AN APPLICATION OF PROPENSITY-SCORE MATCHING: THE EFFECT OF CHILDBEARING ON OBESITY RISK

Whitney R. Robinson, PhD, MSPH
Assistant Professor of Epidemiology, Gillings School of Global Public Health
Carolina Population Center
Lineberger Comprehensive Cancer Center
University of North Carolina at Chapel Hill

Motivation

- To what extent does childbearing contribute to obesity prevalence in women?

- Importance:
  - **Societal**: Ethnic and SES-based disparities in obesity
  - **Public health burden**: To what extent do child-bearing patterns contribute to rising obesity prevalence?
  - **Individual**: Women's decision-making and expectations

Methodological challenges in previous studies

- Study design 1: In post-menopausal women, compare parous vs non-parous
  - Minority of childless women different from other women
  - Timing: Did wt gain precede births – or occur long after?
  - Generalizability: elderly target population, births in 1940s-1970s
- Study design 2: Compare post-pregnancy vs pre-pregnancy weight
  - Does not account for existing trajectory of weight gain
  - Generalizability: births in 1970s, 1980s; not population-based
- Study design 3: Compare weight gain or obesity incidence in parous versus non-parous women
  - Parous women are different from non-parous women
  - Generalizability: Births in 1970s, 1980s; not population-based
  - Possible selection bias: lots of exclusions

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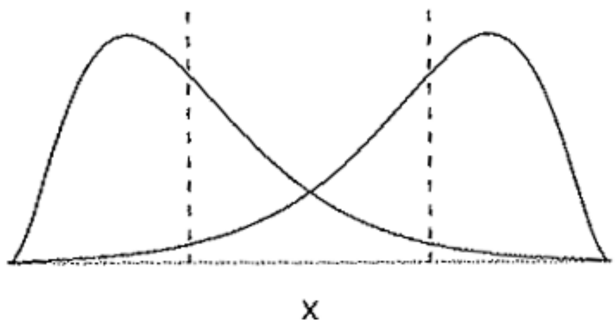
Why propensity scores?

Address confounding

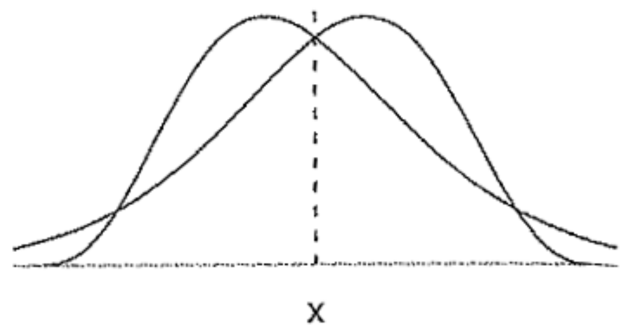
- Lack of comparability between exposed and unexposed, “exchangeability”

- Two aspects of lack of comparability
  - Imbalance – uncontrolled confounding
  - Lack of overlap (“positivity”) – extrapolation
    - indicates possible uncontrolled confounding, no data on which to evaluate

How model-dependent are our inferences?

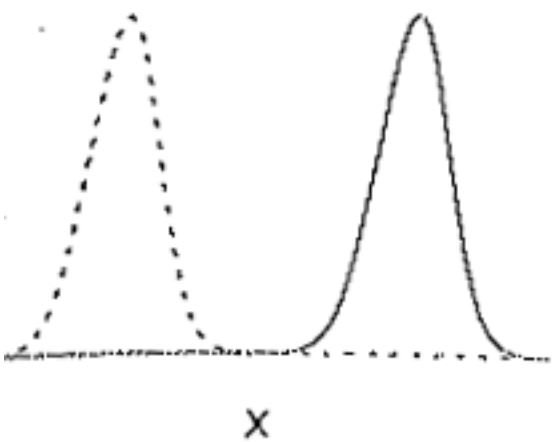


Severe imbalance, good overlap

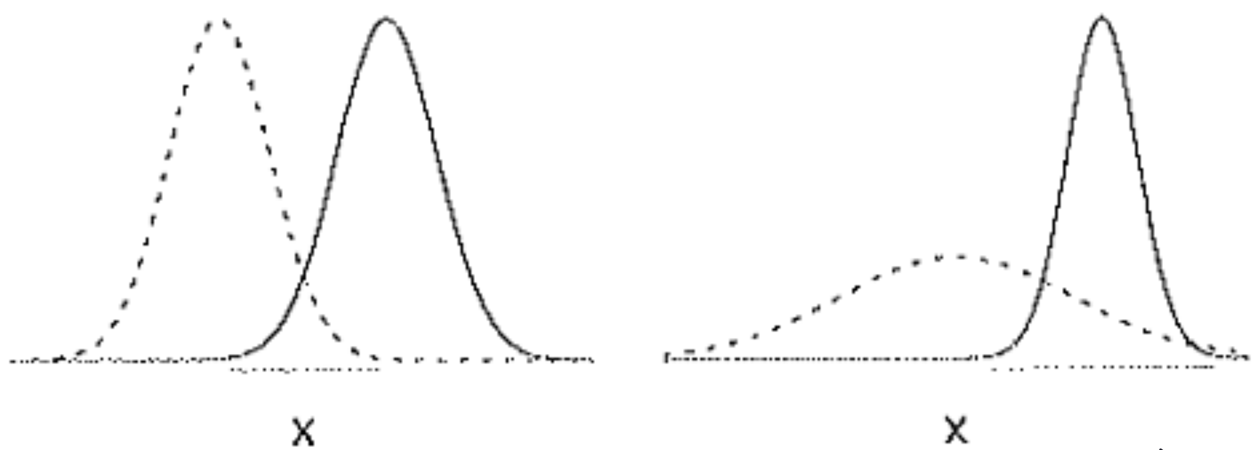


Slight imbalance, good overlap

Severe imbalance, no overlap



Moderate imbalance, partial overlap



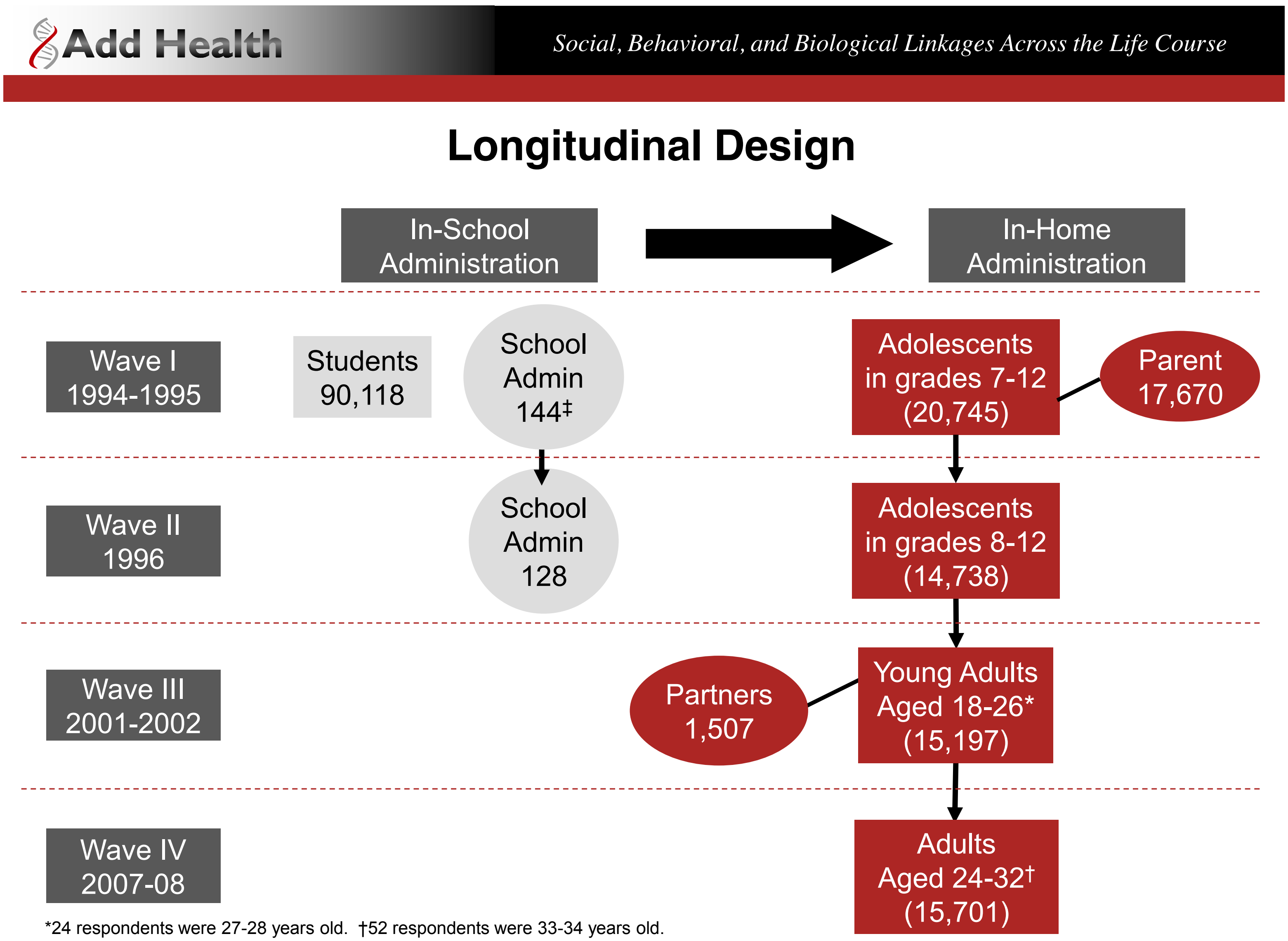
From Gelman and Hill, 2003

Study Design

- Goals:
  - Achieve generalizability
  - Prevent selection bias
  - Improve exchangeability (achieve balance, test for non-overlap)

- Design: Prospective longitudinal cohort comparing parous and non-parous women
  - **Data**: Population-representative contemporary population of child-bearing women
  - **Restriction & variable selection**: Limit exclusions & induced bias
  - **Analysis**: Women in prime child-bearing years & propensity-score matching

Data: Add Health



*24 respondents were 27-28 years old. †52 respondents were 33-34 years old.
‡ 144 schools participated in in school administration. School administration questionnaires from 143 of these schools

Implementation of p-score matching

- **Exposure:** parous/non-parous, wave 4
- **Outcome:** obesity (BMI≥30.0 kg/m^2) at wave 4

- Step 1: Logistic regression to predict "propensity" to parity (exposure)
- Step 2: Assign each respondent a p-score, Pr(parous)
- Step 3: Match each parous women to 1+ non-parous women (ATT)
  - **Stata's psmatch2** (January 2012)
    - How good a match is necessary? calipers: 0.1 sd of p-score
    - Boot-strapping to get 95% CIs, 100 iterations

E. Leuven and B. Sianesi. (2003). "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing". http://ideas.repec.org/c/boc/bocode/s432001.html.

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help for **psmatch2**

Mahalanobis and Propensity score Matching

psmatch2 *depvar* [*indepvars*] [**if** *exp*] [**in** *range*] [, **outcome**(*varlist*)
pscore(*varname*) **neighbor**(*integer*) **ai**(*integer*) **radius**
caliper(*real*) **mahalanobis**(*varlist*) **kernel** **llr**
kerneltype(*type*) **bwidth**(*real*) **spline** **nknots**(*integer*)
common **trim**(*real*) **noreplacement** **descending** **odds** **index**
logit **ties** **quietly** **w**(*matrix*) **ate**]

Description

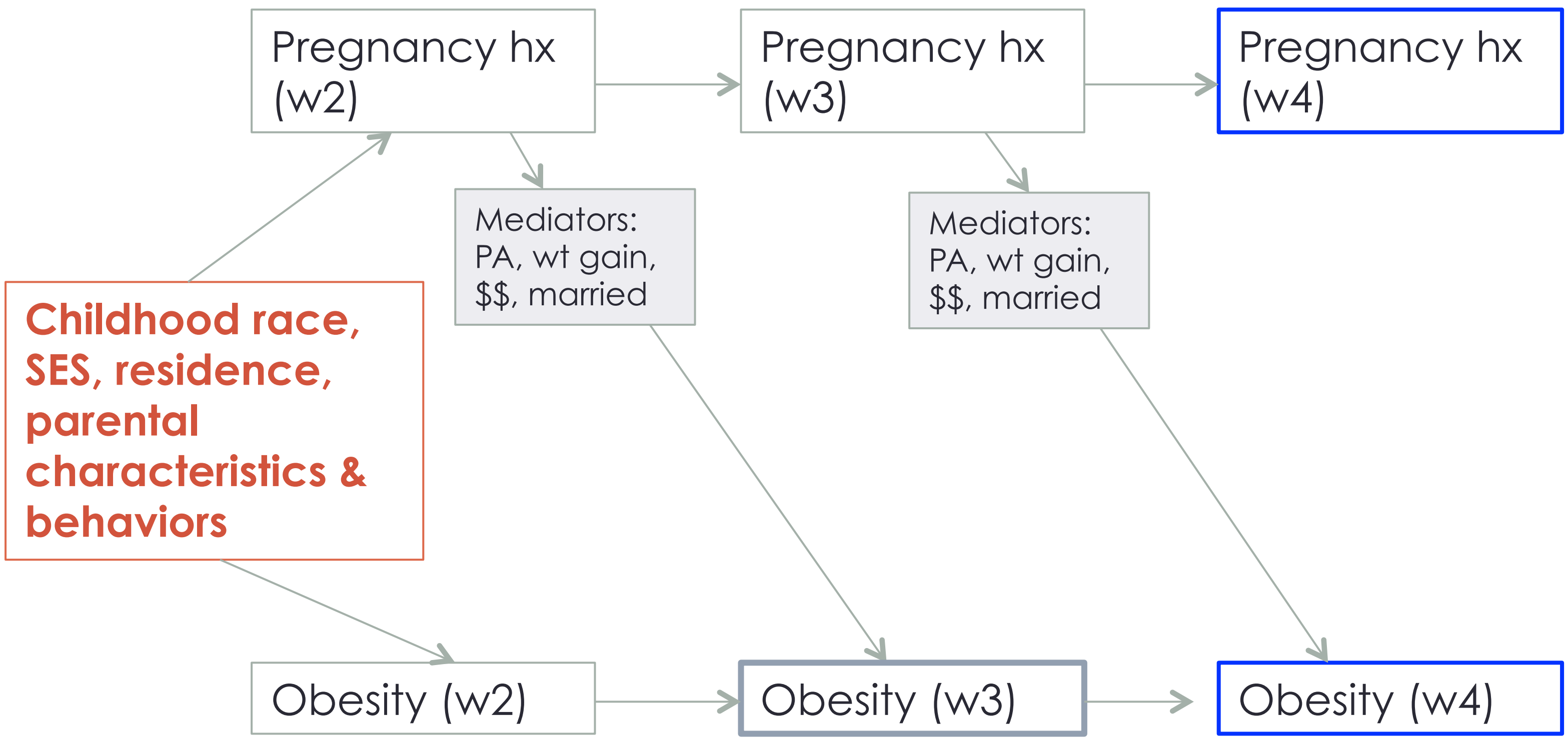
psmatch2 implements full Mahalanobis matching and a variety of propensity score matching methods to adjust for pre-treatment observable differences between a group of treated and a group of untreated. Treatment status is identified by *depvar*==1 for the treated and *depvar*==0 for the untreated observations.

psmatch2 is being continuously improved and developed. Make sure to keep your version up-to-date as follows

```
. ssc install psmatch2, replace
```

By default **psmatch2** calculates approximate standard errors on the

Choosing matching algorithm



Predictor variables: Unique ID of school attended at the first survey, age, age^2, US region (S, NE, MW, W), urbanicity, regionxurbanicity, parental education, Black race, Blackxparental education, immigrant, immigrant black, mexican, cuban, Puerto Rican, Central Am, Other Hispanic, Hispanicximmigrant, chinese, filipino, Vietnamese, etc.,

Creating matching variable, logit1a

```
qui logistic parous
        age_yr_w4 ageyrsq_w4 region1 region2 region4
        rural suburb
        ruralxreg1 ruralxreg2 ruralxreg4
        suburxbreg1 suburxbreg2 suburxbreg4
        highedcat1 highedcat2 highedcat3 highedcat4 highedcat6
        black nonbwrace
        blackxhighed1 blackxhighed2 blackxhighed3 blackxhighed4 blackxhighed6
        usborn gennonblwh genblack
        mexam cuban puertorican centrsoutham otherhisp hispmix
        genmexam gencuban genpuertorican gencentrsoutham genotherhisp
        chinese filipino japan asiaindn korean vietnam asianoth asianmix
        i.scid_n
        if w4_selectf==1, coef;
***************************
* CONSTRUCTING FINAL SAMPLE
* childhood to w4
***************************;
predict pr1a_w4 if w4_selectf==1;
gen logit1a=log(pr1a_w4/(1-pr1a_w4));
```

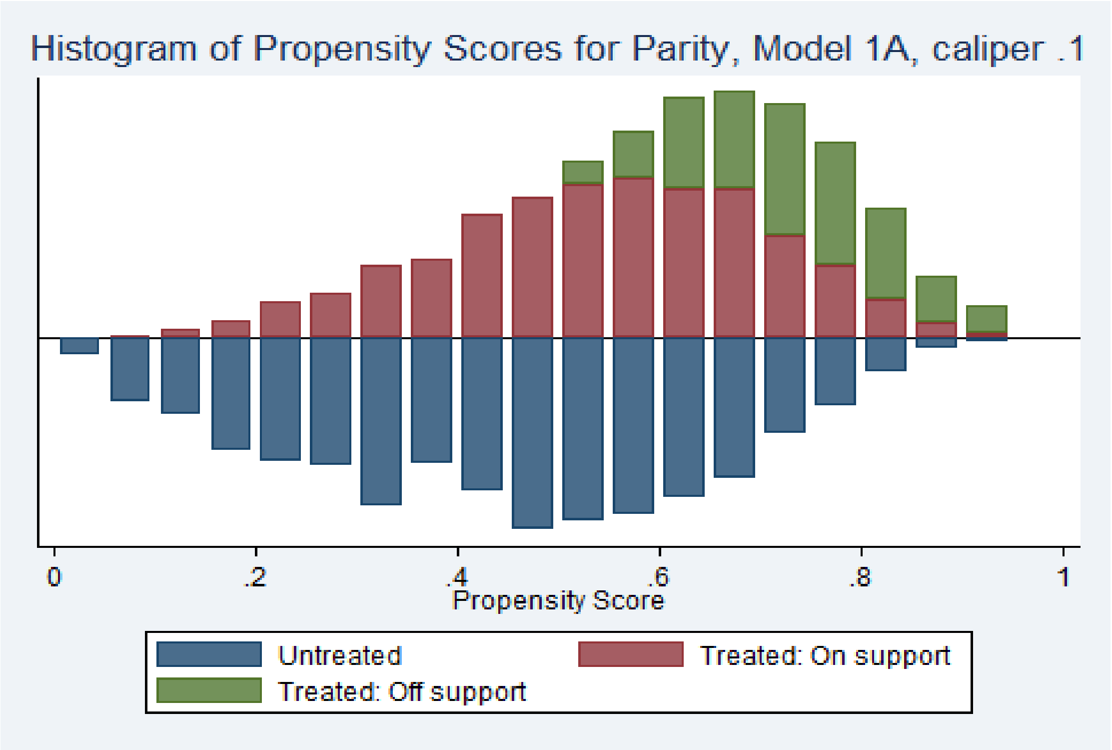
Lack of comparability

Descriptive characteristics by parity in unmatched sample

	Parous	Non-Parous	Total
% (N)	52.3 (3593)	47.7 (3186)	100 (6779)
Region (adolescent residence)			
South	44.1%	32.0%	38.3%
Midwest	32.1%	30.9%	31.5%
West	14.2%	18.9%	16.5%
Northeast	9.7%	18.2%	13.7%
Mother's education			
< HS	23.6%	12.8%	18.5%
> college	3.6%	10.1%	6.7%

% are weighted for complex survey sampling and non-response

Distribution of p-scores by parity



Slight imbalance, good overlap

psgraph, p(pr1a_w4) saving (hist_1log_1-1.gph,replace)
title("Histogram: Model 1A, caliper .1logit, no replace");

Covariate balance before & after matching

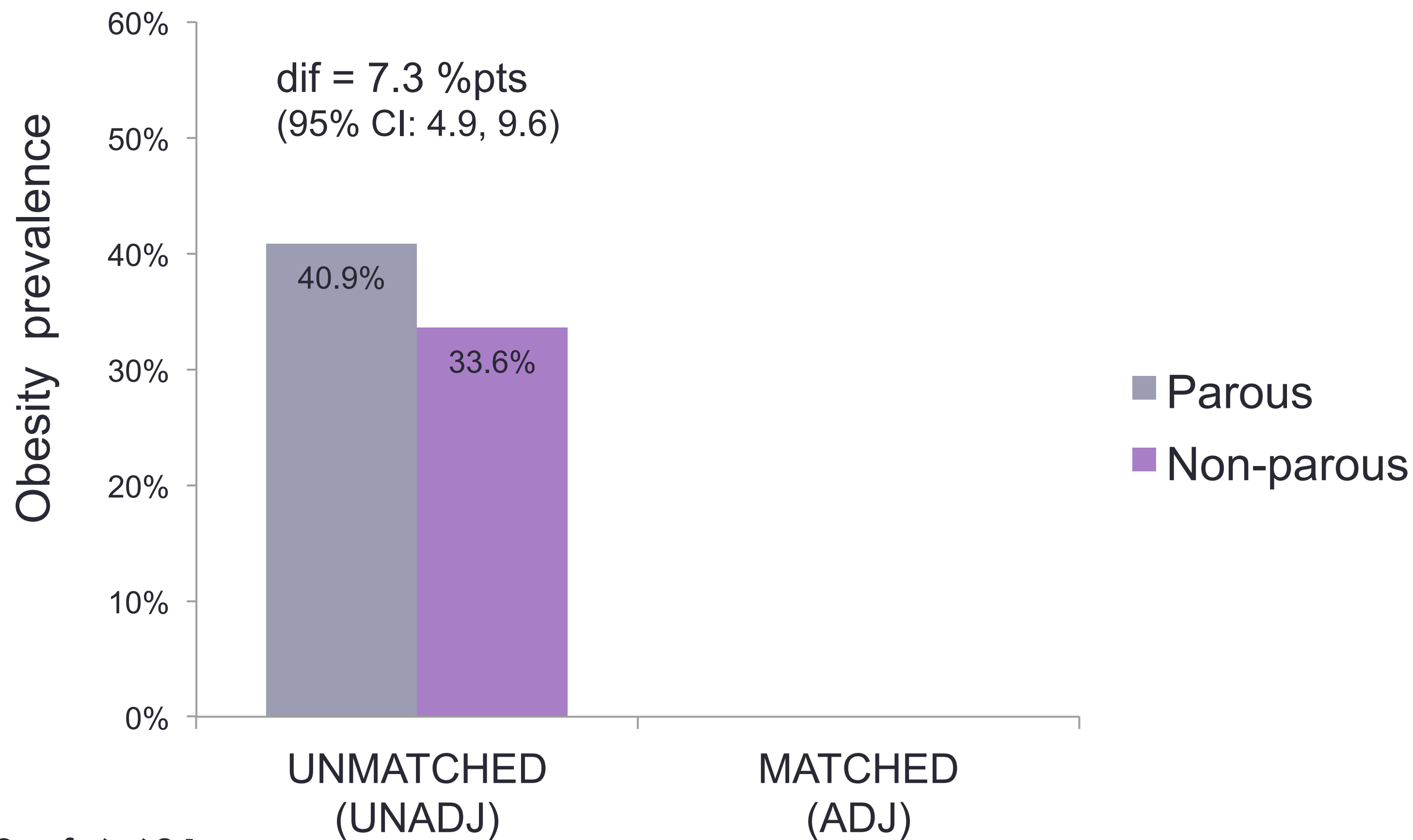
Variable	Sample	Parous	Non-parous	% bias	% reduction |bias|
Age (years), w4					
	Unmatched	28.7	28.1	34	
	Matched	28.5	28.5	-2	94.2
US REGION, w1 (ref=SOUTH)					
West	Unmatched	20.8%	24.8%	-10	
	Matched	22.8%	25.3%	-6	40
Midwest	Unmatched	24.8%	26.1%	-3	
	Matched	23.5%	26.1%	-1	84
Northeast	Unmatched	10.8%	16.2%	-16	
	Matched	13.2%	11.6%	4.5	72
URBANICITY, w1 (ref=urban)					
Rural	Unmatched	19.7%	14.2%	15	
	Matched	16.5%	18.4%	-5	66
suburb	Unmatched	52.8%	53.7%	-2	
	Matched	52.9%	53.7%	-2	16.6
PARENTAL EDUCATION					
<high school	Unmatched	14.6%	7.7%	22	
	Matched	10.6%	10.8%	-1	97.2
vocational degree	Unmatched	8.8%	8.4%	1	
	Matched	10.3%	9.9%	1	-4
RACE & ETHNICITY					
non-H BLACK	Unmatched	25.7%	21.8%	9	
	Matched	24.2%	24.5%	-1	93.1
non-H CHINESE	Unmatched	0.3%	2.3%	-18	
	Matched	0.4%	0.1%	3	81.4

pstest <varlist>

% do not account for complex survey design or non-response

% Obesity in Parous vs Non-parous

Demographic match, 1:1 neighbor, no replacement

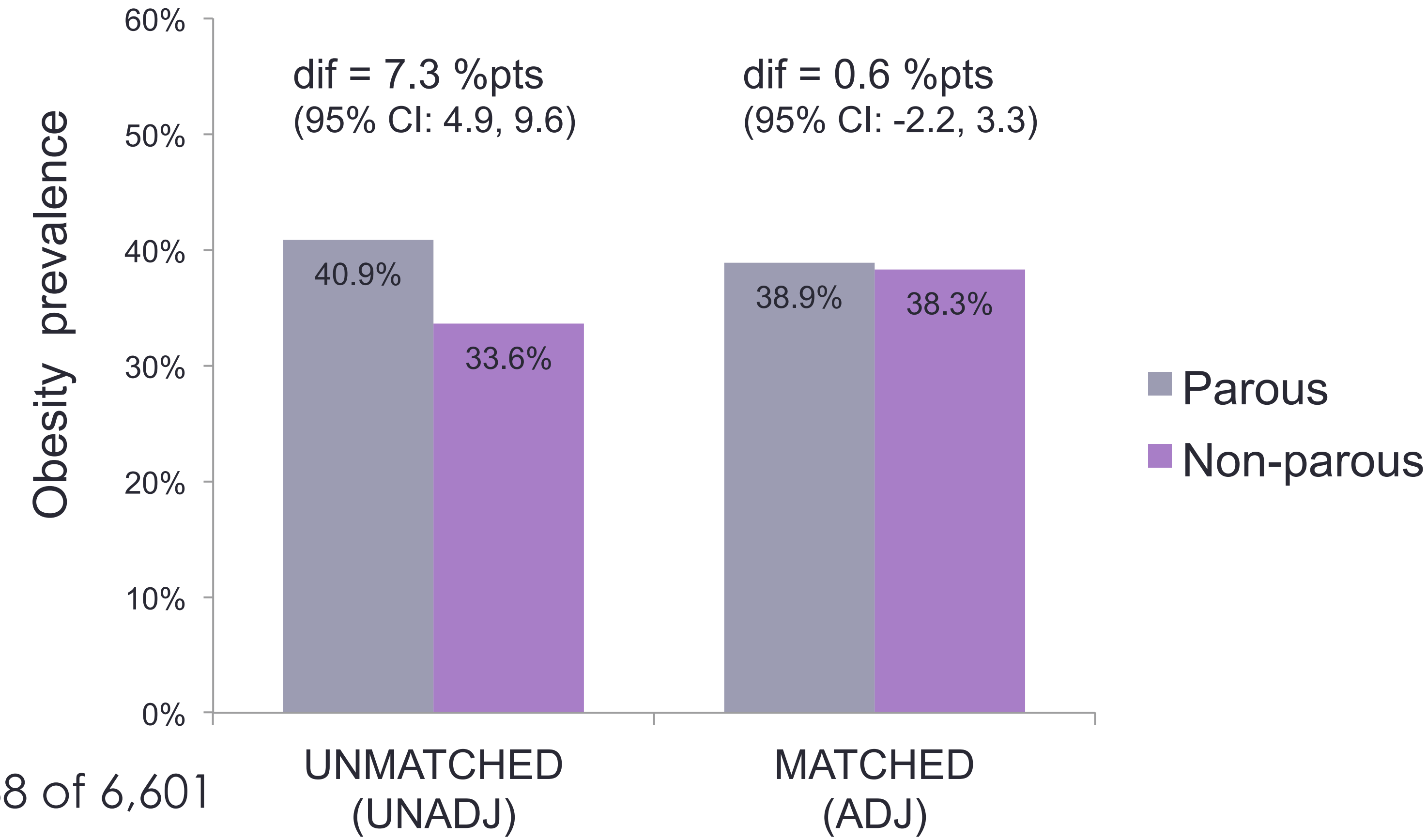


N=5,438 of 6,601

psmatch2 parous, outcome(ob_constr_w4) pscore(logit1a) caliper(.1) com noreplacement descending;

% Obesity in Parous vs Non-parous

Demographic match, 1:1 neighbor, no replacement

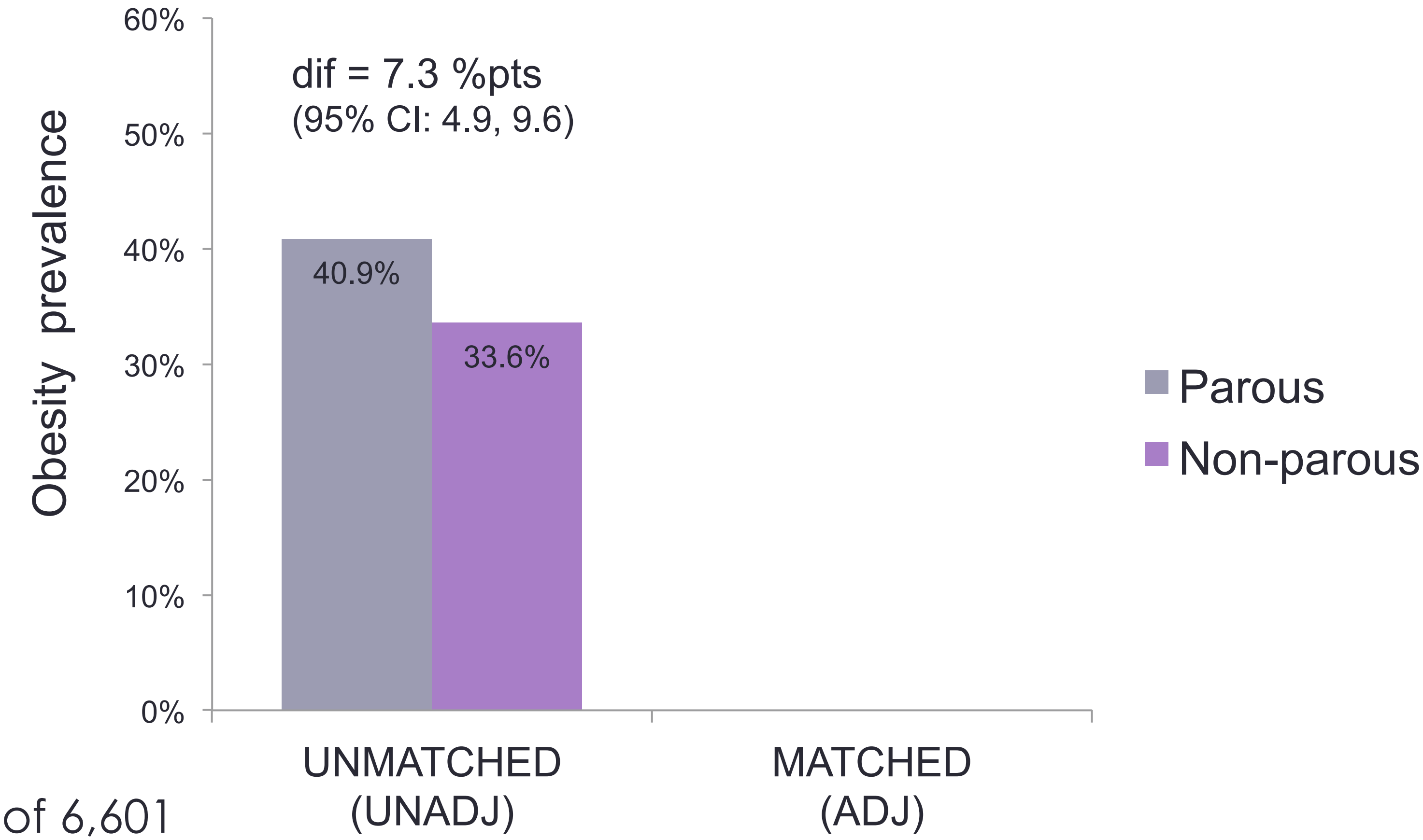


N=5,438 of 6,601

psmatch2 parous, outcome(ob_constr_w4) pscore(logit1a) caliper(.1) com noreplacement descending;

% Obesity in Parous vs Non-parous

Demographic match, 1:1 neighbor, with replacement

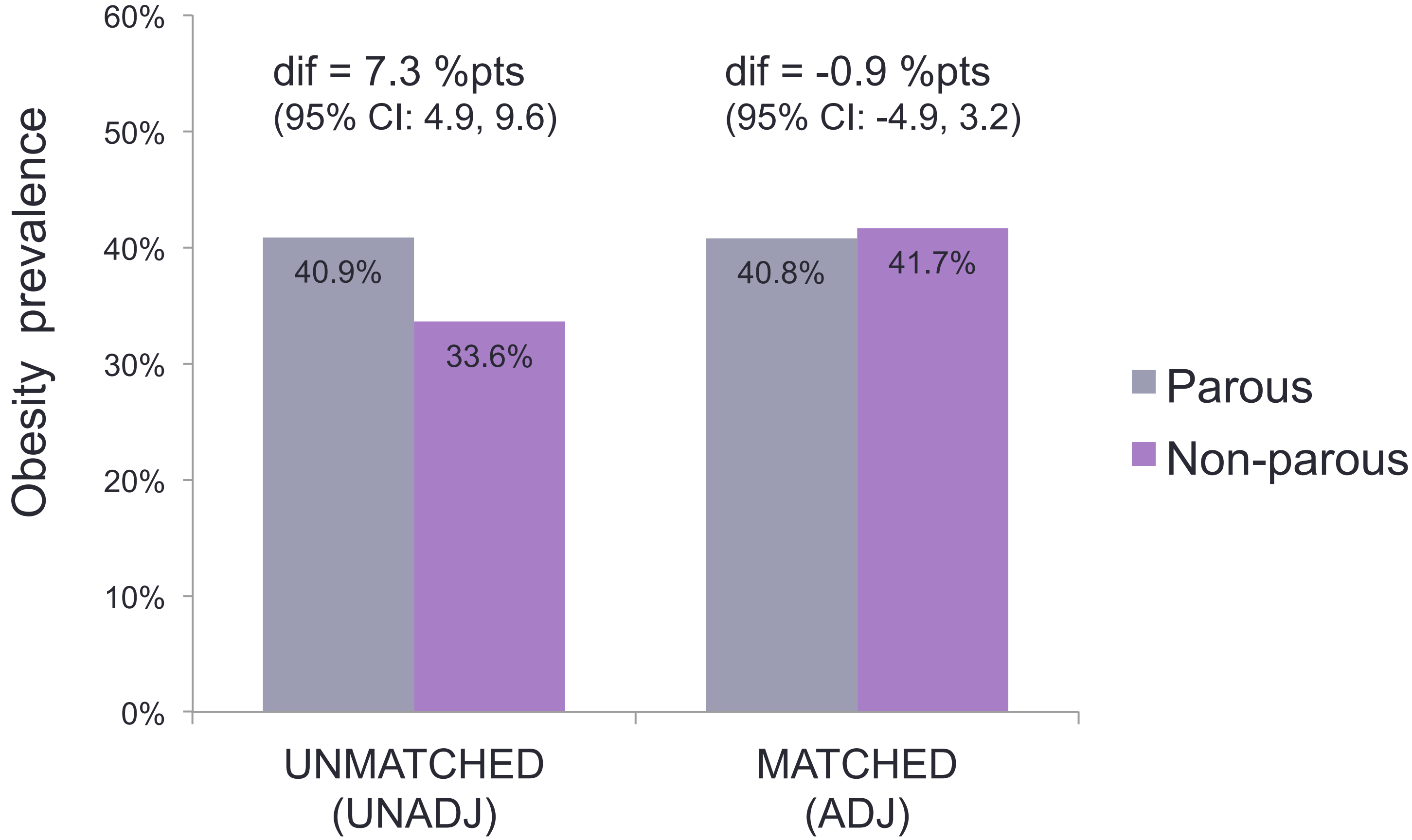


N=6,592 of 6,601

```
psmatch2 parous, outcome(ob_constr_w4) pscore(logit1a) caliper(.1) com;
```

% Obesity in Parous vs Non-parous

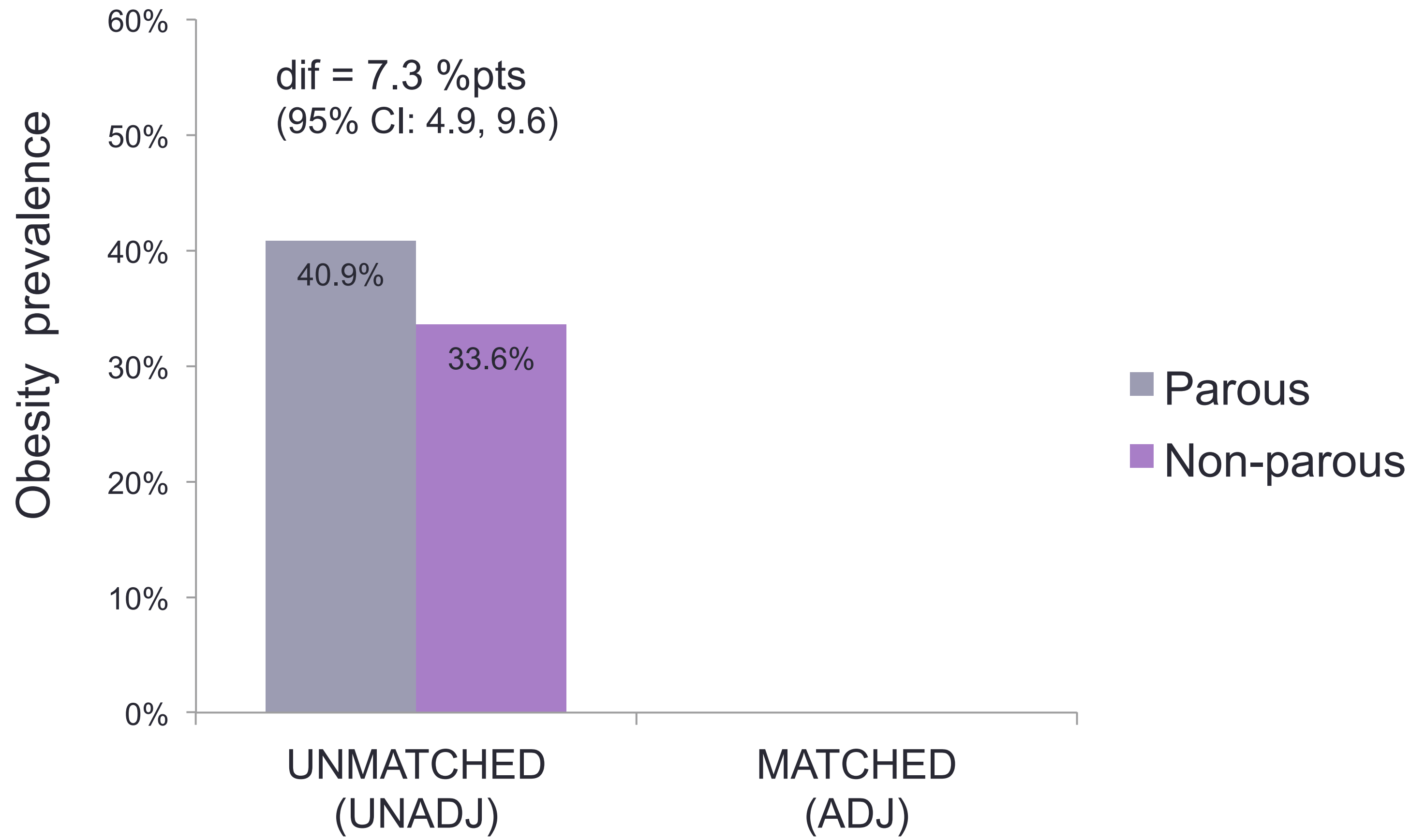
Demographic match, 1:1 neighbor, with replacement



N=6,592 of 6,601

% Obesity in Parous vs Non-parous

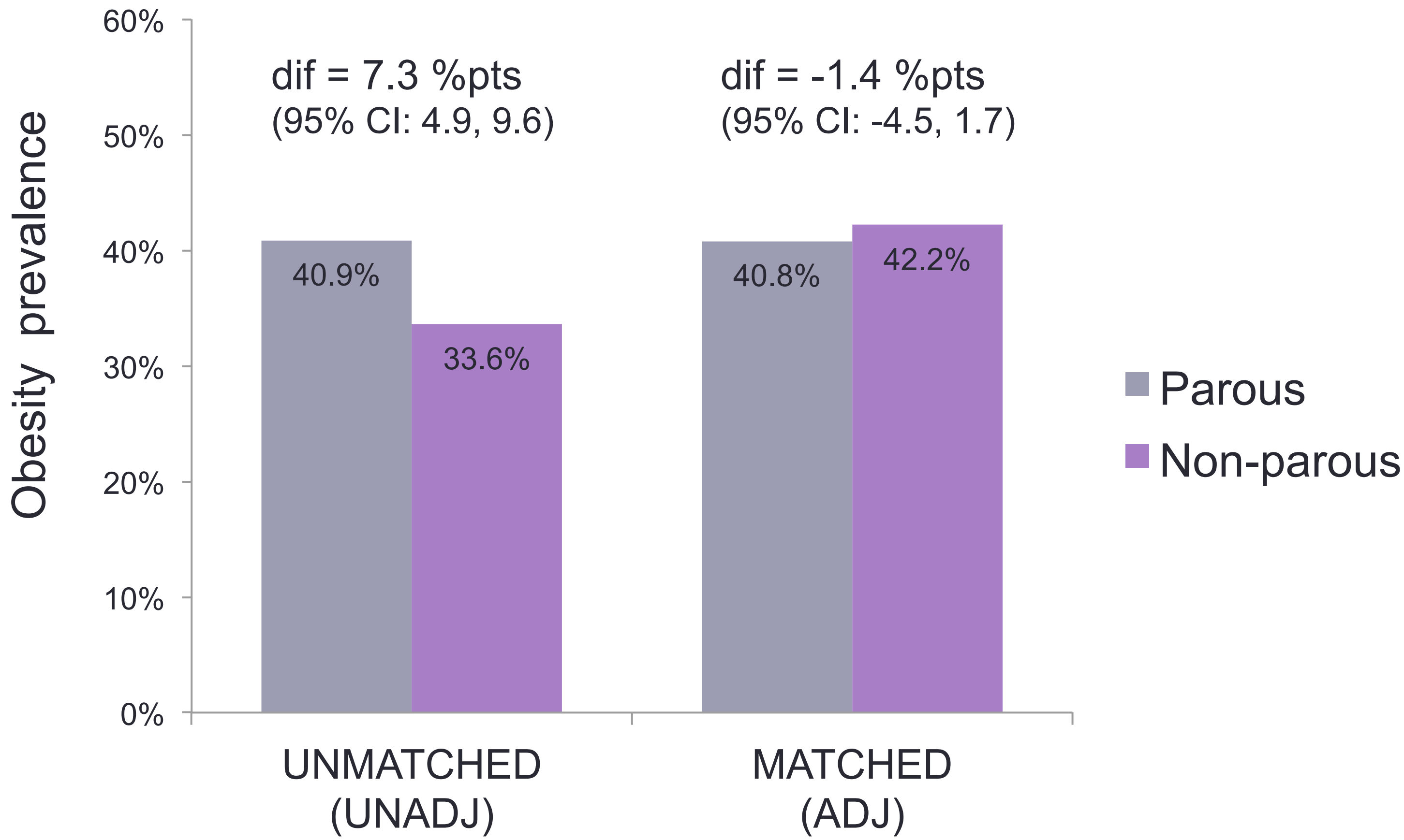
Demographic match, 4:1 neighbor, with replacement



N=6,592 of 6,601

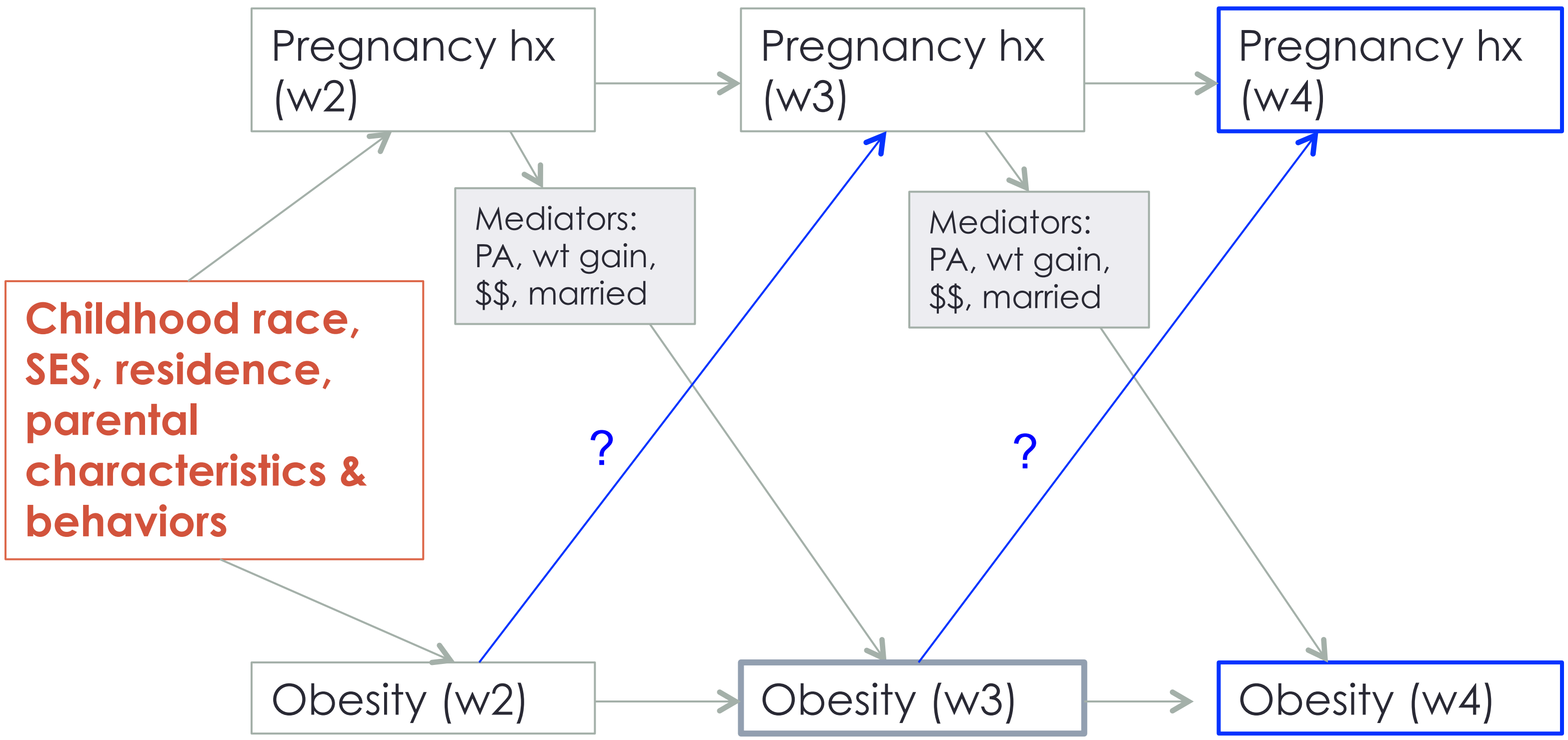
% Obesity in Parous vs Non-parous

Demographic match, 4:1 neighbor, with replacement



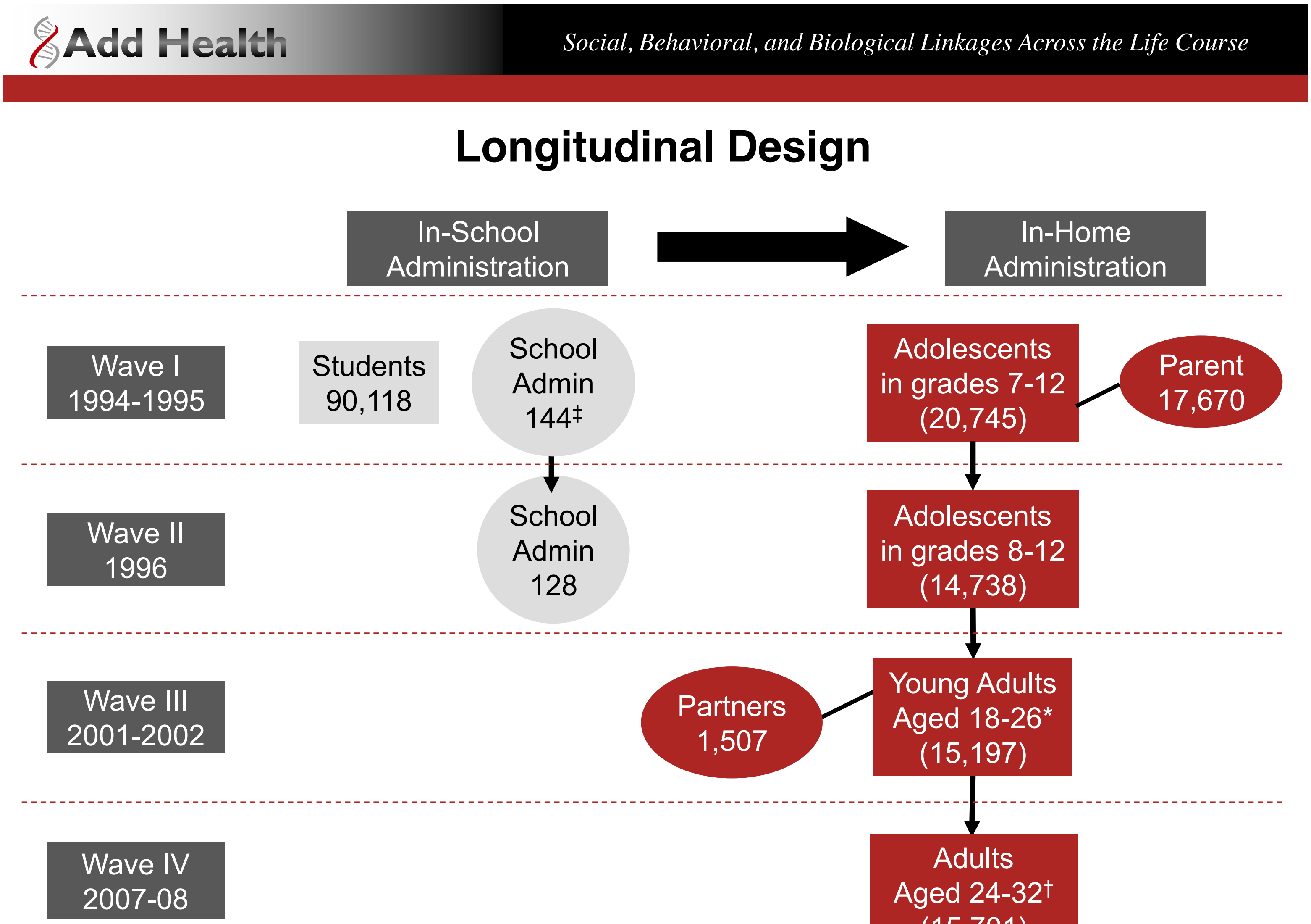
N=6,592 of 6,601

Motivation for w3-w4 incidence analysis



Frisco, M. L., M. M. Weden, A. M. Lippert and K. D. Burnett (2012). "The multidimensional relationship between early adult body weight and women's childbearing experiences." Soc Sci Med **74**(11): 1703-1711.

Add Health: w3-w4 incidence



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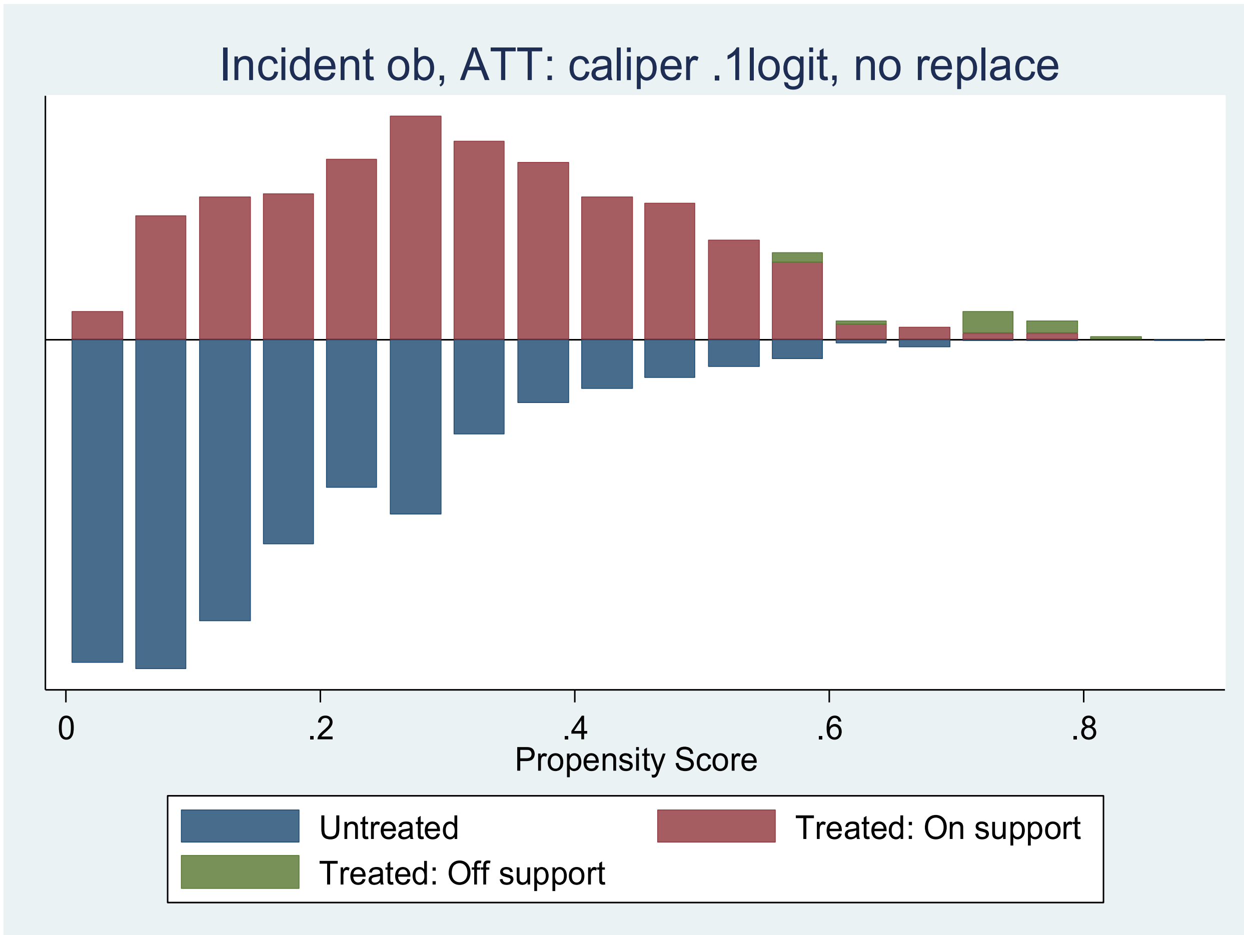
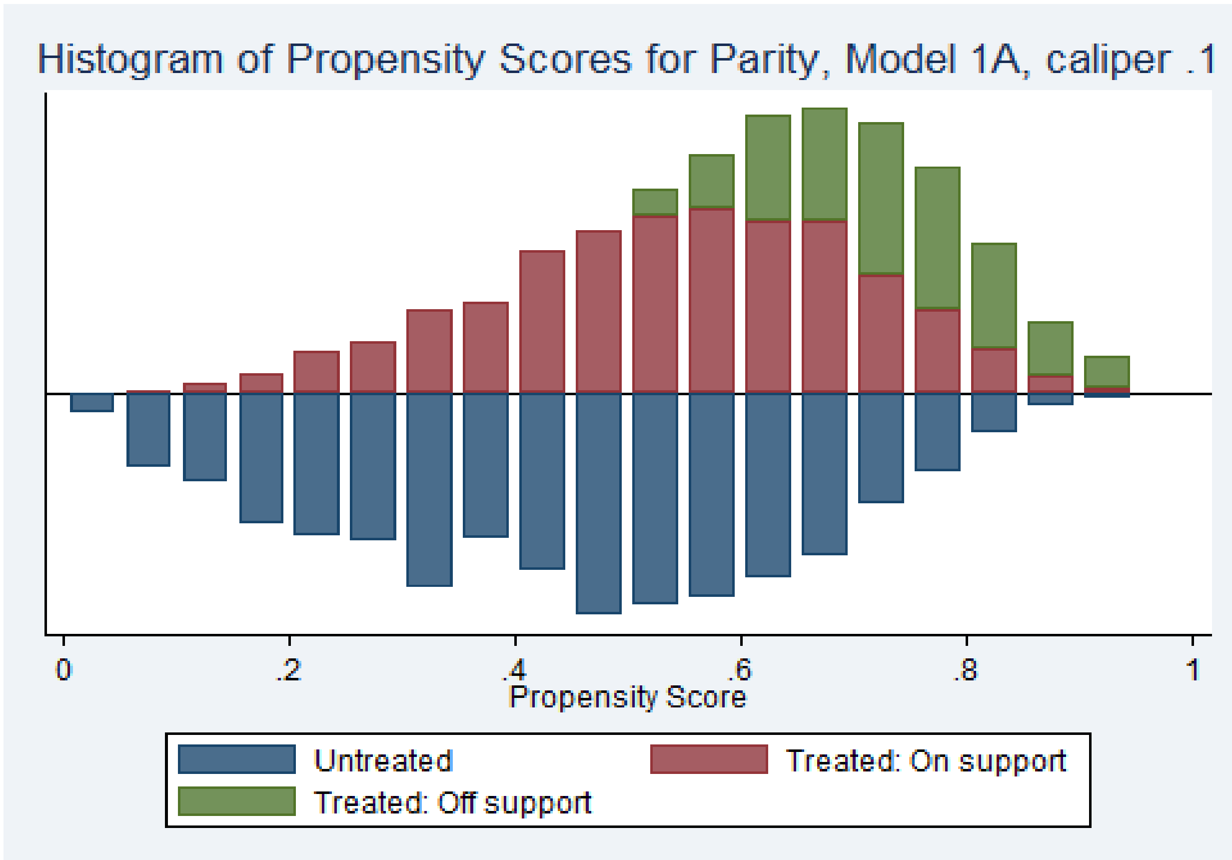
Distribution of p-scores by parity: incidence analysis



More (moderate) imbalance, good overlap

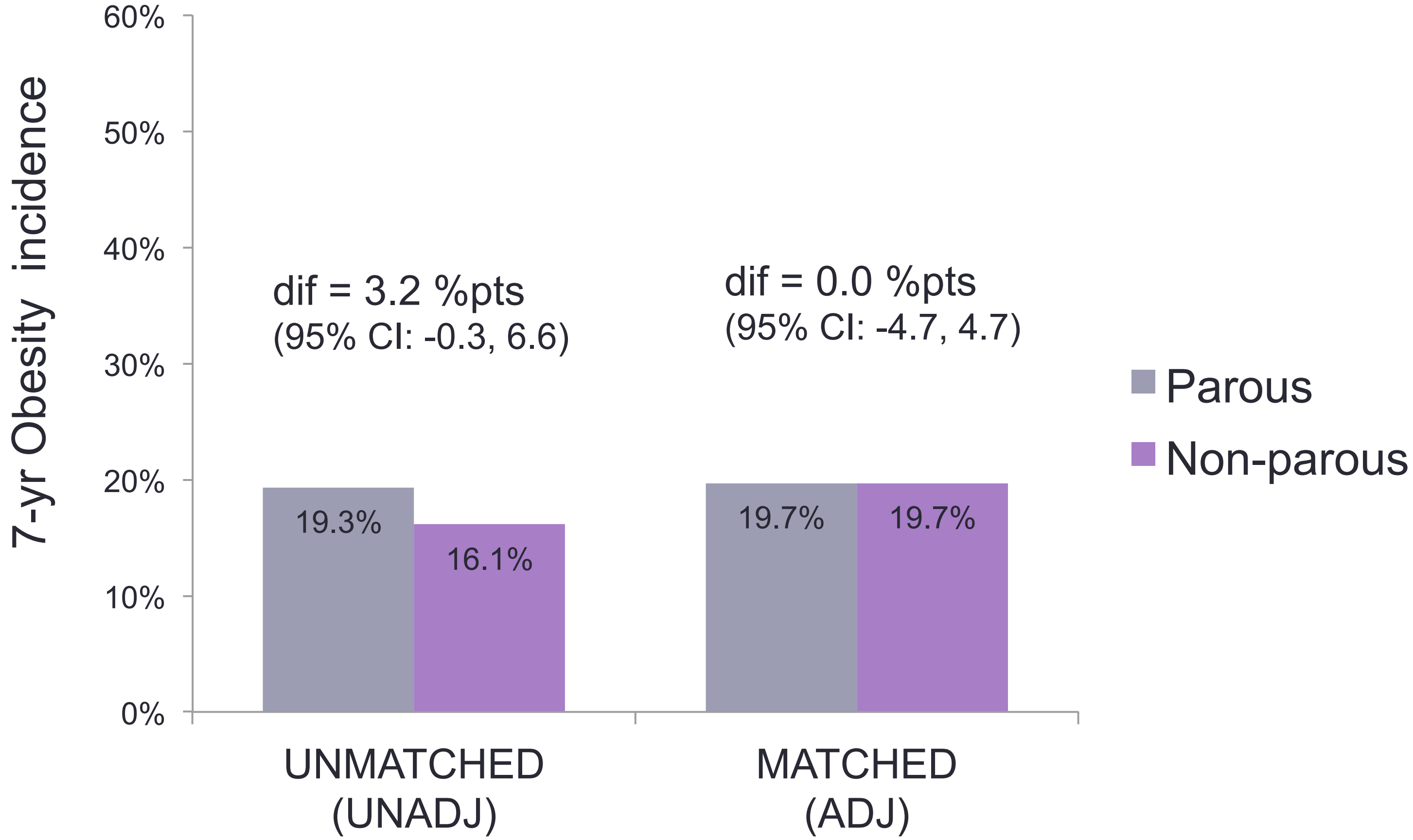
Compare this prevalence graph to incidence graph above



Slight imbalance, good overlap

% Incident Obesity in Parous vs Non-parous

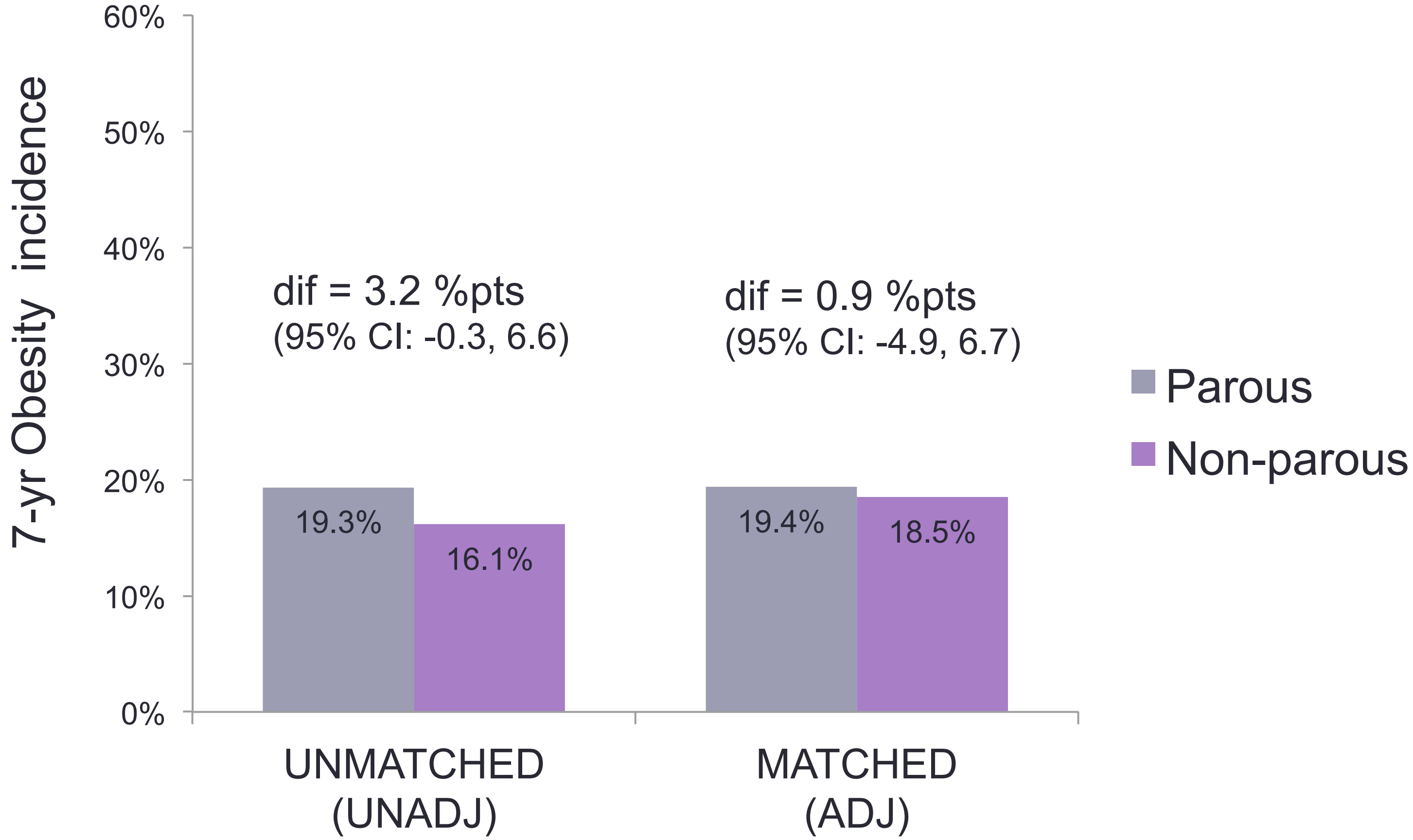
Demographic match, 1:1 neighbor, no replacement



N=2,715 of 2,731

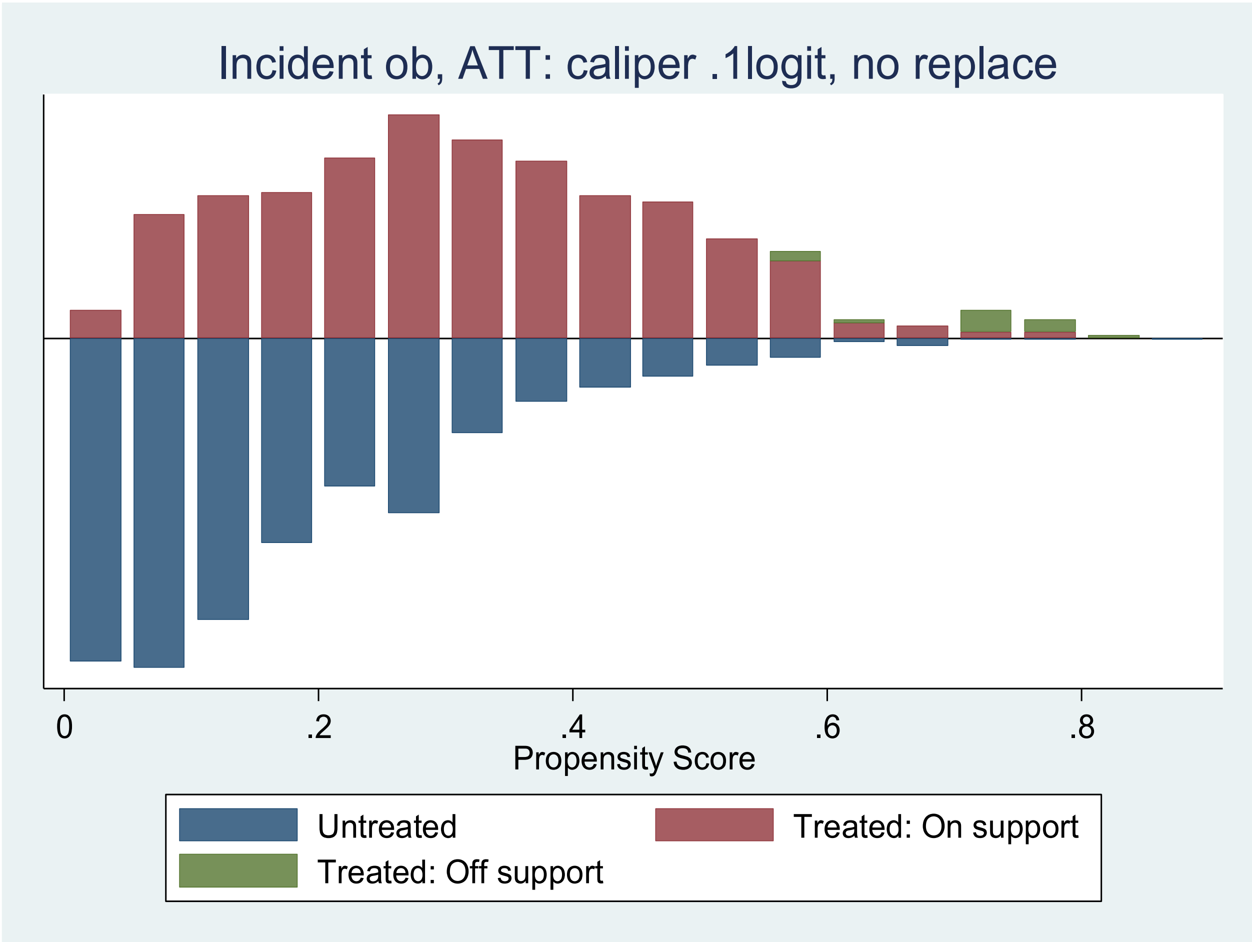
% Incident Obesity in Parous vs Non-parous

Demographic match, 1:1 neighbor, with replacement



N=2,730 of 2,731

Distribution of p-scores by parity: incidence analysis



Moderate imbalance, good overlap

Interpreting results

- Summary: No evidence that child-bearing contributes to obesity incidence or prevalence in young U.S. women

- Target population: women who gave birth by early 20s (incidence) or age ~30 years (prevalence),
  - Population: young mothers of mostly pre-school aged children
  - Causal action: postponing or abstaining from childbearing

- Heterogeneity
  - Marginal effect could mask risk/protectiveness of child-bearing
  - Could attempt to identify at-risk women, e.g., race, pre-preg BMI

- Mechanisms
  - Child-bearing: biological and social phenomenon

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  - RWJF H&SS small grant, University of Michigan
  - Carolina Population Center Summer-in-Residence Grant Writing Fellowship (2012)
  - NCI K01CA172717
- Collaborators:
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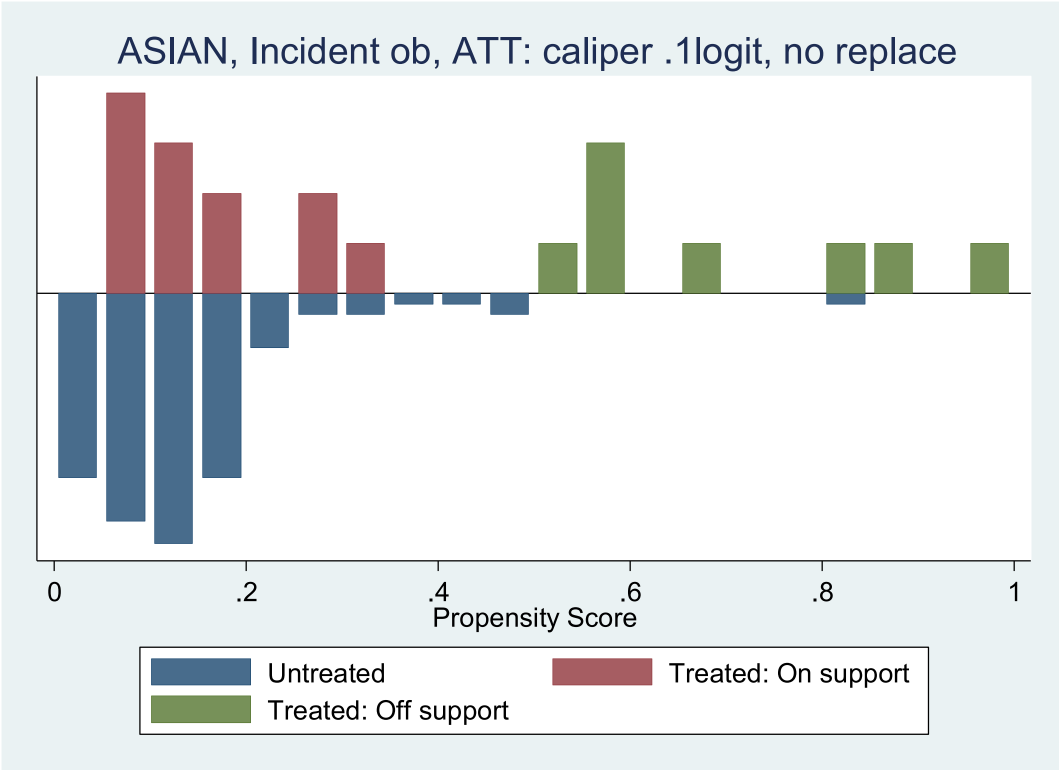
Example with overlap problem



THE END