Influence of Menu Typeface on Customer's Price Perception

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ABSTRACT

Inspired by studies (*Poundstone, 2010; Creger, 2014*) that have been done in menu design for restaurants, we proposed and conducted an experiment to understand the influence of menu typeface, specifically Serif vs Sans Serif, on people's price perception of the food item. Our experimental design includes a full factorial design (2 * 3) exposing online survey respondents to food items in a randomized combination of Serif vs Sans Serif fonts of three font families (PT, Roboto, Josefin). Our study on 241 qualified respondents showed no statistically significant treatment effect of switching menu items from a Sans Serif to a Serif font. But the interpretation of our analysis is limited due to concerns like lack of sample size and poor quality of online survey responses. Hence, we also discuss further improvements to our experimental design for further replications.

1. INTRODUCTION

Running a business is difficult. Running a restaurant where the meal, the ambiance, and the service dictate your revenue is even trickier. Each of those three parts of running a restaurant have even more nuanced elements, ones that should be studied to best understand how to create the ultimate restaurant experience for a customer. One such element is the menu, the one item that is read intently and scrutinized by the customers that will then decide on which dishes they will order and thus whose prices will contribute to the restaurant's revenue. Menus play such an important role in restaurants, so it is no surprise that menus have been carefully studied and optimized to influence a customer's decision. Theories such as placing expensive dishes on the top right corner *(Poundstone, 2010)* have been long debated and shaped the way menus are formatted today *(Creger, 2014)*.

We propose testing if the specific typeface on a menu can make a difference. Fonts are critical in things like newspapers and magazines to birthday cards, making a great case that perhaps an element beyond simply a font, but a specific typeface, is important in restaurant menus too (Poole). In our specific study, we question if the difference between the typefaces Serif and Sans Serif make a difference. The difference in these typefaces lie in the finishing strokes of each letter. The Serif typeface, thought to be traditional and classic, has defined, pointed edges that finish off the letter ends. In contrast, the Sans Serif typeface, thought to be contemporary and modern, has no such defined stroke at the ends of its letters.

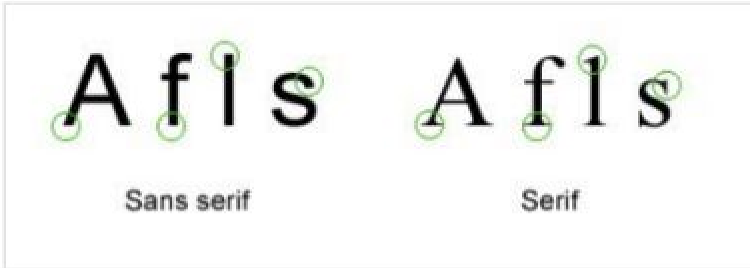

Figure 1 Difference between Sans Serif and Serif typeface, from alexpoole.info

Thus we propose an experiment to test the following research question: does typeface on a menu, Serif versus Sans Serif, really affect a customer's perception of prices. If so, we believe that there may be value in restaurant owners changing their menus to have the typeface that best suits their pricing strategy. We defend our efforts in running an experiment based on several reasons. Firstly, we seek to test a hypothesis that has not yet been tested, and more importantly has no evidence or data to be analyzed from which to draw a conclusion. In addition, testing our hypothesis requires intervention in the real world to obtain the information needed. Lastly, we require the *right* kind of data, encompassing all the required factors and elements of the study, allowing us to make the most informed analysis. These reasons require us to create and conduct our own experiment.

Though we hypothesize that type fact in fact does affect a customer's perception of prices, we have no predisposition in how exactly the effect may take place. Will Serif, the typeface considered traditional and classic make customers think that the items on the menu are the same way and thus expect their prices to be more expensive, or will the modern, contemporary design of the San Serif typeface cause customers to believe that these dishes match that in being fresh and new and thus more expensive (Caplan)? We cannot hypothesize one way or the other and therefore will hold a two tailed hypothesis.

2. EXPERIMENTAL DESIGN

2.1 Control versus Treatment

To the best of our abilities, we designed our survey experiment to account for and accurately measure covariates, demographic data, and our final outcome values.

The goal of our survey design was to show a survey taker various menu items presented in different fonts, some of which contained the Serif typeface and others that had the Sans Serif typeface and allow survey takers to inform us of their perception of that menu item's monetary value. In doing so, every element of the survey was carefully evaluated and included in the survey for a distinct purpose.

Firstly, we determined the definitions for the control and treatment groups. The control scenario consists of menu items written in various fonts (Roboto, PT Sans, Josefin San), all of which belong to the Sans Serif typeface while the treatment scenario consists of menu items in the same font family but the Serif typeface (Roboto Slab, PT Serif, Josefin Slab). With two typefaces and three font families, our experiment had a 2 * 3 factorial design so that we get to investigate the treatment effect of switching from Sans Serif to Serif within different fonts.

2.2 Creating the Survey: Fonts, Menu Items, Quantity

Though we distinguish between the Sans Serif and Serif typeface in our control and treatment scenarios respectively, we display each of our menu items in different fonts as mentioned above. Ultimately, every font we used would be displayed in one of two ways: Sans Serif (control) and Serif (treatment). In deciding which fonts to use, we were restricted in two ways. First, due to budget constraints, we could only choose fonts from those that were available for free on Google docs, the typing platform we used to create our menu item descriptions. Secondly, of these free fonts, we chose fonts that displayed a clear distinction between their Serif and Sans Serif typefaces. These constraints led us to choosing three different font types: Roboto, PT, and Josefin, each in their Serif and Sans Serif typefaces. This translated into 6 different ways we can show each food item. They way we decided to show each food item is via screen shot images of the item in the designated font and typeface.

Next, we designed our survey to host six different menu items. To establish some uniformity, we chose items from various menus that were all priced within the $15 to $25 range. Because we have six different font and typeface combinations, we chose one entree from each of six different restaurants, each of a different cuisine. The six cuisines we chose included: Indian, Mexican, Japanese, Italian, Chinese, and American. We believed that having dishes from various cuisines could help us in our analysis to control for people's biases towards certain cuisines and better estimate our treatment effect.

In addition to these factors, we included some demographic questions to account for covariates in our survey takers as well. This is explained in Section 3 "Experimental Implementation" below.

2.3 Language in Our Survey

One of the most crucial parts of our survey design was the articulation of descriptions in our questions. There were two major components or areas of articulation. One was the description of the restaurant from which the menu item originated. We provided a description of the restaurant as a way for survey takers to have some context on the type of restaurant and where the restaurant was located, hoping to reduce the variance of their responses. Second was the phrasing of our question or prompt to our survey takers to gather their answers which would make up our outcome variable values. Our framed question reads "What is the price you would expect to see for this particular item on the menu for this restaurant?". It allows us to capture the exact perception of the monetary value that this survey taker believed this menu item was worth. This was important to distinguish from what they believed "the standard price of this item" was or "how much they were willing to pay" as both of these statements measure a different outcome variable.

3. EXPERIMENTAL IMPLEMENTATION

After researching survey platforms, we decided to conduct our experiment via SurveyMonkey. The main reason for this was due to the fact that we needed the ability to randomize the 6 different font images that are shown to our subjects for each food item. Each subject needed to have an equal chance to be exposed to treatment (Serif) images and control (Sans Serif) images. SurveyMonkey's A/B question generator gave us the ability to do just that. The details of how this was done is in section 3.2 below.

In terms of our target population, we decided to send the survey only to US based contributors within the SurveyMonkey audience. This is because our restaurants and menu items were chosen from the US. Additionally, this allowed us to standardize our price measurement units in USD. SurveyMonkey randomized the respondent audience for us across major demographics such as age, gender, income and location.

3.1 Covariate Data Gathering

SurveyMonkey provided some covariate information for each respondent like age (in buckets), gender, household income (in buckets), US region, and device type. We decided to collect similar covariate information, but in actual units as opposed to buckets (i.e. actual age, actual income, and zip code). In addition to these covariates, we collected food preference for each respondent - vegan, vegetarian, pescatarian, omnivore, or other. This was used as an additional control in our analysis. The breakdown of each covariate distribution among the total respondents is detailed in Tables 3.1.1 to 3.1.5 below.

ANSWER CHOICES	RESPONSES	
< 18	0.00%	0
18-29	19.16%	105
30-44	25.00%	137
45-60	28.10%	154
> 60	27.74%	152
TOTAL		548

Table 3.1.1 - Sample population breakdown by age

ANSWER CHOICES	RESPONSES	
Male	46.72%	256
Female	53.28%	292
TOTAL		548

Table 3.1.2 - Sample population breakdown by gender

ANSWER CHOICES	RESPONSES	
$0-$9,999	9.85%	54
$10,000-$24,999	12.59%	69
$25,000-$49,999	19.16%	105
$50,000-$74,999	12.04%	66
$75,000-$99,999	11.31%	62
$100,000-$124,999	7.12%	39
$125,000-$149,999	4.74%	26
$150,000-$174,999	1.82%	10
$175,000-$199,999	2.92%	16
$200,000+	4.93%	27
Prefer not to answer	13.50%	74
TOTAL		548

Table 3.1.3 - Sample population breakdown by household income bucket

ANSWER CHOICES	RESPONSES	
New England	9.09%	49
Middle Atlantic	14.66%	79
East North Central	15.77%	85
West North Central	8.53%	46
South Atlantic	13.73%	74
East South Central	3.90%	21
West South Central	10.58%	57
Mountain	10.58%	57
Pacific	13.17%	71
TOTAL		539

Table 3.1.4 - Sample population breakdown by region

ANSWER CHOICES	RESPONSES	
Vegan	3.21%	11
Vegetarian	6.41%	22
Pescatarian	4.08%	14
Omnivore	60.93%	209
Other	25.36%	87
TOTAL		343

Table 3.1.5 - Sample population breakdown by food preference

Overall, the distributions among these covariates look evenly distributed with appropriate spikes and valleys in the Omnivore food preference and East South Central region respectively.

3.2 Price Data Gathering

As discussed in section 3, our experimental design consisted of 6 different food items, which translated into 6 different survey questions - 1 question per food item. Each question consisted of the following:

1. Restaurant's description
2. An image of the food item's name and description in the font and typeface randomly selected with a thick black border highlighting the image
3. A question asking the respondent to enter the price they would expect to see on the menu

As noted in section 3, we chose 3 fonts in two typefaces (Serif - Treatment and Sans Serif - Control), which translated into 6 images, one of which was randomly picked per food item. Figure 3.2 below shows a snapshot of the first food item's survey question.

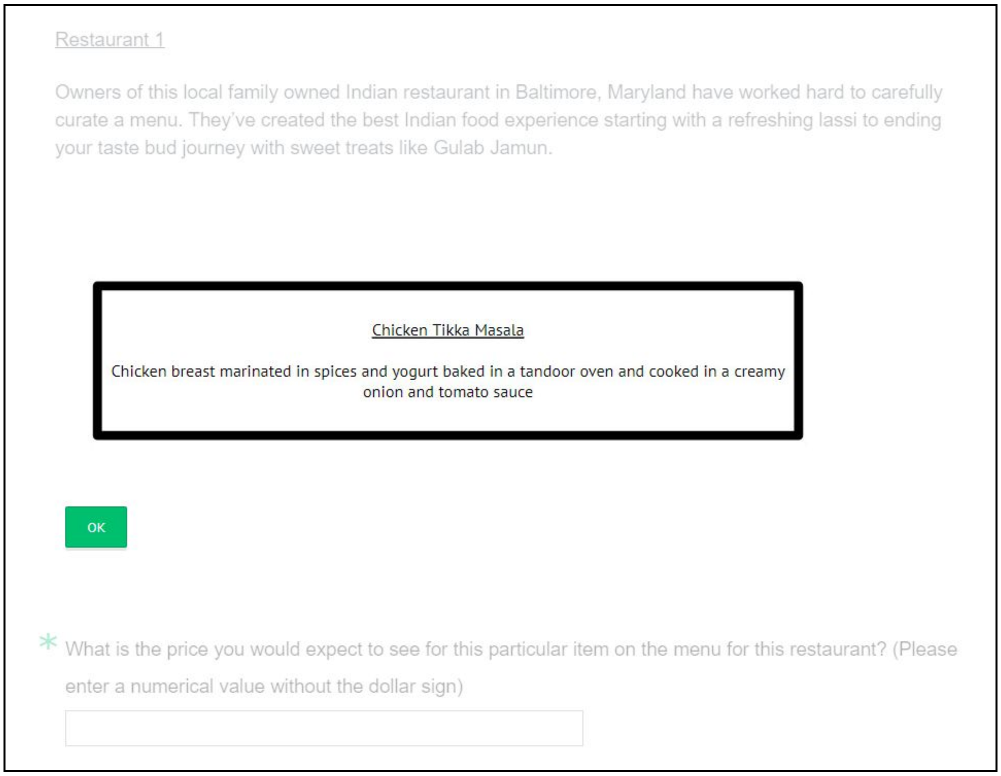

Figure 3.2 First food item's survey question

The description of Chicken Tikka Masala, which is shown in PT Sans Serif in Figure 3.2, was 1 of 6 possible images that SurveyMonkey's A/B image generator supplied to the survey respondent. SurveyMonkey's A/B generator worked by the survey designer supplying it *n* amount of images per question. SurveyMonkey then randomly picked one of those images to be viewed for each question and response instance. Therefore, each image had a *1/n* chance of being viewed for each question. In our case, each image, or font and typeface combo, had a 16.67% chance of being viewed for each food item. This was confirmed, with slight variance, by our final data shown in Section 5 -Table 5.2 further down below.

3.3 Bias Exclusions

As a final question to the survey, we asked our respondents whether they researched the prices of the items via Google. This question allowed us to determine whether the responses were biased via research and remove these responses accordingly from our final analysis.

4. PILOT STUDY

Before sending out a final survey to our audience, we conducted a pilot study of 50 respondents to ensure we received the right data, that our survey design worked as expected and our randomization worked well. As a result of conducting the pilot study, we learned the following:

1. One of our images for one of the 6 items was named incorrectly by duplicating another image's name. Therefore, we weren't able to distinguish which responses applied to which of the two images. This was fixed for the final survey.
2. In our initial pilot study, we didn't have a restriction on range of prices the respondents supplied. Therefore, we received responses with some prices over $100 inflating our effect, most likely incorrectly. This resulted in us constraining the price to be below $100 for the final survey.
3. We realized that our income question may have been too general. Therefore, we changed the wording to be pre-tax gross income versus just income.
4. We realized that our location question was also too general. Therefore, we changed it so users would have to write in their city, select their state from a drop down list of states and write down their zip code.
5. Many respondents from the pilot study ended up taking the survey on their mobile device or tablet. We realized when viewing the images of the food items via a mobile device or tablet, you couldn't differentiate between fonts or typefaces since the images were too small. This resulted in us creating a disqualifying first question by asking respondents what type of device they were using. If they responded with anything other than laptop or desktop, they were automatically disqualified from taking the survey.

Our final survey can be access via this link: [Pricing Research]

5. DATA AND ANALYSIS

5.1 Final Data Collection

In our final experiment, we sent out surveys on SurveyMonkey to a total of 548 respondents. Out of which, we disqualified 245 respondents since they didn't pass the screening criteria of using a desktop/laptop. Out of the people who claimed to use a desktop/laptop, 51 respondents dropped out of our survey midway. For our analysis, we excluded people who did any of the following:

- Respondents who actually were using mobile devices (information provided by SurveyMonkey)
- People who googled for an item price (self-reported)
- People who entered $0 as at least of their estimated price.

After these disqualifications, we ended up with responses from 241 unique respondents. Because we have 6 menu items for each respondent to give us information about, we had in total 1446 observations for our analysis.

Out of these 1446 observations, 733 observations were in a Sans Serif font (control group) and 713 were in a Serif font (treatment group). A detailed and summarized breakdown is shown below:

	Serif	Josefin	PT	Roboto	Total
Item 1	0	41	34	41	116
	1	43	42	40	125
Item 2	0	48	39	53	140
	1	32	35	34	101
Item 3	0	30	46	49	125
	1	37	38	41	116
Item 4	0	43	36	43	122
	1	36	41	42	119
Item 5	0	37	47	36	120
	1	39	42	40	121
Item 6	0	40	41	29	110
	1	47	35	49	131
Total	NA	473	476	497	**1446**

Table 5.1 Detailed breakdown of treatment assignments for each menu item.

Typeface	Josefin	PT	Roboto
Sans Serif	16.39%	16.46%	17.08%
Serif	16.18%	15.84%	16.80%

Table 5.2 Summarized breakdown of font and typeface assignments

For the 241 qualified respondents, 111 were male and 130 were female. Their age ranged from 18 to 86 with an average of 50 and their median annual pre-tax income was $45,350.

5.2 Covariate Balance Check

Besides respondents' price perceptions, we also collected covariates to control for in our treatment effect analysis. As a reminder, these covariates include gender, age, annual pre-tax income, location of residence, and food preference.

To ensure the integrity of our randomization process, we first did a covariate balance check to see whether these covariates had any predictive power for our treatment variable. To do this, we constructed two linear models:

$$Y_{Serif} = 1 \quad \ldots\ldots \ (5.1)$$

$$Y_{Serif} = 1 + \beta_1 * Age + \beta_2 * Income + \beta_3 * Male + \beta_4 * Region + \beta_5 * Food\,Preference \quad .. \ (5.2)$$

Where Y_{Serif} is a binary variable indicating that this item has a serif font when 1 and sans serif font when 0; *Age* is a continuous variable; *Income* is a continuous variable; *Male* is a binary variable indicating a male respondent when 1 and female when 0; *Region* is a vector of binary variables for different regions; *Food Preference* is a vector of binary variables for different food preferences.

We used linear model (1) as a dummy model to be compared as a baseline for the ANOVA analysis where we computed the F statistic of model (2) compared to model (1). As a result, we got a p-value of 0.92, indicating a lack of evidence to reject the null hypothesis that $\beta_i = 0 \ \forall i$. This means that we have balanced covariates and our randomization worked as expected.

5.3 Treatment Effect Modeling

To analyze the treatment effect of our treatment variable, *Serif,* we constructed three different linear models of differing complexities. The first model is a model that includes the full factorial experimental design but no covariates:

$$Y_{Price} = \beta_1 + \beta_2 * Serif + \beta_3 * Font\,Family + \beta_4 * Serif * Font\,Family + \beta_5 * Item\,Number \quad .... \ (5.3)$$

Where Y_{Price} is a continuous variable for people's price perception; *Font Family* is a vector of binary variables for different font families (eg. PT, Roboto, Josefin); *Item Number* is a vector of binary variables for different food items.

The second model includes the full factorial experimental design and covariates we intended to control for:

$$\begin{aligned} Y_{Price} = \ & \beta_1 + \beta_2 * Serif + \beta_3 * Font\,Family + \beta_4 * Serif * Font\,Family + \beta_5 * Item\,Number + \\ & \beta_6 * Age + \beta_7 * Income + \beta_8 * Male + \beta_9 * Region + \beta_{10} * Food\,Preference \quad \ldots\ldots. \ (5.4) \end{aligned}$$

The third model includes the full factorial experimental design, covariates we intended to control for, and another level of interactions between *Serif, Font Family,* and *Item Number.* This is to look for heterogeneous treatment effects of 1) serif font, in a specific font family 2) serif font, regardless of font family 3) a specific font family, regardless of being a serif font or not, on the different food items.

$$Y_{Price} = \beta_1 + \beta_2 * Serif + \beta_3 * Font\,Family + \beta_4 * Item\,Number + \beta_5 * Serif * Font\,Family + \beta_6 * Serif * Item\,Number + \beta_6 * Font\,Family * Item\,Number + \beta_7 * Serif * Font\,Family * Item\,Number + \beta_8 * Age + \beta_9 * Income + \beta_{10} * Male + \beta_{11} * Region + \beta_{12} * Food\,Preference \quad \ldots\ldots (5.5)$$

We then performed OLS regressions for these three models and the results are in the following figure.

	Dependent variable:		
		Item_Price	
	(1)	(2)	(3)
Constant	13.729***	14.410***	14.260***
	(0.540)	(2.283)	(2.895)
Serif	-0.581	-0.300	-1.510
	(0.470)	(0.783)	(1.189)
factor(Font_family)PT	0.809	0.882	-0.996
	(0.603)	(0.831)	(1.434)
factor(Font_family)Roboto	0.347	0.564	0.665
	(0.532)	(0.769)	(1.386)
factor(item_number)2	1.336**	1.330**	0.732
	(0.541)	(0.533)	(1.304)
factor(item_number)3	4.462***	4.455***	5.053**
	(0.653)	(0.648)	(2.050)
factor(item_number)4	3.487***	3.493***	1.206
	(0.801)	(0.796)	(1.531)
factor(item_number)5	5.760***	5.765***	4.364**
	(0.823)	(0.813)	(1.824)
factor(item_number)6	2.403***	2.404***	2.690
	(0.644)	(0.633)	(2.152)
Income		0.00002***	0.00002***
		(0.00000)	(0.00000)
Age		0.006	0.008
		(0.013)	(0.014)
Male		-0.351	-0.280
		(0.473)	(0.482)
factor(Food_Preference)Vegan		-6.076***	-5.902***
		(0.743)	(0.781)
factor(Region)West South Central		-4.690**	-4.203
		(2.142)	(2.624)
Covariates?	No	Yes	Yes
Interaction between Serif and Font?	No	Yes	Yes
Interaction between Serif, Font, and Item?	No	No	Yes
Observations	1,446	1,446	1,446
R2	0.048	0.101	0.118
Adjusted R2	0.043	0.084	0.085
Residual Std. Error	8.854 (df = 1437)	8.659 (df = 1419)	8.654 (df = 1394)
F Statistic	9.046*** (df = 8; 1437)	6.117*** (df = 26; 1419)	3.645*** (df = 51; 1394)
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 5.1 OLS Regressions for model 5.3, 5.4, and 5.5. All interaction terms were insignificant and excluded from this table for clarity. Insignificant levels of food preference and region were also excluded for the same reason.

As shown in the results above, although our results were consistent in terms of the negative treatment effect for our treatment variable, Serif, we didn't see a statistical significance, indicating a lack of evidence to reject the null hypothesis stating that switching between Serif and Sans Serif font doesn't alter the price perception of a food item. However, we did see significance on food items, annual pre-tax income, being Vegan, and being from West South Central US. We can conclude that these are covariates with strong predictive power and should be included in a further study.

5.4 Randomization Inference

To accurately compute a p-value for our observed treatment effect, we decided to run a randomization inference for our observed outcomes. To do this, we replicated a simulated randomization which randomly assigns font family and typefaces (Serif vs Sans Serif) for each of the food item that our respondents saw, just like how it was done in the actual study on SurveyMonkey. Within each replication, we used the model (5.5) to compute the treatment effect, β_2. With 10,000 replications, we then plotted the kernel density estimates of the treatment effect in each simulation under sharp null hypothesis and compared our observed treatment effect (β_2 = -1.510, in model (5.5), as shown in figure 5.1).

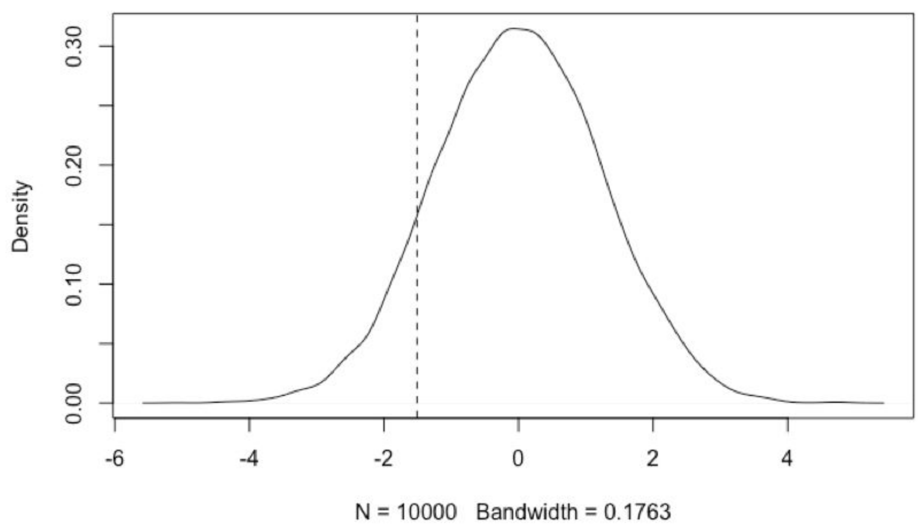

Figure 5.2 Observed treatment effect (dashed vertical line) plotted over the Kernel Density Estimates for our simulated treatment effect under sharp null hypothesis

This analysis resulted in a p-value of 0.22 for the two-sided alternative hypothesis. This indicates a lack of evidence to reject the sharp null hypothesis stating that our treatment had no effect on every individual.

5.5 Power Analysis

Although we could estimate the effect size from our pilot study, the lack of sample size for our pilot study, especially after disqualification criterion we had for our final experiment, likely resulted in an unrepresentative distribution for our effect size calculation. Hence, an ex ante power analysis would have been inconclusive.

However, based on our data from the final experiment, we performed a post-hoc power analysis. To simplify the computation of this power curve, we looked at the power of a two-sample t test comparing the treatment and control groups (Serif vs Sans Serif) using the observed effect size (Cohen's d), without considering all the covariates and interactions.

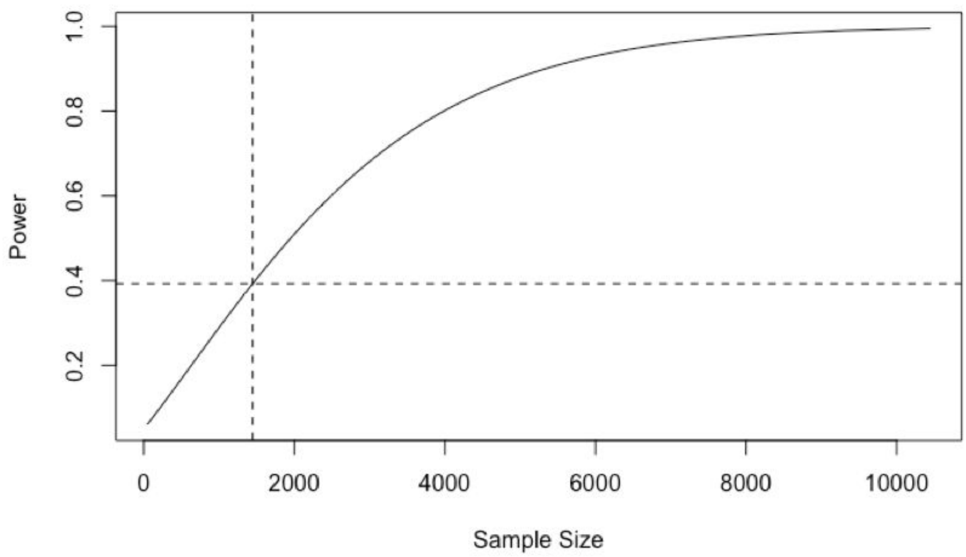

Figure 5.3 Power curve of a two-sample t-test comparing the treatment and control groups using the observed effect size (Cohen's d). The dashed cross lines indicates where our sample size and power is on the power curve

As shown above, with our observed effect size, our sample size only possessed a power of around 0.4.

5.7 Non-Compliance

In our experimental design, the treatment was exposing our subjects to a menu item in Serif font. Non-compliance may occur when our subjects 1) didn't pay much attention to our menu item or 2) couldn't visibly discern the differences between Serif and Sans Serif font. In both cases, they would have been considered as "never-takers" and it's very likely that they are inherently different from the compliers.

Unfortunately, we weren't able to design a way to measure the compliance in our survey without biasing our subjects (we didn't want them to know that we were experimenting with the menu typefaces). Hence, our estimated treatment effect is considered to be an "Intend-to-Treat" effect, strictly speaking.

6. CONCLUSIONS

As mentioned in the previous section, although we identified predictive covariates like income and food item, we didn't see a statistically significant treatment effect of using a Serif font vs a Sans Serif font on people's price perception in our experiment. And through our power analysis, we concluded that our experiment was lacking the power to achieve such significance. Putting aside the fact that we had only 241 qualified respondents, the treatment effect size was very low (Cohen's d = 0.06) and we saw high variance in respondents' answers. Without further replications and improvements upon this experiment, we don't have the confidence to conclude any treatment effect from this experiment.

To further improve this experiment, one of the biggest areas we want to address is to control for variance and improve the statistical precision on our treatment effect estimate. We plan to design a generic question as an "Item 0", which could be something common, like a beef burger in Arial font to be shown to every respondent. With that, we can then standardize their answers on item 1-6. This is similar to a traditional "Difference in Difference" design with a baseline to control for a large amount of the unexplained variance. However, we do see potential problems with this as some respondents could have a biased estimate for the first item, e.g. they overestimate the price for burgers, and, as a result, bias our measure on their price perceptions on the other items.

Another area we want to address is the quality and generalizability of our collected responses. We saw poor quality data from our final collection where some respondents were obviously trolling. We couldn't accurately measure how many of the answers were honest or whether the respondents indeed spent the time and effort to read the menu items. Moreover, we are concerned about the generalizability of our experiment as our data was solely collected from Survey Monkey and there might be things inherently different between people who work on Survey Monkey to people who don't. To address both concerns, we could perform in-person data collection in a variety of places of different demographics. This wasn't feasible in our case due to the time and financial constraints.

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APPENDIX

Restaurant Choices

City	Cuisine	Menu Item	Website Link:	Actual Price:
Baltimore, MD	Indian	Chicken Tikka Masala Chicken breast marinated in spices and yogurt baked in a tandoor oven and cooked in a creamy onion and tomato sauce.	http://www.namastebaltimore.com/	$15.99
Seattle, WA	Mexican	Camarones al Pastor pacific shrimp, grilled pineapple, dried poblano, pickled red onion	https://chavezrestaurants.com/restaurant-home-page/#menu	$20.00
Cleveland, OH	Japanese	Seafood Kushiyaki Shrimp, Scallops, Salmon, and vegetable skewers sautéed in Teriyaki	http://www.shuheirestaurant.com/dinner.pdf	$22.00
Washington DC	Italian	Insalata Nizzarda Nicoise Salad of House-Cured Mediterranean Tuna, Butter Lettuce, Hard Boiled Egg, Anchovy, Potato Green Beans, Tropea Onion, Taggiasche Olives, and Tomato Confit	http://www.cafemilano.com/menus/lunch	$18.00
New York, NY	Chinese	Beef Dry Pot Style Served in a sizzling mini wok and cooked in a spicy hot pot sauce with black mushrooms, bamboo shoots, bell peppers,	http://handynasty.net/brooklyn/menu/	$18.95

		and Sichuan peppercorns		
Denver,CO	American	Caramelized Pork Shank ginger-soy glaze, brussel sprouts, yukon mashed potatoes	https://www.corinnerestaurant.com/dinner-1	$24.95

Restaurant Descriptions

Item #1 - Chicken Tikka Masala - “Owners of this local family owned, Indian restaurant have worked hard to carefully curate a menu. They’ve created the best Indian food experience starting with a refreshing lassi to ending your taste bud journey with sweet treats like Gulab Jamun.”

Item #2 - Camarones al Pastor - “When Gabriel Chávez emigrated from Durango to Seattle he brought his family’s recipes with him. Lucky Seattle.”

Item #3 - Seafood Kushiyaki - “One of the most prominent Japanese restaurants in Cleveland, Ohio. The experience chef and staff aim to brings their loyal customers an authentic and unique dining experience.”

Item #4 - Insalata Nizzarda - “A famous Italian restaurant in Washington DC. Guests savor genuine Italian cuisine in a setting reminiscent of a stylish Milan boutique. Come and enjoy a memorable meal at your own special table or stop by for a signature cocktail at the bar. ”

Item #5 - Beef Dry Pot Style - “This authentic Sichuan restaurant in Manhattan’s East Village, creates dishes that are hard to obtain in other Sichuan style restaurants. With 45 minute waits, this restaurant provides a friendly atmosphere combined with delicious, Chinese cuisine.”

Item #6 - Caramelized Pork Shank - “This is downtown Denver’s newest buzzing dining and cocktail spot serving classic, simple American comfort food with an emphasis on locally-sourced ingredients.”