# Final Project

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**To:** **Lakshmi Iyer, Author of the original paper**

**From:** **Md Mahmudunnobe, Jackie Trang, Claudia Jin**

**Date:** **20 December 2019**

**Re:** **Further analysis of women's power's effect on the increase in crime reporting**

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**Executive summary**

This decision memo discussed on a further analysis on the decision question, "Is there any direct causal effect of increasing women representation in government to the increase of the reporting of crime against women in India." The original paper suggests a significant treatment effect analyzing the full India data, while a replication paper indicates that a state-level analysis weakens that conclusion. As both of them used regression-based models, which is not a good method for causal inference due to their vulnerability to selection bias, we analyzed the data further using more sophisticated methods like genetic matching and synthetic control. Genetic matching showed that the control and treatment units are too poorly matched to derive any causal effect, while a case study using the synthetic control method indicates around 0.01% increase in reporting crimes in Assam. But the result is not very highly significant due to two major limitations of the dataset: having another potential treatment (re-categorization of crime) around the same time (1995) and all the control states used for the synthetic control method have the same treatment effect some year earlier than Assam. *So, our analysis indicates that the treatment effect, if any, can vary through state and we recommend to use more useful control units (i.e. the state or city where the law didn't pass), more sophisticated method considering the limitation of the dataset and more study using the data of different countries to estimate the true causal effect.*

**Introduction (Paper Introduction)**

In 1993, India introduced the 73rd constitutional amendment stating that one-third of seats in local legislatures of its states must be reserved for women. "The Power of Political Voice: Women's Political Representation and Crime in India" by Iyer et al. (2012) investigates this event and finds an association between policy implementation and an increase in the rate of reported total crimes against women and attributes it to women being more empowered to report crimes.

**Replication**

The original paper used Poisson regression to model the overall crime rate against women in India used the treatment variable (1 after passing the law, 0 otherwise) as predictor with other control variables. From the coefficients of the model, they showed that there is around 0.229 increase in total crimes against women per 1000 women (0.022%) and their p-value suggested that it is significant.

Table 2: Women's Political Representation and Crimes against Women

| | No controls (1) | Control for state-specific time trends + other controls (2) |
|---|---|---|
| Panel B: Data used in Iyer et al. (2012) | | |
| Total crimes against women | 0.365* | 0.229** |
| per 1000 women [SE] | [ 0.19 ] | [ 0.084 ] |
| $R^2$ | 0.85 | 0.95 |
| Observations | 391 | 391 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

***Table 1***. Replication of the original paper

We replicate this table with the help of the code provided by a replication paper and we also found the same result as the original paper (Table 1). In the code, they used the *stargazer()* package to print the latex format of the table, which is obtained as a picture using an online latex editor (overleaf, n.d). But we also emphasize on the fact that they used regression which is not reliable for drawing a causal inference.[1]

The replication paper by Andrews, Pradhan & Steenland (2014) critics Iyer et al. (2012) that the increased report crimes is not a result of the state-level implementation of the national amendment in 1993 because not all the state implement the law around 1993. Rather, the change may occur at the year in which crime data were reclassified to introduce more categories of

[1] #***regression***: We follow the replication with regression models the original paper used and realized its unreliability to draw a causal inference, so then we extend the paper with our genetic matching and synthetic control analysis. The interpretation of regression does not only helps us evaluate the paper but also sheds light on the direction of extension that we should pursue to better investigate causal inference.

crimes against women in 1995. We have additional scrutiny to Iyer et al. by replicating a figure in this critic paper showing total crimes against women per 1000 women across states in India of this replication paper. This figure shows very clear indication that though the implementation of the law happened at different times in each state, they all seem to have an increase near 1995. So, we agreed that the change of crime definition classification might affect the total crimes against women for each state, especially for Karnataka and Kerala which has no obvious increase in reporting crimes after state reservation implementation and before 1993.[2] For Andhra Pradesh, Haryana and Himachal Pradesh, however, the state-level implementation might confound the national amendment, so we cannot draw a causal inference between national reservation implementation and total crimes against women per 1000 women.

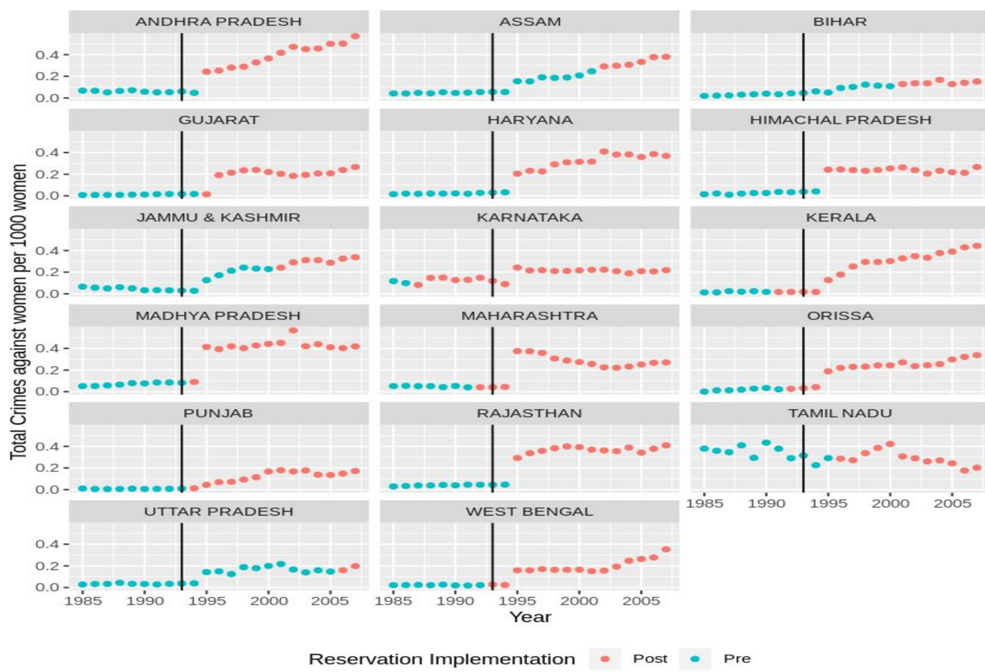



***Figure 1.*** Replication of the replication paper -Total crimes against women across states

Iyer et al. had an assumption of exogeneity in which state-level implementation of the reservation rule and the rate of reported crimes against women are independent. However, this assumption is unconvincing because states that implemented the policy were likely to become

[2] #***studyreplication***: We applied replication methodologies and provided new insights about the interpretation of Table 1 and Figure 1. The replication of figure 1 also helps us question the exogeneity assumption in Iyer et al. paper due to the vast difference in the implementation year across states.

more progressive with a higher level of GDP and literacy level. Figure 1 supports this idea by showing the big magnitude of difference between the year of implementation, which is a source of suspicion. This is kept in mind as we carry genetic matching afterward.

## Extension

### Genetic Matching

Before genetic matching, we divided the dataset into two: *after.data,* consists of data after 1995 and *before.data,* with the before 1995 data. We did so in order to avoid any treatment effect caused by the 're-categorization of crime' which occured in 1995. Initially the genetic matching is performed using the 6 single predictor variables (state id, GDP, female population, literacy level, women literacy, and rural area) which are used as a control variable in the original paper and with an exact matching for 'state' to compare how closely the treatment units (a state in a certain year after implementing the reservation) are related with control units (a state in a certain year before the implementation.). Though the p-value for 'state' increase to 1 (as an effect of the direct parameter), but the lowest p-value after matching still remained less than $10^{-7}$ for both datasets. This result also makes sense qualitatively as it is quite reasonable assumption that the condition in a specific state in 2002 will be very different than than the same state in 1990.

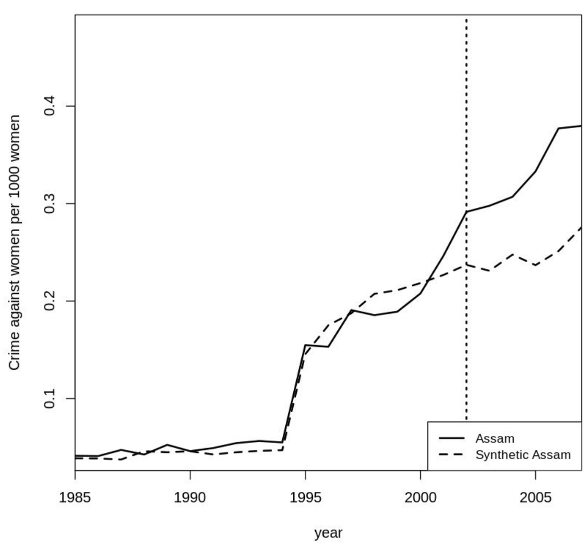
Later we used all possible quadratic and interaction terms along with the single covariates to match on and disregard the exact argument for 'state'. The reason behind this approach is that there might be two very similar state available at same year where one has received treatment (reservation passed) and other do not, these will be more closer match then the match between one single state in two very different time.

Still the after matching lowest p-value didn't increase for the *after.data,* but for *before.data* it increase to 0.02 (*Appendix B*), which is still too poor matching to determine a causal treatment effect. One possible cause for this slight increase in p-value on *before.data* might be the fact that we have more control unit then treatment unit here, while in *after.data* control units is less than the treatment unit. Due to the poor matching, we cannot get any significant causal effect using genmachting, so we did not move any further with GenMatch.

### Synthetic control

Later as a case study, a synthetic control is carried out on the state of Assam. We chose Assam as we have data available from 1985 to 2007 and Assam implemented the policy in 2002. So it ensures the sizeable number of pretreatment data to create a credible synthetic control as well as enough data to compare the outcome in post treatment period. Moreover the treatment of our interest (implementation of reservation) did not happen around the same time of another potential treatment, re-categorization of crime. The predictors are similar to those in the matching section earlier and the outcome variable is the crime against women per 1000 women.

Table 2 *(Appendix C)* shows that synthetic Assam is the weighted average of all other states in the weight range (0.026, 0.087) with Bihar as an exception with an outstanding 0.266 in weight. This is reasonable as Assam and Bihar are two states that implemented the policy around the same time (2002 and 2001) much later than the national year. Table 3 *(Appendix C)* compares the pre-policy characteristics of Assam with Synthetic Assam and the sample of other states. It is evident that across all characteristics of GDP, female population, literacy level, women literacy, and rural area, synthetic Assam provides a closer representation of Assam than the average of the sample of 16 other states.



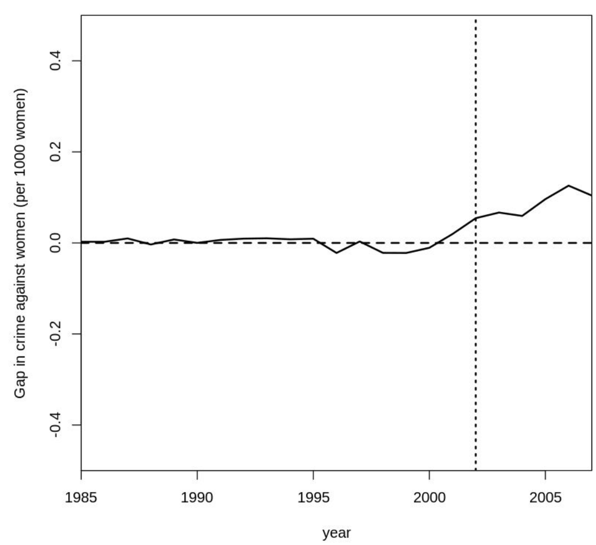




***Figure 2.*** Trend in crime against women in 1985:2007: Assam and Synthetic Assam

***Figure 3.*** Per 1000 women gap between Assam and Synthetic Assam

This is translated to a good fit for synthetic control between Assam and Synthetic Assam in figure 2 and small gap in these crimes in figure 3. The synthetic Assam almost exactly reproduces the number of crimes against women pre-implementation of the state policy without extrapolation. Overall, the state's implementation of the policy seems to have an effect on crimes against women because the outcome for Assam increases compared to the line for synthetic control unit. Therefore, the result supports the notion that the Assam's implementation of the policy had an effect on increased crimes against women. From 2002 to 2007, the number of crimes against women increased by approximately 0.1 per 1000 women.

To understand the credibility of the result, a placebo in time study was carried out assuming that the treatment happened to 1998 instead of 2002.

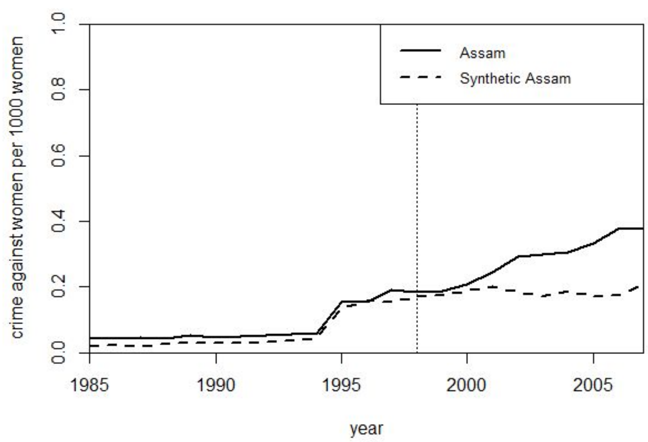



***Figure 4.*** A placebo in-time study for Assam in 1998

Figure 4 displays the result of the in-time placebo with treatment year of 1998. The synthetic Assam continues to highly resembles the crime against women of Assam and there is no divergence between them during the 1998 - 2000 period. Thus, in contrast to the actual 2002 policy implementation of Assam, the 1998 placebo implementation has no noticeable impact. The gaps plot for this placebo test as well as another placebo in time for 1992 (see Appendix D) as a treatment shown the same result. So, the treatment effect observed in figure 2 of the policy implication in Assam is credibly reflected.

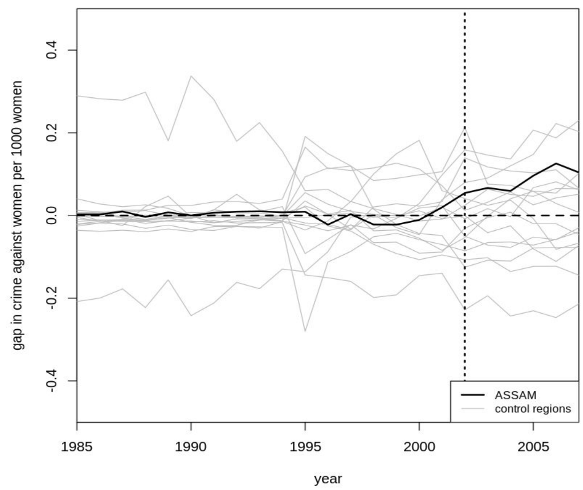



*Figure 5.* Per 1000 women crime against women gap in Assam and 16 other control states.

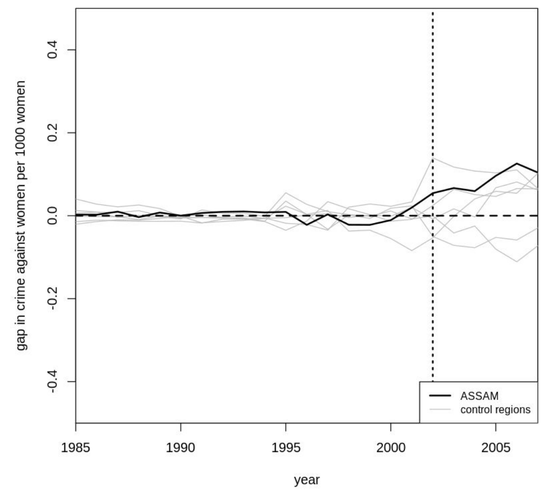



*Figure 6.* Per 1000 women crime against women gap in Assam and 6 other control states.[3]

We also proceed a series of in-space placebo studies by iteratively applying the synthetic control method used to estimate the effect of the policy implementation in Assam to all other 16 states in the donor pool. In other words, in each iteration, we proceed as if one of the states in the donor pool would receive the implementation of the policy in 2002 like Assam to estimate gaps in crimes against women. Figure 5 suggests that per 1000 women crimes against women are not well reproduced for some states, especially those with extremely high number of these crimes during the pre-implementation period. In figure 6, the states which are ill-fitting in pre period (their pre-period MSE is larger than 5 times the Assam pre-period MSE) are eliminated from the placebo studies. Ruling out these states are necessary because running placebo on poor fit units cannot provide meaningful information to measure the gap in crime for well-fitted states prior to 2002 implementation year of Assam. It is evident from figure 6 that the Assam gap is almost the biggest compared to other 6 other control states, suggesting not-by-chance treatment effect.

However, it is important to bear the following two limitations that with the cut off at 5*MSE of Assam, the sample size reduced to only 6 states. Secondly, all states in this data set

[3] ***#dataviz:*** Clearly alternated different cut-off points to eliminate ill-fitting control states because these units do not provide any insights to the other well-fitted states. Taking out redundancy is an important aspect of data visualization.

has implemented this policy sooner or later in the 1985-2007 period, so they may not be qualified as a "control state" in the donor pool as the effect of the implementation might be inherent in their number of crimes against women.[4]

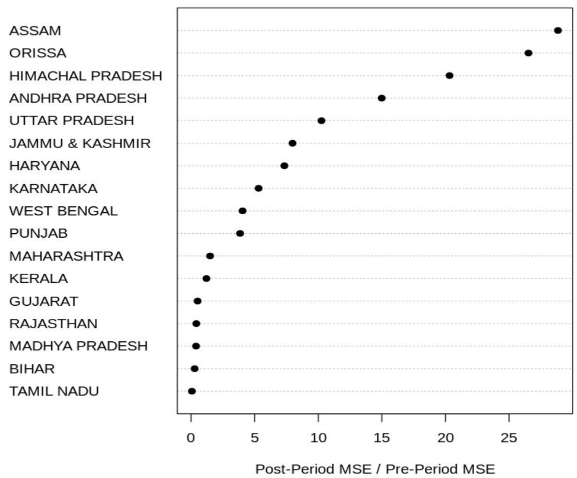



***Figure 6.*** Ratio of post-implementation MSE to pre-implementation MSE

Lastly we plot a dot chart using the all 17 states' post period MSE/ pre period MSE as found in the placebo in time. We can see still Assam is in the highest position. So if the treatment is randomly assigned to the states, then the probability of finding any treatment effect as extreme as Assam will be 1 out of 17. So, we can estimate the p-value of the study as $p = 1/17 = 0.05$.

**Conclusion**

This analysis suggests that there is no causal effect between the implementation of the women-reservation policy on the reported crimes against women due to poor matching on the nationally aggregated level. However, when using synthetic control on the individual state of Assam which implemented the policy much later than the national implementation, we found a treatment effect of the policy adoption on number of crimes against women per 1000 women. Thus, the treatment effect, if any, can vary through state and we recommend to use more useful control units (i.e. the state or city where the law didn't pass), more sophisticated method

[4] ***#constraints:*** Highlighted a special characteristic of this dataset being that every state received treatment at one time or another, creating an extra constraint in trusting the credibility of these in space placebo studies. Also, the significantly reduced sample size also placed a constraint on this placebo test's credibility that we need to work around in our interpretation.

considering the limitation of the dataset and more study using the data of different countries to estimate the true causal effect.

# References

Iyer, Lakshmi, Anandi Mani, Prachi Mishra, and Petia Topalova. 2012. "The Power of Political Voice: Women´s Political Representation and Crime in India." American Economic Journal: Applied Economics, 4(4): 165-93. Retrieved from https://www.aeaweb.org/articles.php?doi=10.1257/app.4.4.165.

Andrews, Kathryn; Pradhan, Elina; Steenland, Maria, 2014, "Replication data for: Art of Modeling Covered the Facts of Data: Uncovering an artifact of the change in reporting system of crimes against women in India". Harvard Dataverse. Retrieved from https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/25677

Overleaf, n.d, Retrieved from https://www.overleaf.com/project

# Appendix

**Appendix A: R code**

Notebook with R code can be found here

**Appendix B: Detailed Matching Results**

Detailed MathBanlance Output can be found here

**Appendix C: Detailed Synthetic control**

**Table 2. Synthetic weights for Assam**

| State | Synthetic Control Weight | State | Synthetic Control Weight |
|---|---|---|---|
| Andhra Pradesh | 0.051 | Madhya Pradesh | 0.033 |
| Bihar | 0.266 | Maharashtra | 0.033 |
| Gujarat | 0.038 | Orissa | 0.031 |
| Haryana | 0.051 | Punjab | 0.087 |
| Himachal Pradesh | 0.026 | Rajasthan | 0.035 |
| Jammu & Kashmir | 0.08 | Tamil Nadu | 0.024 |
| Karnataka | 0.041 | Uttar Pradesh | 0.064 |
| Kerala | 0.054 | West Bengal | 0.085 |

**Table 3. Predictor means before Assam implementation**

| | Treated | Synthetic | Sample Mean |
|---|---|---|---|
| **pcgsdp** | 1.324 | 1.324 | 1.495 |
| **pfemale** | 0.926 | 0.926 | 0.936 |
| **plit** | 0.453 | 0.454 | 0.49 |
| **pwlit** | 0.374 | 0.352 | 0.391 |
| **prural** | 0.884 | 0.771 | 0.745 |

**Appendix D: Placebo studies**

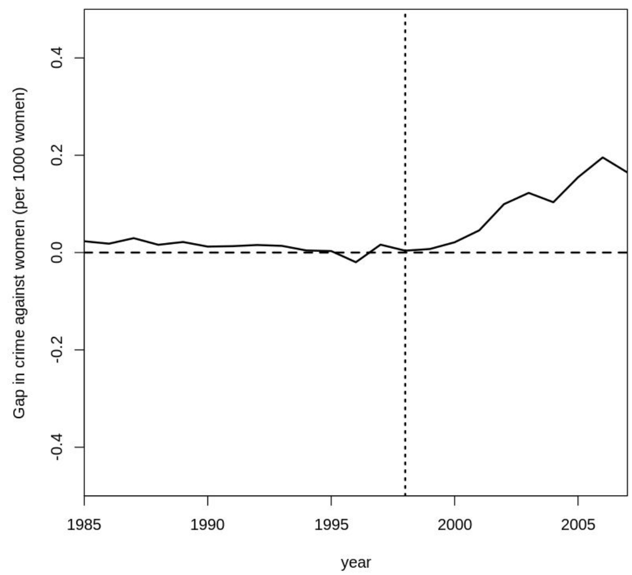



***Figure 7:*** Gaps plot on the placebo study in time assuming 1998 as a treatment for Assam

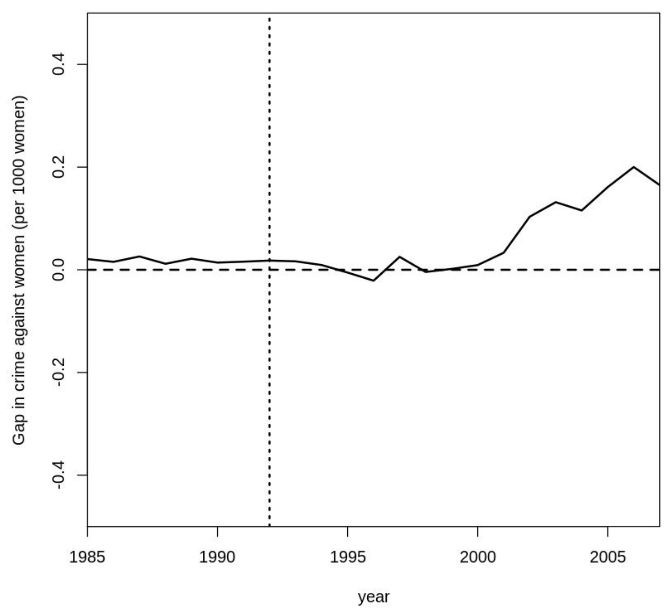



***Figure 8:*** Gaps plot on the placebo study in time assuming 1992 as a treatment for Assam