FLS 6415 - Causal Inference for the Political Economy of Development

Week 10 - Various & Matching

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- As with regression, it succeeds only to the extent we **match on all confounders**
- Unmeasured confounders are a big problem still

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4. Assess balance - re-run the matching process as many times as you can to maximize balance!

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1. Calculate the difference in means between treated and control groups
2. Conduct the normal regression: $Y \sim D$
    - Option to include all our matching variables as controls
    - This will help control for any **residual imbalance** (esp. for continuous variables)

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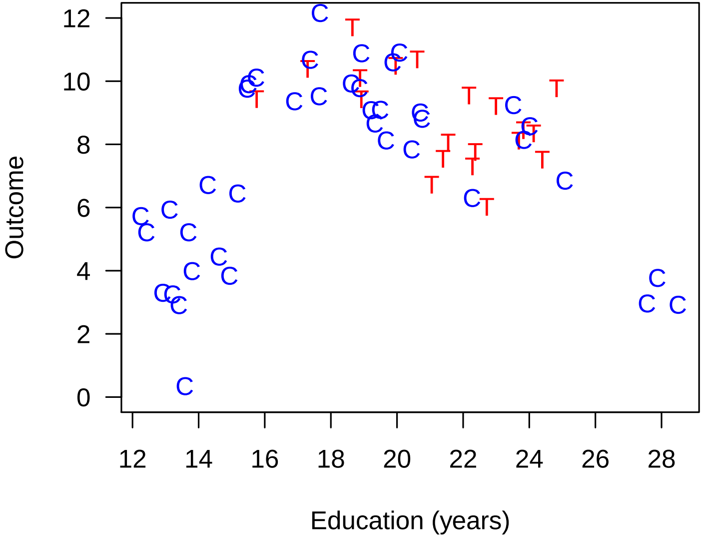
  - And we get better overlap because we're not extrapolating outside of the data
  - True, there are lots of choices in matching, but our aim is just to increase balance, unlike regression which has no success measure
- The disadvantages are:
  - We may change our definition of the causal effect a little
  - We might lose statistical power by discarding too many units
  - A tricky trade-off between number of units and balance

Matching to Reduce Model Dependence

(Ho, Imai, King, Stuart, 2007: fig.1, *Political Analysis*)



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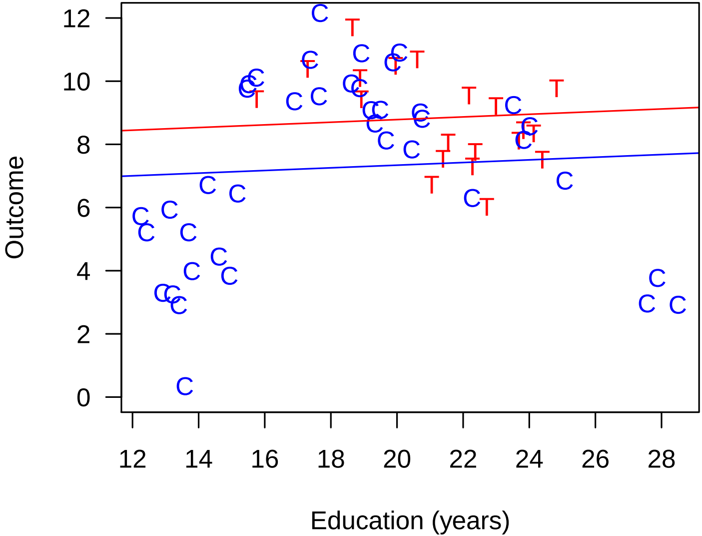

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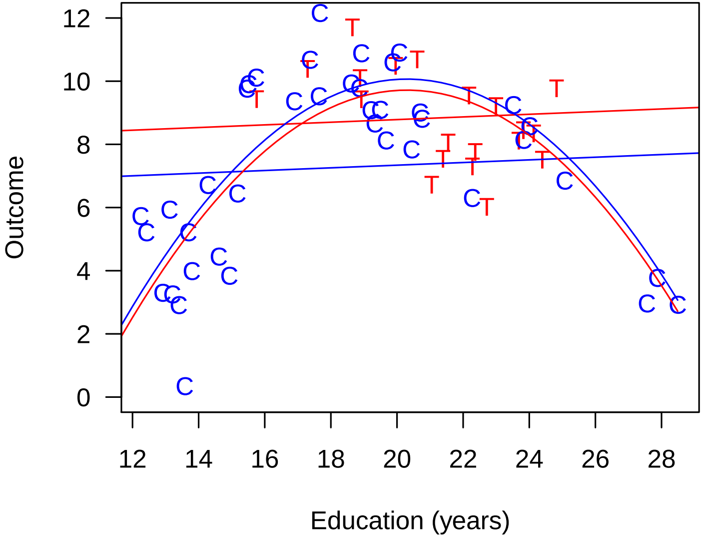

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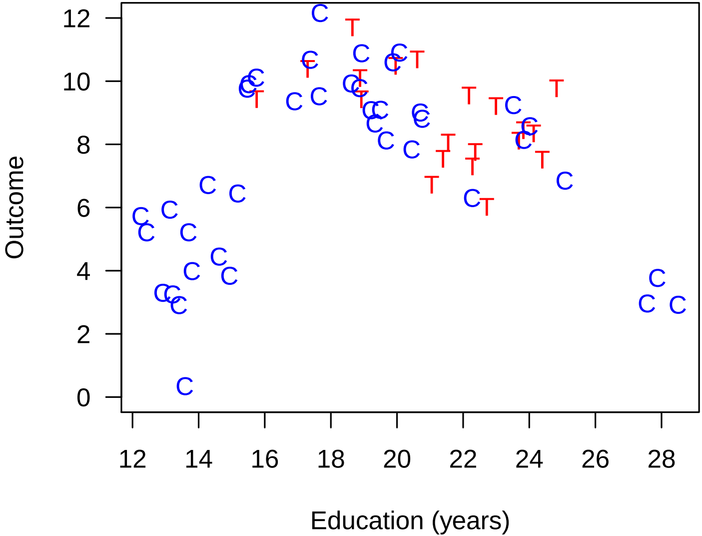

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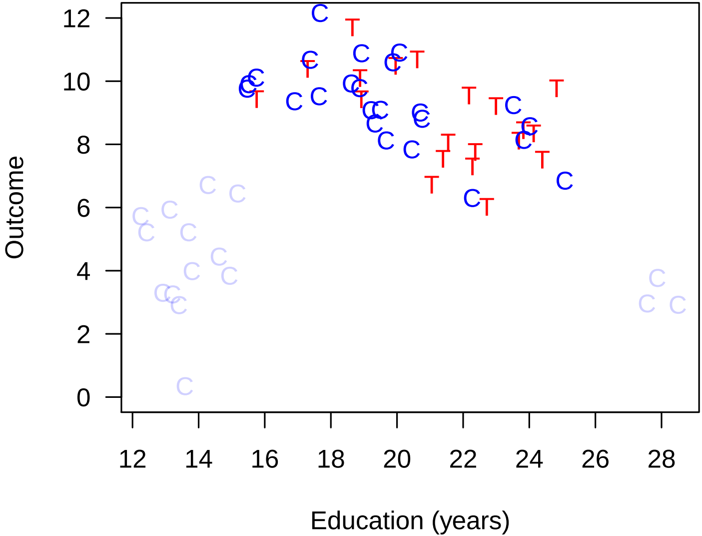

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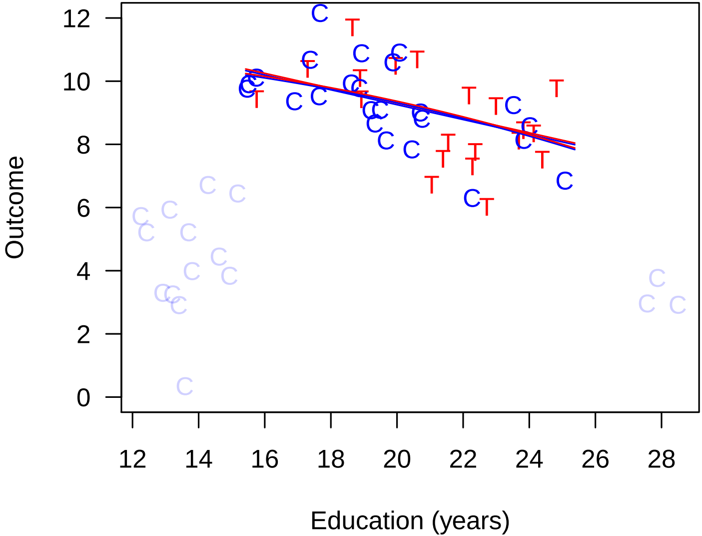

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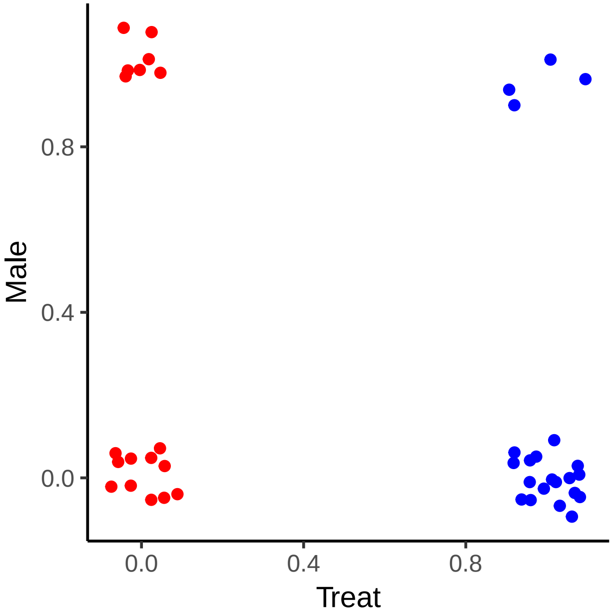
1. Matching on few categorical variables: **Exact Matching**
2. Matching on continuous variables (sequential): **Nearest-Neighbour Matching**
3. Matching to maximize balance: **Optimal/Genetic Matching**
4. Matching on the probability of treatment: **Propensity Score Matching**

Exact Matching



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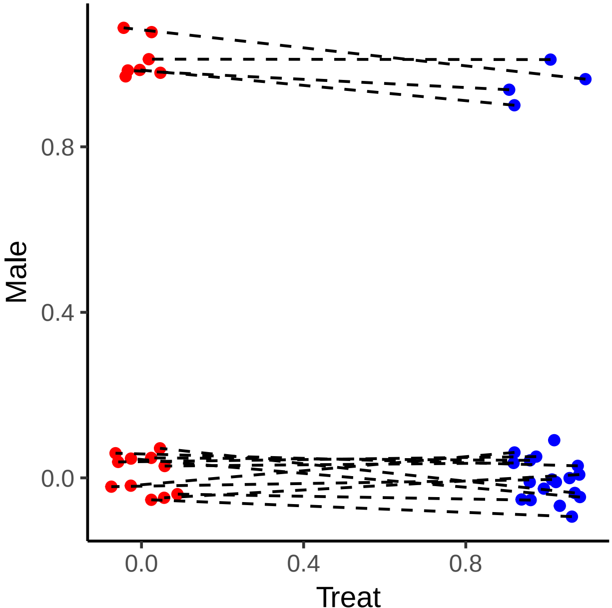

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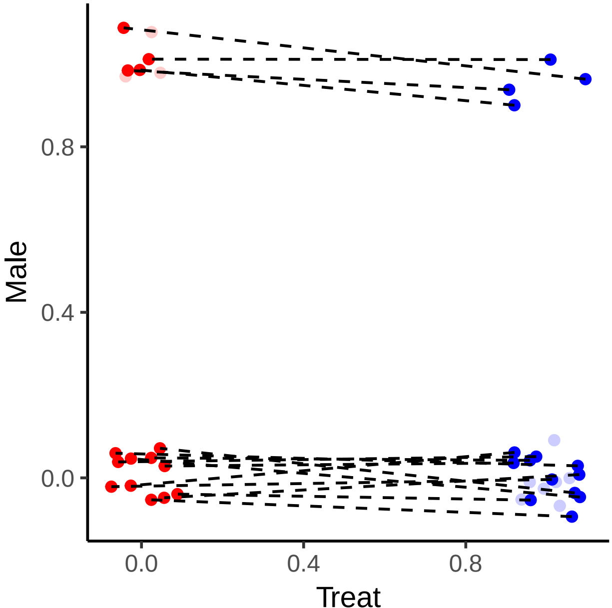

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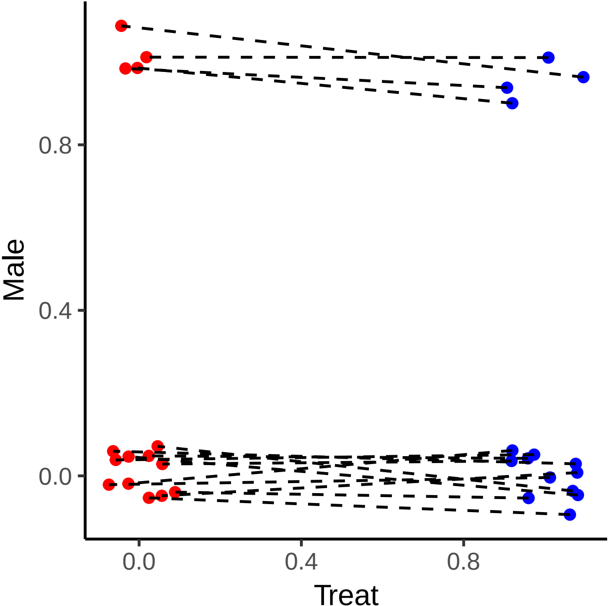

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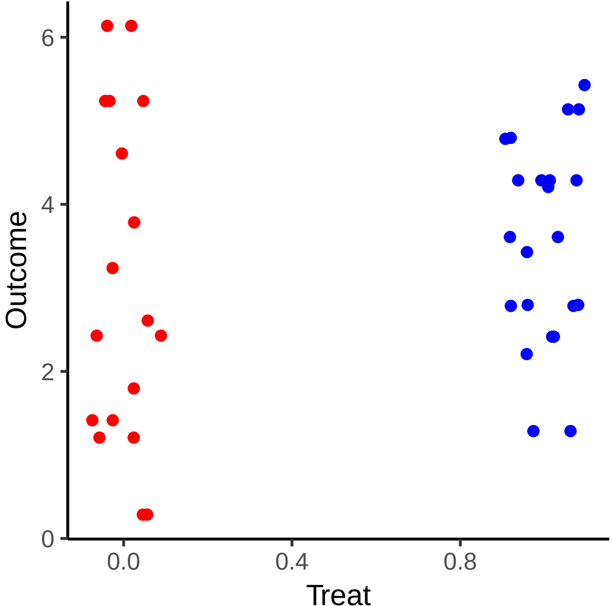
- Then compare the outcome of the **remaining** treated and control units
  - Difference in means
  - Or regression of outcome on treatment

Exact Matching

	Units	Means Treated	Means Control	Mean Diff
1	All	0.18	0.39	-0.21
2	Matched	0.27	0.27	0.00

Exact Matching Analysis



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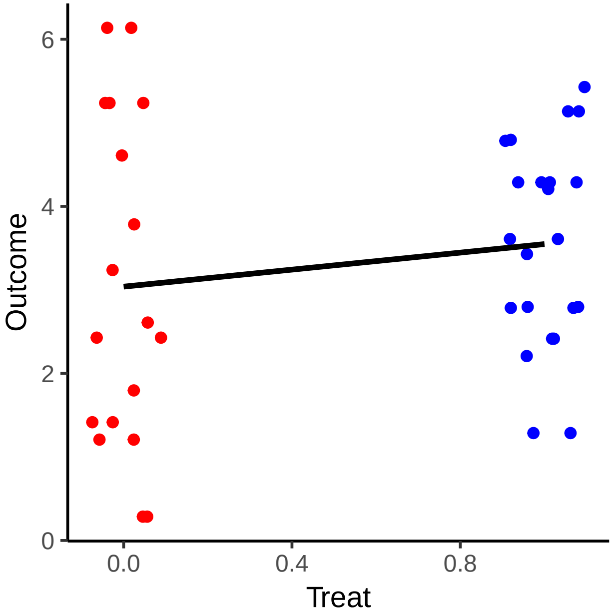

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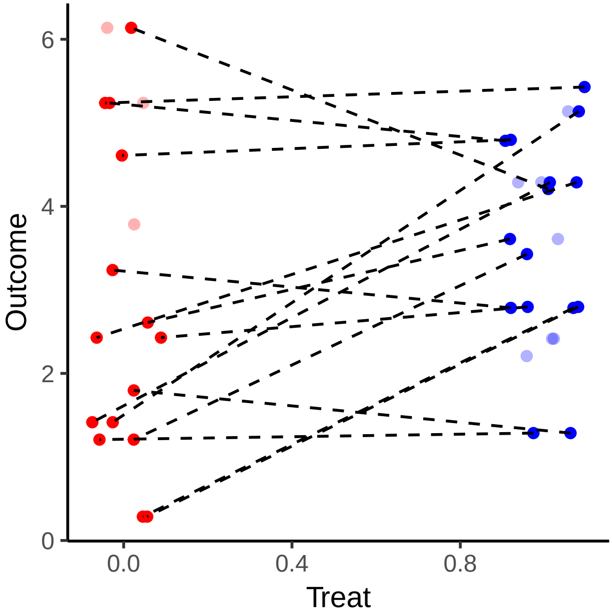

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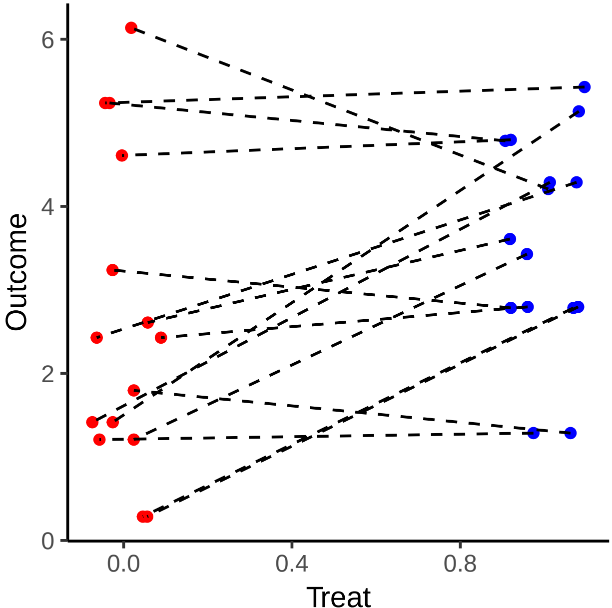

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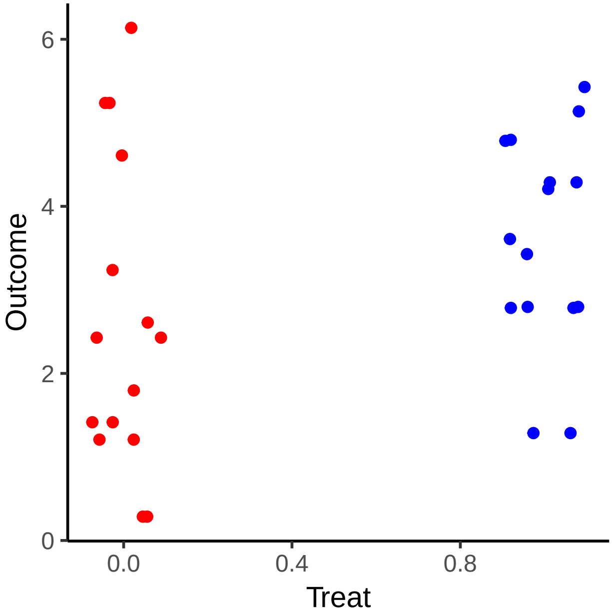

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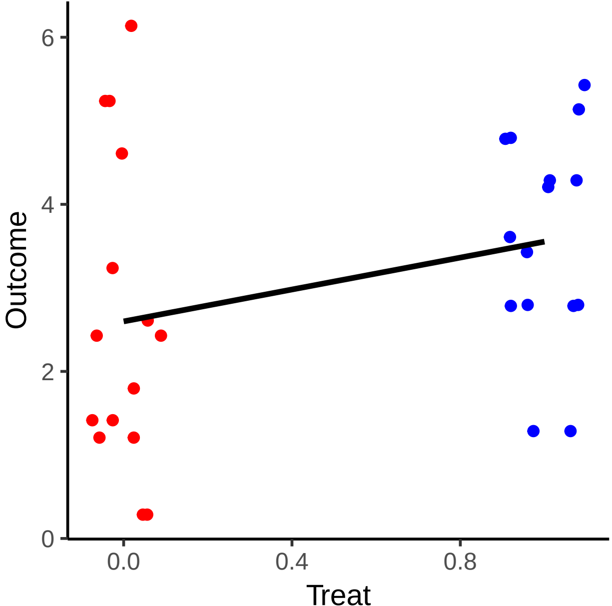

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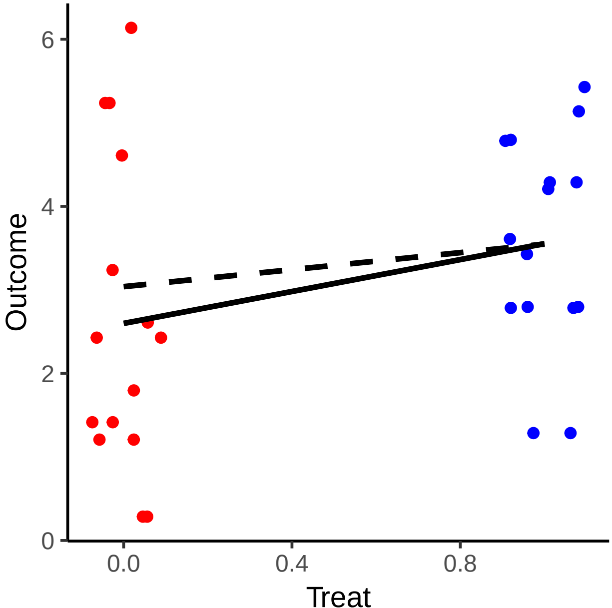

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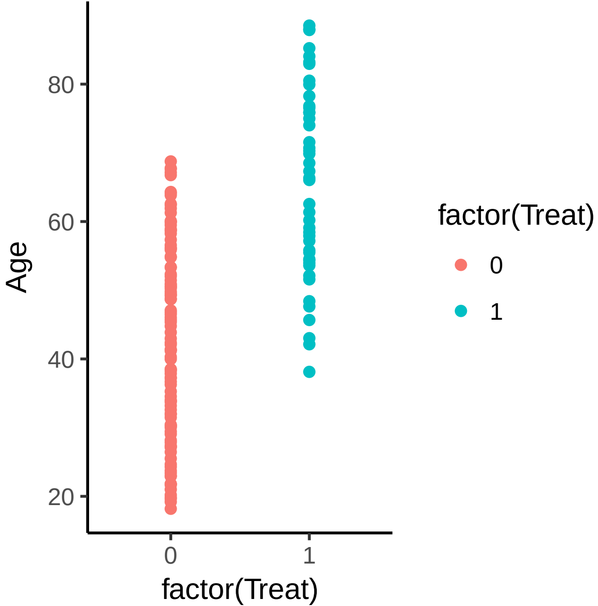

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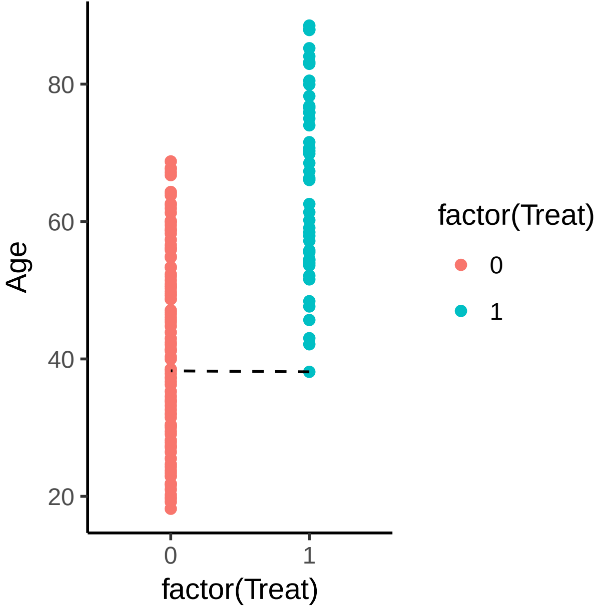

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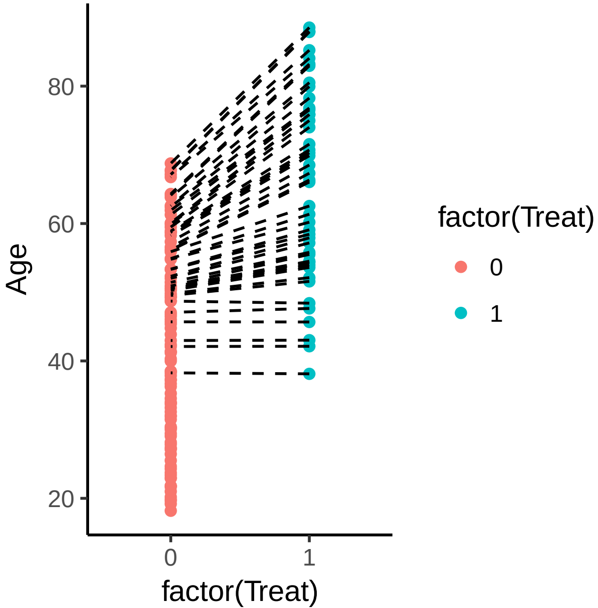

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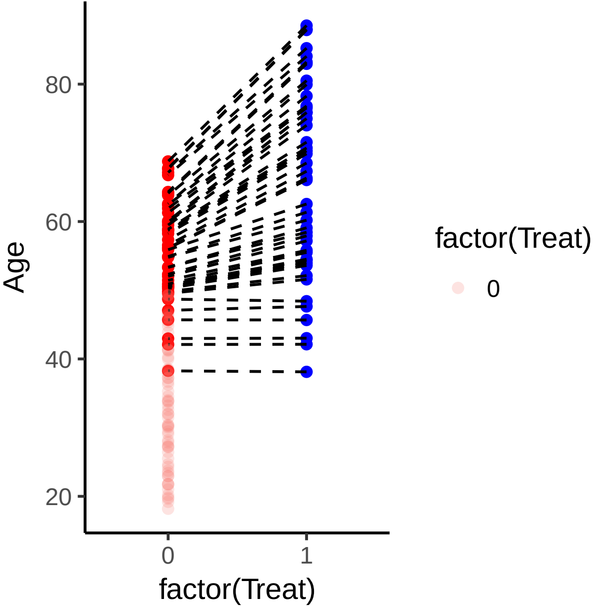

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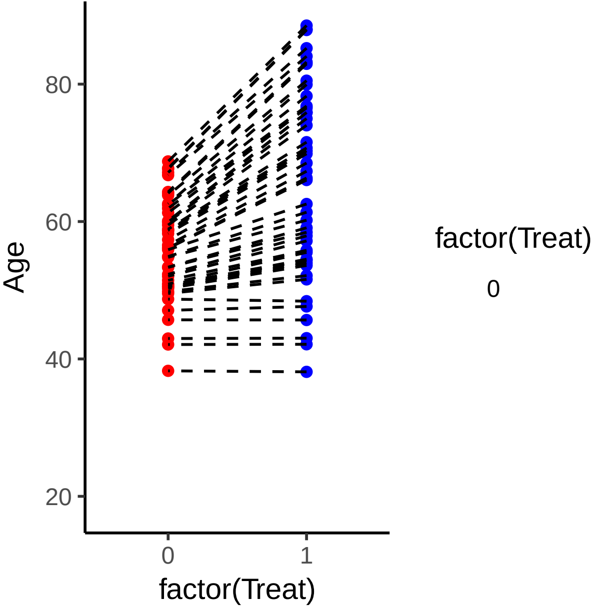

Nearest Neighbour Matching

	Units	Means Treated	Means Control	Mean Diff
1	All	65.70	42.67	23.03
2	Matched	65.70	56.09	9.61

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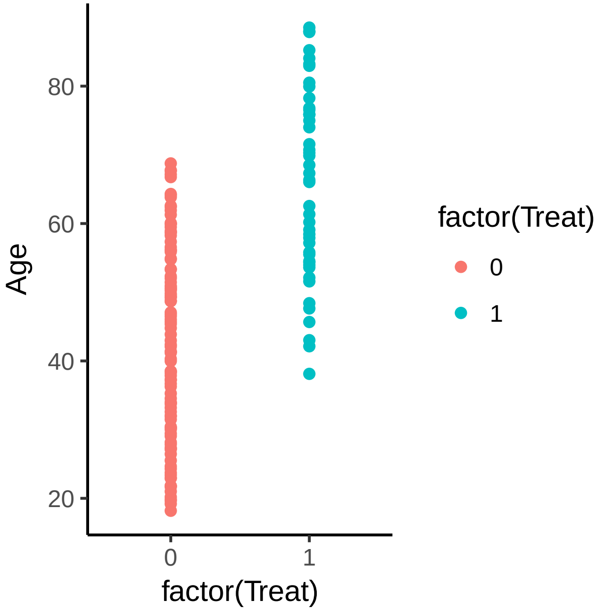
  2. **The order of matching matters:** The first matches use up units that might make better matches for later treated units
     - To maximize balance we need to ’look ahead’ and match in the right order
     - For this we can use optimal or genetic matching, which is fully automated

Nearest Neighbour Matching with Caliper



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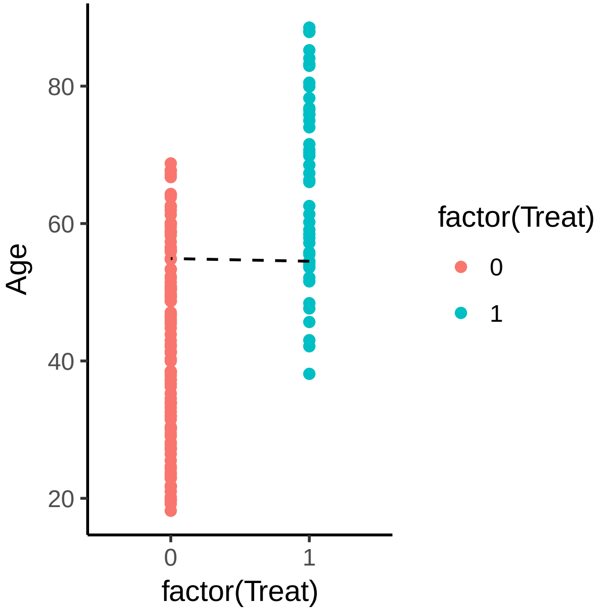

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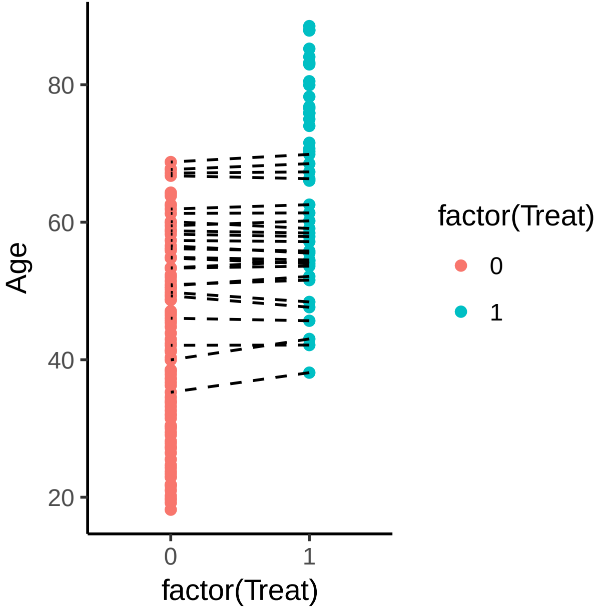

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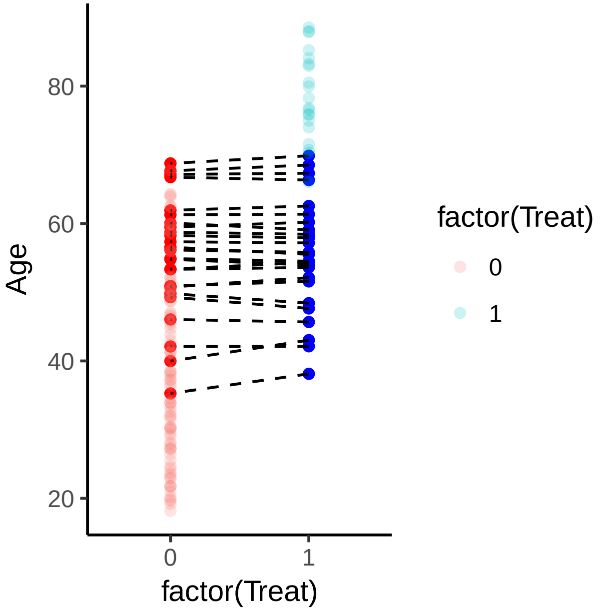

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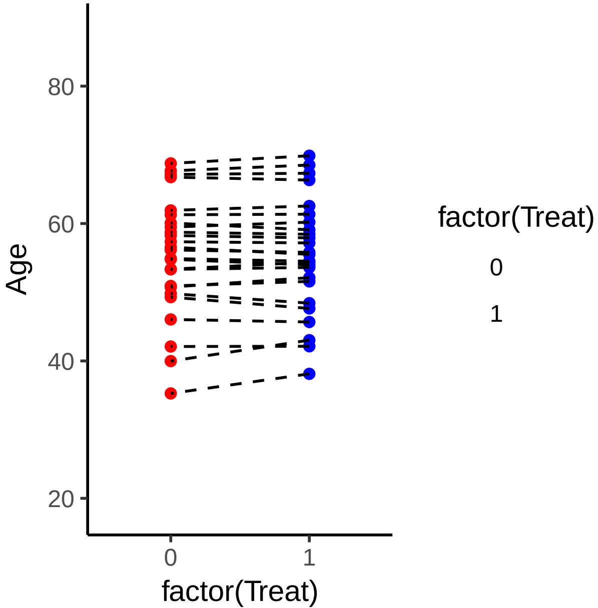

Nearest Neighbour Matching with Caliper

	Units	Means Treated	Means Control	Mean Diff
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- Note: p-values don't mean so much for balance tests

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- Better to compare (standardized) difference in means

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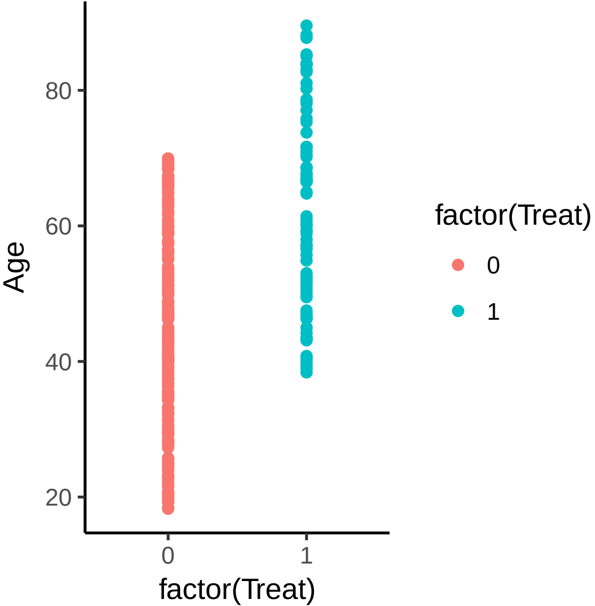

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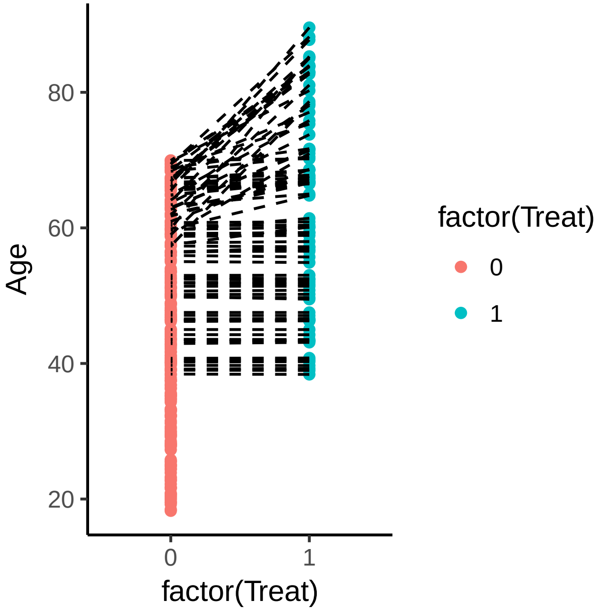

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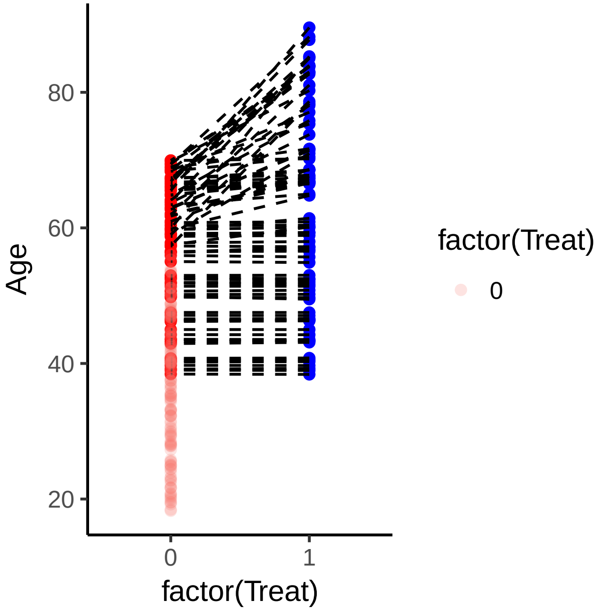

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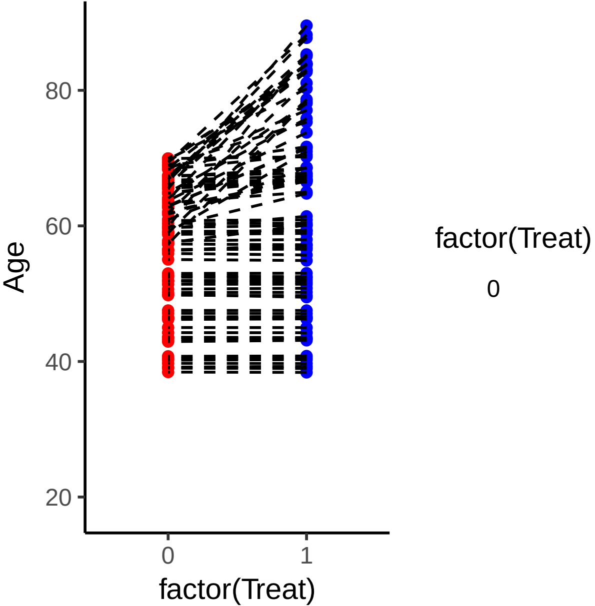

Optimal Matching

	Units	Means Treated	Means Control	Mean Diff
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2	Matched	62.60	57.57	5.03

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  - So let's use the confounders to **predict treatment**
  - That's different to actual treatment status, with the remainder due to 'random' factors (if we include all confounders)
- Then use the propensity score (probability 0-1) to match treated and control units which have the same ex ante probability of treatment

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- But some concerns about drawbacks of propensity score matching
- May have poor balance on individual confounders
- Balance may get worse as we remove more units
- We have to get the functional form of the treatment explanation right (linear, quadratic etc.) so we remain vulnerable to model dependence!

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- Treatment: 1/0
- Confounder: Age
- Logit model predicting treatment:

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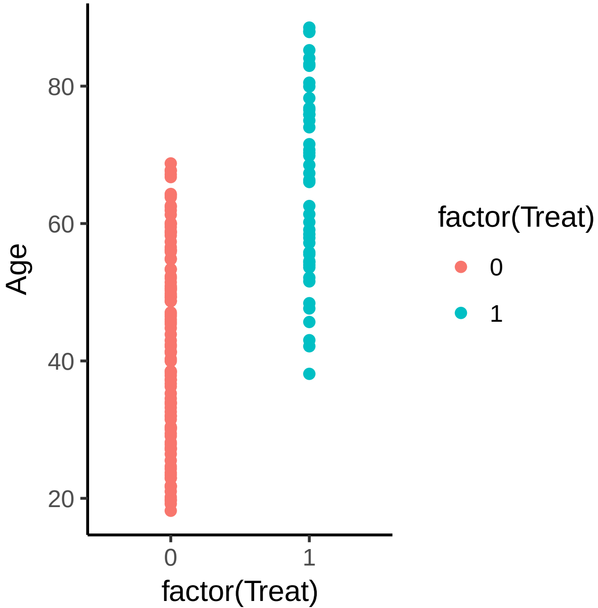
- I.e. match units with a similar *probability* of treatment
- ...Regardless of whether they actually get treated

Propensity Score Matching



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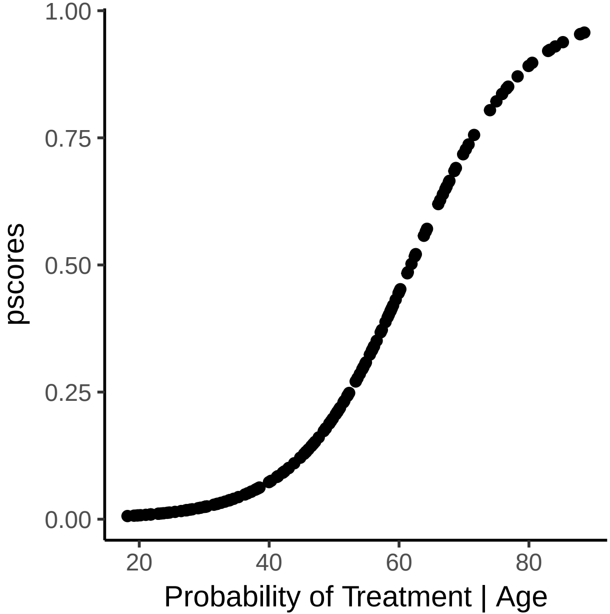

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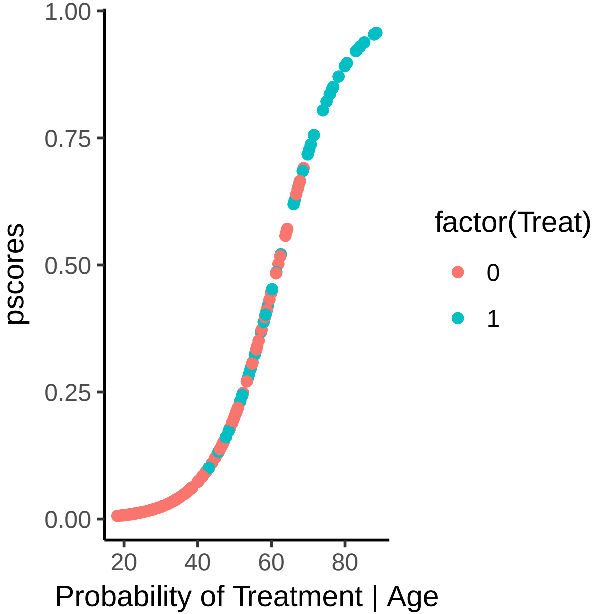

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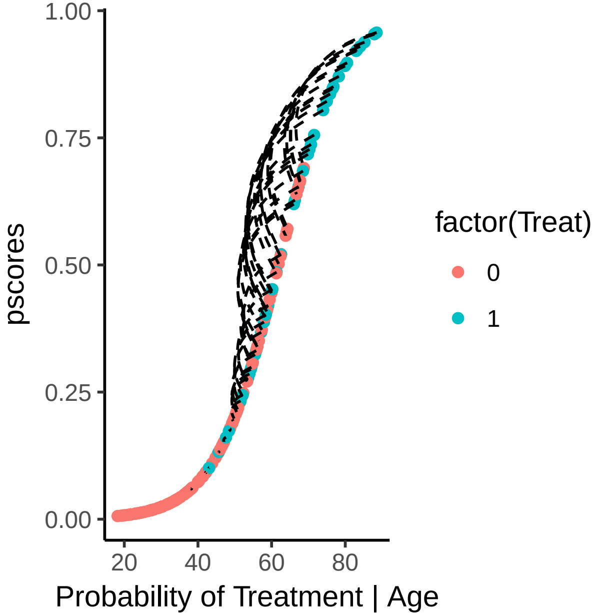

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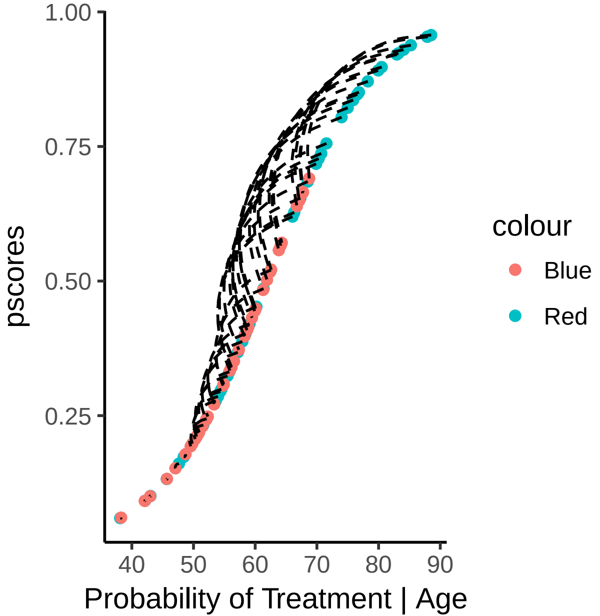
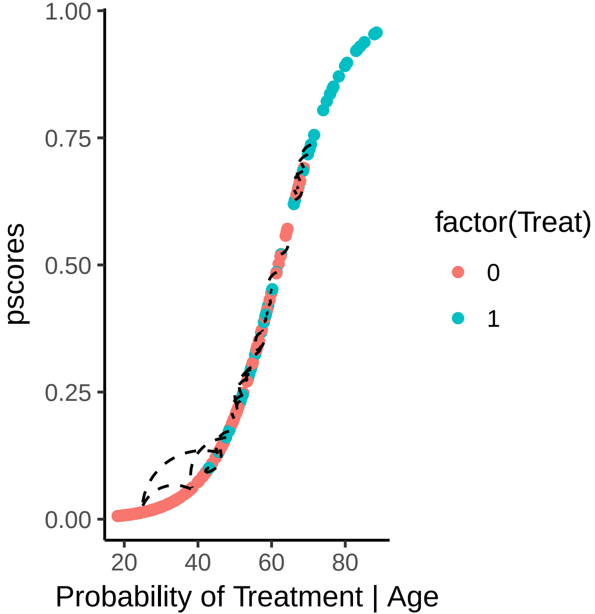


Propensity Score Matching

	Units	Means Treated	Means Control	Mean Diff
1	All	0.57	0.18	0.39
2	Matched	0.57	0.36	0.21

Propensity Score Matching with Caliper



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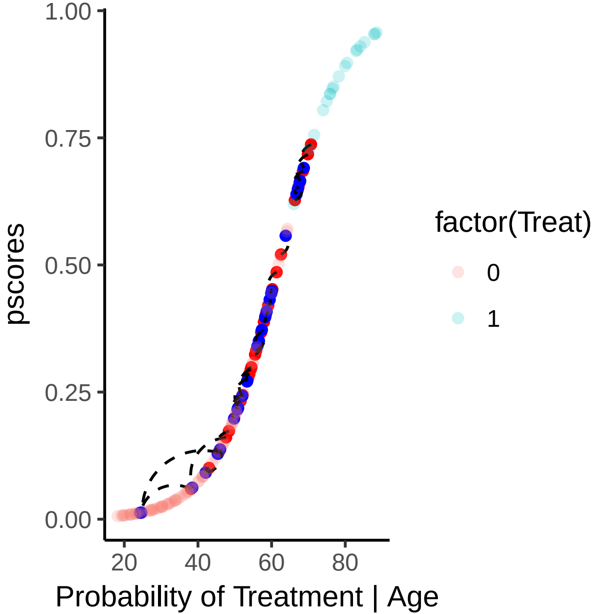

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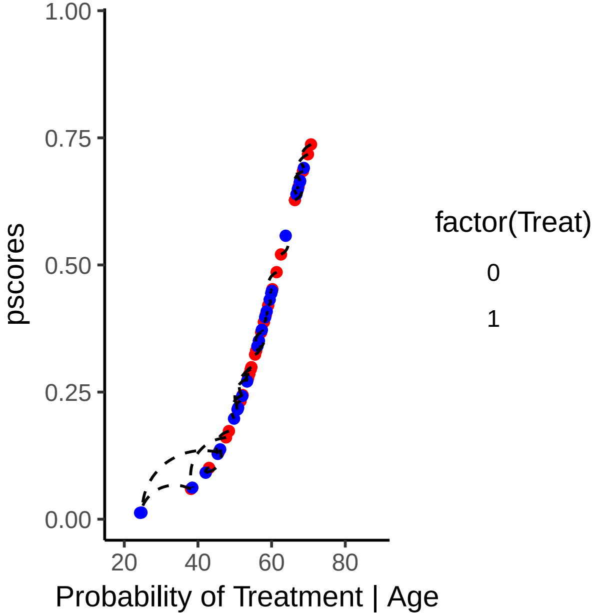

Propensity Score Matching with Caliper

	Units	Means Treated	Means Control	Mean Diff
1	All	0.57	0.18	0.39
2	Matched	0.36	0.34	0.02

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- Try alternative specifications

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- Matching + Regression = "Doubly Robust"
  - If **either** matching produces balance **OR** we have the correct functional form for regression, we can make causal inference

Matching

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- But unobserved confounders mean matching can't recover causal estimates

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Political Economy

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- They already used an RDD on close electoral victories to show incumbents are more likely to get media licences
- But how do media licences affect performance in the next election?
- No ’as-if’ random variation in treatment
- So they use an observational study with matching to create plausible counterfactuals

Political Economy

- **Population:**

Political Economy

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- Clear improvement in balance after matching

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- Simple comparison of means between treated and control group
- ATT causal effect estimate: 0.39% points (17%) increase in vote share if you have a media licence

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Political Economy

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- How does Bolsa Familia affect voting?
- Similar to De La O (2010) but without the natural experiment
- "There were no randomized pilot programs, there are no obvious discontinuities to be exploited, and CCT eligibility and actual coverage are highly correlated with several other socioeconomic variables."

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- Luckily, implementation does not follow perfectly fixed rules - so matching is feasible
- But that also suggests other informal/unobserved factors affect treatment assignment - confounding!

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  4. Regression of Outcome on propensity score by strata

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  - Spending extra R$100 per person through Bolsa Familia increases vote share by 7-15% points
  - Consistent estimates from matching in survey data