“I’s Dined with Ukraine”: Empirical Analysis on Consumer Preference Change After Russo-Ukrainian War

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Abstract: Recently, the Russo-Ukrainian war has become a major shock to the global market. This study investigates the impact of conflict on consumer preference and consumer rationality with empirical analysis. This paper applied the Difference-in-Difference method to measure the external shock’s (war) effect on Ukrainian and Russian restaurants. The restaurants in the control group in the DiD model are selected with the identification strategy of spatial matching. After eliminating the impact of Covid by controlling the Covid Stringency Index as a covariate, the paper constructed a Bayesian structure time series Causal Impact analysis on each Ukrainian and Russian restaurant visitor count to reflect the change in consumer preference caused by the external shock. Then, the paper proposed the mechanism behind the changes in customer visits by adopting a topic modeling approach - Latent Dirichlet Allocation and word cloud method to analyze customer reviews of these restaurants on Yelp. The results showed that terms such as “Support” and “Support Ukraine " had become the trending words in Yelp comments since the start of the war, confirming that consumers tend to show their support by dining in Ukrainian restaurants.

1 INTRODUCTION

The Russian-Ukrainian conflict has been a hot topic on the international stage in the past century. When wars or major pandemics occur, consumers change their preferences and buying patterns in the short or long term (Glick & Taylor, 2010). These consumer behavioral changes could result in many more consequences. One example is when the prohibition caused by war from 1910 to 1933 caused less alcohol consumption and a lower suicidal rate (Zwanka & Buff, 2021). This paper is interested in analyzing consumer preference change after the outbreak of the war: whether people reacted differently to Ukrainian and Russian products or did it have no impact on consumer preferences. Because product sale information is unavailable, consumer flows in restaurants would be a preferred way of research since foot-tracking data is available. Therefore, this paper specifically analyzed the consumer flow of Ukrainian and Russian restaurants to investigate the war's effect on consumer preference. Analyzing every restaurant across the globe is impossible, so this paper focused on restaurants in New York City. Sufficient data to analyze are available for three Russian restaurants (Mari Vanna, Anyway Cafe, Matryoshka) and four Ukrainian restaurants (Veselka, Ukrainian East Village Restaurant, Streecha, and Russian Samovar). Russian Samovar is marked as a Russian restaurant on Yelp. Still, this paper finds evidence indicating that it is owned by a Ukrainian and has supported Ukraine since the beginning of the war (Wasserman, 1989). Therefore, it is considered a Ukrainian restaurant. These six restaurants have sufficient raw_count and normalized_visits data from January 2021 to June 2022.

2 DATA

This study used the SAFE GRAPH data set, which is collected from the physical world and makes monthly updates to their data to assure the accuracy of their dataset. The data is collected by identifying device services with location components, as devices with location services can be identified to determine every user’s time spent at different locations. SAFE GRAPH can account for the potential biases of different types of devices and geographic biases. SafeGraph tested for geographic bias by comparing

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its determination of the state-by-state numbers of home_location devices in the panel to the accurate proportions reported by the 2016 US Census. The result shows that the SafeGraph panel density closely mirrors true population density, as the overall average percentage point difference is < 1%, with a maximum of +/-3% in each state. Furthermore, SAFE GRAPH can eliminate potential bias by collecting data from different cellular carriers. The result shows that the data was collected from 6 major carriers in the US.

Table 1: Shows the distribution of the six carrier types in the SAFE GRAPH dataset. The distribution shows that Verizon is the most common carrier, and the distribution in the dataset is similar to the distribution on the public market.

Carrier	Count	Ratio
Verizon	10,303,871	35.64%
AT&T	7,267,146	25.13%
T-Mobile	7,129,894	24.66%
Sprint	3,685,988	12.75%
Altice	323,221	1.11%
C-Spire	204,800	0.71%

The dataset we used has 866188 rows and 48 columns, with each row representing a specific location's data in a specific week. Some key statistics this study used include raw_visit_ counts and normalized _visits_by _total_visits, These statistics were all collected and analyzed with different methods, yet they all reveal the day-by-day consumer flow to POI in New York City. raw_visit_counts were collected by randomly counting the number of visits to a POI. Normalized data are more complicated and accurate for this study than raw data because they analyze the portion of visits or visitors in a POI compared to visits or visitors in the New York region. Normalized data will result in very small numbers, but they are more accurate by limiting the potential impact from external factors such as the general population flow in the city.

3 DIFFERENCE-IN-DIFFERENCE MODEL AND RESULTS

3.1 Model Specifications

To estimate the causal effect of the Russo-Ukrainian war on the consumer preferences toward Ukrainian and Russian restaurants, we formulate a panel regression model entailing the restaurants of interest and their weekly foot traffic before and after the war through causal identification strategies. The method aims to construct counterfactuals to estimate the effect of an intervention due to the external shock. By comparing the pre-intervention and post-intervention data for both the control group and experimental group, DiD can observe the outcome trend after the intervention and can estimate an external shock’s actual effect on the experimental group. DID is a version of fixed-effect estimation using panel data, e.g.:

γ_0= hypothetical consumers visits to Ukrainian and Russian restaurants if the war did not occur

γ_1 = actual consumers visits to Ukrainian or Russian restaurants after the war occured

γ_0 and γ_1 are both potential outcomes, but only one of them can be observed in reality, i.e., γ_1 when the war actually occurred. Therefore, using DID allows to estimate γ_0 based on several assumptions: the irrelevancy between outcome and intervention, similar trend between control and experimental groups in pre-intervention period, and that exchangeability cannot be assumed between control and experimental groups (Li, Wang & Zhong, 2022).

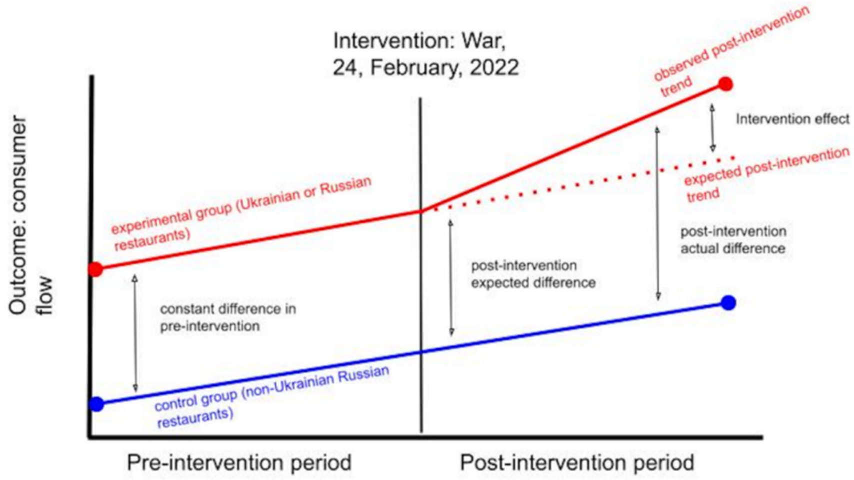

Figure 1: Difference in Difference graphical representation with linear regression.

In the study's setting, the control group (blue) is the non-Ukrainian/Russian restaurants, and the experimental group (red) is the four Ukrainian or three Russian restaurants. The DiD model enables us to establish the counterfactual of the expected post-intervention trend, and predict the intervention effect by comparing it with the observed post-intervention trend. Since DID is a fixed effect model, panel regression can be used to estimate potential outcomes along with dummy variables as the following equation:

$$Y_{it} = a_{it} + b\gamma_{it} + cX_i + \varepsilon_{it}$$

Where Y_{it} is the number of visits to Ukrainian or Russian restaurant i at week t, γ is the intervention dummy variable that equals to 1 for Ukrainian or Russian restaurants in post-intervention period, X is dummy variables for fixed effects such as week and placekey, and ε is the error term. This paper compared the result by controlling for different variables (week, placekey, or both) to validate the consistency and significance of the result. For the DID model, we counted 30 weeks before the first day of the war (February 24, 2022) as the pre-intervention period and 12 weeks after that as the post-intervention period.

3.2 Results

We estimate the effect of war on raw visit counts for the four Ukrainian restaurants shown in Table 2. Overall, the results are consistent and robust when both placekey and week fixed effects are included as control variables, as the intervention effect is estimated to be 9.40 ($p<0.05$). The adjusted R2 is 0.653, showing that the model successfully explains 65.3% of the observations. When only the placekey is controlled, the result is still significant, with the estimated intervention effect of 13.47 ($p<0.01$), and the adjusted R-square to be 0.627. When the control variable is none or week, the result failed to produce a large adjusted R2, but it still yielded a strong and significant intervention effect ($p<0.001$). The result indicates that four Ukrainian restaurants had received an average of 9.4 more customers. Given that the calculated average number of raw_count customers to the Ukrainian restaurant during the pre-intervention period is 45.56, this means that Ukrainian restaurants experienced a 20.6% increase in customers just because of the Russo-Ukrainian war.

Table 2: Raw_visit_counts DiD result for Ukrainian restaurant customer flow.

Dependent Variable	raw_visit_counts	raw_visit_counts	raw_visit_counts	raw_visit_counts
Model	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
Intervention effect	31.695 ***	32.121 ***	13.466 **	9.404 *
	[7.323]	[7.510]	[4.741]	[4.797]
Placekey	No	No	Yes	Yes
Week	No	Yes	No	Yes
Adjusted R2	0.051	0.052	0.627	0.653
# of Obs	942	942	942	942

Table 3 shows the result calculated with normalized_visits_by_total_visits data for Ukrainian restaurants, and it is very consistent with results shown in table 2. When controlling both week and placekey, the intervention effect is estimated to be 5.872e-7 ($p<0.05$) and adjusted R2 to be 0.641. When the control variable is placekey, the intervention effect is estimated to be 8.729e-7 ($p<0.01$) and adjusted R-square equals 0.642. When the control variable is none or week, the intervention effect is strong and significant, but the adjusted R2 is small, indicating the model is not a good fit to the data. During the pre-intervention period, the average number of normalized_visits is 2.849e-6, meaning that 20.6% of more customers decided to eat in these Ukrainian restaurants because of the effect of the war.

Table 3 Normalized_visits_by_total_visits DiD result for Ukrainian restaurants customer flow.

Dependent Variable	normalized_visits	normalized_visits	normalized_visits	normalized_visits
Model	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
Intervention effect	1.932e-6 ***	2.004e-6***	7.729e-7 **	5.872e-7 *
	[4.40e-7]	[4.52e-7]	[2.85e-7]	[2.91e-7]
Placekey	No	No	Yes	Yes
Week	No	Yes	No	Yes
Adjusted R2	0.05	0.043	0.624	0.641
#of Obs	942	942	942	942

Table 4 shows the result generated from Russian restaurants’ raw_visit_counts data. The result is very similar to that of Ukrainian restaurants. When the control variable is none or week, the intervention effect is insignificant and the adjusted R2 proves the model’s unfitness. But when placekey is being controlled, the intervention effect of -2.655 ($p<0.01$) becomes significant with the adjusted R2 to be 0.755 showing the model’s good fit. When both variables are being controlled, the estimated intervention effect is -3.597 ($p<0.01$) and the adjusted R2 equal to 0.78. The average raw_count customers to the Russian restaurants during the pre-intervention period is 16.698, which means that the war caused a 21.5% decrease in consumer flow to Russian restaurants.

Table 4: Raw_visit_counts DiD result for Russian restaurants customer flow.

Dependent Variable	raw_visit_counts	raw_visit_counts	raw_visit_counts	raw_visit_counts
Model	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
Intervention effect	-3.094	-3.218	-2.655 **	-3.597 **
	[1.727]	[2.119]	[1.018]	[1.160]
Placekey	No	No	Yes	Yes
Week	No	Yes	No	Yes
Adjusted R2	0.003	-0.042	0.755	0.780
# of Obs	493	493	493	493

Table 5 shows the result calculated with normalized_visits_by_total_visits data for Russian restaurants, and it is different from the result on table 4. When controlling both week and placekey, the intervention effect is estimated to be -1.341e-7 and adjusted R2 to be 0.731, but it is not statistically significant enough ($p>0.05$). When the control variable is placekey, the intervention effect is estimated to be -1.644e-7 ($p<0.05$) and adjusted R-square equals 0.719. When the control variable is none or week, the intervention effect is strong and significant, but the adjusted R2 is small, indicating the model is not a good-fit to the data. The average number of normalized_visits to the Russian restaurants during the pre-intervention period is 1.826e-6, which means that the war caused a 17.6 % decrease in consumer flow to Russian restaurants

Table 5: Normalized_visits_by_total_visits DiD result for Russian restaurants customer flow

Dependent Variable	normalized_visits	normalized_visits	normalized_visits	normalized_visits
Model	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
Intervention effect	-3.552e-7 **	-2.969e-7 *	-1.644e-7 *	-1.341e-7
	[1.35e-7]	[1.57e-7]	[7.80e-8]	[9.37e-8]
Placekey	No	No	Yes	Yes
Week	No	Yes	No	Yes
Adjusted R2	0.006	-0.04	0.719	0.731
# of Obs	493	493	493	493

4 BAYESIAN STRUCTURAL TIME SERIES MODEL AND RESULTS

4.1 Model Specifications

This paper adopted the Bayesian Structural Time Series Model and applied the Causal Impact analysis on each individual Ukrainian and Russian restaurant (Brodersen, Gallusser & Scott.,2015). This method will predict a counterfactual on a time-series model and predict an external shock's intervention effect as shown in Figure 2. The Russian Samovar restaurant, although labeled as a Russian restaurant on Yelp, was classified as an Ukrainian restaurant in this study because most of its employees are Ukrainians. The restaurant also showed its support to Ukraine after the war happened (Alyson, 2022), such as hosting fund-raisers or posting a blue and yellow flag on the door and a sign that says, "Stand by Ukraine. No War."

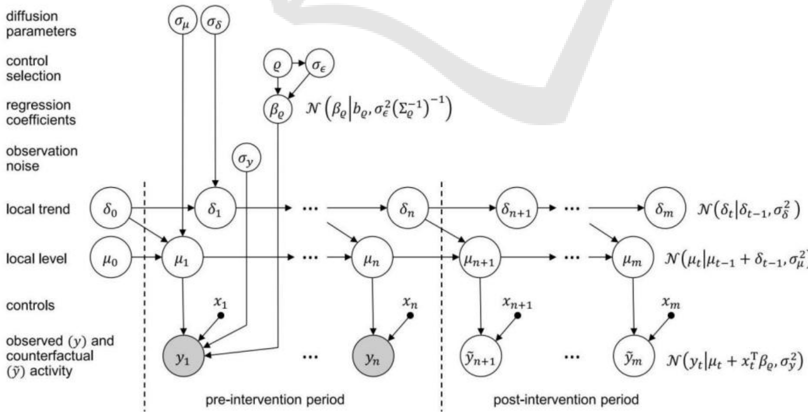

Figure 2: Bayesian structure time-series model and Causal Impact methodology graphical representation.

In the real world, there is the observed data Y1, and the goal is to estimate the counterfactual data Y0, what would happen if the war never occurred. Since there isn't an actual experiment, the "control" group doesn't exist, so the goal of synthetic control is to estimate something that just looks like a control group (Abadie, Diamond & Hainmueller, 2015).

The difference between the counterfactual data and observed data at time t is the intervention's effect. Constructing a Bayesian time-series model, the Causal Impact method can estimate the post-intervention trend by analyzing the pre-intervention and controlling for certain fixed characteristics or “covariates.” The Causal Impact model is based on two important assumptions: 1) There is a controlled time-series that is not affected by the intervention. 2)

The relationship between covariates and time-series, established in pre-intervention, remains stable throughout the post-intervention. In this study, the covariate being used is the covid Stringency Index, which measures the actual effect of Covid in New York.

The Causal Impact model will produce some key statistics such as the predicted customer count, actual customer count, intervention absolute effect and relative effect, their standard deviation, the posterior tail-area p value, and each value’s 95% confidence interval. The model also produces a graph set showing the predicted vs. actual value, point effect, and cumulative effect. Figure 3 shows the graphs produced with the raw_visit_counts of the Ukrainian restaurant Vesekla. The first graph shows the actual customer flow versus the predicted customer 25 to 35 weeks before the war and 10 weeks after the war. The second graph shows the point effect of y versus predicted over time. The third graph shows the cumulative effect after the intervention. A Bayesian structure time-series model along with Causal Impact analysis will be applied to each of the seven Ukrainian or Russian restaurants to estimate the war’s effect on consumer preference change.

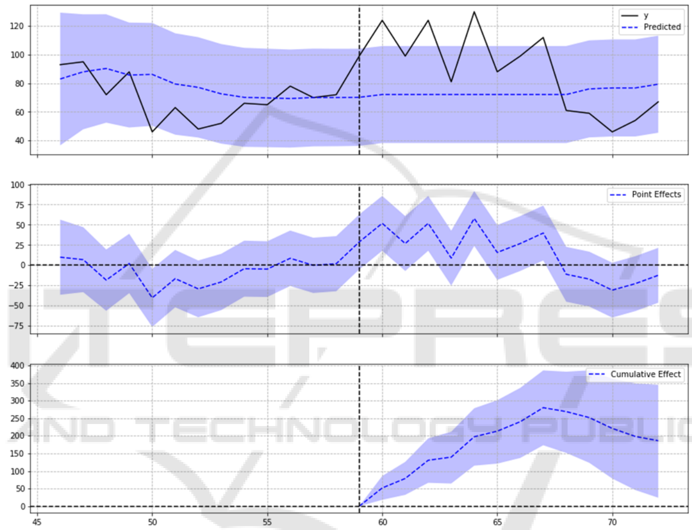

Figure 3: Causal Impact graphing result for Veselka restaurant.

4.2 Results

Table 6 shows the result of causal Impact analysis on Ukrainian restaurants. For each restaurant, the patterns found in raw_visit_counts and normalized_visits_by_total_visits are very similar.

Table 6: Bayesian structure time-series with Causal Impact result for Ukrainian restaurants.

Dependent Variable	raw_visit_counts				normalized_visits_by_total_visits			
Restaurant number	1	2	3	4	1	2	3	4
Actual	88.0	15.62	19.8	110.3	0.53	0.1	0.14	0.69
Prediction	74.19	16.71	11.87	37.83	0.44	0.1	0.07	0.22
S.D.	(4.53)	(2.31)	(3.88)	(14.92)	(0.02)	(0.01)	(0.02)	(0.1)
Relative effect	18.61%***	-6.5%	66.8%***	191.6%**	20.0%***	-4.9%	99.9%***	215.2%***

				*				
S.D.	(6.1%)	(13.8%)	(32.7%)	(39.5%)	(5.5%)	(13.1%)	(35.8%)	(45.1%)
95% confidence interval	[6.2%, 30.2%]	[-33.3%, 21.0%]	[4.0%, 132.2%]	[117.2%, 271.8%]	[9.5%, 31.2%]	[-30.8%, 20.6%]	[27.5%, 168.0%]	[128.6%, 305.4%]

Veselka (1)'s result shows that during the post-intervention period, the response variable had an average value of approx. 88.0. By contrast, in the absence of an intervention, we would have expected an average response of 74.19. In relative effect, the response variable showed an increase of +18.6%. The 95% interval of this percentage is [6.2%, 30.2%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.0). This means the causal effect can be considered statistically significant.

Streecha (2)'s result shows that during the post-intervention period, the response variable had an average value of approx. 15.62. In the absence of an intervention, we would have expected an average response of 16.71. In relative effect, the response variable showed a decrease of -6.6%. The 95% interval of this percentage is [-33.4%, 20.8%]. This means that, although it may look as though the intervention has exerted a negative effect on the response variable when considering the intervention period as a whole, this effect is not statistically significant and so cannot be meaningfully interpreted. The apparent effect could be the result of random fluctuations that are unrelated to the intervention. This is often the case when the intervention period is very long and includes much of the time when the effect has already worn off. It can also be the case when the intervention period is too short to distinguish the signal from the noise. Finally, failing to find a significant effect can happen when there are not enough control variables or when these variables do not correlate well with the response variable during the learning period. The probability of obtaining this effect by chance is p = 31.1%. This means the effect may be spurious and would generally not be considered statistically significant.

Ukrainian East Village Restaurant (3)'s result shows that the response variable had an average value of approximately during the post-intervention period. 0.14. By contrast, without intervention, we would have expected an average response of 0.07. In relative effect, the response variable showed an increase of +99.9%. The 95% interval of this percentage is [31.2%, 170.5%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.0). This means the causal effect can be considered statistically significant.

Russian Samovar(4)'s result shows that during the post-intervention period, the response variable had an average value of approx. 110.3. By contrast, in the absence of an intervention, we would have expected an average response of 37.83. In relative terms, the response variable showed an increase of +191.6%. The 95% interval of this percentage is [117.2%, 271.8%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.0). This means the causal effect can be considered statistically significant.

Table 7: Bayesian structure time-series with Causal Impact result for Russian restaurants.

Dependent Variable	raw_visit_counts			normalized_visits_by_total_visits		
Restaurant number	5	6	7	5	6	7
Actual	29.23	3.42	7.0	0.18	0.02	0.04
Predicted	35.46	5.66	20.02	0.21	0.04	0.12

S.D.	(2.79)	(0.99)	(2.39)	(0.02)	(0.01)	(0.01)
Relative effect	-17.6%**	-39.7%***	-65.0%***	-15.3%*	-42.6%***	-63.4%***
S.D.	(7.9%)	(17.5%)	(11.9%)	(8.4%)	(17.1%)	(11.6%)
95% confidence interval	[-32.5%, -1.7%]	[-75.9%, -7.3%]	[-87.1%, -40.2%]	[-31.5%, 1.3%]	[-76.1%, -9.1%]	[-86.7%, -41.3%]

Table 7 shows the result of causal Impact analysis on Russian restaurants. For each restaurant, the patterns found in raw_visit_counts and normalized_visits_by_total_vists are also similar.

Mari Vanna (5)'s result shows that during the post-intervention period, the response variable had an average value of approx. 29.23. By contrast, in the absence of an intervention, we would have expected an average response of 35.46. In relative effect, the response variable showed a decrease of -17.56%. The 95% interval of this percentage is [-32.54%, -1.7%]. This means that the negative effect observed during the intervention period is statistically significant. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.01). This means the causal effect can be considered statistically significant.

Matryoshka (6)'s result shows that during the post-intervention period, the response variable had an average value of approx. 3.42. By contrast, in the absence of an intervention, we would have expected an average response of 5.66. In relative effect, the response variable showed a decrease of -39.65%. The 95% interval of this percentage is [-75.95%, -7.29%]. This means that the negative effect observed during the intervention period is statistically significant. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.0). This means the causal effect can be considered statistically significant.

Anyway Café (7)'s result shows that during the post-intervention period, the response variable had an average value of approx. 7.0. By contrast, in the absence of an intervention, we would have expected an average response of 20.02. In relative terms, the response variable showed a decrease of -65.03%. The 95% interval of this percentage is [-87.08%, -40.22%]. This means that the negative effect observed during the intervention period is statistically significant. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.0). This means the causal effect can be considered statistically significant.

To summarize, the Bayesian time-series model significantly proved the change of consumer preference through investigating the customer flow on three Russian and three Ukrainian restaurants. The only restaurant which failed to produce a statistically significant result is the Russian restaurant Streecha, with a p-value of 31.07% and 95% confidence interval of [-33.26%, 21.05%]. Even so, it's almost certain to conclude, with the result produced by the Causal Impact analysis, that the consumer preference has been shifted by the outbreak of Russo-Ukrainian war. The consumers, in response to the war, are more willing to dine in Ukrainian restaurants and reluctant to dine in Russian restaurants.

5 DISCUSSION

The DiD and Causal Impact results have shown the shift in consumer preference due to the impact of the Russo-Ukrainian war. When controlling for variables like week or placekey, the DiD model was able to generate robust results to prove an approximately 20.6% increase in customers to Ukrainian restaurants and a 21.5% decrease in customers to Russian Restaurants. The Bayesian structure time-series model and Causal Impact method specifically analyzed each restaurant. The method produced statistically significant results for three of the four Ukrainian restaurants showing the war's positive impact on customer flow. Furthermore, the model successfully proved the war's negative impact on all three Russian restaurants.

This paper, different from many other previous studies, focuses on the micro-level impact of the Russo-Ukrainian war. By investigating the customer flow of Ukrainian and Russian restaurants in New York City, the study successfully proved that the war has a robust effect on changing people's consumer preferences. People in New York, for instance, decided to dine in Ukrainian restaurants to show their attitude and support toward the Ukrainians. On the other hand, Russian restaurants like Mari Vanna suffered customer losses and decreased revenues. In some extreme cases, people expressed their anger toward Russia by harassing and threatening Russian people and their businesses (Anne & Haleluya, 2022). Many restaurant owners can also sense this change in consumer preference. Some owners, for example, decided to rebrand their restaurants from "Russian" to "Ukrainian" or "Eastern European" to avoid customer losses (Kailey, 2022). This phenomenon will not last short, however. Consumer preference will likely continue to change and favor Ukrainian products in the next few years, especially given that the war is continuing and showing no sign of calling a truce. This paper also confirmed the result of previous research stating that major crisis and international events, such as covid, are likely to affect consumer behaviors and activities (Anastasiadou, Chrissos & Karantza, 2020).

6 FUTURE INSIGHT AND IMPROVEMENT

While the result produced by this research is robust and convincing, there could still be some potential flaws that might lead to errors. One limitation of this research is the small sample size. Because of the unavailability of sufficient data, the only observation units are the seven restaurants in New York City. For future research, more samples should be added across different regions to confirm the result's significance. Another way this research could be improved is by adding more control variables. Many factors could impact a restaurant's customer flow. This research did not account for all the possible factors and may have ignored some unfound possibilities and confounding factors.

Future research could also use additional data to examine each restaurant's influence level from the war. Although this research confirmed the war's impact on consumer preferences, it is uncertain why some Ukrainian restaurants experienced higher customer growth than others. Future research could build on top and study some notable characteristics of a restaurant that would determine its level of influence from external shocks like war or covid.

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