Discounting your advertising message : Investigating the effects of including price information in advertising

Job Market Paper

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Abstract

Does the presence of price (discount) information in advertising lower brand preference? Does it increase deal-seeking? Answering these questions requires an empirical comparison of the causal effects of ads that only vary in terms of the presence of price information (holding other information fixed), which the literature currently lacks. To address this, I design and implement a field experiment on a food delivery app with exogenous variation in advertising intensity, the presence of discount information in ads, and discount level for a focal restaurant. I track the effects of ads with and without explicit discount information ('price ads' and 'brand ads') through different stages of the purchase funnel (menu page; cart page; purchase). I find that the presence of explicit discount information in ads increases (decreases) demand at high (low) discount levels. Driving this, is the fact that the presence of discount information in ads creates differences in the rates at which consumers visit the restaurant menu page at different discount levels. Lowered demand at low discounts challenges the conventional wisdom of routinely highlighting any available discount in digital ads. More importantly, by comparing rates of conversion to purchase at the payment stage (cart), I find evidence that price advertising lowers brand preference. Conditional on arriving at cart and seeing the same discount, consumers who received price ads purchase at lower rates relative to those who didn't. This result is robust to controls for self-selection into visiting the restaurant cart page based on observables (with a causal forest), and unobservables (with a multi-stage model of self-selection). Nevertheless, price advertising, combined with a high discount, attracts more people into visiting the restaurant menu page, leading to revenue maximization despite lower conversion. This explains its pervasive use despite negative brand effects. Finally, price advertising for the focal restaurant causes consumers to shift their purchases among non-advertised rivals, towards those on discount, indicating increased deal-seeking on the platform as a whole. This has implications for rivals' pricing decisions and platform policy on ad content. However, these effects disappear within two weeks after the experiment ends. Managerial implications are discussed.

Keywords: Advertising content, field experiment, self-selection model, causal forest

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1 Introduction

Understanding the effects of advertising on demand has long been a major focus of marketing academics (Sethuraman et al., 2011). In particular, researchers have conjectured that advertising which focuses consumers on price instead of brand characteristics may have have negative consequences for brands (Mela et al., 1997). Empirical literature comparing price and brand advertising (Kaul and Wittink, 1995; Mela et al., 1997) has done so in very different contexts. Brand advertising has meant TV advertising by manufacturers and price advertising has meant local retailer advertising with features in newspapers or in-store displays. These types of ads vary in many ways apart from just the presence or absence of price information. For example, brand advertising may convey information about brand attributes which price advertising does not. In this paper, I aim to isolate the causal effects of the presence of explicit price (discount) information in advertising, holding other information fixed. In particular, my objective is to test whether the presence of price information in advertising lowers brand preference for the advertising brand. Testing for the effect on brand preference is difficult since price information in advertising affects demand in two ways, a direct effect of informing consumers of the price and any indirect effect on brand preference.[1] Since these effects are confounded, examining the overall effects on demand doesn't allow us to test specifically for an effect on brand preference. I use a novel approach to solving this problem by comparing rates of conversion to purchase among consumers who received different ads but are at a stage of the purchase funnel (payment stage) when information differences are eliminated. In doing so, I also measure the causal effects of ad creatives with and without explicit price information on overall demand for the advertised brand, elucidate their different effects at different stages of the purchase funnel and measure their spillover effects on non-advertised rivals in order to provide a more complete understanding of the effects of price information in advertising.

For academics, isolating the causal effect of one factor holding everything else fixed is routine and its value is obvious. However, such an exercise has not always been relevant for managers. Historically, the contexts in which price and brand advertising were used were very different. For example, the brand advertising studies in Kaul and Wittink, 1995 considered TV advertising and

[1] Note that lower brand preference would also lead to consumers being more price elastic. However unlike past literature, I don't focus on price elasticity directly for reasons explained later in the introduction

the price advertising studies considered local retailer advertising like features in newspaper inserts, in-store displays etc. In those contexts, brand and price advertising are not substitutes for each other, and studying the effects of the mere presence or absence of price information in advertising may not be very relevant to managers. However, in the online world of display advertising, email marketing and mobile push notifications, brand and price advertising are more comparable substitutes. Advertising in these contexts usually consists of a single image or a short message that is displayed to the consumer. If a discount is available, the conventional wisdom is that the limited space in a display ad should be used to highlight it (instead of more brand information). Google Ads, in its support page for advertisers, specifically mentions that including and highlighting discount information is good practice for creating effective display ads [2]. Firms invest a lot in optimizing their advertising content (Bertrand et al., 2010; Sudhir et al., 2016), but the dimension of whether to include discount information or not, has surprisingly been ignored; the assumption presumably being that more information about a discount is better.

Previous empirical literature (reviewed in Kaul and Wittink, 1995) comparing brand and price advertising has typically focused on effects on price elasticities. They have found that price advertising increases price elasticity and brand advertising decreases it (although some studies have also found that brand advertising decreases price elasticity). The fact that price elasticity increases with price advertising is not necessarily a bad thing for the advertising firm, especially if within-individual changes and changes in the composition of consumers who purchase are confounded. Raising willingness to pay (brand preference) of a marginal consumer who is more price sensitive is good for the brand, although it might lead to aggregate demand facing a brand becoming more price elastic. Also, informing more consumers when prices are low and thus raising demand and lowered prices would also lead to increased price elasticity of demand. However, this is the primary function of price advertising and an increase in price elasticity of demand as a result of this should not alarm the advertiser. What would be more troubling for the advertising brand is if price advertising, in addition to performing its function of informing consumers of discounts also lowered brand preference. However, as discussed above, disentangling the direct effect of providing additional price information and any indirect effect on brand preference is hard by just looking at

[2] https://support.google.com/google-ads/answer/1722134?hl=en

overall demand, since these arise from the same content affect demand at the same time. One way to remove the confound of the direct effect of additional information would be to look at long term effects. Information on current price changes should not affect future behavior, except through within-consumer changes in brand preference or price sensitivity. Mela et al., 1997 looks at the long term effects of promotions and brand advertising on price sensitivity. However, in that study, temporary price reductions, coupons and feature advertising are all considered forms of promotion. The effect of price advertising is not studied separately. Further, they use observational data which comes with the usual endogeneity concerns about measuring the causal effects of price changes and advertising. In this paper, I use a novel approach to show evidence of the contemporaneous causal effect of including price information on demand through a shift in brand preference, after accounting for the direct effect of additional price information.

Theoretical literature on advertising has suggested that it could increase brand preference (Comanor and Wilson, 1979; Bain, 1956). Researchers studying sales promotions have claimed that they could decrease brand preference (Aaker, 2012; Blattberg and Neslin, 1989). Price-advertising, by highlighting discounts and focusing consumer attention on price, could have the same effects. The impact of this would be that conditional on seeing the same price, purchase rates would be lower for an individual who saw a price ad relative to one who saw a brand ad. So, the relevant question is: if a consumer is faced with the same price for a product, does the fact that she has seen a price ad reduce her probability of purchase, relative to if she had seen the same ad without mention of price or hadn't seen any ads? Promotions for a brand could also prompt consumers to look for search for more deals in the category, as a whole (Rothschild, 1987). This prompts another question: does price advertising for a brand also have spillovers (Sahni, 2016) to other brands such that it increases her propensity to purchase other products that offer deals (deal-seeking)?

Measuring the causal effects of advertising on demand is challenging due to endogeneity concerns. In order to measure the causal effects of different types of advertising on demand at different price points, we need exogenous variation in prices, advertising intensity and advertising content. Varying all three dimensions in the same context is difficult. I partner with Swiggy, a food delivery platform in India to generate the required variation described above to study the impact of including price information in advertising. A major concern with previous studies that looked at price and brand advertising in different contexts (TV advertising vs local retailer advertising) is that the ads in those studies differed in many ways apart from the presence or absence of price information. Differences in demand arising from the two types of ads in different contexts cannot be attributed solely to the inclusion of price information. In my field experiment, I was able to use ad creatives that differed solely in price information content. All other relevant information was held fixed. The experiment was conducted on a sample of 195,516 customers for a duration of four weeks. Five different discount levels, five different advertising levels and three different ad creatives that differed in the level of price information content were used. Given the nature of the customer journey on the platform, the experimentally generated data also allow me to study the effects of advertising at each stage of the purchase funnel. One caveat about my experiment is that the platform is a high-discount environment and consumers receive ads with discounts regularly. Thus, even if no discount information is explicitly disclosed in an ad, consumers still have an inherent expectation of discount. Thus, the concept of a 'Brand Ad' is slightly different from that in the literature since it inherently comes with the expectation of a deal.

I find that the while any advertising shifts demand (orders from focal restaurant) out and makes it more elastic (consistent with Erdem et al., 2008), elasticity facing the advertised brand is higher with price advertising relative to brand advertising, thus confirming the proposal in Kaul and Wittink, 1995. Since elasticities are different, the profit maximizing price under the different types of ads are also different. Among the tested discount levels in the experiment, the optimal discounts[3] are: 20% under no advertising, 30% under brand advertising and 40% under price advertising, with 40% under price advertising being the best overall. Thus, managers have to first measure elasticities under the different advertising options and then jointly optimize over both price and type of advertising.

I find that differences in both the search and purchase conditional on search stages of the customer journey drive the differences in elasticity. Consumers use the additional information provided in price advertising to make a more informed search decision (probability of visiting the restaurant menu page changes with discount). Consumers who receive brand ads make the search decision based on their expectations of discount, formed from previous messages received from

[3]Since costs are not known, these are revenue maximizing prices (after accounting for the discount amount)

the platform (probability of visiting the restaurant menu page does not change with discount, but correspond to a discount level between 20% and 30% which is approximately the average advertised discount level on the platform). The type (according to their discount affinity based on purchase history) of people who search (visit the restaurant menu page) at each discount level also changes under price advertising but not under brand advertising. At low discount levels, I find that fewer people search for the brand (visit restaurant menu page) with price advertising relative to brand advertising, consequently leading to lower demand (number of orders). Thus the firm may be better off by removing discount information from the ad for low discount levels. This is consistent with the notion of uninformative advertising as an invitation to search (Mayzlin and Shin, 2011) and directly contradicts the conventional wisdom in digital advertising, including at the partner firm, to regularly include discount information at all discount levels. At higher discount levels, the additional information benefits the firm (leads to more menu visits and orders).

Firms in the digital space can change prices and messaging lower down the purchase funnel, for example, by sending cart abandonment messages with additional discounts. Measuring differences in conversion to purchase post search (at cart) between consumers who received price information in ads and those who did not, after full information including price is revealed to all consumers, is important for managers. This also helps us test for differences in the 'persuasive' effects of the different ads since informational differences are eliminated at this stage. Consumers self-select into search and it is important to account for this when comparing post search conversion rates. I using three different approaches to handle this: (a) I use a parametric model and control for observables constructed using the pre-experimental consumer data. (b) I use a non-parametric Causal Forest approach to match on observables; and (c) I account for selection on unobservables and observables by specifying a multi-stage model of self selection into the various steps of the customer journey and allowing error terms across stages to be correlated. Using all three approaches, I find that price advertising leads to lower post search conversion probability compared to brand advertising. The type of ad which led the consumer to the point of purchase matters, consistent with the hypothesis of a lower 'persuasive' effect for price advertising.

Finally, I find that consumers exposed to price advertising for the focal brand shift their purchases among non-advertised rivals towards those on discount. This is consistent with the hypothesis that consumers exposed to discount (or price) oriented messaging for a brand become more discount seeking in the category as a whole. Thus, price advertising for a focal brand has spillovers to other discounted brands. However, this effect is short-lived (disappears after two weeks). Brand advertising also has spillovers to rival brands, but does not cause a shift towards more discounted brands. This finding has implications for the nature of price competition among firms under different advertising regimes. While price advertising can have adverse effects for firms in terms of increased deal-seeking and reduced brand preference, price advertising along with a 40% discount is the overall revenue maximizing policy for the restaurant. Reduced conversion to purchase is being made up for by getting a larger number of people to search for the brand. This explains why price advertising along with high discounts is prevalent, despite the possible adverse effects.

In summary, this paper makes four contributions. First - using a field experiment, I bring new data that contains the variation needed to directly compare advertising with and without price information and empirically measure the causal impact of the presence of price information in advertising on demand. I show that while advertising shifts demand out and makes it more elastic, the presence of price information in ads further raises elasticity. This implies that managers should jointly optimize over the type of advertising and price. Second, this paper adds to the current literature on the different roles of advertising and how advertising affects the different stages of the consumer purchase funnel. Increased demand elasticity may arise due to directly informing consumers of prices ('informative') which would affect search, or reduced brand differentiation ('persuasive') which would affect purchase conditional on search. I provide empirical evidence in support of both mechanisms. I show that the while price information in ads enables consumers to adjust their decision to search for the brand according to price, it reduces conversion to purchase at the bottom of the purchase funnel. Third, it challenges conventional wisdom in digital advertising about routinely including discount information, if a discount is available. I show that revealing a low discount level (as opposed to not mentioning a discount at all) can actually reduce search and consequently demand. However, if combined with a high discount, price advertising is indeed optimal, thus explaining why the practice of price advertising in combination with high discounts is prevalent. Fourth, it contributes to the literature on advertising spillovers to rivals. I document positive spillovers of advertising to rivals consistent with previous literature and I also find that price advertising differentially benefits rivals that offer discounts. This differential impact has ramifications for price competition among firms under different ad types.

The remainder of the paper is organized as follows. First, I review relevant literature and its relation to this paper. In Section 3, I describe the empirical setting and experimental design. In Section 4, I present results on the impact of the different ads on overall demand. In Section 5 I examine the decision to search for the advertised brand and how the different ads affect this process. In Section 6, examine the conditional purchase decision post search. In Section 7, I examine the spillover effects of focal brand advertising on non-advertised rivals. In Section 8, I present managerial implications and in Section 9, I conclude by summarizing the key findings and directions for future research.

2 Related Literature

This paper contributes to three separate streams of the broader literature on advertising effects:

2.1 Advertising and its impact on price elasticity

Economic theories on the informative and persuasive roles of advertising (summarized in Bagwell, 2007) have opposite predictions on the effects of advertising on price elasticity. Chamberlin, 1933 laid out the basis for these theories. He argued that advertising affects demand because it (i) conveys information to consumers about the existence of products and their prices and qualities and (ii) alters consumers' 'wants' or tastes When advertising communicates information about the existence of the firm's product, the effect is to shift a firm's demand outward. If advertising conveys price information as well, then the firm's outwardly shifted demand curve may be more elastic, as more consumers are informed of a price reduction. But if advertising acts by creating wants through brand development, then the advertising firm's demand curve shifts out and may be made more inelastic. Stigler, 1961 and Nelson, 1970, 1974 who laid the foundations of the informative view of advertising, state that advertising, by providing information about brands can increase the consideration set and lead to higher price sensitivity among consumers. Bain, 1956 and Comanor and Wilson, 1979 who are proponents of the persuasive view, described the role of advertising as creating artificial product differentiation, thus creating brand loyalty and lowering sensitivity to price as a factor in brand choices. Becker and Murphy, 1993 argue that that advertising raises the demand elasticity. Starting from an equilibrium with no advertising, a firm would, ideally, like to target its advertising at marginal consumers whose willingness to pay (WTP) is just below the initial equilibrium price. Increasing the WTP of marginal consumers flattens the demand curve in the vicinity of the initial equilibrium, leading to more elastic demand at that point.

When it comes to price vs brand advertising, Chamberlin directly laid out the 'informative' mechanism by which price advertising could lead to more elastic demand. With price advertising, more consumers can be informed of a price reduction and can respond accordingly. The 'persuasive' mechanism is that price advertising, in contrast to the 'brand-building' effect of brand advertising, can lower brand differentiation by focusing attention on price. While this has not explicitly been stated by anyone in prior literature, there are similar ideas in the promotions literature. Sawyer and Dickson, 1984 claimed that when there are frequent promotions in a category, consumers attribute price as being the main differentiating factor between brands in that category (i.e. reduced brand differentiation on factors other than price). Dodson et al., 1978 proposed that when people purchase a product on discount, they attribute their choice to the low price rather than a high preference for the brand.

Next, we come to the empirical literature. The contradicting theoretical views on the effects of advertising on price elasticity spawned many empirical studies in marketing, summarized in Kaul and Wittink, 1995. Experimental (Bemmaor and Mouchoux, 1991; Moriarty, 1983; Woodside and Waddle, 1975) and observational studies (Popkowski Leszczyc and Rao, 1990; Bolton, 1989) that looked at price advertising contexts, found that price elasticity increases with advertising. Similarly experimental (Staelin and Winer, 1976; Prasad and Ring, 1976; Krishnamurthi and Raj, 1985) and observational (Lambin, 1976; Vanhonacker, 1989; Ghosh et al., 1983) studies that looked at brand advertising contexts found that price elasticity decreases with advertising. There are also important exceptions that include Kanetkar et al., 1992 who found that increased brand advertising increased price sensitivity, and Erdem et al., 2008 who showed that the demand curve facing a brand is shifted outward and made more elastic under brand advertising using a household level brand choice model. Erdem et al., 2008 stress the importance of looking at how the demand curve shifts out as a whole instead of all the different conceptualizations of demand elasticity in the studies reviewed by Kaul and Wittink. They point out that in the earlier studies price sensitivity has been measured by either the interaction between price and advertising in a sales response function, the derivative of the brand choice probability with respect to price, or the price elasticity of demand. And, these quantities have been calculated at various levels of aggregation (i.e., the market, brand or individual household levels). These different conceptualizations of elasticity could give rise to conflicting results - looking at how advertising shifts the demand curve shifts as a whole gives us the full picture. Following a similar theme as empirical studies above, but focusing more on the long term effects, Mela et al., 1997 studied the long term impact of price promotions and brand advertising on consumer price sensitivity. They found that consumers become more price sensitive over the long term if they are exposed to more price promotions and less brand advertising.

This is the stream of literature that is most closely related to this paper. My contributions to this literature are as follows. First, I confirm the finding in Erdem et al., 2008 that advertising shifts out the overall demand curve facing a brand and makes it more elastic. This is consistent with the informative view of advertising. Next, I test whether price ads make demand more elastic relative to brand ads, holding all other factors fixed. I find that this is indeed the case. Further, I test for evidence of two possible mechanisms arising from differences in the 'informative' or 'persuasive' effects of brand and price ads as described above, by examining the effects of these ads on different stages of the purchase funnel. I find evidence in support of both mechanisms. This brings us to the next stream of literature.

2.2 Effects of advertising on different stages of the purchase funnel

Several empirical researchers have tried to distinguish between the effects of advertising on the different stages of the consumer purchase funnel. Johnson et al., 2017 measure display ad effects on increasing website visits and conversions. Clark et al., 2009; Draganska and Klapper, 2011; Terui et al., 2011; Honka et al., 2017 look at whether advertising primarily acts as a shifter of the consumer search process through awareness and consideration or the purchase decision conditional on search.

Related to this, I also provide empirical evidence in favor of the notion of of uninformative advertising as an invitation to search (Mayzlin and Shin, 2011). Mayzlin and Shin set up a theoretical model where a firm that produces advertising messages devoid of information about an attribute may enjoy increased consumer search due to the consumer expectation that they will uncover positive information about that attribute. Brand advertising in my context is uninformative relative to price advertising (i.e. price advertising contains strictly more information), and I find that brand advertising does lead to higher search compared to explicitly specifying a low discount in price advertising.

2.3 Spillover effects of advertising

While spillover effects of price vs brand advertising haven't been studied before, several papers have found evidence of positive advertising spillovers. For example Sahni, 2016 finds experimental evidence of positive spillovers to rivals in online restaurant advertising. Lewis and Nguyen, 2015 and Anderson and Simester, 2013 find evidence of positive spillovers in online and mail advertising respectively. Shapiro, 2018 finds evidence of positive advertising spillovers in the market for antidepressants. I contribute to this literature by investigating the differences in spillover effects of brand and price advertising on non-advertised products in the category - specifically whether other discounted products in the category benefit more from consumers being exposed to price oriented advertising from the focal brand relative to brand oriented advertising.

3 Empirical Context and Experiment Design

The data for this paper come from Swiggy, a food delivery mobile app platform in India. The platform serves multiple cities in India and is one of the largest players in the food delivery business. Swiggy partners with more than 50,000 restaurants and consumers can order meals from any of the partner restaurants that service their location though the Swiggy mobile app. Swiggy regularly sends its customers in-app mobile push notifications informing them of offers, newly listed restaurants etc. The majority of offers advertised through push notifications are applicable on the entire platform or several restaurants on the platform. Some of these offers also inform customers of offers for specific restaurants on the platform. Consumers can click on these push notifications and directly go to the relevant page on the app to take advantage of the offer, or go to the app independently and select a restaurant to order from and then redeem the offer on their order.

I address the challenges in measuring the causal effects of different types of ads at different price points by designing an experiment to create exogenous variation in advertising intensity, price information content in advertising and prices for a focal restaurant on the platform. For this experiment, a focal restaurant on the platform was chosen to be advertised to consumers through in-app mobile push notifications. A sample of Swiggy customers were randomly assigned to receive these push notifications with a frequency of 0, 1, 2, 3 or 4 notifications a week for a period of four weeks. A discount was made available to customers as a percentage off of their total meal value. One of 5 discount levels: 0%, 10%, 20%, 30% or 40% was assigned randomly to consumers in the experiment sample. This discount was valid for all purchases [4] from the restaurant through the entire experiment period. The availability of the assigned discount was also independent of whether the consumer received any ads or not. Anyone who ordered from the focal restaurant also received free delivery on their order as a baseline offering, regardless of the discount level assigned. Customers in the experiment sample were also randomly assigned to one of three ad type conditions: Brand Ad, Intermediate Ad and Price Ad. The brand ad does not contain any information about the available discount. The intermediate ad mentions that there is a discount available but does not specify how much. The price ad highlights the available discount percentage in block letters. Apart from information on the available discount, the remaining information content about the focal brand across the three types of ads is the same. This helps us measure the causal effect of the mere inclusion of price information in advertising. The actual creatives for the different types of ads are shown in Figure 1 and Figure 3 shows an actual screenshot of a phone to demonstrate how the notifications show up on a phone screen.

Randomization of discount level, ad frequency and ad type were done independently of each other, except for one exception - individuals who were assigned 0% discount were only assigned the Brand Ad condition (since they couldn't be given false information of a discount that was not available to them). To clarify the availability of the discount once again, the discount assigned to the consumer was available to them regardless of whether they received an ad or which type of ad they received. Consumers did not have to put in a coupon code to redeem the offer - the offer was

[4] Upto a cap of four purchases a week and a maximum discount amount of Rs. 100 per order. Robustness checks with controls for 'hitting the cap' in terms of maximum number of orders per week or the maximum discount amount were done to ensure that these events don't affect the main findings

automatically applied to any 'cart' that was created by the consumer for the focal restaurant.

Table 1, Table 2 and Table 3 show how the discount, frequency and ad type were distributed among the experiment sample. A total of 195,516 individuals were included in the experiment.

The individuals in the experiment sample were chosen such that:

- They have an android device (as push notification delivery can only be tracked on android and not on iOS)
- They have made atleast one order on Swiggy in the three months preceding the start of the experiment
- They were reachable by push notification during the week before the experiment
- They have had atleast three Swiggy sessions (i.e. they have opened the app atleast three distinct times separated by a gap of atleast 90 minutes) in the month preceding the start of the experiment in which the focal restaurant has appeared in their restaurant listings. This is to ensure that they live or work in the areas serviceable by the focal restaurant (only serviceable restaurants show up in the listings).

To make a purchase from a restaurant, the consumer has to first go to the restaurant menu page. A consumer can reach the menu page of the restaurant in the following ways:

- Click on the push notification ad, following which the Swiggy app opens on the phone and the consumer is taken to a landing page with a link to the restaurant menu page
- Open the app independent of the ad, and click on the focal restaurant on the restaurant listings page
- Search for a cuisine or the restaurant name, following which the focal restaurant shows up as a listing in the search results, which the customer can then click

At the menu page, the different dishes available in the restaurant are displayed along with their individual prices (without discount). The consumer can add dishes that they are interested in purchasing to their cart. At cart, the final price of the meal after discount is displayed to the consumer. She then makes the decision of whether to purchase the meal at the displayed price or not. If she decides to purchase, she can enter her exact delivery location, pay and finish ordering. The different stages of the purchase funnel are diagrammatically represented in Figure 2. Screenshots of the different pages along the customer purchase funnel described above are shown in Figures 3, 4 and 5.

It is important to note that the exact discount percentage available to each customer is either disclosed to the consumer through the price ad, or it is revealed only after the consumer visits the cart page. Thus, until the consumer visits the cart page, the differences along the purchase funnel arise due to the different levels of information disclosed to her through the different types of ads. However, upon reaching the cart, all consumers see full information about the discount regardless of the type of ad they were assigned to. This setup allows us to disentangle differences in demand arising from the differences in the 'informative' and 'persuasive' effects of different ads. Decisions upto the 'cart' stage are driven by 'informative' effects and the purchase decision conditional on reaching cart is driven by 'persuasive' effects.

3.1 Data

I observe a rich set of historical data as well as data generated during the experiment for each consumer - their purchases, their visits to different pages along the purchase funnel, including visits to menu and cart pages of any restaurant. I observe the total meal value that the customer adds to their cart and the final price after applying the available discount. I also observe whether each push notification was sent, received, and clicked on (both for historical and experimental push notifications).

When a push notification is sent, it may not be received by the consumer due to various reasons - she has turned off notifications or uninstalled the app, she is out of reach of the network or in some cases the phone suppresses push notifications in case battery level is below 15%. In case a notification is not received by the consumer, I can observe whether that event is due to either a 'send error' i.e. the app has been uninstalled or push notifications have been turned off, or a 'receive error' i.e. the phone is out of reach of network or push notifications have been temporarily suppressed by the phone. About 44.3% of the sample received atleast one fewer notification than what they were assigned. Most of these instances are due to a single notification not being delivered. Table 4 shows the share of customers that received n fewer notifications than assigned for all values of n upto 16. 13.3% out of the total 44.3% received fewer notifications than they were assigned due to a 'send error' i.e. they turned off notifications or uninstalled the app atleast for some time during the experiment. The remaining 31% received fewer notifications due to network or battery issues. I deal with potential self selection concerns due to people receiving a different number of notifications than what they were randomly assigned to receive in two ways: (1) For some parts of the analysis, I just use the assignment of customers to different types of ads without using the frequency. Only 26 people in the entire sample received zero notifications when they were not assigned to zero ad frequency. Thus, virtually the entire sample received atleast one ad, if they were assigned to receive any ads. Thus, the effect of having being assigned to a particular ad type and receiving atleast one ad is correctly captured. (2) For parts of the analysis that uses a goodwill stock model of advertising, which uses ad frequency, I do a robustness check by restricting the sample to just the people who received exactly the number of ads they were assigned experimentally. Another robustness check is done by replacing the goodwill stock of advertising by a dummy variable indicating whether an ad has been seen on or before by the consumer to measure the effect of having seen atleast one ad of the assigned type. All results carry through.

4 Overall Effect on Demand

In this section, I explore the effects of the different types of ads on overall demand for the focal restaurant. As described in the introduction and literature review sections, past literature has found conflicting evidence of whether advertising increases or decreases elasticity of demand. Further, the differences in elasticities arising from brand and price advertising have never been compared directly in the same context. In this section we will test the hypothesis that the mere presence of price information in advertising increases the elasticity of demand compared to a brand ad that contains essentially the same information except for price. Since other information was held fixed, the effects we find are purely driven by differences in the level of price information included in the ads.

Figure 6 shows the probability of a customer placing atleast one order with the focal restaurant under the different ad conditions. First, we see that all the different types of advertising increase demand. As a baseline, the effect of brand advertising is higher at higher discount levels compared to lower discount levels - showing that the overall demand curve is more elastic under advertising. Then, comparing brand advertising and price advertising, we see that price advertising performs worse at lower discount levels but does better than brand advertising at high discount levels. Thus, the demand curve is more elastic under price advertising compared to brand advertising. The finding that brand advertising leads to higher overall demand flies directly in the face of conventional wisdom in digital advertising that suggests that including discount information is always more effective.

Next, I use the full panel with data at the individual-day level and utilize the variation in ad frequency to measure ad effects using the following demand model:

$$\begin{aligned} y_{it} = \alpha + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \gamma_3 ad_{it}^{intermediate} + \beta discount_i + \nu_1 (ad_{it}) * (discount_i) \\ + \nu_2 (ad_{it}^{price}) * (discount_i) + \nu_3 (ad_{it}^{intermediate}) * (discount_i) + \epsilon_{it} \quad (1) \end{aligned}$$

where

- y_{it} is an indicator variable that is 1 if individual i ordered from the focal restaurant on day t
- ad_{it} is the goodwill stock of advertising for individual i on day t. Goodwill stock is defined as $ad_{it} = \sum_{\tau=0}^{t} \delta^{t-\tau} a_{it}$ where a_{it} is an indicator variable that is 1 if individual i received an experimental notification on day t of the experiment. δ is the advertising carryover factor. Following Shapiro et al., 2018, I use a grid search to fix the value of δ. Model (1) is estimated using OLS repeatedly with different values of δ starting from 0 to 1 with increments of 0.01. The value that returns the best value of R^2 is used. Following this process, δ is fixed at 0.24.
- ad_{it}^{price} is the goodwill stock of price advertising for individual i on day t. $ad_{it}^{intermediate}$ is the goodwill stock of intermediate advertising for individual i on day t. The coefficients on these variables will indicate the difference in the ad effect between price advertising and

brand advertising. To get the total price ad effect, the coefficients on ad_{it} and ad_{it}^{price} must be added. The interpretation of coefficients is similar for $ad_{it}^{intermediate}$ and the interaction terms of discount and advertising.

- $discount_i$ is the percentage discount that is assigned to individual i i.e. 0,10,20,30 or 40

Estimation results using a probit specification as well as OLS for model (1) are shown in Table 5 under specification I and II respectively. For probit, the specification is changed to

$$y_{it}^* = \alpha + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \gamma_3 ad_{it}^{intermediate} + \beta discount_i + \nu_1(ad_{it}) * (discount_i) + \nu_2(ad_{it}^{price}) * (discount_i) + \nu_3(ad_{it}^{intermediate}) * (discount_i) + \epsilon_{it} \quad (2)$$

and

$$y_{it} = 1 \text{ if } y_{it}^* > 0 \text{ and } 0 \text{ otherwise}; \epsilon_{it} \sim N(0,1) \quad (3)$$

We see from both specifications that ads have a positive effect on demand. Further, the intercept term for price advertising is negative indicating that at low discounts, price advertising performs worse than brand advertising. However, the slope of demand (interaction between discount and advertising) is higher for price advertising relative to brand advertising, indicating that as discount level increases, price advertising does better than brand advertising. So demand at high discount levels is higher under price advertising. The OLS specification also tells us that the slope of demand under brand advertising is higher than that under no advertising. Thus, we confirm the insights from Figure 6. Advertising has a positive effect on demand and it increases the elasticity of demand. Price advertising performs worse than brand advertising at low discount levels but better at high discount levels i.e. elasticity of demand is higher under price advertising. The performance of the intermediate ad is not significantly different from the brand ad, suggesting that the mere mention of the word 'discount' does not change the ad effect- but mentioning an exact discount amount and highlighting it does.

Another specification where the dependent variable is changed to the total meal value (order value before discount) is also shown under specification (III), leading to the same conclusions. Under this specification, we capture the effect of discounts and advertising on increasing the probability of ordering from the focal restaurant as well as the effect on increases in meal value conditional on ordering. It is interesting to examine whether the way in which advertising and discounts have an effect on total demand is through increasing the number of orders or also through increasing the meal value that people add to their carts when ordering. In other words, do people add more items to their cart and increase the size of the order under high discount and advertising conditions. To examine this, I run a regression with meal value added to cart(i.e. monetary value of the order before applying the discount) as the DV on discount level and ad stock, for the individual-day combinations when a cart is created for the focal restaurant. I also control for the pre-experiment average order value of each individual to control for self selection of individuals that differ in pre-experiment order size under the different advertising and discount conditions. The results of this regression are reported in Table 6. We see that after accounting for pre-experiment average order value, there seems to be no effect of discounts or advertising on increasing meal size size conditional on placing atleast one item in the cart for the focal restaurant. Thus, the way that advertising and discounts seem to work in this context is through the extensive margin i.e. getting more people to place an order or place orders more frequently. There is no effect on meal value conditional on an order being placed. Thus, for the remainder of the paper, I will only focus on the probability of placing an order and not on the size of the order.

Now that we have examined the effects on demand, we will next look into the different stages of the purchase funnel to investigate the reasons for the differences in demand arising from price advertising and brand advertising. Do the differences in demand arise from differences in informative effects leading to consumers searching differently, or do they arise from differences in persuasive effects leading to consumers converting to purchase at different rates once full information about price has been revealed to them?

5 Effect on Search

One of the primary mechanisms by which advertising is thought to affect demand is through its informative effect on search (Stigler, 1961; Ozga, 1960) . In this section, we will focus on the arrival rates of consumers at the upper stages of the purchase funnel. If price information in advertising affects how consumers search, we should see differences in rates at which consumers who were exposed to different ads with varying price information arrive at the menu page of the restaurant.

Consumers who did not receive information about a specific discount presumably make the decision to search based on expectation of discounts. Since the platform has historically sent out notifications and most of these notifications inform consumers about available discounts on the platform, consumers may have non-zero expectations of discount conditional on receiving a notification, even if the notification does not explicitly mention one. Thus, the consumer will decide to pay her search cost and visit the menu page of the restaurant only if the expected discount justifies this decision. On the other hand, if consumers are explicitly told the exact available discount, they can make the search decision under better information i.e. they will pay the search cost of going to the menu page of the restaurant if they think that the available discount justifies the cost of search.

According to the above hypothesis, if the expectation of discount conditional on receiving a notification about a restaurant is high (above 10%), then brand advertising may lead to higher search relative to price advertising at lower discount levels. This is consistent with the notion of uninformative advertising as an invitation to search (Mayzlin and Shin, 2011). Conversely, if the expectation of discount is low (below 10%), then price advertising should lead to more search at all discount levels.

Based on historical push notifications sent to each customer in the experiment sample, I create a measure of discount expectation conditional on receiving a notification for each customer. The average expected discount conditional on receiving a notification is found to be 23%. Based on this and the above hypothesis of search based on discount expectations, we should predict that brand advertising leads to higher search rates at 0,10% and 20% discount levels and price advertising leads to higher search rates at 30% and 40%.

Figure 7 shows the probability that probability of an individual visiting the menu page of the focal restaurant during the experiment under the different ad and discount conditions. First, we see that ads have a positive effect on search probability at all discount levels. We also see that the probability of search i.e. visiting the restaurant menu page does not change vary with discount level under the ‘No Ad’, ‘Brand Ad’ and ‘Intermediate Ad’ conditions. This makes intuitive sense since people cannot respond to information that they haven’t been given. However, if given price information through price ads, we see that consumers respond to the different discount levels by searching more if there is a high discount available and less if a low discount is available. This confirms that price advertising is indeed has a higher ‘informative’ effect relative to brand advertising in the sense that it leads to consumers’ adjusting their search patterns in response to the price information disclosed to them. However, this higher ‘informative’ effect is not necessarily a good thing for the brand. At low discount levels (10%), we see that a lower number of people search for the brand. If the brand wants to maximize the number of people searching for it under the availability of a 10% discount and at current consumer beliefs, it is better off with brand advertising. The higher level of search at low discounts with brand advertising also translates to higher overall demand as we saw in the previous section. This is empirical evidence consistent with the notion of uninformative advertising as an invitation to search (Mayzlin and Shin, 2011). Conventional wisdom about always including discount information is overturned in this case. However, at high discount levels, the informative effect of price advertising works in favor of the firm.

The search patterns for brand ads and intermediate ads are not significantly different. This is consistent with what we saw for the overall demand patterns as well. The mere mention of the word ‘discount’ does not seem to change the effect of the ad.

Further, we can see that the search probability level for brand and intermediate ads are between the search probability levels for the 20% and 30% price ads. This is consistent with our hypothesis about search based on expectations of discount and the fact that the average expected discount conditional on receiving a notification is found to be 23% in the sample. In order to investigate this further, we can split the sample of individuals according to the measure for expected discounts and look at the search patterns for different sub-samples. Figure 8 shows the probability of visiting the restaurant menu page for individuals with expectations of discount split into three bins - less than 20, between 20 and 30; and greater than 30. We see that the search probability level for brand and intermediate ads are between the search probability levels for the 10% and 20% price ads for those whose discount expectations are less than 20. Similarly, the search probability level for brand and intermediate ads are between the search probability levels for the 30% and 40% price ads for those whose discount expectations are greater than 30. Most of the sample falls in the between 20 and 30 range and their search probability level for brand and intermediate ads are between the search probability levels for the 20% and 30% price ads. This demonstrates that people indeed search according to expectations of discount if they are not explicitly told a specific discount level through price advertising.

Next we look at the second stage of the purchase funnel, which is the cart page. Figure 9 shows the probability that an individual visits the focal restaurant cart page after adding items to the cart. We see a similar pattern as we saw for the menu page. Since price information is only revealed after visiting the cart page, the probability of visiting the cart page does not change vary with discount level under the 'No Ad', 'Brand Ad' and 'Intermediate Ad' conditions. However, it does vary with discount level under the 'Price Ad' condition in the way that we would expect.

We see from Figures 7 and 9 that the 'demand' curves at these stages of the purchase funnel are more elastic under the price ad condition compared to the brand ad condition. Assuming constant conversion rates for the different ad types at each discount level, this would lead to a more elastic demand curve under price advertising. Thus, the result that we saw in the previous section wherein the demand facing the firm was more elastic under price advertising compared to brand advertising could just be driven by the informative effect of price advertising on search. However, there could also be differences in conversion rates conditional on search. We will investigate this further in Section 6.

5.1 Self-selection of consumers into search

Since consumers are able to make the search decision with more information under price advertising, this means that they are able to self select into search according to their discount sensitivity. We might expect that individuals who are highly discount seeking or most price sensitive make the decision to search only under the 40% condition. At the other end, the people who make the decision to search when told there is only a 10% discount should be relatively less discount seeking. Since I observe past purchase behavior of all individuals, I can characterize the people who made the decision to search under the different ad and discount conditions - and test the hypothesis that the group of individuals who searched when told that there is a high discount (or expect a high discount when not told explicitly) are on average more discount seeking than the group on individuals who searched when told that there is a low discount.

Based on pre-experiment purchases I create the following proxies for consumer 'discount-seeking' or price sensitivity:

- Fraction of orders purchased on discount
- Average discount amount used per order conditional on having used a discount
- Average discount amount used per order (unconditional)
- Average 'cost for two' descriptor for restaurants purchased from. Each restaurant on the platform contains a descriptor called 'Cost for two' which indicates what the price of an average meal for two at that restaurant is. This is a characteristic that is provided by the restaurant owner at the time of signing-up with Swiggy. This information appears on the restaurant listings and menu pages. This provides a measure indicating whether a consumer orders from relatively more expensive or cheap restaurants.

Apart from these measures of discount-seeking or price sensitivity, we might also expect that individuals who are familiar with the focal restaurant i.e. those who have made atleast one purchase from the focal restaurant before the experiment are more likely to respond to low discounts and new customers are more likely to respond to high discount amounts.

Figures 10 and 11and show the average of these customer 'characteristics' for individuals who chose to visit the focal restaurant menu page (i.e. self selected into search) during the experiment. From Figure 10 we see that individuals who responded to the 40% discount price ad are those who have made a large share of their previous purchases using a discount i.e. they are more discount seeking. Individuals who responded to the 10% discount price ad are those who have made a relatively smaller share of their previous purchases using discounts. We see a similar pattern when we examine the previous restaurants ordered from as well. Individuals who searched in the 10% price ad condition are people who order from relatively more expensive restaurants and the individuals who searched in the 40% price ad condition are those who order from relatively cheaper restaurants. Individuals who responded searched in the 'No Ad', 'Brand Ad' and 'Intermediate Ad' conditions are pretty similar to each other in terms of these characteristics and they also look similar to the individuals who responded to the 20% and 30% price ads.

Individuals who received no ads also see a message saying 'Exclusive Offer for you' on the restaurant listings page, which might have created an expectation of discount between 20% and 30% for them as well. Restaurants which offer discounts on the platform usually offer discounts in this range, so such an expectation is rational. This would explain why the 'No ad' responders look similar to those who responded to the the brand and intermediate ads in terms of their pre experiment characteristics. The higher level of search under brand advertising is then purely due to the informative effect of brand advertising relative to no advertising. In terms of characteristics indicating price sensitivity, the people who responded to brand ads seem similar to those who responded without ads.

From Figure 11 (a) and (b), we see that that individuals who responded to the 40% discount price ad are those who have used high discounts pre-experiment i.e. they are more discount seeking. Individuals who responded to the 10% discount price ad are those who have used lower discounts for their pre-experiment purchases using discounts. From, Figure 11 (c), we can see that all the different forms of advertising lead to more 'new to restaurant' customers visiting the menu page of the focal restaurant. This is in-line with the informative effect of advertising i.e. it informs new consumers of the existence of this restaurant. There does not appear to be a pattern among the different ad types or discount levels. All the different ads seem to attract new and old customers at similar rates.

6 Effect on Conversion to Purchase Conditional on Search

In the previous section, we saw that the 'demand' curves at upper stages of the purchase funnel are more elastic under the price ad condition compared to the brand ad condition. Assuming constant conversion rates for the different ad types at each discount level, this would lead to a more elastic demand curve under price advertising. Thus, the patterns we saw for demand wherein the demand facing the firm was more elastic under price advertising compared to brand advertising could just be driven by the informative effect of price advertising on search.

However, we want to investigate whether a person who has arrived at cart and now has full information regarding price has a different probability of conversion depending on the ad they saw before conducting their search. In essence, we want to see whether the different types of ads have different 'persuasive' effects, at a stage in the purchase funnel when differences in information have been eliminated. One of the ways in which advertising affects demand (Chamberlin, 1933) describes one of the ways in which advertising works as altering consumer wants or tastes. Bain, 1956 and Comanor and Wilson, 1979 described the persuasive role of advertising as creating artificial product differentiation thus creating brand loyalty. Sawyer and Dickson, 1984 proposed that increased price oriented messaging by a brand might lead to a perception that the key differentiating feature of the brand is the price. In this case, the artificial differentiation that the brand creates through advertising might be reduced, thus reducing the 'persuasive' effect of price advertising relative to brand advertising.

In order to test this, we can look at the conversion rates of individuals who are at the cart page of the focal restaurant, who at this stage have full information about price regardless of the kind of advertising they saw. However, the self-selection into search that we saw in the previous section makes measuring this effect problematic. Since the different ad formats lead to different types of consumers arriving at the cart stage through self selection into search, conditional conversion rates at cart from the different ads may not be directly comparable. This is the classic self-selection issue that many econometricians have faced before (Heckman, 1979; Greene, 2000).

I approach this issue in three ways:

- Create a list of observable characteristics using historical data for each consumer and use those to control for selection based on observables through a parametric model
- Use a matching on observables approach through a non parametric Causal Forest setup (Wager and Athey, 2018)
- Explicitly model the selection and conversion steps as separate stages of the consumer decision process and allow for correlation in the error terms across these steps

The first two approaches rely on the unconfoundedness assumption (Rubin, 1990) to recover the difference in treatment effects of brand ads and price ads. The assumption is that after controlling for observable characteristics, biases in comparisons between individuals who were treated with brand and price ads and arrived at cart are removed, thus allowing for a causal interpretation of those adjusted differences. However, there may be unobservables that are not captured through the characteristics set created by using historical data. For example, the proxies for price sensitivity may not capture some aspect of 'true' price sensitivity, which is a possible confound that is unobservable. Thus, I also include a third approach that allows for selection on both observables and unobservables, but relies on a distributional assumption about how the error terms between the different stages of the decision process are correlated.

6.1 Controlling for observable customer characteristics parametrically

I use a parametric model where each type of ad is allowed to have a different 'treatment' effect on conversion, while controlling for the effect of discount and observable characteristics. The list of customer observable characteristics created using pre-experiment purchase data include: average order value, fraction of orders purchased using discounts, average discount percentage used per order, average restaurant cost for two among restaurants previously purchased from, a dummy indicating whether the customer has made atleast one previous purchase from the focal restaurant.

$$y_{it} = \alpha + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \gamma_3 ad_{it}^{intermediate} + \beta discount_i + \nu X + \epsilon_{it} \tag{4}$$

where X is the set of customer characteristics. The other variables have the same definition as in Section 4. This model is estimated on the subset of data when individual i has created a cart for the focal restaurant.

Estimation results using a probit specification as well as OLS for model (4) are shown in Table 7 under specification I and II respectively. For probit, the specification is changed to

$$y_{it}^* = \alpha + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \gamma_3 ad_{it}^{intermediate} + \beta discount_i + \nu X + \epsilon_{it} \tag{5}$$

and

$$y_{it} = 1 \text{ if } y_{it}^* > 0 \text{ and } 0 \text{ otherwise}; \epsilon_{it} \sim N(0,1) \tag{6}$$

Here too, the coefficient on the ad_{it}^{price} variable will indicate the difference in the ad effect between price advertising and brand advertising. To get the total price ad effect, the coefficients on ad_{it} and ad_{it}^{price} must be added. Under both specifications, we see that price advertising has lower effect relative to brand ads on conversion conditional on search, thus indicating that a consumer who has arrived at cart having seen a price ad converts with lower probability than one who has arrived having seen a brand ad, conditional on both consumers receiving the same discount level and controlling for their observable characteristics.

One explanation for this might be a reference price effect (Mazumdar et al., 2005) - those individuals who arrived at cart expecting a low discount, but see a high discount convert at higher rates compared to those who were informed in advance via price advertising. To test this, I estimate the above model again, but including an additional term that captures the difference between the expectation of discount conditional on receiving a notification (using constructed historical data on previous notifications received) and the actual discount amount displayed at cart. For those who did not receive notifications, the expectation is set to zero. [5] Estimation results are shown in Table 8. The reference term does not show up with a significant coefficient and the sign on the price ad term does not change, so the reference price effect does not explain the lower conversion rates for price ads.

6.2 Matching on observable customer characteristics flexibly with a causal forest

Next, I use a matching on observables approach. One way to approach this would be propensity score matching (Imbens and Rubin, 2015). However this relies on imposing a parametric specification in estimating the propensity score. A causal forest avoids the necessity to impose a parametric specification and is computationally efficient, robust to model mis-specifications, and achieves desired consistency and asymptotic normality, and is thus a preferable approach.

[5] Robustness check done by setting this to 20, 25, 30 to account for the effect of the message displaying 'Exclusive Offer for you' on the restaurant listings page.

I use a causal forest to estimate the difference in treatment effects between price and brand ads. The data used is the subset of data when individual i has created a cart for the focal restaurant. Further since we are interested specifically in measuring the difference in treatment effects between brand and price ads, I restrict attention to the subsample which have been assigned either brand or price ads and were assigned a positive discount. The individuals assigned to brand ads are taken as the control group and the individuals assigned to price ads are taken as the 'treatment' group. A dummy variable indicating conversion to order is the outcome variable. The list of 'X' variables that are used for matching include assigned discount level, average order value, fraction of orders purchased using discounts, average discount percentage used per order, average restaurant cost for two among restaurants previously purchased from, number of ads received by individual i until day t, day number, a dummy indicating whether the customer has made atleast one previous purchase from the focal restaurant and also a 'reference term' as defined in Section 6.1 to capture any reference price effects.

The estimated forest reports an average treatment effect of -0.047*** with SE of 0.007. This means that the probability of conversion to purchase at cart for individuals assigned to price ads was on average 0.047 lower than individuals assigned to brand ads. Since we can estimate heterogenous treatment effects using a causal forest and predict the estimated treatment effect for each individual in the sample, it is interesting to explore this heterogeneity. Figure 12 shows the heterogeneity in the difference in conversion rates between brand ads and price ads for the full sample of individuals who created a cart. We see that some individuals convert at higher rates with price ads, but for most individuals the conversion rate with brand ads is higher, 0.047 being the average difference in probability of conversion. I leave further exploration of the heterogeneity in the difference in treatment effects for future work.

6.3 Modeling the consumer decision process to account for selection on unobservables and observables

The final approach to deal with self selection into visiting the cart page is to explicitly model the selection process. I specify a model where a consumer first makes the decision to visit the focal restaurant menu page based on an expectation of the final price to be paid depending on the type of ad received, her preferences for the restaurant, search cost and any residual advertising effect. The decision to visit the cart page from menu page is made based on the same factors but the effects of these factors can be different at this step. Finally, at cart the consumer discovers the full price to be paid and decides whether to convert based on this revealed price and the 'persuasive' effect of the advertising that she has received in addition to her brand preference.

6.3.1 Model specification

Individual i decides to visit the menu page on day t if

$$v_{1i} - c_{1i} - \beta_{1i} E_{it}[P|Ad^j] + \alpha_{1i} ad^j_{it} + \epsilon_{1it} > 0 \tag{7}$$

where

- v_{1i} captures individual i's preferences for the focal restaurant
- c_{1i} indicates individual i's search cost to visit the menu page
- $E_{it}[P|Ad^j]$ is the final price that individual i expects to pay under information contained in Ad^j where j indicates the type of ad received. The expectation of discount is zero before the first ad is received and then updates after the first ad is received, and stays at the updated level until the end of the experiment.
- ad^j_{it} is the individual's goodwill stock of ad type j at time t

Individual i decides to visit the cart page on day t if

$$v_{2i} - c_{2i} - \beta_{2i} E_{it}[P|Ad^j] + \alpha_{2i} ad^j_{it} + \epsilon_{2it} > 0 \tag{8}$$

where

- v_{2i} captures individual i's preferences for the focal restaurant after having seen the menu

- c_{2i} indicates individual i's search cost to visit the cart page from the menu page
- $E_{it}[P|Ad^j]$ is the final price that individual i expects to pay under information contained in Ad^j where j indicates the type of ad received
- ad^j_{it} is the individual's goodwill stock of ad type j at time t

Individual i decides to visit order on day t if

$$v_{3i} - c_{3i} - \beta_{3i}P + \alpha_{3i}ad^j_{it} + \epsilon_{3it} > 0 \tag{9}$$

- v_{3i} captures individual i's preferences for the focal restaurant at the cart stage
- c_{3i} indicates individual i's cost of finalizing the order by putting in her address, payment method etc.
- P is the actual price seen at cart
- ad^j_{it} is the individual's goodwill stock of ad type j at time t

We can set this model up to allow for selection on unobservables by allowing the error terms in the three stages to be correlated. Specifically they can be assumed to be draws from a trivariate normal distribution with zero means, unit variances and arbitrary covariance terms. We cannot identify search cost and preference parameters separately, so they will be combined as one intercept term. Since I experimentally vary discount, and not the actual price, I replace the price terms above with discounts. I also control for observable characteristics by including a list of characteristics created using historical data as described in the previous sections. Since there is no credible 'exclusion restriction' i.e. a variable that affects the search decision but not the purchase decision, I take a full information maximum likelihood approach to this instead of a Heckman selection approach. The estimation equations are:

$$y^*_{1it} = v_{1i} + \beta_{1i}E_{it}[D|Ad^j] + \alpha_{1i}ad^j_{it} + \gamma_1 X_i + \epsilon_{1it} \tag{10}$$

$$y_{1it} = 1 \text{ if } y^*_{1it} > 0 \text{ and } 0 \text{ otherwise} \tag{11}$$

$$y^*_{2it} = v_{2i} + \beta_{2i} E_{it}[D|Ad^j] + \alpha_{2i} ad^j_{it} + \gamma_2 X_i + \epsilon_{2it} \tag{12}$$

$$y_{2it} = 1 \text{ if } y^*_{2it} > 0 \text{ and } 0 \text{ otherwise} \tag{13}$$

$$y^*_{3it} = v_{3i} + \beta_{3i} D + \alpha_{3i} ad^j_{it} + \gamma_3 X_i + \epsilon_{3it} \tag{14}$$

$$y_{3it} = 1 \text{ if } y^*_{3it} > 0 \text{ and } 0 \text{ otherwise} \tag{15}$$

where

- y_{1it}, y_{2it} and y_{3it} are dummy variables indicating whether individual i visited the menu page, visited the cart page or placed an order from the focal restaurant on day t
- X_i is the set of customer characteristics which include average order value, average discount percentage used in pre-experiment orders, fraction of pre-experiment orders purchased using discounts, dummy indicating whether the individual purchased atleast once from the focal restaurant pre-experiment and average restaurant cost for two among restaurants previously purchased from
- ad^j_{it} is the individual's goodwill stock of ad type j at time t
- $E_{it}[D|Ad^j]$ is the expected discount under information contained in Ad^j where j indicates the type of ad received. The expectation of discount is zero before the first ad is received and then updates after the first ad is received, and stays at the updated level until the end of the experiment
- D is the actual discount seen at cart

6.3.2 Distributional Assumptions

Since very few individuals visit menu or cart more than once, it is not possible to estimate individual specific parameters. Instead we allow for individual heterogeneity by assuming that the intercept and the coefficients on discount and advertising come from a normal distribution with means and variances to be estimated. Off diagonal elements are fixed at zero. Suppose the vector $(v_{1i}, v_{2i}, v_{3i}, \beta_{1i}, \beta_{2i}, \beta_{3i}, \alpha_{1i}, \alpha_{2i}, \alpha_{3i})$ is denoted by θ, then $\theta \sim N(\mu, \Sigma)$. Mean parameters μ and diagonal elements of Σ are estimated. The error terms $(\epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i}) \sim N(0, \Sigma_\epsilon)$ i.e. the three equations are set up as a trivariate probit. The diagonal terms of Σ_ϵ are set to 1 and the off diagonal terms $\rho_{12}, \rho_{13}, \rho_{23}$ indicating the covariances between (ϵ_1, ϵ_2), (ϵ_1, ϵ_3) and (ϵ_2, ϵ_3) are terms to be estimated.

6.3.3 Estimation Methodology

Estimation is done using simulated maximum likelihood. To simplify notation, suppose the equations 10, 12 and 14 are denoted as

$$y^*_{1it} = W'\eta + \epsilon_{1i} \tag{16}$$

$$y^*_{2it} = Y'\zeta + \epsilon_{2i} \tag{17}$$

$$y^*_{3it} = Z'\delta + \epsilon_{3i} \tag{18}$$

The likelihood (π_{it}) for an observation that has $y_{1i} = y_{2i} = y_{3i} = 1$ is $Pr(\epsilon_{1it} > -W'\eta, \epsilon_{2it} > -Y'\zeta, \epsilon_{3it} > -Z'\delta) = \Phi(W'\eta, Y'\zeta, Z'\delta; \rho_{12}, \rho_{23}, \rho_{13})$ where Φ denotes the standard normal CDF.

The likelihood (π_{it}) for an observation that has $y_{1i} = y_{2i} = 1$ and $y_{3i} = 0$ is $Pr(\epsilon_{1it} > -W'\eta, \epsilon_{2it} > -Y'\zeta, \epsilon_{3it} < -Z'\delta) = \Phi(W'\eta, Y'\zeta, -Z'\delta; \rho_{12}, -\rho_{23}, -\rho_{13})$

The likelihood (π_{it}) for an observation that has $y_{1i} = 1$ and $y_{2i} = 0$ $Pr(\epsilon_{1it} > -W'\eta, \epsilon_{2it} < -Y'\zeta) = \Phi(W'\eta, -Y'\zeta; -\rho_{12})$

The likelihood (π_{it}) for an observation that has $y_{1i} = 0$ is $Pr(\epsilon_{1it} < -W'\eta) = 1 - \Phi(W'\eta)$

Since there are terms in η, ζ and δ that are random, specifically, $(v_{1i}, v_{2i}, v_{3i}, \beta_{1i}, \beta_{2i}, \beta_{3i}, \alpha_{1i}, \alpha_{2i}, \alpha_{3i})$ denoted by $\theta \sim N(\mu, \Sigma)$, we will integrate the likelihood of each observation over the distribution of parameters $\pi_{it} = \int \pi_{it}(\theta) d\Omega(\theta)$ where $d\Omega(\theta)$ is the density of $\theta \sim N(\mu, \Sigma)$. This integration is implemented using a Monte Carlo simulation method; I take draws of θ from the distribution and compute an average value of π_{it} for these draws.

The log likelihood for each observation is

$$\begin{aligned} log(\pi_{it}) = (y_{1it})(y_{2it})(y_{3it}) log(\Phi(W'\eta, Y'\zeta, Z'\delta; \rho_{12}, \rho_{23}, \rho_{13})) \\ + (y_{1it})(y_{2it})(1 - y_{3it}) log(\Phi(W'\eta, Y'\zeta, -Z'\delta; \rho_{12}, -\rho_{23}, -\rho_{13})) \\ + (y_{1it})(1 - y_{2it}) log(\Phi(W'\eta, -Y'\zeta; -\rho_{12})) + (1 - y_{1it})(1 - \Phi(W'\eta)) \end{aligned} \tag{19}$$

The total log likelihood is $\sum_{it} log(\pi_{it})$ [6]

6.3.4 Results

The estimated mean and standard deviations for the intercept, price and ad terms at each stage are reported in Table 11. We see from these results that even after allowing for selection on unobservables and controlling for observables, the estimated effect of price advertising on conditional conversion at cart is lower than that for brand advertising. This suggests that the persuasive effect of price advertising is indeed lower than that for brand advertising.

Thus the overall effect of demand being more elastic under price advertising is driven both by a higher informative effect and a lower persuasive effect.

7 Spillover effects

Next, we examine whether demand for other restaurants on the platform changes as a result of consumers receiving ads for the focal brand. Previous literature has documented spillover effects from advertising (Sahni, 2016; Shapiro, 2018). In this case, we want to see whether the different ad types have different spillover effects - specifically whether other discounted products in the

[6] To save computation time, I subsampled individuals such that the individuals who had atleast one visit to cart and 10000 other randomly selected individuals in the experiment were kept in the estimation sample

category benefit more from consumers being exposed to price oriented advertising from the focal brand relative to brand oriented advertising.

Figure 13 shows the average number of orders made from non-focal restaurants under the different ad conditions. We see that advertising does indeed have positive spillover effects consistent with previous literature (Sahni, 2016; Shapiro, 2018). However, the magnitude of spillover effects do not differ by ad type.

Next we want to test whether the consumers who received price ads for the focal restaurant became more discount-seeking on the platform. Mela et al., 1997 document changes in price sensitivity of consumers over the long term as a result of exposure to promotions and brand advertising. They find that consumer price sensitivity increases over the long term if they see frequent promotions and decreases if consumers are exposed to more brand advertising. In this context, the analogous hypothesis would be that consumers seek more discounts if they are exposed to price oriented advertising and they do not seek discounts if they are exposed to brand oriented advertising.

Figure 14 shows how the fraction of orders on discount for non focal restaurants changes over time. Week 0 is the week before the experiment started. Week 1 to week 4 are the weeks during which the experiment was on and Weeks 5 to 7 are post-experiment weeks. We see that consumers who received price ads indeed became more discount seeking on the platform. The share of discounted orders from non-focal restaurants increases for the consumers exposed to price ads, but not for consumers exposed to brand or intermediate ads. As they were exposed to advertising that highlighted the availability of a discount at the focal restaurant, they also seem to choose other restaurants that have discounts available compared to the groups that did not receive price advertising. This is in-line with the finding in Mela et al., 1997. Thus, price-oriented advertising for a focal brand has positive spillovers to other discounted brands. However, this effect dies out within a couple of weeks after the end of the experiment, and doesn't seem to persist for the long term. Brand advertising also has positive spillovers to other brands, but it does not cause a shift towards more discounted brands.

8 Managerial Implications

The findings in this paper have several implications for managers who want to jointly optimize pricing and advertising. First, at low discount levels, price advertising leads to lower overall demand. This directly contradicts general practice in the digital advertising industry of always highlighting price discounts in digital ads, if they are available. In contexts characterized by high discounts, leading to high consumer expectations of discount, managers must be careful about highlighting discounts in ads that are lower than consumer expectations.

Further, since the elasticity of demand is different under advertising, price optimization must be done using the correct elasticity if the manager plans to advertise and make a discount available at the same time. Moreover, since demand elasticity also varies with the type of advertising, the profit maximizing price, type and intensity of advertising must be decided on jointly.

The self-selection of different types and numbers of consumers into searching for the product under brand and price advertising at different discount levels has implications for targeting of advertising content. At low discount levels, brand advertising can lead to higher search and demand compared to price advertising. i.e. it can increase the probability of search if targeted towards people with high expectations of discount conditional on receiving a notification. Of course, these beliefs will get updated as well, so care must be taken not to disappoint the consumer too often by repeatedly revealing to them a price at cart that is higher than their expectations.

The fact that price advertising lowers conversion to purchase conditional on search has implications for targeting of point-of-sale discounts. For example, firms often use cart abandonment reminders or discounts to induce customers who have abandoned their cart to finish a purchase. The fact that people who see different ads convert at different rates at the cart stage implies that cart abandonment discounts can be targeted according to the type of advertising that the consumer received. A given individual who has seen a brand ad is likely to need a lower cart abandonment discount than one who has seen a price ad.

The above implications are directly relevant for Swiggy, the firm that ran this experiment. With its rich set of historical consumer data, and the findings from this experiment, Swiggy could predict the probability of search and purchase for each customer (i.e. a set of customer characteristics) under different discount levels and advertising type. Thus, it can jointly optimize prices along with advertising type and target both discounts and advertising content. Since it already sends cart abandonment notifications, it can further include a personalized discount along with these according to customer characteristics and the type of advertising seen.

Managers might also wish to screen customers while running a promotional campaign. If servicing the search process for a customer is expensive (perhaps in an offline setting where servicing costs are high), the firm would rather have a lower number of customers who are more likely to convert make the initial search rather than a higher number of people who are less likely to convert. If the available discount is high, they can use brand advertising to attract a smaller group of individuals who are more likely to convert after they discover the true price. For example at a 30% discount in the experiment, the number of orders is similar, but the number of menu page visits made by consumers who received a price ad is higher.

Firms and academics often use two price points to estimate the demand curve by making a linearity assumption. Since brand ads lead to a similar number of people visiting the cart at all discount levels, there is a point of demand inelasticity when conversion hits 100%. This point leads to a non linearity in the demand curve under brand advertising, which may lead to mismeasurement of the slope of demand under the linearity assumption. This has to be kept in mind while designing experiments to measure price elasticities under different forms of advertising.

Finally, the spillover effect has implications for how firms on a common platform compete under different advertising regimes. If the platform encourages or sends more price oriented messaging to consumers, firms on the platform may end up competing more on prices as consumers become more discount seeking. Non advertising firms may optimally offer discounts during periods when consumers on the platform receive more price oriented messaging. This is also relevant to platforms that have the ability to regulate the advertising content that firms on its platform use. They may want to limit the use of price oriented messaging to prevent consumers from becoming more discount seeking and thus reducing platform commissions, or becoming more liable to switch to rival platforms that offer additional discounts.

9 Conclusion

In this paper, I show that the inclusion of price information has a causal effect of increasing the elasticity of demand. Further, I show that this occurs due to differences in the way price and brand advertising affect both the search and purchase (conditional on search) stages of the purchase funnel. Price advertising, through the provision of additional information lowers (raises) the probability of search at low (high) discount levels compared to brand advertising. It also leads to self-selection of different types of consumers (according to their price sensitivity) into search. Highlighting discount information can hurt the advertising firm at low discount levels by lowering search and demand. The probability of conversion to purchase after the consumer obtains full price information (after accounting for self-selection through search) is also found to be lower under price advertising, demonstrating that price information in advertising lowers its 'persuasive' effect. These findings extend previous literature on the effects of advertising on demand elasticity and also challenge the conventional wisdom in digital advertising of typically including discount information in ads. The different effects of price information should be considered by firms in their joint optimization over pricing and messaging at different stages of the purchase funnel. Finally, I find that price advertising causes consumers to shift their purchases among rival (non advertised) firms to those that offer discounts. This has implications for competition among firms under different advertising regimes.

A key limitation of this study is that the variation in advertising types and prices is purely cross-sectional. Thus, I am unable to make comments on 'within-individual' changes in price elasticity in response to different types of advertising. I am also unable to say anything about how different sequences of advertising types or different sequences of discounts affect consumer behavior. These are interesting topics to explore in future research.

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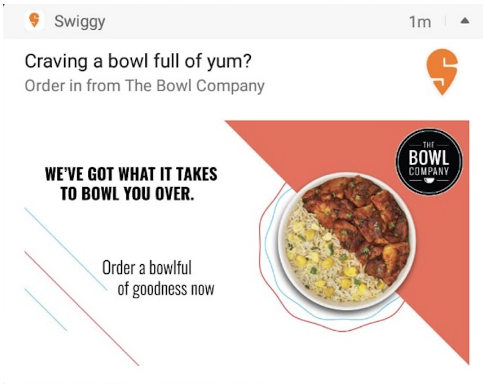
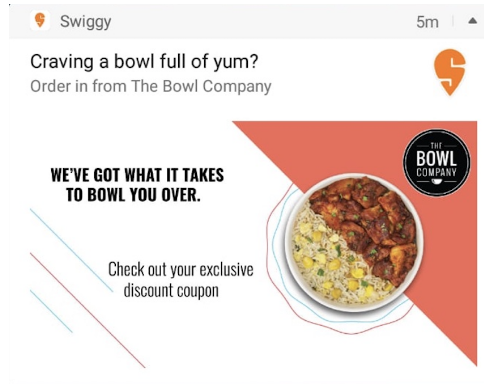
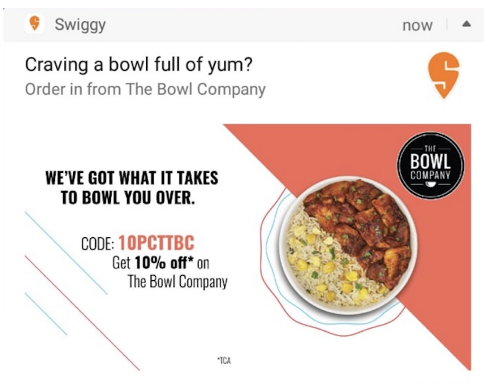
10 Tables and Figures



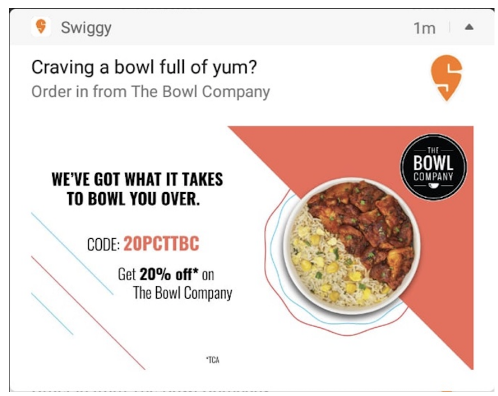
(a) Brand Ad



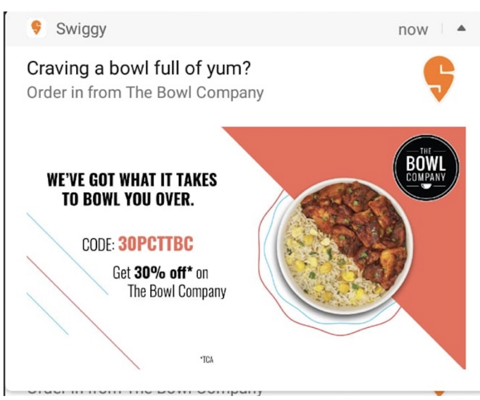
(b) Intermediate Ad



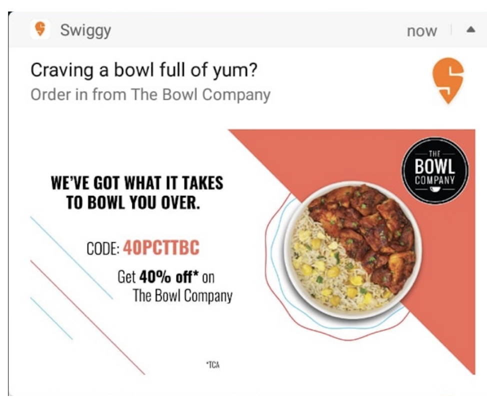
(c) Price Ad 10%



(d) Price Ad 20%



(e) Price Ad 30%



(f) Price Ad 40%

Figure 1: Different Ad Creatives

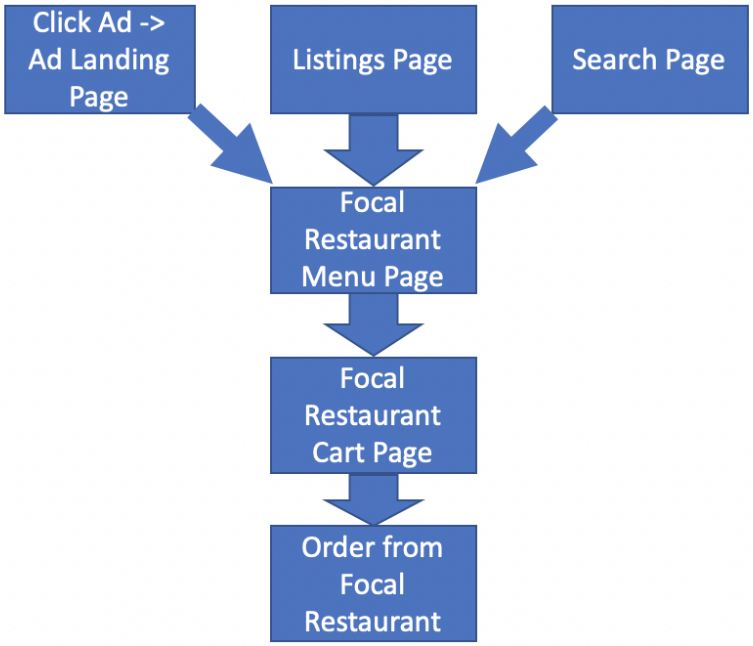
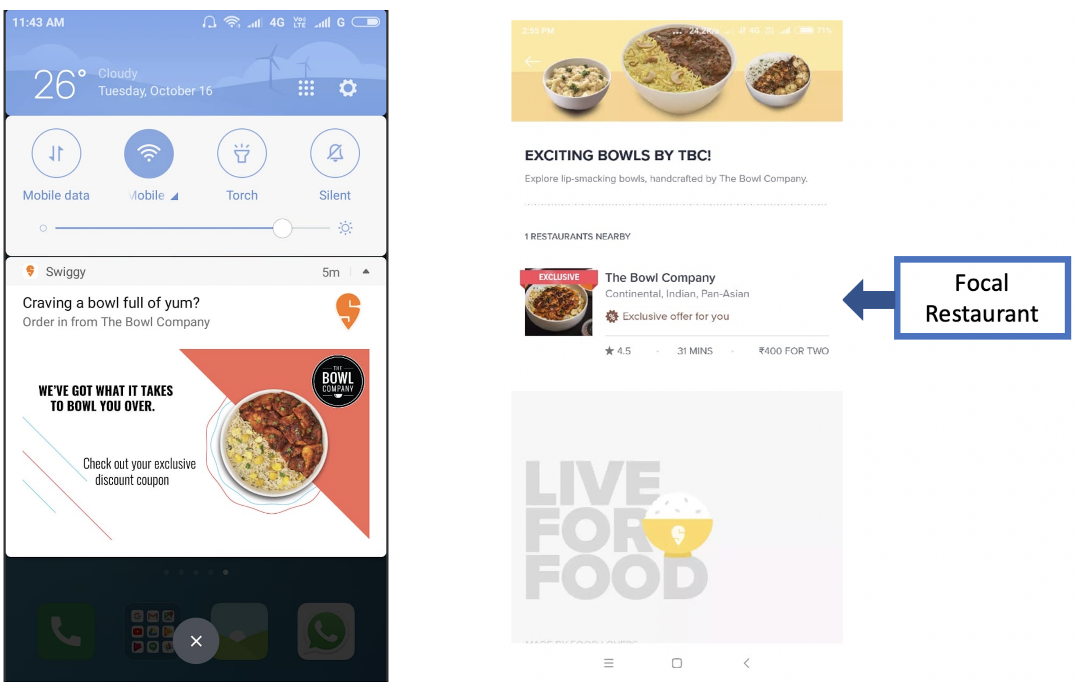


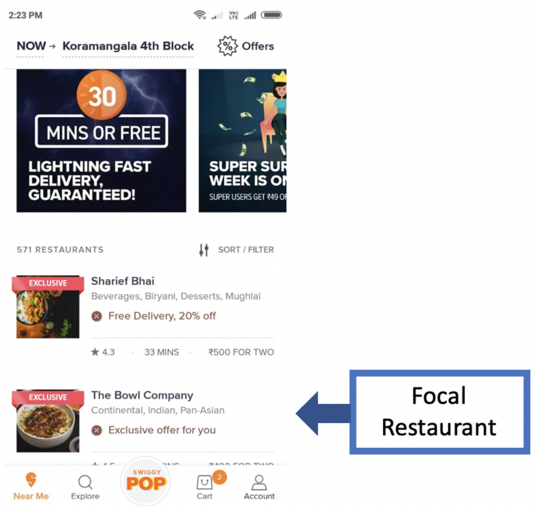
Figure 2: Steps in the purchase funnel



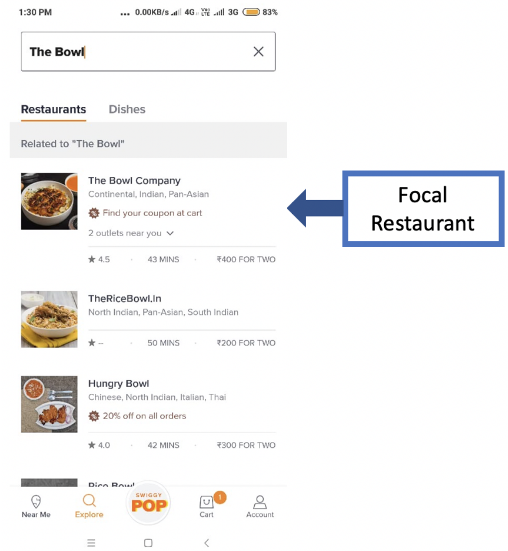
(a) Push notification pop up on phone screen

(b) Landing Page after clicking the push notification

Figure 3: Screenshot of ad push notification on an Android phone and the landing page after clicking on the ad

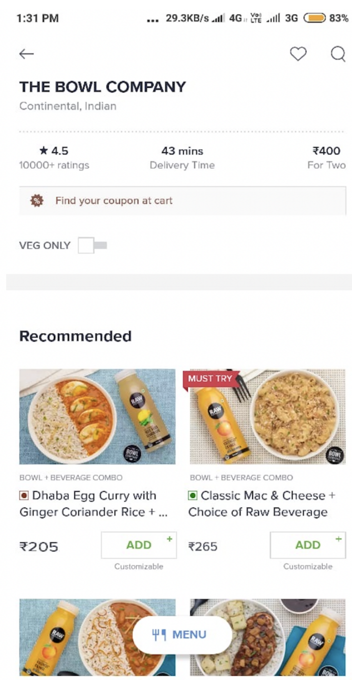


(a) Listing Page

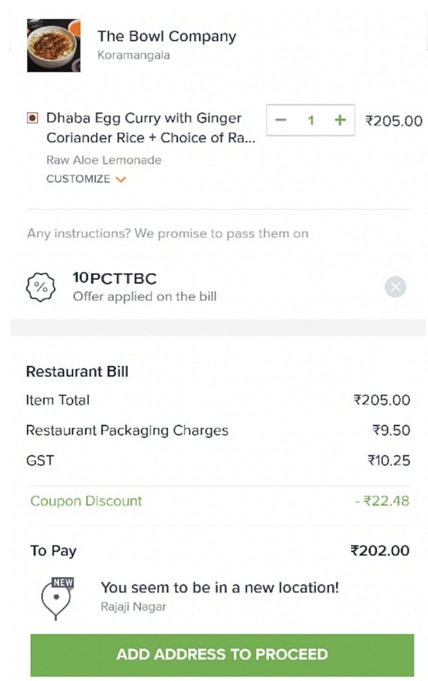


(b) Search Page

Figure 4: Listing and Search pages

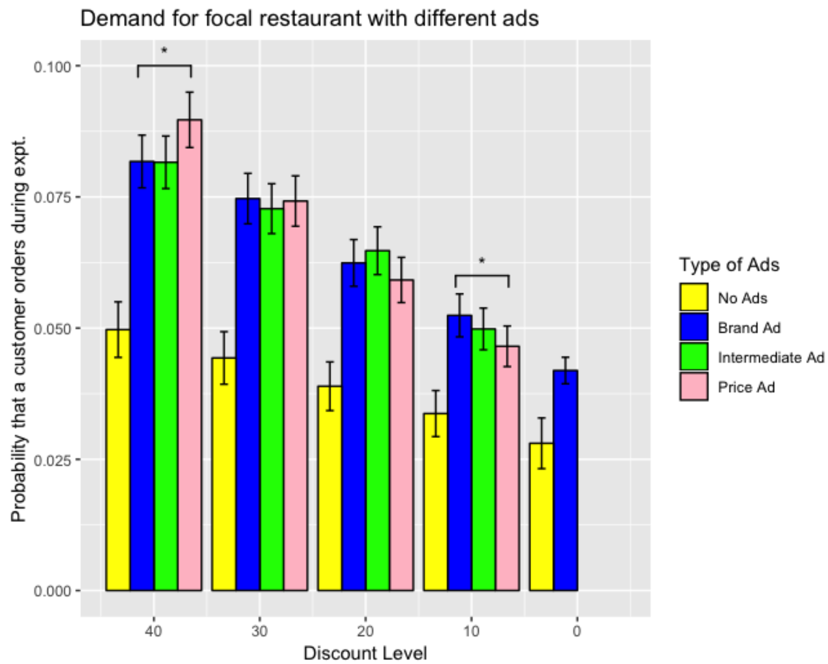


(a) Menu Page of Focal Restaurant



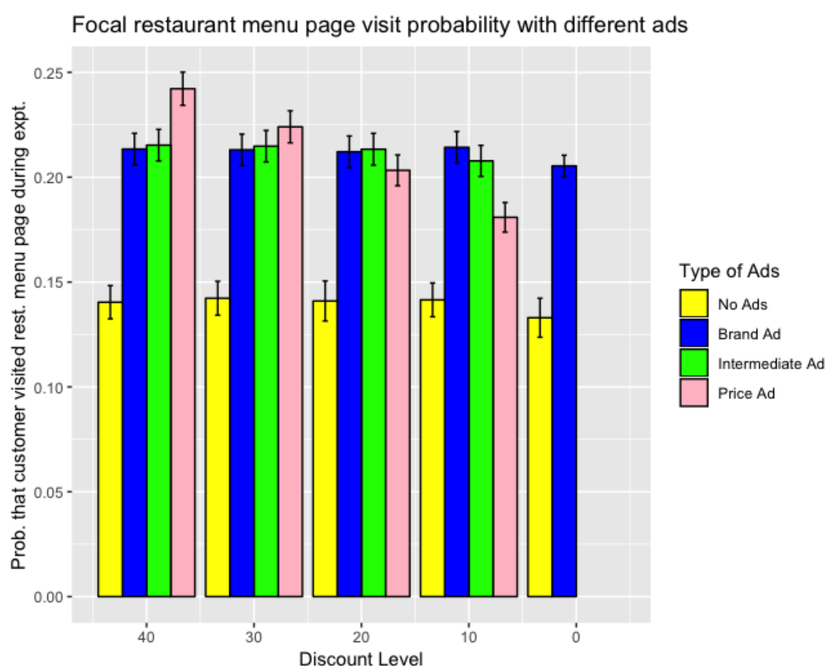
(b) Cart Page for Focal Restaurant with assigned discount auto-applied

Figure 5: Menu and Cart pages



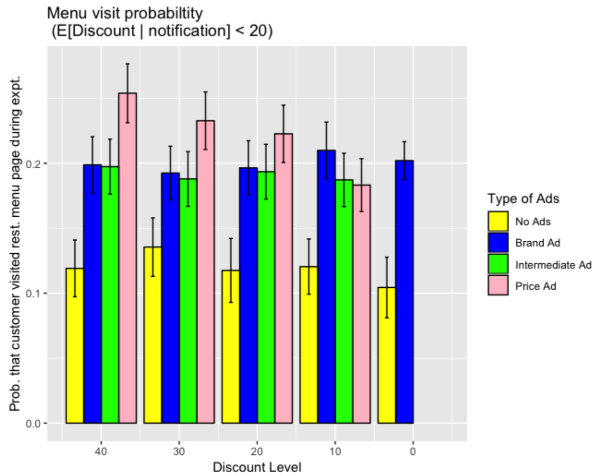
Error bars report 95% confidence intervals

Figure 6: Effect of the different types of ads on demand for the focal restaurant

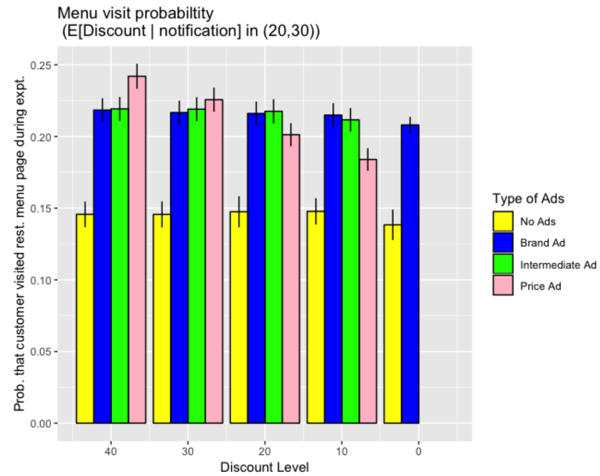


Error bars report 95% confidence intervals

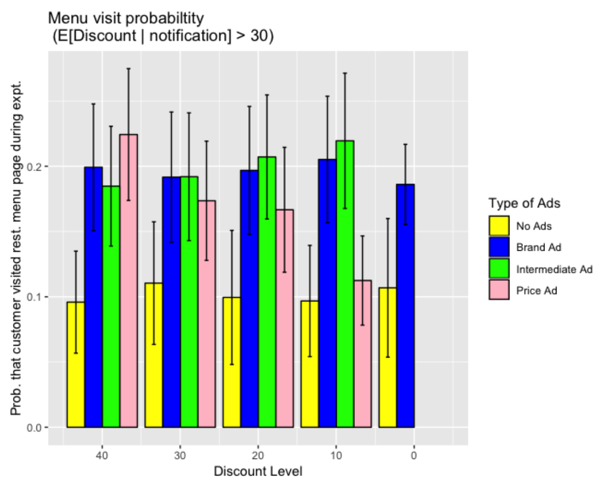
Figure 7: Effect of the different types of ads on probability of visiting the focal restaurant menu page



(a) Prob. menu page visit for E(Discount with Notification < 20)

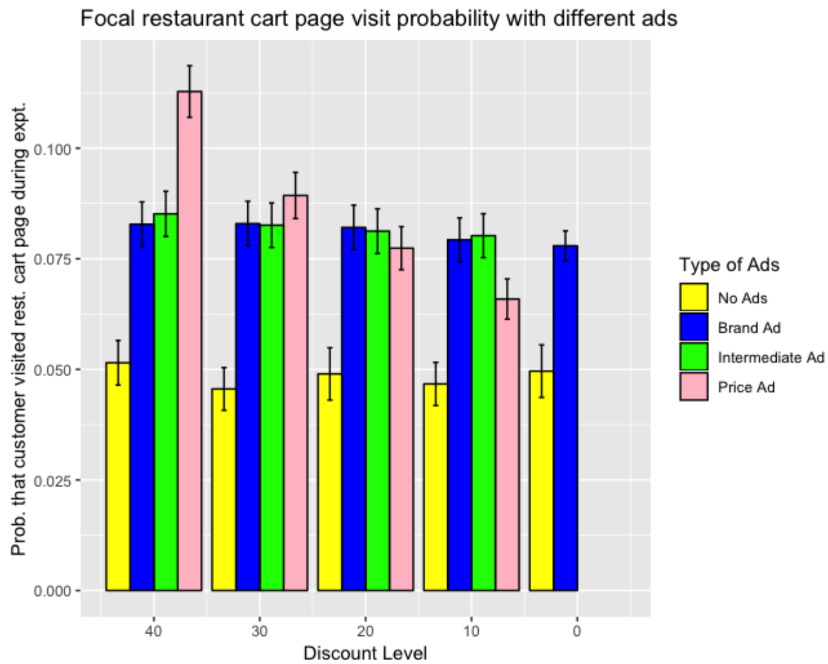


(b) Prob. menu page visit for E(Discount with Notification in (20,30))



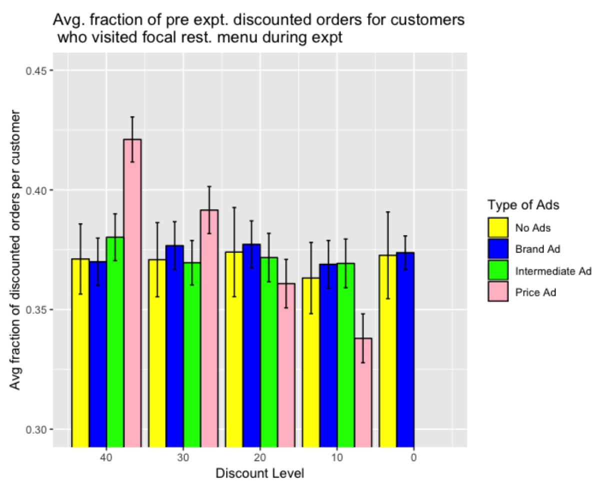
(c) Prob. menu page visit for E(Discount with Notification > 30)

Figure 8: Effect of different types of ads on the probability of visiting the focal restaurant menu page. Sub-samples split by expectations of discount conditional on receiving a notification. This figure demonstrates that customers who receive brand or intermediate ads make the decision to search based on their expectations of discount

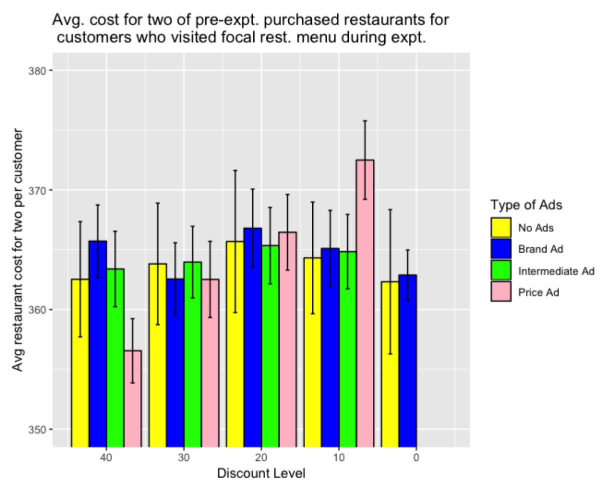


Error bars report 95% confidence intervals

Figure 9: Effect of the different types of ads on probability of visiting the focal restaurant cart page

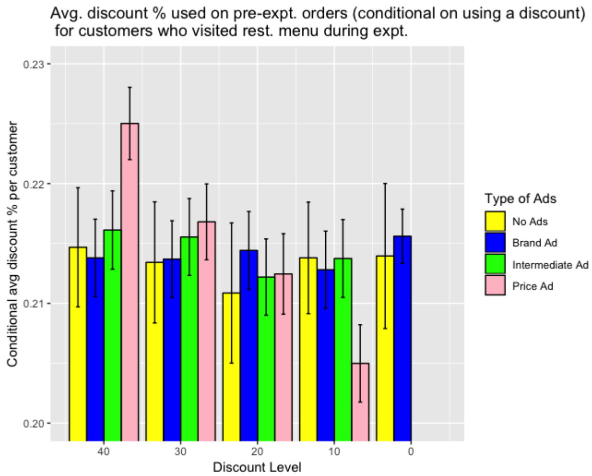


(a) Pre expt. fraction of discounted orders

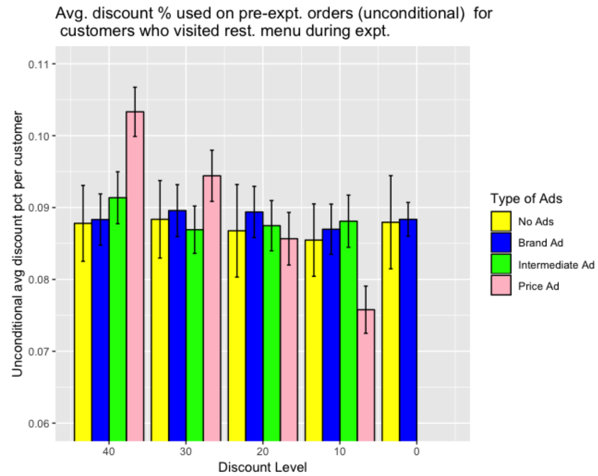


(b) Pre expt. avg restaurant cost for two

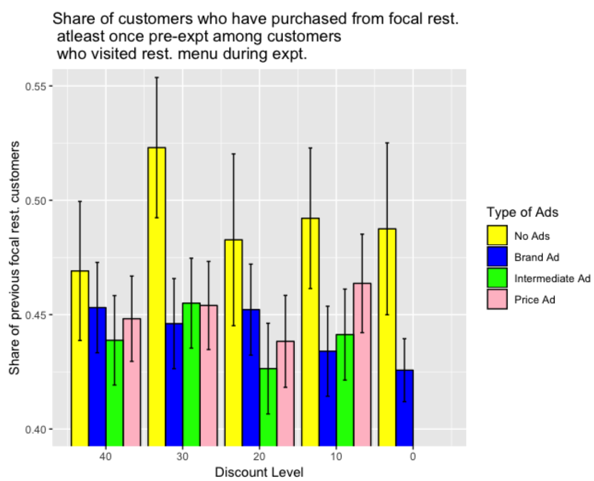
Figure 10: Pre experiment customer 'characteristics' for individuals who chose to visit the focal restaurant menu page under different discount and ad conditions (1)



(a) Pre expt. conditional avg. discount used



(b) Pre expt. unconditional avg. discount used



(c) Share of customers who have purchased atleast once from focal rest. pre-expt.

Figure 11: Pre experiment customer 'characteristics' for individuals who chose to visit the focal restaurant menu page under different discount and ad conditions(2)

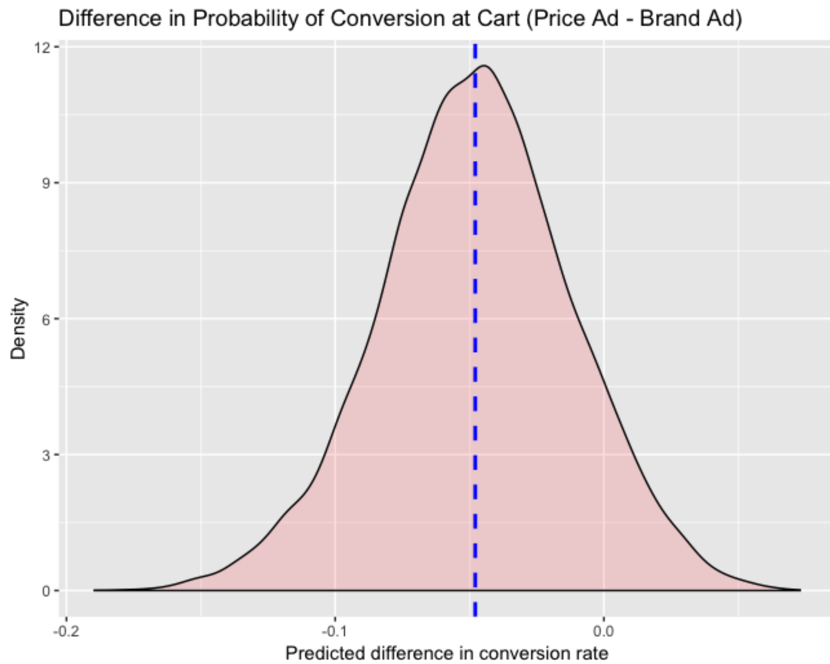
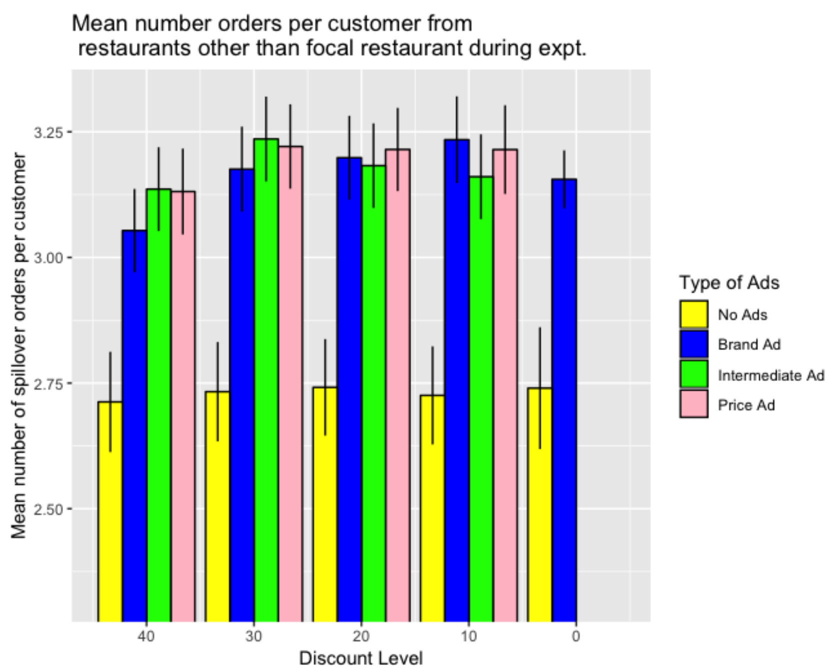
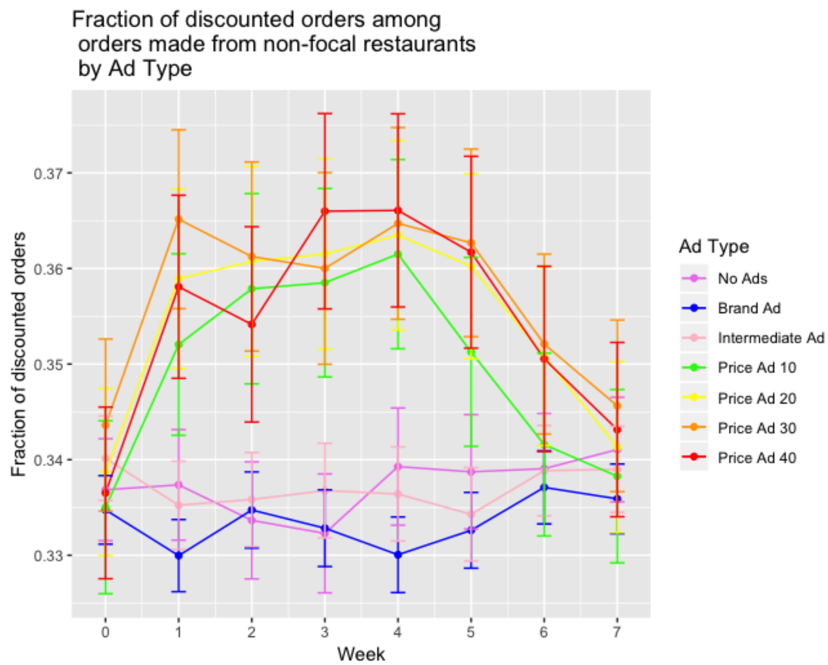


Figure 12: Distribution of differences in probability of conversion at cart after having been treated with a price ad and brand ad



Error bars report 95% confidence intervals

Figure 13: Mean number of orders per customer from non-focal restaurants



Error bars report 95% confidence intervals

Figure 14: Fraction of discounted orders from non-focal restaurants made by customers under the different ad conditions

Table 1: Discount Distribution

Discount Level	% of customers assigned
0%	15%
10%	21.25%
20%	21.25%
30%	21.25%
40%	21.25%

Table 2: Frequency Distribution

Frequency of notifications (per week)	% of customers assigned
0	17.5%
1	17.5%
2	25%
3	27.5%
4	12.5%

Table 3: Ad Type Distribution

Ad Type	% of customers assigned
Brand Ad	33.33%
Intermediate Ad	33.33%
Price Ad	33.33%

Customers assigned 0 discount level were all assigned the brand ad. The above distribution is for those who were assigned non zero discount only

Table 4: Difference between total number of notifications randomly assigned and actually received

Difference	% of customers
1	21.46%
2	8.81%
3	4.35%
4	2.31%
5	1.53%
6	1.53%
7	1.23%
8	0.58%
9	0.62%
10	0.55%
11	0.67%
12	0.15%
13	0.15%
14	0.16%
15	0.21%
16	0.001%
Atleast 1	44.3%

Table 5: Effect of Ads on Demand for the Focal Restaurant

	DV: Ordered from restaurant				DV: Meal value ordered from rest.	
	Probit (I)		OLS (II)		OLS(III)	
	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	-2.896***	0.009				
ad	0.131***	0.014	0.001***	0.0001	0.314***	0.054
ad^{price}	-0.069**	0.028	-0.001***	0.0003	-0.249*	0.113
$ad^{intermediate}$	0.004	0.028	-0.0002	0.0003	-0.022	0.126
$discount$	0.007***	0.0003	0.00006***	0.000003	0.018***	0.001
$discount * ad$	-0.0003	0.0005	0.000019**	0.000007	0.0058*	0.0026
$discount * ad^{price}$	0.0021*	0.001	0.000034*	0.00001	0.0082(.)	0.0047
$discount * ad^{interm.}$	-0.0001	0.001	0.000007	0.00001	-0.00007	0.005
Day FE			Yes		Yes	
No. Obs	5,474,448		5,474,448		5,474,448	

Significance Codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, (.) $p \leq 0.1$
Std. Errors clustered at the individual level

Table 6: Meal value conditional on preparing a cart for the focal restaurant

	Estimate	SE
Discount	-0.29	0.56
Ad Stock	-2.36	2.95
Pre-expt. avg. order value	0.42***	0.03

Std. Errors clustered at the individual level

Table 7: Effect of Ads on conditional conversion at cart

	Probit (I)		OLS (II)	
	Estimate	SE	Estimate	SE
Intercept	0.035	0.072		
ad	0.068**	0.023	0.015	0.009
ad^{price}	-0.1404***	0.031	-0.0402***	0.011
$ad^{intermediate}$	-0.044	0.032	-0.0107	0.0109
$discount$	0.0166***	0.0006	0.0054***	0.0002
Customer Characteristics	Yes		Yes	
Day FE			Yes	
No. Obs	28,319		28,319	

Significance Codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, (.) $p \leq 0.1$
Std. Errors clustered at the individual level

Table 8: Effect of Ads on conditional conversion at cart with additional term included for 'reference effect'

	Probit (I)		OLS (II)	
	Estimate	SE	Estimate	SE
Intercept	0.028	0.073		
ad	0.067**	0.024	0.019*	0.009
ad^{price}	-0.133***	0.031	-0.0365**	0.011
$ad^{intermediate}$	-0.034	0.032	-0.0081	0.011
$discount$	0.0164***	0.0008	0.005***	0.0003
Diff. bet. expected and actual discount	0.0003	0.0007	0.0004	0.0003
Customer Characteristics	Yes		Yes	
Day FE			Yes	
No. Obs	28,319		28,319	

Significance Codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, (.) $p \leq 0.1$
Std. Errors clustered at the individual level

Table 9: Three stage model estimation results

	Order Stage		Cart Stage		Menu Stage	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Intercept	0.029	0.009	-1.079***	0.135***	-2.557***	0.217
	(0.072)	(0.077)	(0.003)	(0.004)	(0.011)	(0.015)
ad	0.047(.)	0.012	-0.055***	0.012	-0.246***	0.026***
	(0.024)	(0.027)	(0.013)	(0.016)	(0.001)	(0.002)
ad^{price}	-0.102***	0.047	-0.003	0.001	- 0.003	0.001
	(0.029)	(0.031)	(0.017)	(0.022)	(0.005)	(0.006)
$ad^{intermediate}$	-0.031	0.025	0.0009	0.0002	-0.002	0.001
	(0.028)	(0.03)	(0.017)	(0.021)	(0.005)	(0.006)
$discount$	0.019***	0.005***	0.006***	0.002***	0.029***	0.001***
$(or E_i[D\|Ad_j])$	(0.0008)	(0.001)	(0.0003)	(0.0004)	(0.0001)	(0.0002)

Significance Codes: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, (.) $p \leq 0.1$
Estimates for coefficients on customer characteristics not shown here

11 Appendix

11.1 Randomization Checks

I ensure the assignment of discount level, ad frequency and ad type is sufficiently randomized by examining the correlations between the treatment variables and pre-treatment customer characteristics

Table 10: Randomization Checks 1

	Brand Ad assigned		Intermediate Ad assigned		Price Ad assigned	
	Correlation	p-value	Correlation	p-value	Correlation	p-value
Avg. Order Value	-0.0003	0.87	0.001	0.57	-0.0004	0.83
Previous focal rest. customer	-0.0002	0.92	0.003	0.11	0.003	0.17
Avg. discount % used	0.0001	0.94	-0.001	0.48	-0.0004	0.82
Avg. rest. cost for two	0.001	0.41	0.003	0.17	0.0008	0.7
Fraction of orders made on discount	-0.0008	0.71	-0.001	0.46	-0.0003	0.88
Expected discount conditional on receiving a notification	0.001	0.47	0.0005	0.81	-0.001	0.65

Table 11: Randomization Checks 2

	Discount Level		Ad Frequency	
	Correlation	p-value	Correlation	p-value
Avg. Order Value	0.0000	0.98	-0.002	0.33
Previous focal rest. customer	0.002	0.26	-0.001	0.6
Avg. discount % used	0.0009	0.68	-0.002	0.22
Avg. rest. cost for two	-0.001	0.41	0.002	0.29
Fraction of orders made on discount	-0.0003	0.86	-0.003	0.12
Expected discount conditional on receiving a notification	-0.001	0.53	0.003	0.14