What’s the Effect of Having a Daughter:

How a High P-Value Can Make You Happy

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Code : https://gist.github.com/anonymous/1287c316caf364872d698e3ddfd7b591

Stefano Iacus, Gary King, and Giuseppe Porro (IKP) look at a paper by Washington (2008), and show that having a daughter correlates with members of the U.S. House of Representatives voting more liberally, especially on reproductive rights issues[1] (Iacus, King, and Porro, 2011). IKP uses Coarsened Exact Matching (CEM) to test the reliability of Washington's results. We are not trying to show the same correlation but rather rematch the data using Genetic Matching and estimate a different causal effect.

The first divergence of our assumptions comes in the covariates we find useful for balance. IKP uses "totchi", total number of children, but we do not. The total number of children is affected by our treatment (having a girl) and therefore is not eligible as a covariate. IKP also uses religious groups by assigning them values 0 – 4, forcing our function to believe the religions assigned to 0 and 4 are less likely to be matched than the religions assigned to numbers closer together i.e. 2 and 3 or 1 and 2[2]. Similar to IKP I omit all representatives who have a missing datapoint, allowing the code to be easier to deal with[3].

To replicate Gary's initial findings we match on the covariates he matches on to see if we can get a good leximin p-value. He matches on: "female", "white", "srvlng", "age", "demvote", and "repub". These make a lot of (common) sense because we can assume each of these is likely to influence the causal effect as follows: "female": more likely to vote in favor of female reproductive rights; "white" :

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[1] #plausability : Logically, it is possible to deduce that individuals who have daughters are more likely to be empathetic or sympathetic to reproductive rights issues. This understanding was very useful when checking the data and reviewing the "Estimates" (Figures 1.2 and 2.2). The "Estimates" are constantly negative, close to zero numbers leading us to negative, almost negligible, effect.

[2] #scibreakdown : IKP misidentifies "totchi" as a confounding variable, possibly skewing the matches and eventually the results. They also incorrectly assign "rgroup" to number 0 through 4 causing the "No Religion" and "Other Religions" to be seen as highly unlikely to match and "Protestant" and "No Religion" as highly likely to match. The differences in common attitude for reproductive rights is very religion specific and his assignment does not show this but rather incorrectly skews. I fix this by assigning each religion to a binary form and comparing each religion equally to each other and the rest of the data. Similarly, I assign all Christian religions to one variable because their views on reproductive rights tend to be very similar if not the same.

[3] I was hesitant to omit all NA because of the following example : 1. No females have datapoint X because it does not apply. 2. We delete all females. 3. All females showed us something very important we now do not see. This does not appear to be the case here but is a possibility.

difference in race is an easy covariate to match on; "srvlng" : the time spent in this job might change your opinion or voting habits; "age" : the older you are, the more conservatively you vote (roughly ~ younger people tend to be more liberal); "demvote" : pleasing your constituents forces a predictable voting record; "repub": obvious confounder because party affiliation strongly corresponds to attitudes on reproductive rights. The assumptions for my covariates differ below:

1. It is not important to balance on the "srvlng" because it is unlikely that the time spent as a representative will change voting habits significantly given our reliance on "demvote".
2. It is important to balance for "all_christ" because religions of the Christian denomination tend to be more conservative on reproductive rights.

When matching for IKP's covariates, the leximin p-value I obtain is 0.542 with the worst match on the variable "age"(Figure 1.1). Although a great match, from the estimate we deduce, we can infer nothing (Figure 1.2). The estimate is -0.040351 but the associated p-value is 0.92889, a p-value so high we cannot even come close to thinking about throwing away our null hypothesis. The graphs show a clear difference in the balance of matched and pre-matched covariates (Graphs 1.1 - 1.4).

When matching for my covariates ("female", "white", "age", "demvote", "repub", and "all_christ") the leximin p-value's are sometimes larger than those achieved through IKP's covariates. A few of my achieved leximin p-value's were 0.51464, 0.44479, 0.485, and the best overall, 0.59871. The graphs below (Graphs 2.1, 2.2, and 2.3) are from a leximin p-value of 0.47969 because even though it is not the best, it is still very good (Figure 2.1). Similarly our inferences fall short because the estimate -0.10526 is accompanied by a p-value of 0.81842 (Figure 2.2). Similar to IKP, the graphs show a clear difference in the balance of matched and pre-matched covariates (Graphs 2.1 - 2.4).

Overall it is very cool and very clear that we were able to match really well on a few key covariets, deemed important from our logic and from IKP. However, in the wise words of Skye Hersh, "we matched really well and we can't draw any conclusions". Quite a bummer if you ask me.

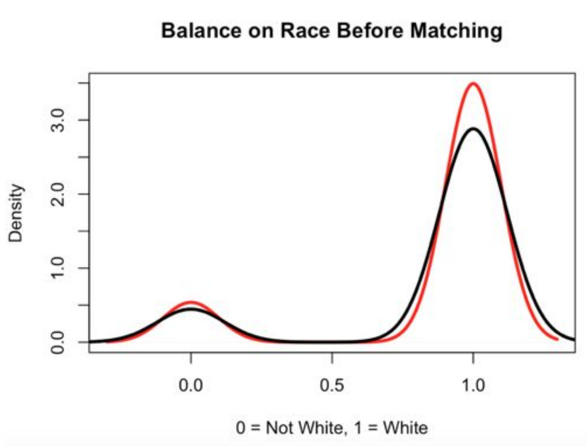
IKP Covariates

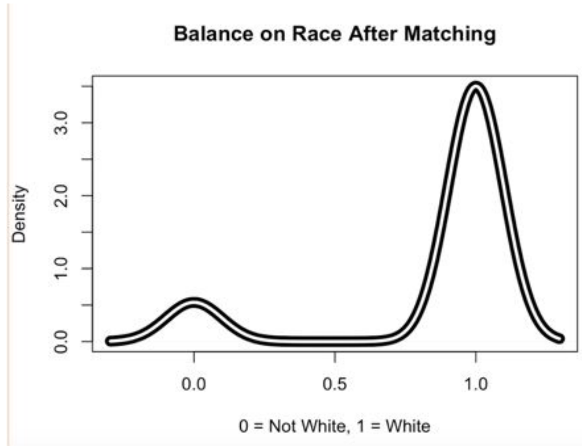
```
Before Matching Minimum p.value: 0.003974
Variable Name(s): age  Number(s): 4

After Matching Minimum p.value: 0.542
Variable Name(s): age  Number(s): 4
```

Figure 1.1

```
Estimate...  -0.040351
AI SE......  0.45214
T-stat.....  -0.089245
p.val......  0.92889
```

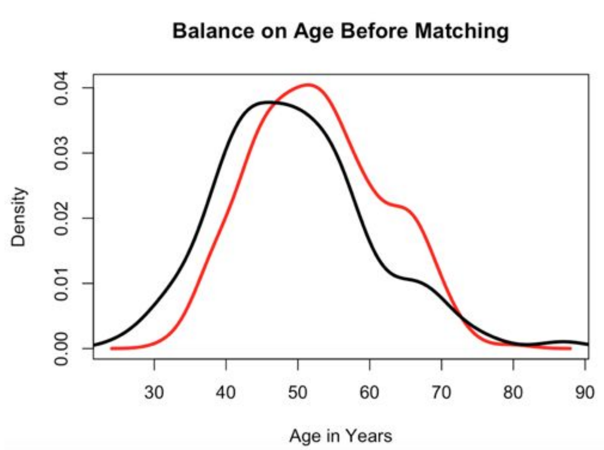
Figure 1.2

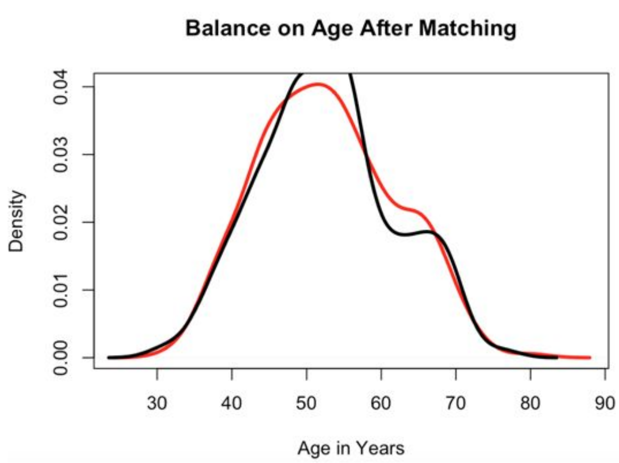




Graph 1.1 **Graph 1.2**

These graphs represent the balance on race before and after matching. Graph 1.1 shows the treatment in red and the control in black, distributions that are slightly off. Graph 1.2 shows the treatment in black and the control in white laid on top of the treatment distribution. Graph 1.2 shows how the distributions are shifted and after Matching achieve perfect balance. This is the same for covariates "female" and "repub".





Graph 1.3 **Graph 1.4**

These graphs represent the balance on age before and after matching. In both graphs the red represents the distribution of the treated units and black the control. This is the most visual example of balancing a covariate to more closely replicate randomization.

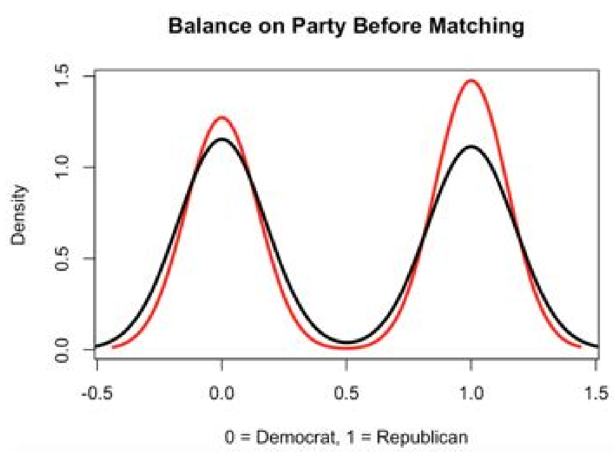
My Covariates

```
Before Matching Minimum p.value: 0.003974
Variable Name(s): age  Number(s): 3

After Matching Minimum p.value: 0.47969
Variable Name(s): female  Number(s): 1
```

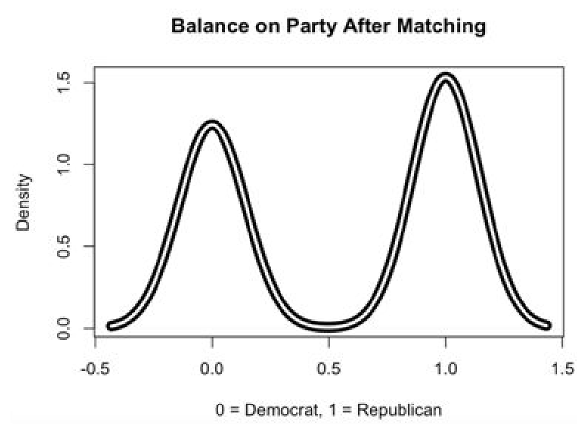
Figure 2.1

```
Estimate...  -0.10526
AI SE......  0.45852
T-stat.....  -0.22957
p.val......  0.81842
```

Figure 2.2

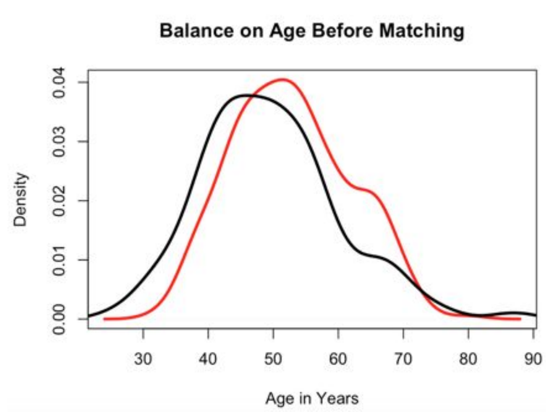


Graph 2.1

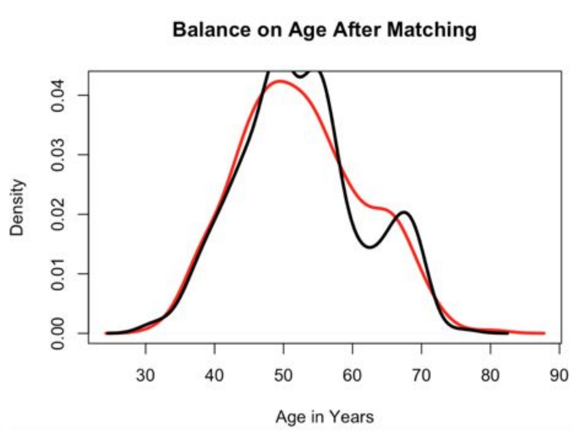


Graph 2.2

These graphs show the balance for the Party distribution (either Democrat or Republican). Perfect matching, and corresponding graphs, can be seen with the other binary variables "white" and close to perfect matching with "female". The red



Graph 2.3



Graph 2.4

Similar to Graphs 1.3 and 1.4, the balance on Age before and after matching is visually defined. The treatment units are shown in red and control units are in black for Graphs 2.3 and 2.4.

Bibliography

Iacus, S.M., King, G., Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. Journal of the American Statistical Association, 106(493), 345-361.

Washington, E. L. (2008), "Female Socialization: How Daughters Affect Their Legislator Fathers' Voting on Woman's Issues," American Economic Review, 98 (1), 311–332. [354,355]