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# Discussion of “The Effect of Maternal Labor Supply on Children: Evidence from Bunching”

Carolina Caetano, Gregorio Caetano, Eric Nielsen, and Viviane Sanfelice

**Andrew Goodman-Bacon**

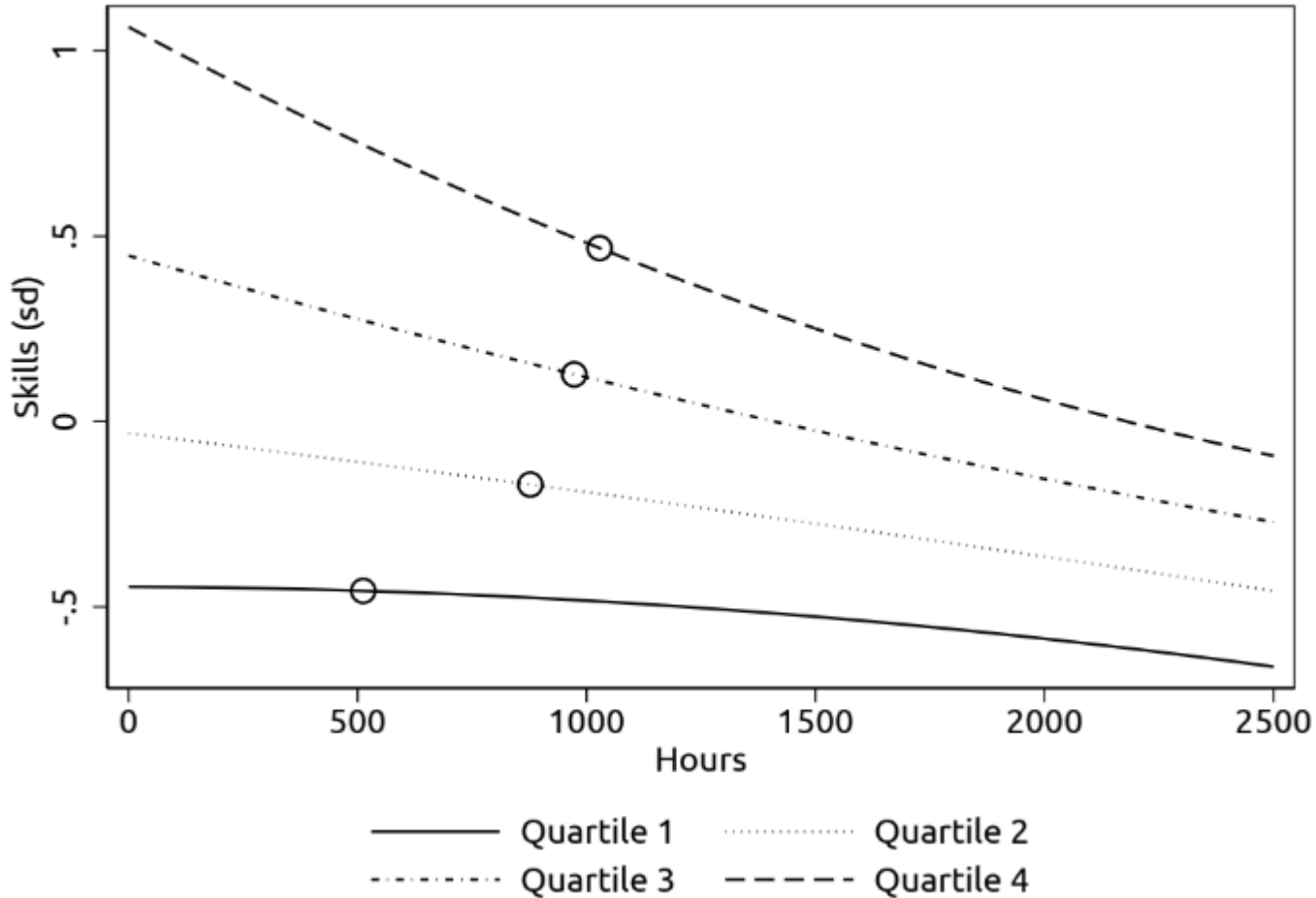
Senior Economist, OIGI

November 17, 2022

The views expressed here are the presenter's and do not necessarily represent those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

# When moms work more, their children learn less

Figure 1: Children's Cognitive Skills – Quartiles of Maternal AFQT



# A COVID-19 labor force legacy: The drop in dual-worker families



Katherine Lim

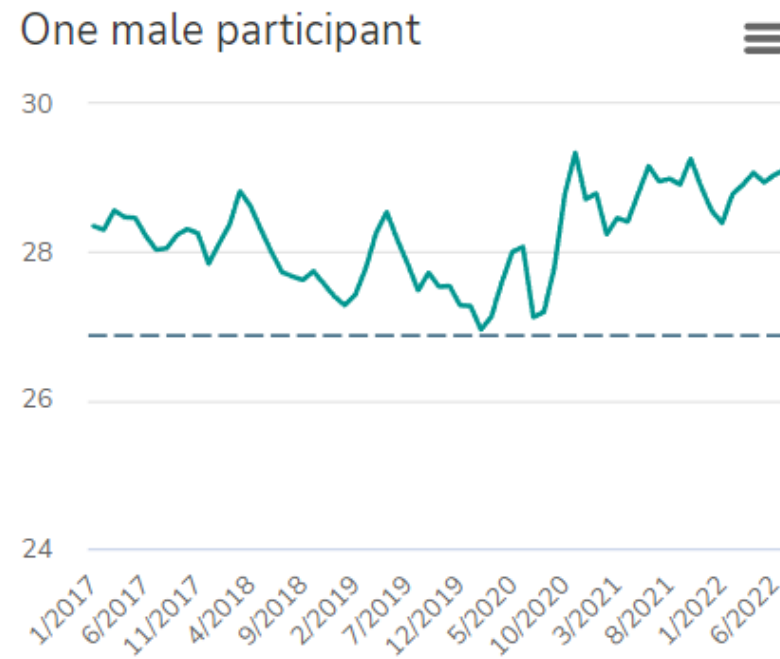
Economist, Community Development and Engagement



Ryan Nunn

Assistant Vice President, Community Development and Engagement

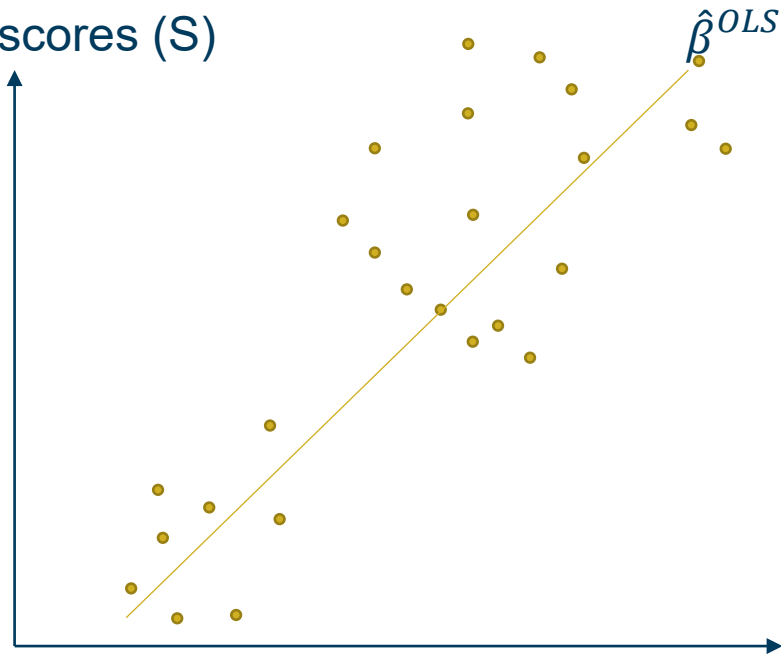
Shift from dual-participant to solo-participant couples without four-year degrees is persistent



# How does this approach work?

$$S_i = \alpha X_i + \hat{\beta}^{OLS} L_i + \epsilon_i$$

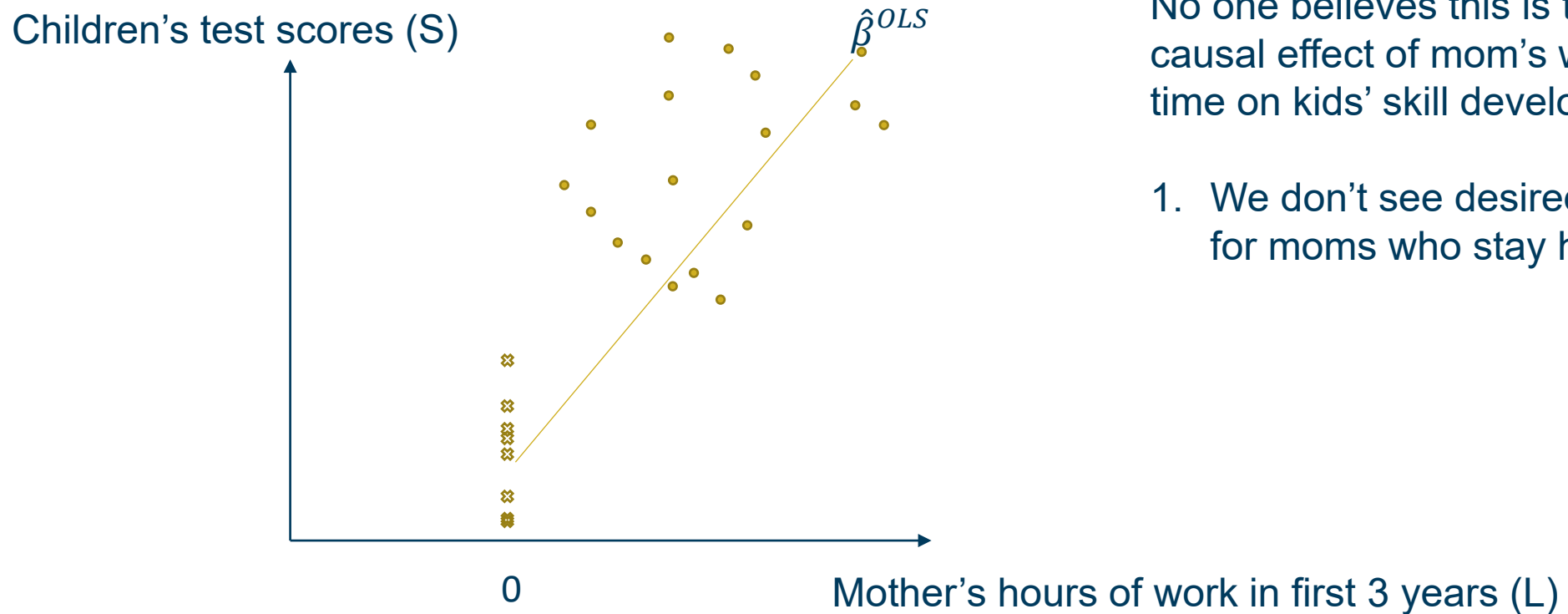
Children's test scores (S)



Mother's hours of work in first 3 years (L)

No one believes this is the causal effect of mom's work time on kids' skill development

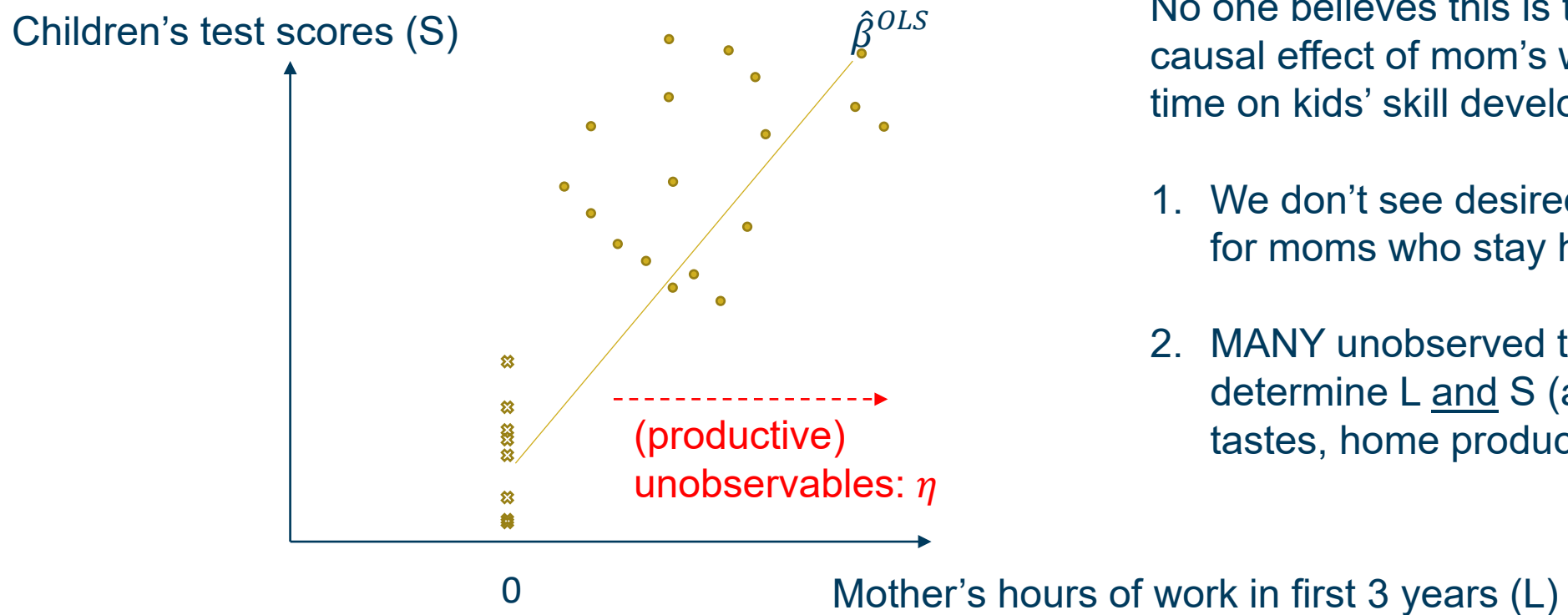
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No one believes this is the causal effect of mom's work time on kids' skill development:

1. We don't see desired work for moms who stay home

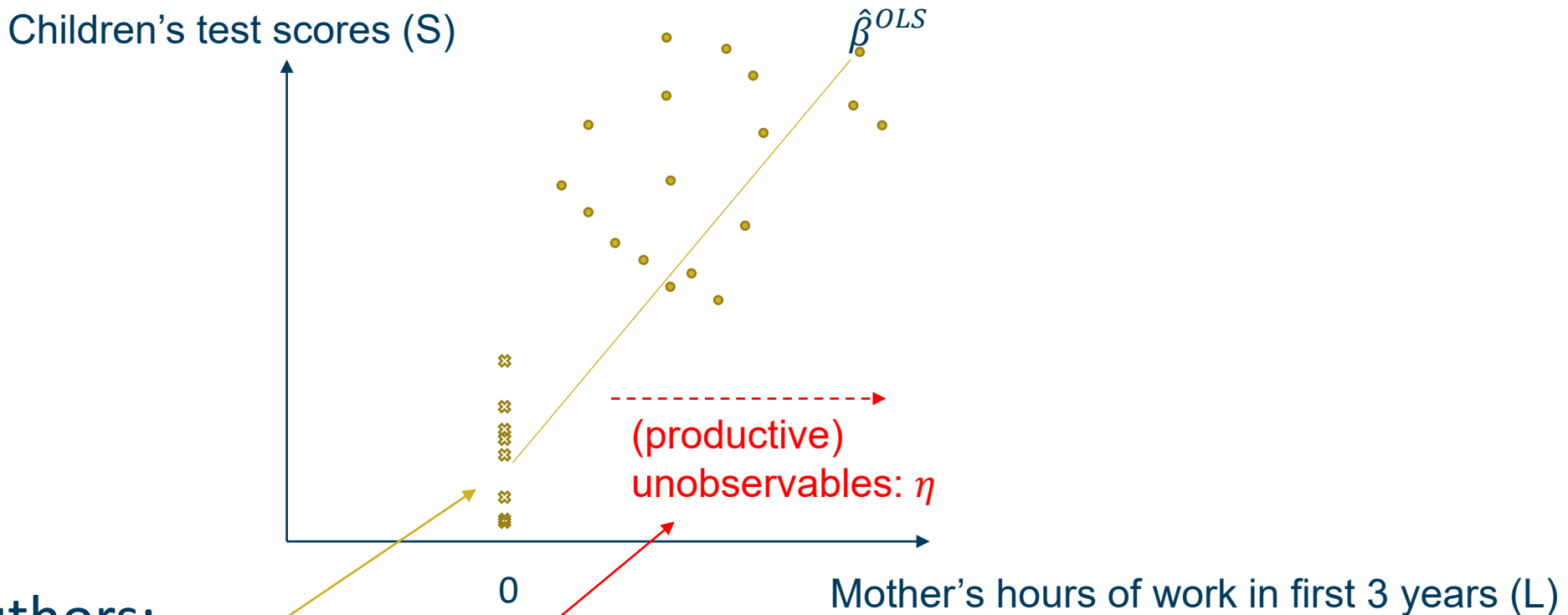
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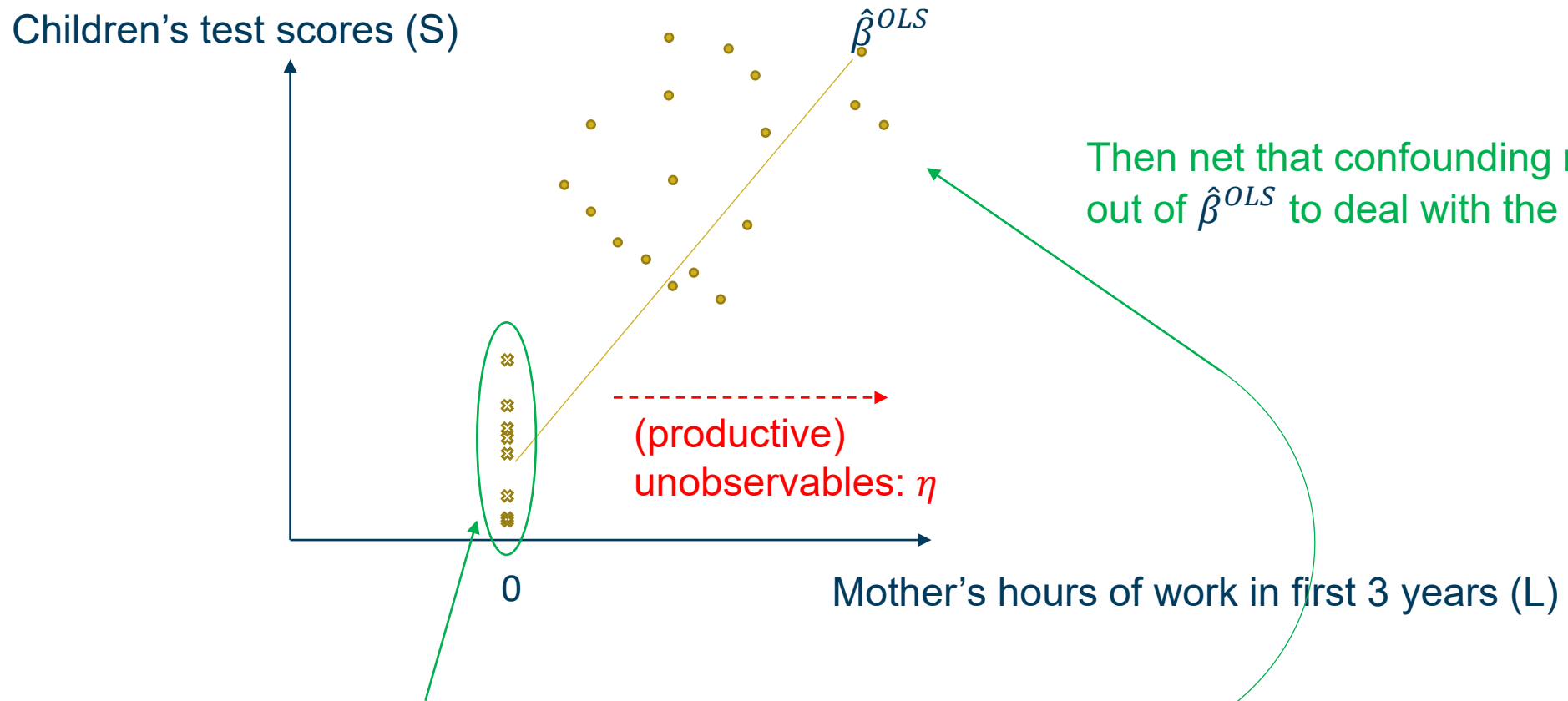
1. We don't see desired work for moms who stay home
2. MANY unobserved things determine L and S (ability, tastes, home productivity)

# How does this approach work?



These authors:  
“But what if **these moms**  
could fix this **problem?**”

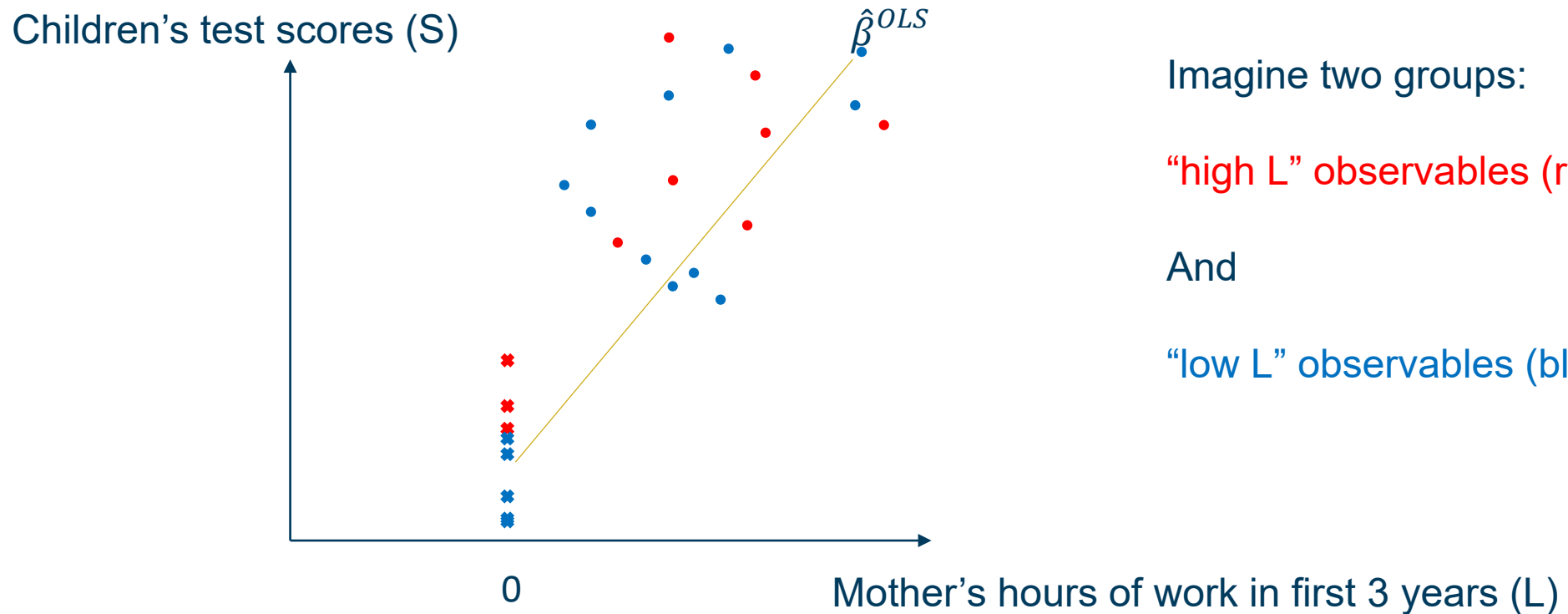
# How does this approach work?



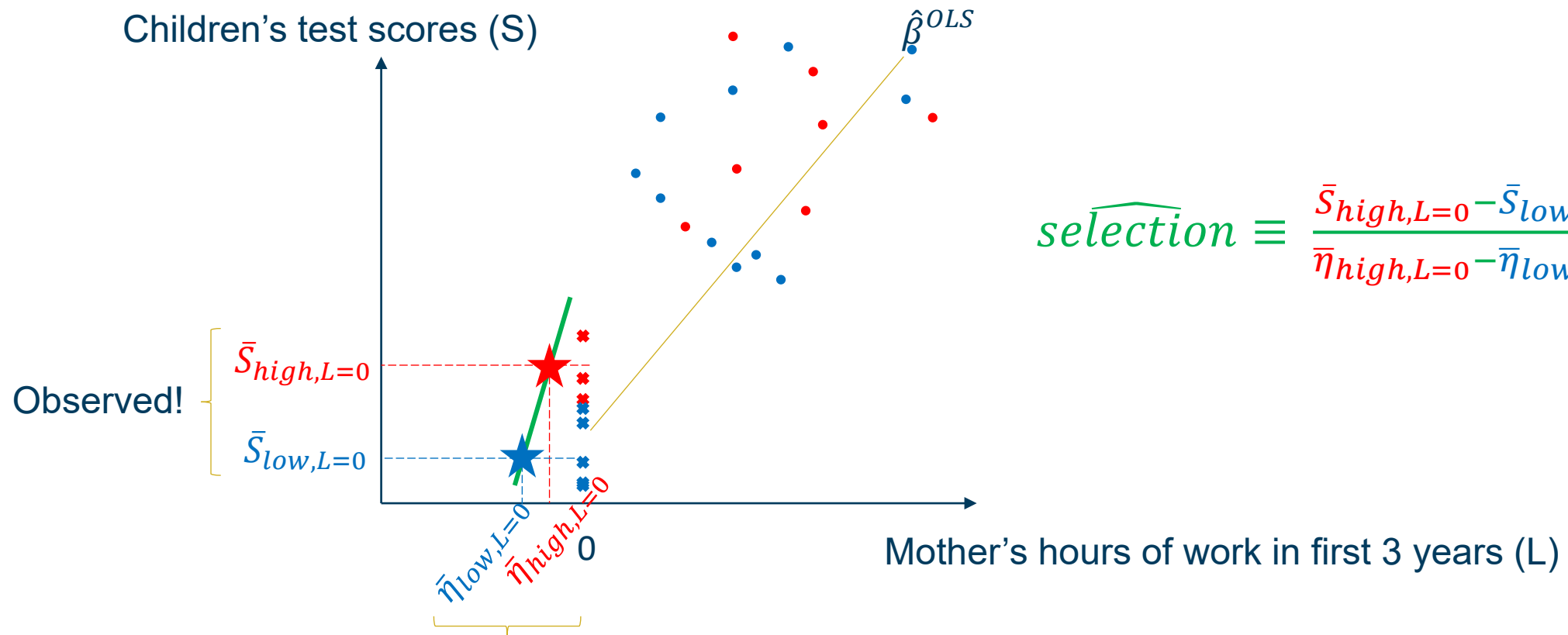
If we could just figure out their unobservables, we could estimate how unobservables affect kids because these moms don't *actually* work.



# How does this approach work?



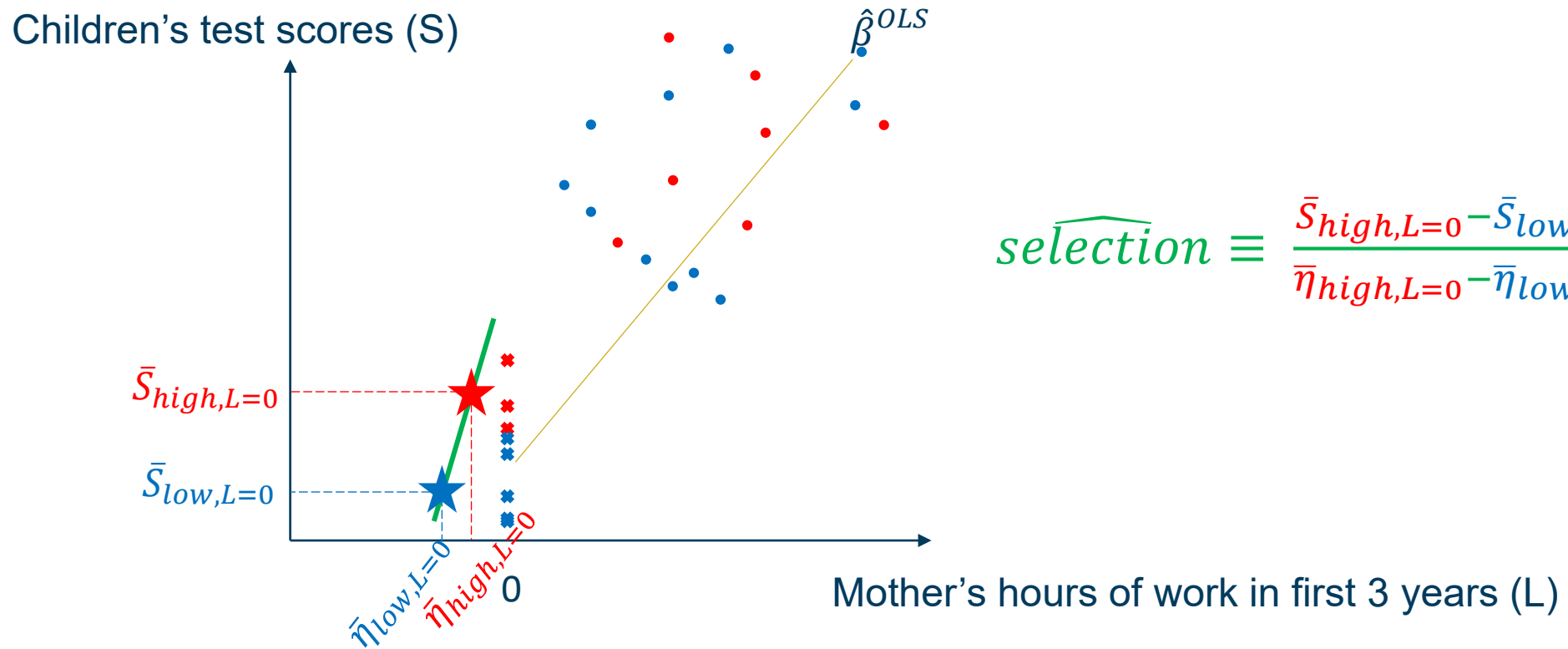
# How does this approach work?



$$\widehat{selection} \equiv \frac{\bar{S}_{high,L=0} - \bar{S}_{low,L=0}}{\hat{\eta}_{high,L=0} - \hat{\eta}_{low,L=0}}$$

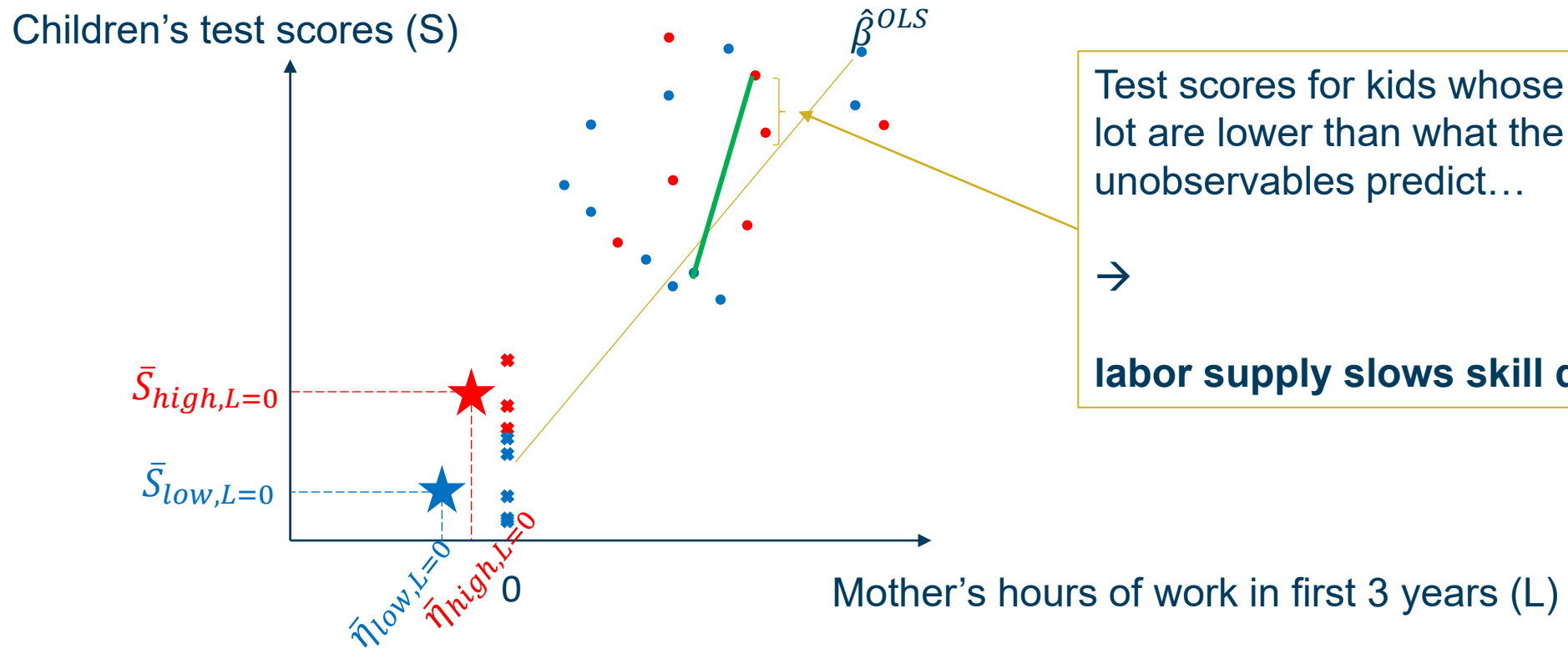
If we can estimate mean unobservables...

# How does this approach work?



$$selection \equiv \frac{\bar{S}_{high,L=0} - \bar{S}_{low,L=0}}{\bar{\eta}_{high,L=0} - \bar{\eta}_{low,L=0}}$$

# How does this approach work?



Test scores for kids whose moms work a lot are lower than what the moms' unobservables predict...

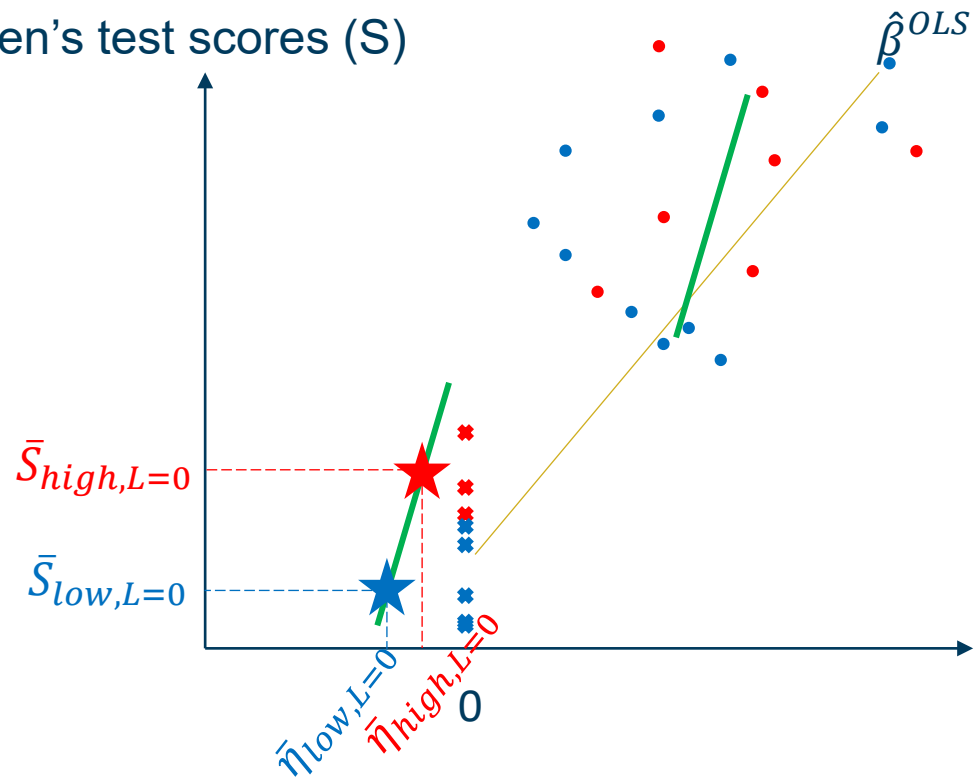


**labor supply slows skill development.**

# It's all about imputing $\eta$

Selection  $> \hat{\beta}^{OLS} \rightarrow L$  is bad

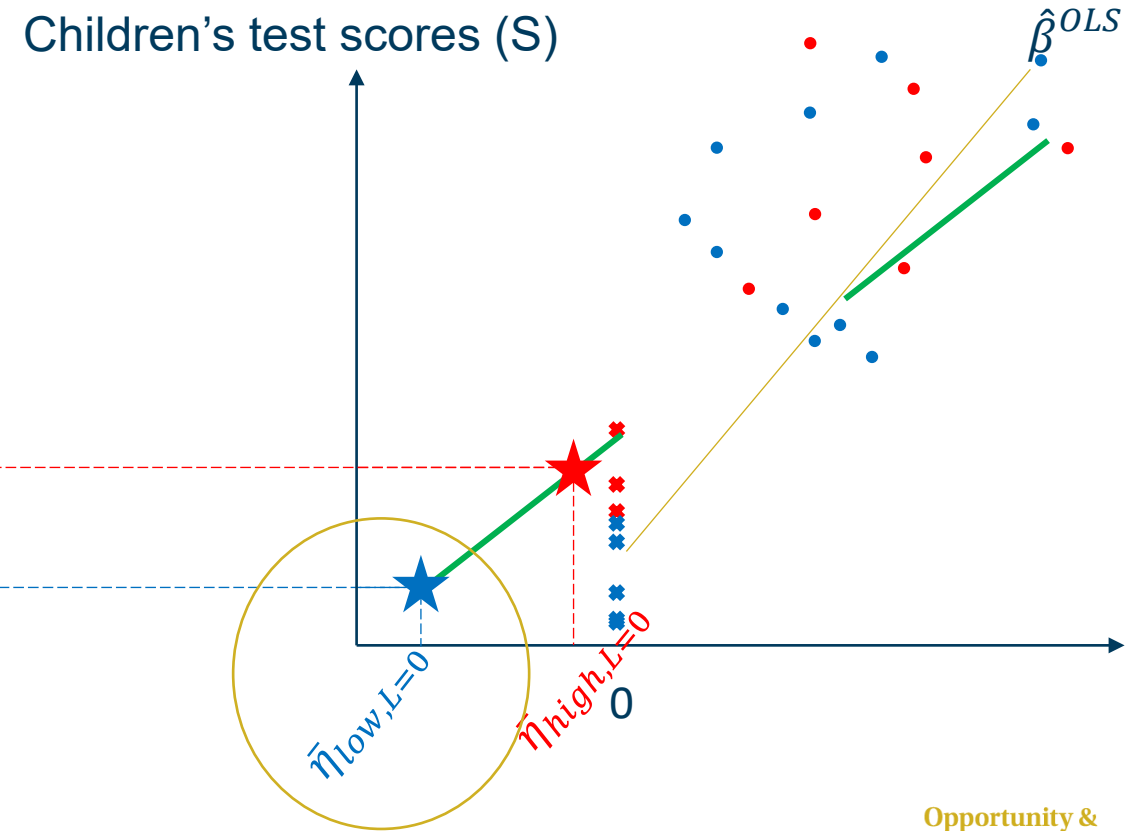
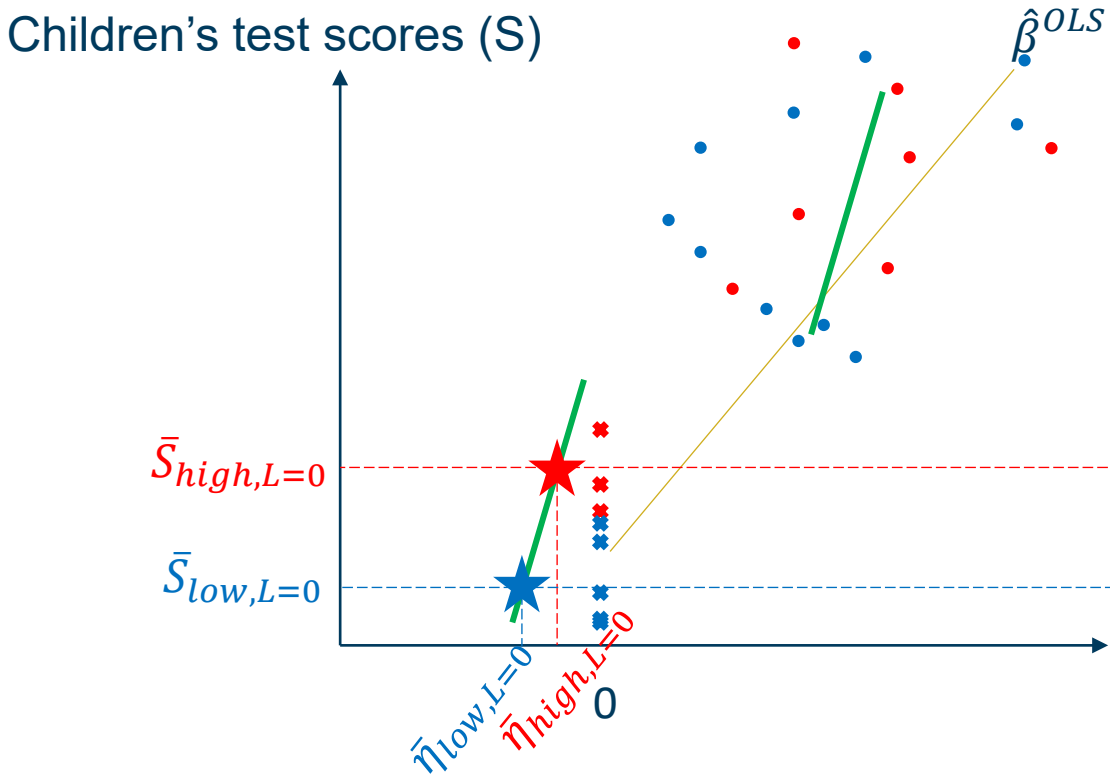
Children's test scores (S)



# It's all about imputing $\eta$

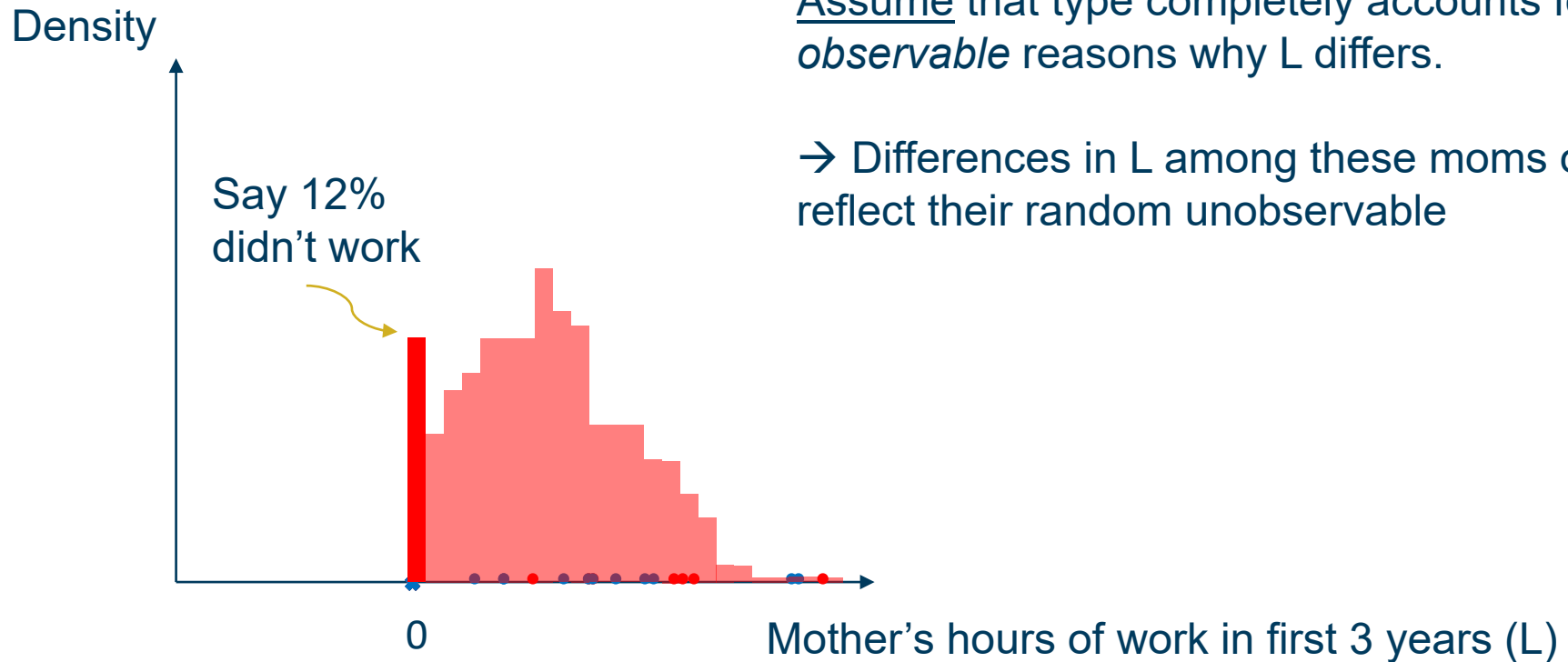
Selection  $> \hat{\beta}^{OLS} \rightarrow L$  is bad

Selection  $< \hat{\beta}^{OLS} \rightarrow L$  is good!



All we did was impute a little differently

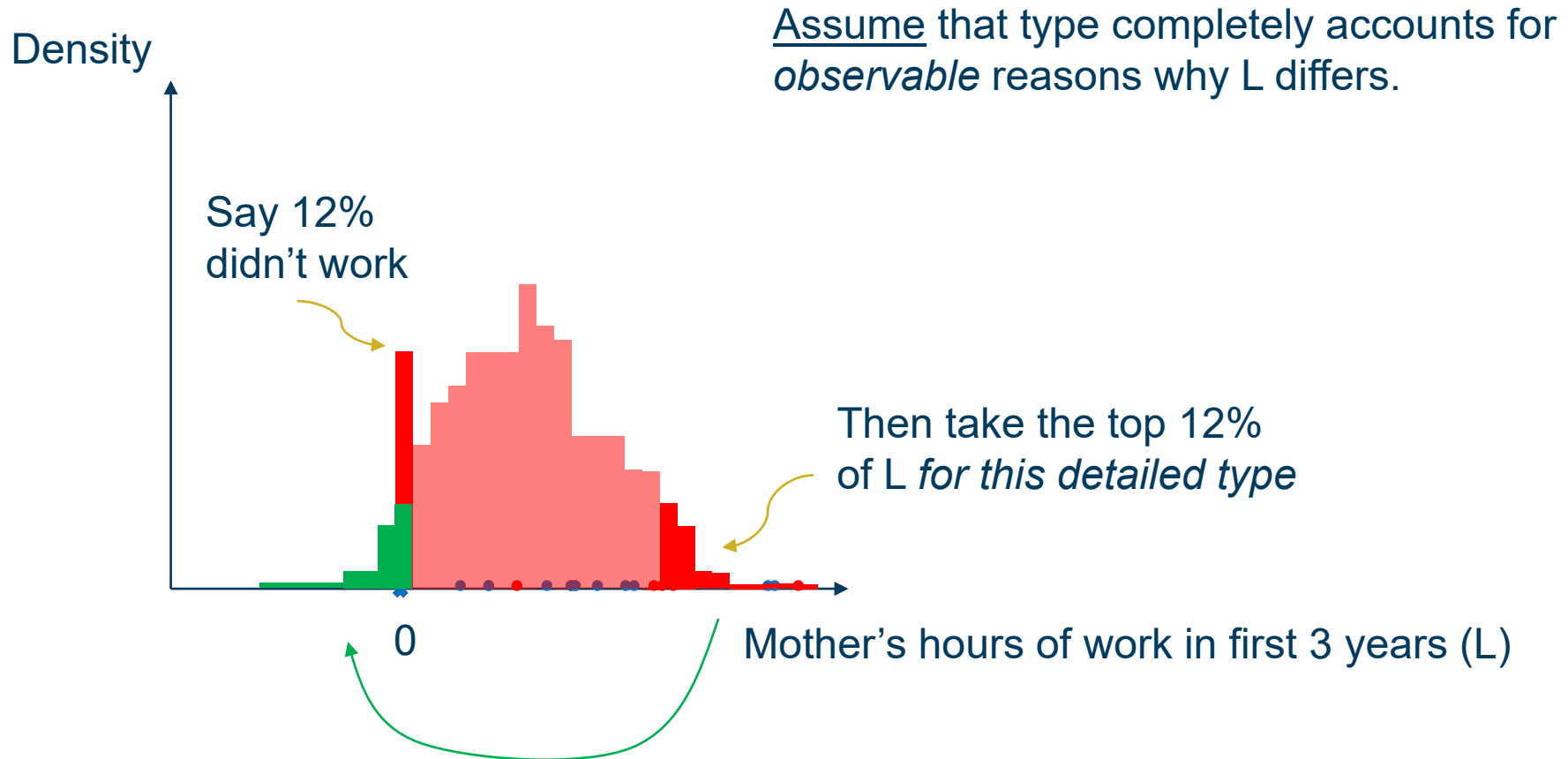
# How to impute $\eta$ ?



Assume that type completely accounts for *observable* reasons why L differs.

→ Differences in L among these moms only reflect their random unobservable

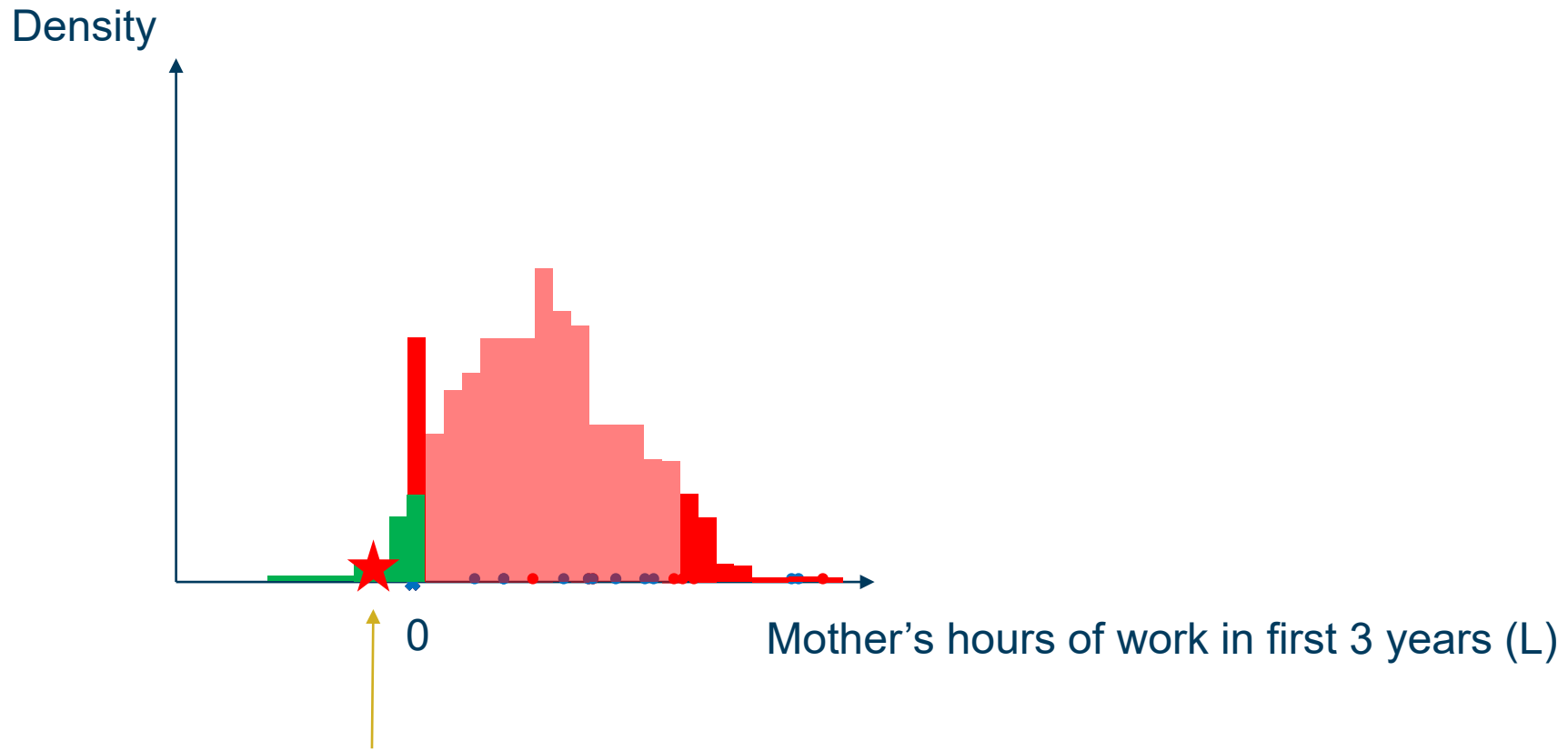
# How to impute $\eta$ ?



Assume symmetry in the distribution of unobservables and stick that mass down here.

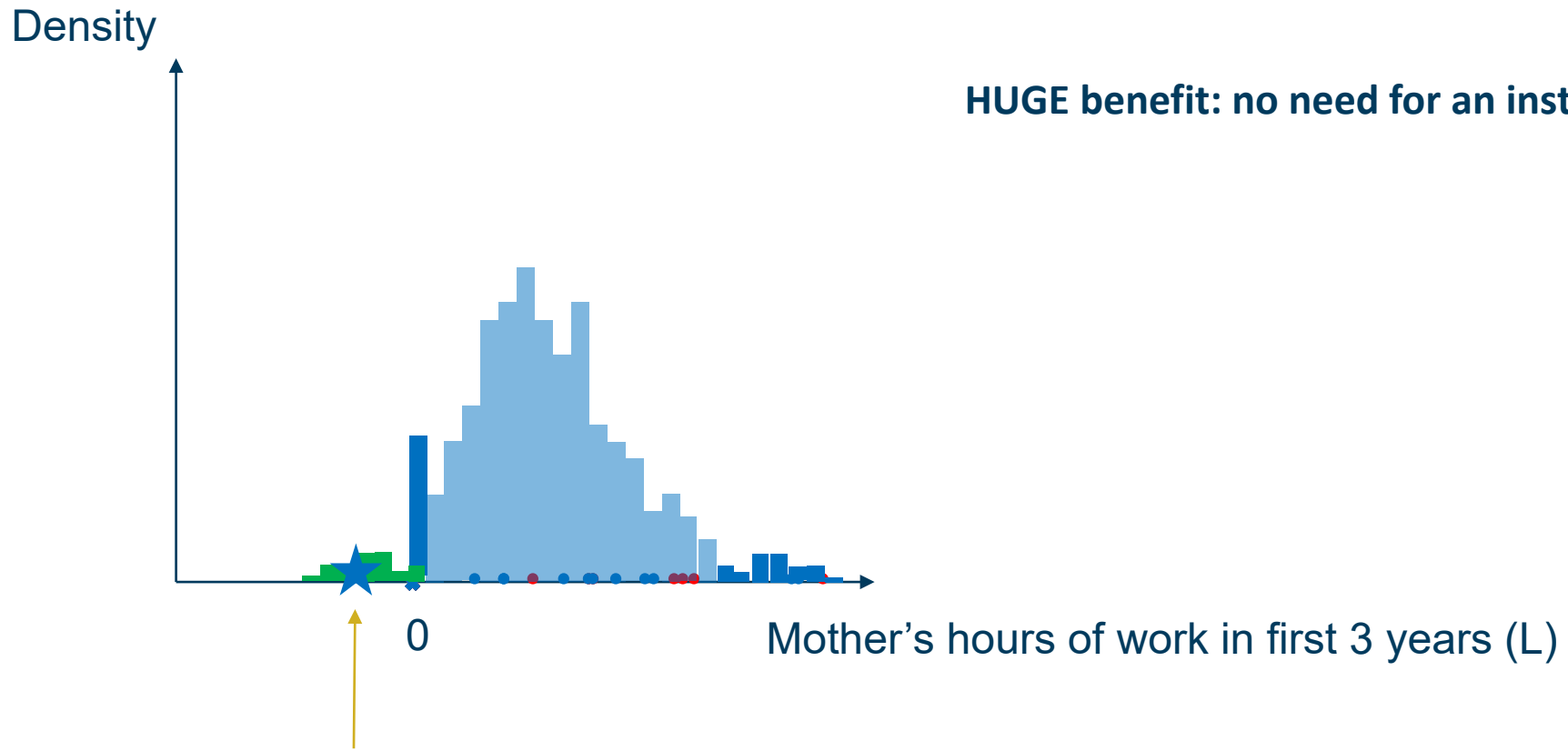


# How to impute $\eta$ ?



Now we “know”:  $E[\text{unobservables} | L = 0, \text{high } L \text{ type}]$  (call it  $\bar{\eta}_H$ )

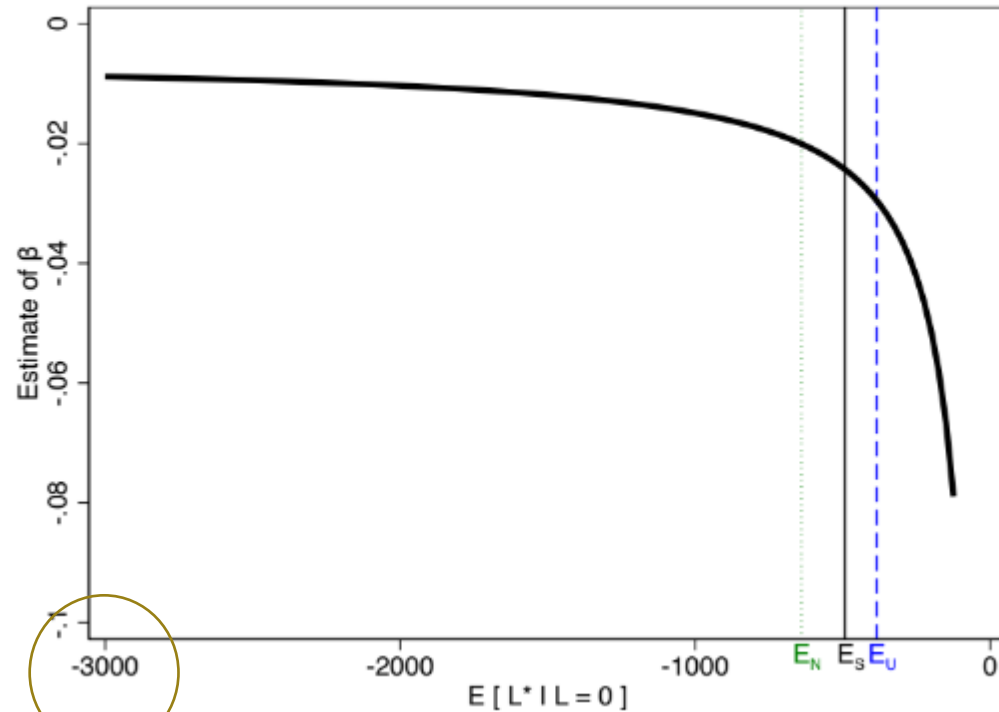
# How to impute $\eta$ ?



Now we “know”:  $E[\text{unobservables} | L = 0, \text{low } L \text{ type}]$  (call it  $\bar{\eta}_L$ )

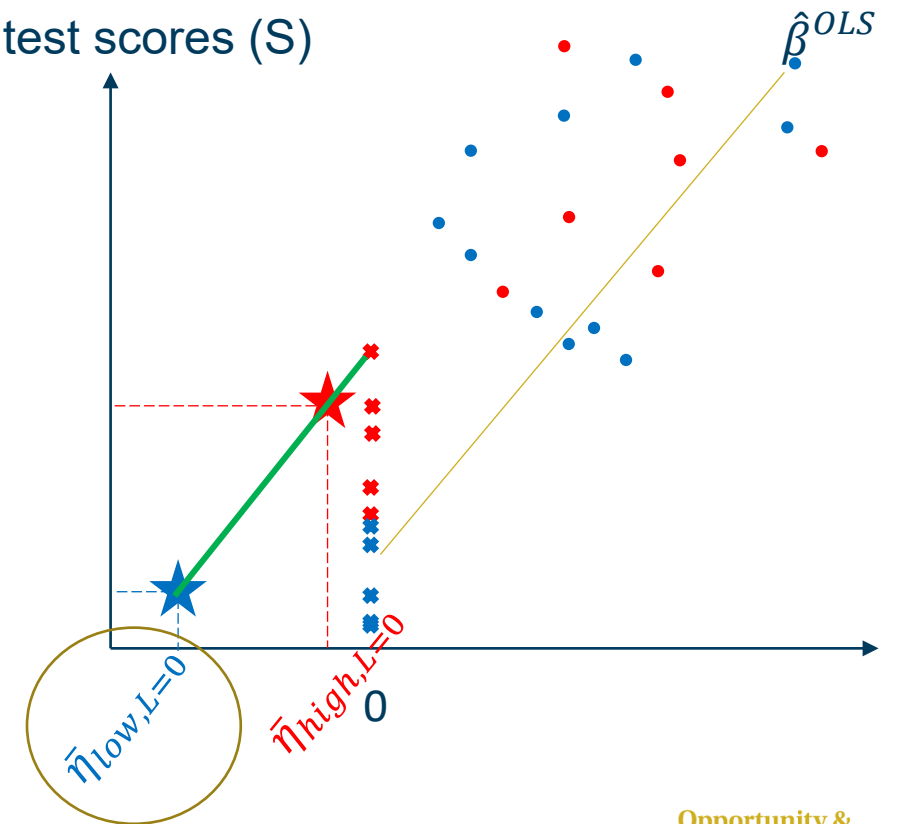
# Issues with $\eta \leftarrow$ are there none?

Figure 5: Model from Section 5.1:  $\hat{\beta}$  for each counterfactual true value of  $\mathbb{E}[L^*|L=0]$  Why isn't this exercise about  $E[L^*|L=0, X]$ ?



Apparently the relevant selection estimate still implies a negative effect even at the most extreme hours assumption

Children's test scores (S)



# Issues with $\eta$

Table 1: Summary Statistics

	Mean	Std.Dev.
<i>Outcome variables</i>		
PIAT Reading Recognition	105.33	14.04
PIAT Math	99.72	14.03
<i>Treatment variable</i>		
Mother's average hours worked in 3 first years	847.64	838.18
<i>Bunching variables</i>		
Mother worked 0 hours in 3 first years	0.25	0.44
<i>Control variables</i>		
Mother's AFQT score	38.20	28.21
Mother's wage year prior to the birth of the child	14.69	11.04
Mother's education less than high school	0.23	0.42
Mother's education completed high school	0.43	0.50
Mother's education some college	0.19	0.40
Mother's education completed college	0.10	0.30
Mother's education more than college	0.04	0.20
Mother's age less than 20 years old	0.11	0.32
Mother's age 20 to 24 years old	0.33	0.47
Mother's age 25 to 29 years old	0.28	0.45
Mother's age 30 to 34 years old	0.18	0.39
Mother's age 35 years old or more	0.09	0.29

## Other income (spouse or unearned/wealth)?

Mother's spouse present	0.60	0.49
Mother's spouse highest grade	12.83	2.69
Child's age at test (in months)	75.07	14.13
Sex of child (male=1, female=0)	0.51	0.50
Birth order of child	2.06	1.18
Child is Hispanic	0.21	0.40
Child is Black	0.29	0.45
Family size	3.85	1.91
Lives in north region	0.15	0.36
Lives in north-central region	0.23	0.42
Lives in south region	0.35	0.48
Lives in west region	0.19	0.39

**Age and composition of other siblings?  
(a baby with an toddler gets a VERY different treatment than a baby with a 4<sup>th</sup> grader...)**

## Big Sisters

Pamela Jakiela, Owen Ozier, Lia Fernald, and Heather Knauer\*

June 29, 2020

# Unobserved home productivity

What if the unobservable is not taste for work (latent labor supply), but the returns to home production (ie. childcare)?

## EVALUATING PUBLIC PROGRAMS WITH CLOSE SUBSTITUTES: THE CASE OF HEAD START\*

PATRICK KLINE AND

CHRISTOPHER R. WALTERS

impact of moving from home care to Head Start is large—on the order of 0.37 standard deviations. By contrast, estimates of

TABLE VIII  
TREATMENT EFFECTS FOR SUBPOPULATIONS

Parameter	(1) IV	Control function		
		(2) Covariates	(3) Sites	(4) Full model
$LATE_h$	0.247 (0.031)	0.261 (0.032)	0.190 (0.076)	0.214 (0.042)
$LATE_{nh}$		0.386 (0.143)	0.341 (0.219)	0.370 (0.088)
$LATE_{ch}$		0.023 (0.251)	-0.122 (0.469)	-0.093 (0.154)

# Upshot

Fascinating, clear, creative new empirical approach.

Fits well with complementary methods (not just IV, but things like Altonji/Elder/Taber/Oster)

Biggest challenge is not robustness in that the results change, but cementing the case that this is not just a robustly omitted co-determinant of NILF and children's test scores.