Heterogeneous Effects in Matching Grants

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Heterogeneous Effects in Matching Grants

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1. Introduction

Many believe that interventions by charitable organizations are an effective way to push up the macro-level economy. The charitable organizations help flow the resources between two asymmetric economies and smoothen the developing process. Charitable action is considered to be a blessing for countries with low resources, such that the government has a shortage of investment opportunities for the important sectors. Charitable organizations bring together individuals from two different economies—one who is aware of the problem and wants to take care of it and the other for whom a difference would be made.

As per charitable giving statistics, in 2020, the largest source of charitable giving came from individuals at $324.10 billion (National Philanthropic Trust, 2021), which accounted for 69% of total charitable giving. Evidently, the amount is incredibly high. Developing economies often get support from international charitable organizations to fight against poverty and strengthen educational and health sectors. As per statistics, charitable giving has grown 4.1 percent over the past year. Almost 4.5 percent of worldwide donors have enrolled in a monthly giving program. According to demographic Fundraising statistics, the average donor's age in the United States is 64 years and they participate in two charitable gift programs yearly. Statistics show that corporate philanthropy and matching grants and giving increased by more than 15 percent for 6 out of 10 companies. About Matching gift fundraising statistics, $2-$3 billion is donated through the matching gifts program annually. Every one out of 3 donors show interest in donating a high amount if there is a matching.

The takeaway from the statistics is that nowadays matching significant variables towards the donation is increasing. Indeed, charity is an important socioeconomic activity. Therefore, it is always interesting for researchers of different fields to understand why people do charity and the motivations behind charitable giving. The most important findings will be related to target questions such as: Who is giving? Why are they giving? What are the variables that influence such giving? Here, we are mostly going to discuss why people are giving.
2. Thesis Design and Objective

For my master’s thesis, I chose a paper based on a natural field experiment and explored how matching grants affect charitable giving. The thesis is designed in a particular way. The main objective is application of causal forest to identify the variables which are responsible for the treatment of heterogeneity without making any prior assumptions. Moreover, the need to estimate those variables are significant whether it is for charitable giving or not. At the very first, I wrote a literature review targeting the question, "Why do people do charitable giving?". Afterward, I discussed the original paper and compared my result with the original result; finally, treatment heterogeneity using machine learning algorithms was discussed. The algorithms used are causal forest and Lasso.

The motivation to use the causal forest is because it is the most advanced and new method to get an overview of how treatment effect works on different variables. However, the application of machine learning algorithms like the causal forest is not common in development economics. Similar to every artificial intelligence algorithm, the causal forest method helps researchers work with heterogeneous treatment analysis smoothly, as it does not need any parametric assumptions. It gives the flexibility to work with a high dimensional data set. The original paper looks at treatment heterogeneity and interacted treatment with different variables based on their assumptions and other references.

LASSO was chosen as it is a well-known technique for prediction. LASSO uses regularization and shrinks the unnecessary coefficients to zero. I chose the variables retained by LASSO and ran OLS to identify treatment heterogeneity for those variables. I want to check how LASSO works for variable identification and how those variables are responsible for heterogeneous treatment effects. Firstly, a literature review will be provided. The literature review will give an overview of charitable giving in the economy, though it is limited in its own way.
3. Literature Review

It is incredibly challenging to understand the magnitude of giving. Charitable donations seem a selfless and caring act. However, researchers from disciplines like sociology, psychology, and development economics want to dive much deeper to understand the reasons behind this act of giving. Over time, the nature of charitable giving has been changing, creating a need for researchers to understand the motivations and causes behind it. There is plenty of considerable theoretical and experimental literature on the factors determining the causes behind charitable giving and the importance of charity.

Bekkers and Wiepking (2011) write an outstanding academic literature review after analyzing 500 articles on charitable giving. Their interest centralizes on why people donate money to charitable organizations. After analyzing many papers from different disciplines on charitable giving, they identify eight main determinants. These are a) awareness of need; b) solicitation; c) costs and benefits; d) altruism; e) reputation; f) psychological benefits; g) values; and h) efficacy. Among these mechanisms, charitable giving under altruism is a little complicated. Identifying altruism is difficult because sometimes altruism depends on the household’s background and family history. In the later part, we discuss with reference how effective altruism influences charitable giving.

The main three agents in a charitable giving model are the donor, the organizer, and the recipients. Interestingly, these charitable organizations influence people and convince them to give their charity, not once but multiple times. In another article (Karlan et al., 2019), the authors mention that impulsive and deliberate marketing strategies also influence charitable giving along with the reasons like generosity, social prestige, etc. Nudge marketing techniques can influence human behavior towards charitable giving. The article exemplifies how a social appeal influences impulse donors to act quickly only to enjoy their inside generosity. This article also gives an idea of why people do not donate. First, donors rarely donate as much as they would like to. Second, donors rarely give according to demonstrated impact. It implies that donors are limited in their decision-making—the limitation in making decisions encourages individuals to not donate. Considering the varied reasons behind charitable giving, we can divide the donors into several groups. We can start with altruistic donors. Altruism is the most common philosophical explanation for donation. Pure altruistic donors donate without any expectation of personal gain and are concerned about social well-being. Altruistic donors are aware of society and this awareness of need motivates the donor to donate. Altruistic donors always examine the cost-
effectiveness of their donation. In the case of pure altruism, donors are concerned about other donations, and donations by others are a perfect substitute under pure altruism. As a result, the crowding-out effect is active under pure altruism. With the rise of other donations, pure altruistic donors stop donating. Another group of donors donates under social pressure to avoid social criticism. The other group of donors gives to enjoy a kind of "warm-glow" from giving. There is a tension between personal gain from charitable donation and donation under pure altruism.

Warm glow-giving is an economic theory that describes the emotional reward of giving to others. Continuing with Andreoni (1989, 1990), individuals enjoy immense pleasure and satisfaction for "doing their part" to help others. The essence of this satisfaction represents the selfish pleasure derived from "doing good," regardless of the actual impact of one's generosity. When people make donations to provide public goods privately, they may gain utility from increasing the total supply of that public goods. However, they may also benefit from society in exchange for their giving. The theory of warm glow posits that giving under altruism helps to maximize the utility of the giver to give. Household charitable giving is an important source of revenue in the United States and understanding the factors influencing charity is, therefore, important for researchers.

Ross Gittell and Edinaldo Tebaldi (2006) try to understand which variables influence charitable giving. They conclude that personal income, capital gains, religious group affiliation, age, volunteerism, and educational attainment are the main factors affecting household giving. Their analysis estimates that personal income is the key factor for household charitable giving decisions in the United States. Their model suggests that an increase of 10 percent in average personal income can increase the state's average giving per tax filer by approximately 8 percent. It is always attractive to analyze the relationship between economic incentives and pro-social behavior. Roland Benabou and Jean Tirole (2006) have mentioned that it is in human nature to engage in costly activities for themselves and be of benefit to others. This paper finds how people's proactive social activities can be connected with altruism motivation, self-material interest, and social image concern. People engage with these prosocial activities to get some immediate and expected benefits in the long term. For example, a large group of donors could donate under social pressure either to maintain their social reputation or due to the pressure of solicitation. Giving under social pressure is just the opposite of warm-glow giving and it is demand-driven and inversely affects the individual utility, which causes the loss of social welfare.

Stefano DellaVigna et al. (2009) present a theoretical framework to distinguish donors in consideration of their motivation towards donations. One is the group of donors who want to
donate, and the other is who donate under social pressure. They design a door-to-door fundraiser so that some households are informed with a flyer about the exact time of solicitation on their doorknobs so that they have the flexibility to attend or avoid the fundraiser. Authors observe that prior notification about fundraisers reduces the share of households opening the door at the time by 9 percent to 25 percent. If the flyer allows checking a do-not-disturb box, it reduces giving by 28 to 42 percent. They observe that half of the donors would prefer not to be contacted by the fundraiser as they are not interested in donations or might prefer to donate less. They find evidence from their door-to-door solicitation that both altruism and social pressure affect this kind of experiment. They estimate that the welfare effect of these door-to-door campaigns is negative. The estimated social pressure cost of saying no to a solicitor is $3.80 for an in-state charity and $1.40 for an out-state charity. Continuing with another paper, Andreoni, Rao, and Trachtman (2011) study the giving and avoidance response to the presence of a bell ringer at the doors of a supermarket. They find that verbal requests by the solicitor increase the number of donors by 55 percent and the number of donations by 69 percent. An interesting observation is the intuition behind a donation of scarce resources like blood and organs.

Lacetera and Macis (2008) have shown that sometimes altruism is not enough to motivate people to donate a scarce resource like blood, for which there is no substitute apart from the human donation. While donating blood is voluntary and with alarming shortages, "pure" altruism is not enough to guarantee a steady blood supply. They have shown that rewards and economic incentives like extra (paid) leisure and social recognition work as positive catalysts to motivate donors to donate blood for purely altruistic reasons. In this paper, the authors also find out how individuals are responsive to their decision to donate blood with standard economic intuition. They find that a substantial portion of employed donors donate in a way that they can enjoy a long weekend. In contrast, Carl Mellstrom and Magnus Johannasseon (2008) show in their paper based on a field experiment that blood donors' supply decreases with introducing payment. The experiment is on Richard Titmus' claim that monetary compensation for donating blood might reduce the supply of blood donors (Titmuss 1970). In this case, the crowding-out effect is significant only for women.

Current studies show that neuroscience and economics can be powerful tools for studying the cognitive processes behind human social interaction (Tusche et al., 2016). Though the terminology and objectives for the two subjects are quite different, they can generate insights into human behavior. It will be helpful to design the market and set the market strategy for the future. In the paper, Tusche et al. (2016) use multivariate decoding techniques and delineate three
distinct psychological processes for altruistic decision-making (affective empathy, cognitive perspective-taking, and domain-general attention shifts), linking them to dissociable neural networks computations and identifying their relative influence across individuals. Both socio-cognitive routes contribute to variance in altruistic choices within and across individuals. According to their findings, this functional segregation of empathy and perspective-taking extends to pro-social decision-making settings.
4. Main Paper Discussion and Comparison of the Results

The work presented here as part of a master’s thesis replicates a portion of the paper written by Karlan and List (2007). I have tried to understand the reasons behind charitable giving and present a review of the reasons behind charitable giving. Before explaining the methodology and the results of our work, we are presenting a brief overview of the original paper, Karlan, and List (2007), does price matter in charitable giving? which I choose to replicate here. The paper is on a natural field experiment that targeted over 50,000 donors to get a broad understanding of the economics of charity by randomizing them into separate groups to explore whether matching offers the promotion of charitable giving. The organization in the paper that the authors worked with to collect the data is a liberal nonprofit organization in the United States. The organization mainly works on social and policy issues and under it is the United States internal revenue service code 501(c) 3, so the donations are tax-deductible. The organization asks prior donors for donations through a direct mail solicitation.

Solicitation is an essential mechanism behind charitable giving. Solicitation is an important mechanism out of the eight mechanisms for charitable giving mentioned in the paper by Bekkers and Wiepking (2011). There is no wonder that an announcement that a match is available with a donation increases the revenue per solicitation. The donation increases by 19 percent as a result of the announcement of matching grants. The paper also successfully explores that the match offers a significantly increased probability of charitable giving. Matching donations is a promise bounding up with conditions from the leader donor or by the organizer to others to match the contributions of others at a specific rate. In this paper, the authors also look for different effects on charitable giving when an organization offers a higher matching ratio. They find that matching increased the donation amount. However, the higher match ratios (in the paper, they are looking for $1: $1, $3: $1, and $2: $1) have no additional impact on the contribution towards charitable giving. In the point of treatment heterogeneity, the paper finds that the treatment effect is slightly more effective for the individuals who do not donate in the year 2005.

This paper critically analyzes how the matching donations vary between democratic or republican U.S. states when the program organizer is a liberal nonprofit organization. They identify that the treatment effect is only effective in the red state, while even the treatment effect is significant for the blue county under the red state. In the paper table 5, panel A presents the effect of treatments with the Bush vote share. The treatment effect is only effective and significant
for those states where the vote share is more than 50 percent. This has been replicated in Table 5; the result is significant as it looks for treatment heterogeneity under political circumstances. In the original paper, the treatment effects are 0.16 for states with a vote share of 50 to 52.5 percent, and for this study, it is 0.16 and both are significant at a 5 percent level. The treatment effect with a vote share of more than 60 percent is 0.008 in the original paper and for this study, it is 0.008 and both are significant at a 1 percent level. Therefore, the results are close enough.

Panel B, Table 5 shows the treatment effect for two states from the county level. Treatment effect for red county under-red state is 0.010*** (0.002) and treatment effect for blue county under red state is 0.007*** (0.003). In this analysis, the effects are, 0.009*** (0.002) and 0.007*** (0.003), which is again close enough. Panel C, Table 5 analyses the effect of treatment considering an organization's activity under two states and the treatment effect for the red state is 0.009*** (0.003). For this study, it was 0.007*** (0.003), which is significant at the 0.01 level.

In the main paper, Table 5 shows how the matching grant treatment was ineffective in blue states yet quite effective in red states. In the paper, the authors also estimate the price elasticity of charitable giving. Along with price movements from control to treatment cells, price elasticity was found to be roughly −0.225. While in this paper, the higher match ratios have no additional impact on the contribution towards charitable giving, the authors continue their investigation to understand the impact of match ratios on charitable giving. Karlan and List (2011) conduct a new study in 2011 using another natural field experiment. During this time, almost 20,000 prior donors get two direct mail solicitations along with the matching grants $1:$1 and $1:$3. This time they concluded that a larger match ratio is not always effective. Evidence from another natural field experiment designed by Stefen Huck and Imran Rasul (2011) indicated that the donation is matched by the lead donor. They find that the announcement of a matching gift increases the donation amount, but the response rate does not increase. The matching scheme raises the total donation received, including match value, but partially crowds out the actual donation given, excluding match value.

I am ending my discussion with the recent paper by Karlan, and List (2020). This paper is based on two natural field experiments and one survey experiment. The work is done with a very well-known charitable organization, Bill and Melinda Gates Foundation. The experiment is designed in this way: half portion of the potential donors get offered a $2: $1 matching grant from BMGH and the other half gets the same matching grants but from an anonymous donor. One of the major findings from this experiment is that a matching grant from Bill and Melinda Gates Foundation outperforms a matching grant from an anonymous. According to researchers,
BMGF outperforms due to quality signals. Moreover, under altruism, charitable giving is a personal decision to some extent, where a donor wants to maximize the altruistic nature and get satisfaction.
5. Heterogeneous treatment effect analysis using machine learning algorithms

5.1. Causal Forest:

Heterogeneous treatment effect (HTE) analysis is essential to understand how a given treatment might affect different subgroups in a population. The treatment might vary for every individual or subgroup in a population. It is essential to know which effect is high and for which variable the effect is low before policy recommendation. Though it is vital for making policies, HTE analysis has not been widely recognized and used for disciplines like development economics. A probable reason behind its underuse is that data are often high dimension and high complexity, which imposes significant challenges for applying HTE analysis methods. The causal forest is the most recent advanced tree-based HTE method that can handle HTE analysis's complexity. The causal forest method is an improved version of the random forest machine-learning algorithm (Wager & Athey, 2018). The causal forest method can overcome potential issues observed under HTE analysis using the single-tree method. The causal forest is an ML-based algorithm with no underlying assumptions on the data; therefore, it enjoys the flexibility to handle complex real life practical problems. This section provides an overview of the heterogeneous treatment effect. We use this causal forest method to identify which variables are responsible for treatment heterogeneity in the model. Here, the HTE is used to estimate treatment effects within the sample size to understand whether the individual responds to the treatment or not. The advantage of causal effects over the other traditional methods is that causal forest works without any parametric assumptions with the interaction terms and they provide statistical analysis using observed covariates and indicate which variables are most strongly associated with heterogeneity. The heterogeneous treatment effect, also known as the conditional average treatment effect, is calculated after improvising some conditions on some covariates. Several other methods exist to identify the heterogeneous treatment effect. These are Nearest neighbor matching, Series estimation, and Kernal methods. (Crump et al. 2008) develop and apply tools for identifying the presence of treatment heterogeneity in settings with selection on observable.

After analyzing eight experimental evaluations of welfare programs, researchers found that the treatment effect heterogeneity and non-zero treatment effects, which were missing at the testing time, focus on inference concerning average treatment effects. In addition, Lee 2009
develops a trimming procedure for bounding average treatment effects in the presence of sample selection. Behind this method, the assumptions are 1) the regressor of interest should be independent of the errors in the outcome and selection equation, and 2) the selection equation can be written as a standard latent variable binary response model. Under these assumptions, the methods prove that the trimming procedure yields the tightest bounds for the average treatment effect, which is consistent with the observed data in the methods. A broad overview of the methods developed over the year to recognize treatment effects is provided below, specifically those identifying heterogeneous treatment effects within the model.

5.1.1. General Code (step by step):

```
data <- read_csv("data path")

Y <- data %>% select ("variable of interest") %>% scale (center = TRUE, scale = TRUE) %>% as.matrix()

X <- data %>% select ("select all variables you want to keep") %>% scale (center = TRUE, scale = TRUE) %>% as.matrix()

W <- new_data %>% select ("treatment variable") %>% scale (center = TRUE, scale = TRUE) %>% as.matrix()

forest <- causal_forest(X,Y,W,sample.fraction = "", min.node.size = "", num.trees="")
tau.hat <- predict(forest, estimate.variance = TRUE)
```

5.1.2. Important variables Identified by Causal Forest Method:

In our analysis, our outcome variable (Y) is `out_gavedum` (donors give anything after getting treatment or not) a binary outcome and the “X” variables are `treat_ratio2` (Was the matching offer a 2:1 ratio?), `treat_ratio3` (Was the matching offer a 3:1 ratio?), `treat_size25` (Was the maximum threshold $25k?), `treat_size50` (Was the maximum threshold $50k?), `treat_size100` (Was the maximum threshold $100k?), `red0` (red state), `blue0` (blue state), `pwhite` (proportion of white), `pblack` (proportion of Black), `ave_hh_sz` (average household size), `median_hhincome` (median household income), `powner` (proportion of owner), `hpa` (highest previous amount), `page18_39` (proportion of age between 18 to 39), and `year5` (the donor has given anything in year
The “W” variable is “treatment”, which indicates if the previous donor got the matching offer or not.

The mean heterogeneous treatment effect is 0.12. The important variables we get after running causal forest are page18_39 contributes 0.146 percent of treatment effect, highest previous amount contributes 0.140 of treatment effect, the proportion of white with 0.136 of treatment effect, months since the previous donation contribute 0.134 of treatment effect, the proportion of black contribute with 0.125 of treatment effect, median household income contribute 0.109 of treatment effect, average household size with 0.105 of treatment effect, donated in the year 2005 contribute with 0.009 of treatment effect, powner contribute 0.078 of treatment effect, red-state contribute 0.008 of treatment effect and for blue state 0.005 of treatment effect.

In the original paper, the authors mention that “matching” has a positive effect on donation, but a higher match ratio does not have an extra impact. Here, we also find that after running a causal forest, the match ratios and threshold size have not caused treatment heterogeneity. These are the top three most important variables identified by the causal forest for which heterogeneous treatment exists within the model. I choose all variables identified by causal forest and run a regression, table A, using probit to check if these variables are significant when interacted with treatment or not. My regression result shows that treatment is significant with redstate, powner, and proportion of age group between 18 to 39. Without any prior assumptions, the causal forest shows that the variables are significant when we interacted with treatment. These make the causal forest the best among other methods. The histogram below shows the distribution of heterogeneous treatment effects.
5.2. LASSO:

LASSO is a shrinkage procedure for prediction. LASSO helps to reduce the problem of overfitting and problems like multicollinearity. LASSO imposes a penalty for the variable which is not important for prediction and makes the coefficient zero. In our analysis, we use LASSO and select the variables retained by it. We only select variables that interact with treatment and run OLS regression to get the treatment heterogeneity. As we know, ordinary least squares suffer from an overfitting problem though it is the most practical and straightforward algorithm for regression-based analysis. If the model contains many covariates and interaction terms, OLS can mislead it. Some sophisticated methods can be used in place of OLS if there are many covariates. One of the methods is the least absolute shrinkage and selection operator (LASSO), a well-known technique for regression-based prediction analysis to select relevant covariates. Lasso set the irrelevant regression coefficient to zero and returns only the relevance coefficient. If a model contains large numbers of covariates and interaction terms, then LASSO is superior for coefficient estimation and model selection. In our analysis with LASSO, we choose the essential coefficient, making other coefficients zero, which cannot explain variability in the model. This Shrinking nature makes LASSO superior for feature selection. In our analysis, the coefficients of the significant covariates that interacted with treatment are the highest previous amount and the year5 variable identified by LASSO, though the coefficients are small. The mean heterogeneous treatment effect is 0.002 for post-LASSO. LASSO estimator depends on the adjustment parameter lambda. This lambda can be any value between zero to infinity and this parameter controls the strength of the shrinkage.

5.2.1 Methodology:

LASSO conducts variable selection by shrinking the coefficients of some variables to exactly zero and leading to a simpler model. To perform LASSO, we first choose our endogeneous and exogenous variables and divided the dataset into train and test. After building the model, we make our prediction using the test dataset and evaluate the model. Following which, we perform OLS as a post-LASSO model and estimate out treatment heterogeneity for variables retained by Lasso in the first stage. Our independent or exogenous variables are out_gavedum, treat_ratio2, treat_ratio3, treat_size25, treat_size50, treat_size100, red0, blue0, P_white, P_black, ave.hh_sz, median hhincome, power, hpa, page18_39, and year5. For this analysis, the variables considered are shown in Table 3 and Table 6 from the main paper. My
interest is to look at how treatment heterogeneity works for different common variables like age, race, income family size, etc. In the paper, to examine the relationship between income level and charitable donations, the authors merge their data with demographic census data aggregated with zip code level. In the original paper, Table 6 summarizes the results authors get after merging their experimental data with census data. In our analysis, we performed only on the experimental dataset from the natural field experiment.

The red state is the only significant coefficient covariate mentioned in the original paper interacting with treatment. LASSO retains the variables interacted with treatment—the highest previous amount and that donated in the year 2005. I used these two variables for post-LASSO and with OLS and the mean heterogeneity is obtained as 0.002. There are other sophisticated methods for prediction like ridge regression and elastic net. Ridge works faster than LASSO but the latter has the advantage to optimize lambda in a way that all unnecessary parameters eliminate from the model while selecting the best feature for prediction and minimizing the mean sum square errors.

6. Conclusion:

For my master’s thesis, I aim to explore the treatment heterogeneity using a fifteen-year-old paper that is a well-known in its field. Machine learning algorithm was used for this purpose. Due to a lack of accessibility of the census data that the authors use for the analysis in the later part of their paper, I have to complete my work considering only the natural field dataset, which was available. In the future, I would like to explore the causes of charity and how religious faith encourages people to donate in the context of developing countries and I intend to use deep learning algorithms, and as it is an emerging field in computer science, I would like to learn and use it for economics.

Nowadays, it is ubiquitous to apply Machine learning algorithms in applied economics. In fields like financial economics, market designing, real estate analysis, market research, product analysis, and media analysis, where data complexity is remarkably high and data size is too large to make vague assumptions, machine learning makes things easy. A/B testing is a standard analysis using machine learning algorithms and it is a common technique for every tech company for product analysis and consumer behavior analysis. Machine learning gives the flexibility to work with many datasets and efficiently handle the degree of complexity. Jean et al. (2016) work with machine learning to predict poverty. They are collecting a well-organized, reliable dataset
for developing their study. Most of the time, data from household-level surveys are misleading and not generous. Building policies based on such a dataset with several assumptions would be a risk for policymaking.
References


Statistical Sources:
   Double the Donation, matching gift made easy,
   https://doublethedonation.com/tips/matching grant-resources/nonprofit-fundraising-statistics/#donations


Data Source:
   https://github.com/gsbDBI/ExperimentData/tree/master/Charitable/ProcessedData
Table 5: panel A presents how the treatment effect under political environment. Subsample by Bush Vote share.

<table>
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</tbody>
</table>

Table 5: panel B, presents treatment effect for between blue state and red state.
### Table A
Probit Regression

| Marginal Effects | df/dx   | Std. Err. | Z      | P > |Z| |
|------------------|---------|-----------|--------|-----|-----|
| **Number of Observation** | 50083   |           |        |     |     |
| **Variable Names** |         |           |        |     |     |
| treatment        | -2.5856e-03 | 6.2738e-03 | -0.4086 | 0.68284 |
| page_18_39       | -3.2663e-02 | 1.3224e-02 | -2.4700 | 0.01351** |
| hpa              | 2.0251e-05  | 1.2883e-05 | 1.5720  | 0.11596 |
| pwhite           | 1.3279e-03  | 7.2468e-03 | 0.1832  | 0.85461 |
| red0             | -4.3634e-03 | 2.1815e-03 | -2.0002 | 0.04548** |
| year5            | 4.0495e-03  | 2.0653e-03 | 1.9607  | 0.04991** |
| median_hhincome  | -2.7815e-09 | 5.3523e-08 | -0.0627 | 0.95003 |
| powner           | -1.1974e-03 | 1.0925e-02 | -1.0961 | 0.27306 |
| mrm2             | -1.0754e-03 | 1.1940e-04 | -9.0027 | <2e-16**** |
| ave_hh_sz        | 5.3207e-03  | 2.9130e-03 | 2.0232  | 0.04305** |
| treatment*median_hhincome | -7.4906e-08 | 6.4862e-08 | -1.1549 | 0.24815 |
| treatment * page18_39 | 2.2681e-02  | 1.5758e-02 | 1.7967  | 0.07238* |
| treatment * hpa  | -9.0057e-06 | 1.5547e-02 | -0.5831 | 0.55980 |
| treatment * pwhite | -5.7735e-03 | 8.6995e-03 | -0.6637 | 0.50691 |
| treatment * red0 | 5.6341e-03  | 3.0395e-03 | 1.8536  | 0.06379* |
| Treatment * powner | 2.4094e-02  | 1.3214e-02 | 1.8234  | 0.06824* |
| treatment * year5 | -1.1651e-04 | 2.4603e-03 | -0.0474 | 0.9615 |
| treatment * ave_hh_sz | -4.8509e-03 | 3.5395e-03 | -1.3706 | 0.17050 |

Signif. Codes: 0 “****” 0.001 “***” 0.01 “**” 0.05 “*” 0.1 “ ” 1