Consider a display ad for Old Navy® that announces a discount. Such price advertising mentions the brand and often shows a picture of the product, thus informing consumers of the brand and some characteristics (the ‘brand advertising effect’). It also highlights a discount, thus informing consumers of the existence of a discount (the ‘pure promotion effect’). There could be a third effect, the ‘discount spotlighting effect’ - a reduction in brand preference from price advertising that arises from the brand choosing to highlight a discount in its advertising and marketing itself based on low price. These three effects are typically confounded and, in particular, the ‘discount spotlighting’ effect has not been studied before. Two identical consumers, one who has seen a brand ad and then found out about the discount separately, and another one who has seen a price ad, have the same information about the brand and the discount. However, they will have different probabilities of purchase due to the ‘discount spotlighting’ effect.

I demonstrate the existence of this effect by designing and implementing 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. More broadly, I use this experiment to investigate the differences in the effects of ads with and without explicit discount information (‘price ads’ and ‘brand ads’) on (1) demand, (2) the different stages of the purchase funnel (menu page; cart page; purchase), and (3) non-advertised rivals. Managerial implications are discussed.

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

---

*PhD candidate in Marketing at the University of Chicago Booth School of Business. sbiswas@chicagobooth.edu*
1 Introduction

Understanding the effects of advertising on demand has long been a major focus of marketing academics (Sethuraman et al., 2011). An important question that is still unanswered is: what is the impact of including discount information in an ad relative to including only ‘brand-enhancing’ information? Previous literature (Mela et al., 1997; Kaul and Wittink, 1995) has compared the effects of brand advertising (eg. TV ads) with price advertising/promotions (eg. newspaper features, in-store displays, temporary price reductions), without isolating the effects of the presence of discount information in advertising. In particular, previous empirical literature studying price advertising has not separated its three different effects: the brand advertising effect, the pure promotion effect and the ‘discount spotlighting’ effect.

To clarify, price ads (like the Old Navy® display ad below) generally contain some brand information (like the name of the brand and a picture of the product) and highlight the presence of an available discount.

![Old Navy® Price Ad](image)

Figure 1: Old Navy® Price Ad

Such ads may have three distinct effects:

- The brand advertising effect - this is the effect of informing consumers of the existence of the brand (Nelson 1970) and may also increase brand preference (Comanor and Wilson 1979). This effect is common to both brand and price advertising, and is presumably positive for the advertised brand at all stages of the purchase funnel, i.e. awareness, search and conditional purchase.

- The pure promotion effect - this is the same effect that would exist if the consumer saw a shelf discount of the same amount at the store. A large discount (relative to expectations)
will increase search (for more product information), and will increase conditional purchase due to the lower price. However, knowing that the brand is offering a discount could also affect brand preference negatively \cite{Blattberg and Neslin, 1989} and this might lower search and conditional purchase.

- The ‘discount spotlighting’ effect - a consumer may infer that a firm that chooses to highlight a discount in its advertising is not differentiated in any way apart its low price, and hence is marketing itself based on price. This would negatively affect brand preference and would lower search and conditional purchase. This is an effect that price advertising has, but not brand advertising. Also, this effect is different from the pure promotion effect as it arises from the fact that a discount is *highlighted in an ad*, and not from the fact that the discount exists. It is unique to price advertising.

A newspaper feature or an in-store display (which are the types of price advertising studied in previous literature) that mentions the brand and its lowered price has the combined effects of brand advertising, pure promotion and ‘discount spotlighting’. Thus, these effects are confounded in previous empirical literature on price advertising. The main objective of this paper is to demonstrate the existence of the ‘discount spotlighting’ effect, separated from the brand advertising effects and the pure promotion effect, something that previous literature has not done. More broadly, I investigate the effects of including discount information in advertising on overall demand and elucidate its influence on each stage of the purchase funnel (search and conditional purchase). In addition, I examine how ads with and without explicit discount information differentially affect non-advertising rivals.

Why is the issue of discount information in advertising important? Unlike in the offline world where brand advertising is done through eg. TV and price advertising is done through eg. newspaper inserts, and these are separate and serve different purposes, online ads are limited to an image to be displayed to the consumer, an email subject like or a short pop-up message on the phone. In the online context, brand ads and price ads are substitutes for each other. Whether the firm should use the limited advertising space to highlight a discount is not clear. Firms invest a lot in optimizing their advertising content \cite{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. Notwithstanding ‘conventional wisdom’ of firms such as Google that highlighting discount information is good practice for display ads\footnote{https://support.google.com/google-ads/answer/1722134?hl=en}, studying the effects of the inclusion of discount information is an important and open question for researchers and practitioners.

Why is the ‘discount spotlighting’ effect, in particular, important? Managers primarily care about the overall effects of advertising on demand. However, in the online context, they have the ability to direct their marketing messages at each stage of the funnel. To best leverage this ability, understanding how the different types of ads differentially affect the different stages of the purchase funnel is important. Consider two identical customers who have ended up at the payment stage, one who has arrived at the payment stage having seen a brand ad and another who has seen a price ad. The discount available to both of them is the same. At this stage, both customers have identical information about the brand and the available discount. However, the ‘discount spotlighting’ effect might lower the probability of purchase of the customer who has seen the price ad\footnote{Another relevant phenomenon is the reference price effect. The customer who saw the brand ad and did not expect a discount might be more likely to purchase as the price is lower than his expectation. I rule this out as a potential factor in my data. But more generally, it could be something that managers need to consider for their decision of whether to include discount information in ads.}. A cart abandonment message with an additional discount might need to be sent to convince this customer to purchase. Also, the future purchase patterns of these two customers might be different due to differences in brand preference arising from the ‘discount spotlighting’ effect. Thus, besides academic interest in understanding the constituent parts of an overall effect, the ‘discount spotlighting’ effect is relevant to managers as well.

In order to separate the ‘discount spotlighting’ effect from the brand advertising effect and the pure promotion effect, we have to compare demand from consumers who have identical knowledge of the same discount, have seen the same brand information in advertising, but only differ in whether they have seen an ad that highlights discount information or not. Comparing the behavior of consumers who have arrived at the payment stage of the purchase funnel (while accounting for self-selection, so that we compare arguably identical consumers) having seen different ads (which were randomly assigned to them) is an ideal way to do this. We can leverage the power of experimentation.
and the ability to track the entire purchase funnel in the online advertising context. First, we need ads that only differ in the presence or absence of discount information. Next, we need a discount to be made available and the availability of discount should be independent of the type of ad. Ideally, we want to measure the effects at several different discount levels in order to rule out alternate explanations such as increased price sensitivity and reference price effects. With the ‘discount spotlighting’ effect, we expect that the conversion rates to purchase would be higher with brand ads (relative to price ads) at all discount levels, and the difference should increase (or stay the same) with increasing discount level. Increased price sensitivity under price advertising would predict that high discounts would be more effective under price advertising, i.e. if brands can have higher conversion rates, but the difference in conversion rates between consumers who have seen brand ads and price ads should decrease with increasing discount. A reference price effect would predict that conversion to purchase with brand ads is higher when the discount seen is higher than expectations, but is lower when the discount seen is lower than expectations. Having different price points would also help us understand how the entire demand curve shifts under different advertising types, enabling us to comment on joint optimization of price and advertising. Finally, to measure ad effects, we need variation in advertising intensity. Thus we need exogenous variation in ad type, discount level and ad frequency, and these three should all vary independently. Varying all three dimensions independently in the same context is difficult.

I partner with a food delivery platform to generate the required variation described above to study the impact of including price information in advertising for a focal restaurant on the platform. The experiment was conducted on a sample of 195,516 customers for a duration of four weeks. Randomization was done at the customer (login) level on the platform. Five different discount levels (0%, 10%, 20%, 30%, 40%), five different advertising frequencies (0, 1, 2, 3, 4 times a week) and two different types of ad creatives that differed in only in terms of whether there was an explicit mention of discount or not. The two different types of creatives were: a brand ad that did not mention anything about a discount, and a price ad that explicitly mentioned the percentage.

---

3 One caveat about the experiment context 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 upon receiving an ad. Thus, the concept of a ‘brand ad’ is slightly different from that in the literature in that it inherently comes with the expectation of a deal even if nothing about a deal is explicitly mentioned.
discount that is available and highlighted (bold letters) it. 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. The results from the experiment are described below.

First, I compare the effects of the different types of ads on overall demand for the focal restaurant (probability of placing an order). I find that all ads raise demand at all discount levels. Ad effects are bigger at higher discount levels, i.e. advertising shifts the demand curve out and also makes it more elastic (consistent with Erdem et al., 2008). Comparing the different types of ads, we see that at low discounts (10%), brand advertising is most effective and at high discounts (40%), price advertising is most effective. The demand curve is thus more elastic under price advertising relative to brand advertising. Among the tested discount levels in the experiment, the optimal discounts are: 20% under no advertising, 30% under brand advertising and 40% under price advertising, with 40% under price advertising being the best overall. This illustrates that when setting prices, managers should first measure elasticities under the different advertising options and then jointly optimize over both price and type of advertising.

Next, I examine the effects of the different types of ads on the probability of searching for or considering the focal restaurant (visiting the restaurant menu page). As might be expected, consumers use the discount information conveyed to adjust their decision to visit the restaurant menu page - those who received a price ad with a 40% discount are more likely to visit the restaurant menu page compared to those who received a price ad with a 10% discount. Consumers who receive brand ads have similar probabilities of visiting the restaurant menu page at all discount levels. This directly demonstrates the effect of conveying discount information in ads. Consumers who receive the additional information can make the decision to visit the restaurant menu page according to the revealed discount, whereas consumers who don’t have to make the decision based on their expectations of the available discount. The rates of visit to the restaurant menu page

4 An additional creative (intermediate ad) that only mentioned that there was a discount available without mentioning the exact percentage discount and without highlighting it was also used. The effects of this ad were very similar to the brand ad

5 Besides looking at the outcome of whether an order is placed (the extensive margin), I also look at the size of the order (intensive margin) and find no effect on meal value conditional on an order being placed

6 Since costs are not known, these are revenue maximizing prices (after accounting for the discount amount)
through the brand ad correspond to a discount level between 20% and 30% with the price ad. This is approximately the average historical (pre-experiment) discount level advertised through notifications on the platform, and hence consumers expect a discount between 20% and 30% when they receive an ad, even if an explicit discount is not mentioned in it. The type (according to their discount affinity based on purchase history) of people who visit the restaurant menu page at each discount level also changes under price advertising but not under brand advertising i.e. consumers self-select themselves into visiting the restaurant menu page according to their knowledge of the available discount and how sensitive they are to discounts. At low discount levels, fewer people visit the restaurant menu page with price advertising relative to brand advertising, leading to lower demand (number of orders). This directly contradicts the conventional wisdom in digital advertising, including at the partner firm, to highlight any available discount in ads. At higher discount levels, the additional information benefits the restaurant (leads to more menu visits and orders) - this is the primary purpose of using price advertising. It attracts additional customers to check out the brand attracted by the availability of a high discount.

After visiting the restaurant menu page and adding items to their cart, consumers move to the payment (cart) page if they wish to continue beyond the menu page. At this stage, the available discount (in percentage as well as actual amount) is revealed to all consumers. Information differences between consumers are now eliminated. By comparing rates of conversion to purchase among consumers who received different ads (which were randomly assigned to them) at this stage, we can test for the effect of including price information on brand preference. However, as described above, consumers self-select themselves into visiting the restaurant menu and cart pages. A direct comparison is no longer valid as we need to compare identical sets of consumers. I use three different approaches to account for self-selection (so that we compare arguably identical sets of consumers who have been randomly assigned different types of ads), using traditional econometric methods as well as modern advances in machine learning: (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 a large set of observable characteristics; 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 a consumer who receives price advertising has a lower post-search probability of purchase relative to brand advertising or no advertising. This points to a lowered brand preference under price advertising through the discount spotlighting effect. Comparing the sizes of the discount effect and the discount spotlighting effect on conversion to purchase, we see that the negative discount spotlighting effect would have to be offset by an additional discount of around 7% to 8% (for an average customer) in order to achieve the same conversion rates to purchase at cart. I also rule out alternate explanations of a reference price effect and increased price sensitivity (i.e. a larger price co-efficient conditional on arriving at cart for the advertised restaurant) by examining how the effect varies with discount level. In the post-experiment period (two weeks), differences in demand between consumers who received brand ads and price ads are statistically indistinguishable from zero.

Finally, I examine consumer purchases among non-advertised rivals. First, I find that consumers who received any ads purchase more on the platform indicating positive spillovers to non-advertised rivals. The number of orders made from non-advertised rivals is not different under the different ad types. However, 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 oriented messaging for a brand become more discount-seeking in the category as a whole. Other restaurants which indicate that there is a discount available on the restaurant listings page of the app benefit from higher purchase rates from consumers who received price ads for the focal restaurant. Thus, price advertising for a focal brand has spillovers to other discounted brands. However, this effect is short-lived (disappears after two weeks). This finding has implications for the nature of price competition among firms under different advertising regimes and platform policy on ad content. When more discount oriented ads are sent to consumers, non-advertised firms may optimally offer more discounts and this may in turn lead to lower revenues for the platform as consumers shift towards buying more on discount.

While price advertising can have adverse effects for firms in terms of increased deal-seeking in the category and reduced brand preference for the advertised brand, recall that price advertising along with a 40% discount is the overall revenue maximizing policy for the restaurant. Reduced conversion to purchase is being offset by getting a larger number of people to search for the brand,
and enough of these people purchase to make this the optimal strategy for the firm. It also does not cause lowered demand in the post-promotion period relative to brand advertising. This explains why price advertising along with high discounts is prevalent among firms online and offline, despite the possible adverse effects raised in this paper and previous literature. However, since price advertising leads to increased purchasing from non-advertised rivals’ that offer discounts and leads to lower commissions for the platform, there is a possible misalignment of incentives regarding ad content between the platform and restaurants on the platform.

In summary, this paper makes four contributions to the literature. First and foremost - it contributes to the literature comparing the effects of brand advertising and price advertising/sales promotions by demonstrating the existence of the ‘discount spotlighting’ effect - a mechanism by which brand preference is reduced when a firm chooses to market itself based on low price and highlights a low discount in its advertising. Second, it contributes to the same literature by demonstrating that in combination with a high discount, price advertising can be the revenue maximizing strategy for the firm. Lower conversion to purchase is offset by the fact that highlighting a large discount in price advertising attracts a large number of consumers into searching for the product. This explains the ubiquitous use of price advertising, despite the possible negative consequences raised by this paper and previous literature. Third, it contributes to the literature on measuring the effects of advertising on different stages of the purchase funnel (search and purchase). This paper shows that the presence of price information in advertising affects both search and the purchase decision conditional on search. The presence of price information enables consumers to adjust their decision to search according to the available discount, but it also results in lowered brand preference leading to lower conversion at the purchase stage. Fourth, it contributes to the literature on advertising spillovers to rivals. It documents positive spillovers of advertising to rivals consistent with previous literature; but more importantly, it shows that price advertising differentially benefits rivals that offer discounts. Apart from the above contributions to the literature, this paper also challenges conventional wisdom in digital advertising about routinely highlighting any available discount. It shows that revealing a low discount level (as opposed to not mentioning a discount) can actually reduce search and consequently demand, at least in contexts where discounts are high and frequent.
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, I examine the conditional purchase decision post search. In Section 7, I look at post-experiment demand. In Section 8, I examine the spillover effects of focal brand advertising on non-advertised rivals. In Section 9, I present managerial implications and in Section 10, 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 and also to some related literature on sales promotions:

2.1 Effects of brand advertising, price advertising and sales promotions

Previous literature that has compared brand advertising and price advertising has mainly focused on price elasticity. Theoretical literature in economics has claimed that advertising, by inducing product differentiation in the consumers’ mind, can increase brand preference (Bain 1956; Comanor and Wilson 1979).

While there is no theory view specifically on price advertising, theories on sales promotions predict that they lower brand preference and increase price elasticity. For example, according to the attribution theory, (Sawyer and Dickson 1984), 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). Self perception theory (Dodson et al. 1978) proposes that when people purchase a product on discount, they attribute their choice to the low price rather than a high preference for the brand, which lowers probability of purchase when the discount is taken away. Other researchers have also proposed that sales promotions leads to lowered brand preference, although without an underlying theory (Blattberg and Neslin 1989; Yoo et al. 2000; Aaker 2009).
Previous empirical literature looking at brand advertising and price advertising has also mainly focused on price elasticity (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, 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 found that price elasticity decreases with advertising. Some studies also found the opposite effect for brand advertising, Kanetkar et al., 1992 found that increased brand advertising increased price sensitivity, and Erdem et al., 2008 showed that the demand curve facing a brand is shifted outward and made more elastic under brand advertising. Kalra and Goodstein, 1998 and Mitra and Lynch Jr, 1995 added to the analysis in Kaul and Wittink, 1995 by dividing non-price advertising into different types and examining the effects of these types of advertising on price sensitivity. Jedidi et al., 1999 showed that advertising increased brand equity in the long term whereas promotions reduced brand equity. They defined promotions purely as price reductions and did not look at price advertising.

The above empirical literature hasn’t isolated the effect of including discount information in advertising. Studies looking at price and brand advertising have done so in separate contexts (different sets of products, consumers, media etc.) and ad messages that only differ in price content haven’t been compared. Further, the three different effects of price advertising have not been separated. Even when examining the effect of promotions, disentangling the direct effect of the discount on demand (i.e. the price effect) and any indirect effect of the promotion on brand preference is challenging. One way to remove the confound of the direct price effect would be to focus on long term effects. Current price changes should not affect future behavior, except through within-consumer changes in brand preference or price sensitivity (or changes to reference prices). Mela et al., 1997 use observational data to examine the long term effects of promotions and brand advertising on price sensitivity. They found that brand advertising lowers price sensitivity in the long term, while promotions raise it. Mela et al., 1997 is the most similar to this one as it directly compares the effects of brand advertising and promotions for the same set of products and on the same set of households. However, the focus of that paper is different from this one.
they were interested in brand advertising vs. promotions, and not price advertising. In their study, temporary price reductions, coupons and feature advertising are combined together as ‘price-oriented promotions’. The effect of price advertising is not separated from the availability of a temporary price reduction or coupon. Further, the effect of discount information in ads is not isolated and the different effects of price advertising are not separated.

As mentioned above, previous empirical literature comparing brand and price advertising has typically focused on 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 (as is the case in many of the studies reviewed in [Kaul and Wittink, 1995]). 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 a more elastic aggregate demand curve for the brand. Also, informing more consumers when prices are low and thus raising demand at 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. Thus in this paper, I focus on brand preference instead of price elasticity. Of course, a lower brand preference would lead to higher price elasticity, but the source of the increase in elasticity is more clearly defined.

I contribute to this literature by empirically establishing the existence of the ‘discount spotlighting’ effect - a reduction in brand preference that occurs when a firm chooses to market itself based on low price and highlights a low discount in its advertising. In addition, I contribute to this literature by empirically showing that in combination with a high discount, price advertising can be the revenue maximizing strategy for the firm. Lower conversion to purchase is offset by the fact that highlighting a large discount in price advertising results in more consumers searching for the product. This explains why the use of price advertising is prevalent, despite the possible negative consequences raised by this paper and the literature described above.
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. This paper contributes to this literature by showing that the presence of price information in advertising affects both search and the purchase decision conditional on search. The presence of discount information enables consumers to adjust their decision to search according to the available discount, but also results in lowered brand preference leading to lower conversion at the purchase stage.

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 through 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.

As described in the introduction, to demonstrate the existence of the ‘discount spotlighting’ effect and to more broadly understand the effects of price vs brand advertising, I design an experiment to create exogenous variation in advertising intensity, price information content in advertising and prices for a focal restaurant on the platform. For the 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 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

---

7 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.
also randomly assigned to one of two ad type conditions: Brand Ad and Price Ad\(^8\). The brand ad does not contain any information about the available discount. 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 different ad types 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 2. Figure 4 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 was done at the customer (app login ID) level and these were randomized independently of each other. One exception was that 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 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

\(^8\) An additional creative (intermediate ad) that only mentioned that there was a discount available without mentioning the exact percentage discount and without highlighting it was also used. The effects of this ad were very similar to the brand ad and hence I do not show this separately in the results.
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 3. Screenshots of the different pages along the customer purchase funnel described above are shown in Figures 4, 5 and 6.

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 is revealed 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 discount 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 the ‘discount spotlighting’ effect from the ‘brand advertising effect’ and the ‘pure promotion effect’. At this stage, since brand
knowledge and knowledge of the discount are the same across all consumers, and the only difference between them is the type of ad they saw, any differences in conversion to purchase are a result of the ‘discount spotlighting effect’.  

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 at least 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

\footnote{There could also be differences as a result of increased price sensitivity due to price advertising or a reference price effect from the consumer seeing a discount that is higher or lower than their expectations (for brand ads). I rule out these alternate explanations later}
frequency. Thus, virtually the entire sample received at least one ad, if they were assigned to receive any ads. Thus, the effect of having been assigned to a particular ad type and receiving at least 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 at least one ad of the assigned type. All results carry through. The results from the experiment are described in the following sections.

4 Overall Effect on Demand

In this section, I study the effects of the different types of ads on demand for the focal restaurant. Figure 7 shows the probability of a customer placing at least one order with the focal restaurant under the different ad conditions. We see that all ads raise demand at all discount levels. Ad effects are bigger at higher discount levels, i.e. advertising shifts the demand curve out and also makes it more elastic (consistent with Erdem et al. 2008). Comparing the different types of ads, we see that at low discounts (10%), brand advertising leads to highest demand and at high discounts (40%), price advertising results in highest demand. The demand curve is thus more elastic under price advertising relative to brand advertising (i.e. the difference in demand between 10% and 40% discount is higher under price advertising relative to brand advertising). Among the tested discount levels in the experiment, the optimal discounts are: 20% under no advertising, 30% under brand advertising and 40% under price advertising, with 40% under price advertising being the best overall. This illustrates that when setting prices, managers should first measure elasticities under the different advertising options and then jointly optimize over both price and type of advertising. Also, the finding that brand advertising leads to higher overall demand at low discounts highlights that caution should be exercised when applying the conventional wisdom in digital advertising that suggests that any available discount should be highlighted in digital ads. We will explore the mechanism behind this finding in the next section.

\[\text{\footnotemark[10]}\text{Since costs are not known, these are revenue maximizing prices (after accounting for the discount amount)}\]
The figure does not utilize the variation in ad frequency. Next, I analyze the full panel with data at the individual-day level and utilize the variation in ad frequency to measure ad effects on demand using the following model:

\[
y_{it} = \alpha + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \beta \text{discount}_i + \nu_1 (ad_{it}) \ast (\text{discount}_i) \\
+ \nu_2 (ad_{it}^{price}) \ast (\text{discount}_i) + \epsilon_{it} 
\]  

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. \(\delta\) is the advertising carryover factor. Following Shapiro et al., 2018, I use a grid search to fix the value of \(\delta\). Model (1) is estimated using OLS repeatedly with different values of \(\delta\) 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, \(\delta\) is fixed at 0.24.
- \(ad_{it}^{price}\) is the goodwill stock of price advertising for individual \(i\) on day \(t\). The coefficient on this 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. The interpretation of coefficients is similar for the interaction terms of discount and advertising.\(^{11}\)
- \(\text{discount}_i\) is the percentage discount that is assigned to individual \(i\) i.e. 0,10,20,30 or 40

\(^{11}\)Similar terms are also included for intermediate ads. Brand ads and intermediate ads are found to have similar effects. This holds true for all results in the remaining sections of the paper as well. We are primarily interested in interpreting the differences between price and brand ads. Thus, in the interest of brevity, results for intermediate ads are not reported separately and the terms in equations are not shown, although they are used in estimation.
under specification I and II respectively. For probit, the specification is changed to

\[ y_{it}^* = \alpha + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \beta discount_i + \nu_1 (ad_{it}) \ast (discount_i) \]
\[ + \nu_2 (ad_{it}^{price}) \ast (discount_i) + \epsilon_{it} \]  

and

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

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 7. 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.

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 consumers searching
differently, or do they arise from differences in consumers converting to purchase at different rates
once full information about price has been revealed to them?

5 Effect on Search (Menu Page Visits)

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. The main finding here is
that the rate at which consumers visit the menu page of the focal restaurant differs with discount
level for price advertising, but not with brand advertising. Consumers self-select themselves into
visiting the restaurant menu page in response to different types of ads according to their knowledge
or expectation of available discount. This demonstrates the primary purpose of conveying discount
information to consumers using price advertising - managers do this hoping that many consumers
check out the product (i.e. search for it), being attracted by the presence of a high discount. If
discount information is not conveyed through ads, consumers have to make the search decision
based on their expectations of price. In what follows, I will discuss this in more detail.

If price information in advertising affects how consumers search, we should expect to see differ-
ences 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 received brand ads, that do not mention a discount, presumably make the decision to search based on their expectation of available discounts. Most notifications that the platform has sent consumers historically convey information on discounts. Thus, consumers may expect a non-zero discount conditional on receiving a notification from the platform, even if the notification does not explicitly mention one. The consumer will pay a 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 in the experiment.

Based on historical push notifications sent to each customer in the experiment sample, I create a measure of expected discount conditional on receiving a notification for each customer (which is simply the average of all discount amounts mentioned in previous notifications received). The average expected discount conditional on receiving a notification is found to be 23%. Based on this number 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 8 shows the 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 vary with discount level under the ‘No Ad’
and ‘Brand 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. However, this 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 (23% expected discount conditional on receiving an ad), it is better off using brand ads. 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 of mentioning any available discount in ads is proved to be wrong in this case (and is generalizable to similar high discount contexts eg. Groupon®). However, at high discount levels, the informative effect of price advertising works in favor of the firm i.e. leads to higher search and demand.

We see that the search probabilities for brand ads are between those for the 20% and 30% price ads. This is consistent with the notion of search based on expected discounts and the fact that the average expected discount conditional on receiving a notification is found to be 23%. In order to delve deeper into this, I split the sample of individuals according to the measure for expected discounts and look at the search patterns for different sub-samples. Figure 9 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 probabilities for brand ads are between those for the 10% and 20% price ads for consumers whose discount expectations are less than 20. Similarly, the search probabilities for brand ads are between those for the 30% and 40% price ads for consumers whose discount expectations are greater than 30. Most of the sample falls in the ‘between 20 and 30’ range and their search probabilities for brand ads are between those 20% and 30% price ads. This demonstrates that people indeed search according to their expectations of discount if they are not informed of specific discount level through price advertising. The notion of a ‘brand ad’ in this context might be different from that in the literature, where the assumption is that a brand ad does not evoke any expectation of a non-zero discount.
Next, we look at the second stage of the purchase funnel, which is the cart page. Figure 10 shows the probability that an individual visits the focal restaurant cart page after adding items to the cart from the menu page. 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’ and ‘Brand Ad’ conditions. However, it does vary with discount level under the ‘Price Ad’ condition in the way that we would expect.

5.1 Self-selection of consumers into search

Since consumers are able to make the search (menu page visit) decision with more information under price advertising, this means that they are able to self select into search according to their knowledge of the available discount and their sensitivity to discounts. We might expect that individuals who are highly discount seeking or most price sensitive make the decision to visit the menu page only under the 40% condition. On the other hand, the people who make the decision to visit the menu page 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 visited the menu page under the different ad and discount conditions - and test the hypothesis that the group of individuals who visited the menu page 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 the price of an average meal for two people, at that restaurant. 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. We can interpret this quantity as indicating whether a consumer orders from relatively more expensive or cheap restaurants.

Apart from these proxies for discount-seeking or price sensitivity, we might also expect that individuals who are not familiar with the focal restaurant, i.e. those who have not made a single purchase from the focal restaurant before the experiment, are more likely to respond only to high discounts. Thus I create a dummy variable that indicates whether the consumer is a ‘previous restaurant customer’ i.e. has ordered at least once from the focal restaurant before the start of the experiment.

Figures 11 and 12 show the mean 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 11 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 ‘cost for two’ of previous restaurants ordered from. 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 visited the menu page in the ‘No Ad’ and ‘Brand 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 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 12 (a) and (b), we see that individuals who responded to the 40% discount price ad are those who have used high discount amounts on their pre-experiment orders i.e. they are more discount seeking. Individuals who responded to the 10% discount price ad are those who have used lower discount amounts for their pre-experiment purchases. From, Figure 12 (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. However, the different ad types or the different discount levels do not attract new customers at different rates.

6 Effect on Conversion to Purchase Conditional on Search

This is the section that drives the main result of the paper. By comparing rates of conversion to purchase among consumers who received different ads (that were randomly assigned to them) and are at the cart stage where they have full product information including the available discount, we can test for the residual impact of discount information in advertising, after differences in consumer knowledge of the available discount have been eliminated. Self-selection into visiting the cart page makes this comparison problematic (as we are no longer able to directly compare identical sets of consumers) but I address this using both traditional econometrics methods and modern machine learning methods. After accounting for self-selection using these different methods (i.e. comparing arguably identical sets of consumers who were randomly assigned different ads), I show that consumers who receive price advertising convert to purchase at lower rates compared to those who received brand advertising or no advertising. Since we are comparing arguably identical consumers who have the same knowledge of the brand and the available discount, and they only differ in whether they were randomly assigned to receive price ads or brand ads, the difference in conversion rates to purchase must be due to the ‘discount spotlighting’ effect. I also rule out alternate explanations like increased price sensitivity due to price advertising or reference price effects. Having said this, we must also remember that the overall revenue maximizing strategy for the restaurant was a 40% discount with price advertising. The negative effect on brand preference was offset by the fact that many people visited the restaurant menu page attracted by the high
discount and enough of them purchased to make this an optimal strategy. This explains the prevalent use of price advertising combined with high discounts, despite possible negative effects brought up in this paper and previous literature.

In what follows, I go into more detail.

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, using a high dimensional set of consumer characteristics constructed from pre-experiment historical data
- 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 (i.e. we are comparing arguably identical individuals who have been randomly assigned the different ad types), thus allowing for a causal interpretation of those adjusted differences. However, there may be unobservables that are not captured through the set of characteristics created from 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 at least one previous purchase from the focal restaurant. The model is as follows:

\[ y_{it} = \alpha_t + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \beta discount_i + \nu X + \epsilon_{it} \]  \hspace{1cm} (4)

where \( X \) is the set of customer characteristics and \( \alpha_t \) is a day fixed effect. 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

\[ y^*_{it} = \alpha + \gamma_1 ad_{it} + \gamma_2 ad_{it}^{price} + \beta discount_i + \nu X + \epsilon_{it} \]  \hspace{1cm} (5)

and

\[ y_{it} = 1 \text{ if } y^*_{it} > 0 \text{ and } 0 \text{ otherwise; } \epsilon_{it} \sim N(0, 1) \]  \hspace{1cm} (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 negative effect relative to brand ads on conversion conditional on search. This indicates 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. Comparing the sizes of the estimates (from probit or OLS) for the discount effect and the discount spotlighting effect on conversion to purchase, we see that the negative discount spotlighting effect would have to be offset by an 8% additional discount (for an average customer) in order to achieve the same conversion rates to purchase at cart.

One explanation for this difference 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 (constructed using 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. For those who received price ads, the expected discount is the actual available discount as they are informed about it. 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. The reference price effect is not a driving factor here and does not explain the lower conversion rates for price ads.

6.2 Matching on observables using 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. Recent advances in machine learning (Wager and Athey, 2018) have made it possible to match on a high dimensional set of consumer characteristics in a non-parametric way while also allowing for arbitrary interaction effects between variables, using a causal forest. 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.

\footnote{Robustness checks 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 set of observables used is much larger than the one in the previous subsection, so that matching can be done using an extensive set of characteristics. 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, number of orders made from the focal restaurant, fraction of previous notifications clicked on, fraction of previous orders made from the same cuisines as the focal restaurant, number of total orders made on the platform, length of time active on platform, total number of cuisines ordered from, total number of restaurants ordered from, average number of orders made from platform in a week, average discount level in previous notifications received, standard deviation of discounts in previous notifications received.

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 the causal forest allows us to estimate heterogenous treatment effects and predict the estimated treatment effect for each individual in the sample, we explore this heterogeneity. Figure 13 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

\[13\] This is not the actual discount level for those who received price ads, as setting this to the actual discount level would render this term useless for matching individuals who received brand ads and price ads. Instead this is defined similarly for all individuals as a characteristic that captures the discounts in previous notifications sent to the customer.
in probability of conversion. Figure [14] shows the distribution of these effects at different discount levels. We see at all discount levels, price ads perform worse than brand ads in terms of conversion rate. Also, differences between price ad and brand ad conversion rates increase with discount level i.e. the negative effect on brand preference is greater at high discount levels. Thus, a brand choosing to highlight a deep discount in its advertising could suffer a loss of brand equity. Figure [15] shows the effects for new and previous customers of the focal restaurant. We see that the difference in conversion rates is higher for new customers. This is inline with our intuition as new customers do not have well-formed brand preference for the focal restaurant and hence are more likely to be influenced by the fact that it chose to highlight a discount in its advertising.

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 base brand preference 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 effect of the advertising that she has received in addition to her base brand preference.

6.3.1 Model specification

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

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

where

- $v_{1i}$ captures individual $i$’s base preference 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

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

where

• $v_{2i}$ captures individual $i$’s base preference 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

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

• $v_{3i}$ captures individual $i$’s base preference 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 letting 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 base 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 Section 6.1. The set of observable characteristics is limited to the ones in Section 6.1 rather than the more extensive list in Section 6.2 in order to keep estimation tractable. 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:

\[ y_{1it}^* = v_{1i} + \beta_{1i}E_{it}[D|Ad^r] + \alpha_{1i}ad_{it} + \delta_{1i}ad_{it}^{price} + \gamma_1 X_i + \epsilon_{1it} \]  \hspace{1cm} (10)

\[ y_{1it} = 1 \text{ if } y_{1it}^* > 0 \text{ and } 0 \text{ otherwise} \]  \hspace{1cm} (11)

\[ y_{2it}^* = v_{2i} + \beta_{2i}E_{it}[D|Ad^r] + \alpha_{2i}ad_{it} + \delta_{2i}ad_{it}^{price} + \gamma_2 X_i + \epsilon_{2it} \]  \hspace{1cm} (12)

\[ y_{2it} = 1 \text{ if } y_{2it}^* > 0 \text{ and } 0 \text{ otherwise} \]  \hspace{1cm} (13)

\[ y_{3it}^* = v_{3i} + \beta_{3i}D + \alpha_{3i}ad_{it} + \delta_{3i}ad_{it}^{price} + \gamma_3 X_i + \epsilon_{3it} \]  \hspace{1cm} (14)

\[ y_{3it} = 1 \text{ if } y_{3it}^* > 0 \text{ and } 0 \text{ otherwise} \]  \hspace{1cm} (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

- $ad_{it}$ is the individual’s goodwill stock of ads (of any type) at time $t$
- $ad_{it}^{price}$ is the individual’s goodwill stock of price ads at time $t$. The coefficient on this term
gives the difference between price ads and brand ads. To get the full effect of price ad goodwill
stock, we need to add the coefficients on $ad_{it}$ and $ad_{it}^{price}$
- $E_{it}[D|Ad^j]$ 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 $\theta$, then $\theta \sim N(\mu, \Sigma)$. Mean parameters $\mu$
and diagonal elements of $\Sigma$ are estimated. The error terms $(\epsilon_{1i}, \epsilon_{2i}, \epsilon_{3i}) \sim N(0, \Sigma_e)$ i.e. the three
equations are set up as a trivariate probit. The diagonal terms of $\Sigma_e$ are set to 1 and the off diagonal
terms $\rho_{12}, \rho_{13}, \rho_{23}$ indicating the covariances between $(\epsilon_1, \epsilon_2)$, $(\epsilon_1, \epsilon_3)$ and $(\epsilon_2, \epsilon_3)$ 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
\[ y_{1it}^* = W' \eta + \epsilon_{1i} \quad (16) \]
\[ y_{2it}^* = Y' \zeta + \epsilon_{2i} \quad (17) \]
\[ y_{3it}^* = Z' \delta + \epsilon_{3i} \quad (18) \]

The likelihood \( (\pi_{it}) \) 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 \( \Phi \) denotes the standard normal CDF.

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

Since there are terms in \( \eta, \zeta \) and \( \delta \) 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 \( \theta \) from the distribution and compute an average value of \( \pi_{it} \) for these draws.

The log likelihood for each observation is
\[
\log(\pi_{it}) = (y_{1it})(y_{2it})(y_{3it}) \log(\Phi(W' \eta, Y' \zeta, Z' \delta; \rho_{12}, \rho_{23}, \rho_{13}))
+ (y_{1it})(y_{2it})(1 - y_{3it}) \log(\Phi(W' \eta, Y' \zeta, -Z' \delta; \rho_{12}, -\rho_{23}, -\rho_{13}))
+ (y_{1it})(1 - y_{2it}) \log(\Phi(W' \eta, -Y' \zeta; -\rho_{12}))
+ (1 - y_{1it})(1 - \Phi(W' \eta)) \quad (19)
\]

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

\[ \text{To save computation time, I subsampled individuals such that the individuals who had at least one visit to cart and 10000 other randomly selected individuals in the experiment were in the estimation sample.} \]
6.3.4 Results

The estimated mean and standard deviations for the intercept, price and ad terms at each stage are reported in Table 12. 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 or no advertising. This is evidence of the ‘discount spotlighting’ effect. Comparing the sizes of the estimates for the discount effect and the discount spotlighting effect on conversion to purchase, we see that the negative discount spotlighting effect would be offset by an approximately 7% additional discount (for an average customer) in order to achieve the same conversion rates to purchase at cart. This is similar to what we obtained in Section 6.1.

Similar to Section 6.1, I re-estimate the model with an added reference term in the last step which captures the difference between the expectation of discount conditional on receiving a notification (the difference is zero for price ads). Results are shown in Table 10. We see that the effect of the reference term comes out to be statistically insignificant and the other results do not change. This shows that the reference price effect is not an important driving force in this experiment.

6.4 Ruling out alternate explanations

Apart from an effect on brand preference due to ‘discount spotlighting’, there could be two other reasons for price advertising leading to lower conversion to purchase relative to brand advertising. The first is a reference price effect. As discussed in Section 6.1 and Section 6.3, this has been ruled out by adding an additional term that controls for the difference between expected discount percentage before the cart stage and the actual discount percentage seen at cart. Also, since discount expectations under brand ads is between 20% and 30% (as explained in Section 5), we should see conversion under brand ads be lower than price ads at 10% discount level as the expected discount is higher than the actual discount. We can see from Figure 14 that conversion under brand ads is higher at 10% as well, indicating that the reference price effect is not a driving factor in this context.

Another explanation is that the consumers’ price sensitivity increases i.e. the co-efficient on
price, conditional on arriving at cart is larger in absolute value under price advertising compared to brand advertising. If so, we should expect that conversion to purchase at high discounts should be high under price ads, i.e. even if brand ads are more effective, the difference between price ad and brand ad conversion rates would be lowest at high discount rates. Figure 14 shows the opposite pattern, thus ruling out this explanation. Note that lowered brand preference would lead to consumers being more price elastic even without a direct effect on the price co-efficient.

7 Post-Experiment Demand

Next, we examine whether the different types of advertising have different impacts on post-experiment demand. Do the differences in demand arising from the different types of ads and discounts persist after the discounts and ads are no longer available or being sent to consumers?

There could be several different predictions: (1) Since ads and discounts make more customers buy during the experiment, these same consumers would also be more likely to buy post-experiment, as they have tried the product once and it is a popular restaurant (thus presumably of high quality). Also, there is no issue of stockpiling as this is a perishable product (2) Having received a discount during experiment, consumers would be less likely to buy if the discount is taken away as their reference price is lowered (Mazumdar et al. 2005), or if their brand preference is lowered due to the existence of discount (Dodson et al. 1978; Sawyer and Dickson, 1984) (3) The ‘discount spotlighting’ effect might make consumers who received price advertising less likely to buy due to lowered brand preference.

Figure 16 shows the probability with which a customer that is assigned to each of these cells orders from the focal restaurant in the two weeks after the experiment’s end. We see that the differences between ad types do not persist for two weeks post-experiment. At all discount levels, demand from consumers who were sent price ads and those who were sent brand ads are statistically indistinguishable. Thus, the differences in the effects of the different types of ad appear to be short term i.e. they disappear within two weeks after the ads stop. The ‘discount spotlighting’ effect, does not cause lower demand (statistically significant) in the post-experiment period for consumers exposed to price ads (relative to brand ads).
However, there is a persistent base ad effect and a base discount effect. Those who saw any ad, and those who received a high discount are more likely to purchase in the post-promotion period, relative to those who received low discounts or did not receive any ads. This is inline with prediction (1) above. Increased demand during a promotion period through ads and discounts leads to greater demand in the post-promotion period as well.

8 Spillover effects

Next, we examine whether demand for non-advertised restaurants on the platform changes as a result of consumers receiving ads for the focal restaurant. 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 category benefit more from consumers being exposed to price oriented advertising from the focal brand relative to brand oriented advertising.

Figure 17 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 discount oriented advertising relative to brand oriented advertising.

Figure 18 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 ads. Being exposed to advertising that highlights the availability of a discount at the focal restaurant, causes an increase to the likelihood of choosing to order from other restaurants that have discounts available (discount information is present on the restaurant listings page). 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 rivals, but it does not cause a shift towards more discounted brands.

This has implications for optimal pricing of rival brands and optimal ad content policy for the platform. If restaurants on the platform end up sending more price oriented ads to consumers, consumers may become more ‘deal prone’ on the platform. Non-advertising restaurants would then optimally offer discounts as well. Since these messages are only being sent to existing customers of the platform, these customers just end up switching from restaurants without discounts to ones with discounts. Since the platform makes money from a commission on restaurant revenue, this could lead to lower revenues for the platform. Managing the right mix of brand and price advertising on the platform is therefore called for. As mentioned above, price advertising with 40% discount was the revenue maximizing option for the restaurant. But since the platform loses commissions and revenue if more customers buy on discount, the platform might prefer that the advertising restaurant use the brand-ad with 30% discount, which is its 2nd best option. This misalignment of platform and restaurant incentives regarding ad type has implications for the way the platform regulates restaurant advertising, either through differential pricing of ads or capping the number of price ads that can be sent.

9 Managerial Implications

The findings in this paper have several implications for managers who want to optimize pricing and advertising. First, at low discount levels, price advertising leads to lower overall demand relative to brand advertising. This directly contradicts general practice in the digital advertising industry of highlighting any available price discount in digital ads. 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, the revenue maximizing price points under no advertising, price advertising and brand advertising were different, price and type of advertising must be jointly optimized.

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 ‘discount spotlighting effect’, which leads to lower conversion to purchase at cart, 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 (assuming that such a discount is profitable for the firm).

The above implications are directly relevant for Swiggy. 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 mis-measurement 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. Advertising firms and the platform might have misaligned incentives in terms of type of advertising. Non advertising firms may optimally offer discounts during periods when consumers on the platform receive more price oriented messaging, and consumer purchases on the platform would be discounted more heavily. This may lower platform revenue unless it is offset by new customers joining the platform being attracted by increased discounting. Thus, although discount oriented advertising may be optimal for advertising restaurants, it may not be optimal for the platform. Since platforms have the ability to regulate advertising content that participating firms use, they may want to limit the use of price oriented messaging to prevent consumers from becoming more discount seeking, or becoming more liable to switch to rival platforms that offer additional discounts.
10 Conclusion

In this paper, I show that the inclusion of discount information in advertising has a causal effect of decreasing brand preference through the ‘discount spotlighting effect’. I also justify the prevalence of price advertising by showing that the negative effect of ‘discount spotlighting’ on conversion to purchase is offset by attracting many more consumers to search for the product at high discount levels. Further, I illustrate the effects of price and brand advertising on overall demand, search and purchase conditional on search. I show that discount advertising may lower search and purchase at low discount levels, thus challenging conventional wisdom in digital advertising that any available discount should be highlighted. 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 price competition among firms under different advertising regimes and optimal platform policy regarding advertising content.

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 how different sequences of advertising types or different sequences of discounts affect consumer behavior. Another limitation is that there was only one advertised brand. So effects of different firms competing with different types of advertising were not studied. These are interesting topics to explore in future research.

References


11 Tables and Figures

![Brand Ad](image)
(a) Brand Ad

![Price Ad 10%](image)
(b) Price Ad 10%

![Price Ad 20%](image)
(c) Price Ad 20%

![Price Ad 30%](image)
(d) Price Ad 30%

![Price Ad 40%](image)
(e) Price Ad 40%

Figure 2: Different Ad Creatives
Figure 3: Steps in the purchase funnel

Figure 4: Screenshot of ad push notification on an Android phone and the landing page after clicking on the ad
Figure 5: Listing and Search pages

(a) Listing Page
(b) Search Page

Figure 6: Menu and Cart pages

(a) Menu Page of Focal Restaurant
(b) Cart Page for Focal Restaurant with assigned discount auto-applied
Error bars report 95% confidence intervals

Figure 7: Effect of the different types of ads on demand for the focal restaurant

Error bars report 95% confidence intervals

Figure 8: Effect of the different types of ads on probability of visiting the focal restaurant menu page
Figure 9: 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 ads make the decision to search based on their expectations of discount.
Error bars report 95% confidence intervals

Figure 10: Effect of the different types of ads on probability of visiting the focal restaurant cart page

Figure 11: Pre experiment customer ‘characteristics’ for individuals who chose to visit the focal restaurant menu page under different discount and ad conditions (1)
Figure 12: Pre experiment customer ‘characteristics’ for individuals who chose to visit the focal restaurant menu page under different discount and ad conditions(2)
Figure 13: Distribution of differences in probability of conversion at cart after having been treated with a price ad and brand ad
Figure 14: Distribution of differences in probability of conversion at cart after having been treated with a price ad and brand ad for different discount levels.
Figure 15: Distribution of differences in probability of conversion at cart after having been treated with a price ad and brand ad for previous and new focal restaurant customers.

Figure 16: Post experiment demand from focal restaurant.

Error bars report 95% confidence intervals.
Error bars report 95% confidence intervals

Figure 17: Mean number of orders per customer from non-focal restaurants

Error bars report 95% confidence intervals

Figure 18: Fraction of discounted orders from non-focal restaurants made by customers under the different ad conditions
Table 1: Discount Distribution

<table>
<thead>
<tr>
<th>Discount Level</th>
<th>% of customers assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>15%</td>
</tr>
<tr>
<td>10%</td>
<td>21.25%</td>
</tr>
<tr>
<td>20%</td>
<td>21.25%</td>
</tr>
<tr>
<td>30%</td>
<td>21.25%</td>
</tr>
<tr>
<td>40%</td>
<td>21.25%</td>
</tr>
</tbody>
</table>

Table 2: Frequency Distribution

<table>
<thead>
<tr>
<th>Frequency of notifications (per week)</th>
<th>% of customers assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>17.5%</td>
</tr>
<tr>
<td>1</td>
<td>17.5%</td>
</tr>
<tr>
<td>2</td>
<td>25%</td>
</tr>
<tr>
<td>3</td>
<td>27.5%</td>
</tr>
<tr>
<td>4</td>
<td>12.5%</td>
</tr>
</tbody>
</table>

Table 3: Ad Type Distribution

<table>
<thead>
<tr>
<th>Ad Type</th>
<th>% of customers assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand Ad</td>
<td>33.33%</td>
</tr>
<tr>
<td>Price Ad</td>
<td>33.33%</td>
</tr>
<tr>
<td>Intermediate Ad</td>
<td>33.33%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Difference</th>
<th>% of customers</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>21.46%</td>
</tr>
<tr>
<td>2</td>
<td>8.81%</td>
</tr>
<tr>
<td>3</td>
<td>4.35%</td>
</tr>
<tr>
<td>4</td>
<td>2.31%</td>
</tr>
<tr>
<td>5</td>
<td>1.53%</td>
</tr>
<tr>
<td>6</td>
<td>1.53%</td>
</tr>
<tr>
<td>7</td>
<td>1.23%</td>
</tr>
<tr>
<td>8</td>
<td>0.58%</td>
</tr>
<tr>
<td>9</td>
<td>0.62%</td>
</tr>
<tr>
<td>10</td>
<td>0.55%</td>
</tr>
<tr>
<td>11</td>
<td>0.67%</td>
</tr>
<tr>
<td>12</td>
<td>0.15%</td>
</tr>
<tr>
<td>13</td>
<td>0.15%</td>
</tr>
<tr>
<td>14</td>
<td>0.16%</td>
</tr>
<tr>
<td>15</td>
<td>0.21%</td>
</tr>
<tr>
<td>16</td>
<td>0.01%</td>
</tr>
</tbody>
</table>

Atleast 1: 44.3%

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

<table>
<thead>
<tr>
<th>DV: Ordered from restaurant</th>
<th>DV: Meal value ordered from rest.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Probit (I)</td>
</tr>
<tr>
<td></td>
<td>Estimate</td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.896***</td>
</tr>
<tr>
<td>ad</td>
<td>0.131***</td>
</tr>
<tr>
<td>adprice</td>
<td>-0.069**</td>
</tr>
<tr>
<td>discount</td>
<td>0.007***</td>
</tr>
<tr>
<td>discount * ad</td>
<td>-0.0003</td>
</tr>
<tr>
<td>discount * adprice</td>
<td>0.0021*</td>
</tr>
<tr>
<td>Day FE</td>
<td>Yes</td>
</tr>
<tr>
<td>No. Obs</td>
<td>5,474,448</td>
</tr>
</tbody>
</table>

OLS (II)                     | Estimate  | SE  |                      |
|                             |           |     |                      |
| Intercept                   | 0.001***  | 0.0001 |                    |
| ad                          | -0.001*** | 0.0003 |                    |
| discount                    | 0.00006***| 0.00003 |                  |
| discount * ad               | 0.000019**| 0.00007 |                  |
| discount * adprice          | 0.00034*  | 0.00001 |                  |
| Day FE                      | Yes       |      |                      |
| No. Obs                     | 5,474,448 | 5,474,448 |                  |

OLS(III)                     | Estimate  | SE  |                      |
|                             |           |     |                      |
| Intercept                   | 0.314***  | 0.054 |                    |
| ad                          | -0.249*   | 0.113 |                    |
| discount                    | 0.018***  | 0.001 |                    |
| discount * ad               | 0.0058*   | 0.0026 |                  |
| discount * adprice          | 0.0082(.) | 0.0047 |                  |
| Day FE                      | Yes       |      |                      |
| No. Obs                     | 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

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount</td>
<td>-0.29</td>
<td>0.56</td>
</tr>
<tr>
<td>Ad Stock</td>
<td>-2.36</td>
<td>2.95</td>
</tr>
<tr>
<td>Pre-expt. avg. order value</td>
<td>0.42***</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Std. Errors clustered at the individual level
### Table 7: Effect of Ads on conditional conversion at cart

<table>
<thead>
<tr>
<th></th>
<th>Probit (I)</th>
<th>OLS (II)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>SE</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.035</td>
<td>0.072</td>
</tr>
<tr>
<td>ad</td>
<td>0.068**</td>
<td>0.023</td>
</tr>
<tr>
<td>ad_price</td>
<td>-0.1404***</td>
<td>0.031</td>
</tr>
<tr>
<td>discount</td>
<td>0.0166***</td>
<td>0.0006</td>
</tr>
<tr>
<td>Customer Characteristics</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Day FE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. Obs</td>
<td>28,319</td>
<td>28,319</td>
</tr>
</tbody>
</table>

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’

<table>
<thead>
<tr>
<th></th>
<th>Probit (I)</th>
<th>OLS (II)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>SE</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.028</td>
<td>0.073</td>
</tr>
<tr>
<td>ad</td>
<td>0.067**</td>
<td>0.024</td>
</tr>
<tr>
<td>ad_price</td>
<td>-0.133***</td>
<td>0.031</td>
</tr>
<tr>
<td>discount</td>
<td>0.0164***</td>
<td>0.0008</td>
</tr>
<tr>
<td>Diff. bet. expected and actual discount</td>
<td>0.0003</td>
<td>0.0007</td>
</tr>
<tr>
<td>Customer Characteristics</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Day FE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. Obs</td>
<td>28,319</td>
<td>28,319</td>
</tr>
</tbody>
</table>

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 trivariate probit model estimation results

<table>
<thead>
<tr>
<th></th>
<th>Order Stage</th>
<th>Cart Stage</th>
<th>Menu Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev</td>
<td>Mean</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.029</td>
<td>0.009</td>
<td>-1.036***</td>
</tr>
<tr>
<td>(0.072) (0.077)</td>
<td>(0.035)</td>
<td>(0.027)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>ad</td>
<td>0.047(.)</td>
<td>0.012</td>
<td>-0.015</td>
</tr>
<tr>
<td>(0.024) (0.027)</td>
<td>(0.013)</td>
<td>(0.016)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>ad_price</td>
<td>-0.102***</td>
<td>0.047</td>
<td>-0.002</td>
</tr>
<tr>
<td>(0.029) (0.031)</td>
<td>(0.017)</td>
<td>(0.022)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>discount</td>
<td>0.014***</td>
<td>0.005***</td>
<td>0.006***</td>
</tr>
<tr>
<td>(0.0008) (0.001)</td>
<td>(0.0003)</td>
<td>(0.0004)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>(or E_i[D</td>
<td>Ad_j])</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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
Table 10: Three stage trivariate probit model estimation results with reference term added in the last stage

<table>
<thead>
<tr>
<th></th>
<th>Order Stage</th>
<th>Cart Stage</th>
<th>Menu Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev</td>
<td>Mean</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.025</td>
<td>0.008</td>
<td>-1.024***</td>
</tr>
<tr>
<td>ad</td>
<td>0.051(.)</td>
<td>0.012</td>
<td>-0.013</td>
</tr>
<tr>
<td>adprice</td>
<td>-0.095***</td>
<td>0.044</td>
<td>-0.005</td>
</tr>
<tr>
<td>discount</td>
<td>0.015***</td>
<td>0.004***</td>
<td>0.007***</td>
</tr>
<tr>
<td>Diff. bet. expected and actual discount</td>
<td>0.0005</td>
<td>0.0003</td>
<td>(or E[D</td>
</tr>
</tbody>
</table>

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
12 Appendix

12.1 Randomization Checks

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

Table 11: Randomization Checks 1

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

Table 12: Randomization Checks 2

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