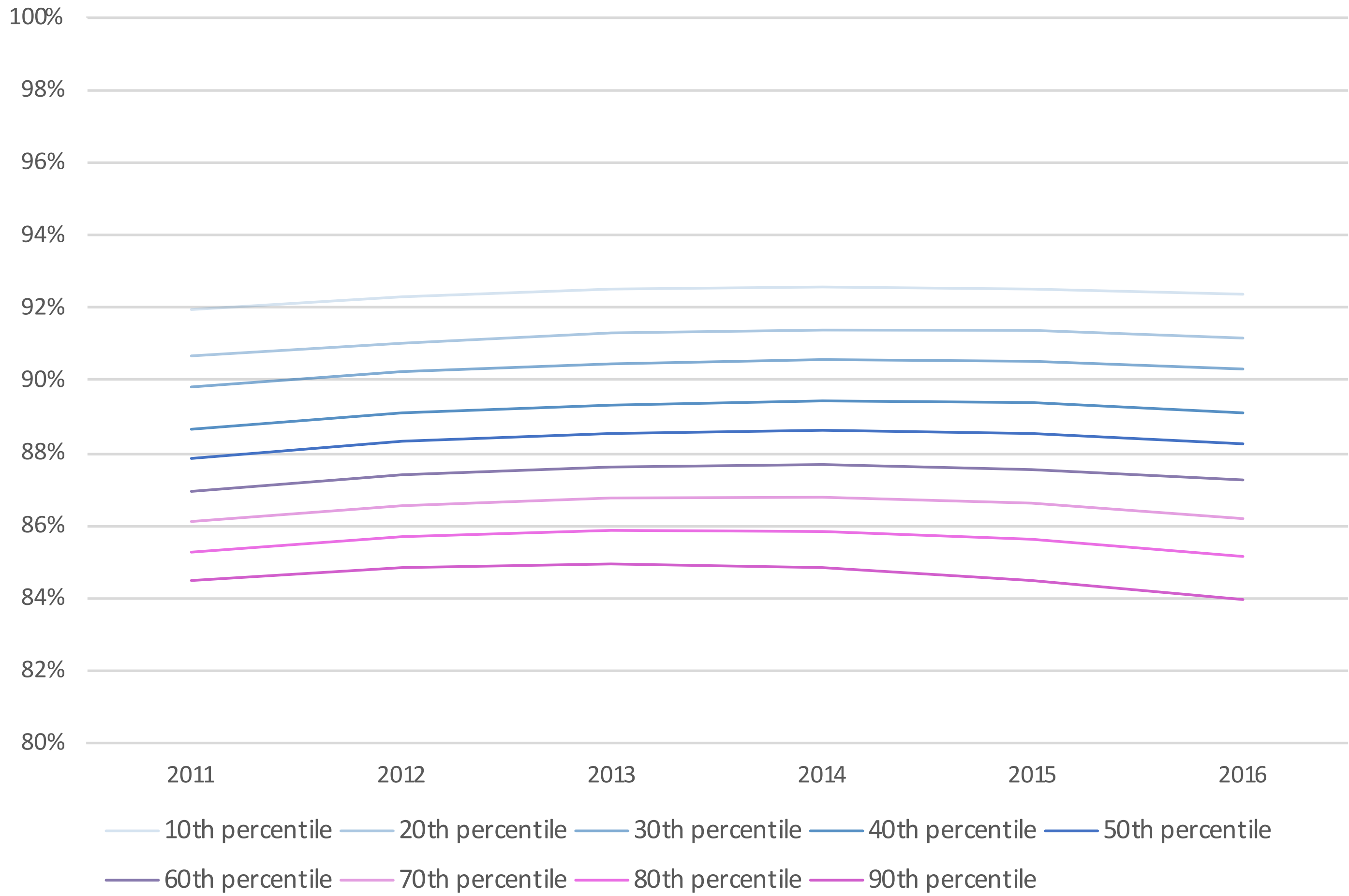
- Predicted attendance rates for **secondary schools** with different levels-of-need



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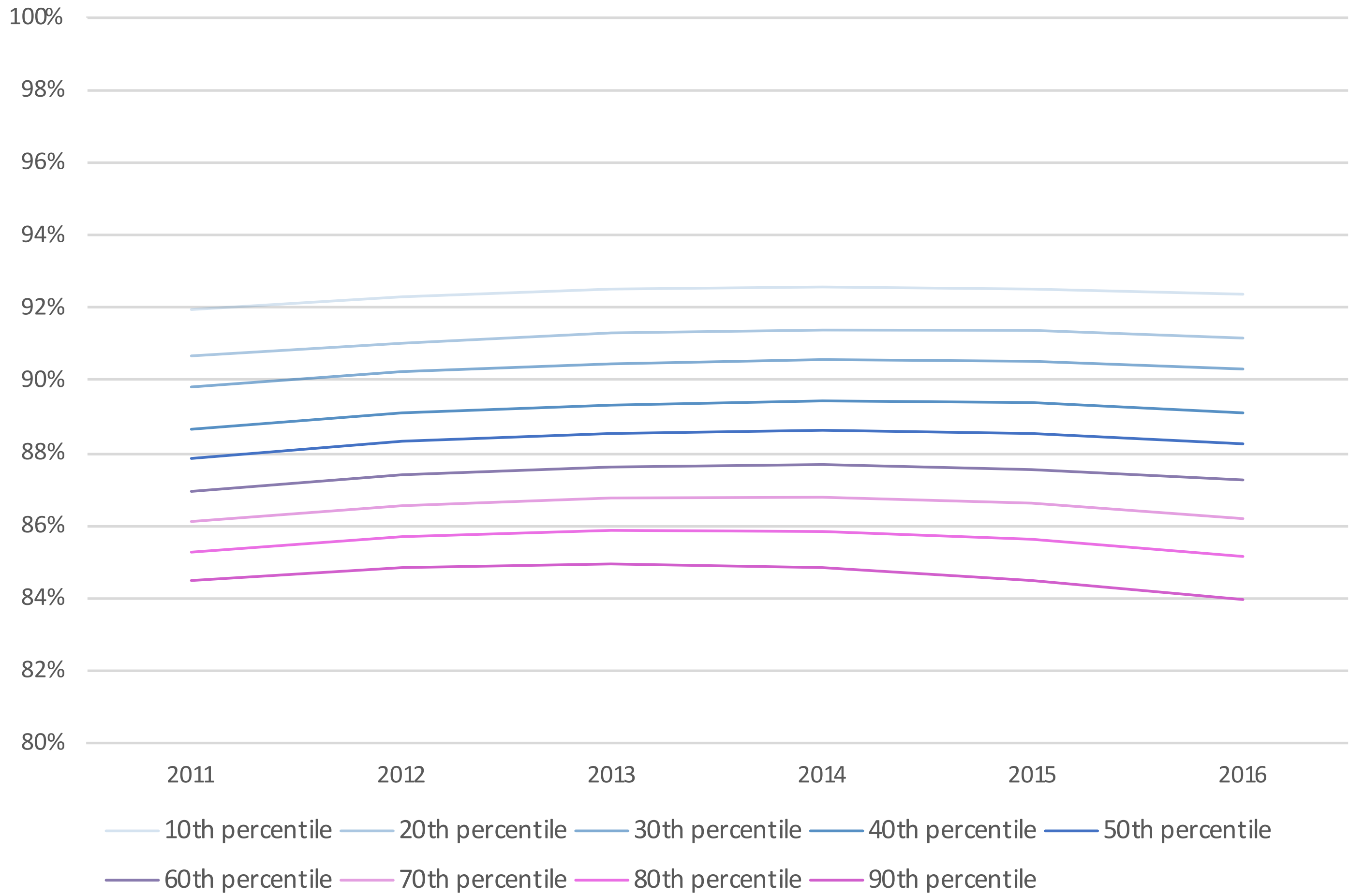

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- Map data to outcomes
    - During the past 4 weeks how often have you been spoken to by a teacher or principal for any of the following reasons:

	Never	Once a week	2/3 times a week	Almost every day
Being disruptive in class	X			
Making inappropriate comments		X		
Getting into fights	X			
Breaking a school rule		X		
Lying or cheating			X	

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Step 1) $$\Pr(Y_{ij} = k|\alpha_i, \boldsymbol{\beta}_i, \theta_j) = \frac{\exp(k\alpha_i\theta_j + \beta_{ik})}{1 + \sum_{s=1}^{K_i}\exp(s\alpha_i\theta_j + \beta_{is})}$$

Step 2) $$f(\mathbf{y}_j|\widehat{\mathbf{B}}, \theta_j) = \prod_{i=1}^{I}\Pr(Y_{ij} = y_{ij}|\widehat{\mathbf{B}}, \theta_j)$$

Step 3) $$L_j(\widehat{\mathbf{B}}) = \int_{-\infty}^{\infty} f(\mathbf{y}_j|\widehat{\mathbf{B}}, \theta_j)\phi(\theta_j)d\theta_j$$

Step 4) $$\omega(\theta_j|\mathbf{y}_j, \widehat{\mathbf{B}}) = \frac{f(\mathbf{y}_j|\widehat{\mathbf{B}}, \theta_j)\,\phi(\theta_j)}{L_j(\widehat{\mathbf{B}})}$$

Step 5) $$\tilde{\theta}_j = \int_{-\infty}^{\infty}\theta_j\omega(\theta_j|\mathbf{y}_j, \widehat{\mathbf{B}})d\theta_j$$

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$$\beta_{20} \cdot \text{ICSEA CMC}_{js} + \beta_{30} \cdot \text{Year 9 CMC}_{js} +, \ldots, + \beta_{60} \cdot \text{Year 12 CMC}_{js},$$

for $s = 1,2, \ldots, 80$ schools, $j = 1,2, \ldots, n_s$ students,

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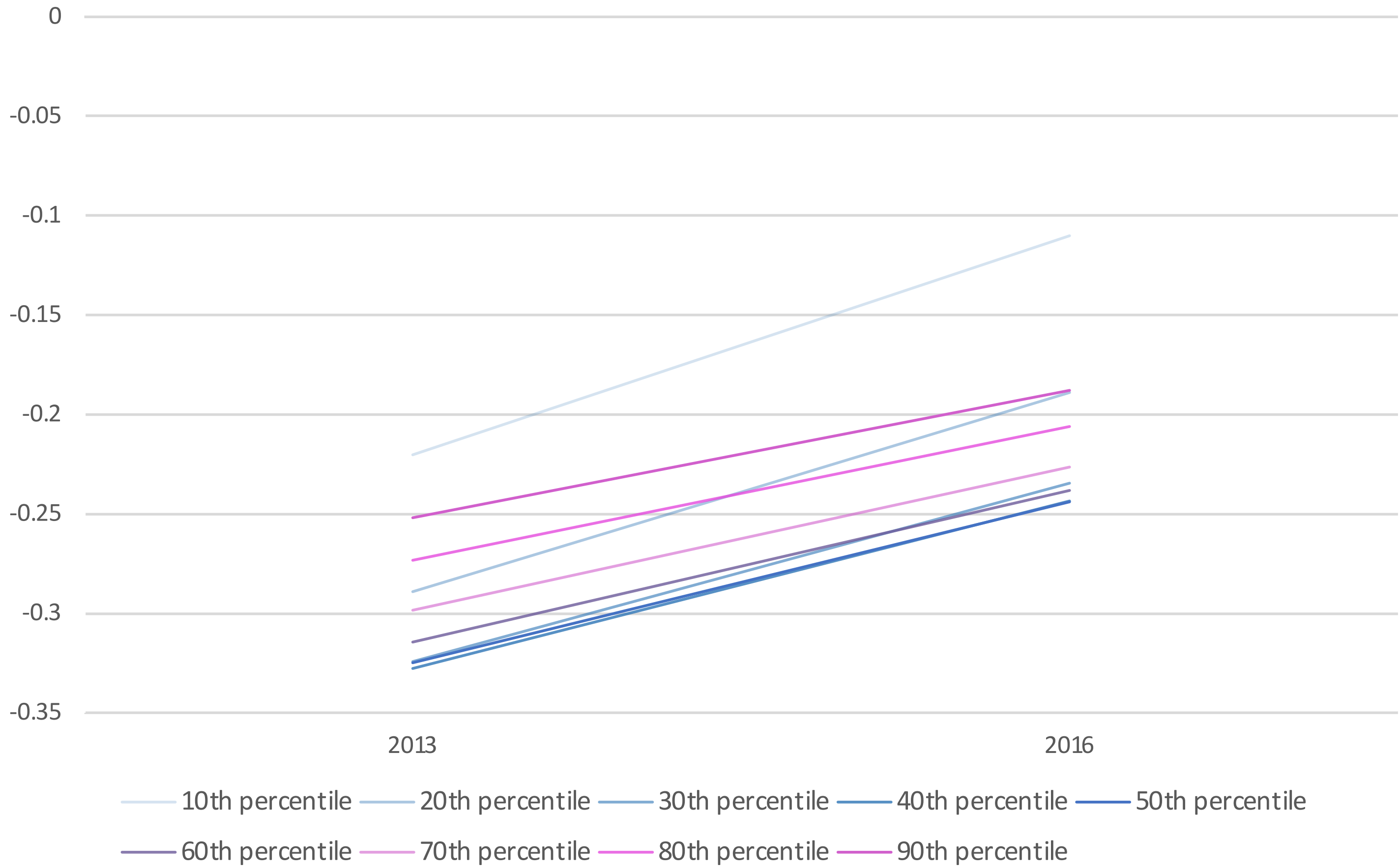

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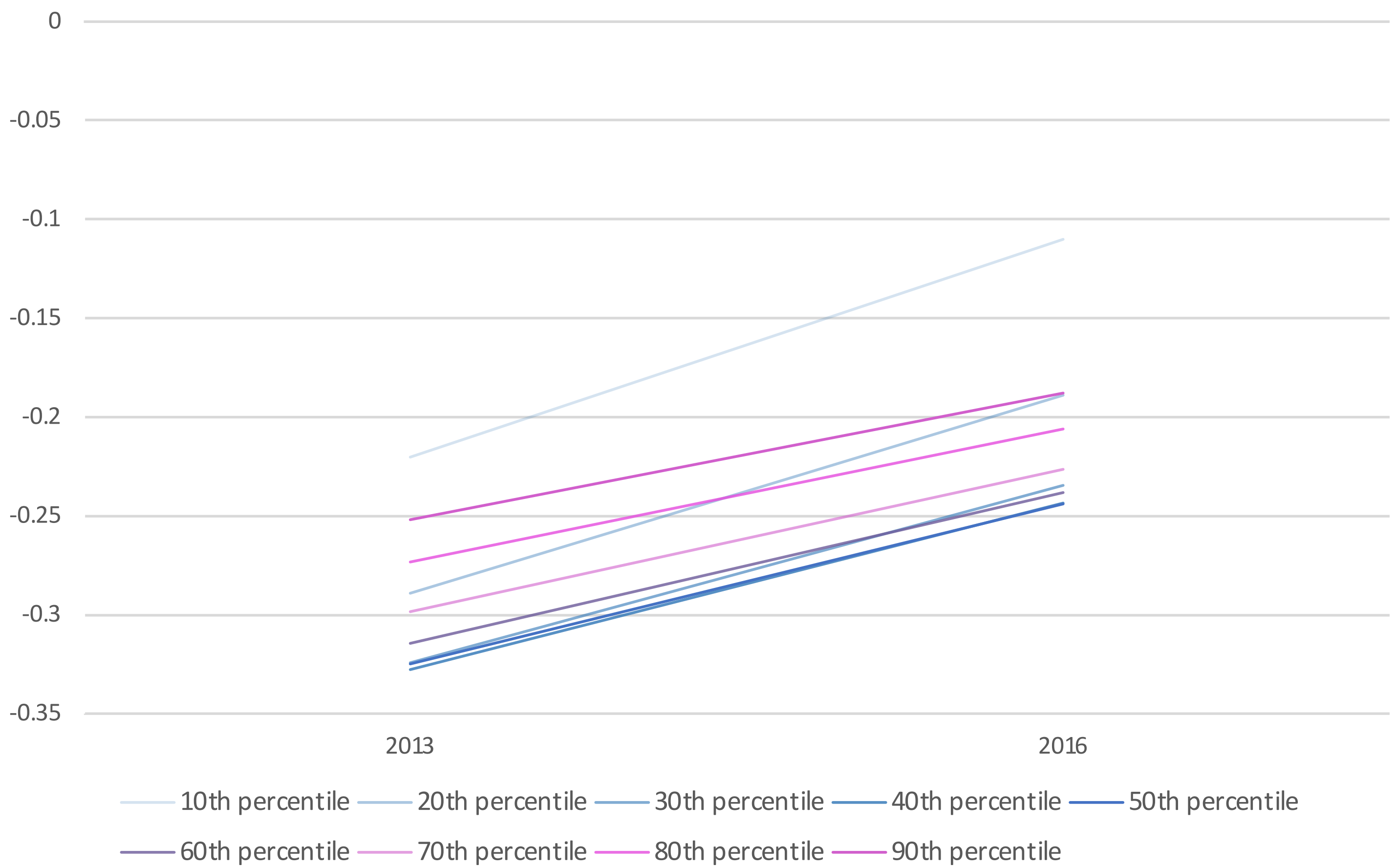

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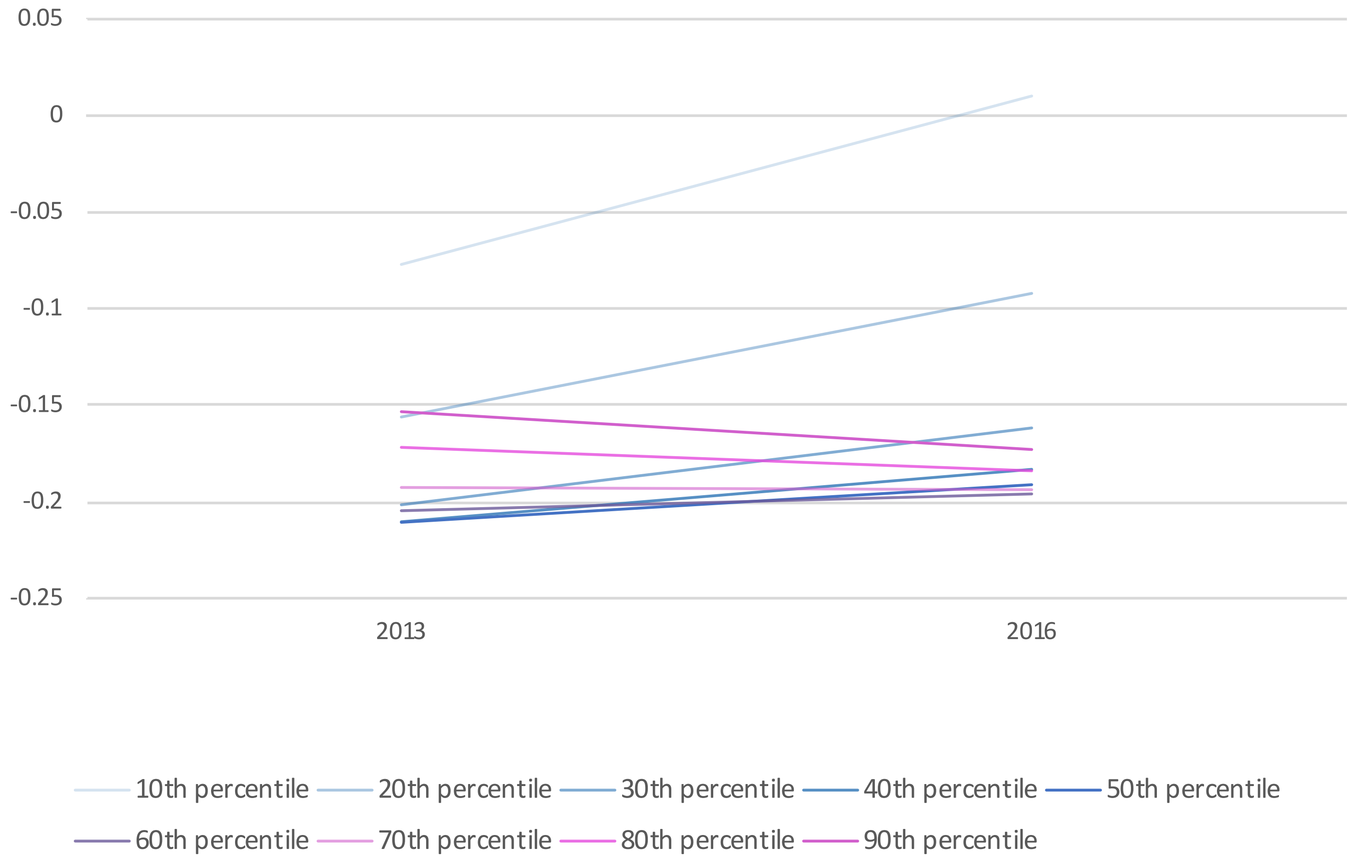

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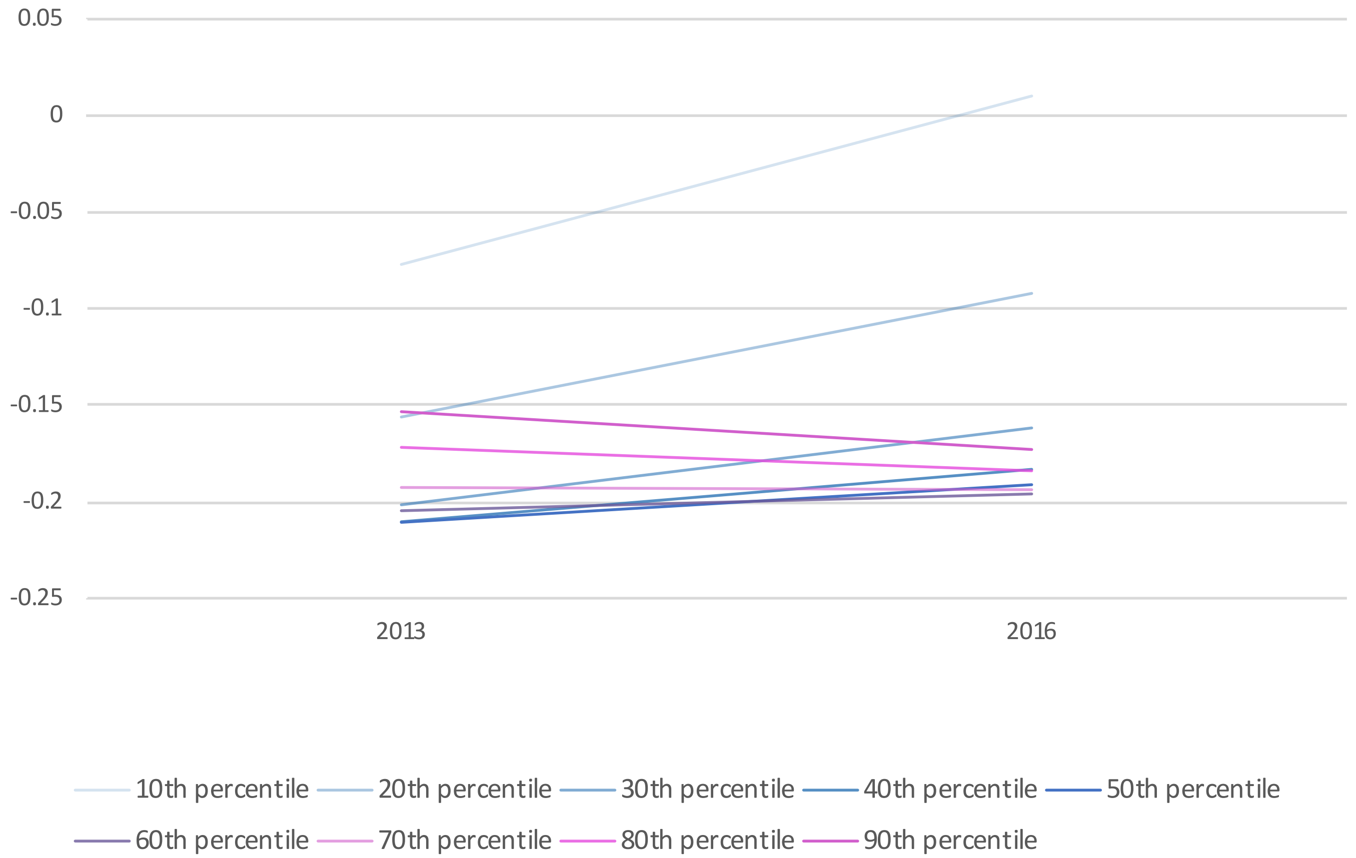

Scoping and operationalising research questions

Reading Recovery (RR) evaluation

- Literacy intervention targeting students in the bottom 20% of Year 1
- Involves one-to-one literacy tuition over a 12 to 20 week time period
- Offered in over half (approximately 60%) of NSW government primary schools
- In 2018, approximately 14% of all Year 1 students participate in the intervention (costing $50M)

Are literacy outcomes for students who participate in RR greater than those for comparable students who do not participate in RR?

- Possible to identify counterfactual potential outcomes using quasi-experimental methodologies
    - Requires good data and diagnostics
    - Also requires some untestable assumptions

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- Map data to outcomes
  - Use Literacy Continuum data from the end of Year 1
  - Also include baseline data from Term 4 Kindergarten and other student- and school-level factors to control for the impact of important confounders

- Formalise analysis approach
  - Use a series of ordered logistic mixed-effects regression models to estimate the effect of RR
  - Model the interaction between treatment and baseline literacy measures to assess treatment effect heterogeneity

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Reading Recovery (RR) evaluation

- Features of the policy/initiative

$$\text{treat}_{\text{js}} \begin{cases} = 1 \text{ if student j in school s was a Reading Recovery student} \\ = 0 \text{ otherwise} \end{cases}$$

- Map data to outcomes

$$y_{\text{jsa}} \begin{cases} = 1 \text{ if student j in school s was placed in the first cluster of the } a^{th} \text{Literacy Continuum aspect at the end of Year 1} \\ = 2 \text{ if student j in school s was placed in the second cluster of the } a^{th} \text{Literacy Continuum aspect at the end of Year 1} \\ \vdots \\ = K \text{ if student j in school s was placed in the } k^{th} \text{ cluster of the } a^{th} \text{Literacy Continuum aspect at the end of Year 1} \end{cases}$$

for $a = 1,2, \ldots, 7$ Literacy Continuum aspects

- Formalise analysis approach

$$\begin{aligned} \Pr(y_{\text{js}} > k) = g(&\beta_1 \cdot \text{treat}_{\text{js}} + \beta_2 \cdot \text{T4 K Reading } 2_{\text{js}} + \beta_3 \cdot \text{T4 K Reading } 3_{\text{js}} + \beta_4 \cdot \text{T4 K Reading } 4_{\text{js}} + \\ &\beta_5 \cdot (\text{treat}_{\text{js}} \cdot \text{T4 K Reading } 2_{\text{js}}) + \beta_6 \cdot (\text{treat}_{\text{js}} \cdot \text{T4 K Reading } 3_{\text{js}}) + \beta_7 \cdot (\text{treat}_{\text{js}} \cdot \text{T4 K Reading } 4_{\text{js}}) + \\ &\textstyle\sum_{c=1}^{34} \gamma_c \cdot x_{\text{cjs}} + u_s - \alpha_k), \end{aligned}$$

for $j = 1,2, \ldots, n_s$ students, $s = 1,2, \ldots, S$ schools, $c = 1,2 \ldots, 34$ control covarites, and $k = 1,2, \ldots, K - 1$ cutpoints

Scoping and operationalising research questions

Reading Recovery (RR) evaluation

- Features of the policy/initiative

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Presenting the results

Lit. Cont. Aspect	Lit. Cont. Aspect Level (T4K)	Odds Ratio	Lit. Cont. Aspect	Lit. Cont. Aspect Level (T4K)	Odds Ratio
Reading Texts	Level 1 or below	**2.67***	**Phonics**	Level 1 or below	0.96
	Level 2	1.50		Level 2	1.01
	Level 3	**0.42***		Level 3	**0.28***
	Level 4 or above	**0.09***		Level 4 or above	**0.14***
Comprehension	Level 1 or below	1.3	**Phonemic Awareness**	Level 1 or below	0.85
	Level 2	**0.53***		Level 2	**0.52***
	Level 3	**0.30***		Level 3	**0.29***
	Level 4 or above	**0.13***		Level 4 or above	**0.22***
Aspects of Writing	Level 1 or below	0.98	**Concepts about Print**	Level 1 or below	1.11
	Level 2	**0.40***		Level 2	**0.53***
	Level 3	**0.22***		Level 3	**0.33***
	Level 4 or above	**0.11***		Level 4 or above	**0.05***
Aspects of Speaking	Level 1 or below	0.78			
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	Level 3	**0.44***			
	Level 4 or above	**0.34***			

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Scoping and operationalising research questions

Reading Recovery (RR) evaluation

- Features of the policy/initiative
  - Literacy intervention targeting students in the bottom 20% of Year 1

- Map data to outcomes
  - Use Literacy Continuum data from the end of Year 1
  - Also include baseline data from Term 4 Kindergarten and other student- and school-level factors to control for the impact of important confounders

- Formalise analysis approach
  - Use logistic regression model to estimate conditional probabilities of treatment for each student
  - Match students based on the estimated probabilities
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  - Step 1 – $\mathrm{Pr}(\mathrm{treat}_j = 1) = \mathrm{g}(\sum_{c=1}^{37} \gamma_c \cdot \mathrm{x}_{cj})$,

    $\text{for j} = 1,2, \ldots, \text{n students, and c} = 1,2 \ldots, 37 \text{ control covarites}$

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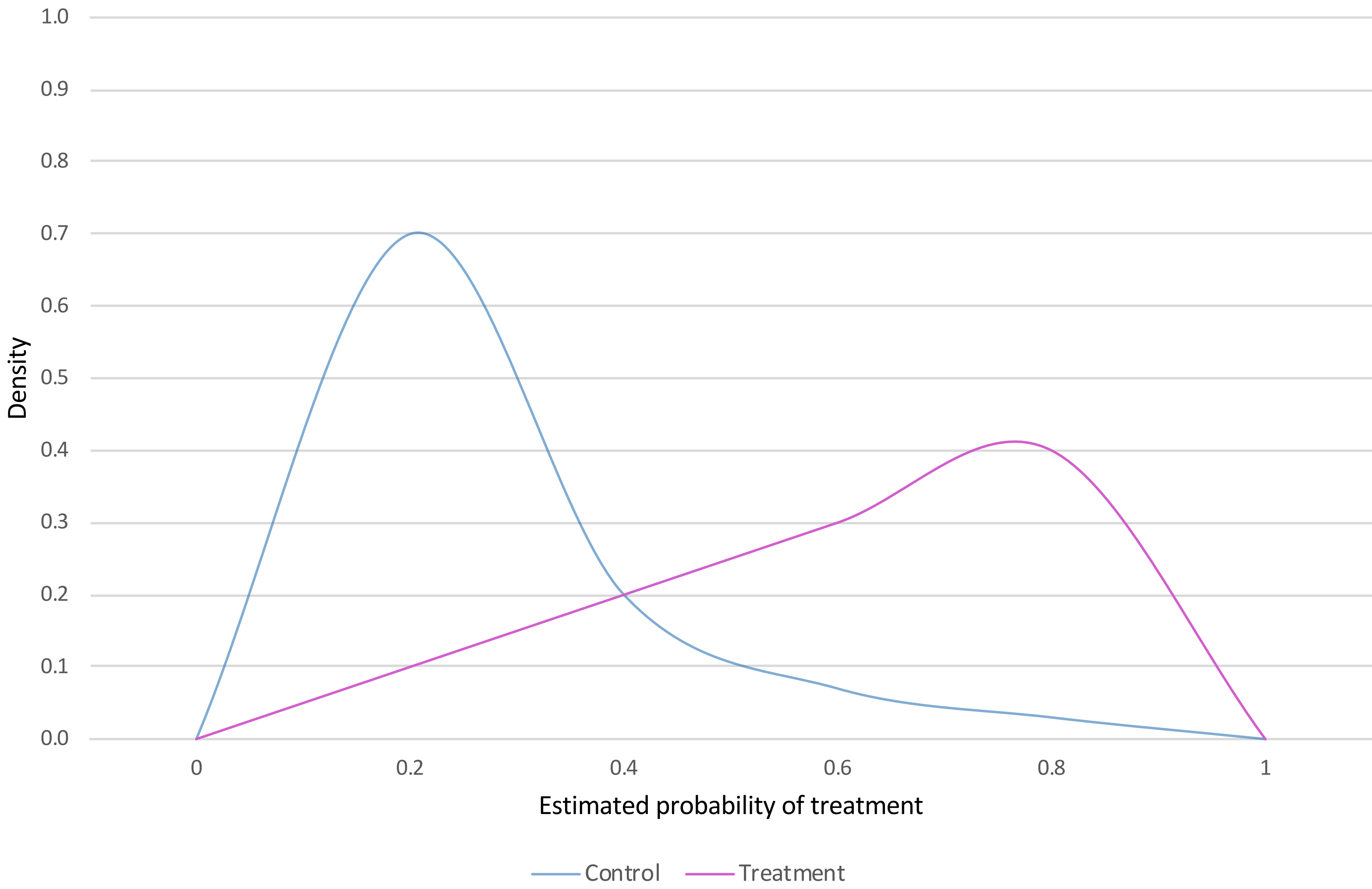

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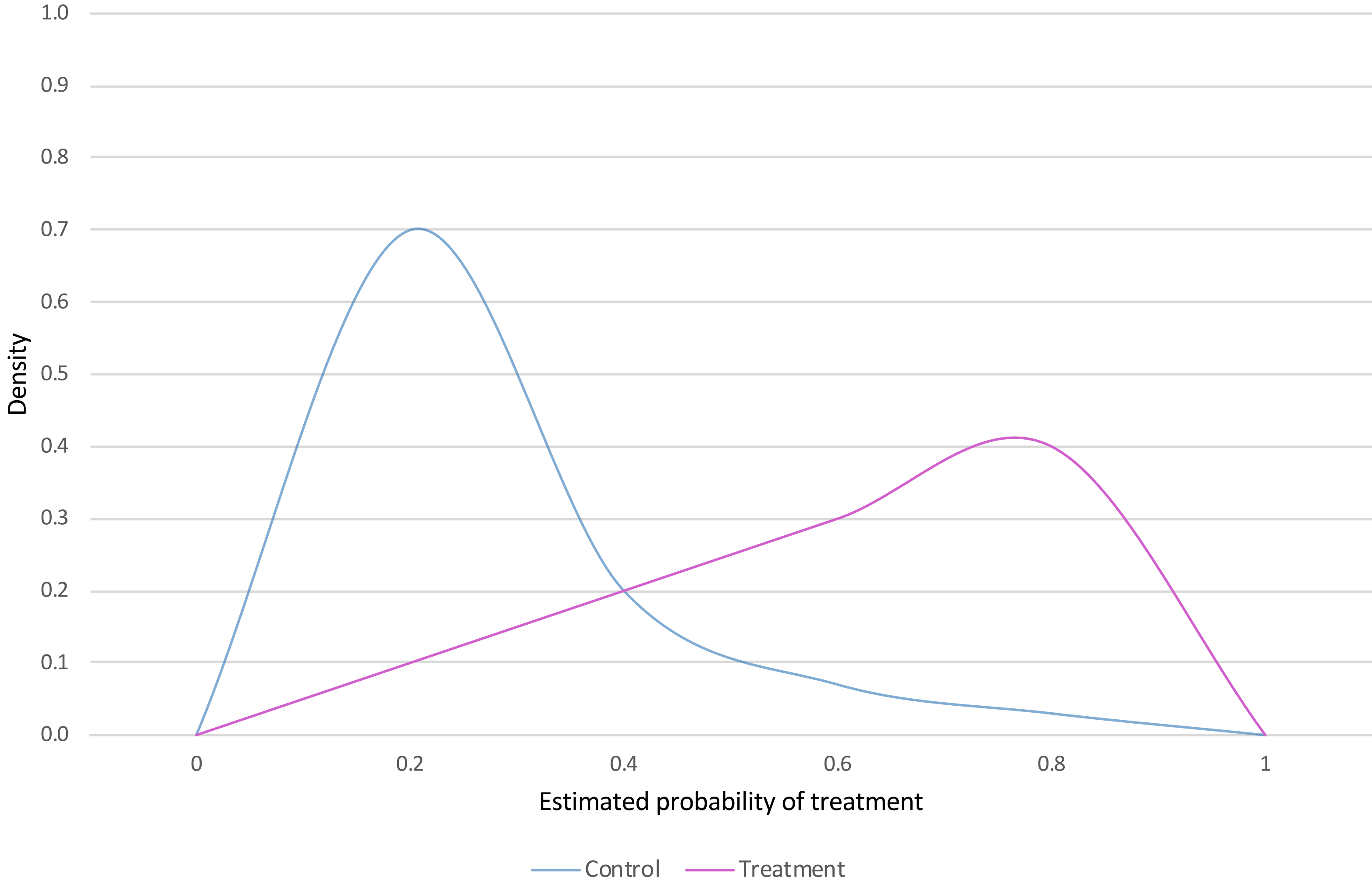

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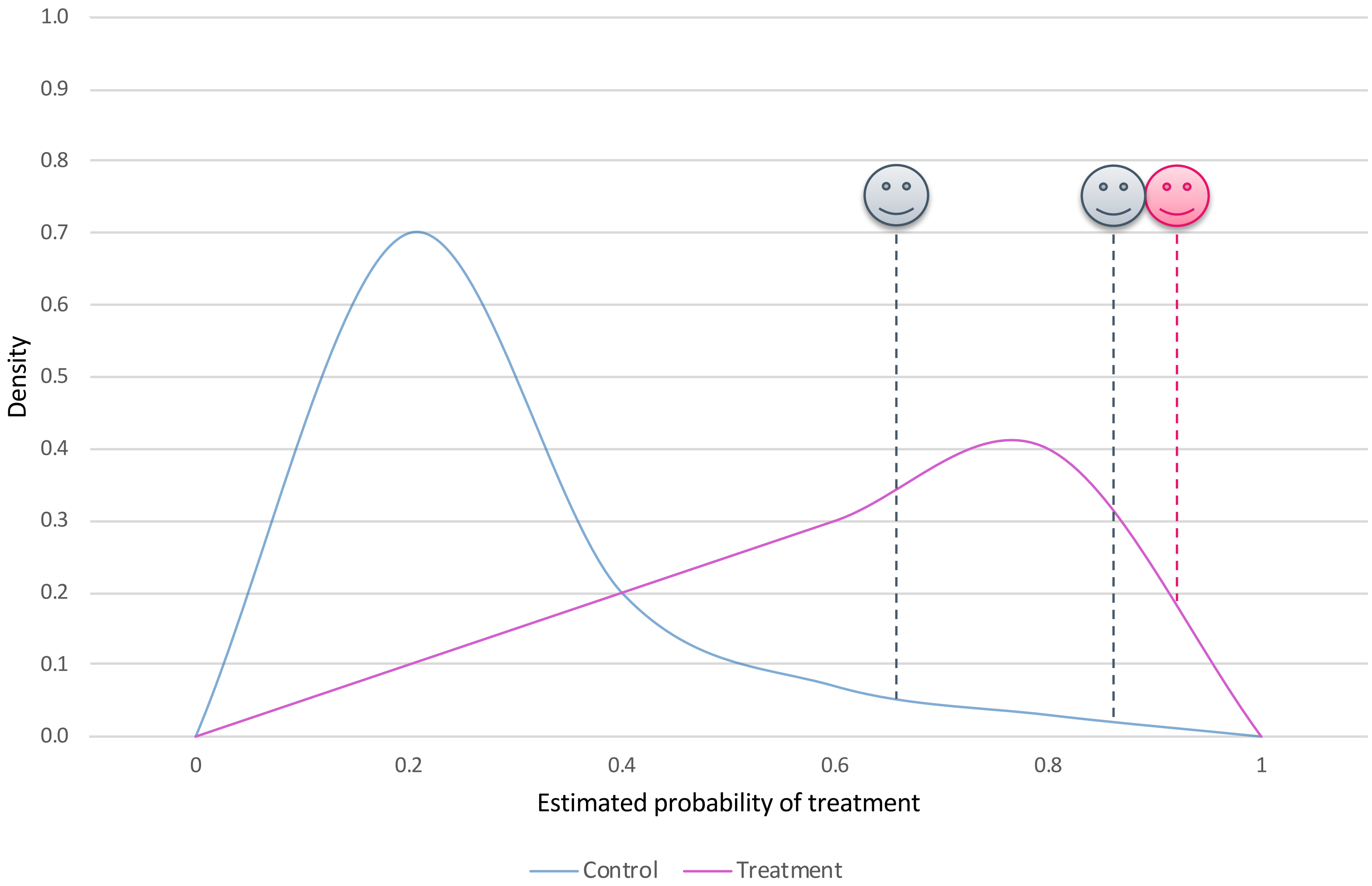

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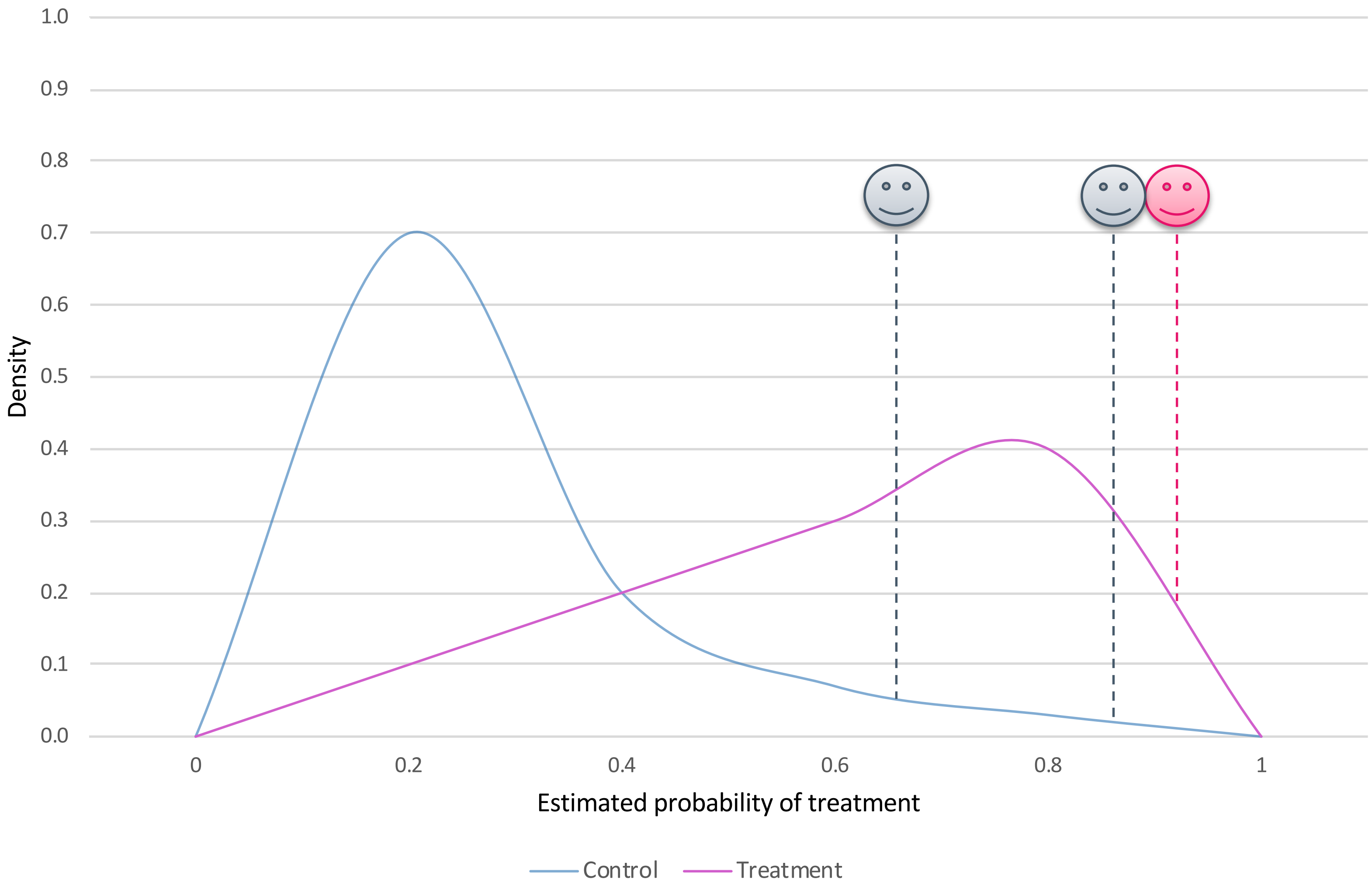

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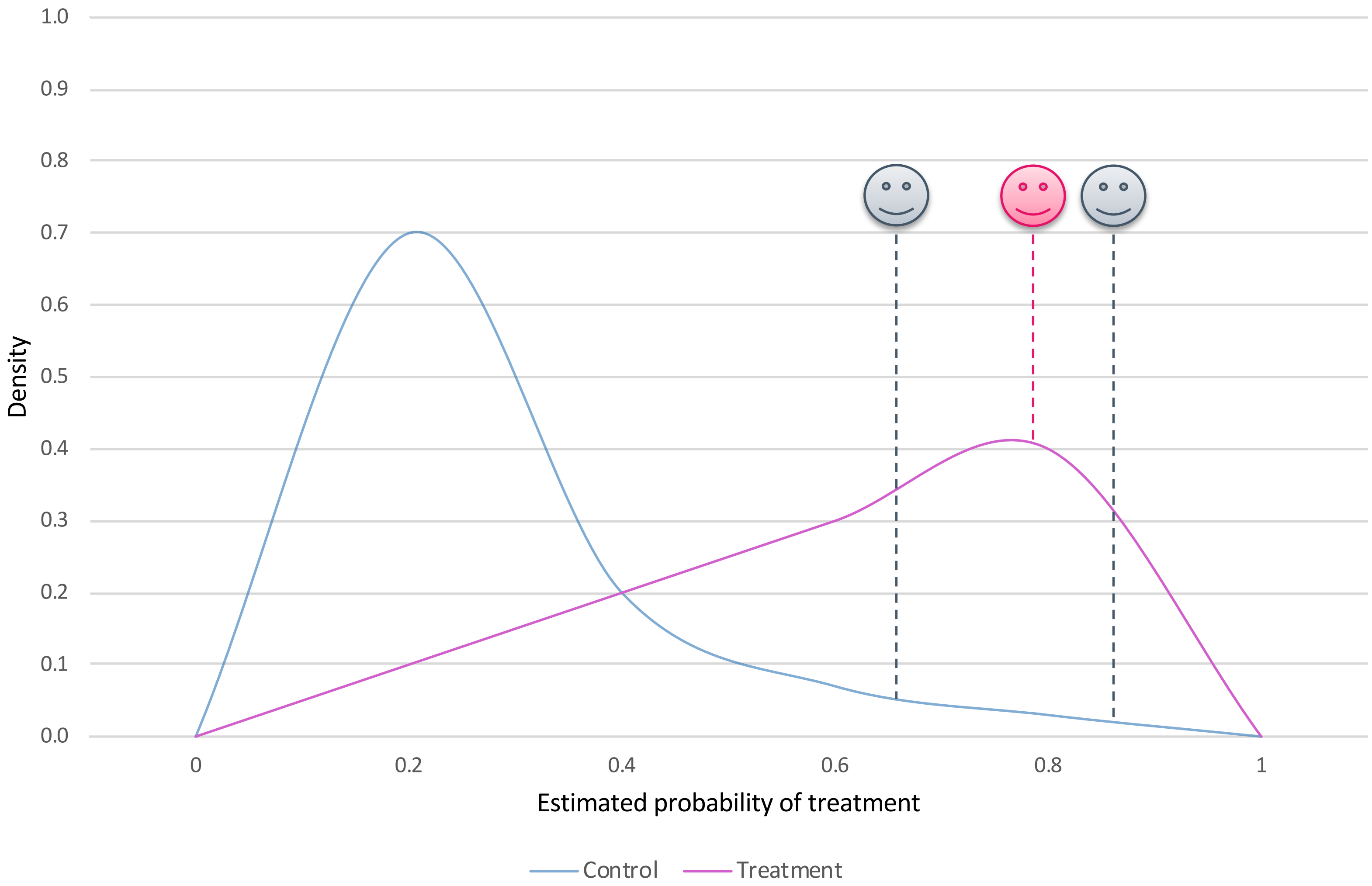

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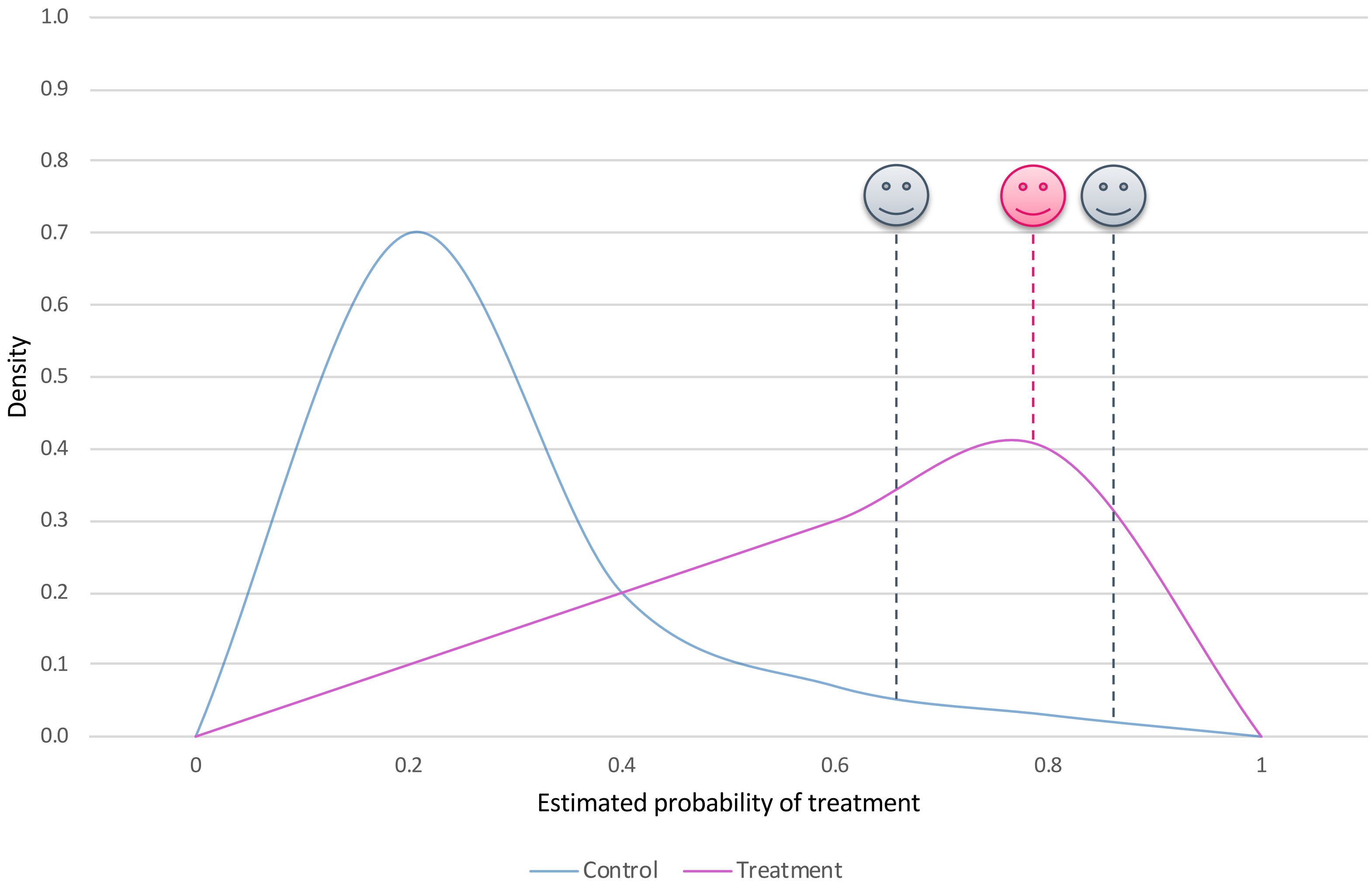

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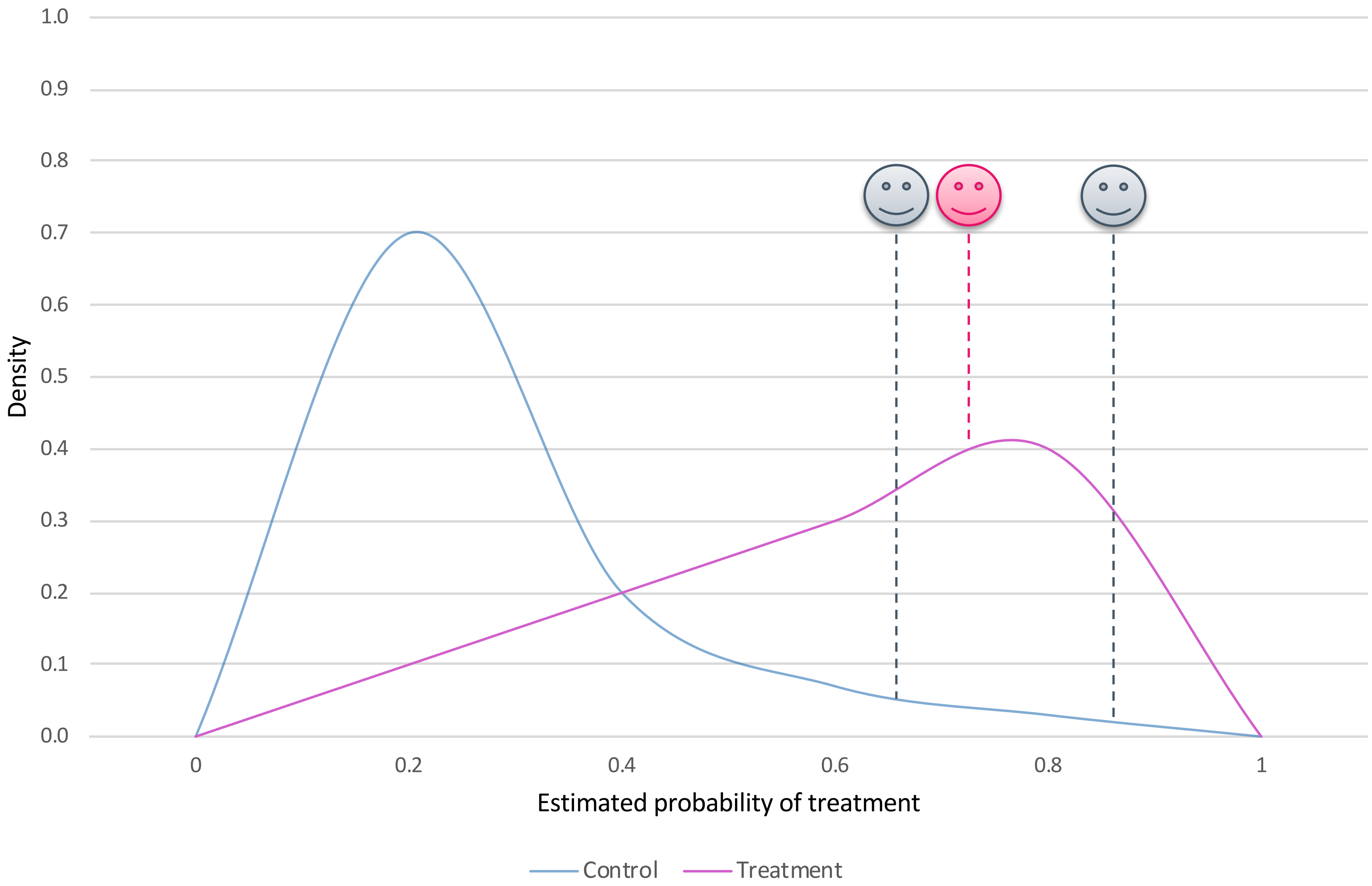

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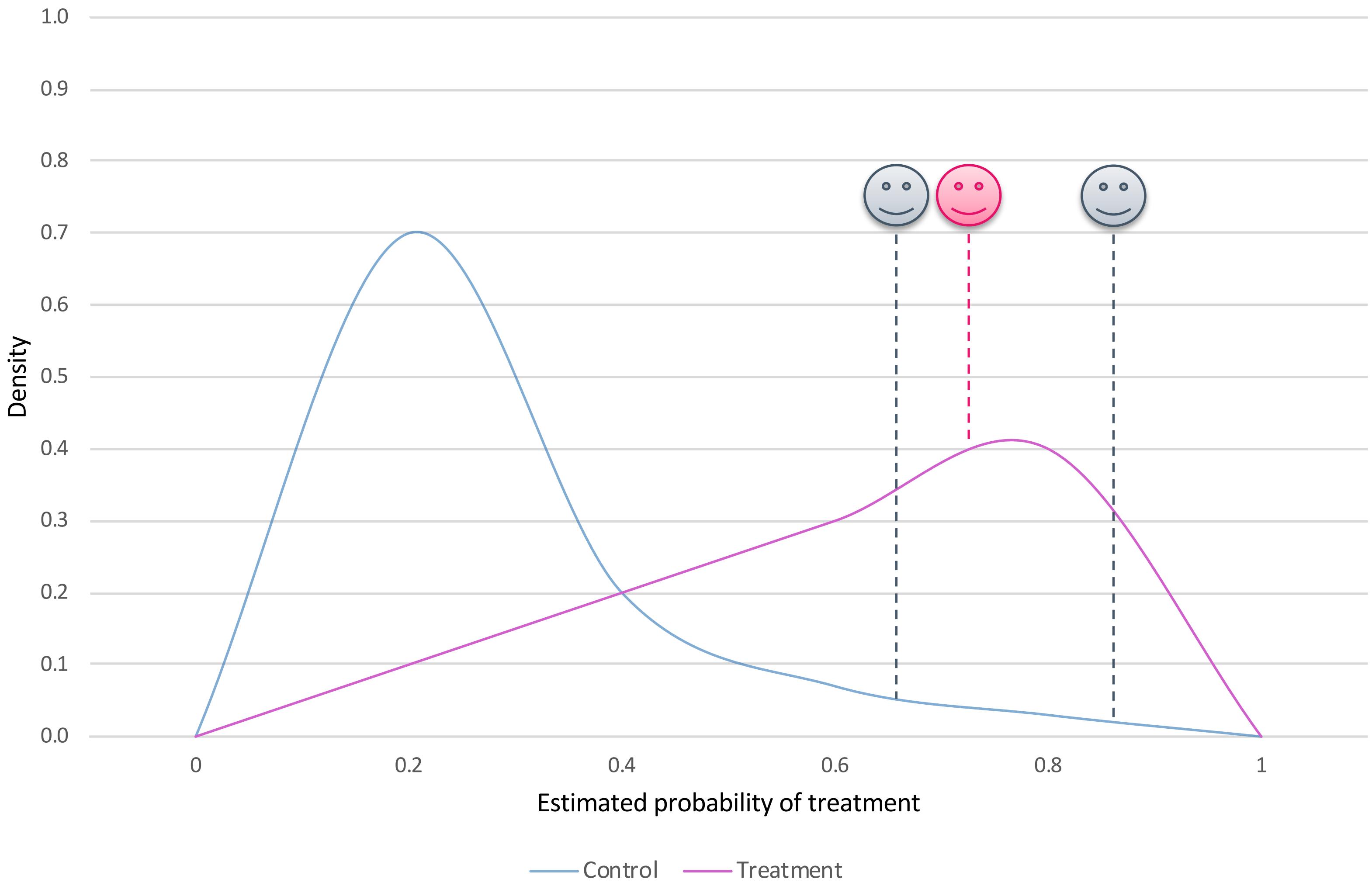

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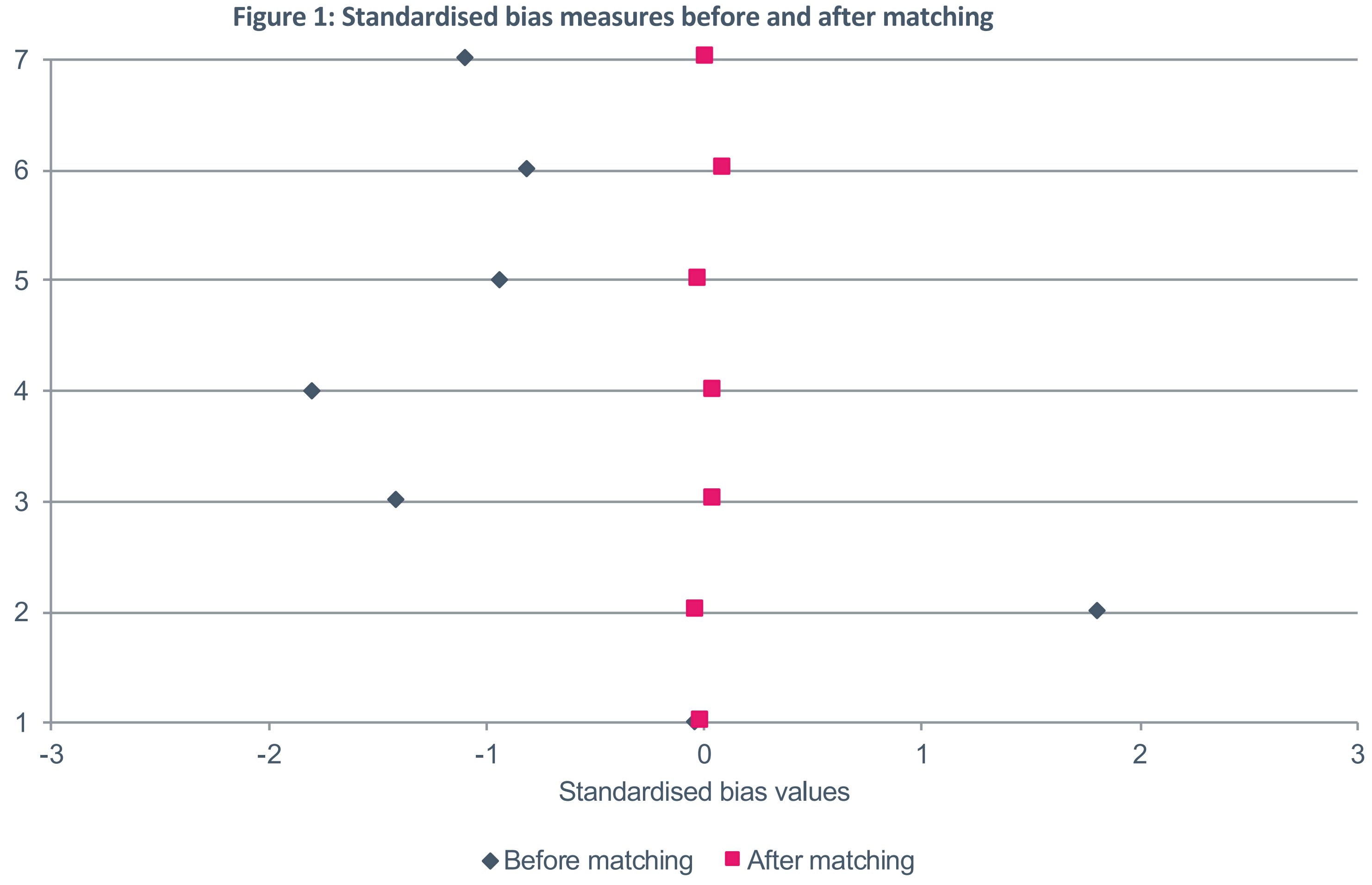

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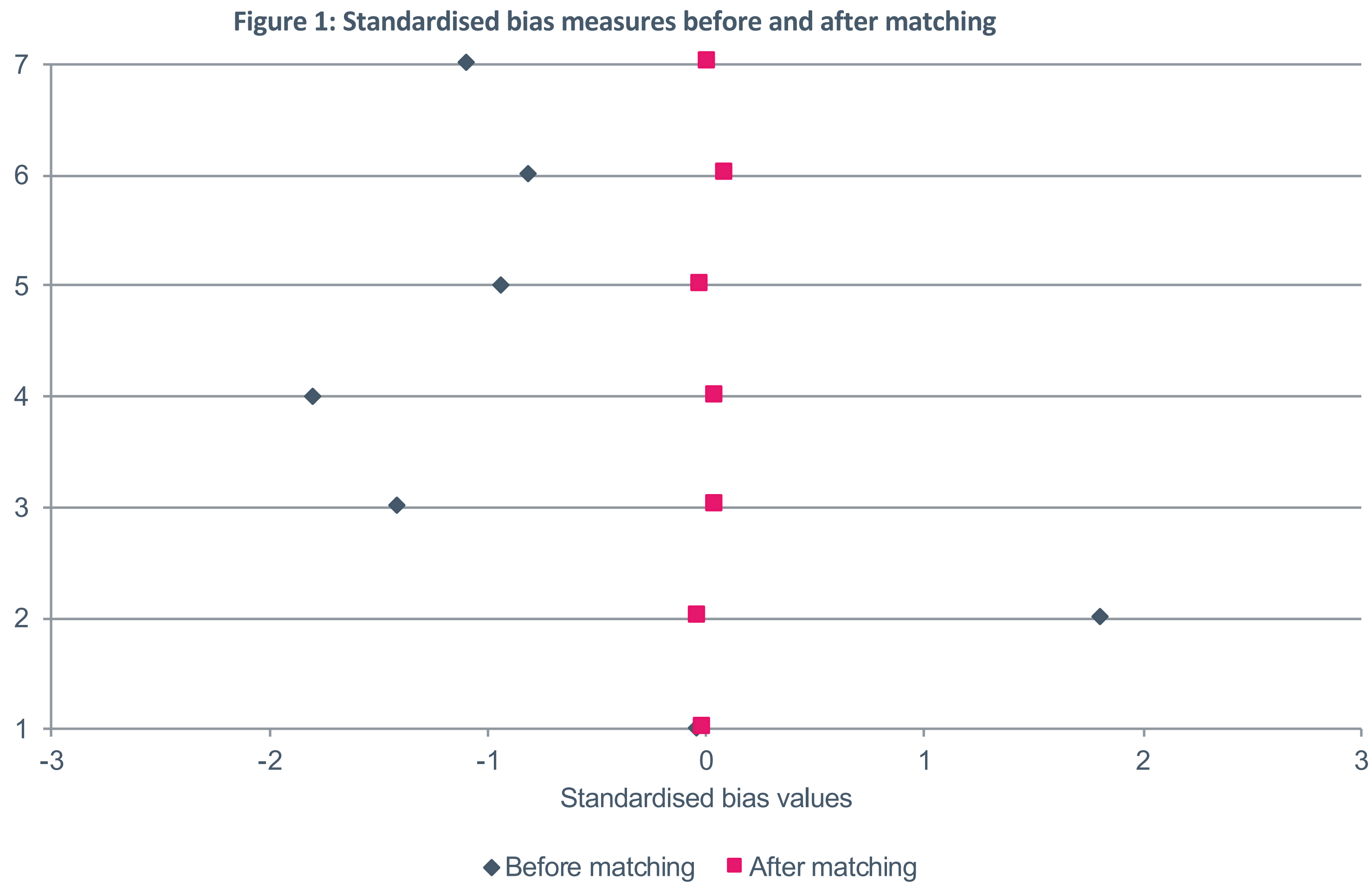

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Influencing the research design phase

Literacy and Numeracy Action Plan (LNAP) Phase 2 evaluation

- Features of the policy/initiative ($85M)
    - Instructional leadership
    - Diagnostic assessment
        - Transition from NSW Literacy and Numeracy Continua to new Learning Progressions
    - Differentiated teaching
    - Tiered interventions

Does the Strategy result in improved K-2 student outcomes?

- Transition to new Learning Progressions means we will not have the same outcome measures across treatment arms
- Use historical data to select a sample of similar schools for early transition to Learning Progressions

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- Our goal was to estimate the probability that each school would be involved in the LNAP in 2017 using historical student data
    - Schools with similar probabilities of treatment are expected to have similar levels of the observed covariates
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- We selected all the Kindergarten students who were enrolled in a public school in the first term of 2013 (n = 71,633), tracked their school movements and academic performance up to Year 3, and then used a school-level logistic regression model to estimate the conditional probabilities

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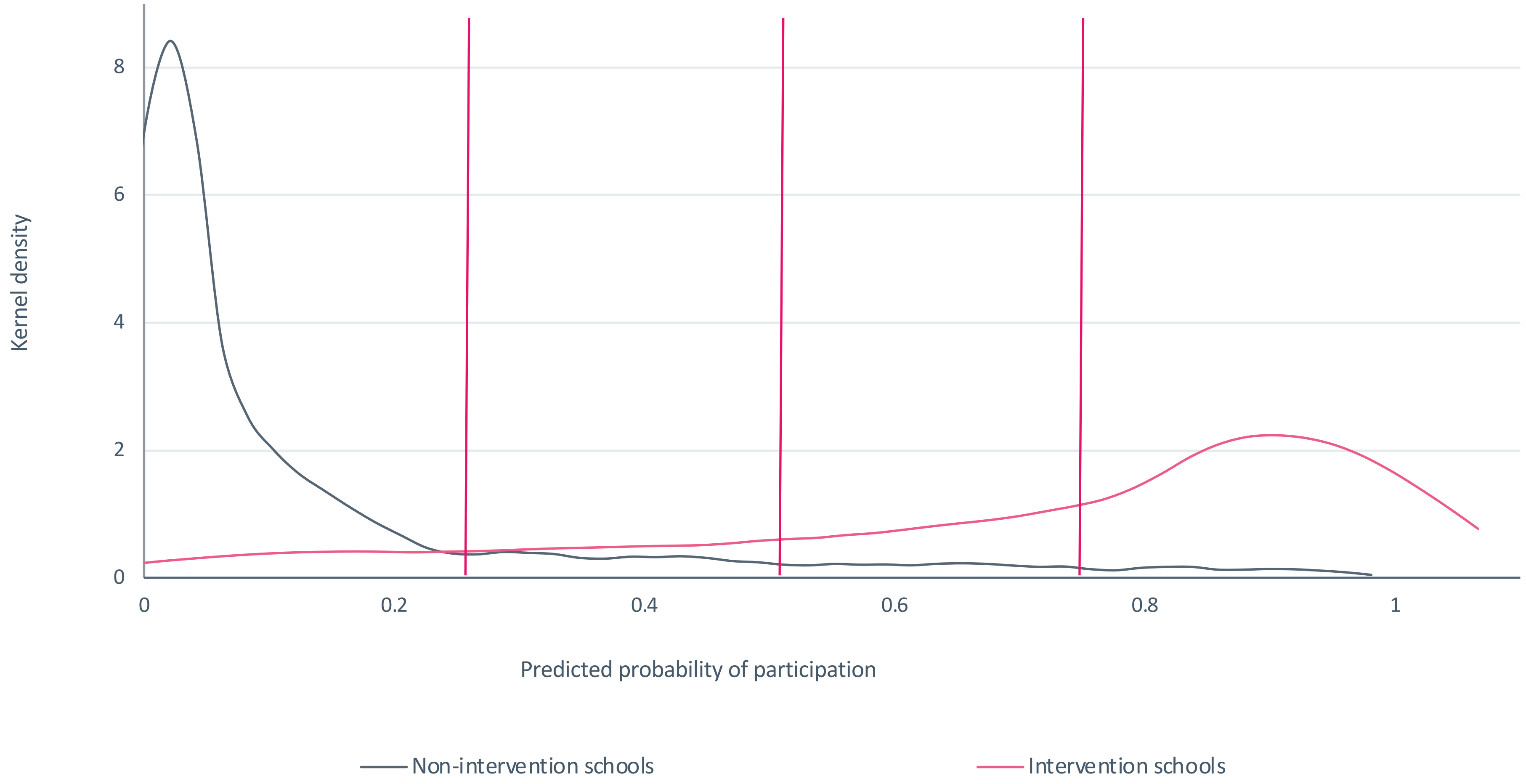

Table 2: Distributions of the intervention and non-intervention schools across the four strata					
	Strata 1	Strata 2	Strata 3	Strata 4	Total
Non-intervention schools	829 (86.26%)	73 (7.60%)	37 (3.85%)	22 (2.29%)	961
Intervention schools	50 (10.20%)	58 (11.84%)	96 (19.59%)	286 (58.37%)	490

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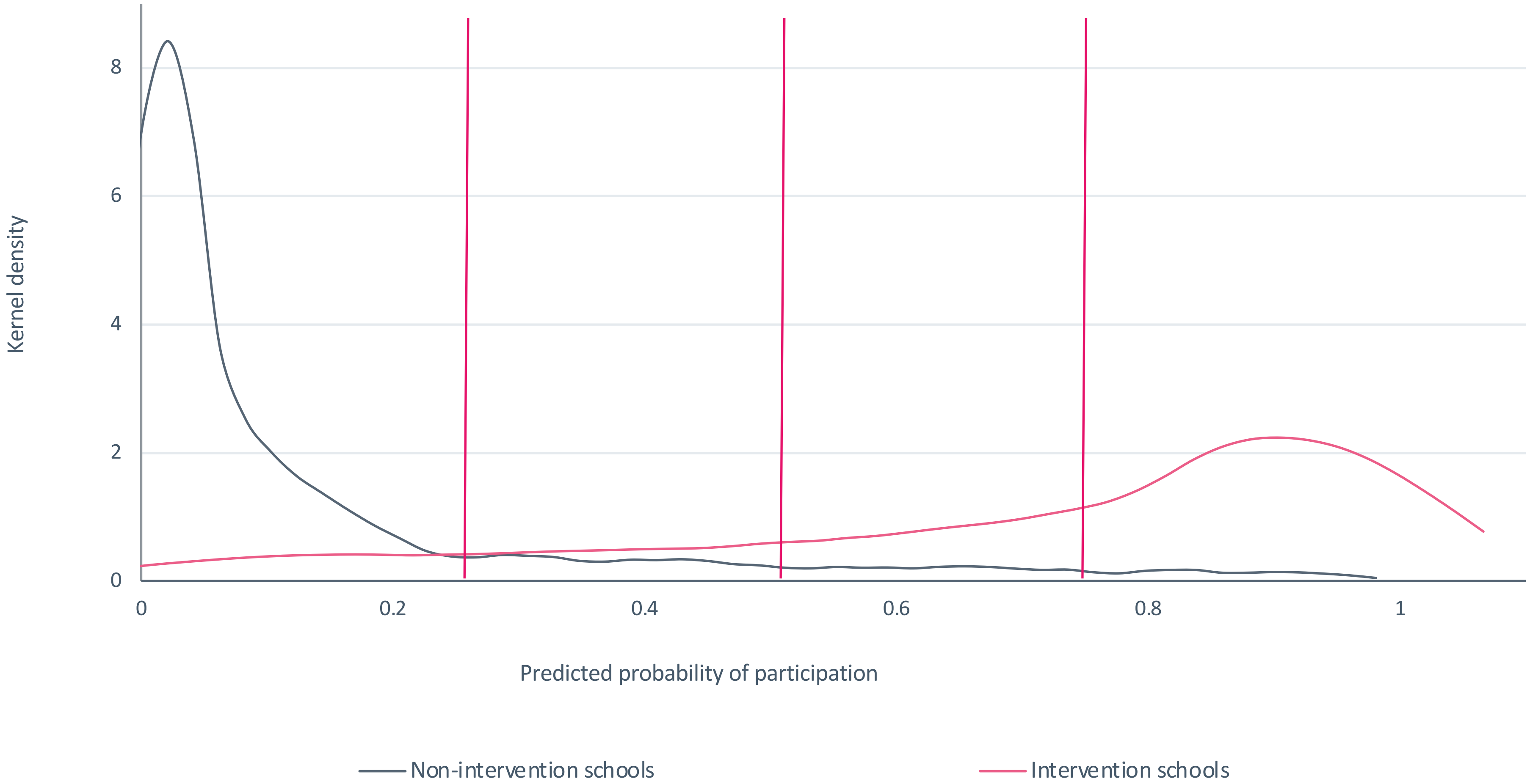

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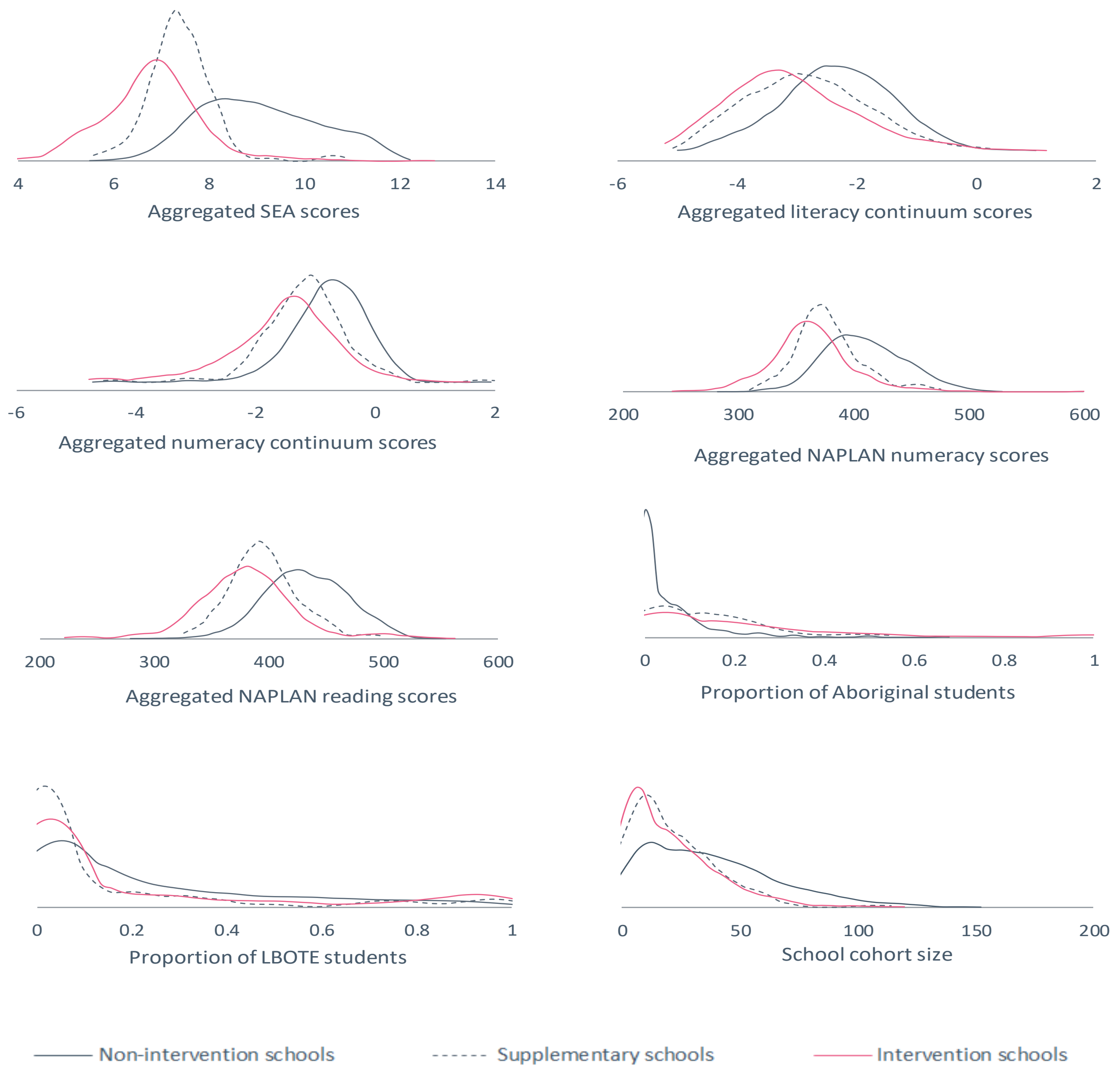

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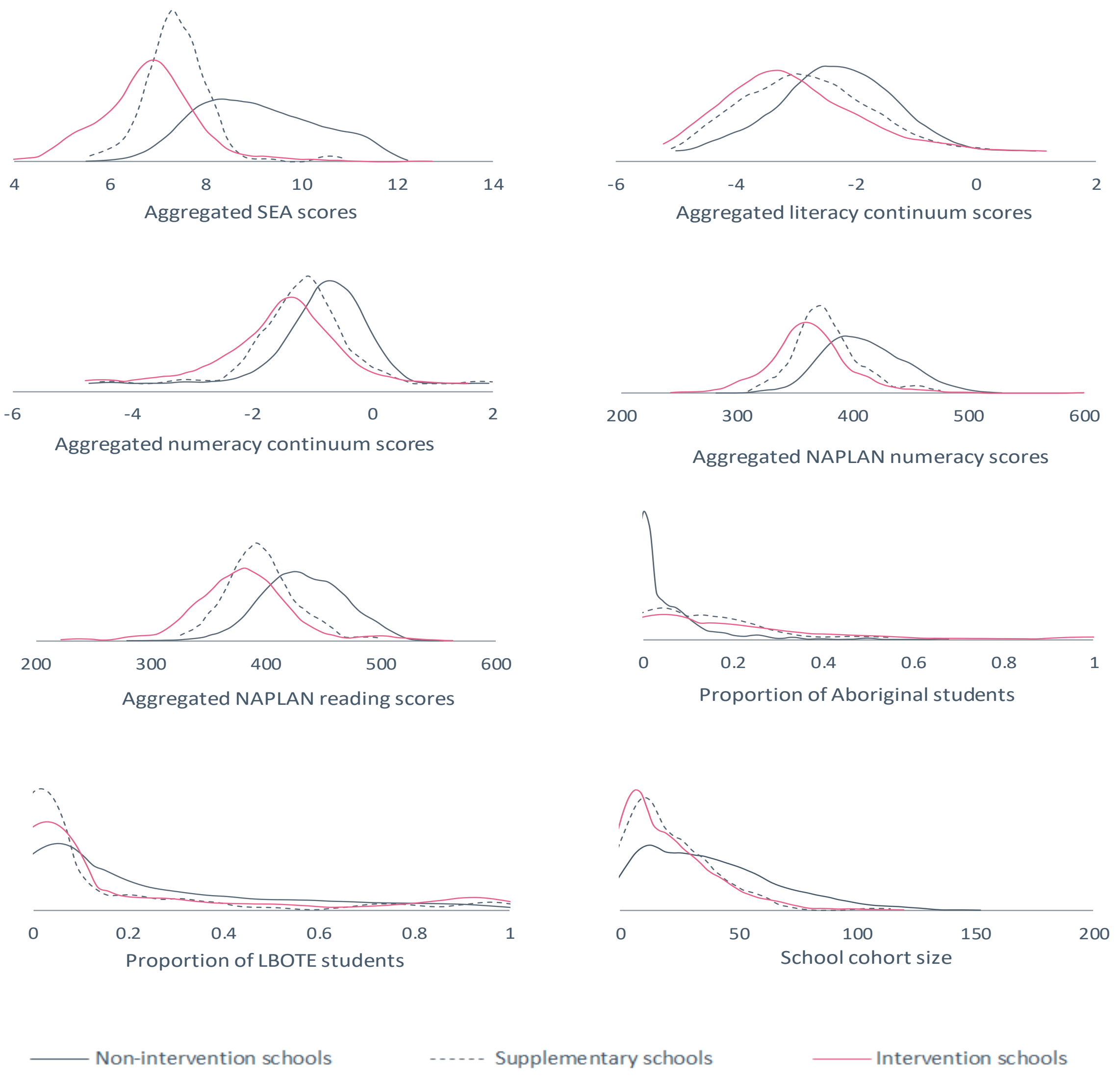

Final thoughts

- Where possible, consider an RCT
  - But…

- Without randomisation, advanced statistical methods can help answer your evaluation questions: e.g.
  - Use program logic to look for differential effects (dose/response)
  - Create a pseudo-control group **after** the fact
  - Create a comparison group **before** data collection (without randomisation)

- It is possible to convey complex statistical findings in a easy to understand manner

Get in touch with CESE

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- Sign up to our newsletter – **www.cese.nsw.gov.au/contact-us**