The Nonlinear and Heterogeneous Effects of Parental Income on Children's Educational Attainment

Ian Lundberg
Cornell
ilundberg@cornell.edu

Jennie E. Brand
UCLA
brand@soc.ucla.edu

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How computing looked **in the 1950s**

Source: NASA

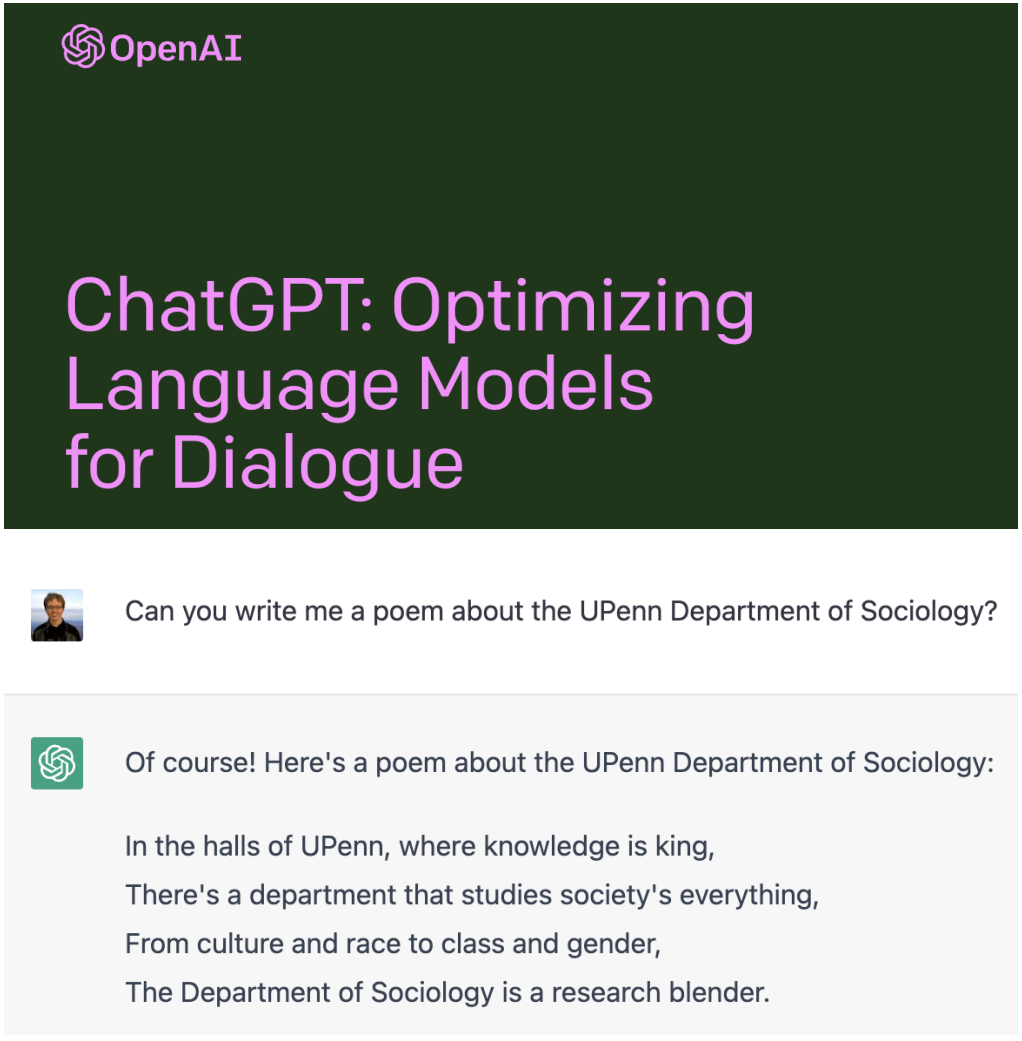
How computing looked **in the 1980s**

Source: Wikimedia

How computing looks **today**

Source: Apple

How computing looks **today**



Source: OpenAI

Computing has advanced rapidly since the 1960s

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How has quantitative social science changed?

How stratification research looked **in the 1960s**

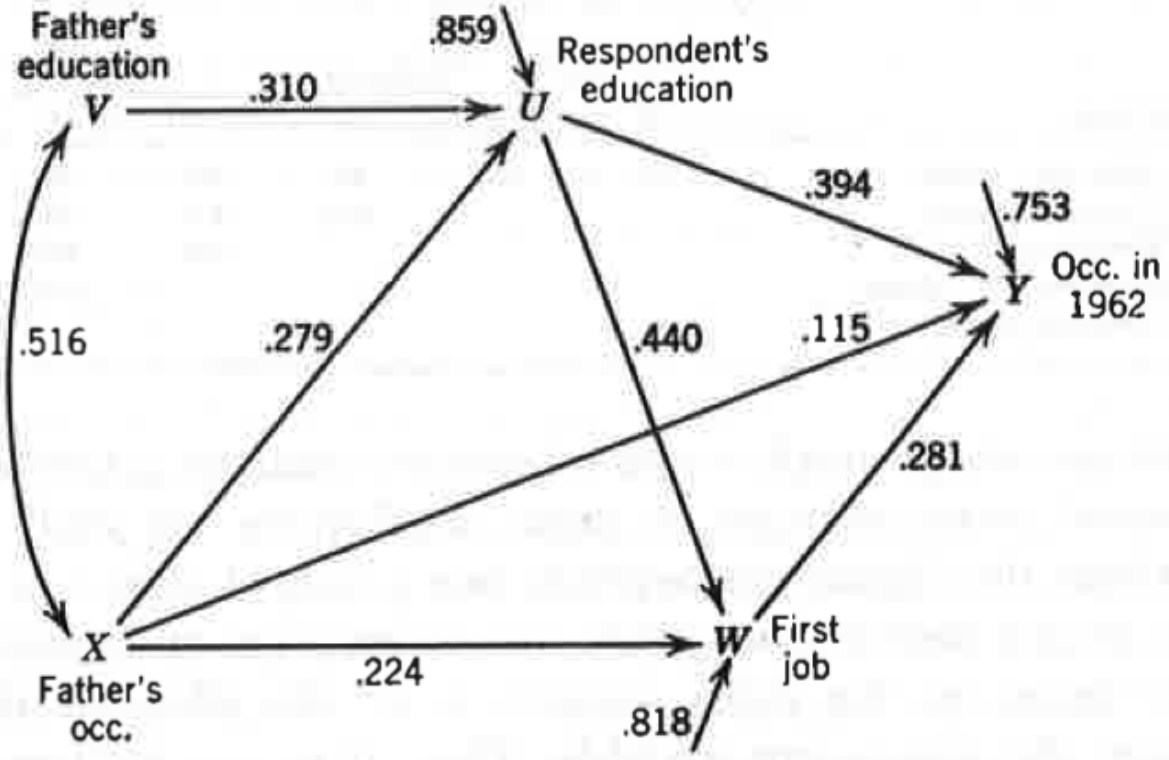

Figure 5.1. Path coefficients in basic model of the process of stratification.

Source: Blau & Duncan 1967

How stratification research looks **today**

	Logistic Regression	
	Enrollment in College by Age 20	
	(1)	(2)
log(Family Income in Adolescence)	0.961***	0.451***
	(0.045)	(0.056)
Race (white / other omitted)		
Hispanic		0.010
		(0.105)
Non-Hispanic Black		0.205*
		(0.099)
Parents' education		
One parent finished college		0.944***
		(0.087)
Both parents finished college		1.374***
		(0.129)
log(Family Wealth in Adolescence)		0.211***
		(0.023)
Constant	−11.049***	−8.028***
	(0.501)	(0.549)
Observations	4,777	4,777
Log Likelihood	−2,542.000	−2,391.006
Akaike Inf. Crit.	5,088.000	4,800.012
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- We've learned a ton that way
- We can interpret regressions
- We have small sample sizes

How might we move on from regression?

Road map for today

- Data
- Theory and hypotheses
- Causal inference
- Estimation + Results
- Discussion

Data

National Longitudinal Survey of Youth, 1997 Cohort

- Ages 12–17 in 1997
- Treatment: Family income in 1997
- Outcome: College enrollment by age 20
- Confounders
  - Family wealth
  - Parents' education
    - Neither finished college
    - One finished college
    - Both finished college
  - Race
    - Hispanic
    - Non-Hispanic Black
    - Non-Hispanic White / Other
- Raw sample $n = 8{,}984$. Analytical sample $n = 4{,}777$

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For whom is college enrollment most responsive to income?

H1: Those with low income or wealth

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H2a: Those whose parents do not hold BAs

- Theory: Biggest effect on kids at highest risk

H2b: Those whose parents hold BAs

- Theory: These parents know how to effectively convert financial capital into higher education opportunities

These theories invoke a **causal claim**

Causal inference: A missing data problem

	Factual treatment	Outcome under treatment value: Placebo	Outcome under treatment value: Drug
Person 1	Placebo	●	○
Person 2	Drug	○	●
Person 3	Drug	○	●
Person 4	Placebo	●	○

Causal inference: A missing data problem

	Factual treatment	Outcome under treatment value					
		\$10k	\$20k	\$30k	\$40k	\$50k	...
Person 1	\$30k	○	○	●	○	○	○
Person 2	\$20k	○	●	○	○	○	○
Person 3	\$50k	○	○	○	○	●	○
Person 4	\$40k	○	○	○	●	○	○

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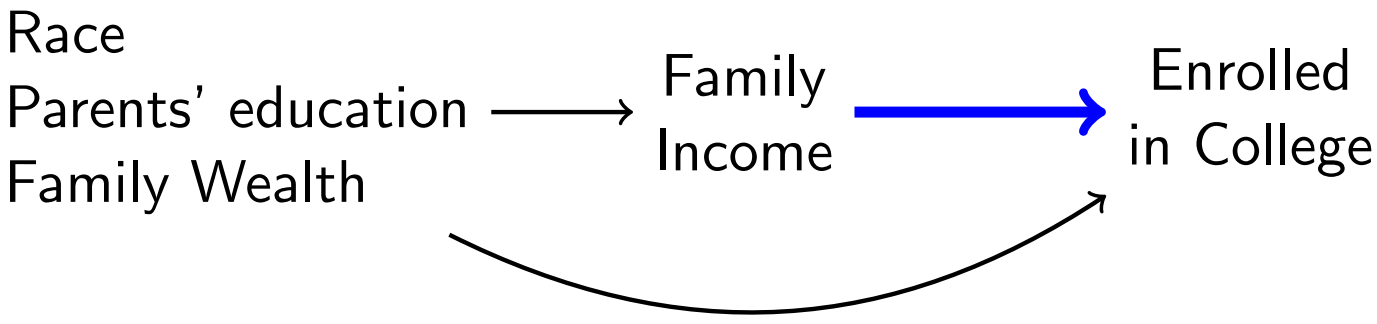
Consistency

$Y = Y^A$

See Vanderweele 2009

Causal assumptions

Exchangeability
Greenland, Pearl,
& Robins 1999



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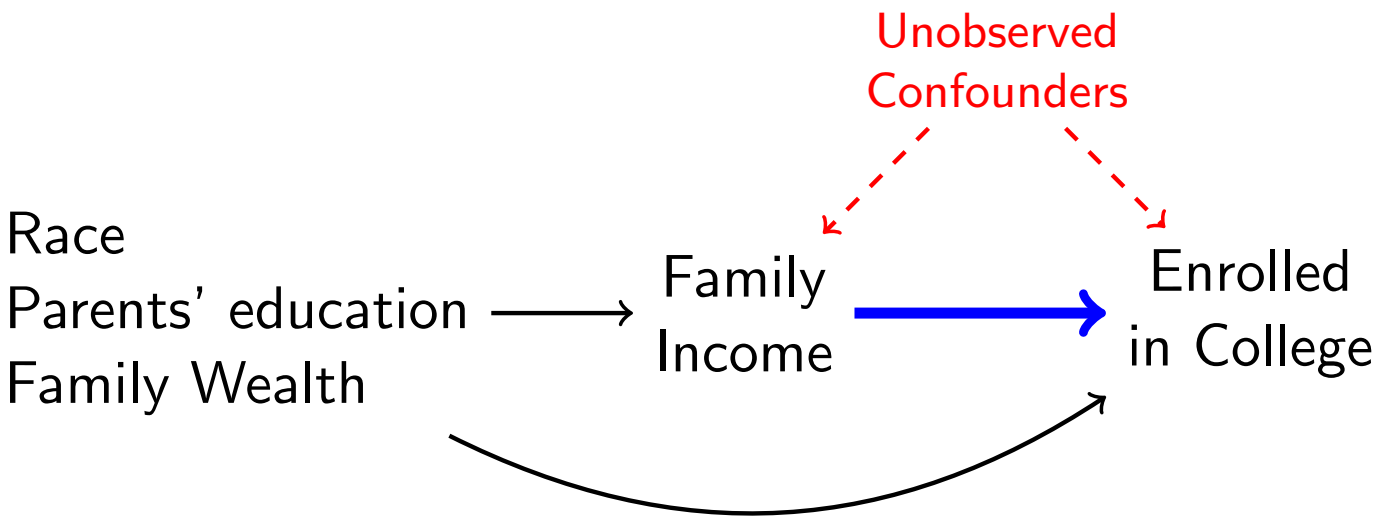

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The **extrapolation problem**:
Within a population subgroup,
many treatments are unobserved

See Westreich & Cole 2011

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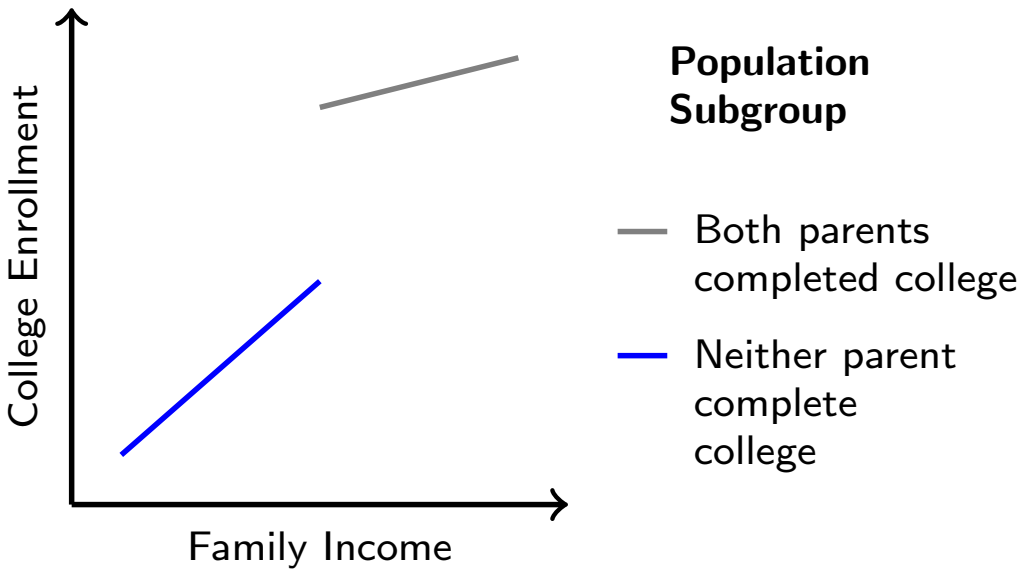

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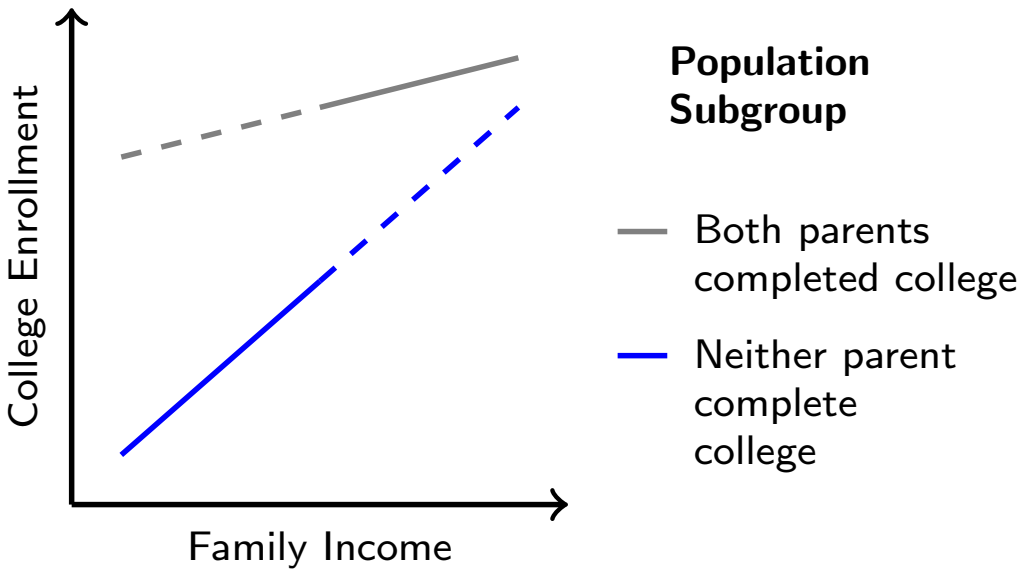

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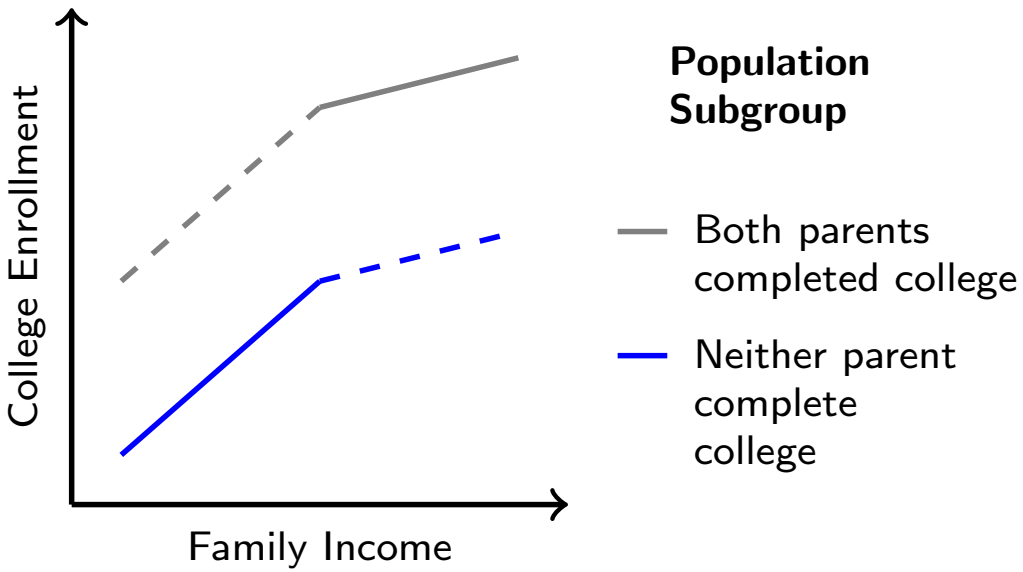

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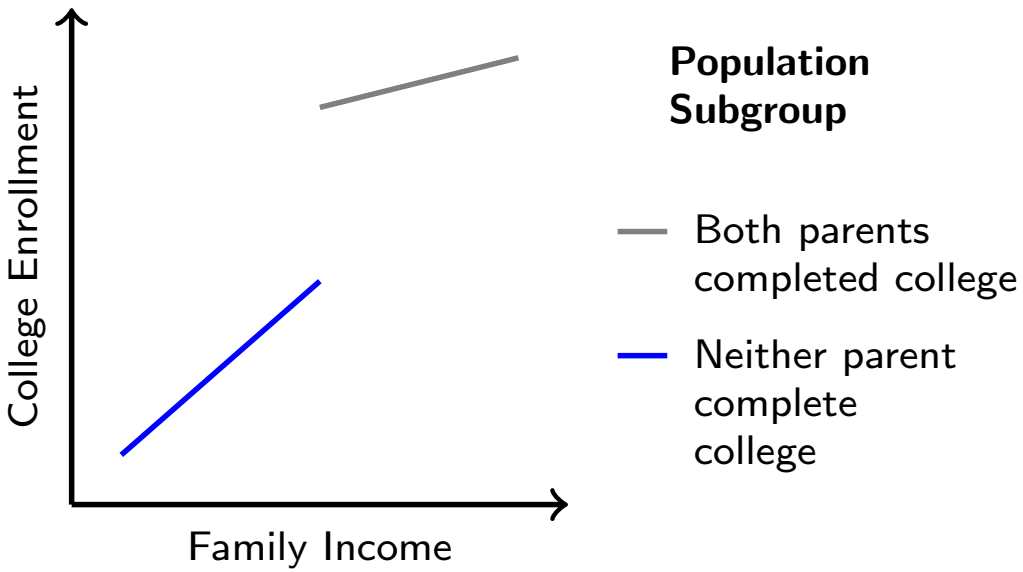

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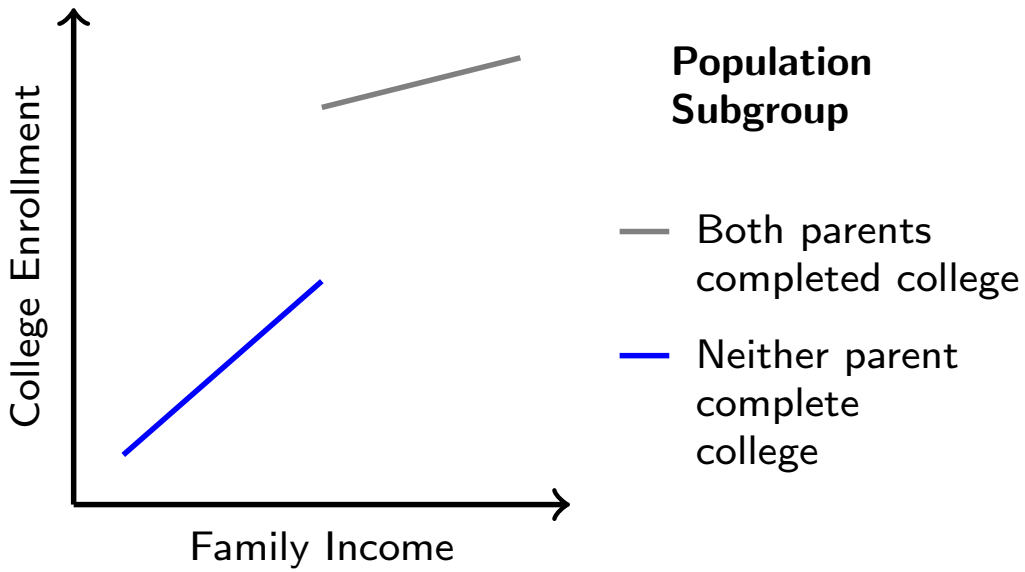

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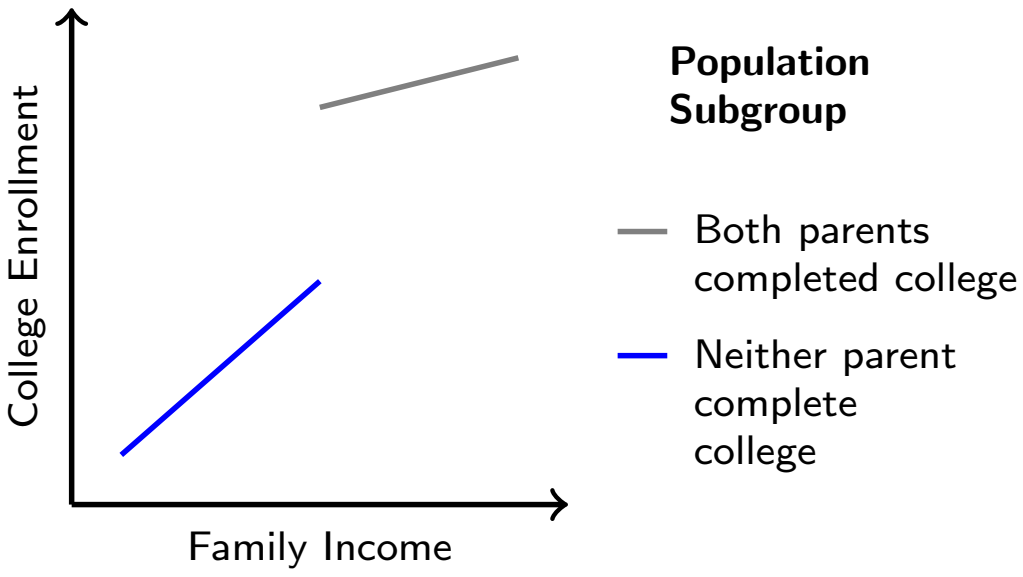

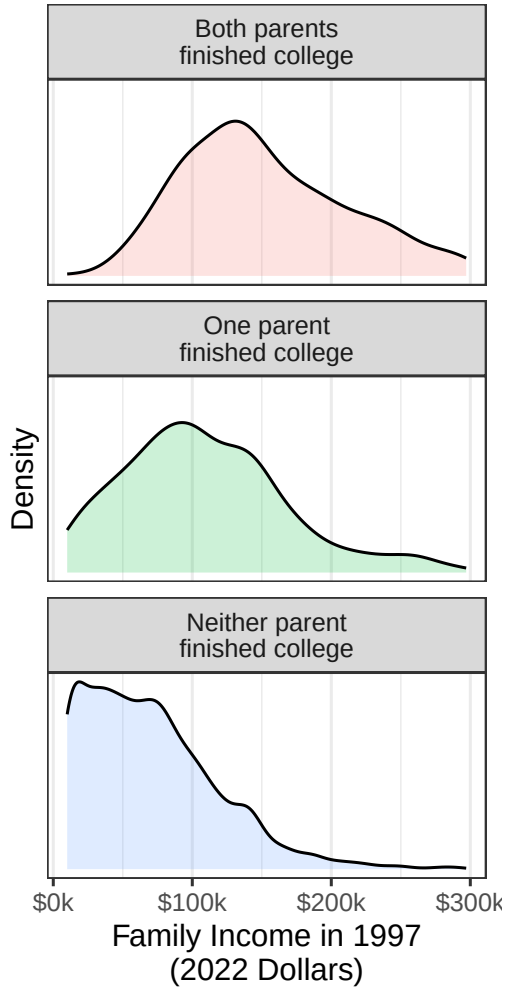

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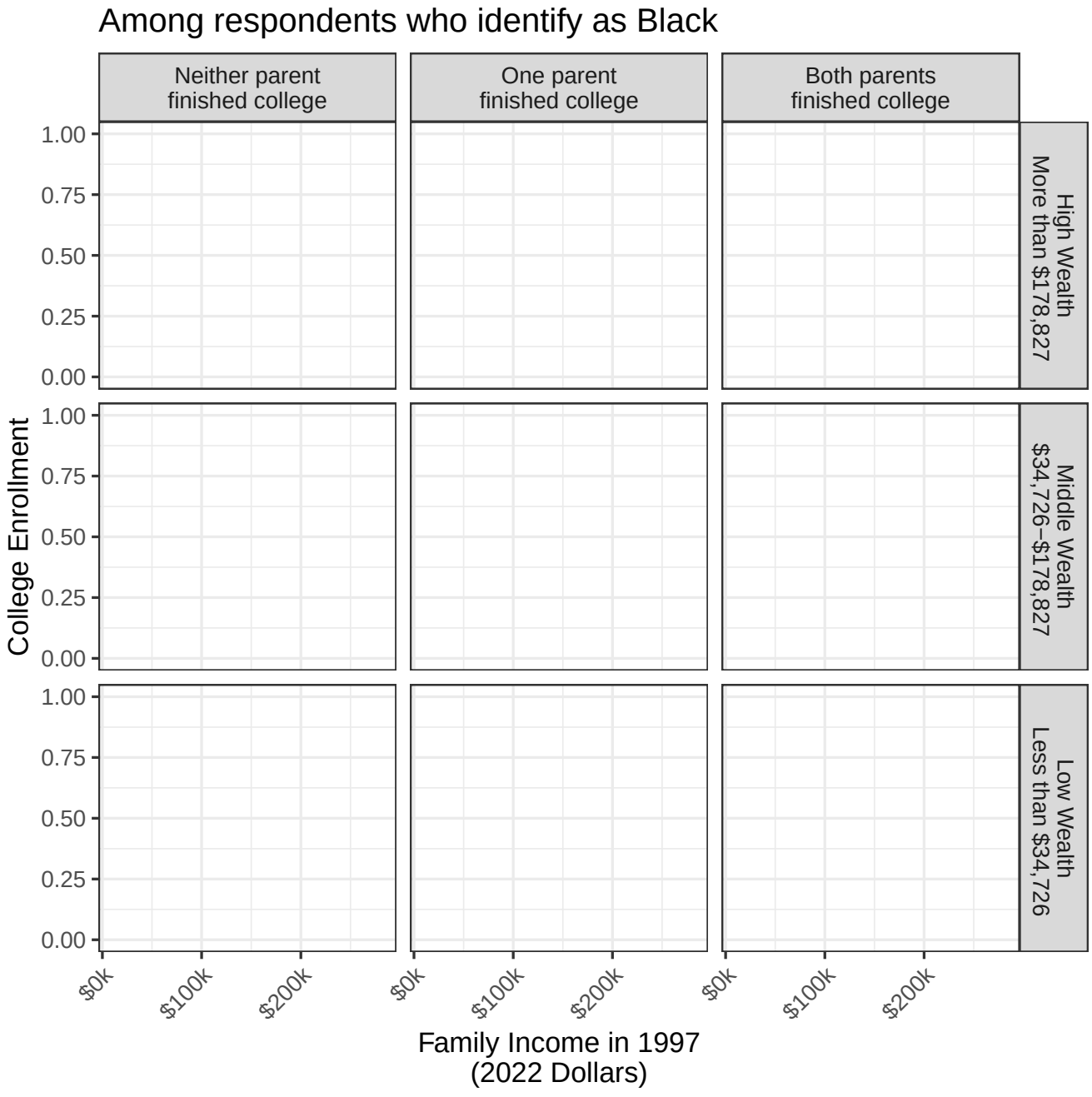
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Neither parent finished college
One parent finished college
Both parents finished college
High Wealth More than $178,827
Middle Wealth $34,726–$178,827
Low Wealth Less than $34,726
College Enrollment
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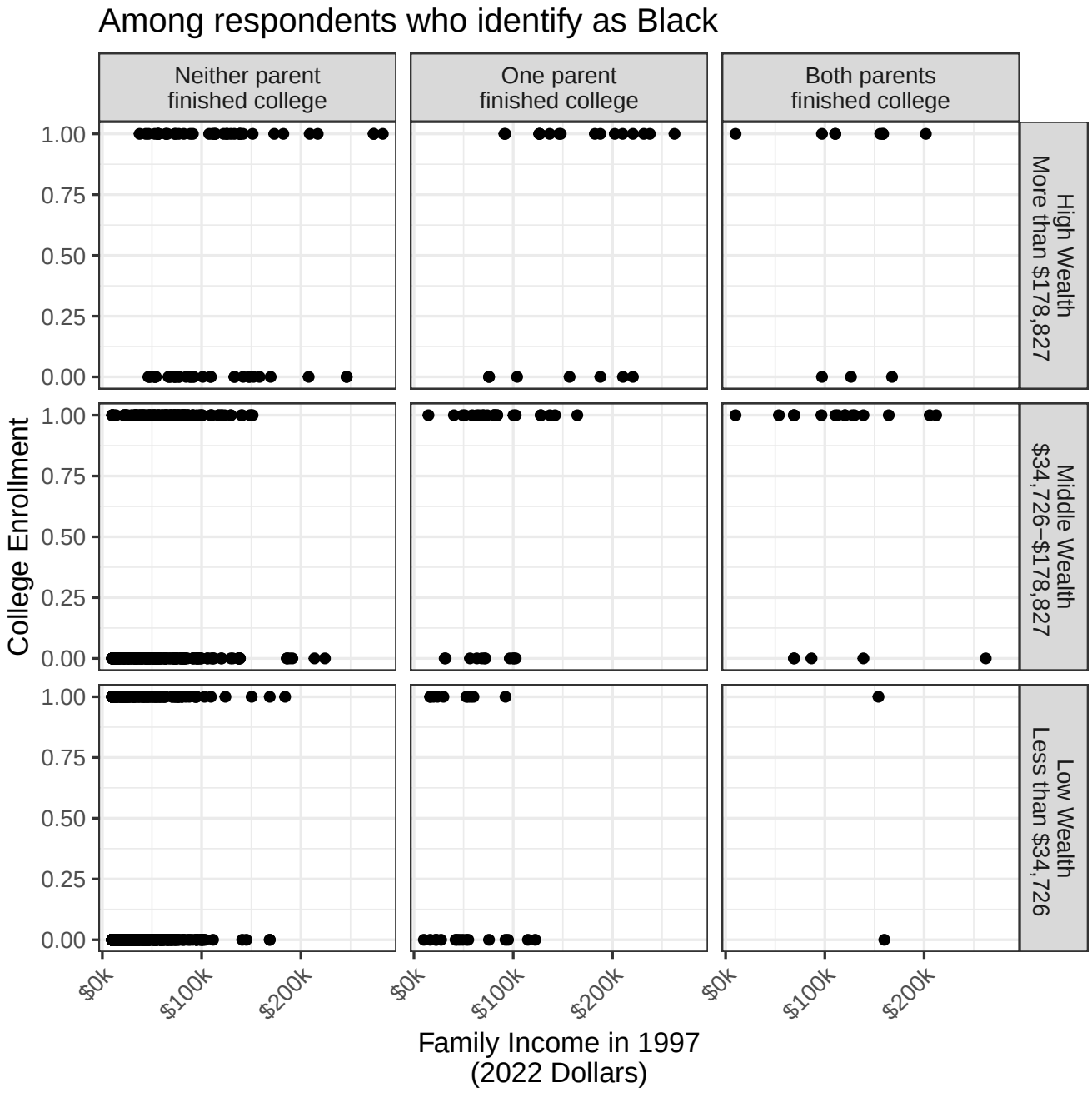
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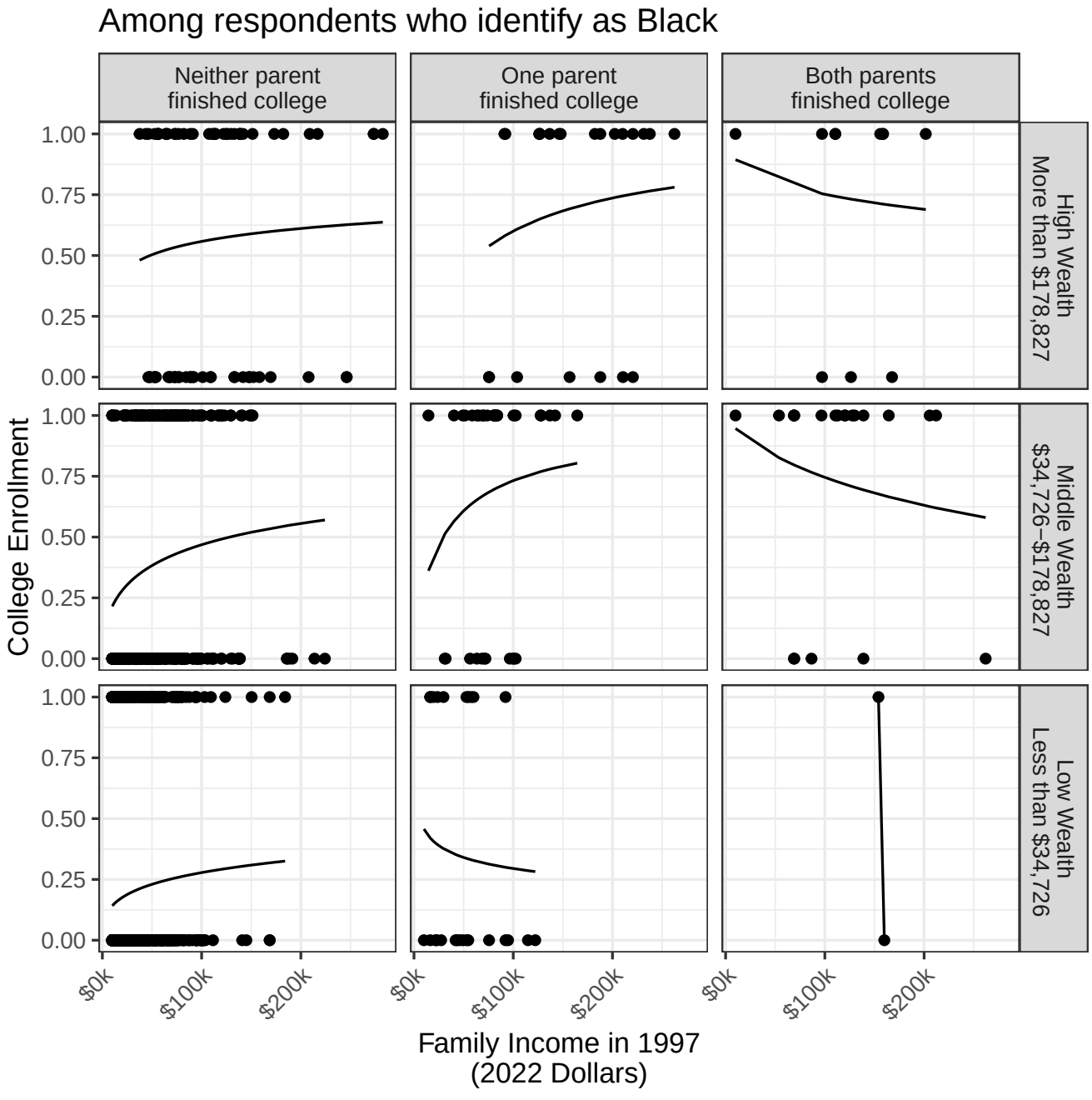
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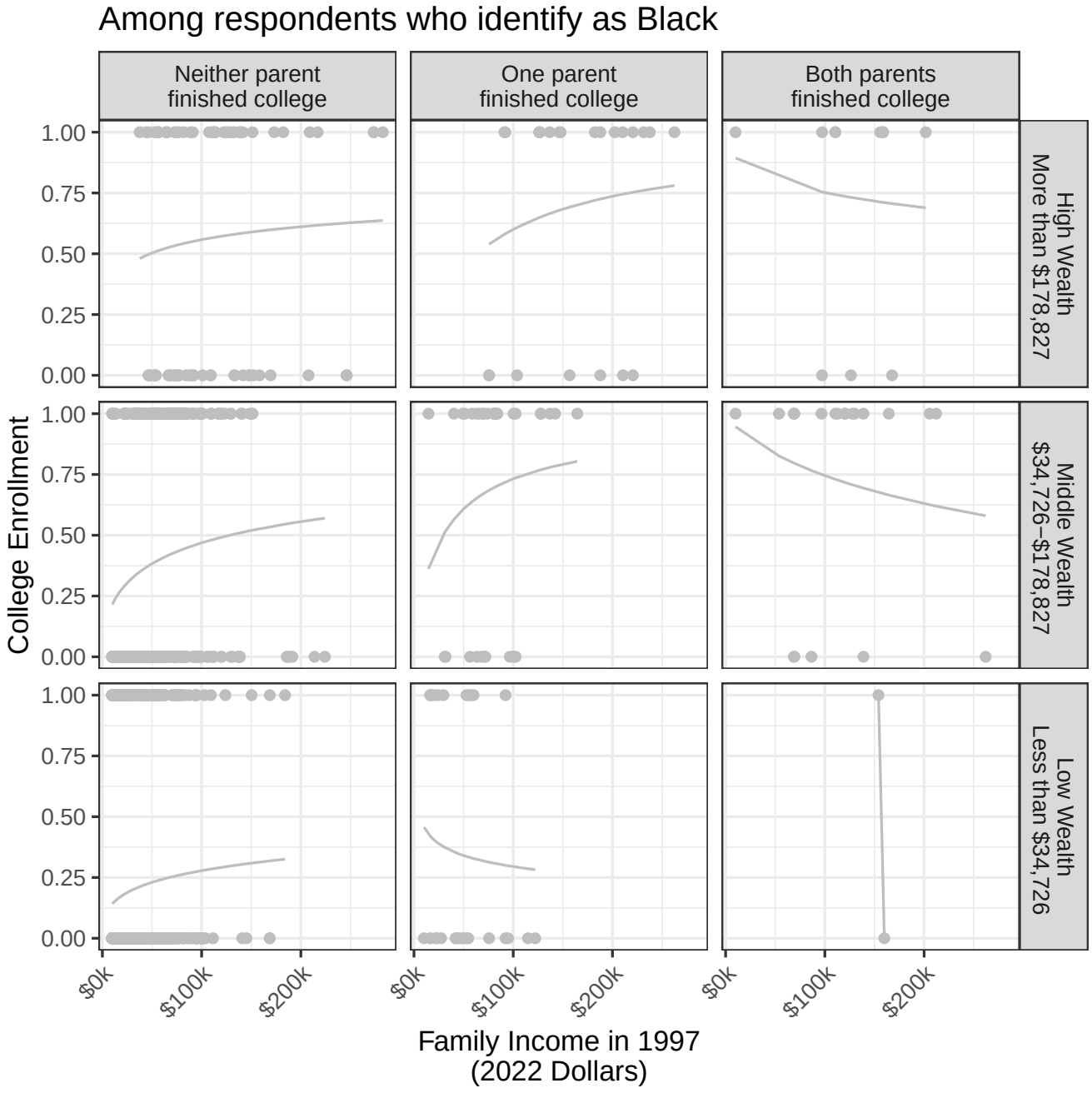
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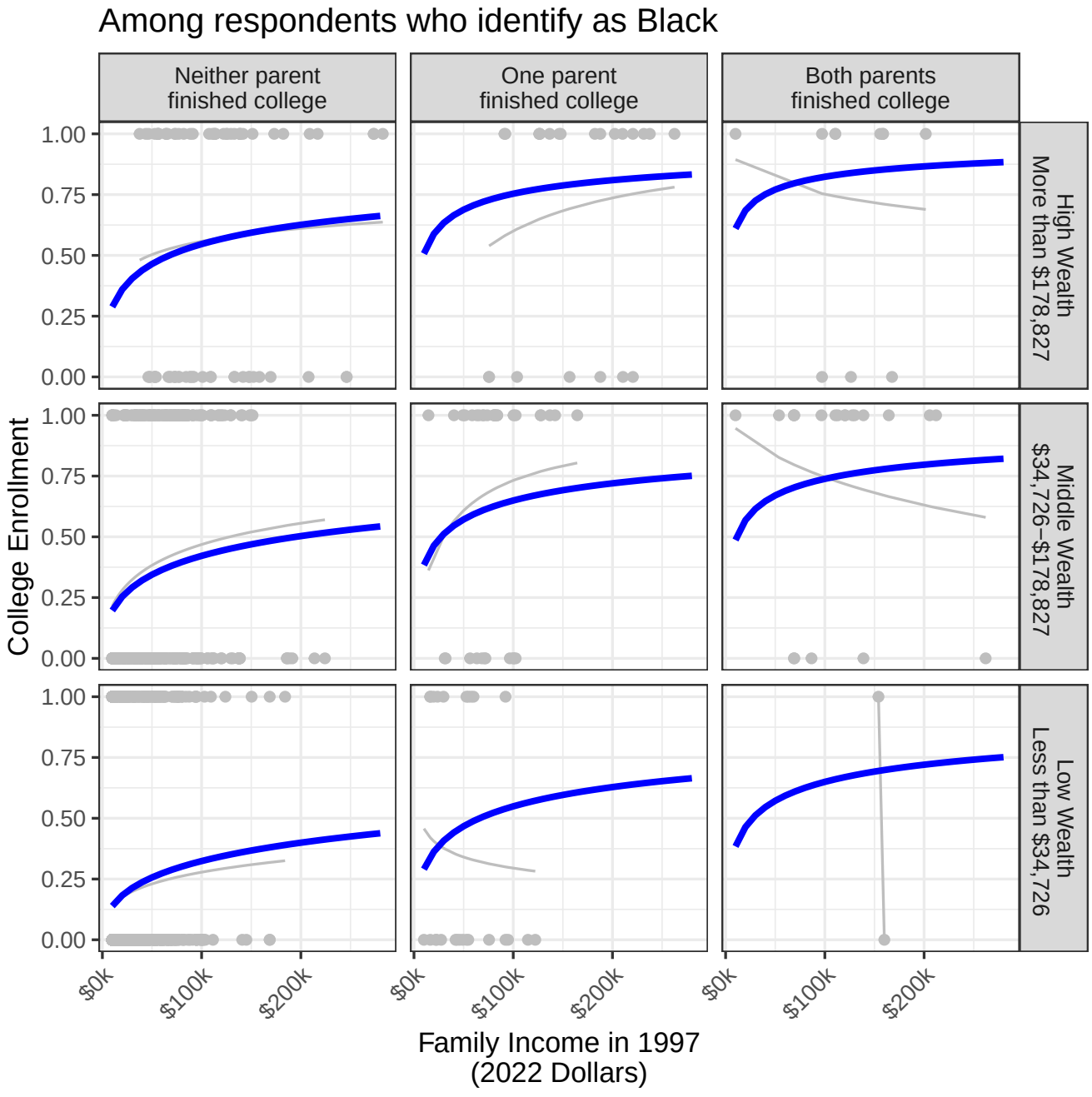
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Structure: Additive logistic regression

$$\text{logit}\left(\frac{\text{P}(Y=1 \mid \vec{X})}{1-\text{P}(Y=1 \mid \vec{X})}\right) = \alpha + \beta \times \text{log(Income)}$$
$$+ \vec{\gamma} \times \text{(Parents' Education)}$$
$$+ \vec{\eta} \times \text{(Race)}$$
$$+ \vec{\lambda} \times \text{log(Wealth)} \times \text{WealthTercile}$$

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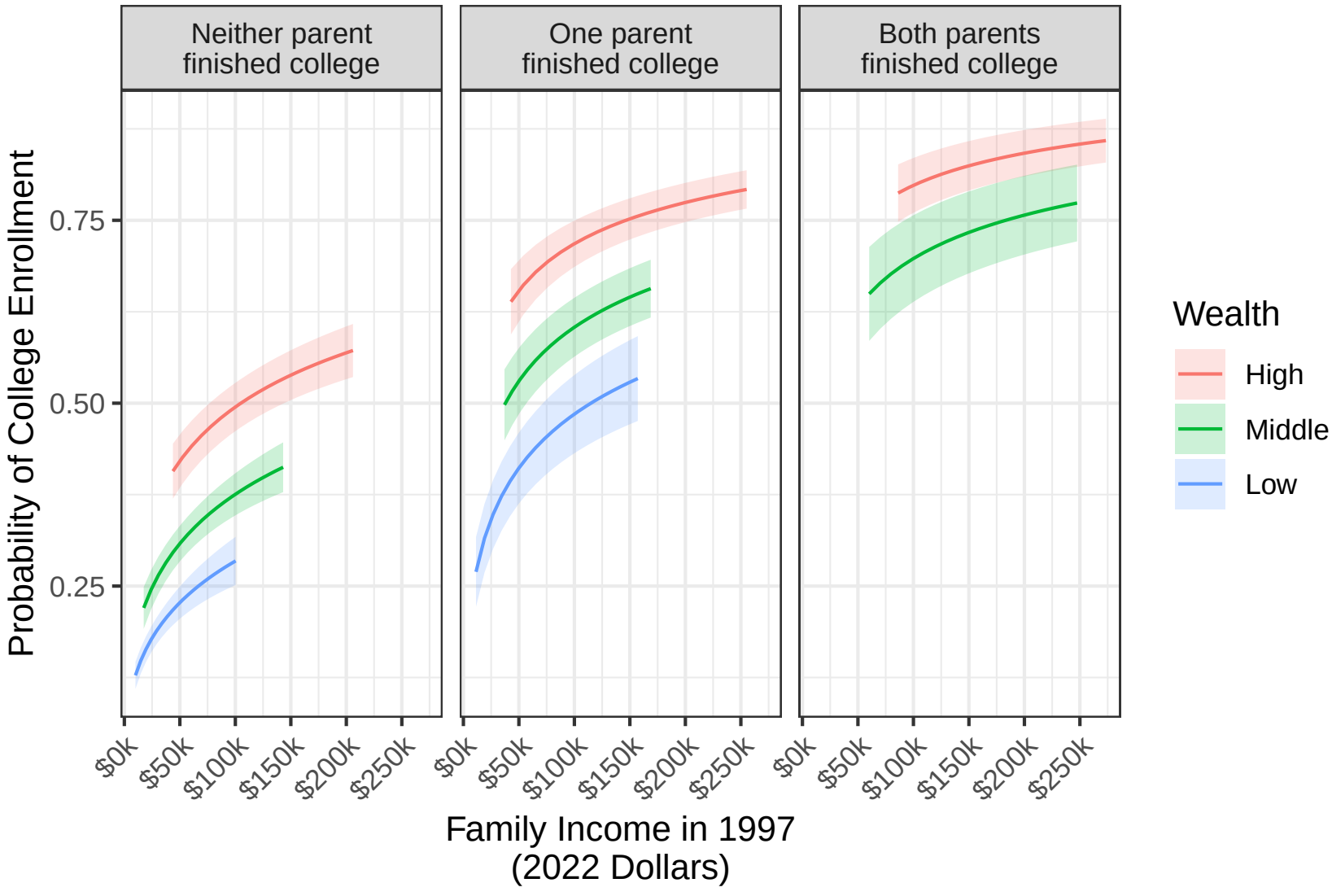
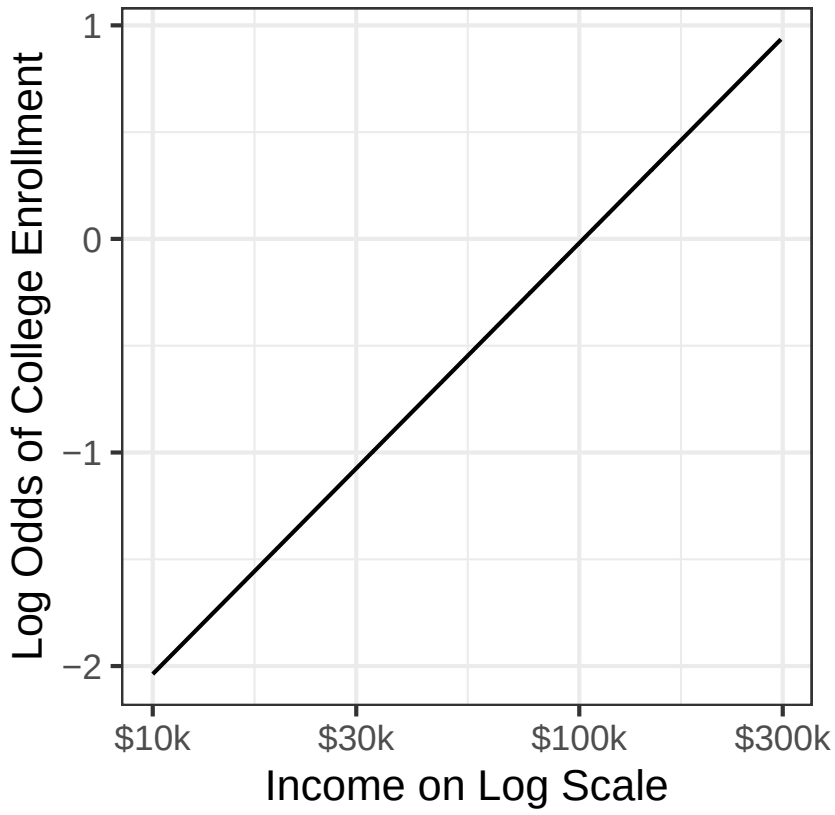


Flexibility: Generalized additive model + interactions

Wood 2017, R package `mgcv`



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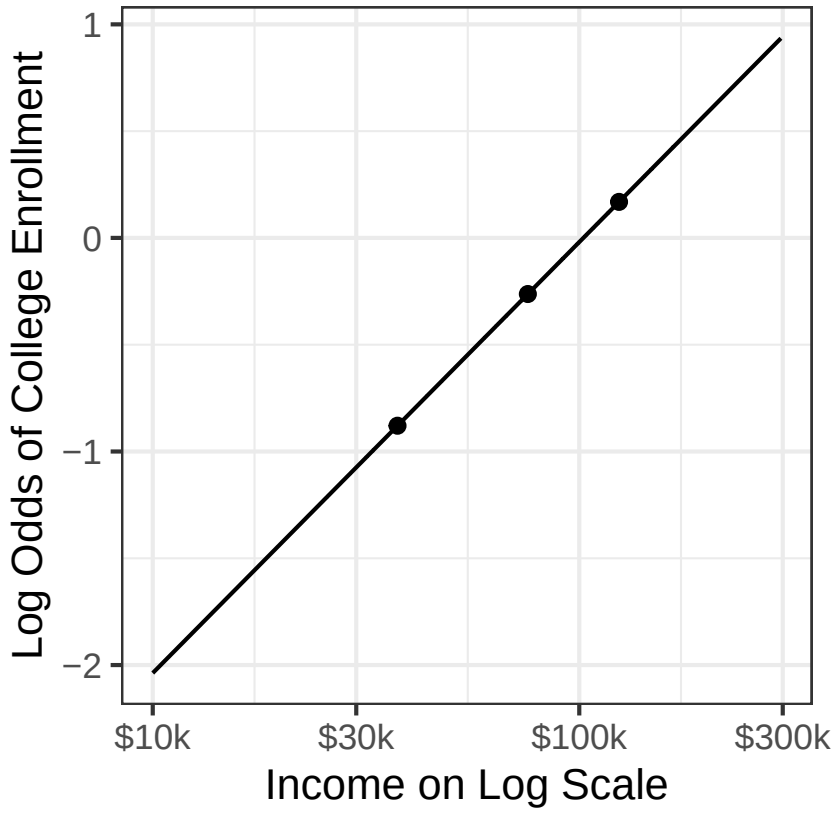

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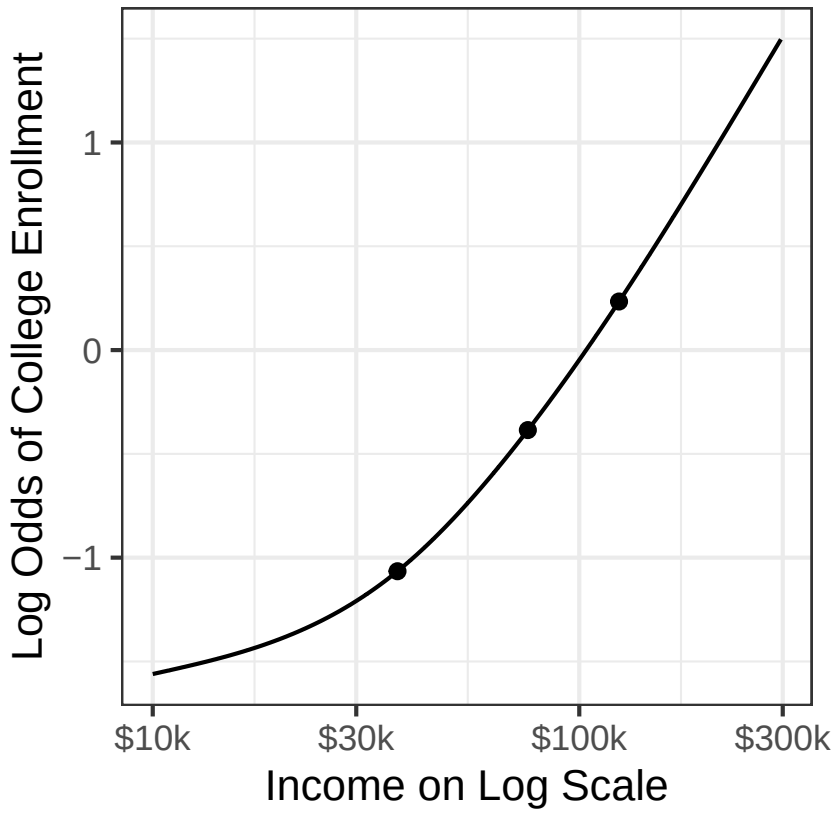

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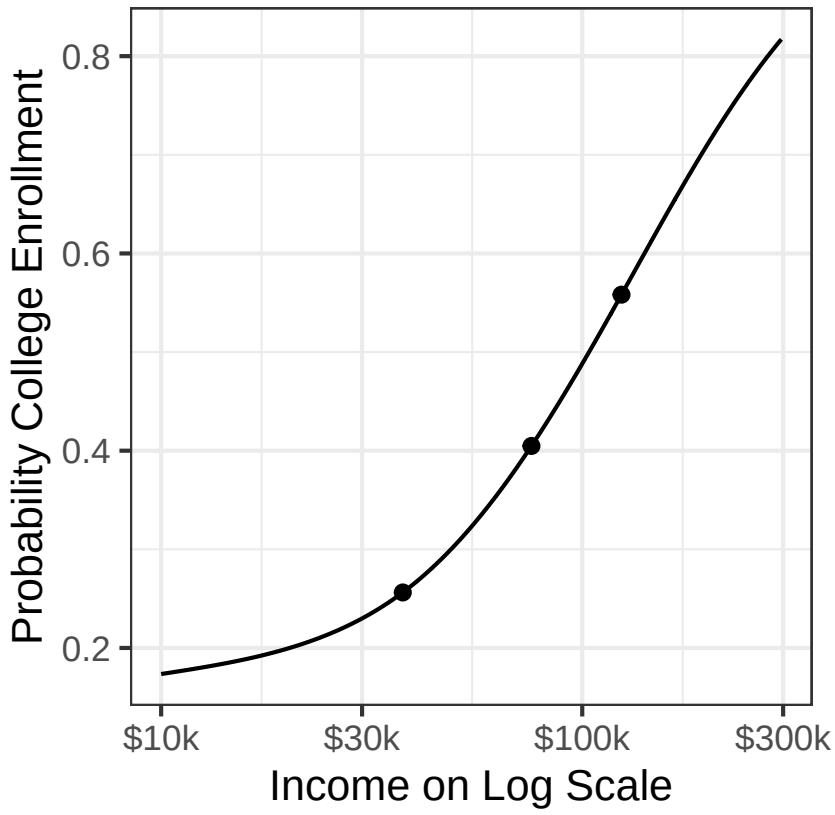

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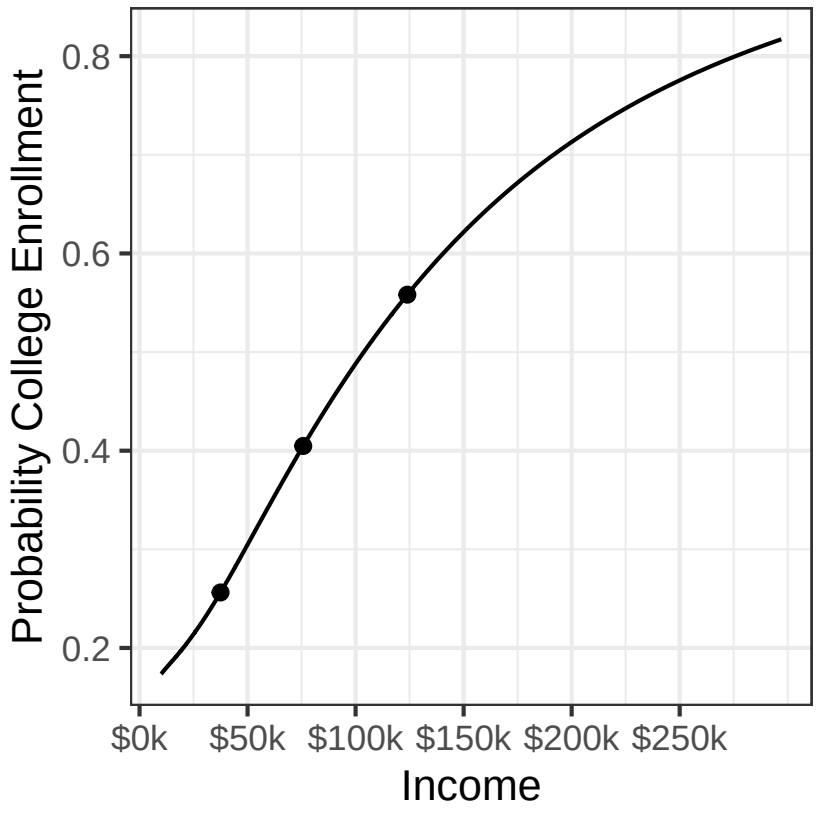
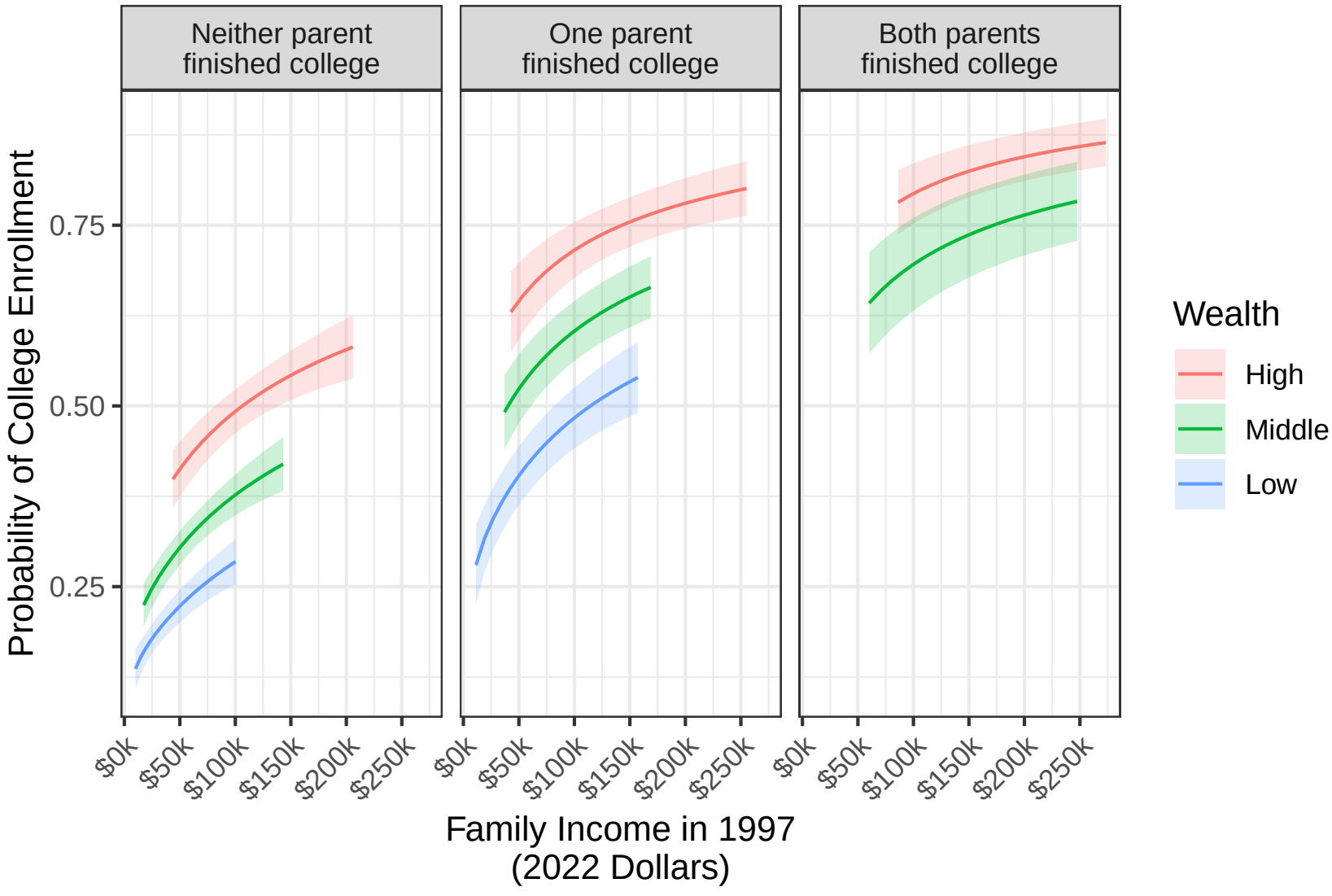
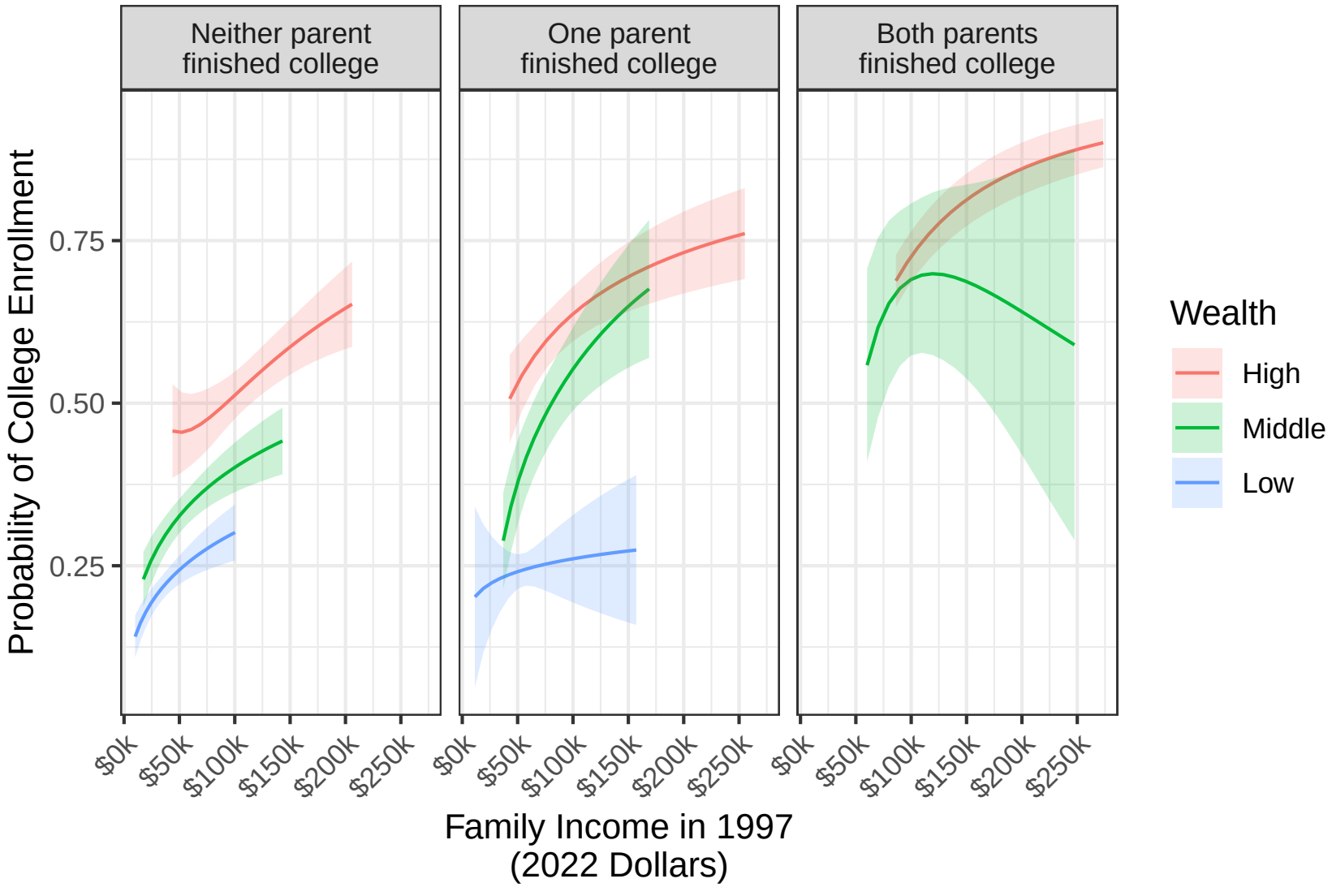


Linear model



Smooth model with interactions

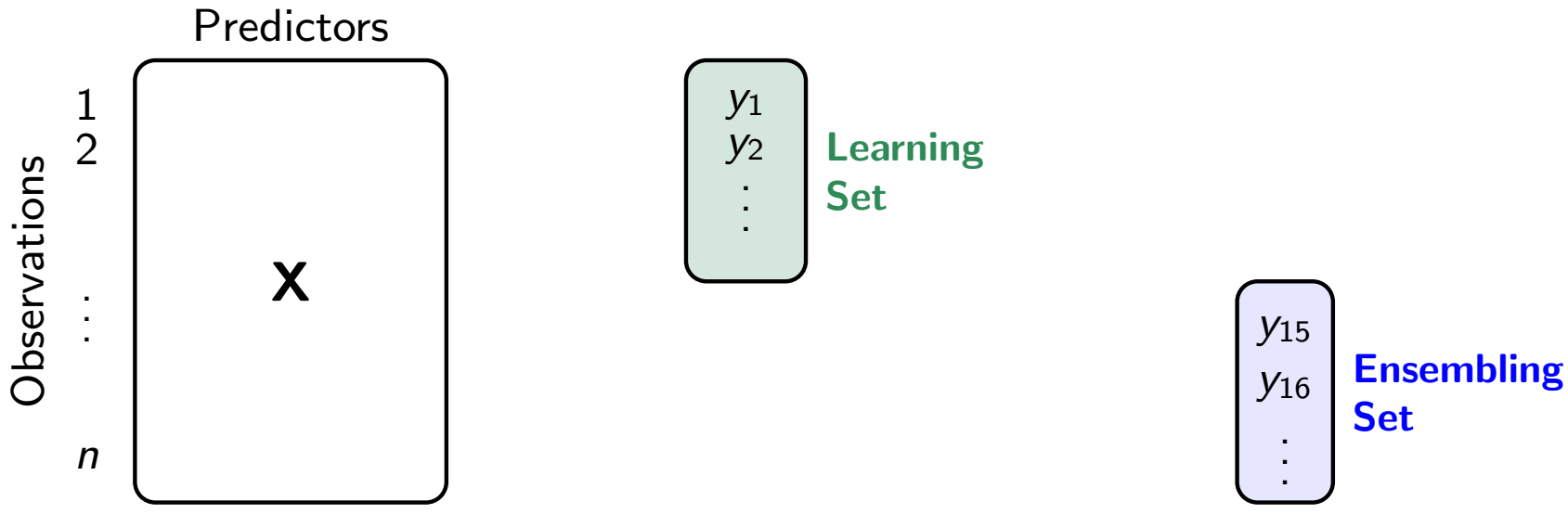


Many base learners

- Standard logistic regression
  - Additive
  - Income $\times$ Education
  - Income $\times$ Wealth
  - Income $\times$ Race
  - Income $\times$ Education $\times$ Wealth
  - Income $\times$ Education $\times$ Race
- Each of the above, but with smooths

Ensemble

See **Super Learner**
Van der Laan et al. 2007



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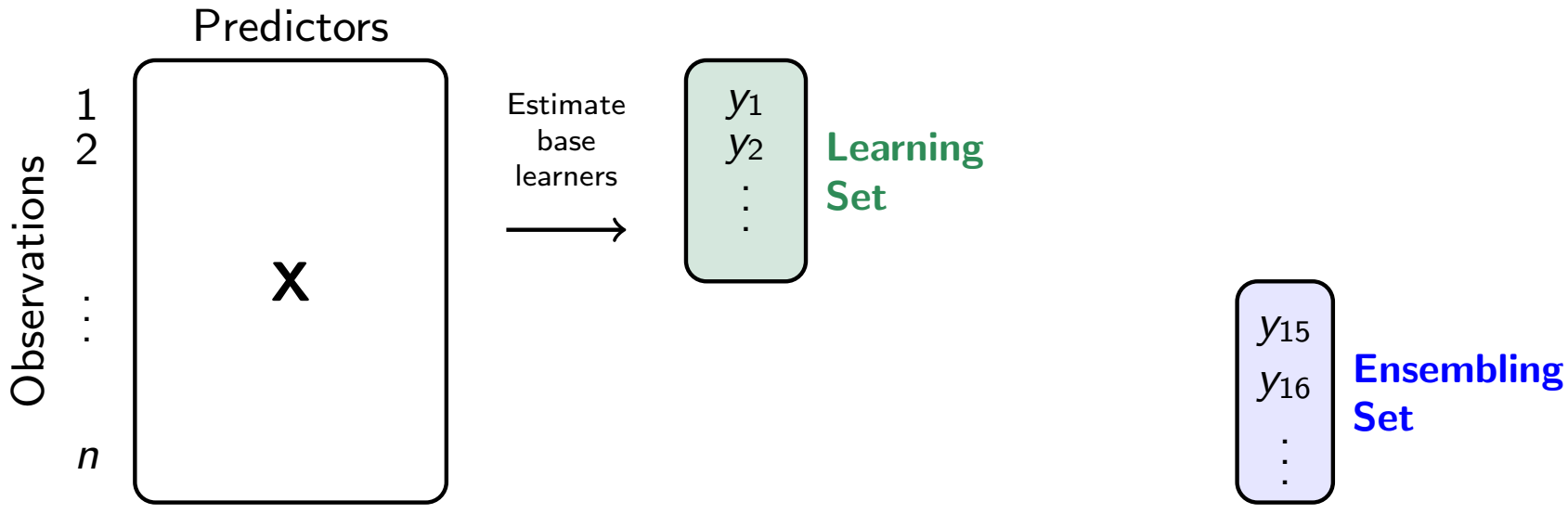

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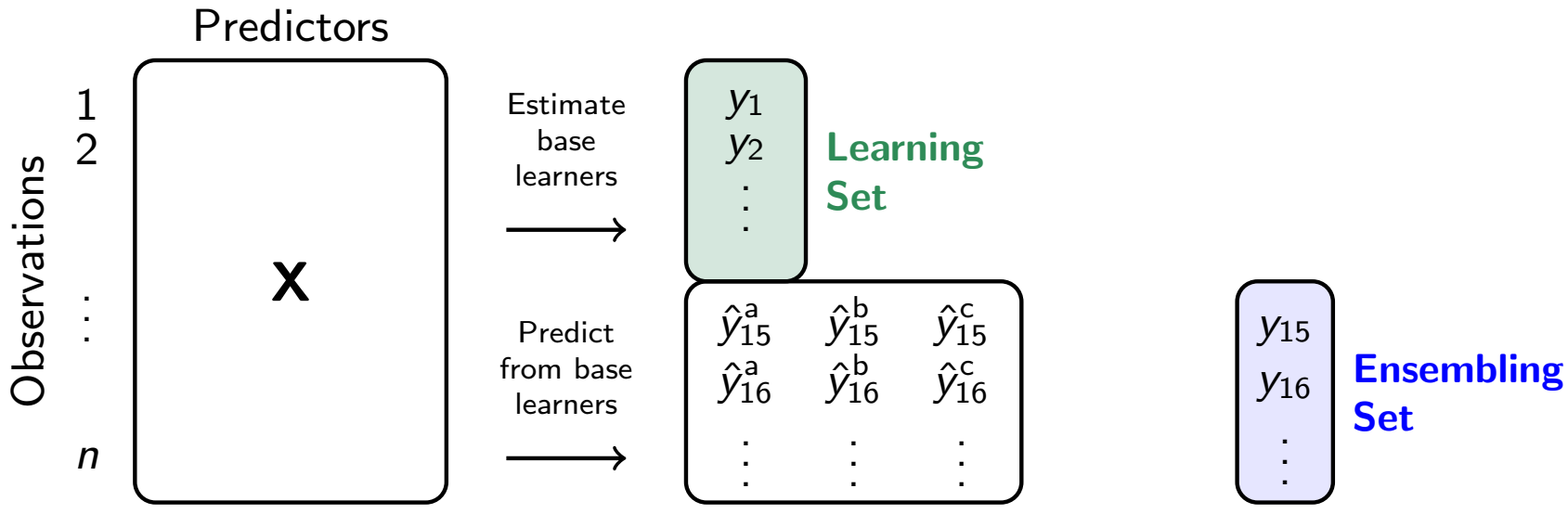

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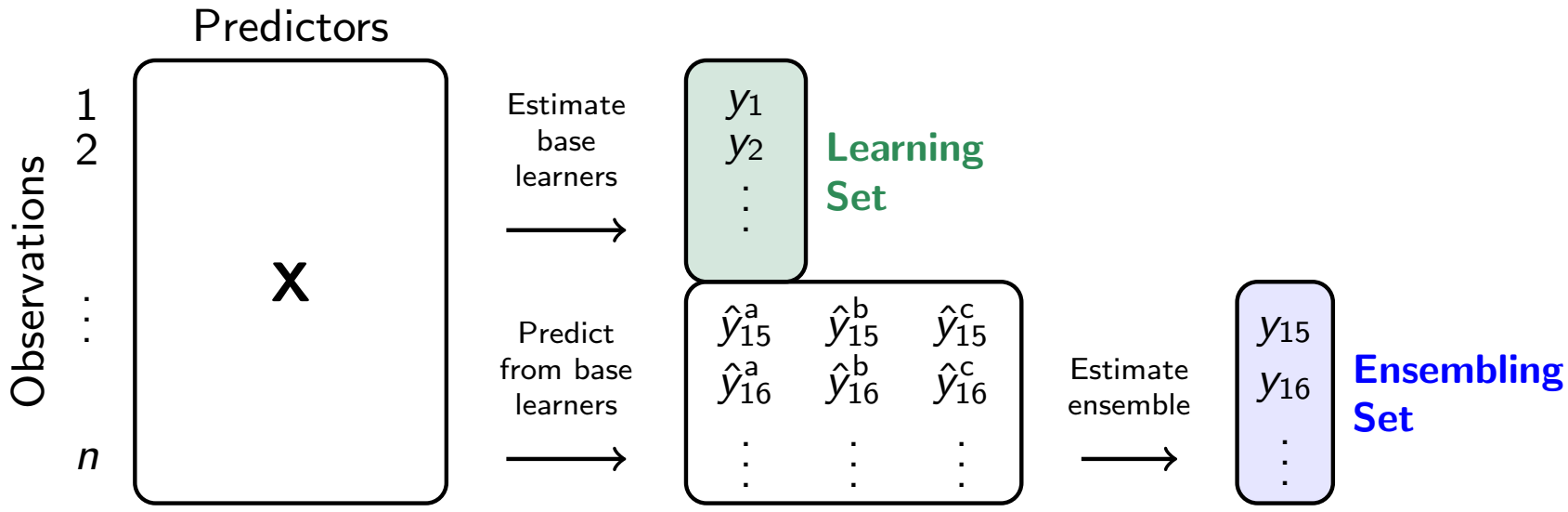

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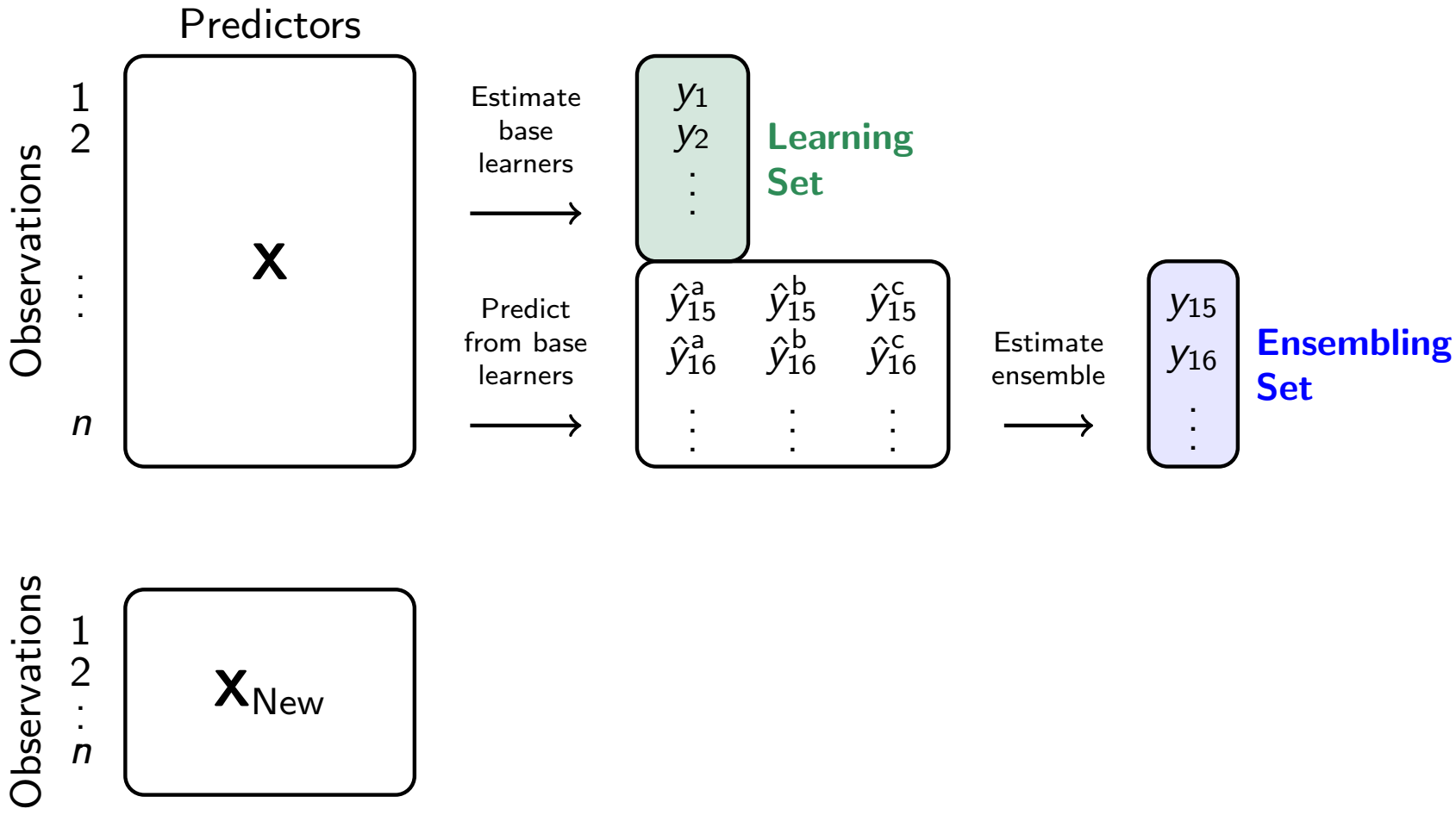

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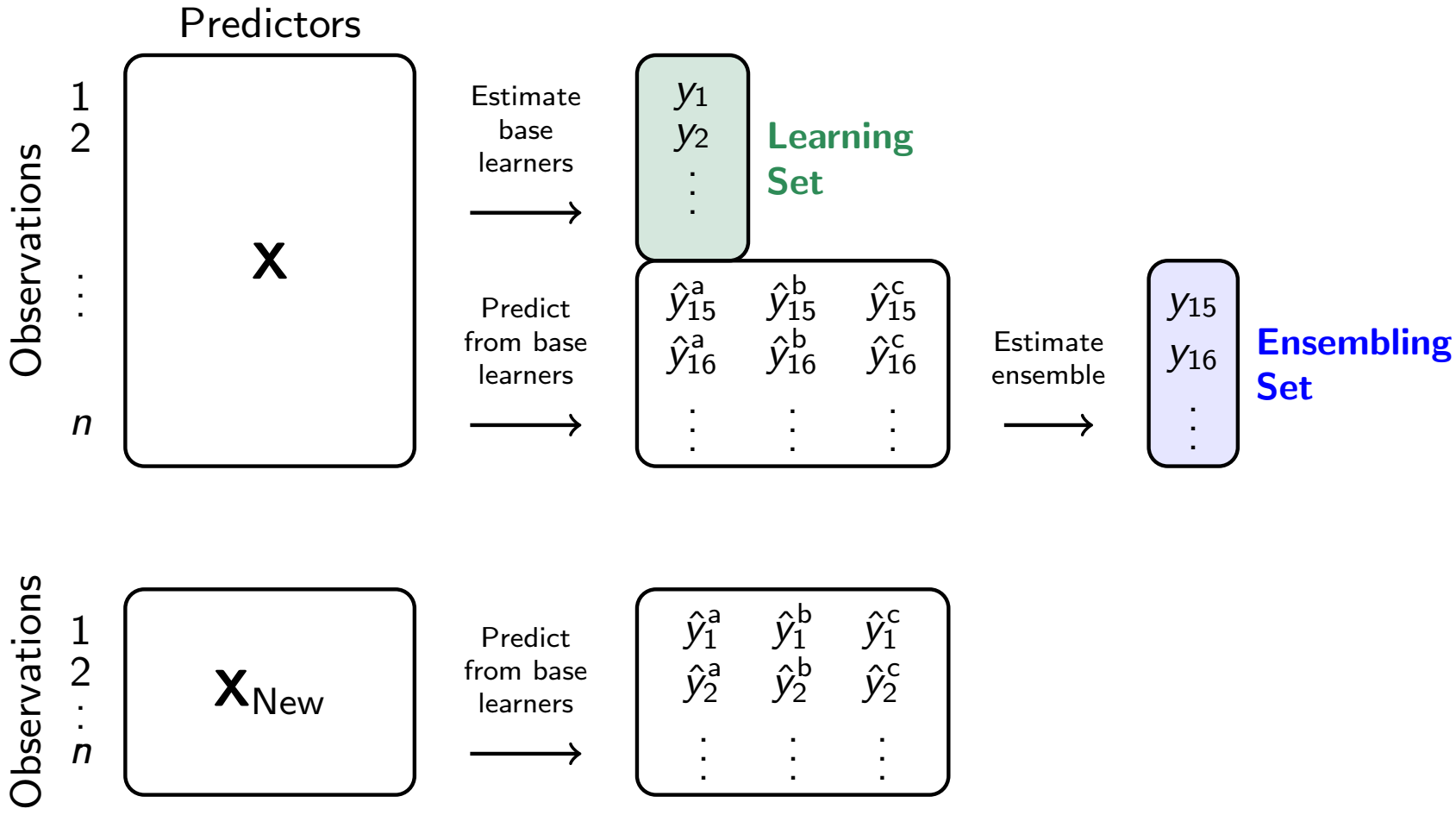

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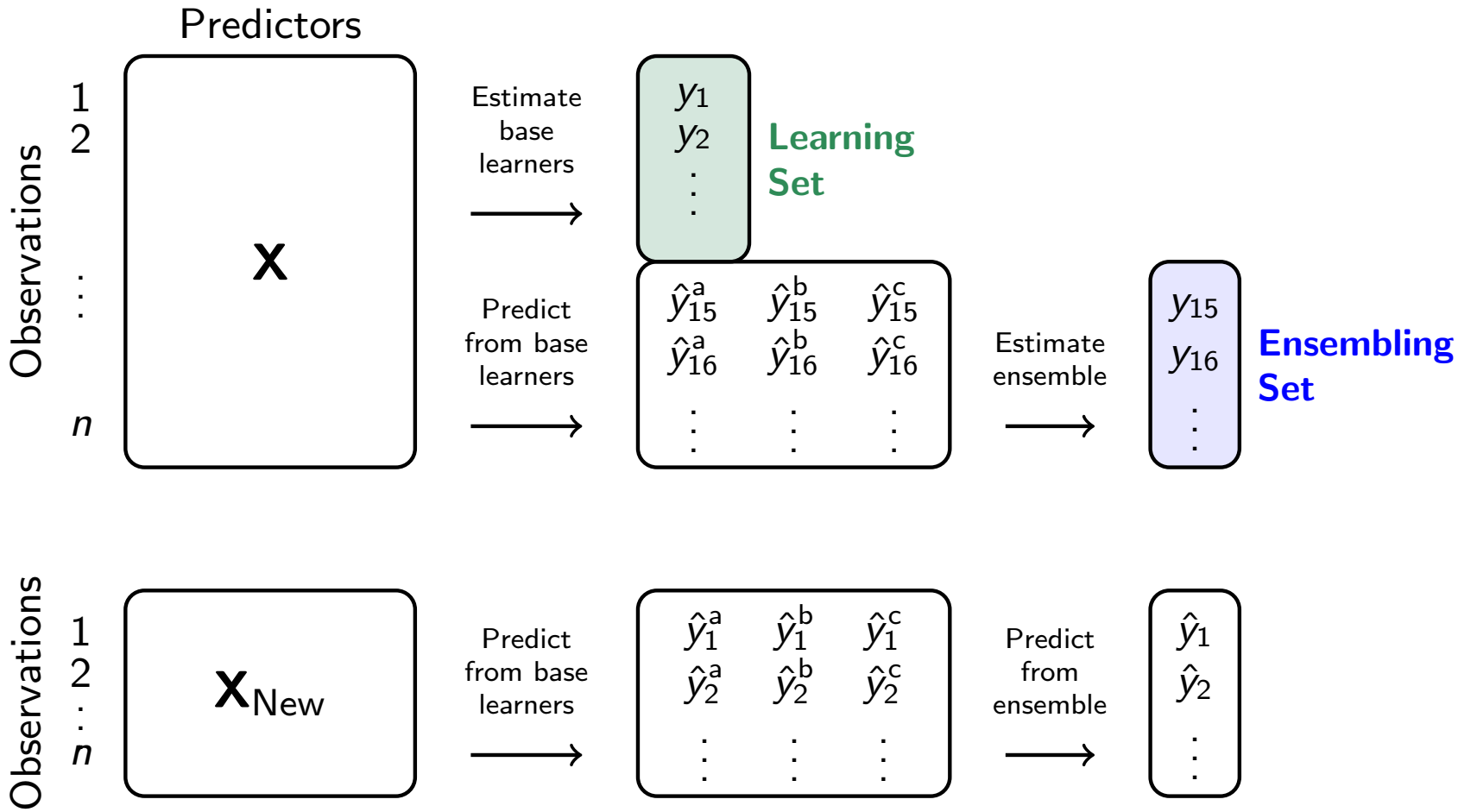

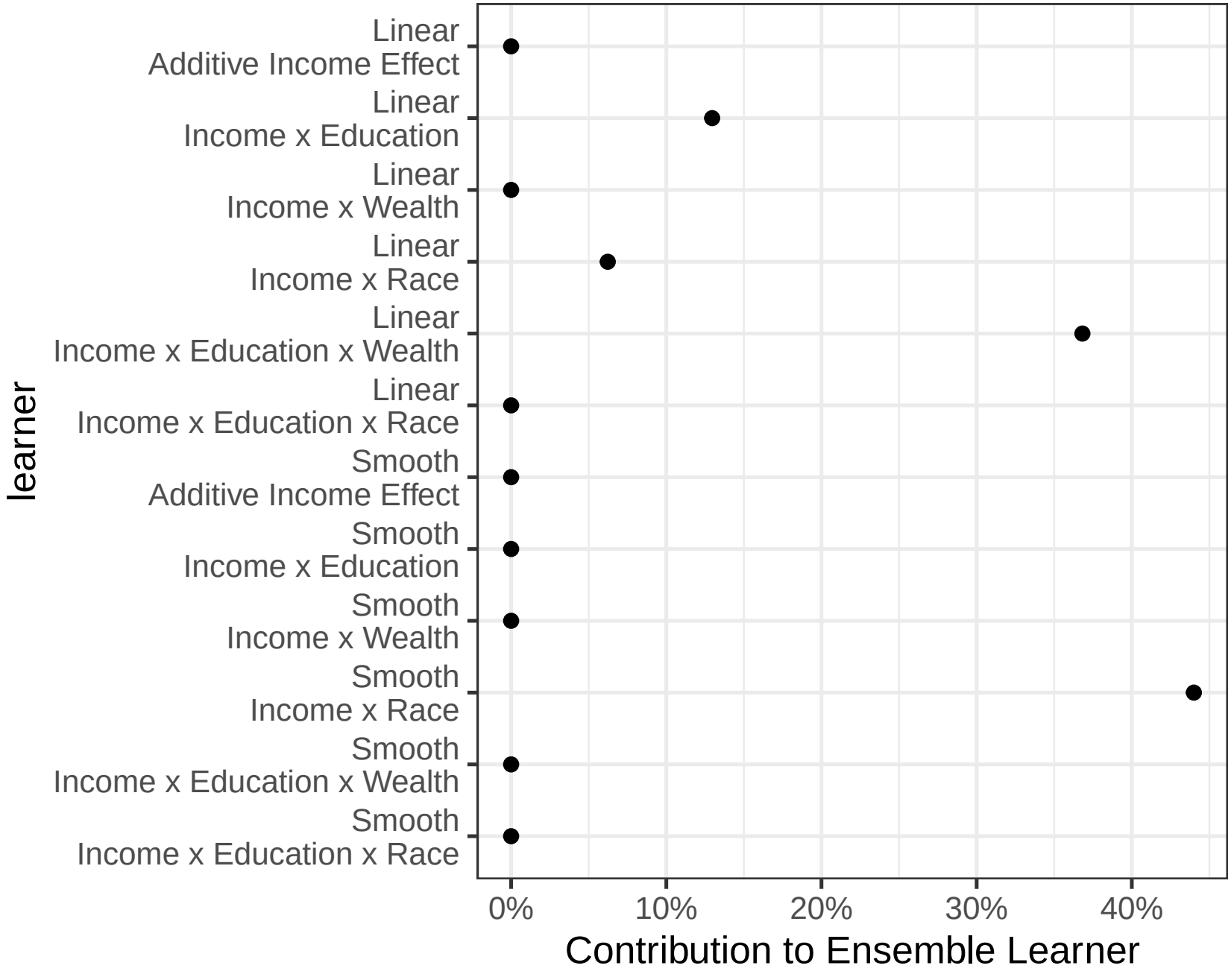
learner
Linear
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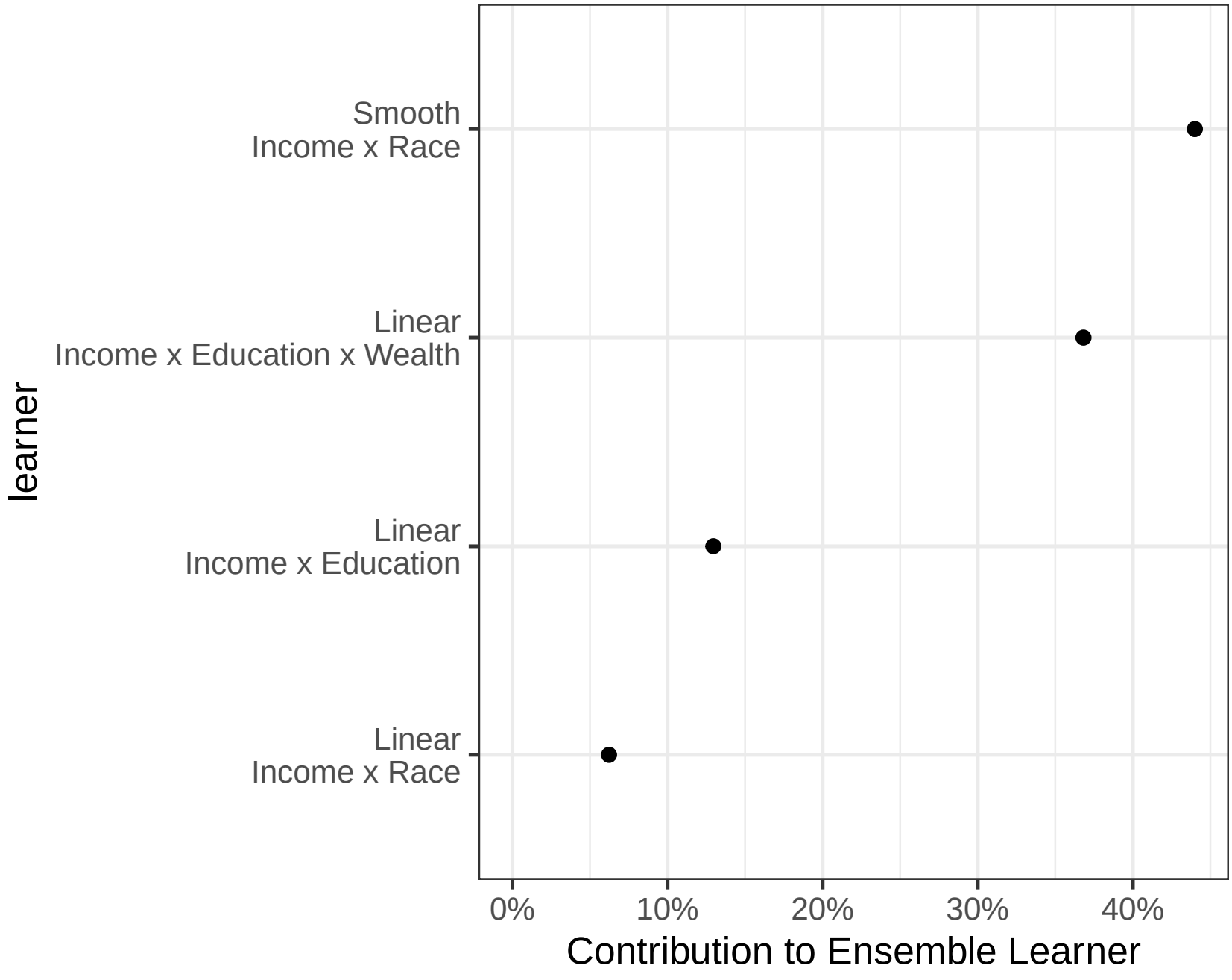
Linear
Income x Education
Linear
Income x Wealth
Linear
Income x Race
Linear
Income x Education x Wealth
Linear
Income x Education x Race
Smooth
Additive Income Effect
Smooth
Income x Education
Smooth
Income x Wealth
Smooth
Income x Race
Smooth
Income x Education x Wealth
Smooth
Income x Education x Race
0%
10%
20%
30%
40%
Contribution to Ensemble Learner


learner
Smooth
Income x Race
Linear
Income x Education x Wealth
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Income x Education
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0%
10%
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30%
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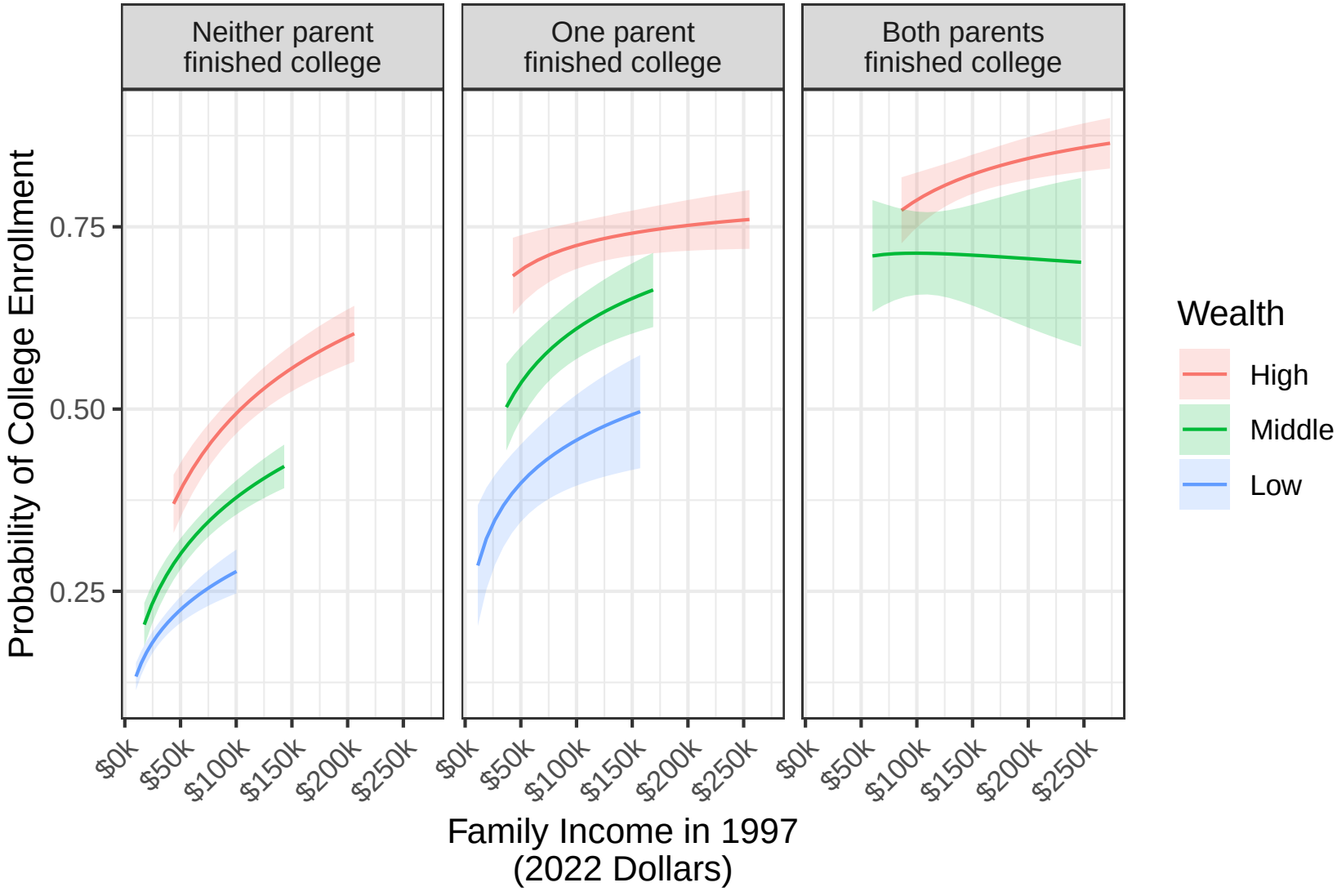
Contribution to Ensemble Learner

Ensemble results

Estimate omitted if $n < 25$



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Ensemble results

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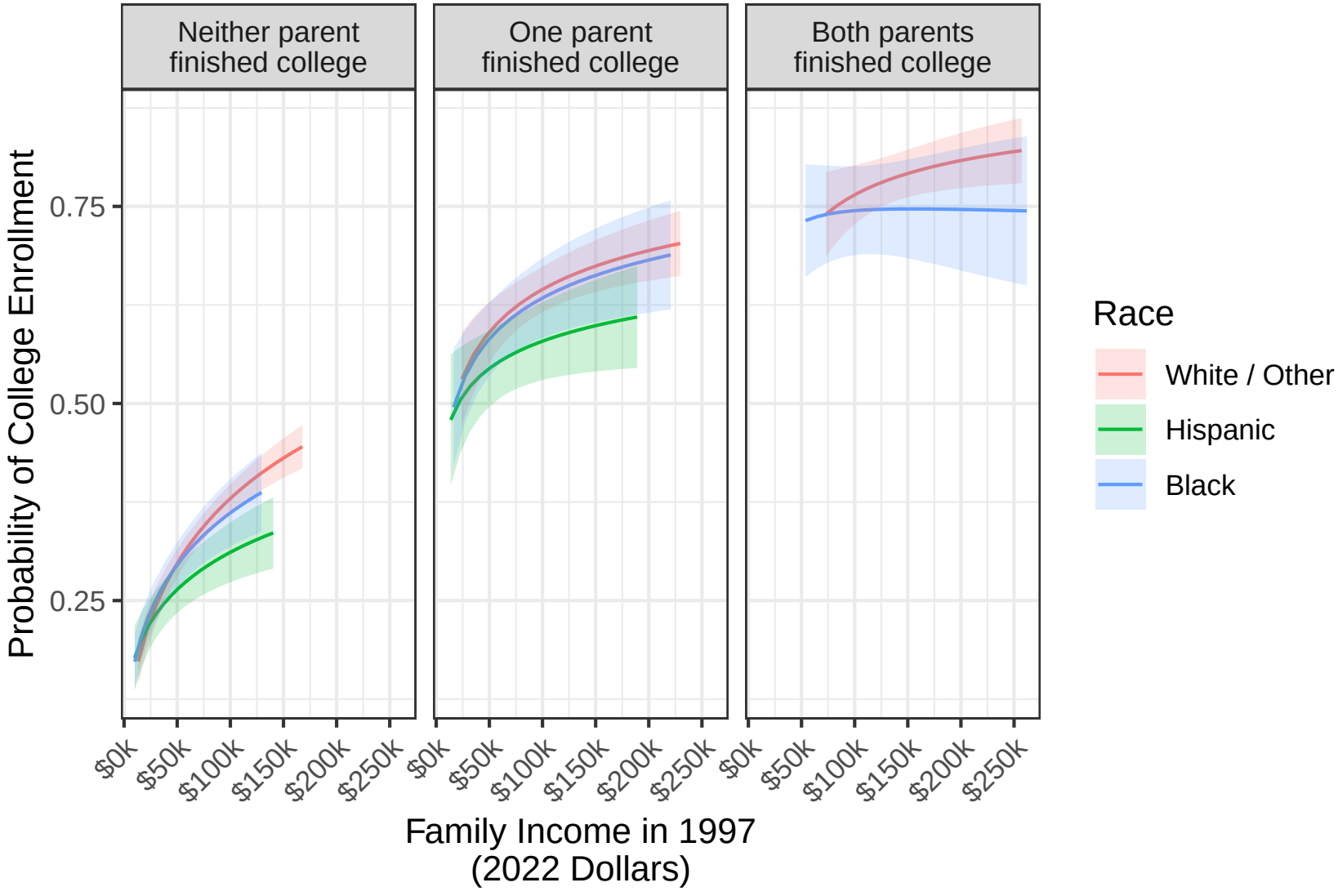

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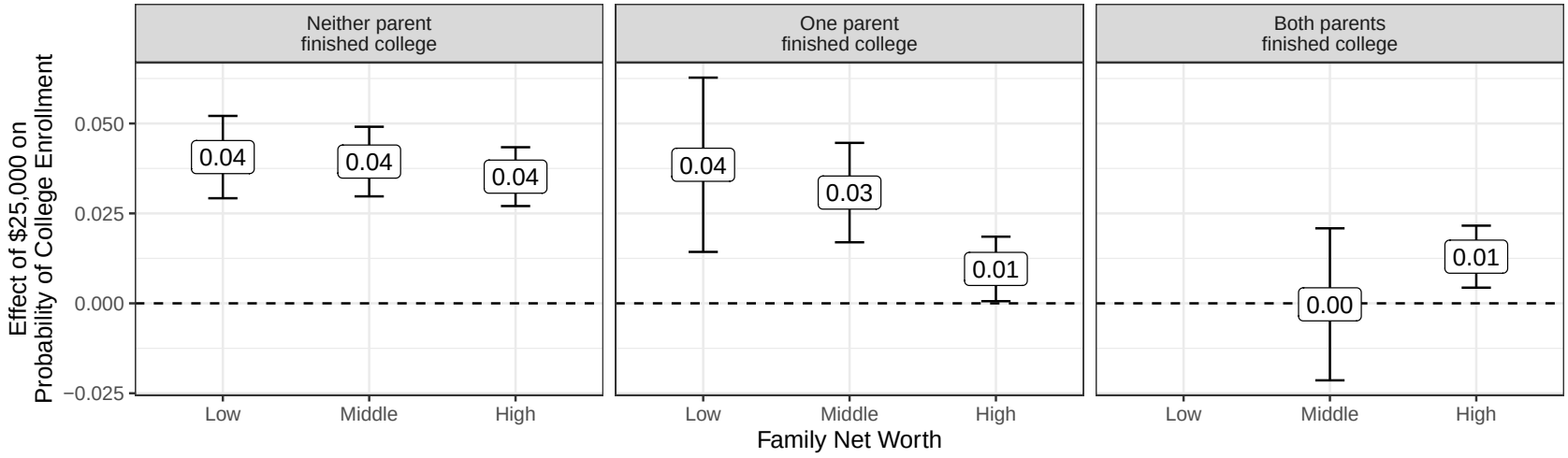
Aggregate point estimates

1. Predict at observed values
2. Predict with \$25,000 extra
3. Difference and average

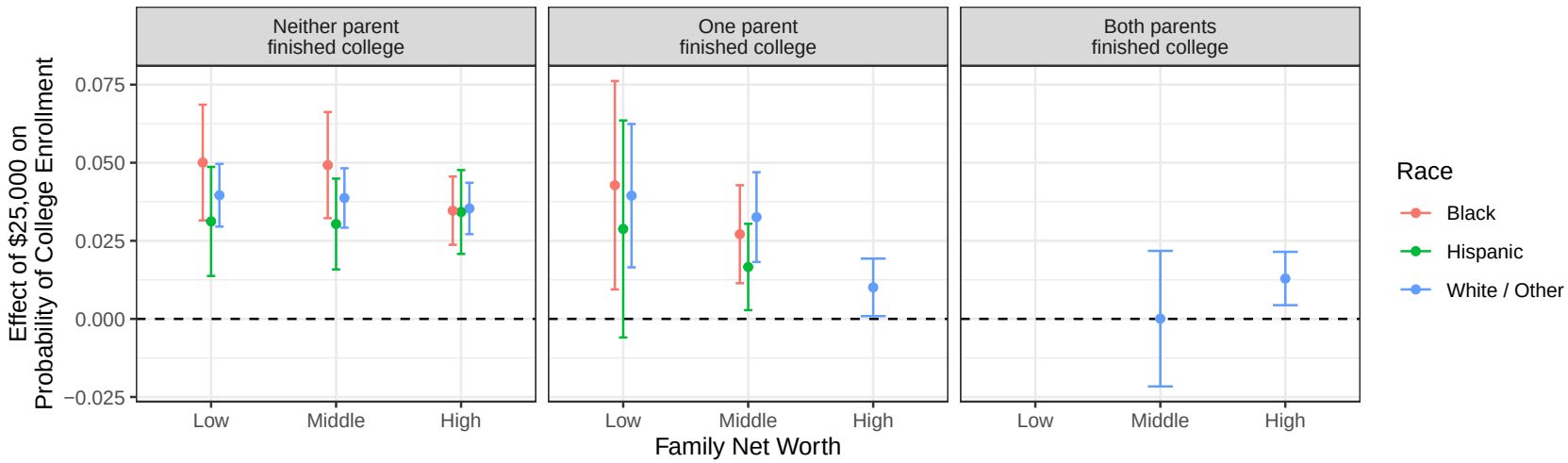
Ensemble results

Estimate omitted if $n < 25$



Ensemble results

Estimate omitted if $n < 25$



DISCUSSION

Scholars of social stratification face a tension

$$\begin{aligned} \text{theory} &\rightsquigarrow \text{belief in effect heterogeneity} \\ \text{small samples} &\rightsquigarrow \text{estimation of additive models} \end{aligned}$$

Scholars of social stratification face a tension

theory	$\rightsquigarrow$	belief in effect heterogeneity
small samples	$\rightsquigarrow$	estimation of additive models

Middle Ground

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Middle Ground

search for heterogeneity
(flexible model)

Scholars of social stratification face a tension

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Middle Ground

search for heterogeneity
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assume structure
(additive model)

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theory $\rightsquigarrow$ belief in effect heterogeneity
small samples $\rightsquigarrow$ estimation of additive models

Middle Ground

search for heterogeneity (flexible model)

assume structure (additive model)

data-driven weighted average

Our biggest estimate:

If neither parent finished college,
a $25,000 income boost raises
college enrollment by 4 percentage points

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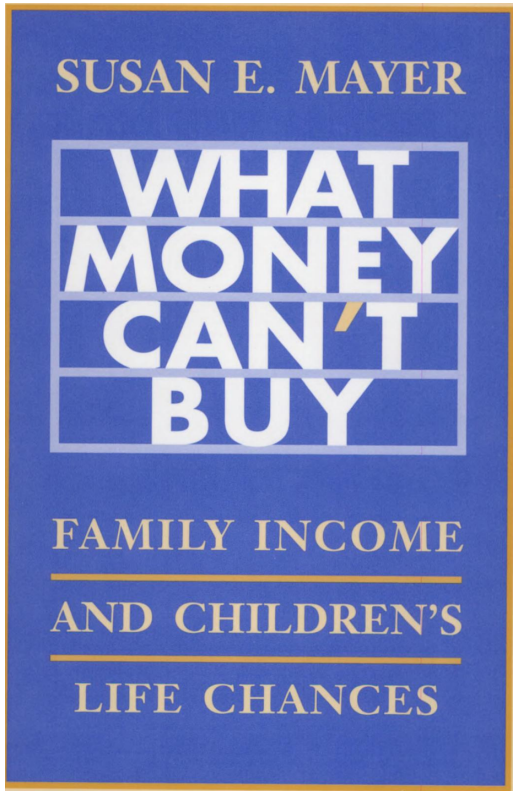

In a world where effects are small,

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it is all the more important to find
the subgroups for whom they are larger

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Do this with trees

Athey & Imbens 2016
Brand et al. 2021

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Do this with trees — Athey & Imbens 2016, Brand et al. 2021

Do this with forests — Wager & Athey 2018

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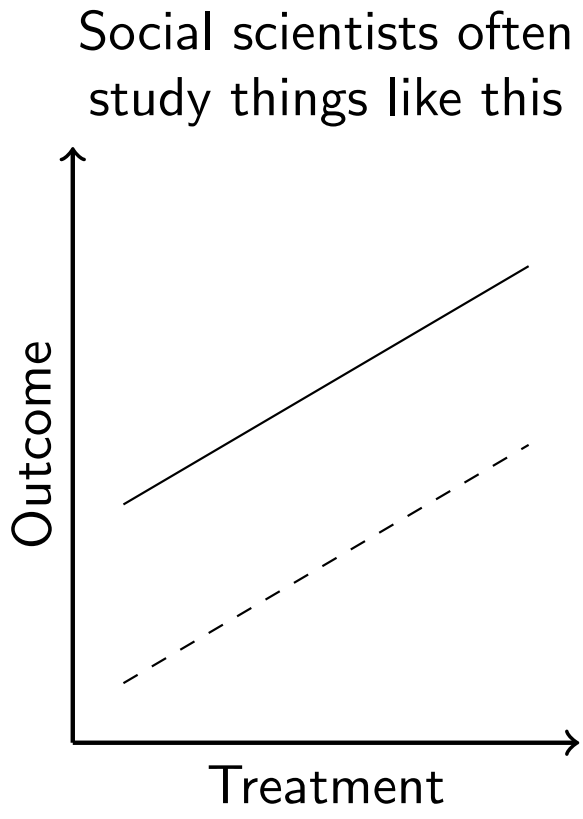
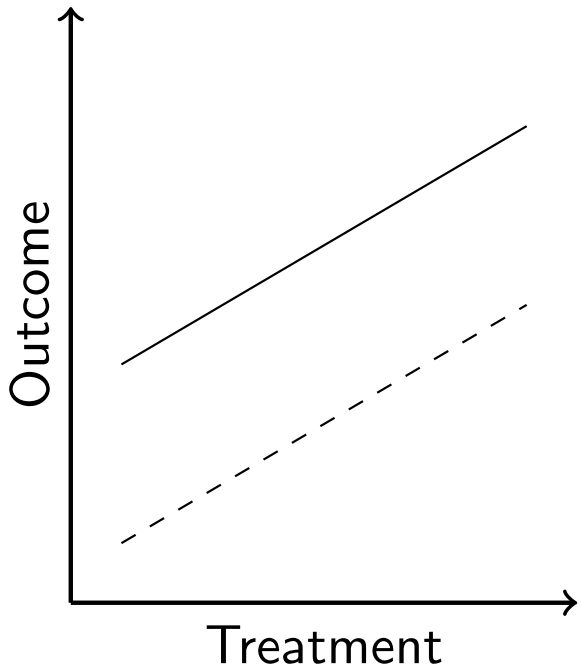
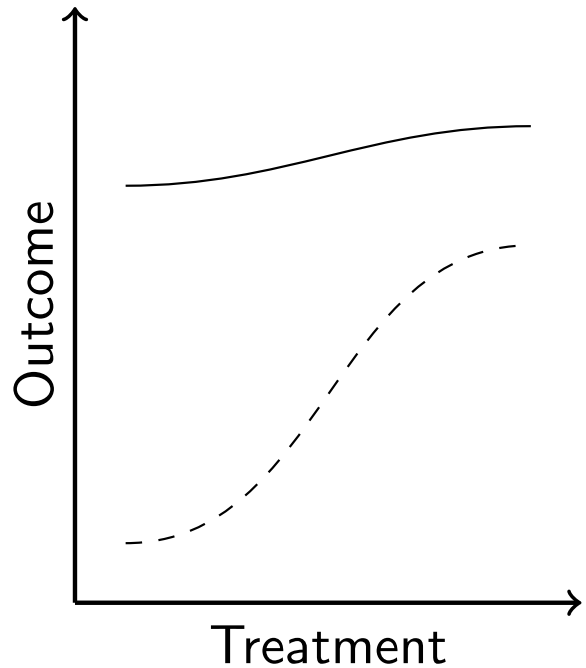
Do this with trees	Athey & Imbens 2016
	Brand et al. 2021
Do this with forests	Wager & Athey 2018
Do this with targeted learning	Van der Laan & Rose 2018


Social scientists often
study things like this
Outcome
Treatment

Social scientists often study things like this



Perhaps sometimes we should study them like this

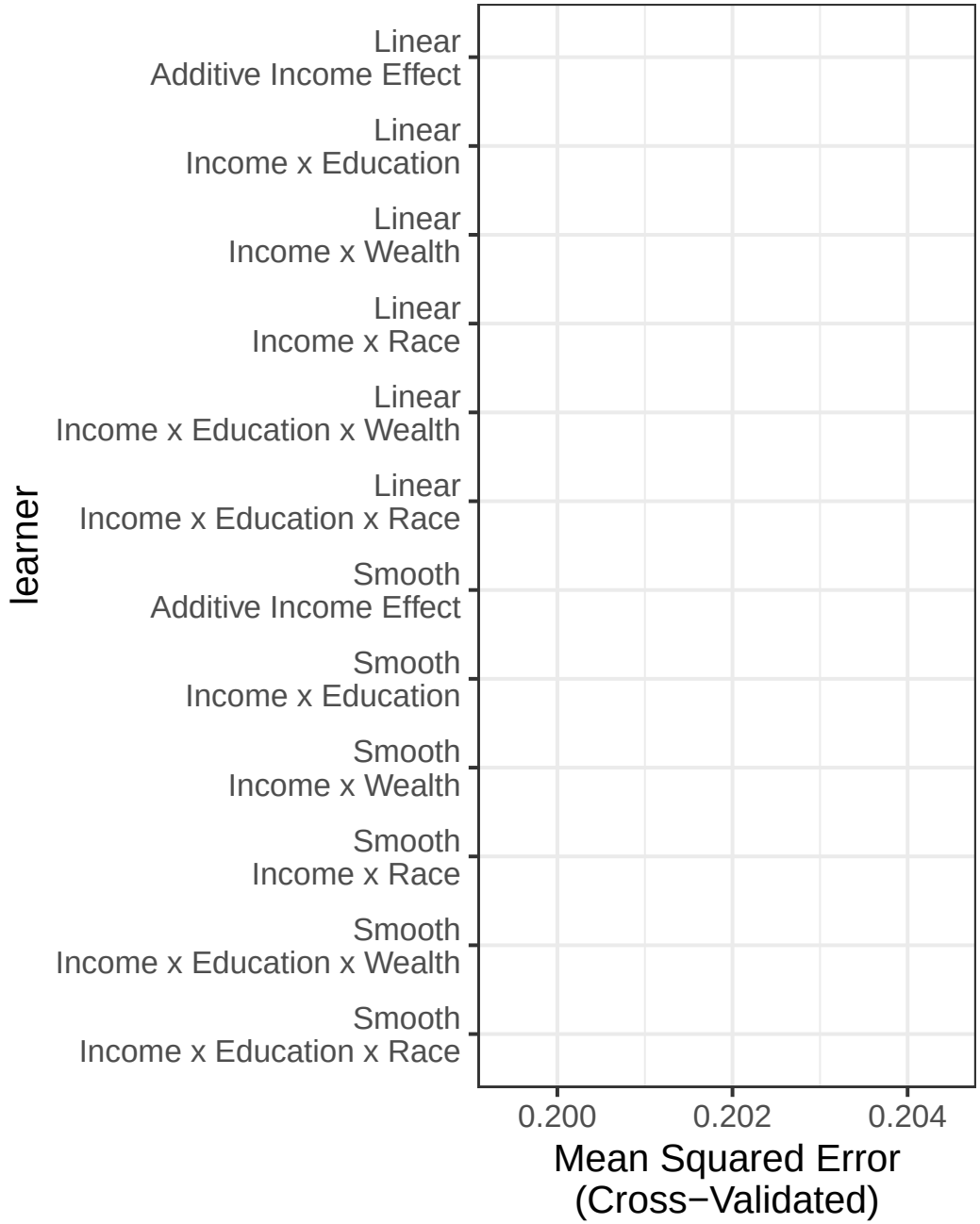


Thanks!

Ian Lundberg
ilundberg@cornell.edu

Jennie E. Brand
brand@soc.ucla.edu

How did the base learners perform?



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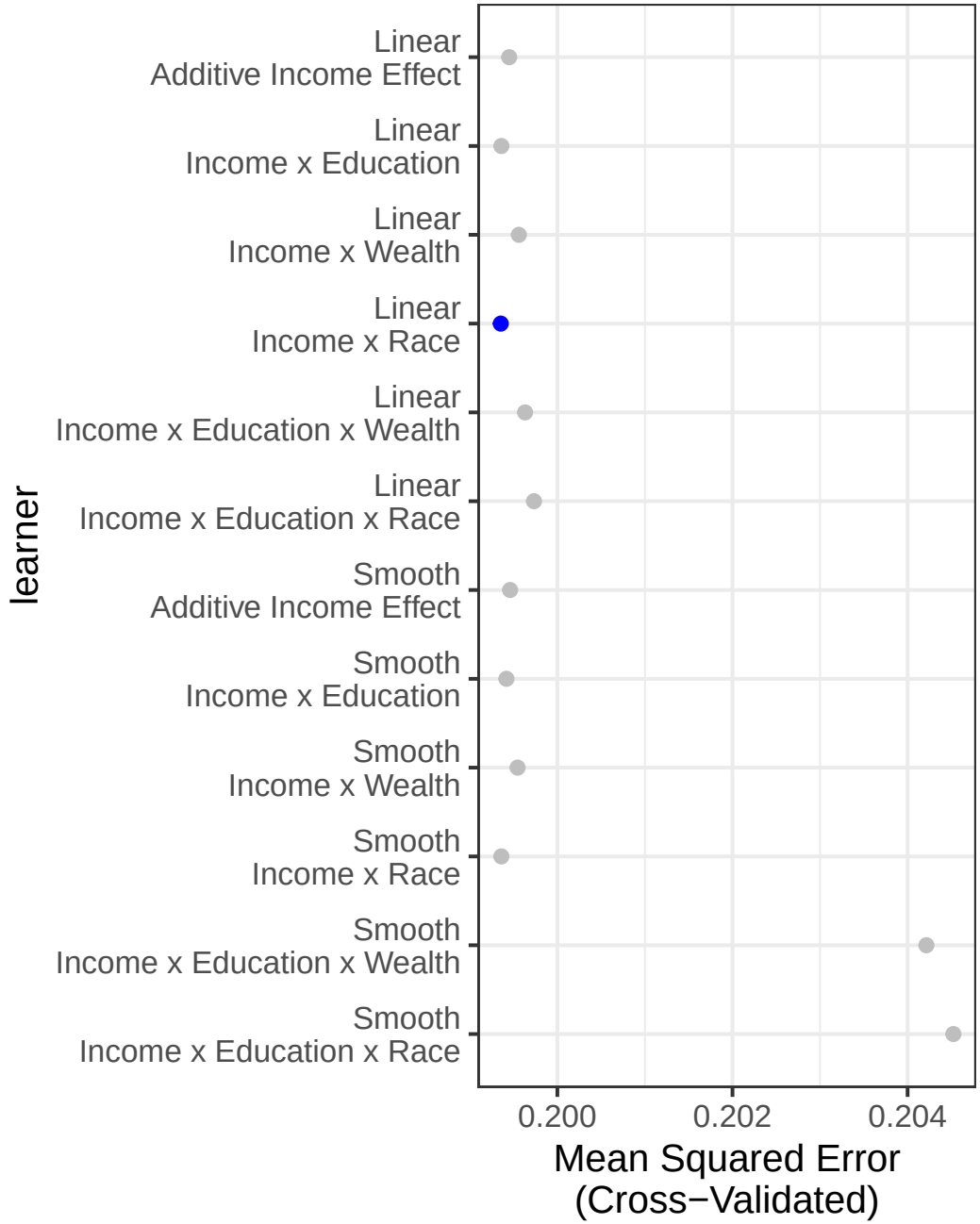
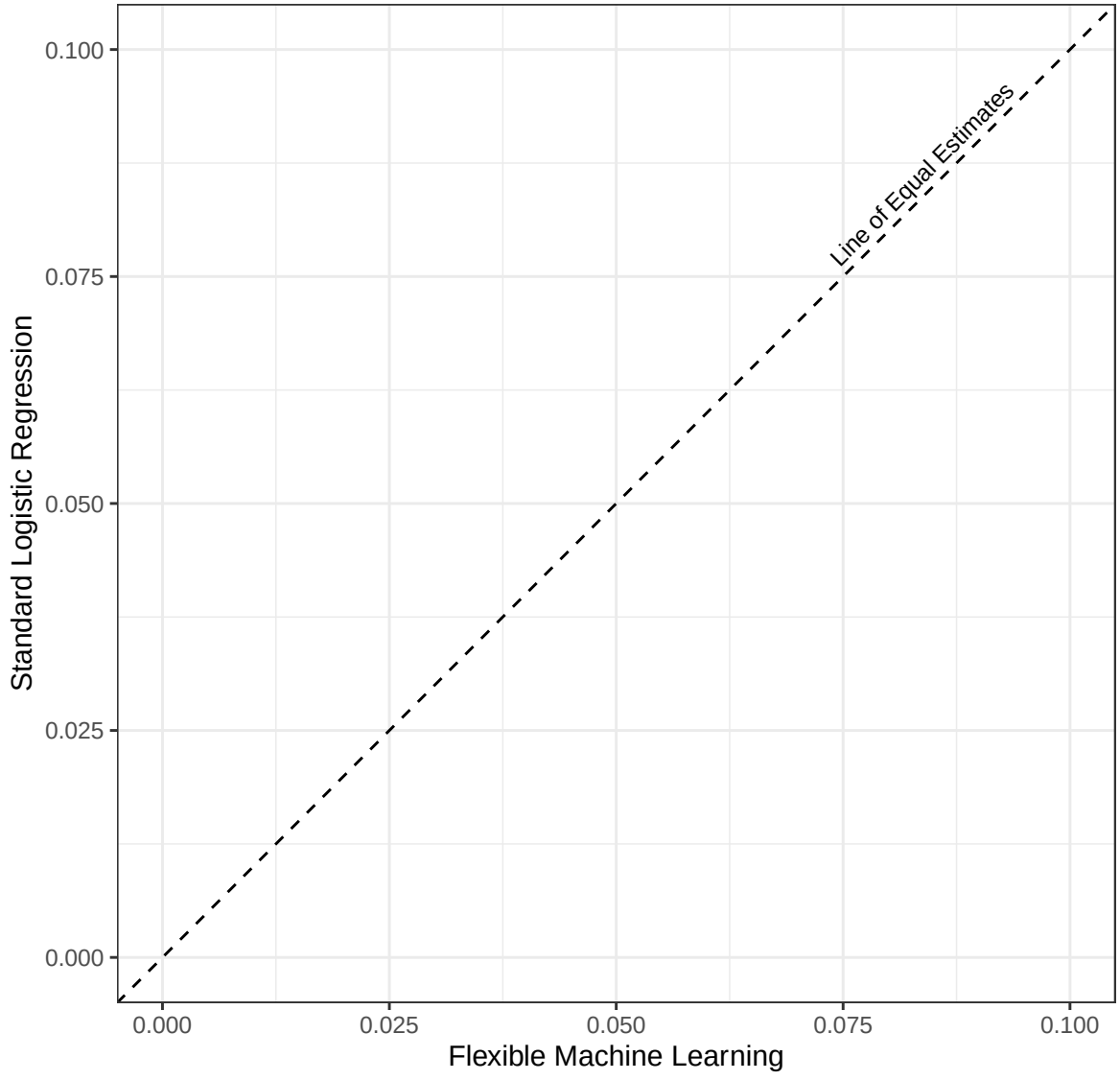


How different was machine learning?

Effect of extra $25k



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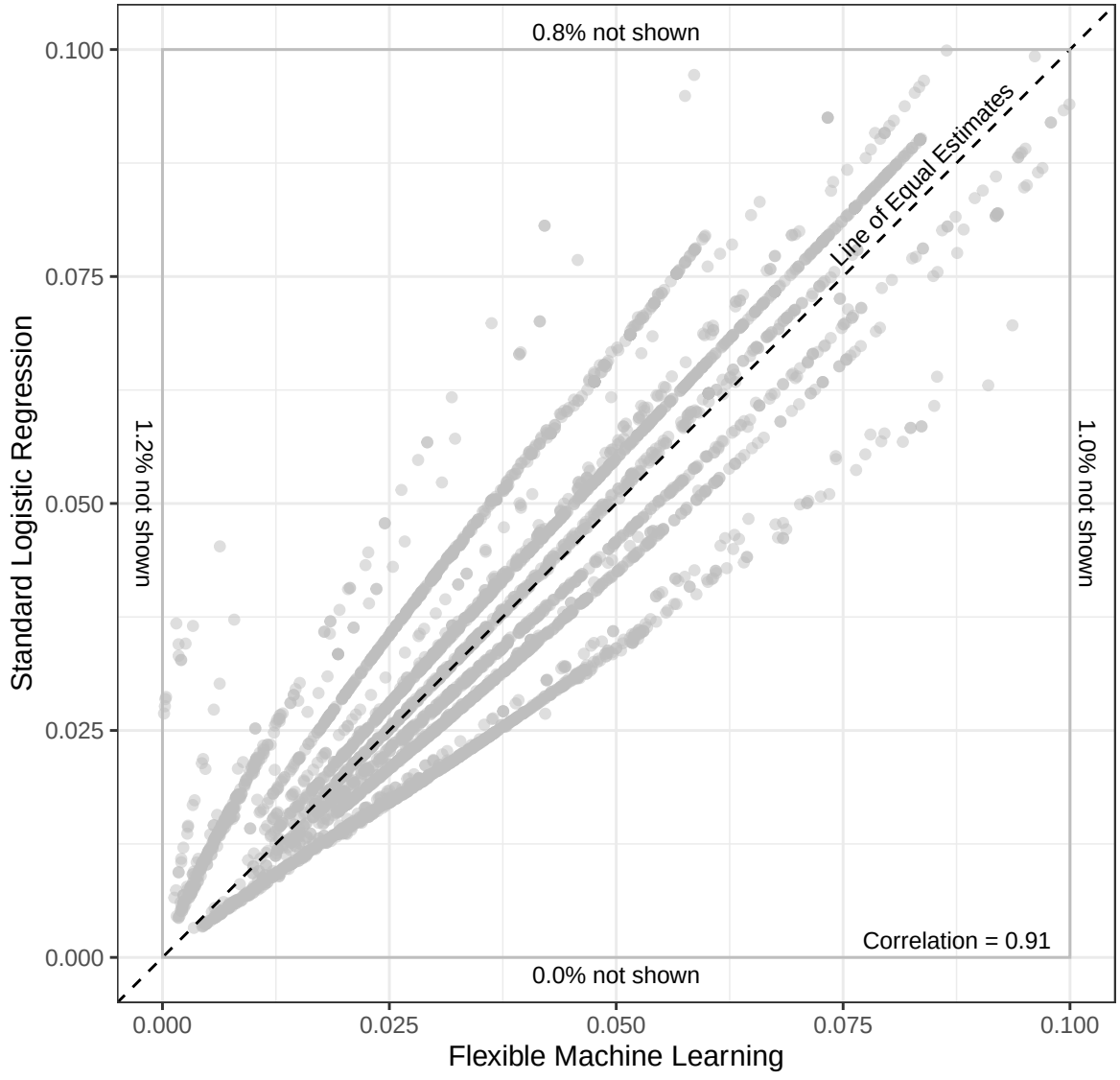

Sample restrictions

Raw sample	8,984
Observed at age 25+	8,408
With valid income	6,198
With income not top-coded	6,074
Non-missing wealth	5,418
Valid enrollment outcome	4,856
Valid completion outcome	4,777

Standard errors

Let $\hat{\theta}_1, \hat{\theta}_2$ be estimates that are random variables due to sampling variability. Let π_1, π_2 be weights on them. For simplicity, we will take the ensemble weights π_1, π_2 to be known, although this misses one source of uncertainty.

$$\begin{aligned}
\mathsf{V}(\pi_1\hat{\theta}_1 + \pi_2\hat{\theta}_2) &= \pi_1^2\mathsf{V}(\hat{\theta}_1) + \pi_2^2\mathsf{V}(\hat{\theta}_2) + 2\pi_1\pi_2\mathsf{Cov}(\hat{\theta}_1, \hat{\theta}_2) \\
&= \pi_1^2\mathsf{V}(\hat{\theta}_1) + \pi_2^2\mathsf{V}(\hat{\theta}_2) + 2\pi_1\pi_2\mathsf{Cor}(\hat{\theta}_1, \hat{\theta}_2)\mathsf{SD}(\hat{\theta}_1)\mathsf{SD}(\hat{\theta}_2) \\
&\leq \pi_1^2\mathsf{V}(\hat{\theta}_1) + \pi_2^2\mathsf{V}(\hat{\theta}_2) + 2\pi_1\pi_2\mathsf{SD}(\hat{\theta}_1)\mathsf{SD}(\hat{\theta}_2)
\end{aligned}$$

First difference, by education and race