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SUBTITLE

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Abstract

ABSTRACT

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*Code and data are available at: <https://github.com/yangg1224/groupproject-.git>

1 Introduction

2 Data

In this report, we use the R statistical programming language (R Core Team 2020). To be specific, we use the “tidyverse” package to process data (Wickham et al. 2019), “kableExtra” package to generate tables (Zhu 2020), “ggplot2” is used to draw diagrams (Wickham 2016), “ggthemes” is used to change the diagram theme. (Arnold 2019)ADD ANY PACKAGE HERE. The survey conducted by Petit Poll collects the following data:

- Geographical information (FSA, Region)
- Type of restaurant (Fast food, fast casual, casual dining, premium casual, family style, fine dining)
- Number of years opened so far
- Services provided (delivery, take-out)
- Number of employees and salary of employee
- Cost to run the restaurant (Fixed, variable)
- Revenue per month
- Potential COVID-19 cases

Appendix C shows screen captures of the online version of the survey. In addition, we consulted several open datasets about the health inspection from each region, including Peel (“Peel Health Inspections,” n.d.), Halton (“Food Premises Dinewise,” n.d.), York (York 2019), Durham (“Health Inspection,” n.d.), and Toronto (“Number of Restaurants in Toronto,” n.d.).

The data section illustrates the intervention and data gathering methodology. Also, we describe detailed information on our dataset, with several data visualizations such as tables and graphs.

2.1 Intervention

In this experiment, we conducted a randomized controlled trial and randomly assigned subjects to two groups: the treatment group and the control group. Within this experiment, the treatment group receives an intervention and the control group is not being treated.

In our case, the intervention is having restaurants open for indoor dining. Our experimental subjects are restaurants in the GTA that are currently in operation. We assumed all restaurants in Ontario are closed for indoor dining at the moment. During the shut-down, all restaurants in the control group were forbidden to offer dine-in and patio services according to the COVID-19 lockdown policy set out by the Ontario government (“Ontario Continues to Support Restaurants During Covid-19 Pandemic,” n.d.). However, take-out and delivery services were acceptable. Our intervention involves randomly selecting restaurants to reopen for indoor dining in the GTA. The restaurants in the treatment and control group were picked through stratified sampling. This experiment was conducted by Petit Poll and was authorized by the Ontario Department of Public Health.

We randomized the control and treatment groups through stratified sampling. In other words, we divided all restaurants in Ontario into smaller strata. Each strata was grouped based on region. After stratification, we took random samples from each region, in proportion to its share of the population within the total population (Nickolas 2020). The distribution of all strata shows as following (see more information in Appendix A):

- Toronto - 29.5%
- Durham - 12.8%
- York - 21.9%
- Peel - 24.6%
- Halton - 11%

We then use a random number generator to randomly select a certain number of restaurants from a list of restaurants that was ordered alphanumerically. This list was procured by health inspection records that indicate all of the open restaurants within each region. Procedurally, we set the minimum number and the maximum number based on the number of restaurants within the given list. If the randomly generated number was 59, we chose the 59th restaurant in the list. We repeated the process until the treatment group and the control group were established with the corresponding number of restaurants.

To ensure the separation of treatment and non-treatment groups, we relied on stratified random sampling based on regions. After stratification, the number of restaurants in the treatment and control groups were the same. This ensures that the treatment is the only source of potential differences in outcomes between the two groups and not based on convenience of access for citizens within each region (Nickolas 2020). Moreover, ad-hoc analysis showed that the proportion of restaurant types were the same between control and treatment groups. This reduces the likelihood that citizens would migrate between groups for particular restaurant types.

The experiment ran for two and a half months from December 1, 2020 to February 15th, 2021. We distributed a consent form to 11,325 restaurants within the GTA on December 1st, 2020, and received 3,454 responses to participate in our survey by December 15th, 2020. We randomly sampled an equal number of respondents into the treatment group and control group. On December 16th, the intervention was announced for the selected 1,637 restaurants in the treatment group. We reserved half a month for the restaurant to prepare for reopening. The treatment group reopened the restaurant from January 1st to January 31st, 2021. We considered one month as the minimum effective period for a validity reopening. During the intervention, all restaurants in the treatment group were allowed to offer dine-in, patio services, delivery service, and takeout services. The survey itself was conducted for a half month from February 1st, 2021 to February 15th, 2021. Finally, we collected 3,274 responses in total from both the treatment group and control group by February 15th, 2021.

2.2 Data Gathering Method

The population included all restaurants in the GTA, excluding the ones that were completely closed. The sampling frame was all restaurants listed in the health inspection reporting program of all five regions. Currently, GTA has approximately 25,351 restaurants, including 7500 in Toronto, 3260 in Durham, 5553 in York, 6235 in Peel, and 2803 in Halton. We use a stratified sampling method to randomly select restaurants in each region. We sent consent forms to 11,325 restaurants, and received 3,454 responses, which reflects a 30.5% response rate. The final sample was 3,274 restaurants that responded to the paper survey. We arrived at 3000 as a sample size to ensure enough statistical power in our sample.

We use stratified random sampling to obtain a sample that best represents the entire population. Unlike simple random sampling, which randomly selects data from the entire population, stratified random sampling takes each stratum in direct proportion to the population in each region compared to the total population in GTA. Stratified random sampling reflects the population more accurately than simple random sampling. With simple random sampling, it is not guaranteed that any particular subgroup or type of restaurant is chosen (Murphy 2020). In contrast, SRS ensures each subgroup within the population has proper representation within the sample. In other words, it captures key population characteristics in the sample. Stratification gives a smaller error in estimation and greater precision than the simple random sampling method. The greater the differences between the strata, the greater the gain in precision (Hayes, n.d.).

The collection instrument for this survey was paper questionnaires sent by mail. We first sent consent forms to obtain permission within the early stages of the experiment to randomly selected restaurants in a list of all restaurants per region. We did not use electronic questionnaires or surveys sent by email in order to prevent a non-response bias from the few restaurants that do not have a commercial email address or who don't check their email frequently. Additionally, we avoided choosing in-person interviews in order to reduce close contact and lessen the chance of virus transmission.

The total estimated cost was approximately \$20,958. To be specific, the average cost to print a page for black and white is around 5 cents ("Printing Costs: How to Accurately Calculate Your Printing Cost Per Page,"

n.d.). According to Stamps, the cost of a one-ounce First Class Mail stamp is \$0.55 for one way (“How Much Is a Stamp?” n.d.). Each envelope cost 15 cents (“USPS®Rate Change Effective January 26, 2020,” n.d.). We sent 11,000 informed consents first, and then sent 3454 paper surveys after. When we mail the consent form and survey, we include a prepaid envelope with a stamp in each single package to encourage survey response. Therefore, we spent \$15,950 on consent forms and \$5,008 on paper surveys. See more details in Appendix B.

We took three steps to deal with the non-responses. First of all, we tested the survey before sending them out. We kept the survey short. A one-minute survey normally has a higher response rate than a 15 minutes survey (Stephanie 2020). Besides, we sent reminders to the participants through mail or phone, if we did not receive responses in the first week. It ensured the surveys were sent to the right address. In addition, we would offer incentives in exchange for completing the survey.

During the early stage of designing the survey, we determined that it was unnecessary to collect the personal information of the restaurant owner. Also, the survey did not ask the restaurant’s name and address but only the first three digits of postal code (FSA code), which encodes region-level information. The survey was conducted anonymously; therefore, the risk of unauthorized collection, use, and disclosure of personal information was kept to a minimum.

We did not use an electronic questionnaire sent by email. An email survey will require participants to send their responses back to us by personal email. Meanwhile, physical questionnaires can be sent back anonymously, without the sender’s name and return address.

In the questionnaire, most questions are multiple-choice, and we were not asking any open-end questions about the personal experience. In particular, when it comes to the cost structure of restaurant operations, which is deemed as sensitive questions by business owners, only the direction of change was asked instead of a specific amount. Thus, it would be impossible to reverse engineer the financial details and to infer private attributes about restaurants such as store names and locations using this dataset.

When conducting the survey, we strictly follow the terms of reference for the safe collection, retention, use, disclosure, and disposal of personal information, in accordance with the Act. During the survey, we reviewed the term of reference periodically. At the final stage of the experiment, we checked all conditions and made sure they were fully complied with.

Participation in the survey was considered on a voluntary basis. Thus, we sent out the informed consent in order to provide participants as much information as possible. The consent should include the following:

- The main purpose of the research.
- The name of the institution that conducts the research.
- How the information will be disclosed.
- How much time the survey will take.
- How the respondent will be informed about the final result.

We have also considered how the data will be stored for future use. All data will be replaced with code and stored separately from the survey response. Petit Poll will be responsible for ensuring the confidentiality, integrity, and accessibility of the dataset under supervision of the Ontario government.

2.3 Descriptive Analysis

After discussing data gathering method, we sampled data in R (R Core Team 2020). We totally have **3274** observations, and 14 of following features according to the questionnaires.

- **type** : Categorical identifier [“Treated” or “Control”] for each observation
- **Q1** : First three digits of the postcode
- **Q2** : Categorical identifier for distinguishing the type of restaurants

Table 1: First 6 rows Raw data

type	PostCode	Region	Type	Fanchise	operation_years	Takeout	Delivery	Size	Hourly_rate	COVID	Fixed_Cost	Flex_Cost	Total_revenue
Control	M5W	Toronto	Family Style	Franchise	11	Yes	No	1-10	20.11	No	No change	No change	44140
Control	L7C	Peel	Fine Dining	No	10	Yes	No	1-10	23.31	No	No change	No change	42217
Control	L7C	Peel	Family Style	No	2	Yes	Yes	1-10	16.74	No	No change	Decrease	37507
Control	L6A	York	Fast Casual	No	2	Yes	Yes	1-10	19.21	No	No change	No change	41194
Control	L6H	Halton	Premium Casual	No	1	Yes	No	1-10	15.22	No	No change	No change	56615
Control	L4Z	Peel	Fast Food	No	3	Yes	No	1-10	15.60	No	No change	No change	51303

- Q3 : Region name in GTA
- Q4 : Describe whether the restaurant is a franchise (“Franchise” or “No”)
- Q5 : The length of the operation years for each restaurant
- Q6 : Describe whether the restaurant offer takeout service (“Yes” or “No”)
- Q7 : Describe whether the restaurant offer delivery service (“Yes” or “No”)
- Q8 : Number of employees in the restaurant (category type)
- Q9 : Average employee hourly rate (CAD)
- Q10 : Describe whether the restaurant has been a site of a potential COVID case (“Yes” or “No”)
- Q11 : Describe the restaurant’s fixed costs change situation
- Q12 : Describe the restaurant’s flexible costs change situation
- Q13 : The restaurant’s past month revenue (CAD)

The first six rows of raw data is shown in the Table1. (Table 1)

2.3.1 EDA

Taking a deep look at all the features from survey questionnaire, we learned some demographic features about the restaurants in GTA:

- From figure1(Figure 1) and figure2(Figure 2), we noticed that more restaurants are located in Toronto (around 500) and Peel (around 400). The number of restaurants in Hilton is similar to the number in Durham. Meanwhile, Casual dining takes the lead in the restaurant type in GTA, with around 26%. Then it comes to Family style restaurant, accounting for 20%. Fast food restaurant, fine dining restaurant and Premium casual restaurant almost equally make up 10%. There is no big difference between treated group and control group in terms of restaurant number and type distributions.
- In terms of employees salary, the average hourly rate before and after intervention is both around 17 CAD. In contrast with two boxplots, we can see there is a slight increase in the treated group. The reason behind might because the employee take more risks to go for work, accordingly they will receive higher salary. (Figure 4)

«««< HEAD * The attributes of the restaurant determine its management mode, so whether the restaurant is a franchise is quite important factor. From the pie charts, we found the portion of franchise rate in treated group is slightly lower than control group. We assume in treated group, the branch franchise restaurants must follow the rules and policies set by their head office. [find a reference] Considering the potential cost of COVID issues, chain restaurants will face greater risks, which is why they are less likely to be in the treated group. ===== * The attributes of the restaurant determine its management mode, so whether the restaurant is a franchise is quite important factor.(Nhamo, Dube, and Chikodzi 2020) From the pie charts, we found the portion of franchise rate in treated group is slightly lower than control group. We assume in treated group, the branch franchise restaurants should follow the rules by the head office. Considering the potential cost of COVID issues, chain restaurants will face greater risks, which is why they are less likely to be in the treated group. »»»> 756d6dc61fab00708c1a9ac52f36e83af22df18 (Figure ??)

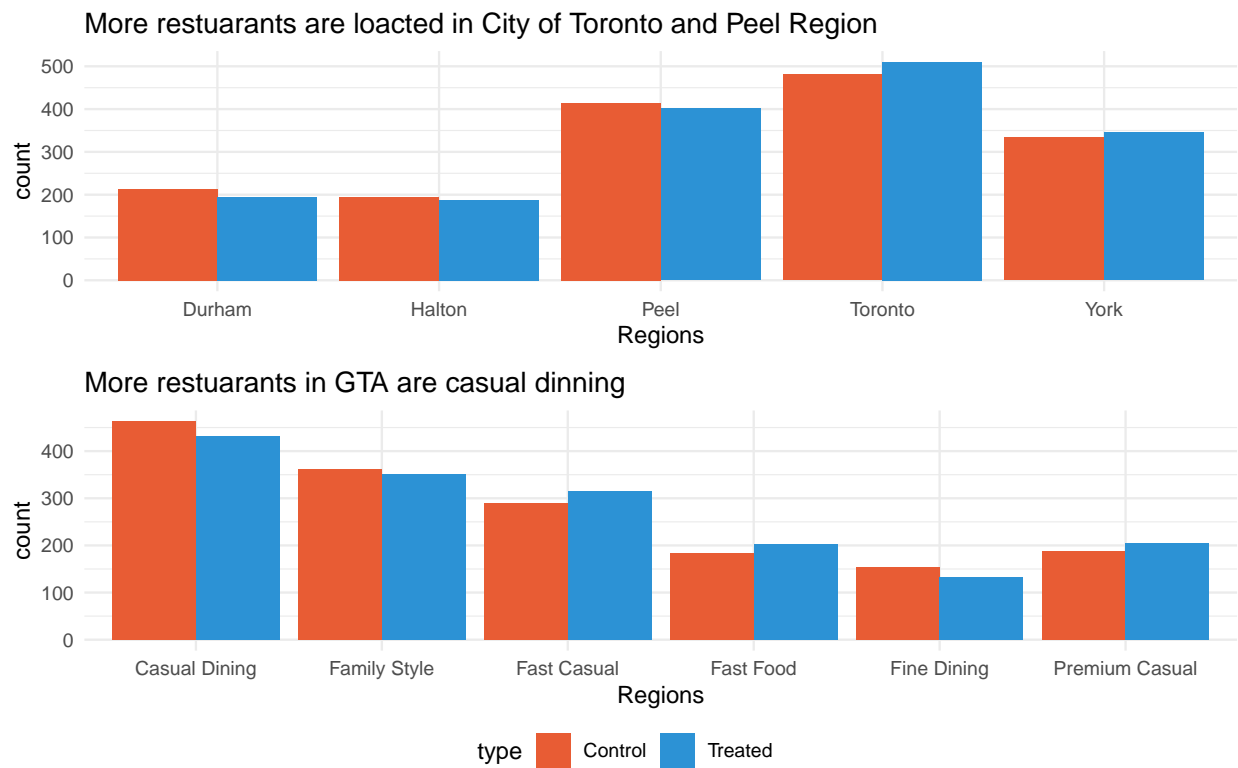


Figure 1: Restaurant numbers and types

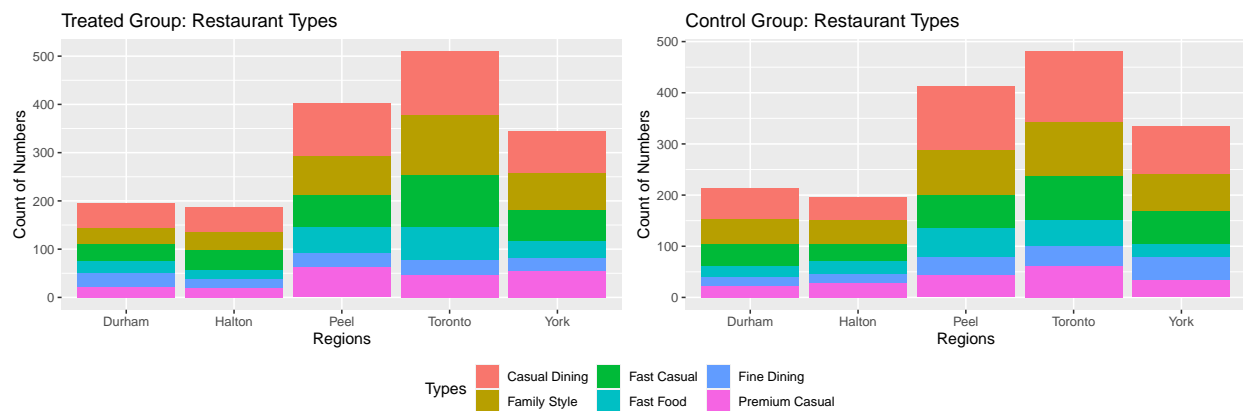


Figure 2: Restaurant types



Figure 3: (#fig:salary distribution)Salary Distribution

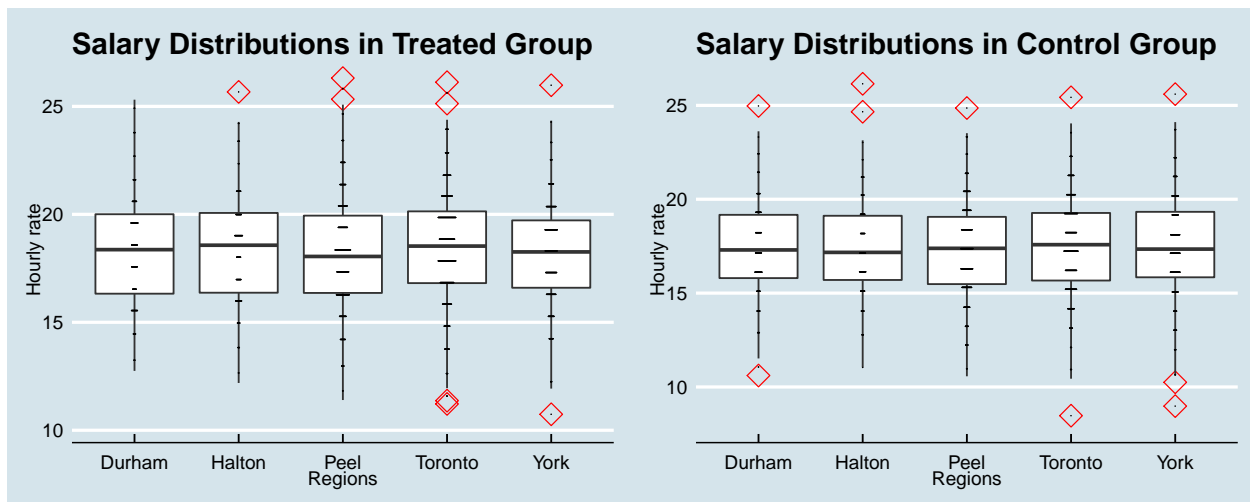
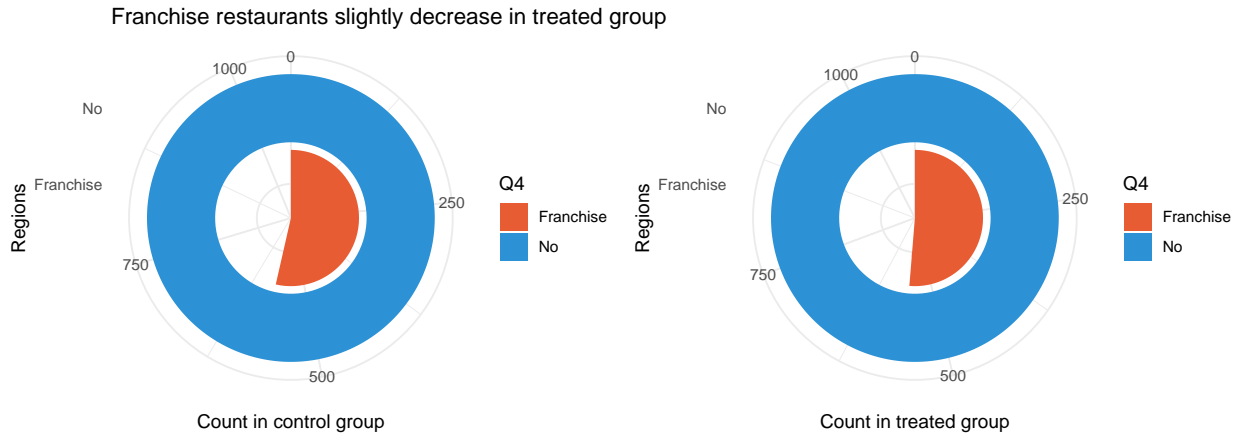


Figure 4: Employee salary distribution



«««< HEAD * The polar bar graph illustrates the distribution of employee numbers, as can be shown in figure below. (Figure 5) Because of the COVID lockdown restriction, no restaurant is allowed to open for large group dine-in or outdoor patio, which in turn causes the layoff in servers. In particular, large restaurants would want to further cut labor costs by laying off extra helpers in the kitchen to maintain only essential operations for food production. So in the control group, there is 0 restaurant which has more than 30 employees. Most of the restaurants have 10 to 20 employees, as a result of labor force layoff. =====

- The polar chart illustrates the employee numbers distribution, as can be seen in figure below. (Figure 5) Because of COVID rule, no restaurant is allowed to open for large group dine in. For large size restaurant, they all make corresponding actions to reduce their flexiable costs, such as reduce the full time employees. So in the control group, there is 0 restaurant which has more than 30 employees. Most of restaurant has 10 to 20 employees. »»»> 756d6dc61fab00708c1a9ac52f36e83af22df18

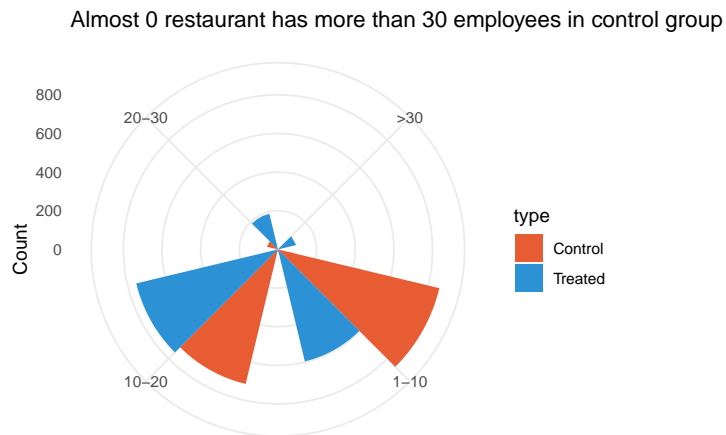


Figure 5: Employee numbers distribution

Table 2: T Test on the Restaurant’s revenue

mean_of_Treated	mean_of_Control	p.value	conf.low	conf.high	method	alternative
63143.44	49358.97	0	11638.18	15930.76	Welch Two Sample t-test	two.sided

2.3.2 T-Test

The t-test is used to compare the sample mean of our Treated group and Control group. The goal is to determine whether the intervention has an effective effect on the treated group. Our hypothesis is the intervention will have positive impact towards the restaurant’s revenue. (Kim 2015) The t-test results is represented in the Table2(Table 2). The package **Broom** (Robinson, Hayes, and Couch 2021) is used to clean the t test results and convert it into the dataframe. The p value we get is $< 2.2e-16$, as the p value would indicate a significant result, meaning that the actual p value is even smaller than $2.2e-16$ (a typical threshold is 0.05, anything smaller counts as statistically significant).(Kim 2015) So we can interpret hypothesis not rejected which means that the re-opening of restaurants has a significant effect on treated group in terms of revenue increase.

2.3.3 Correlation matrix

Correlation matrix shows internal relationships between restaurant feature variables and our variable of interest, restaurant revenue. (Figure 6) Intensity and direction of relationship is indicated by the color scale from red to blue (+1 to -1. descendant). Categorical variables are encoded to factors. Insignificant coefficient is barred with symbol “x”. More detailed analysis will be conducted in finding part.

3 Discussion

3.1 Overview

3.2 Findings

3.2.1 Finding ONE: Higher salary and more job opportunities in treatment group

The treated restaurants have been opening for in-door dining and patio for a month while the control group must comply with the lockdown policy during COVID-19 second waves in GTA. The additional operating channels (in-door dining and patio) demand rehiring of previously layoff servers in the dining rooms and extra chefs in the kitchen. Under the surging demand for labor force and the potential risk due to exposure to human-contact, the restaurants have to offer higher salaries to compensate for employees’ potential risk of infection and entice them away from competitor restaurants. From the salary distribution boxplots (Figure ??) we can see that overall salary pay levels are higher in the treatment group across 5 regions in GTA, including average rate and all other distribution percentiles. As for job opportunities, the treated restaurants hire more labor force. To cater to the increased demand from dine-in orders, the open restaurants hire more servers and chefs, which result in a size expansion in the number of employees. The number of restaurants having more than 10 employees are larger in the treatment group, whereas there are no restaurants operating with more than 30 employees in the control group. (Figure 5)

3.2.2 Finding TWO: Cost structure changes in treatment group

Labor cost is one of the main components of variable cost for restaurants. The hiring surge for the restaurants open for dine-in increases the expenditure on human capital and thus an increase in variable cost. In addition, dine-in and patio options potentially increase the demand for food ingredients, which is another major source

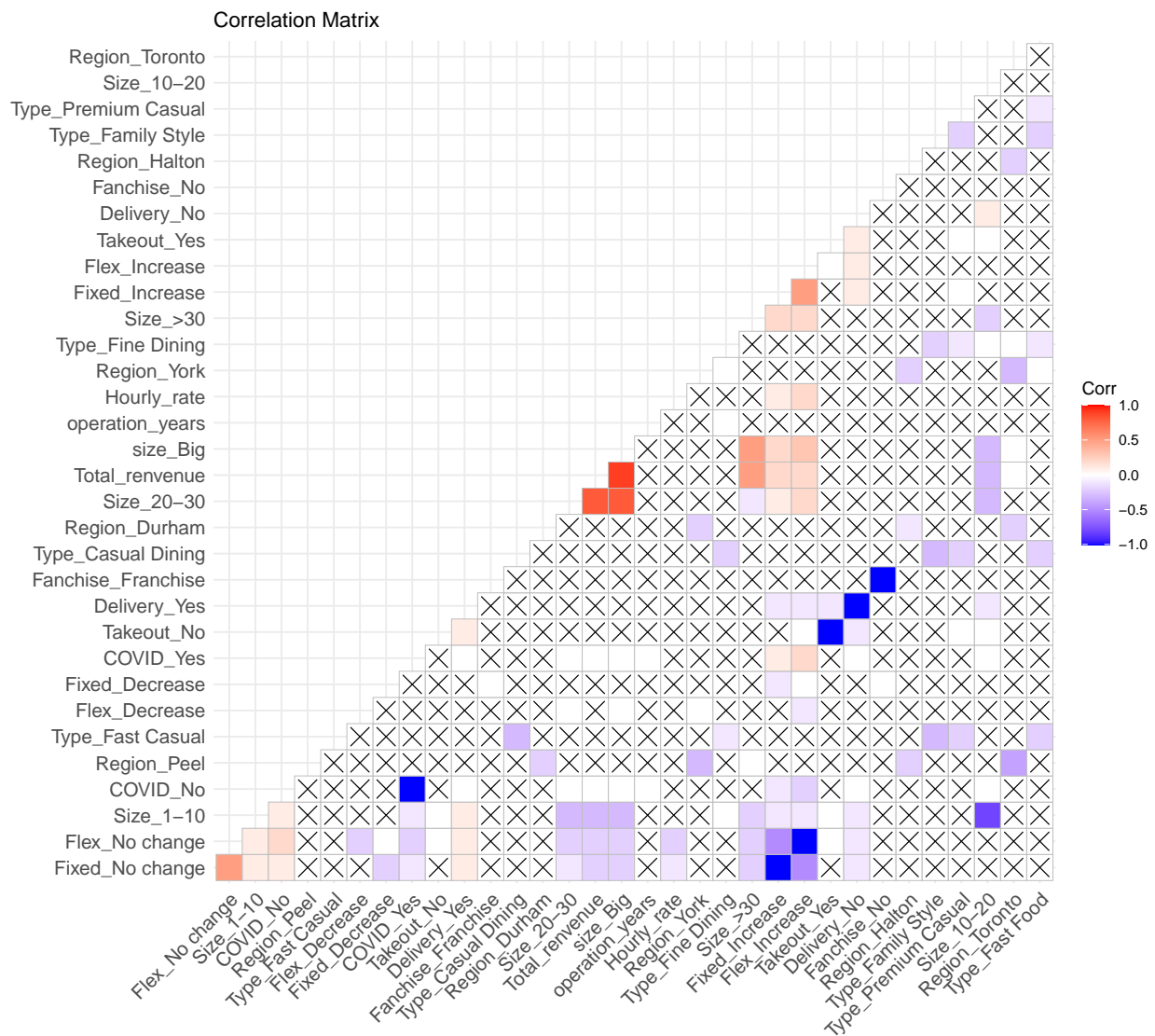


Figure 6: Correlation matrix

of variable cost. As a result, most of the open restaurants have increased variable costs. For fixed costs, about half of the open restaurants experience a cost increase and the other half have no change in fixed costs. (Figure @ref(fig:var_fix))

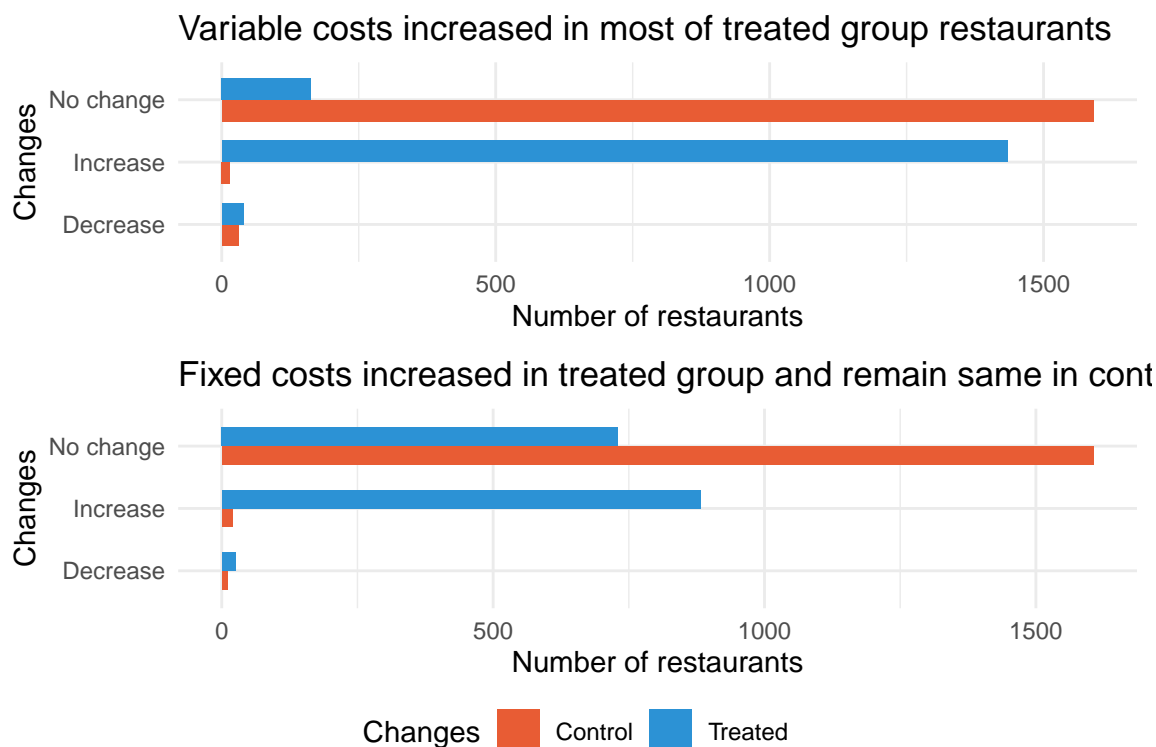


Figure 7: (#fig:var_fix)Invention effect on Variable and Fixed cost

3.2.3 Finding THREE: Significant revenue increase in treatment group

The re-opening implementation enables the treated restaurants to operate indoor dining and patio services besides offering delivery and/or pickup as before during lockdown. The additional line of business attracts more customers to visit stores to order dishes and beverages. The increased food sales earn extra revenue for those restaurants. As demonstrated through the revenue histogram (Figure @ref(fig:revenue_distribution)), the treatment group has higher revenue levels overall than the control group. The restaurants follow binomial distributions based on restaurant sizes. Restaurant size and revenue level are positively correlated. According to the correlation heatmap (Figure 6), bigger restaurants generate more revenues than small ones. Restaurants having fewer than 20 employees are defined to be small, which are most of the cases in the total samples. Both small and big restaurants generate higher revenues in the treated group. The t-test [cross ref: t-table] further verifies our finding that the restaurants allowed for re-opening earn significantly more than the control group; the average revenue for the treated is \$63,144 while below \$5,000 for the control group.

Invention effect on Revenue distributions

3.3 Limitation

3.3.1 Self-selection, late-responders and non response bias

In our consent form and followup survey, 30.5% of restaurants agreed to participate in our survey and 180 subjects dropped out in the survey. On the one hand, participants can choose whether to participate in the

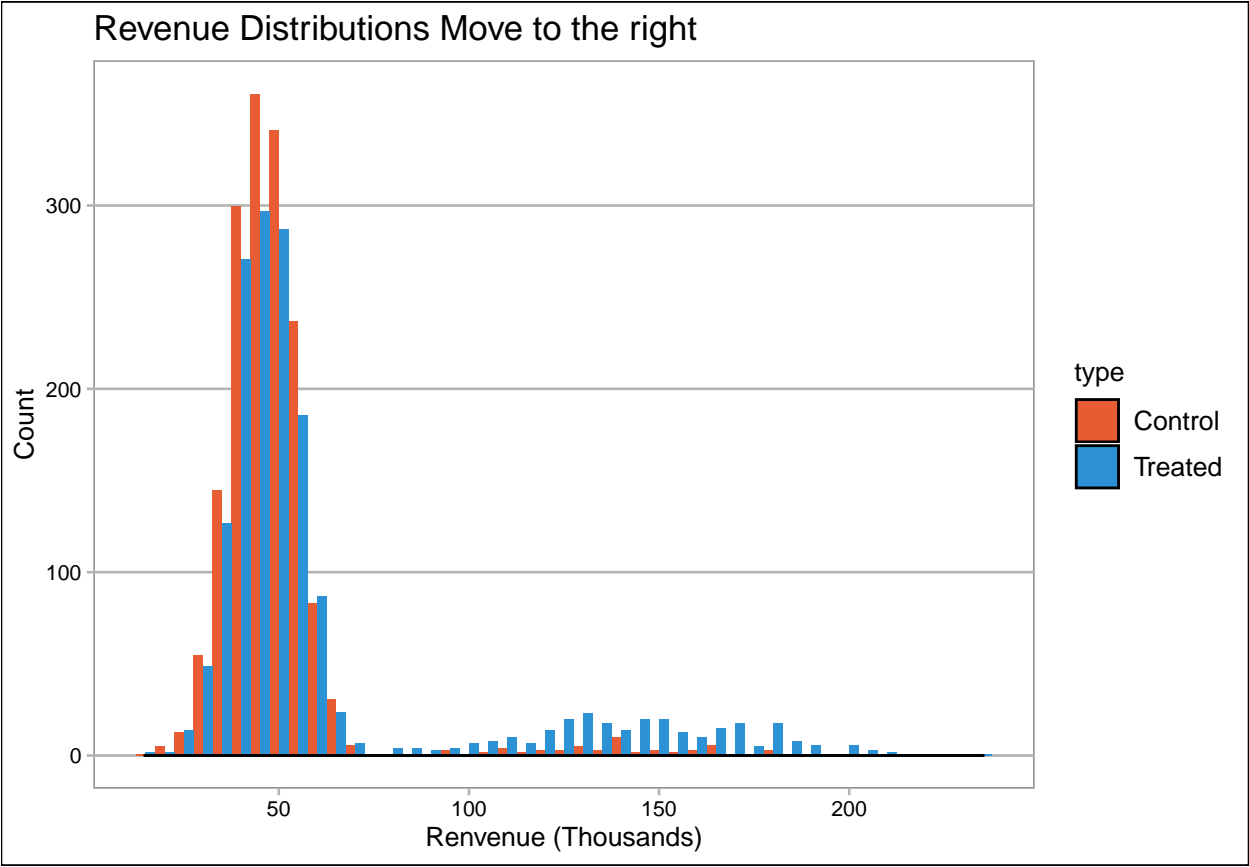


Figure 8: (#fig:revenue_distribution)Invention effect on Revenue distributions

survey. It is possible that the restaurant owners who operate smoothly during lockdown are more willing to discuss the topic on restaurant operations and more likely to agree to participate in the survey. Upward bias can exist in the statistics for the respondents which distorts the representation for the population caused by self-selection. On the other hand, within the short time experiment period, we might not receive all the survey mails back because some of them respond late. Participants who do not respond may differ in characteristics and outcomes from those who respond. If that is the case, self-selection bias and non-response bias exist in the sampling procedures. Since we do not have data on non-responders, we cannot directly compare them with respondents to detect the bias. The paper claim that late-responders share similar characteristics with non-responders (Kypri et al. 2011), then the comparison can be made in order to check for potential non-response bias during data collection. (Turk A 2019)

3.3.2 Response bias - desirability bias

Since it is a self administered study that responders fill out the survey without an interviewer, the information reported by restaurant owners themselves may be inaccurate or even dishonest. Therefore, there are potential response biases such as social desirability bias and over/undervaluation, caused by the impression that responders are motivated to reinforce socially desirable behaviors and deny those that are not in their answers. Making the survey anonymous, employing a third party or choosing neutral tones can dis-associate sensitive questions with presumed social judgements and thus mitigate this bias. (“Social Desirability Bias – Are We as Good as We Say We Are?” n.d.) These methods were implemented by this survey. For example, the survey uses a neutral tone in questions, it did not ask for restaurant names, and the study was delegated by the Ontario government to us, a professional polling company.

3.3.3 Data unobtainable for those completely closed - imperfect sampling frame and potential sampling bias

The choice of experiment population subjects are limited to all restaurants in GTA that are on the contact list provided by the Ontario government since the owners of restaurants that are completely closed are not reachable through mailing or phone. Although stratified sampling is conducted within the sampled population to ensure representativeness of the population, the excluded closed restaurants restricted our sampling coverage and made sampling procedures less random. {Lavrakas (2008)} If unsampled data characteristics are different from our population systematically in nature, the randomized control assumption would be weakened. Here we claim that our research interest lies on the impact of COVID shutdown on restaurant revenue, therefore it is reasonable to exclude the observations with null revenue.

3.3.4 Experiment drop-outs

There are an equal number of dropouts in the control and treatment groups during the survey (90 out of 3454 in each). Dropout occurs for many reasons: death, no longer willing to participate, no longer available, geographic move, or negatively impacted by treatment conditions. (“Experimental Mortality and Internal Validity,” n.d.). Despite equal dropout rates, dropout might still affect internal validity if statistical behavior of dropouts are different from completers. (Bell et al. 2013) Given that only a small portion of subjects dropped out, its impact is assumed to be negligible.

3.3.5 Time length of our experiment - only one month

Our experiment lasts for only a month, which is the minimal duration needed in order to observe any change in monthly accounting bookkeeping settled, employee paychecks paid along with other expenditures such as rent and hydro bills. It may take longer to observe any seasonality and time trends that could impact the operation conditions of the restaurant industry and confound our treatment result. The paper argues that one month is sufficient for our research purpose since statistical significance in business operation differences can be observed in the data between two groups according to the two-sample t-test result (Table 2)).

3.3.6 Privacy problem on postal code

Questions on identifying information are avoided or offset to a general level to abide by research ethics. For example, to protect the privacy of restaurants involved in the survey, We did not ask about restaurant names, and the location of restaurants is proxied by FSA code, the first three digits of postal code, which only encodes the region-level information. Thereby, it would be impossible to reverse engineer the restaurant identity by any ill-intended third parties. Furthermore, postal code is a proxy for socioeconomic status. Wealth level would confound the restaurant’s choice of location and its ability to pay rent and attract high-end customers, which correlates with revenue and eventually biases the model. (Link-Gelles, Westreich, and Aiello 2016) Consequently, the privacy concern is addressed by the use of FSA code.

3.3.7 Rough geographic representation by FSA

Due to the limited geographic location information about restaurants, the exploratory spatial analysis on restaurant location distributions can not be realized. The FSA code only provides the region-level information, which is not detailed enough to plot a heat map. However, weighing the importance of data privacy in survey ethics, this limitation in rough geographic representation is negligible.

3.4 Future Directions

After addressing potential biases and limitations in our experiment design, we state that those problems are mitigated by our design in sampling, data gathering, and survey process under the Randomized Controlled Trial framework. There are no systematic biases in the experiment process, the variable features are randomized, and the restaurants in control and treatment groups share similar underlying characteristics other than the external implementation of reopening policy. Therefore the internal validity of treatment effect on variable of interest holds. (Meldrum 2000) The only source of variation in restaurant revenue comes from our treatment of reopening the restaurant for full-operation. Next we would like to explore the alternatives in enhancing our study from the aspect of external validity and quantitative modeling.

3.4.1 External validity

In order for the findings to be generalizable to other situations and settings in the real world, experiments should be conducted in broader scales and longer durations. (Devroe, n.d.) The choice of population could be every restaurant outside of GTA across provinces in Canada in order to control for region-specific influence on the restaurant industry. The experiment time frame can be prolonged to year-base, or multiple monthly experiments can be conducted in random months and compare their final result to rule out the time trend effect on restaurant business operations.

3.4.2 Model building

In order to quantify the extent of statistical influence of each feature on the operating of restaurants besides the treatment effect of opening restaurants we have observed with the experiment treatment, linear regression and feature importance metrics can be applied in building a statistical model. Statistical inference can further identify the individual; statistical significant factors that cause variations in restaurants revenues. Along with our Randomized Control Trial experiment framework, the study would provide our client, the Ontario government, with an insightful understanding of the effect of COVID-19 shut-downs on restaurant businesses.

Table 3: Detailed information for stratification

Region	Number of Restuarants	Proportion(%)	Sample Selected
Toronto	7500	29.58	48430
Durham	3260	12.86	21051
York	5553	21.90	35858
Peel	6235	24.59	40262
Halton	2803	11.06	18100
Total	25351	100.00	1637

Table 4: Estimated Cost

Components	Cost per unit	Total cost for each component
Printing Cost	0.05	738.95
Envelope Cost	0.15	4433.70
Stamp Cost	0.55	16256.90

4 Appendix

4.1 Appendix A

4.2 Appendix B

4.3 Appendix C: Screenshot of the survey

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