Randomized Controlled Trial Examining the Impact of Covid-Shutdown on Ontario Restaurants in 2021*

The Potential Loss of Income and Employment

Youjing Li, Ken Lee, Renjing Liu, Jialin Zhao

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Abstract

Covid-19 has had an immense impact on countries around the world, prompting governments to invoke restrictions balancing between the physical health and the economic health of their constituents. This research paper will focus on exploring the potential effects of government shutdowns on Ontario restaurants, the heart of local economies and communities. More specifically, we will conduct a randomized controlled trial on the effect of shutdowns on restaurants, using stratified random sampling and clustering to gather representative and controlled samples, while using simple random sampling to implement the shutdowns (treatment). All in all, the potential income and employment losses discovered from this experiment and its surveys will not just help us understand the impact of shutdowns on restaurants, but inform prospective policies and programs developed by government officials.

Contents

*Code and data are available at: https://github.com/kenllee97/Examining-the-Impact-of-Covid-Shutdowns-on-Ontario-Restaurants

1 Introduction

Local businesses, especially restaurants, are the soul of many cities, providing not just a source of food, but also culinary diversity, culture, and employment for the population. In fact, these restaurants are vital contributors to the local community, donating to food banks, hosting fundraisers, and much more. Hence, with the presence of COVID-19, it is clear why the Ontario government would want to understand more about the potential effects a shutdown could have on the restaurants. Nevertheless, limiting the spread of this virus should be a top priority, but shutting down restaurants could have an immense effect on the local community, and hence affect the livelihoods of many Ontario residents. After all, many other factors have already had an adverse impact on the restaurant industry. For instance, studies like the "COVID-19 and restaurant demand: Early effects of the pandemic and stay-at-home orders" (Yang Yang 2020) have shown that a 1% increase in new COVID cases results in 0.0556% of daily restaurant demand, while stay-at-home orders have been associated with a decrease of 3.30% in restaurant demand.

Therefore, this paper will focus on examining the effects of COVID shutdowns on restaurants, taking into account factors such as the net profit/loss of the businesses, the permanent closure of the restaurant, number of employees, wages, and food price. After all, shutting down a restaurant does not just affect the restaurant owners, as people may lose their jobs, have their wage/salary decrease, and prices for food may increase to compensate for losses.

For this research, we will first describe the intervention of this experiment where randomized controlled trial testing will be conducted on a sample of the restaurant population in Ontario. The methodology involved will then be defined, illustrating how we will be observing the restaurants, what will be measured, the population and sample of the experiment, and the predicted cost of gathering the data. At last, upon denoting all the details of our experiment's intervention method and survey methodology, we will be exploring our findings of the effects of COVID shutdowns on restaurants in the discussion section. All in all, this study will highlight the potential losses in profits and employment caused by restaurant shutdowns, helping Ontario government officials make better-informed decisions regarding the COVID restrictions such as shutdowns.

2 Experiment Design

2.1 Intervention design & Survey methodology

The intervention was conducted on the restaurant population in Ontario throughout a one-month period. To gather samples that better represent the population of restaurants across various cities in Ontario, stratified sampling was implemented where strata were defined through the city of the restaurants. Within these groups, they were further clustered into subgroup samples based on two shared traits, city and size of the restaurant. Only after separating them into these subgroups is simple random sampling used within each of these samples, to randomly apply the treatment, separating them into treatment and control groups. Additionally, the performances of these restaurants were measured respectively at the end of April 2021 (Before the intervention, helping us just have an idea of the performance of the sample collected) and May 2021 (After the treatment) using surveys. Hence, upon surveying the restaurants at the end of May, we were able to compare the difference between treatment and control groups of all clusters, helping us understand the net impact of COVID shut-downs on Ontario restaurants. All in all, the details and reasoning for our experiment design will be further explored in the following steps.

2.2 Step 1: Extracting Restaurant List From Yelp

First, we extracted a list of 32499 restaurants operating in the Ontario area from the Yelp API as the frame. We took the novelty effect into account, filtering the new restaurants out of the population, as the new restaurants might achieve a better turnover (As customers are more excited to try out new things), which can not be attributed to the non-intervention impact.

2.3 Step 2: Sample Size Calculation

Based on (*Sample Size Formula* 2021), the equation below (Equation 1) was used to help us calculate the total sample size.

Equation 1:

$$n = \frac{\frac{Z^2 \times p(1-p)}{e^2}}{1 + (\frac{Z^2 \times p(1-p)}{e^2 N})} \tag{1}$$

Where Z is the z score; e is the margin of error;N is the population size; p is the population proportion; n is the sample size

To carry out this calculation, we set the margin of error, e, the maximum distance desired for the sample estimated to deviate from the true value, to be 5%. The confidence level, which is a measure of certainty regarding how accurately a sample reflects the population, is set to be 0.95. Zfor a 95% confidence level is 1.96. The population proportion, denoted by p, is set to be 0.5, describing a percentage value associated with a population. Thus, the minimum sample size needed is calculated as 380, which means 380 or more restaurants are needed to have a confidence level of 95% that the real value is within 5% of the surveyed value. Hence, we have decided to survey around 2,000 restaurants, to also further account for non-responses

2.4 Step 3: Stratified Sampling and Simple Random Sampling

Upon seeing the sample size needed to conduct an experiment whose results can be used to infer the population of restaurants in Ontario, stratified sampling was used to select a sample that properly represented the number of restaurants across distinct cities in Ontario. In other words, we divided the restaurants into different subgroups (stratum) based on cities in Ontario, preserving the right proportion of restaurants by city in the population, while helping maintain a lower sampling error in estimation, as well as a lower standard deviation. This ultimately allows us to have a valid representation of the population, enhancing our experiment's external validity as we would be able to more easily generalize from the sample to the entire Ontario restaurant population. In fact, the higher precision of the sample derived from stratified sampling would also mean that a smaller sample could be used, giving us an option to reduce the cost of surveying restaurants. Hence, after identifying the required proportion of samples needed from each city, simple random sampling was used in each city to gather the required sample. This ultimately ensures that the samples vary across each city, allowing for a better representation of the restaurants in the cities, as each restaurant has the same probability of being sampled.

2.5 Step 4: Clustering and Controlling for Variables

To control for variables in the experiment, the samples collected were then clustered into groups based on the cities they are located in and the size of the restaurant (determined by the number of employees). This ultimately ensures that all types of represented Ontario restaurants can be placed in the control or treatment group once simple random sampling is implemented in each of the clusters. This would allow us to make performance comparisons within the clusters (between the treated group and the control group), allowing us to better argue that any variations of outcomes can be attributed to only the treatment (the shutdown). Of course, it would be optimal to control for more variables, such as the type of restaurant or the rating of the restaurant, but we decided to only do it based on city and size as adding more variables would result in significantly more clusters (further complicating the experiment and decreasing the sizes of clusters)

2.6 Step 5: Implementing Random Treatment

After identifying the multiple clusters of samples, simple random assignment will also be conducted in each cluster, separating the samples into a control group and a treatment group with the same number of restaurants. In other words, each restaurant within the clusters has an equal chance of being treated or not treated. This ultimately ensures that there is no bias when picking what restaurants to shut down, maintaining the internal validity of the experiment.

2.7 Step 6: Determining the Time Frame of the Experiment (Supplement not part of the Intervention)

One of the main issues regarding the separation of treatment was the network effect. This was because the shutting down (treatment) of one restaurant could potentially result in the increment in performance of another restaurant that remained open (control). After all, the demand for food would not change much as customers would still need to eat, meaning that if one restaurant is closed, they can still go for the ones that are still open, resulting in the absorption of new and more customers for open restaurants.

To address this issue, we decided to allow all the sampled restaurants to operate normally in the first month, so we could have an idea of their level of performance. This would basically allow us to compare their performance at the end of the intervention to see if open restaurants did better than their previous run, giving us a sense of the network effect. Of course, one thing we have to emphasize is that this comparison does not have much internal validity or significance as there would be too many random factors across time periods which could result in a difference in performance. Hence, it just serves as a supplemental insight for us to have a brief idea of the potential impacts of the network effect.

However, to further enhance the supplemental insight and maintain some control in the experiment, we found two months in which the total sales of restaurants historically varied the least. Therefore, even though it still does not make the comparison internally valid, we have at least facilitated the comparison to a certain extent. In fact, by recording their surveying the restaurants before the intervention, we are able to get more accurate data regarding their location and size, further helping us cluster them. Nonethelss, we do have to disclose that because this part of the experiment is really just a supplement and not directly involved with the intervention, we have decided not to simulate the data for the previous month, but keep this to have it in mind.

Nevertheless, we found the monthly survey dataset of food services and drinking places containing aggregated data of monthly sales for restaurants in different geographies since 1998 (*Monthly Survey of Food Services and Drinking Plances* 2020). We filtered the dataset to only the geography as Ontario and limited the time period from 2016 to 2019. There were 47 observations in the dataset and 3 attributes: month, the year of that month, and Total Sales. An additional attribute to reflect monthly sales change was created during analysis by subtracting the total sales of the current month from the total sales of the previous month, and divided by the latter. The observations were aggregated by different months, we then calculated the average sales change in each month. Figure 1 below compares the average percentage change (compared with the previous month) of Ontario's restaurant sales across different months within the most recent four years. The result indicates restaurants in Ontario have a stable business performance in April and May.

Based on that, April and May were picked for the experiment, where April would just serve as a means to collect extra data and help us have an idea of the network effect, while May served as the actual part of our intervention.

Hence, we believe this supplemental comparison would still be interesting to examine, as the two groups are still controlled in at least 2 ways: i). On average characteristics, such as the type of restaurant or location, would remain the same as they would be compared with themselves ii). The treatment in the second month would have no direct or indirect effect on their previous performance (Paul J. Gertler 2016). As a result, this comparison would be an interesting supplement to have a further idea on the impact of the network effect and would be explored in our limitations discussion. Nevertheless, it does not completely attribute to the changes to the network effect, as there are many different factors between time periods that can have an effect on the performances.

2.8 Step 7: Survey Methodology and Cost

The survey is generated using Google Form and is set to only one response per user to avoid duplicate responses. In addition, the survey includes an explanation of the experiment, denoting how the experiment

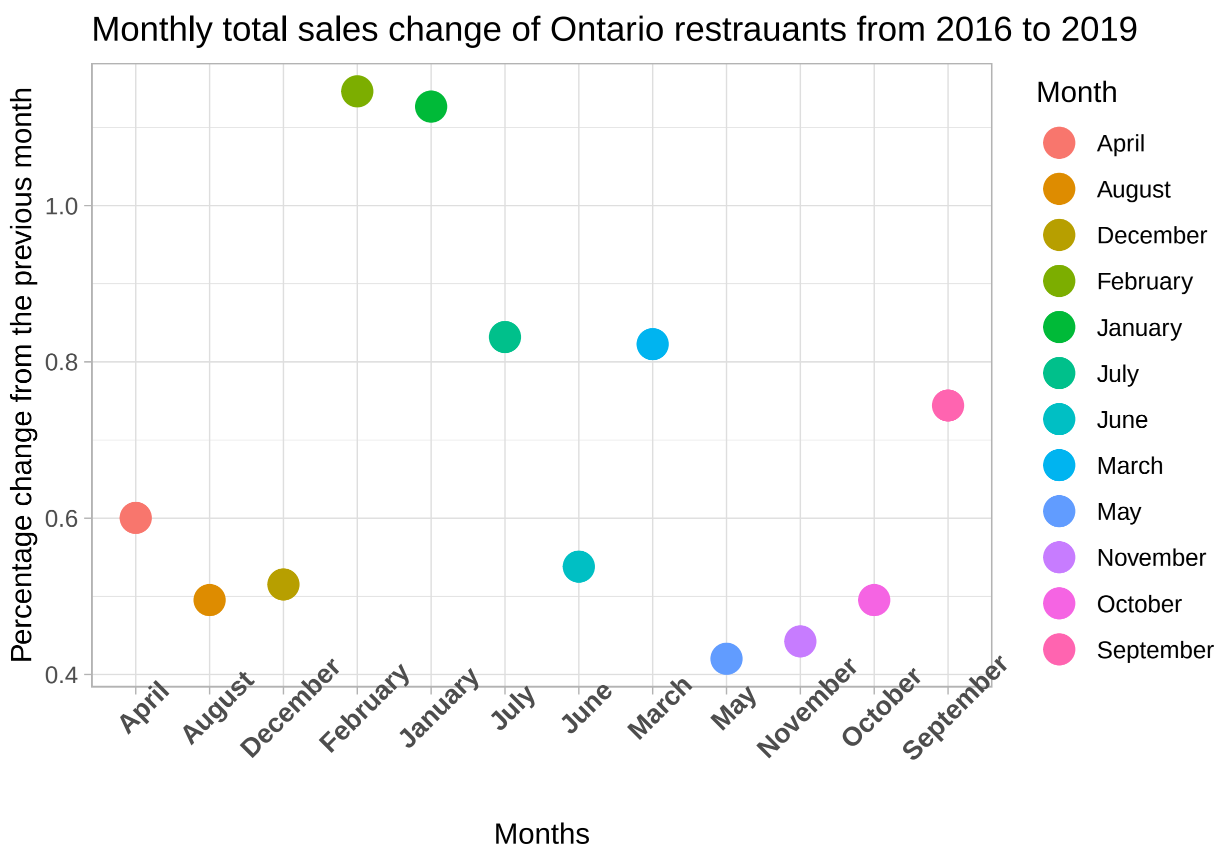

Figure 1: Ontario's restaruants business performances

will be conducted and upcoming surveys that they would still need to fill out in the following two months. For instance, it would explain how they would be allowed to operate normally in the first month, but some may be randomly picked to be shut-down in the second month. Of course, it would also indicate the compensation that would be given to them for shutting down (while also specifying that the compensation would not form part of the restaurant's revenue as to not intervene with the experiment).

Additionally, we will be assuring the participants that their data would ultimately be anonymous and stored safely for their privacy, ensuring there are no privacy concerns and increasing the response rate. After all, the research data we collect from surveys will fall under the Municipal Freedom of Information and Protection of Privacy Act (Information and Ontario 2015). Personal information such as the respondent's location, or opinions will be encoded into different classifications to hide sensitive personal information, and the survey will also be conducted anonymously to ensure all information is handled in a de-identified manner. The information we collect, use and analyze will not be disclosed to any third-party and only for research-purpose which comply with privacy protection provisions of the Acts. At last, the survey explanation would also include the importance of this study as it could inform government plans regarding how restaurants' laws are imposed. This would encourage respondents to answer the surveys, reducing the nonresponses. Of course, we made sure to state that their responses would not directly affect, but just inform government decisions, as some respondents may want to answer dishonestly to affect potential governmental outcomes.

More specifically, since we obtain detailed information for these 4,000 selected sample restaurants, such as email and phone number through Yelp API, the survey will first be conducted through an email survey, where we attach and send the survey link to associated email contact manually and respondents would be given a chance to opt-out of the study, preventing further contact from us. Nevertheless, upon a non-response, a similar follow-up email survey will be sent to reduce non-responses. Again, this survey would give the respondent a second chance to opt-out of this study. At last, if the emails garner no responses, a final phone call survey would be implemented to further reduce non-responses. These email and phone surveys will help us obtain information about each restaurant in these two control and treatment groups after performing the stratified sampling technique for the target population.

The survey methodology process would be repeated three times, before the first month to provide the purpose of the experiment and options to opt-out/opt-in, at the end of the first month to have an idea of their usual performance, and at the end of the final month to evaluate the performance of the restaurants after treating half of them with a shutdown. Additionally, respondents will also be informed in the first survey that they will be rewarded after completing all three surveys with an incentive (such as a government check for $2,000) in order to achieve a higher response rate and ensure participation in the experiment. More specifically, restaurants that complete all surveys and randomly get selected to be treated will receive a $2,000 government check, while the ones that remained open will receive a $1,000 check, to make up for the unfair perception. In fact, to make sure the restaurants selected to be treated stay treated, we will be conducting audits on a weekly basis, checking on their Yelp Statuses, online delivery service availability.

Additionally, to make the deal sweeter, an additional $10 Amazon gift card will be awarded at the end of the last survey to further encourage participation. A track record of the responses would also be used to make sure restaurants do not send in two surveys and receive more than one gift card. If any of the restaurants that participated in the first survey decide not to participate in the upcoming surveys, or open up when they are supposed to be treated or vice-versa), they will not be able to obtain the compensation, and their previous data points in the past survey would be omitted. In fact, since we could not guarantee each respondent will take the survey eventually, weight-class adjustments will be implemented by increasing the sampling weights of respondents to manage the variation caused by unit non-responses, in order to help us deal with non-response bias which could affect the validity of the research analysis and lead to an underestimation or overestimation of the true outcome.

The construction of the survey itself will be free with the Google Form platform and we will conduct the survey through email and phone only in which there will be no cost for sending an email survey but an extra expense of calling non-response participants is required. Since the survey will be implemented in April and May, a two-month prepaid phone plan from Koodo mobile which is $25 per month with unlimited province-wide calling will be purchased.

In terms of costs, the government compensation checks are estimated to be around a total of $10 million. The estimated cost of the additional Amazon gift cards would amount to a total of $40,000, while the two-month prepaid phone plan would amount to $50 ($25 per month). Fortunately for the experiment, the manual labour of sending out surveys, and checking up on the restaurants (Making sure they are not violating the terms of the experiment) would be conducted by a group of unpaid interns happy to gain experience. All in all, the total cost of the experiment would be $10 million and $40,050, where the government would be subsidizing the $10 million worth of checks, and we would be responsible for the $40,050.

3 Survey Design and Data

3.1 Survey

To determine how restaurants are coping with COVID-19 in Ontario, a survey is developed to collect data pertaining to restaurant operations, finances, and staffing. The short survey consists of 10 questions and targets the government's major concerns—revenue shifts, labour changes, and business survivals; these topline metrics are collected from individual restaurants along with differentiating business characteristics such as the size of the business, source of debt, current operation status, Yelp star rating, and the number of customer reviews. The aims of this report are to assess how restaurants with varying characteristics are surviving during the pandemic and to predict how shutdown measures in Ontario will impose changes to the already struggling restaurant industry. Stratified sampling is incorporated to ensure a correct representation of the sampling population–Ontario. Cities with varying characteristics are chosen with distinct population sizes. Toronto, Ottawa, Hamilton, London, and Thunder Bay are selected and their city populations are scaled to 58%, 20%, 11%, 8%, and 3% in order to give an accurate number of representations of the overall number of restaurants in the province (*City Population* 2021). Clustering of restaurant characteristics, specifically by city and by business size, is well-considered with data to back up each proposed simulation (see Section 3.2 Simulated Data).

The survey is designed for participants to complete in 4 minutes to prevent survey fatigue. A series of numerical and categorical sections are built into the survey and are listed as optional in cases when an answer is unknown or is private to the respondent. The decision to keep all responses optional is to avoid response bias where a false selection is forcefully selected. For categorical responses, the questions are either formatted as a multiple-choice question or as a ranking question on a scale of 1 to 5. Respondents are also free to enter numerical responses in text boxes. Instructions are provided for numerical responses. For revenue and employment, it is assumed that all restaurants are negatively impacted by COVID-19 and losses occurred both in terms of sales and employees. A number "0" is assigned under cases where no losses are observed. While the benefits of making all responses optional reduce bias in the dataset, invalid entries are also expected as an outcome of having optional responses. In addition, instructions are provided to guide users throughout the process. The additional time associated with reading and interpreting instructions can add to survey fatigue. As a result, the number of questions is kept to a minimum to hopefully generate more quality responses. Altogether, the survey aimed to predict Ontario's restaurant industry trends is based on the current COVID-19 pandemic and delivers straightforward results to the government of Ontario.

3.2 Simulated Data

For the simulation, we use R (R Core Team 2020) and packages such as "Tidyverse" (Wickham et al. 2019) to analyze the data. Additionally, R packages like "knitr" (Xie 2015) and "tinytex" (Xie 2021) were used to compile and create this PDF file. At last, "ggplot2" (Wickham 2016) and "kableExtra" (Zhu 2020) were also used to create graphs and tables.

Responses are simulated for the control and the treated groups based on trends reported in 2020. At the same time, the validity of derived results is ensured by referring to benchmark measurements from cities that do not have the experiments running. According to Quarterly Forecast from Statistics Canada and Restaurants Canada, a 19% increase in food service sales is expected from April to May if shutdown measures were to be removed; in comparison, if shutdown measures were still in place, a 2% increase is predicted (*Operations Report 2020* 2020). The drastic difference might be partly caused by the removal of shutdown measures and partly caused by the network effect–some restaurants will see a boost in sales due to other restaurants closing and in turn boosting the average sales. For the purpose of this paper, we will not be simulating the data for the month of April for simplicity and because it does not really play a major role in the main intervention. However, we will be referring to it for our limitations in our discussion section. In other words, this paper and data simulation will focus only on the differences between controlled and treated groups in the same time period (May) to determine possible scenarios when the government of Ontario decides to implement shutdown measures.

Question 1 asks for the total sales decline in percentage compared to the same month pre-pandemic. According to trends in 2020, a 37.2% average decline in foodservice sales is most likely when consumers are more cautious about returning to restaurants once containment measures are lifted; a 48.2% average decline is expected where containment measures are in place (*Operations Report 2020* 2020). As a result, Poisson distributions with lambdas equaling to 37.2 and 48.4 are chosen to simulate possible responses for the control group and the treatment group, respectively. Poisson distributions are chosen because most revenue forecasts fall below the average decline rates stated (*Operations Report 2020* 2020). Likewise, the employment declines in Question 2 are also estimated from the operations report. Since the majority of the employment losses fall in the 40-50% range and 95% of the declines are within 10% range from 45% loss (*Operations Report 2020* 2020), a mean of 45 and a standard deviation of 5 is defined for the control group and the mean is shifted to 50 while keeping the standard deviation the same for the treatment group. The reason for shifting up employment loss by 5% is because greater layoffs are expected as restaurants are forced to close. Lastly, Question 3 surveys restaurant owners based on how worried they are that the restaurant will not have enough liquidity over the next 3 months. The expected probabilities of 3%, 10%, 18%, 26%, and 43% are assigned to extremely worried, very worried, moderately worried, slightly worried, and not at all worried respectively for the treatment group based on survey results collected from business owners during shutdown (*Operations Report 2020* 2020). For the control period, 3%, 10%, 18%, 31%, and 37% are assigned because it is assumed that restaurant owners will still be worried due to the great drop in sales but less worried compared to when shutdown measures are in place.

These 3 topline metrics—revenue loss, employment loss, and outlook on business survival—are evaluated against fixed characteristics like size of the business, source of debt, current operation status, Yelp star rating, number of customer reviews, price points, and location of the business. In Ontario, 25% of the restaurants operate on a "Micro" scale with 1-4 employees, 73% of restaurants are "Small" with 5-99 employees, and 2% are "Medium" businesses with 100-499 employees(*Businesses - Canadian Industry Statistics* 2021). Sources of debt are based on survey results and range from 44% to 76% for each of the categories sampled—rent, vendors, taxes, payroll, and insurance (*Operations Report 2020* 2020). Since the experiment aids to measure the effect of shutdown measures on control and treated groups, more than 92% of the restaurants will be closed or open depending on the shutdown measures (*Disruptions to Restaurants* 2021). The number of customer reviews is simulated with normal distribution between 0 to 500 since most restaurants have an even distribution of customer reviews (*Disruptions to Restaurants* 2021). Lastly, business characteristics such as Yelp star rating and price points are simulated as normal distributions with a mean of 3.5 and 2.0 respectively (*Disruptions to Restaurants* 2021).

At a glance, the average revenue and employment losses appear evenly distributed across cities and restaurants of varying sizes from simple aggregations displayed in Table 1 and Table 2. However, as we dive deeper into the differences between controlled and treated groups, more insights are uncovered and are presented in Figures 2 to 14.

Table 1: Losses by Location

Selected City	Average Revenue Loss (%)	Average Employment Loss (%)
Hamilton	42.84	47.41
London	42.30	47.58
Ottawa	42.24	47.25
Thunder Bay	42.83	47.65
Toronto	42.70	47.45

Table 2: Losses by Business Size

Restaurant Size	Average Revenue Loss (%)	Average Employment Loss (%)
Medium (100-499)	42.48	46.77
Micro (1-4)	42.31	47.32
Small (5-99)	42.70	47.47

The sampling size for both the control and treated groups is set to 2000 to be inclusive of the 5 cities identified (see Table 1). 2000 is in consideration of any invalid entries and is way beyond the minimum sampling size of 380 calculated from Equation 1.

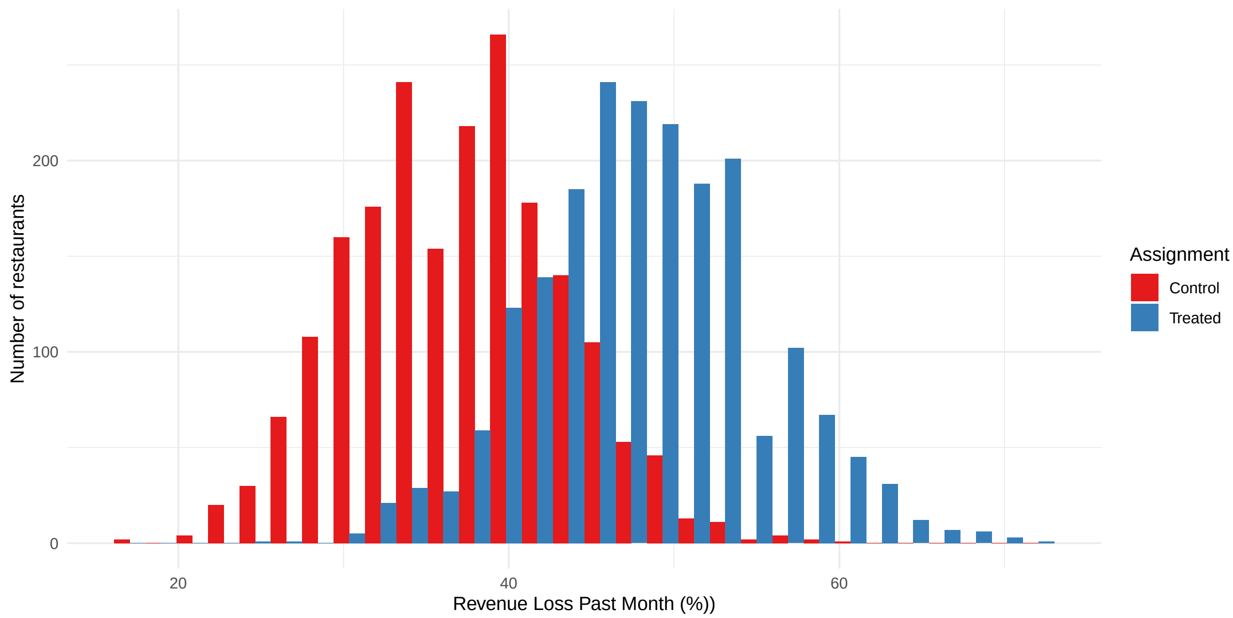

Figure 2: Topline Metrics - Revenue Loss

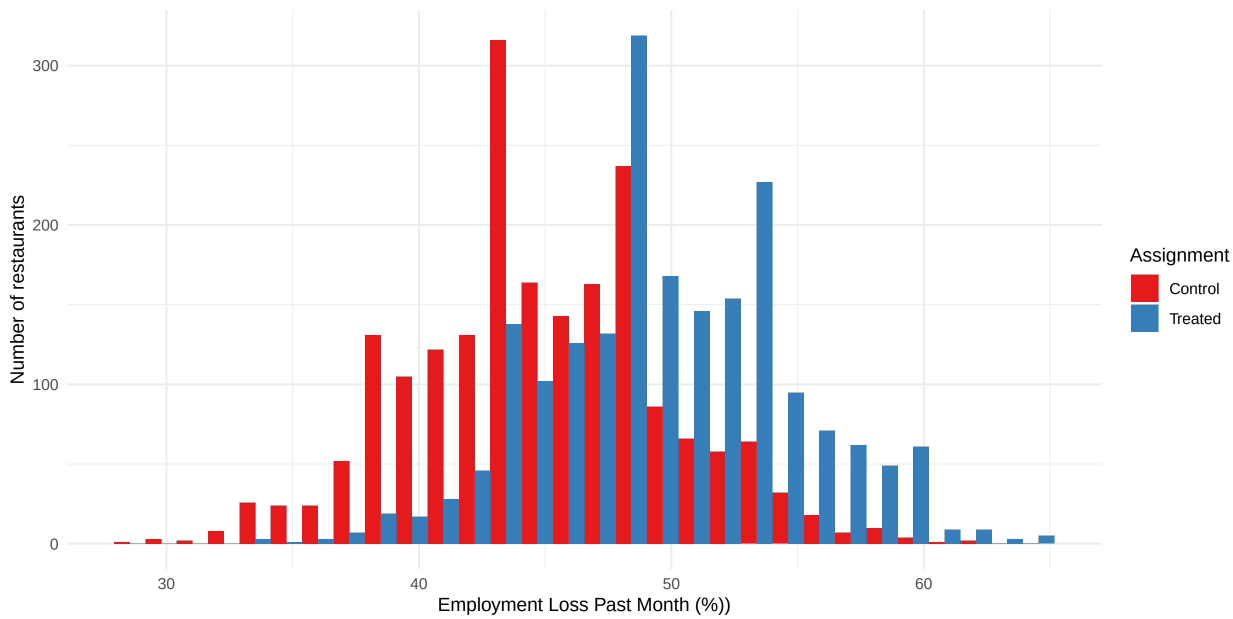

Figure 3: Topline Metrics - Employment Loss

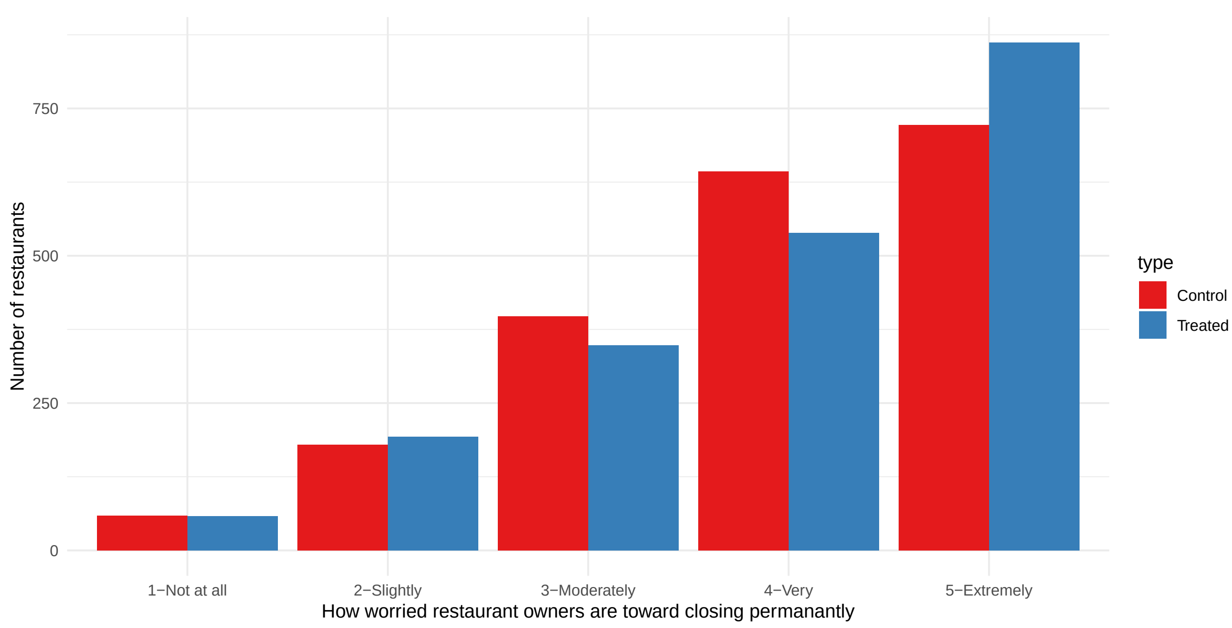

Figure 4: Topline Metrics - Outlook on Business Survival

Figure 5: Employment Loss by Business Size

Figure 6: Employment Loss by Source of Debt

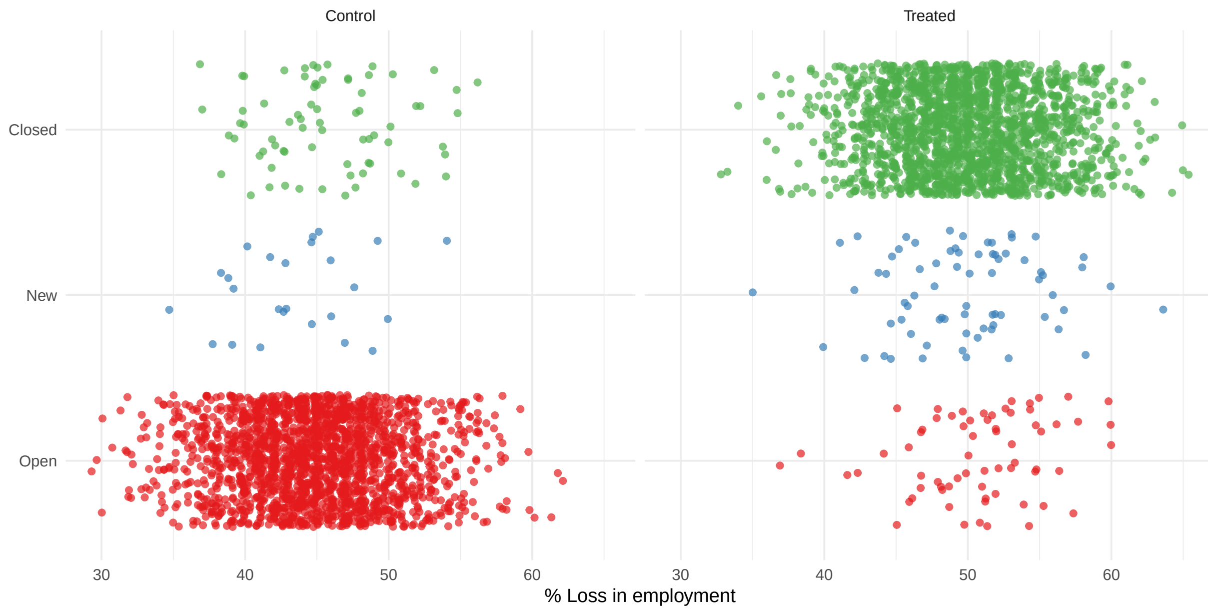

Figure 7: Employment Loss by Operation Status

Figure 8: Employment Loss by Location

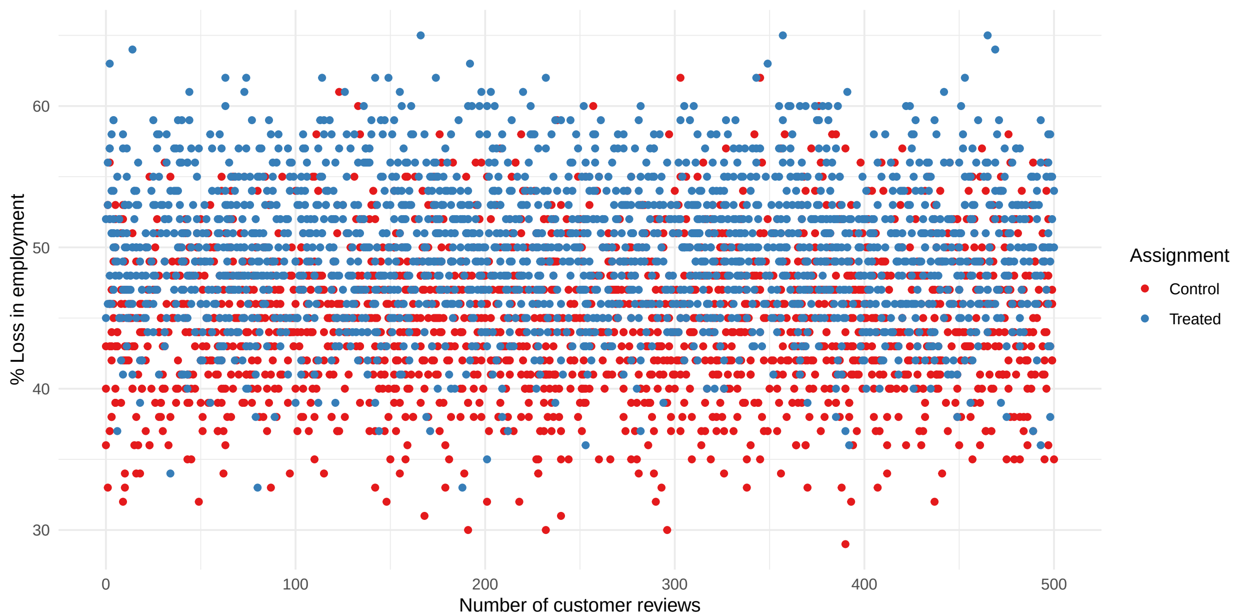

Figure 9: Employment Loss by Number of Customer Reviews

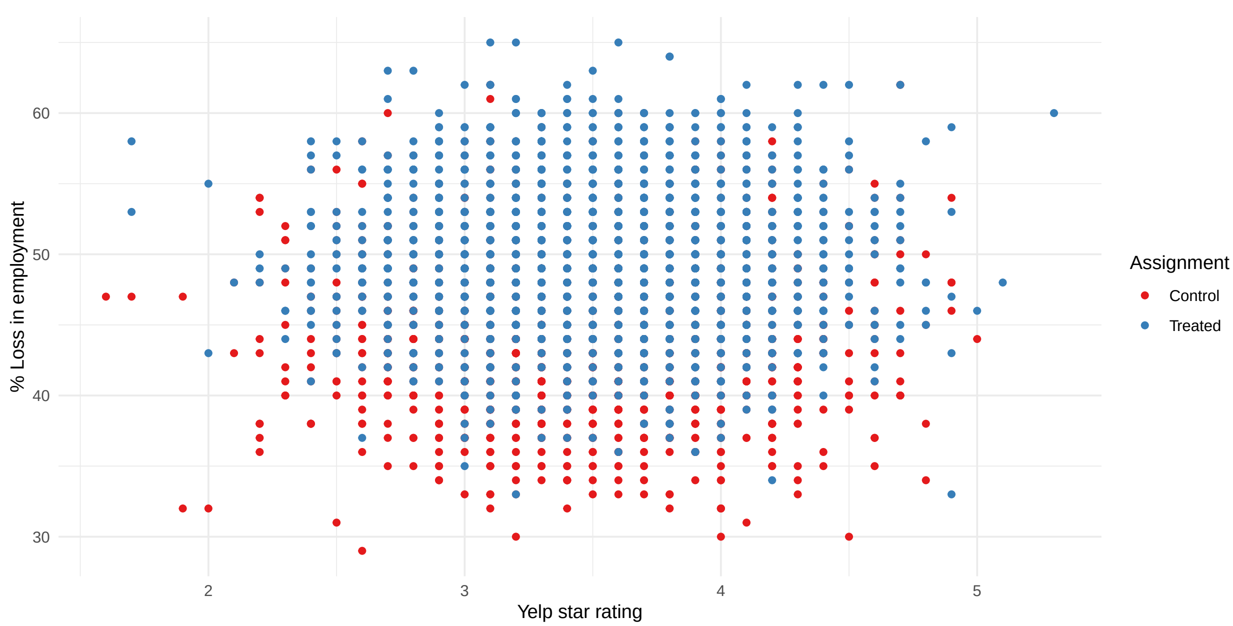

Figure 10: Employment Loss by Yelp Star Rating

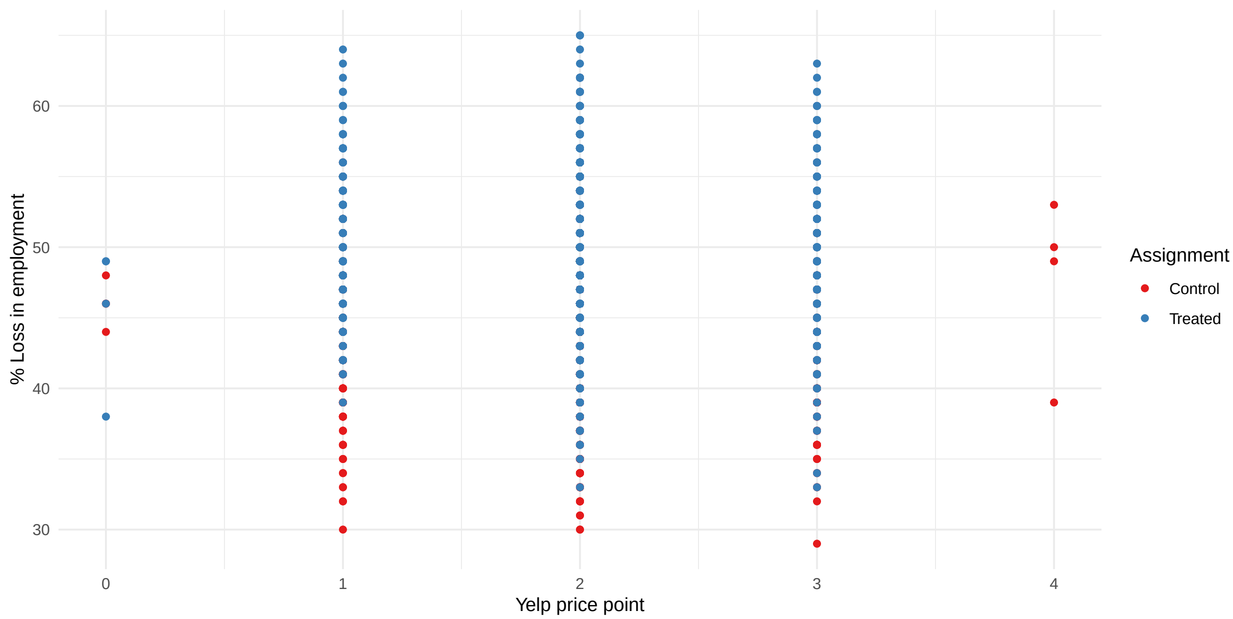

Figure 11: Employment Loss by Restaurant Price Point

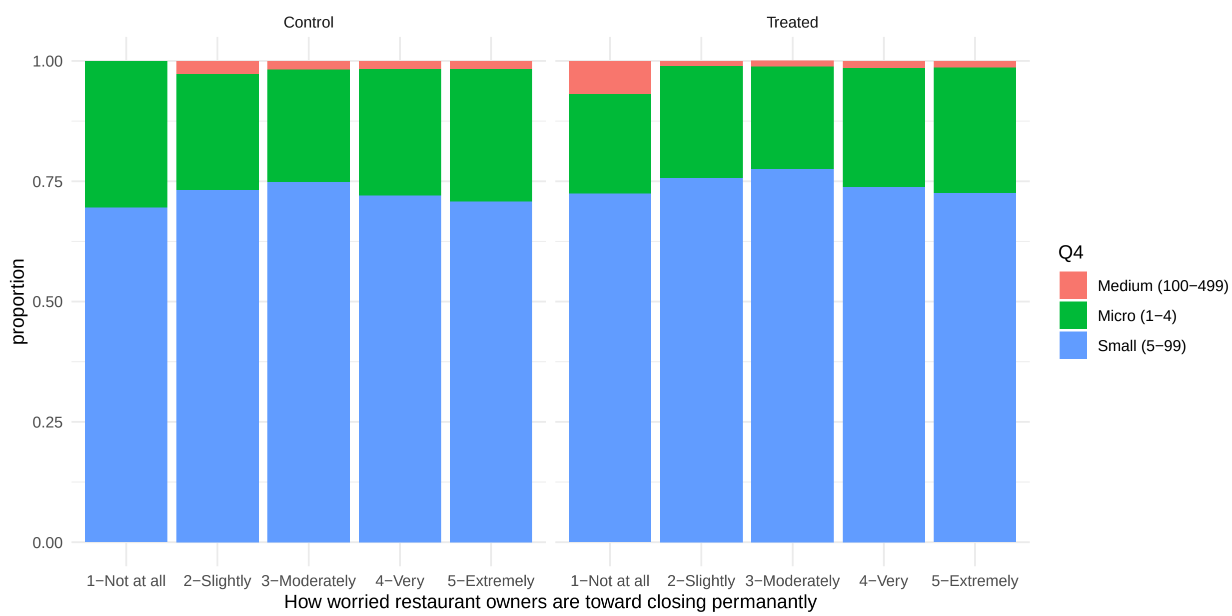

Figure 12: Business Survival Outlook by Company Size

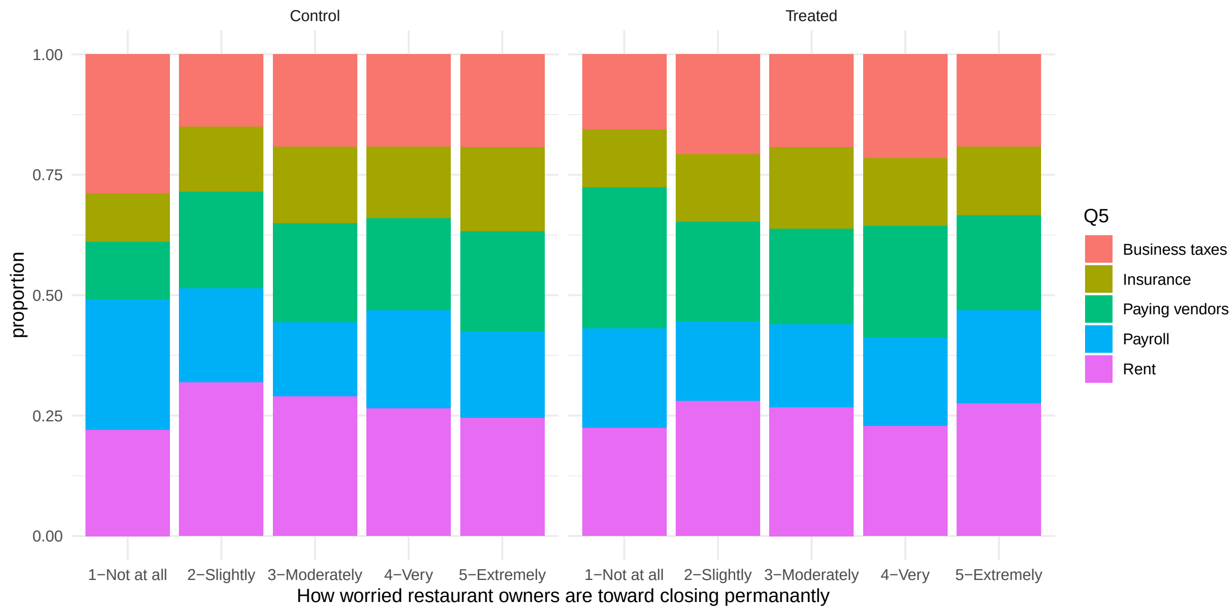

Figure 13: Business Survival Outlook by Source of Debt

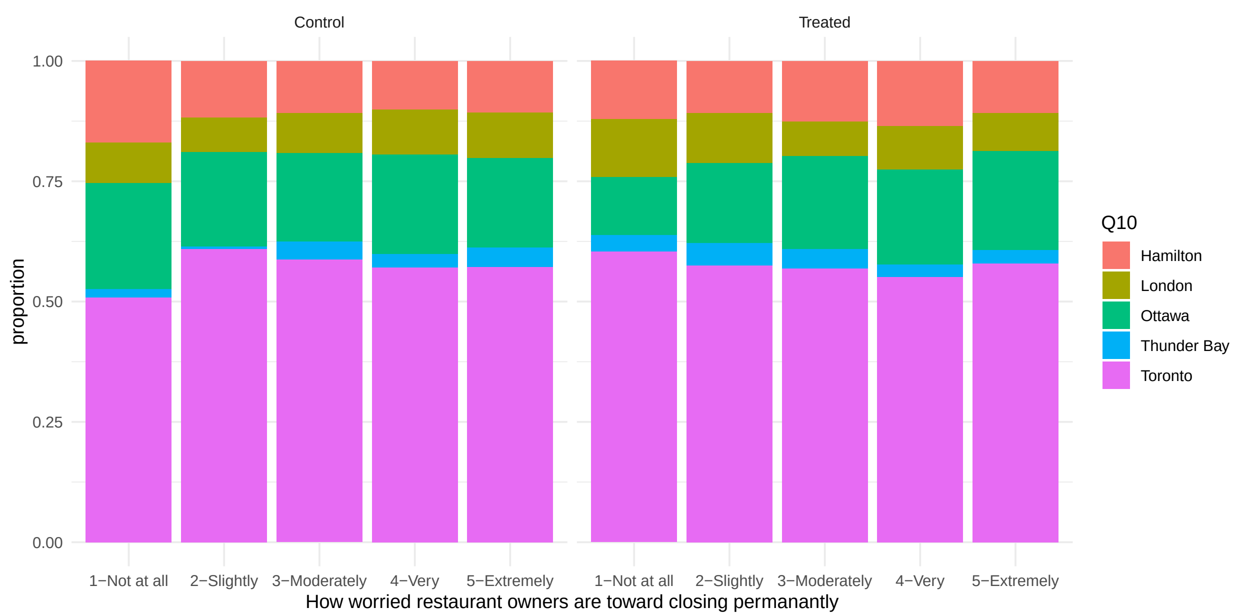

Figure 14: Business Survival Outlook by Location

4 Discussion

Upon conducting the surveys and obtaining the data for the experiment, the performance of shut-downed (treated) restaurants was compared with the performance of open restaurants (control). Hence, we were able to examine the difference in revenue, employment, and survivability of the restaurants in both groups.

4.1 Main findings

4.1.1 Loss in Revnue

Figure 2 shows the loss in revenue for control and treated scenarios. It is clear from the graph that more losses in sales are expected when shutdown measurements are in place compared to a time where shutdown measures are removed. While sharing a relatively symmetric distribution centered around 42%, restaurants that are in the control group primarily fall in the 30-40% range whereas the treated group has more restaurants with declines over 40%. That is why a bimodal shape is observed in Figure 2. The overlapped distributions present the likelihood that similar declines will be witnessed for the two groups. Perhaps the overlapped distribution explains a scenario if we were to implement on and off containment measures in the same month. From Figure 2, the most probable decline resulting from fluctuating containment measures would be around 42%–the peak of overlap.

4.1.2 Loss in Employment

Figure 3 shows the loss in employment in the restaurants sampled. Compared to the loss in revenue observed in Figure 2, Figure 3 shows a greater overlap, indicating less dramatic changes in employment as shutdown measures are implemented. Because the changes in employment are more subtle, the losses in employment are also evaluated against varying business characteristics to see if there are differences between businesses that operate differently. From Figure 5 to Figure 8, the loss in employment is mapped against factors such as the size of the business, source of debt, location, and operation status. We can see that from these graphs that control and treated groups are very similar in their fixed properties but differ in range for loss of employment—the majority of the data fall in the 35% to 55% range for the control group whereas for the treated group, the range of decline is shifted 5% to the 40% to 60% range. Since both scenarios, controlled or treated, are simulated using a normal distribution with the same standard deviation, Figure 9, Figure 10, and Figure 11 are symmetric in shape when we plot employment loss against locations, customer reviews, and Yelp star ratings.

4.1.3 Likelihood to Survive

As discussed in Section 3.1 Simulated Data, the likelihood that a business will survive is primarily based on restaurant owners' perceptions on whether they have enough liquidity to last for 3 more months. From a practical perspective, restaurant owners' self-perceptions directly impact their decisions on whether they are renewing their business licenses. Therefore, the amount of worry from restaurant owners gives an accurate assessment of the likelihood that a business will survive despite all the revenue losses. The bar charts in Figure 4 show the increasing number of worries from categories "1-not at all worried" to "5-extremely worried." More restaurants fall under the "5-extremely worried" undertreat compared to control.

Further investigations from Figure 12 reveal that when controlled (under no shutdown), medium-sized companies never occurred in the "1-not at all worried" category. However, when treated, medium-sized companies take the greatest proportion in the "not at all worried" category compared to the other scales. This trend indicates that when shutdown measures are implemented, the businesses that are smaller in scale tend to shift toward higher levels of worries whereas the medium-sized companies stay relatively calm. Perhaps more government funding is provided for larger-sized companies during the shutdown, so these businesses have more confidence when shutdown measures are implemented. In Figure 13, little variations are shown in terms of relative proportions for the source of debt since all of the survey results indicated a relatively even distribution (*Operations Report 2020* 2020). Lastly, as stratified sampling is controlled to allow a realistic representation of the Ontario population, each city has a different distribution as indicated in Figure 14. However, from Figure 14, we can see that Toronto has the largest influence–having the largest number of restaurants in the province–and takes a great proportion in the concentration of restaurants with varying levels of concerns. In comparison, Thunder Bay has a smaller sample size and therefore generates more obvious results–more worried when no shutdown measures are implemented compared to when shutdown measures are in place. This interesting finding that businesses have more confidence when shutdown measures are implemented could be due to reduction in payroll costs, availability of government funding, and maybe even better mental health for business owners when they take a break from daily restaurant operations.

4.2 Limitations

4.2.1 Network Effect

One of our major limitations was our inability to control for the network effect in the experiment, which was the closure of one restaurant (treatment) potentially resulting in the increment in performance of another restaurant that remained open (control). Even though we did attempt to detect it and enhance our understanding of such effect by comparing between April and May, where Ontario's restaurants have been historically proven to have the least change in performance, it still did not have much internal validity or statistical significance as there were too many unobserved random factors across time periods which could result in a difference in performance.

For example, restaurant demand can change significantly due to other factors, such as the government providing economic packages, increasing individual's income, and motivating more of them to increase their consumption from open restaurants. Additionally, there may have been a change in trend, causing individuals to consume from certain types of restaurants over others, further complicating the measuring and control of the network effect. Hence, due to the significant amount of random factors caused by time, the performance comparisons between open restaurants in the two months would be hard to attribute to the network effect. For this reason, the comparison across baseline month and intervention month might generate a bad estimate of the network effect. We will try to improve it in our future work.

4.2.2 Response Bias

The measurement of characteristics and detailed circumstances of the effects of COVID shutdowns on restaurants is conducted through the questionnaire format survey where the outcomes depended on randomly selected samples whose responses determine the effectiveness of the survey. Response bias is something that can not be avoided entirely and is a challenge that researchers make an effort to minimize the risk from the survey since ignoring the possible effects could lead to an unintended impact on the fairness and the validity of the assessments. There are two types of response bias involved in this survey, demand response and extreme response. Demand response is one of the most common response biases in which participants are aware of the purpose of the survey and they might answer the question in a way that helps the finding of the experiment rather than their actual opinion and situation. The extreme response bias is presented when respondents provide extreme answers and it is commonly seen in the Likert-scale question that to examine the certain level of rating(Prins 2019). In addition, COVID-19 has hit the restaurant industry enormously where restrictions were first put in place starting from 2020. The food service has changed under the pandemic that was shifted from dining in the restaurant to order to go, and many Ontarians used platforms such as Uber Eats, DoorDash, and Skip the Dishes to order meals with delivery to home services. According to the Restaurant Outlook Survey from Restaurants Canada, 55% of respondents reported having third-party delivery only brings slight profit to their business since 30% of the payment for each order will be charged as the service fee. (Canada 2019) So it will not be a surprise to have extreme response bias and demand response bias exist within our experiment and survey where respondents might exaggerate the current situation resulting in an overestimation from the question 1, 2 and 3 in order to avoid a long-term restriction of shutting down restaurants entirely in the future.

4.3 Future Work

4.3.1 Covid Cases

Since the Ontario government wants to understand the potential impact of the shut-down restriction on food services as responses to the ongoing pandemic, this experiment focuses on examining the effects of shutdowns on the restaurant industry in revenue shifts, lay off, business survivals as three major metrics but not include the daily status of new cases in Ontario. The total number of new cases could be regarded as an indicator to reflect whether these shutdowns have a direct effect on the health and performance of the overall population. More specially, for future research, daily new cases that are reported by Toronto Public Health could be used to support the evaluation of the experiment to investigate and monitor the effectiveness of the shutdowns in coping with the pandemic in Ontario. After all, the whole purpose of shutting down businesses is to limit the spread of Covid, balancing between the economic and health well-being of the population. Of course, this would also be quite a challenging experiment to control for, as there could be many factors contributing to the decrease of Covid cases.

4.3.2 Measurement of the network effect

Based on our limitations in measuring the network effect. We will also try to find a new way to objectively reflect the magnitude of this impact on our intervention. To be more specific, designing another intervention to reflect the average effect of network impact on Ontario's restaurants, instead of comparing the outcomes of the control group before and after participating in the intervention. The result would be supplemented with the results of this project, providing extra knowledge about the net impact of the shut-down on restaurants in Ontario and further informing prospective governmental policies and regulations.

Appendix I - Survey Screenshots

Click to view COVID-19 Impact Assessment Survey on Microsoft Forms.

COVID-19 Impact Assessment - Ontario Restaurants

The survey will take approximately 4 minutes to complete.
Dear owner of the restaurant business,

To determine how restaurants are coping with COVID-19 in Ontario, on behalf of the government of Ontario, the Petit Poll would like to request your input on the current stage of your restaurant in terms of operations, finances, and staffing. The short survey consists of 10 questions and targets the government's major concerns—revenue shifts, labour changes, and business survivals; these metrics are collected from individual restaurants anonymously along with differentiating business characteristics such as size of business, source of debt, current operation status, Yelp star rating, and number of customer reviews.

The aims of this report are to assess how restaurants with varying characteristics are surviving during the pandemic and to predict how lockdown measures in Ontario will impose changes to the already struggling restaurant industry. Your response will be recorded anonymously and a copy of the final report will be mailed to you as our appreciation for your time.

Thanks,
Petit Poll

4 mins

1. What is the total sales decline (in percentage) compared to the same month pre-pandemic?
***put "0" if no loss occurred

The value must be a number

2. What percentage of your staff were laid off due to COVID-19?
***put "0" if no employees are laid off

The value must be a number

3. On a scale of 1-5, how worried are you that your restaurant won't have enough liquidity over the next 3 months?
***5=extremely worried; 4=very worried; 3=moderately worried; 2=slightly worried; 1=Not at all worried

☆ ☆ ☆ ☆ ☆

4 mins

4. What is the employment size of your restaurant?

- Micro (1-4)
- Small (5-99)
- Medium (100-499)
- Large (500+)

5. What are the main sources of your total business debt?

- Rent
- Paying vendors
- Business taxes
- Payroll
- Insurance

4 mins

6. What is the current operation status of your restaurant?

- Open throughout the pandemic
- Temporary closed due to the pandemic
- I started my business during the pandemic

7. How many customer reviews your restaurant has on Yelp?

The value must be a number

8. What rating your restaurant has on Yelp(on a scale of 1-5)?

The value must be a number

4 mins

9. What price point is your restaurant set to on Yelp(on a scale of 1-4)?

The value must be a number

10. Which city is your restaurant located in?

- Toronto
- Ottawa
- Hamilton
- London
- Thunder Bay

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