Heterogeneity of Work From Home

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Abstract

Unlike previous paper by Bloom et al. (2015) [6], I find heterogeneity of work from home policy. I use widely used causal random forest to identify heterogeneities. I find those above median worse off while those below median better off in terms of previous productivity. I also find that previous low performers improve their productivities from the policy. However, current causal forest frame work do not account for unobserved heterogeneity.

1 Introduction

I study heterogenous treatment effect of work from home policy on productivity using causal random forest method by Athey and Wager (2018) [3]. I revisit Bloom et al. (2015) [6]. This paper studies the effect of work from home policy on performance. The main outcome variable is productivity of workers. The treatment variable is working four days a week at home and to work the fifth shift in the office. This paper finds no heterogeneity. In table O4 of their paper, they interacted the treatment with characteristics of workers. In this paper, I study heterogeneity using causal forest. Unlike previous paper, I find heterogenous effect by previous performance. Previous lower performers improved with treatment while those who were in average had negative effects.

2 Background

I revisit Chinese experiment from Bloom et al. (2015) [6]. This paper studies the effect of work from home policy on productivity and other outcomes. To identify the effect of policy, the paper conducts field experiment on Chinese call center.

The estimation is based on individual-week level. I study main outcome variable, productivity. Productivity measure is defined as overall performance z-score measure. The treatment variable is whether the worker worked from home.

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Bloom et al. (2015) [6] finds positive effect of work from home policy on productivity. However, they do not find heterogeneity. In table O4 of their paper, they interact the treatment interacted to characteristics of workers. The characteristics are child, female, female with child, commute more than 2 hours, whether renter, young, short prior experience, short tenure, living with parents, living with spouse, living with friends, or previous performance. None of coefficients are significant. Instead, I study the heterogenous effect using causal random forest method by Athey and Wager (2018) [3]. This method more powerful than other methods with irrelevant variables.

3 Empirical Strategies

The causal random forest is the adaptation of random forest to causal framework. The original random forest paper, Breiman (2001) [5] splits groups using covariates. Among the potential splits, the algorithm choose the one that minimize criterion function, for example, minimizing MSE (Mean Squared Function).

Causal forest of Athey and Wager (2018) [3] builds on the causal forest of Athey and Imbens (2016) [2]. Athey and Imbens (2016) [2] propose to minimize MSE within leaf while maximizing variance of treatment effect across leaves.

I use heterogeneous treatment effect analysis using causal random forest. Although average treatment effect is informative about overall effect of treatment, it may not be the case that the effect are heterogeneous. It is possible that the previous lower performer benefit from the policy. Understanding such different response help us to target the most effective group.

Following Athey and Wager (2019) [4], I use cluster-robust version of random forest. I treat individuals as separate cluster. This is a conservative approach.

4 Results

I first discuss the average treatment effect. The results are shown in Table (1). Unlike original paper, I find no significant treatment effect. The coefficients are similar to when I exclude both year-week dummies and person fixed effect from original regression. These variables record low variable importance, thereby dropped from causal forest analysis.

Secondly, I evaluate whether causal forest recovers heterogeneity of treatment effect. Following Athey and Wager (2019) [4], I group observations where CATE (Conditional Average Treatment) above and below median. I estimate the average treatment effect separately for those below median and above median. The clustered-robust forest finds statistically significant heterogeneity between two groups. The lower group performs better while higher groups performs worse after the treatment.

In addition, I may find heterogeneity by some of covariates. I report measures of variable importance on Table (2). I find previous performance as the most important variable, 12% level. In the table, I find that the importance level for women are more than 10%. The results show that previous productivity is an important variable for heterogeneity. I find that the individuals with lower productivity improve when the policy has been adopted. In figure (1), I show heterogeneous treatment effect by covariates by previous performance. In contrast, I do not find heterogenous effect on women. In figure (2), I find no difference between men and women.

These findings are related to economics of working from home. Although a number of papers documented importance of heterogeneous effect of WFH on gender [Goldin and Katz 2011 [8]; Goldin 2014 [9]], and family responsibilities [Allen et al. 2015 [1]; Hotz et al. 2017 [10]], little has been documented on the heterogenous effect on previous performance. For the best of my knowledge, Dutcher (2012) [7] studies heterogenous effect of previous productivity on telecommuting. Compared to findings from Dutcher (2012), I find previous lower performer gains most productivity. The results are consistent to results from creative tasks of Dutcher (2012) [7]'s findings but contradicts to that of routine tasks from the same paper.

Table 1: Causal Forest: Average Treatment Effect and Test For Heterogeneity

	Cluster-Robust
effect (ATE)	0.0325
	(0.0578)
effect above median	-0.0805
	(0.0866)
effect below median	0.1539
	(9,9745)
95% CI for the difference	(-0.458, -0.01)
Observations	17,814

5 Discussion

I find average treatment effect different from that of original paper. This can be due to the fact that causal forest do not account for the fixed effect as discussed by Jens et al. (2021) [11]. I will further use Jens et al. (2021) [11] to control for group level heterogenous effect.

6 Conclusion

Unlike previous paper by Bloom et al. (2015) [6], the analysis using causal random forest finds heterogenous treatment effect of work from home on productivity. We find no heterogenous effect on having child, or women as results similar to findings from Bloom et al. (2015) [6].

In conclusion, we find heterogeneity that previous paper could not find. I investigate the heterogeneity using random forest.

Figure 1: Variation with Previous Performance

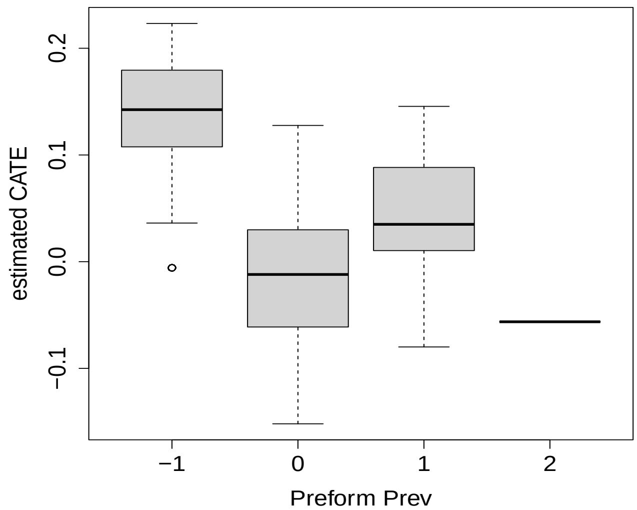
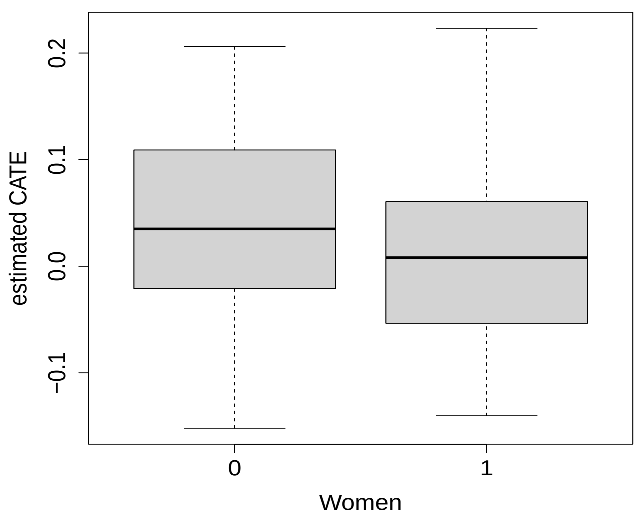


Figure 2: Variation for Women



Appendices

Table 2: Variable Importance in Cluster-robust Causal Forest

Variable	Importance (%)
Previous Performance	15.6
Women	10.6
Short Tenure	9.5
Young	9.4
Live With Parents	9.2
Live With Spouse	8.8
Rental	8.6
Short Experience	8.5
Commute	8.1
Have Children	6.5
Live With Friend	5.2

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