Do Coupons Expand or Cannibalize Revenue?
Evidence from an e-Market

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Abstract

Many firms that struggle to survive try to increase their consumer base. We empirically study the effectiveness of one such attempt: the use of coupons. We use a unique method to connect demand for e-coupons through daily-deal sites with regular firm sales. We ask whether firms can indeed use e-coupons as a means to price discriminate by attracting new consumers without losing (cannibalizing) revenue from existing ones, and whether these consumers come back after the end of the promotion. In addition, we ask what types of businesses are most likely to benefit from such promotions. We find that offering an e-coupon increases demand both during and after the deal, suggesting that e-coupons can be used both to price discriminate and to advertise, but that the effect on the firm's profits depends on the type of firm. On average, e-coupons increase profits.

Keywords: Daily-deal websites, two-sided markets, price discrimination, customer retention

1 Introduction

Firms often attempt to increase their sales or their market share in an industry. In some industries, these attempts include investing in research and development to improve the product that is offered. In other industries, especially service industries offering experience goods, this strategy may not work if many consumers do not know about your firm. In that case, more effort is exerted to make consumers aware of your product in the first place.

This paper analyzes a well-established strategy which firms use to increase visibility and attract new consumers: the use of coupons. On one hand, coupons allow firms to find and attract new consumers by increasing their visibility. On the other hand, firms may have difficulties ensuring that their efforts reach the "right" consumers. Obviously, a price discount for existing customers that does not attract new customers would decrease profits.

We evaluate the relative sizes of different potential effects of coupons. In particular we ask two questions. First, how well can firms attract new customers without cannibalizing revenue from existing ones? That is, can coupons function as a price discrimination tool? Second, what types of firms benefit from offering e-coupons even if price discrimination is difficult and revenue cannibalization cannot be avoided? Even if a firm is not able to isolate new customers from existing ones in their efforts to expand their business, the effort may pay off in the long run if many of the new customers come back. A short-term decrease in profits from existing consumers can lead to a larger long-term increase in profits from the new ones.

We estimate the treatment effect of coupons: how many consumers use coupons, how many of those are new customers, and how many of those return to the firm after the promotion has ended? We observe price and quantity data, which allows us to quantify each of these, as well as to determine profit implications, and we compare the changes in profits to changes in surplus to other market participants.

Our vehicle for studying these effects are electronic coupons (e-coupons) for restaurants through the daily-deal website Groupon. In the past decade, the traditional coupon through newspapers and the mail has increasingly been replaced by daily-deal sites like Groupon and LivingSocial, but their e-coupons remain similar to traditional coupons in many ways.[1] However, there are

[1] Groupon has continuously been among the top 100 visited websites in the United States over the past years,

some differences. Most importantly, e-coupons solve a data problem that researchers of traditional coupons have faced. While traditional coupons were distributed through newspapers and therefore may have been missed by many households, we know how many e-coupons were distributed and seen, because a consumer has to actively purchase an e-coupon before using it. Finally, e-coupons for restaurants are more likely to be redeemed immediately after purchase because their redemption requires little effort once purchased.

Our main analysis consists of three parts. First, we present a simple model of demand for restaurants that offer e-coupons. Next, we create a measure for this restaurant demand and we estimate how demand changes when e-coupons are offered. Last, we apply our estimation results to the model to determine the sizes of the price discrimination, cannibalization, and market expansion effects, as well as long term profit changes from offering coupons.

In the first part, our model identifies the sources of demand for a restaurant that offers e-coupons. A firm that offers e-coupons draws revenue from three sources: 1) existing consumers who bought an e-coupon but would have bought from the firm at the regular price too, 2) new consumers who would not have bought from the firm at the regular price who searched and bought an e-coupon, and 3) existing consumers who buy from the firm at the regular price. Determining the relative sizes of these three sources is an essential part of this paper, as it allows us to identify the different effects of issuing e-coupons.

Second, we deal with the fact that we do not observe food sales or the number of customers who visit the restaurant by using alcohol as a proxy for sales and arguing that it is a valid proxy. We compare alcohol revenue in restaurants before and after e-coupons become available in a difference-in-differences setting. Here, we take advantage of a law in Texas that prevents restaurants from offering coupons for alcohol.[2] Since the price of alcohol does not vary across consumers, an increase in alcohol revenue is likely to correspond to an increase in sales and demand for the restaurant. The idea behind this approach is that someone who drinks one glass of wine with their meal will do so whether she pays the full price or the discounted e-coupon price for the meal. Existing consumers who happen to use an e-coupon do not cause an increase in alcohol sales, but new consumers will.

according to Alexa.com.

[2]Rule 45.101(b), Title 16 of the Texas Administration Code says that "no holder of a manufacturing, wholesale, or retail level license or permit may give any rebate or coupon redeemable by the public for the purchase of or for a discount on the purchase of any alcoholic beverage."

We further provide qualitative evidence that this assumption holds.

Third, we determine the long-term effect of e-coupons: the preference shift after the coupon has expired. We include alcohol revenue in the nine months after the e-coupon was issued in our difference-in-differences analysis to measure the long term promotional effect of the price discount, in addition to its short term price discrimination and cannibalization effects. We then translate these into an overall change in restaurant profits.

It is unclear which firms and which consumers stand to gain or lose the most from using coupons, or more specifically e-coupons. The presence of a daily-deal site could benefit some firms but still have a negative impact on the industry. Daily-deal sites could even lead to a prisoner's dilemma in which it is optimal for firms to use the site when it is available, although firms would be better off if the platform did not exist.

We find that e-coupons work as a price discrimination tool as much as they work as an advertising tool. Offering e-coupons allows firms to attract new customers, increasing alcohol revenue by over twelve percent during the e-coupon offer. Many of the new customers return after the deal ends, as the revenue increase is persistent. On average, firms see an increase in profits of close to \$15,000 over half a year, as the short and long term increases in demand outweigh the decrease in revenue that comes from offering lower prices to some of the regular customers and from sharing the revenue from the e-coupons with the daily-deal site. The fraction of firms which increase their profit with e-coupons fits reported fractions from restaurant surveys well.

Finally, we provide evidence about the overall welfare effects of the presence of e-coupons. We make inferences on consumer surplus changes, and we use some industry information to bound the platform's profit. We compare these to the estimated changes in restaurant profits. Accounting for the increase in consumer surplus due to the lower prices, and accounting for the profit to the website, close to 65 percent of all restaurants' e-coupons strictly increase total surplus, although most do so by a small amount.

Previous literature has found evidence that firms use coupons as a tool to price discriminate (see Narasimhan, 1984). Consumers who use coupons are likely more price sensitive. If that is the case, firms can extract consumer surplus through second-degree price discrimination: charging the regular price to consumers who do not use Groupon, and charging the discounted price to those who are willing to search the daily-deal site.[3]

This paper contributes to a literature of price discrimination by quantifying the short and long term effects of indirect price discrimination in a market for experience goods. It analyzes the effects of price discrimination on firm profits under certain market conditions, and it compares these to likely changes in consumer surplus (see Holmes, 1989; Stole, 2007). When the match quality between a supplier and a consumer of an experience good or service is not known ex ante, a firm may have an incentive to lower its price in order to increase information and to secure a large customer base more quickly (see Bergemann and Välimäki, 1997). The results of this paper imply that e-coupons can indeed serve as an instrument for diffusing this type of information.

Much of the literature on indirect price discrimination (starting with Mussa and Rosen (1978) and Salant (1989), among others) indicates that under certain conditions a firm can increase profits by offering their good or service in two different qualities. Those consumers who value the product highly choose another version than those who value it less. Yet, the context of e-coupons differs from traditional second degree price discrimination because firms cannot freely choose the relative product qualities (see Anderson and Dana, 2009), because the daily-deal platform controls the price discount, and because the platform takes a large cut (usually 50 percent) of the revenues from the e-coupons. News articles point towards contracts that favor the daily-deal site and tend to exploit firms. Anecdotes about firms losing money during Groupon deals have been abundant in local news in recent years.

The paper also contributes to a growing literature on e-coupons. It is most closely related to Edelman, Jaffe and Kominers (2014), who analyze under what conditions a business can benefit from issuing e-coupons, and when e-coupons work as price discrimination or advertising tools. While their paper is purely theoretical, our results support some of their findings. Other work finds that offering coupons through daily-deal sites can have a negative effect on the reputation of a business (Byers, Mitzenmacher and Zervas, 2012). Dholakia (2010, 2011) provides much survey-based evidence that some businesses can benefit from using e-coupons by reaching new consumers. Our paper supports the findings in these papers. It is the first to provide an empirical analysis of the effect of such coupons (and e-coupons) on firms and consumers in the short run and in the long

[3] Note that list prices do not necessarily rise when a firm starts to price discriminate. See Thisse and Vives (1988) and Corts (1998) for more detailed analyses of non-uniform pricing strategies in imperfect competition.

run.

The remainder of the paper proceeds as follows. We describe the evolution of the e-coupon industry in detail in section 2. We then develop a model of price discrimination, cannibalization, market expansion, and complementarities in section 3. We then show the data and provide some preliminary evidence in section 4. Section 5 applies the data to the model. It describes the estimation strategy and quantifies the different parts of demand. Finally, we calculate profit changes and determine welfare implications in section 6. We conclude in section 7 with a brief discussion.

2 Background: Electronic Coupons

Daily-deal websites started gaining popularity in the mid-2000s. A website called Woot was introduced in July 2004 as one of the first successful websites offering daily deals, which have been focused on merchandise articles. It was acquired by Amazon.com in 2010. Since Woot's introduction, there has been a surge in websites that offer coupons for services as well as for goods. Most notably, LivingSocial and Groupon have become the leaders in this market. LivingSocial officially launched a daily-deal business after acquiring BuyYourFriendADrink.com in 2009, a few months after Groupon had been introduced in November 2008. Together, Groupon and LivingSocial accounted for 75% of the daily-deal market in August 2012.[4]

Both Groupon and LivingSocial have expanded their daily-deal operations in recent years. They now include many offers in a variety of product categories each day in most metropolitan areas in the United States. Most deals today last several days to weeks. In addition to these rather well-known websites there are hundreds of smaller daily-deal sites.[5] While Groupon and LivingSocial have established large networks of firms and consumers, many of these sites specialize in certain categories, and many of them struggle to survive.

It is unclear ex ante whether using a deal-a-day website increases a firm's consumer base as those consumers who use the e-coupons may already be loyal customers of the firm, although there is some evidence that e-coupons do attract new consumers. Customer experience analytics company ForeSee found in a 2011 survey that 91% of consumers have done (44%) or plan to do

[4]http://www.bloomberg.com/news/2012-08-15/groupon-loses-market-share-as-online-daily-deals-decline.html

[5]For instance, an aggregator of daily-deal websites, Yipit.com, collects deals from 2276 of these sites (http://yipit.com/data/raw/, accessed June 24, 2014).

(47%) business again with the company they last purchased an e-coupon from.[6] At the same time, 66% of daily-deal site users have already been frequent (40%) or infrequent (26%) customers of the establishments they last purchased an e-coupon from. The remaining 34% are consumers they would not have been able to reach without the platform.[7] This suggests that companies can benefit from an advertising effect if they offer e-coupons.

Companies have shown reluctance about dealing with those kinds of websites though, because the firms have little control over the details of the deal. Usually, the daily deal site suggests a deal to the vendor. The vendor can negotiate the magnitude of the discount, the share of the revenue going to either party, and the duration of the offer. Anecdotal evidence suggests that the terms set by the website often prevail, and "horror stories" about small businesses can frequently be found in the news.[8] A 2011 survey conducted by email and social media marketer iContact shows that 70% of small businesses "hate" Groupon.[9] Yet, firms have started gaining more control as competition among daily-deal sites has increased.[10]

Despite the controversy about the usefulness of daily-deal sites to firms, more and more deals are available at a given time. Groupon, for example, offered over 1000 deals at any given time in Boston, Massachusetts, and close to 1000 in Minneapolis, Minnesota, in late 2014. We use the variation in deal timing and restaurant characteristics among those deals to estimate the benefits and costs of such sites to different market participants.

3 Model

Here we provide a simple model of a firm's use of coupons. The model allows us to identify the relative sizes of the different effects of coupons: revenue cannibalization, temporary market expansion (pure price discrimination), and long-term expansion (advertising). It is then applied

[6]http://www.foreseeresults.com/research-white-papers/_downloads/daily-deal-commentary-2012-foresee.pdf

[7]Our results suggest very similar fractions.

[8]Consider, for example, a little bakery that had to hire additional bakers to make 102,000 cupcakes as a result of a Groupon deal. See http://www.businessinsider.com/london-baker-makes-102000-cupcakes-groupon-deal-2011-11, accessed 12/15/2014.

[9]See http://www.prnewswire.com/news-releases/one-in-four-small-businesses-hates-social-media-icontact-survey-uncovers-love-affair-with-facebook-and-cooling-passion-for-groupon-132522353.html, accessed 12/15/2014.

[10]We talked to several companies that offered discounted products through daily deal sites, including in the restaurant, fitness, and merchandise categories. The role of competition in this context would certainly be an interesting dimension to study as well, but a lack of data prevents us from performing an analysis on the effects of competition (see, for example, Rysman, 2004).

to a dataset of e-coupons and restaurant demand, both to test the model's implications and to quantify these three effects.

Let p^G be the price level of the firm's coupon, and let p^R be the regular price level - without the coupon. Suppose there is just one firm in a market.[11] Consumers vary on three dimensions: 1) whether they have previously bought from the firm (their experience level), 2) their valuation ϕ, their match quality with the firm, and 3) their cost or disutility of using coupons.

Consumers become experienced and find out their valuation after visiting the firm once. For illustrative purposes, we assume that consumers can have three match qualities: high, medium, or low, and they form expectations over their valuation if they have not purchased from the firm previously. Consumers are risk neutral. Their "costs" of using coupons are denoted by c^G. In the e-coupon industry, these costs may be the hassle of signing up for the website (and the inflow of emails to sort through), the limited choice set, downloading a mobile phone app or printing the coupon, and the risk of looking "cheap" when using the e-coupon. We assume that these costs are uniformly distributed over $[0, C]$, where $C \geq p^R$ is a constant. Some consumers do not associate using e-coupons with a cost, while others are very unlikely to use an e-coupon.

Next, we discuss how inexperienced and experienced consumers make their purchasing decisions when a coupon is available. We then explain how we use the model to identify each source of demand, and how we estimate these sources given the available data.

3.1 Inexperienced Consumers

Consumers who have never purchased from the firm have an expected valuation $E[\phi]$. We assume that $p^G < E[\phi] < p^R$, so that risk neutral consumers would not try the firm at the high price level p^R, but those consumers with a low disutility c^G use the coupon (and visit the firm) if it is offered. Given the distribution of the disutility from coupons, $c^G \sim U[0, C]$, a fraction

$$\frac{E(\phi) - p^G}{C} \tag{1}$$

[11] While a model with more firms would allow us to examine consumer behavior more closely (including the possibility of intertemporal substitution across firms and a taste for variety), a model with a monopolist firm suffices to identify each of the effects that each firm sees.

of those consumers with unknown match quality will use the coupon. These consumers expand the restaurant's customer base at least temporarily.

Once these consumers have purchased from the firm, they know their match quality $\phi \in \{\phi_L, \phi_M, \phi_H\}$, where $\phi_L < p^G < \phi_M < p^R < \phi_H$. In the next period (without a coupon), those with a high valuation will return even at the high price, while those with a medium match quality will only return when a coupon is offered. Those with $\phi = \phi_L$ will not return at all. The high-match consumers make up the advertising effect.

3.2 Experienced Consumers

Consumers who have previously bought from the firm know their match quality when a coupon is offered. Low-match quality consumers will not visit the restaurant, but some medium- and all high-match quality consumers will. Consider first the medium-match consumers. A fraction

$$\frac{\phi_M - p^G}{C}, \tag{2}$$

or those consumers with a low disutility $c^G < \phi_M - p^G$, will buy the e-coupon but will not return when there is no coupon. Together with the medium and low valuation inexperienced consumers, these consumers make up the temporary market expansion. This is the pure price discrimination benefit.

High type consumers who would have purchased from the firm even in the absence of coupons continue to do so, but whether they use the coupon or pay the regular price depends on their disutility of using coupons. Given our distribution of c^G, a fraction

$$\frac{p^R - p^G}{C} \tag{3}$$

of the regular customers has a cost of using coupons that is low enough that the consumer chooses to use the coupon. This is the cannibalization effect. The remaining regular consumers still buy from the firm but pay the high price.

3.3 Identification

Suppose we observe measures of demand for the e-coupons themselves, and each firm's total sales before, during and after an e-coupon promotion. We can combine these measures with the assumptions above to identify the three effects on demand in the short and long term: price discrimination, cannibalization, and market expansion.

Demand for the coupons comes from three sources: those consumers who have never tried the firm before; those with a medium match quality (ϕ_M) and low disutility c^G who take advantage of the e-coupon but will not return at the regular price; and those who use the e-coupon but would have bought from the firm anyway. We can write demand for e-coupons as,

$$Q^G = \underbrace{\left(\frac{E(\phi) - p^G}{C}\right)\mu^n}_{\text{expansion}} + \underbrace{\left(\frac{\phi_M - p^G}{C}\right)n^k_M}_{\text{pure price discrimination}} + \underbrace{\left(\frac{p^R - p^G}{C}\right)n^k_H}_{\text{cannibalization}}, \tag{4}$$

where μ^n denotes the number of consumers who do not know their match quality, and n^k_M and n^K_H are the number of consumers who know their match quality, with a medium and a high quality match, respectively. The new consumers may or may not come back without an e-coupon, whereas medium-valuation experienced consumers will not return at the full price.

Changes in *total firm demand* during e-coupon promotions are due to only two of those "types": new (inexperienced) consumers and those who have a medium match quality. Total demand for the firm during the promotion is given by

$$\Delta Q^T_{\text{during}} = \underbrace{\left(\frac{E(\phi) - p^G}{C}\right)\mu^n}_{\text{expansion}} + \underbrace{\left(\frac{\phi_M - p^G}{C}\right)n^k_M}_{\text{pure price discrimination}} \quad . \tag{5}$$

The difference between equations (4) and (5) identifies the regular consumers who use the coupon although they would have bought from the firm anyway - the cannibalization effect.

Finally, the difference between sales before and after an e-coupon is issued must be due to new consumers who found out they have a high match quality and decide to return even at the high price. This difference is given by

$$\Delta Q^T_{\text{after}} = \underbrace{\left(\frac{E(\phi) - p^G}{C}\right) n^n_H}_{\text{advertising}}, \tag{6}$$

where n^n_H denotes the number of consumers who did not know their match quality before, but found out they had a high valuation.[12] Given demand for e-coupons and for the firm overall, the cannibalization and the advertising effects are easily identified, while market expansion and price discrimination for experienced consumers cannot be separately identified without stronger assumptions.

In addition to providing a vehicle for identifying the different effects of price promotions, the model allows us to make inferences on what types of firms are most likely to benefit from such promotions. The relative sizes of the each of the effects depend on the distribution of consumer valuations and experience levels. If, for example, a firm currently has a small customer base (and μ^n is large), the advertising effect may be strongest. On the other hand, if a firm has a lot of loyal customers (a large n^k_H), it may see more revenue cannibalization. As a result, one would expect more small and independent businesses and fewer well-established establishments to offer e-coupons. This is what we see in the data.

3.4 Demand for Alcohol

In order to apply our model to an industry, we need to establish a connection between e-coupon demand and firm sales. Granular sales or demand data are not readily available on the firm level, but we circumvent this problem by analyzing coupons for restaurants. We utilize the fact that alcohol revenue information is available in Texas. By law, alcohol is not part of a coupon in that state. We use this to our advantage by assuming that liquor and food expenditures are strongly separable. Consumers who go to a restaurant make their decision on alcohol expenditure independently of their expenditure on food, so that consumers who use an e-coupon spend the same amount on alcohol as they would if they did not use an e-coupon. The idea is that consumers drink a glass of

[12]In the estimation we control for overall restaurant growth with time fixed effects.

wine with their meal regardless of the price of food, conditional on the restaurant they attend.[13]

Let $\ell_{ij} > 0$ be consumer i's expenditure on liquor in restaurant j. For simplicity, let $\ell_{ij} = \ell_j$ for all consumers i of restaurant j. Restaurant j's revenue from alcohol sales is given by

$$L_j = q_j \ell_j,$$

where q_j is the number of visitors to restaurant j, including both e-coupon consumers and "regular" customers. Note that a restaurant's liquor revenue increases proportionately with the number of consumers when they choose their alcohol consumption independently of their food expenditure, conditional on the food they eat. In the estimation we assume that consumers spend a constant fraction λ of their *non-discounted* restaurant bill on alcoholic beverages. We choose λ for each restaurant type after phone conversations with staff and management from several Texas restaurants.[14]

4 Data

Our database consists of two main datasets. First, we obtain information on e-coupon sales through a dataset put together by Byers, Mitzenmacher and Zervas (2012). They collect data on all deals through Groupon, from January 3 to July 3, 2011 for 20 major cities.[15] Second, we collect restaurant liquor revenue data from the Tracking Alcoholic Beverage Sales (TABS) report.[16] This report tracks all restaurant and bar alcohol sales in Texas, as determined through public tax records. We supplement these datasets with restaurant information from each restaurant's Yelp website.

The dataset on e-coupon sales for restaurants includes 2,794 offers through Groupon over a time period of six months.[17] The website offers e-coupons in a variety of cities. An e-coupon

[13]We have conducted informal phone interviews with staff from several restaurants in Texas. Without exception, they reported that e-coupon users either drank as much as or less than non-e-coupon users. In this case our assumption leads to an under-estimation of the market-expanding and advertising effects of e-coupons. Since we find that most restaurants benefit from issuing e-coupons, our qualitative results are not affected by this assumption. We show how our analysis changes when coupon users systematically drink less in appendix Section A.2.

[14]While we are confident in our choices of λ, we test for robustness by using different values for λ.

[15]These are: Atlanta, Boston, Chicago, Dallas, Detroit, Houston, Las Vegas, Los Angeles, Miami, New Orleans, New York City, Orlando, Philadelphia, San Diego, San Franciso, San Jose, Seattle, Tallahassee, Vancouver and Washington, D.C.

[16]See http://www.alcoholsales.com/About.htm.

[17]Byers, Mitzenmacher and Zervas also collect information on LivingSocial, the second largest deal-a-day website.

for a restaurant usually consists of a fixed dollar amount that can be redeemed for any meal. In many states (including Texas), it may not be used towards alcoholic beverages. We observe several measures of timing, prices and demand. We know when and how long the offer was available through the website, the regular price (value) and the discounted price, whether it was a featured offer (atop the website and with more space), where a product/service is sold, the type of food that is served, and the number of e-coupons bought. The information is at the level of an e-coupon offer.

Table 1 shows summary statistics on those characteristics. Groupon chooses to feature almost a quarter of its restaurant deals. Restaurant deals sell a large number of e-coupons, with the mean (median) restaurant deal selling close to 1,000 (706) times. One can imagine that a small restaurant may not be able to accommodate all Groupon customers at once, and that capacity constraints can become binding in this market if the restaurant is not able to spread its customers over a longer time period. It should be helpful that while most offers are available on the website for two days or less, the e-coupon itself usually expires several months after purchase. Lastly, there is little variation in the discount percentage across offers as 73 percent of the offers are discounted at 50%. There is, however, some variation in the value of the e-coupon. We interpret this variation as variation in the restaurants' levels of "fanciness".

Most of the differentiation across e-coupons is introduced through restaurant characteristics. We collect information about each restaurant from their Yelp websites (as of October 2014). In addition to the number of reviews that a restaurant has received, Yelp provides information about features such as the ambiance, noise level, whether the restaurant delivers, whether it provides wifi internet to its customers, and several other attributes, including whether the restaurant is still open in October of 2014.

On those dimensions, our set of restaurants matches the industry average well, especially considering that most restaurants offering e-coupons are independent establishments rather than chain restaurants. For instance, 70 percent of the restaurants in our dataset are still open today. A study by Restaurant Brokers suggests that up to 90 percent of independent restaurants close during the first year, and those who survive have an average life span of five years.[18] In addition,

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We do not include this website because fewer months and far fewer offers are covered in the dataset. In addition, demand for each of those deals is significantly smaller.

[18] See http://everydaypublic.com/?p=241828.

Parsa et al (2006) find that 59.7 percent of restaurants failed within three years of their business opening between 1996 and 1999.

Yelp also provides information on the type of food that is offered. We aggregate their food type classifications into six categories: American, Asian, Bars, Italian (pizza and pasta), Mediterranean (except Italian restaurants), and Mexican (and Latin American) food.

We combine the data on demand for e-coupons with a proxy for overall restaurant demand: monthly alcoholic beverage sales in Texas. The data on alcohol sales help us connect e-coupon sales with regular restaurant demand as described in the model and estimation sections. Revenue from alcohol sales is only available for 74 of the Dallas and Houston restaurants that offer e-coupons, so we add a control group of 41 other randomly selected restaurants which offer alcohol in those two cities. The addition of the control group provides more precise estimates. The characteristics (as listed on their Yelp websites) of those restaurants that offer e-coupons are not significantly different from those in the control group, although they may be better suited for running e-coupon promotions for other (unobservable) reasons.[19] On average, these 115 restaurants from Dallas and Houston earn $29,997 in revenue (with a standard deviation of 42,744) from alcoholic beverages per month between January 2010 and December 2012.

5 Specification and Results

We estimate the degrees of the short- and long-term market expansion effects in a difference-in-differences analysis of monthly alcohol sales at Texas restaurants before, during, and after e-coupons are offered and valid. Since restaurants issue e-coupons at different points in time, we can estimate a differential change in alcohol revenue as e-coupons become available and as they expire, and the differential change in restaurant traffic follows directly. Section 3.4 implies that if an e-coupon is purchased by a consumer who would not have visited the restaurant at full price, then the restaurant's liquor sales will increase, whereas the restaurant will not have an increase in its liquor sales if an existing consumer purchases the e-coupon.

The temporary market expansion effect of the daily-deal site is the change in alcohol sales

[19] Adding these 41 restaurants in the estimation gives us a smaller effect of e-coupons on alcohol sales than if we only include those restaurants that have offered e-coupons. If restaurants that offer e-coupons are inherently different from those that do not, our results are likely to underestimate the true effect of e-coupons.

when an e-coupon becomes available, whereas the advertising effect is what remains of the market expansion after the e-coupon has expired. Formally, we estimate:

$$\log\left(L_{jt}\right) = \beta_0 + \beta_1 G_{jt}^{\text{during}} + \beta_2 G_{jt}^{\text{after}} + \gamma_j + \mu_t + \epsilon_{jt}, \tag{7}$$

where L_{jt} is restaurant j's liquor revenue in month t, and G_{jt}^{during} and G_{jt}^{after} are dummy variables that indicate that restaurant j's e-coupon is valid in month t, and that it expired before month t, respectively. G_{jt}^{before} is omitted in the regression. The e-coupon effect on alcohol sales is calculated in percentage terms as $\exp(\beta_1) - 1$. We further control for restaurant characteristics by including restaurant fixed effects γ_j, and for time trends by including month and year dummies μ_t. We cluster standard errors by restaurant to account for common group effects and to reduce the potential for overstating significance due to serial correlation (see Bertrand, Duflo and Mullainathan, 2004).

The effect of offering coupons likely varies over the months after the e-coupon is offered. We address this by using the time (in months) after the deal starts as the explanatory variables of interest in a second specification:

$$\log(L_{jt}) = \left(\sum_{m\in M} \beta_m \cdot \mathbb{1}(t - t_{\text{coupon}} = m)\right) + \beta_{after} G_{jt}^{\text{after}} + \gamma_j + \mu_t + \epsilon_{jt}, \tag{8}$$

where t_{coupon} is the month in which the e-coupon becomes valid, and M is the number of months that the e-coupon keeps its validity.

Table 2 shows that offering a coupon indeed has a market-expanding effect.[20] Columns 1 and 2 assume that consumers will redeem the e-coupon at any point while the e-coupon is still valid.[21] Columns 3 and 4 assume that the e-coupon is redeemed immediately after purchase, or at least during the month of purchase. This would be the case, for example, if a consumer looks at the website with the intent of going to a restaurant. The last two columns provide a more detailed analysis by examining the effect in each month after the e-coupon is offered, as in equation (8). We focus on these results here and in the remaining analysis. We also show results with the control restaurants (columns 1, 3, and 5) and without them (columns 2, 4, and 6).

[20] In the estimation, we drop those offers with unusually large values (over \$300) and unusually high demand (over 6,000 e-coupons sold) because observations beyond these cutoffs are rare. Estimations with different cutoffs (for example, 5000 e-coupons sold) provide very similar results.

[21] The e-coupons are most often valid for six months after their purchase.

Offering an e-coupon through Groupon leads to an increase in liquor sales of 13.9% (= $\exp(0.130) - 1$) to 22.0% (= $\exp(0.199) - 1$) in the month of the offer. This effect is significant at the 1 percent level. The effect decreases slightly over the following three months but picks back up after that, although these coefficients are estimated less precisely. The measured effect is larger when including the control firms, suggesting that restaurants which offer e-coupons could be inherently different from those which do not. We did not see any differences on observable characteristics between treated and control restaurants, however. Even more, our prior would be that those firms which used e-coupons were closer to failing (and therefore needed to find a way to increase their consumer base), so that we would have expected a smaller effect when including the control firms. It is also possible that the treatment restaurants do not provide sufficient variation in the timing of the e-coupon treatment, so that the estimates may pick up time trends as well. We continue with the results from column 6 (no control firms) in order to provide the most conservative estimates of the market expansion effect on profits, and we report how the results change if we include the control firms when appropriate.[22]

Finally, Figure 1 shows that the effect of e-coupons on liquor sales is large and significant from the time the e-coupon becomes available, and it persists for a while, although it becomes insignificant after two months. This specification does not include the control group.

5.1 Cannibalization and Market Expansion

In order to estimate what fraction of the e-coupons was sold to existing and to new customers, we translate the percent changes in alcohol revenue into absolute terms. We do so by multiplying the percentage changes by the mean monthly alcohol revenue before the e-coupon became available for each restaurant, $E[L_j|\text{before}]$. On average, the monthly increase in alcohol revenue is \$4082 although it varies by restaurant type. Bars see the largest increase while Italian restaurants seem to have the lowest alcohol revenue.

Next, we translate this increase in alcohol revenue into an increase in the value of food consumed, assuming that an average consumer visiting a restaurant of type r spends a certain

[22]It could be that the market expansion effect of e-coupons varies by restaurant type. Appendix section A.1 shows that the effect is strongest for Mediterranean restaurants, although the differences across restaurant types are not significant.

fraction λ_r of their non-discounted bill on alcohol. Based on our informal phone interviews with staff and managers from at least two Texas restaurants of each restaurant type r, we choose $\lambda_r = 0.3$ for American, Italian, Mediterranean, and Mexican Restaurants, 0.2 for Asian restaurants, and 0.7 for bars. The translation from alcohol sales into food value straightforward as $F_{jt} = L_{jt}\frac{1-\lambda_r}{\lambda_r}$, where F_{jt} is the value of food.[23]

Figure 2 shows the changes in both alcohol and food sales in the month in which the e-coupon is offered. As mentioned above, bars see the largest absolute increase in alcohol revenue. However, American, Mexican, Mediterranean and Asian restaurants likely see a larger absolute impact on food sales because their customers typically spend a larger part of their bill on food. On average, the (non-discounted) value of monthly food sales increases by \$5000 (Italian) to \$10,000 (American), depending on restaurant type r.[24] These values represent $\Delta Q^T_{\text{during}}$ from equation (5), the combination of new consumers (expansion), those with a medium match quality (pure price discrimination), and those with high valuations and low costs of using e-coupons (cannibalization).

We compare these increases in total demand to the non-discounted value of all e-coupons sold by the restaurant, which corresponds to Q^G in equation (4). On average, the Texas restaurants sell 960 e-coupons for \$27.15. Depending on the restaurant type, the value of the average e-coupon offer to a restaurant ranges from \$11,000 (bars) to \$28,000 (American restaurants).

The difference between $\Delta Q^T_{\text{during}}$ and Q^G is due to coupon buyers who do not translate into additional customers in the restaurant. In the model, we attribute this to cannibalization: consumers who would have visited the restaurant at the full price but instead bought the e-coupon. Of course, it is also possible that people who bought the e-coupon did not get around to visiting the restaurant at all, although this concern is not as big with electronic coupons because consumers are more likely to redeem if they pay for the e-coupon in advance, as as opposed to traditional coupons which are paid for at redemption. Since we cannot empirically distinguish the former from the latter, we focus our attention on the fraction of e-coupon buyers who become new consumers in Figure 3, rather than on the level of cannibalization.

[23] For some restaurants these values of λ would imply that more new customers would visit the restaurant than e-coupons are sold. In those cases we impose a λ that bounds the increase in food expenditures at the value of the e-coupons that were sold. We also check for robustness of our choices when calculating profit changes due to the use of coupons.

[24] When including the control restaurants, the average increase in alcohol revenue is \$6482. and the corresponding mean increase in food sales is \$11,294.

Some restaurant types manage to attract new customers more successfully than others. Mediterranean (Spanish, Greek, and Middle Eastern) restaurants are able to turn 54 percent of e-coupon buyers into new customers, whereas only 15 percent of e-coupon buyers of Italian (pizza and pasta) restaurants are new customers who visit the restaurant.[25] These patterns are sensible and match survey-based evidence well (see Dholakia, 2010). In our classification, Mediterranean restaurants include Greek, Spanish, and Middle Eastern restaurants. These tend to be smaller in size and possibly less well-known, so that an e-coupon can in fact reach many people who are not regular customers yet. On the other hand, Italian and American restaurants tend to be larger and may be more likely to have an established customer base which could take advantage of the e-coupons when they are offered.

Our results show that restaurants can indeed increase the demand for a restaurant both in the short run and in the long run. These increases vary depending on the restaurant type, with more "exotic" restaurants being able to attract and retain a larger fraction of new customers, while some of the more "mainstream" restaurants face more cannibalization. These results are consistent with the model's implication that the distribution of new and experienced consumers affects the relative sizes of each of the effects of offering e-coupons.

6 Profits and Welfare Considerations

The above result that e-coupons can help expand the customer base explains why restaurants (and other firms) agree to offer e-coupons through daily-deal sites despite the "horror stories" of some firms' struggles with daily-deal sites. However, it is unclear whether and how much firms benefit or lose from using the e-coupon platform. At the same time, how does the effect on firms compare to benefits or costs to consumers, and to the platform's profits? In order to answer these questions, we first calculate changes in restaurant profits based on the results from above, and we then compare these to likely changes in consumer surplus and to the platform's profits.

[25] Note that we have chosen the regression results that would give us the most conservative fractions of new customers. Our results can therefore be seen as a lower bound of new consumers, an upper bound of cannibalization, and a lower bound on profits as shown in Section 6.1.

6.1 Restaurants

Restaurant and firm owners working with Groupon told us that Groupon most often takes half of the revenue from each e-coupon sold. We take this as an assumption. In addition, restaurants face a marginal cost for every meal they serve. Since marginal costs are difficult to recover when prices are set outside of the observed choice set, we rely on industry information for marginal costs. The 2010 edition of the Restaurant Industry Operations Report by the National Restaurant Association finds that both limited service and full service restaurants of all levels spend about 33 cent of each dollar made on the cost of food and beverages. We treat this as the marginal cost, assuming that the additional customers can be served by the existing staff. In line with this, we set the marginal cost per dollar at $mc = 32.35\%$ for "cheaper" restaurants (those with e-coupon values below \$30), mc =33.8% for "average" restaurants, and mc =32.17% for more expensive restaurants (those with e-coupon values of \$50 and more). These costs imply that restaurants in fact lose money on each redeemed e-coupon when the e-coupon provides a 50 percent discount.

6.1.1 Profits

Our difference-in-differences analysis shows that restaurant liquor sales increase significantly when an e-coupon is available. We have assumed that alcoholic drinks make up a certain fraction λ_r of a customer's (non-discounted) bill at a restaurant of type r. If restaurant j's monthly liquor revenue increases by $\alpha_{j,t}$ dollars in month t of the offer (compared to the pre-Groupon level), its monthly food revenue increases by $\frac{\alpha_{j,t}(1-\lambda_r)}{\lambda_r}$ dollars. Assuming that the e-coupons are redeemed immediately (in the first month of its validity), the change in restaurant j's profits is

$$\begin{aligned} \triangle\pi_j \quad = \quad & \underbrace{0.5p_j^G Q_j^G - mc_j p_j^R Q_j^G + (1-mc_j)\alpha_{j,1}}_{\text{profit from e-coupons}} \\ & - \underbrace{(1-mc)\left[p_j^R Q_j^G - \frac{\alpha_{j,1}(1-\lambda_r)}{\lambda_r}\right]}_{\text{revenue cannibalization}} + \underbrace{(1-mc_j)\sum_{t=2}^{T}\delta^{t-1}\frac{\alpha_{j,t}}{\lambda_r}}_{\text{advertising effect}}, \end{aligned} \qquad (9)$$

where p_j^G is the discounted price of the e-coupon, p_j^R is the regular price (the value of the e-coupon), and Q_j^G is the observed number of e-coupons sold. We let the discount factor $\delta = 0.9$. We choose the same λ_r as above, and we try different values of λ in robustness checks.

6.1.2 Results

Table 3 shows the changes in restaurant profits over six months as a result of offering an e-coupon on the daily-deal site. The table shows the mean and median effects of offering an e-coupon by restaurant type, using the estimates from the difference-in-differences estimation which allows for time-varying effects, as in equation (8) and column 6 of Table 2.

Table 3 suggests that some restaurant types are quite likely to benefit from offering an e-coupon, whereas others are more likely to be hurt. Most bars, American, and Mediterranean restaurants increase profits. These restaurants may be able to attract consumers who have not visited before, and they may provide an atmosphere that customers want to return to.[26] Moreover, bars draw much of their revenue from alcoholic beverages. If they can attract new customers with food, they likely spend money on drinks as well. Italian and Asian restaurants, on the other hand, are more likely to lose from offering e-coupons. They may have a large base of regular customers and they might not appeal as much to consumers who do not already frequent the restaurant regularly.

Restaurants see a mean (median) net gain of $15,669.13 ($6729.60) per e-coupon offer. This change in profits varies significantly across restaurants. Figure 4 illustrates this variation. While some restaurants benefit a lot from offering an e-coupon, 36 percent of the restaurants in our sample lose some of their profit.[27] Our results match survey evidence well: in Dholakia (2010), 32 percent of businesses report that their Groupon promotion was unprofitable.[28]

6.1.3 Robustness to Different Values of λ

Much of our analysis is driven by our choice of λ. We confirmed with several restaurants of each type that our guesses are reasonable. However, some restaurants may experience different ratios. If we increase λ by 0.1 for each restaurant, the fraction of e-coupon buyers who become first-time visitors decreases by 5 percentage points (Italian restaurants) to 18 percentage points (bars). The sizes of these differences depend on the initial values of λ.

[26] American restaurants include steak and seafood restaurants, which may not have as much of a following as the more "stereotypical" American burger restaurants.

[27] When using the difference-in-differences estimates that include the control firms (column 5 of Table 2), only 19 percent of restaurants lose profit.

[28] The survey included 150 businesses, which were not limited to restaurants.

While the fraction of new customers compared to experienced ones seems rather sensitive to our choice of λ, the implications for restaurant profits are more robust. Figure 5 shows that the distribution of changes in profits remains relatively unchanged as we add or subtract 0.1 from our initial guess of λ. In fact, the change in profits remains stable for much larger values of λ, but it grows larger as we reach values of λ that suggest there is no cannibalization at all.

6.2 Consumers

We have shown that some firms benefit from using e-coupons. The obvious next question is whether consumers benefit as well. Ideally, we would like to estimate a dynamic demand model in which consumers learn their valuation of a restaurant after trying it once. However, data limitations prevent us from estimating a dynamic demand model for e-coupons.

Given the usual process of offering e-coupons, we expect consumer surplus to increase for two reasons. First, e-coupons introduce an additional, cheaper option into the consumer's choice set without changing the characteristics and prices of the existing options. Increasing the choice set likely increases consumer surplus in the short run. Second, after using an e-coupon, consumers have more information about their valuation for a restaurant. They may now visit that restaurant even at the high price if they find out they really like it, increasing consumer surplus in the long run.

A static nested logit estimation of demand for e-coupons picks up the first reason for an increase in consumer surplus. It suggests that an e-coupon offer increases consumer surplus on average by \$3836.78.[29] This number is sensible: on average, consumers save a total of \$13,602 (958 e-coupons sold times \$13.42 saved per e-coupon) on each e-coupon offer. Since some people associate using e-coupons with a cost, the lower mean increase in consumer surplus is expected.

These estimates do not include the long term effect of e-coupons on consumers and should therefore be seen as a lower bound on the increase in consumer surplus. The true effect is likely not much larger, however, as most of the static increase in consumer surplus is due to the price discount, and the price discount is only available once.

[29] See appendix section A.3 for details. This estimation also shows that e-coupon users are relatively price elastic, with a mean price elasticity of -2.47. This supports previous literature showing that coupon users are more price elastic, and that coupons can therefore serve as a tool for price discrimination.

Including the effect on consumers increases the benefits of offering coupons when the non-coupon option remains unchanged. Now, only 27 percent of the restaurants' e-coupon offers have a negative effect on total surplus, and this number decreases to 5.8 percent if we use the estimates which include the control firms.

6.3 The Role of the Platform

The platform takes a cut of approximately 50 percent of the total revenue from each e-coupon sold. On average, the platform therefore earns $6737 per offer, while the costs include setting up the contract and the web page for the offer. The website faces no significant marginal costs for each e-coupon sold, and free entry suggests that the costs of setting up the offer are likely less than $6737.[30] We expect that e-coupons increase welfare more than what we found above.

Finally, some buyers do not redeem their e-coupon and simply let it expire. In 2011, the e-coupon lost all its value. In that case, total surplus is unchanged: consumers pay for the e-coupon, and the restaurant and the platform split that revenue. Today, an expired e-coupon loses its promotional value but is still worth the price the consumer paid. Now, total surplus may increase if the consumer eventually uses the e-coupon to visit the restaurant. Some of the revenue that the restaurant would have made is simply transferred to the platform, but the consumer may have learned that the restaurant is a good match, making her more likely to return.

7 Conclusion

We study how offering a coupon affects consumption decisions and firm profits in an industry for experience goods. In particular, we quantify the sizes of three effects: temporary price discrimination from offering a lower-priced option, revenue cannibalization from regular customers taking advantage of that option, and the long term market expansion from new customers who buy from the firm again after the promotion. We further ask how these effects change firm profits in the long run in the restaurant industry. To our knowledge, this is the first paper to empirically analyze and quantify these effects.

[30] Groupon likely makes some positive profit because its large network of firms and consumers gives them an advantage over other daily-deal sites.

We find that offering a coupon attracts new consumers, and many of the new consumers come back after the promotion has ended. We also find that the relative sizes of the cannibalization and expansion effects depend on the restaurant type, and that lesser-known firms are more likely to attract new consumers in the long term.

Firms can benefit from offering the lower-price option because they can reach consumers who have not bought from the firm before, and some of these consumers may come back. However, the firms also pay a "commission" to the daily-deal site, so that the overall effect on profits is unclear, with 64 percent of the firms in our dataset gaining from offering e-coupons, and 36 percent losing some of their profit.

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A Appendix

A.1 Effect by restaurant type

The main specification in section 5 assumes that all restaurant types see the same differential change in alcohol revenue as a result of offering an e-coupon. However, it is possible that some restaurants are better able to expand their customer base than others. Here we interact the indicator variables from equation (7) with our categories of restaurant types, assuming as in Table 2 both that the e-coupon is redeemed at some point while it is valid (columns 1 and 2), and that the e-coupons are redeemed immediately (columns 3 and 4).

Table 4 suggests that the effect of e-coupon offers on alcohol sales does not vary significantly across restaurant types. Many restaurant types see an increase in alcohol revenue in some of the specifications, but these increases are not estimated precisely due to data limitations. We continue with the main specification in the remainder of the paper.

A.2 Robustness Check: Coupon Users Drink Less Alcohol

Our model and main analysis assume that coupon users and regular customers drink the same amount of alcohol with their meals. This assumption could be violated for two reasons: budgeting and selection. In the former case, restaurant visitors have more money left in their budget to spend on alcohol if they spend less on food. In the latter, e-coupon consumers are those who drink less alcohol than "regular" customers because they are more price elastic. Our informal phone interviews with staff from ten of the Texas restaurants in our dataset suggest that budgeting is not a large concern in our analysis. Without exception, restaurants either reported that they "haven't noticed a difference between Groupon users and other customers," or that "Groupon users probably drink less."

We address the selection issue here. We assume in this section that coupon users have a 50 percent lower λ than regular customers, meaning that they spend less money on alcohol than regular customers. We first translate the e-coupon sales into alcohol revenue using our new values of $\lambda_r^{\text{coupon}}$ as $L_j^{\text{coupon}} = p_j^R Q_j^G \frac{\lambda_j^{\text{coupon}}}{1-\lambda_r^{\text{coupon}}}$. Then we re-calculate the level of cannibalization (and the fraction of new consumers) by comparing the alcohol revenue from the e-coupons to the total increase in alcohol revenue.

Not surprisingly, the lower λ leads to a lower calculated level of revenue cannibalization and a larger fraction coupon users who would not have visited the restaurant without the discount. Figure 6 shows the new implied fractions of coupon users who become new consumers. On average, the fraction who turn into new consumers increases from 37 to 62 percent.

These fractions are then translated into profit changes, as in Section 6.1. The lower levels of cannibalization lead to a larger profit increase. On average, profits increase by \$20,860, as opposed to \$15,669 in the main specification. Here, 71 percent of restaurants benefit from offering coupons.

A.3 Demand for e-Coupons

A dynamic demand structure that would allow for varying consideration sets (see Goeree, 2008) is not possible given our data. However, a static demand estimation provides insight into one large component of the effect of coupons on consumer surplus: the effect of the price discount. We include a formal analysis of demand for e-coupons in a nested logit setting which allows tastes to be correlated across restaurant offers here.

Consider a market M with J_M restaurants denoted by $j \in \{1, ..., J_M\}$, each selling one product ("food"). A market is defined as a metropolitan statistical area (MSA). Consumers choose which restaurant to visit or to purchase an e-coupon for, or to eat at home. Consumers know about all restaurants in the city. Consumer i's utility for an e-coupon from restaurant j is given by

$$u_{ij} = X_j\beta - \alpha p_j + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}, \tag{10}$$

where X_j describes the restaurant and e-coupon characteristics, including the type of food, the ambiance, whether the restaurant delivers and whether alcohol is served, as well as the deal duration, the value of the e-coupon, and whether the deal was a featured deal. ξ_j denotes the unobserved taste preferences for restaurant j. For example, service quality and restaurant decor are visible to the consumer but unobservable to us. Finally, ϵ_{ij} is a Type 1 Extreme Value i.i.d. shock to consumer preferences and ζ_{ig} is common to all products within group g (all restaurant deals) for consumer i. It follows a distribution such that $\zeta + (1-\sigma)\epsilon$ also follows a Type 1 Extreme Value distribution. The parameter σ describes the correlation of tastes across the restaurant deals on Groupon.

The utility of the outside option (not purchasing an e-coupon) is normalized to 0. Let $\delta_j = X_j\beta - \alpha_i p_j + \xi_j$. Berry (1994) shows that one can estimate equation (10) as

$$\ln(s_j) - \ln(s_0) = X_j\beta - \alpha p_j^G + \xi_j + \sigma \ln\left(\frac{s_j}{1-s_0}\right) \equiv \delta_j + \sigma \ln\left(\frac{s_j}{1-s_0}\right), \tag{11}$$

where $\frac{s_j}{1-s_0}$ is the e-coupon's share *within* the daily-deal site on a given day.

This nesting structure introduces an endogeneity issue: the log-share of a deal within the daily-deal website is affected by the same unobserved variables as the log-share of the same deal in the market. We account for this endogeneity by instrumenting for the offer's share on the website with the number of deals on the daily-deal platform on that day. Meal prices are set by the firms outside of the daily-deal site, and the e-coupon values and discount rates are set by the platform (most often at 50%). We interpret the value of the e-coupon as a proxy for restaurant "fanciness," so that the coefficient on the value does not enter the price elasticity. Own-price elasticities are given by $e_j = \frac{\alpha p_j^G}{1-\sigma}\left(1 - \sigma\frac{s_j}{1-s_0} - (1-\sigma s_j)\right)$, where p_j^G is the discounted price.

We instrument for the e-coupon price p_j^G using information on how often the retaurant had previously worked with the daily-deal site. Anecdotal evidence suggests that those firms with more e-coupon experience have more control over the discount setting process. The estimation is done across twenty markets (the twenty cities) for each day.

Table 5 shows the demand estimates and robust standard errors for three different demand specifications. The coefficients have the expected signs throughout. People like a lower price after controlling for coupon value as it indicates a better "deal." Featured items are more visible and thus purchased more often. It is unclear ex ante whether e-coupon buyers prefer a large-value e-coupon, and the small and insignificant coefficient is not surprising. As expected, e-coupon purchasers are relatively price elastic, with mean own-price elasticities over -2.

Specification (3) allows correlations of preferences to vary between e-coupons and the outside good. In a well-specified model, the correlation of preferences lies between zero and one. Our estimates of correlations are small but significantly different from zero, indicating that a regular logit model is misspecified. Adding one more restaurant to the e-coupon platform would affect sales of e-coupons for other restaurants on Groupon more than sales of restaurants that are not on Groupon. We proceed with the results from specification (3).

A.3.1 Consumer Surplus

Although price discrimination is traditionally thought to transfer surplus from consumers to firms, consumer surplus increases with the presence of a daily-deal website because their choice sets increase. Consumers can self-select into e-coupons, and the option and price of going to the restaurant without an e-coupon remain unchanged. Rosen and Small (1981) show that the change in consumer surplus has a tractable closed form solution. In our (nested logit) application, the change in consumer surplus to the representative consumer extends to

$$\triangle E[CS] = \frac{1}{\alpha}\left[\ln\left(1+\left(\sum_{j\in J^G}\exp\left\{\frac{\delta_j}{1-\sigma}\right\}\right)^{1-\sigma}\right) - \ln\left(1+\left(\sum_{j\in J^0}\exp\left\{\frac{\delta_j}{1-\sigma}\right\}\right)^{1-\sigma}\right)\right], \quad (12)$$

where α is the coefficient on the e-coupon's price, J^G is the choice set when the daily-deal website is available, and J^0 is the choice set without the restaurant's e-coupon offer.

Table 6 shows that consumers benefit by an average of $3,836 per e-coupon. This amounts to an average of 0.6 cent per consumer and offer. A back-of-the-envelope calculation indicates that the per-offer benefit to consumers is at most $15,000 (1,000 e-coupons sold per offer with an average saving of $15). Since some people associate using e-coupons with a cost, the lower mean increase in consumer surplus is expected.

Table 1: Summary statistics: Groupon offers

Variable	Mean	Std. Dev.	Min	Max
Featured	0.234	0.423	0	1
Value	29.37	21.40	4	300
Discount %	51.10	2.92	40	83
Offer duration (days)	1.751	0.838	0	8
Quantity	984.09	917.56	0	5979
N	2657			

Table 2: Changes in Liquor Sales

	(1)	(2)	(3)	(4)	(5)	(6)
	Coupon duration		Immediate redemption		Each month	
During Groupon	0.200***	0.119**	0.208***	0.131**		
	(0.0473)	(0.0358)	(0.0457)	(0.0373)		
After Groupon	0.292**	0.117	0.239***	0.115**	0.295**	0.121
	(0.0913)	(0.0682)	(0.0636)	(0.0419)	(0.0926)	(0.0756)
1st month					0.199***	0.130***
					(0.0446)	(0.0374)
2nd month					0.184***	0.106*
					(0.0503)	(0.0406)
3rd month					0.186***	0.105*
					(0.0535)	(0.0436)
4th month					0.168**	0.0869
					(0.0568)	(0.0448)
5th month					0.206***	0.123**
					(0.0566)	(0.0444)
6th month					0.230***	0.144**
					(0.0619)	(0.0540)
7th month					0.244***	0.146*
					(0.0683)	(0.0625)
Restaurant dummies	✓	✓	✓	✓	✓	✓
Month dummies	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓
Control restaurants	✓		✓		✓	
N	2782	1969	2782	1969	2782	1969
Restaurants	113	74	113	74	113	74
adj. R^2	0.033	0.040	0.031	0.040	0.032	0.038

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Mean changes in restaurant profits from offering an e-coupon

Restaurant type	Mean	Std. deviation	Median
American	20397.93	22436.36	16520.78
Asian	492.59	18924.57	-1580.21
Bars	53801.30	60477.20	35400.10
Italian	-132.72	20014.10	-2096.82
Mediterranean	13239.22	25932.24	18106.21
Mexican	19485.47	32195.27	8977.55

Note: All values in $.

Table 4: Changes in Liquor Sales by Restaurant Type

	(1)	(2)	(3)	(4)
	Coupon duration		Immediate redemption	
During*American	0.145*	0.0576	0.200**	0.115
	(0.0662)	(0.0601)	(0.0680)	(0.0623)
During*Asian	0.226***	0.139*	0.220**	0.139
	(0.0615)	(0.0553)	(0.0738)	(0.0711)
During*Bars	0.190*	0.135	0.288*	0.240
	(0.0731)	(0.0732)	(0.131)	(0.126)
During*Italian	0.233*	0.153	0.182	0.106
	(0.0991)	(0.103)	(0.107)	(0.115)
During*Mediterranean	0.298**	0.213*	0.170	0.0872
	(0.0997)	(0.0894)	(0.0983)	(0.0875)
During*Mexican	0.147	0.0664	0.218*	0.139
	(0.0896)	(0.0749)	(0.0910)	(0.0838)
After*American	0.182	-0.00161	0.144	0.0140
	(0.108)	(0.0988)	(0.0795)	(0.0662)
After*Asian	0.265*	0.0792	0.229**	0.0980
	(0.108)	(0.0988)	(0.0792)	(0.0658)
After*Bars	0.251	0.0994	0.193*	0.108
	(0.142)	(0.141)	(0.0784)	(0.0785)
After*Italian	0.428***	0.253*	0.356***	0.233*
	(0.120)	(0.114)	(0.0992)	(0.0950)
After*Mediterranean	0.420***	0.238*	0.365***	0.238**
	(0.122)	(0.110)	(0.102)	(0.0876)
After*Mexican	0.265	0.0881	0.208	0.0813
	(0.135)	(0.0883)	(0.117)	(0.0935)
Restaurant dummies	✓	✓	✓	✓
Month dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Control restaurants	✓		✓	
N	2728	1915	2728	1915
Restaurants	111	72	111	72
adj. R^2	0.037	0.052	0.034	0.051

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Discrete choice demand results

	Logit	IV Logit	IV Nested Logit
E-coupon price	-0.0193	-0.162	-0.172
	(0.0118)	(0.161)	(0.159)
Deal value	-0.00136	0.0669	0.0721
	(0.00573)	(0.0771)	(0.0758)
σ(Sites)			0.130*
			(0.0536)
Featured deal	0.760***	0.777***	0.726***
	(0.0454)	(0.0545)	(0.0548)
Deal duration	-0.418***	-0.420***	-0.457***
	(0.0310)	(0.0365)	(0.0371)
Alcohol	0.120*	0.131*	0.128*
	(0.0504)	(0.0561)	(0.0534)
Dressy	0.0754	0.127	0.121
	(0.0946)	(0.114)	(0.109)
Delivery	-0.0882*	-0.0970*	-0.107*
	(0.0423)	(0.0436)	(0.0419)
No parking	0.0388	0.0258	0.0212
	(0.0402)	(0.0455)	(0.0428)
City dummies	✓	✓	✓
Restaurant type dummies	✓	✓	✓
Time-of-day dummies	✓	✓	✓
Day-of-week dummies	✓	✓	✓
Mean elasticity	-0.275	-2.314	-2.474
Observations	2015	2015	2015
R^2	0.581	0.482	0.647

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Increase in Consumer Surplus per Restaurant Offer

Restaurant type	IV Nested Logit
American	3724.294
Asian	4131.28
Bars	3102.063
Cafes	3001.272
Italian	3536.124
Mediterranean	3789.046
Mexican	3997.47
others	4571.377
Total	3836.781

Figure 1: Liquor sales before and after Groupon

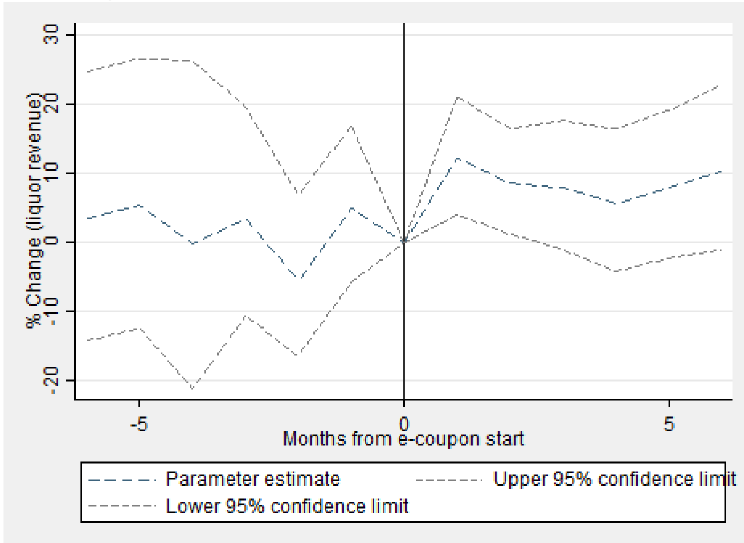

Figure 2: Increase in alcohol and food consumption from e-coupons

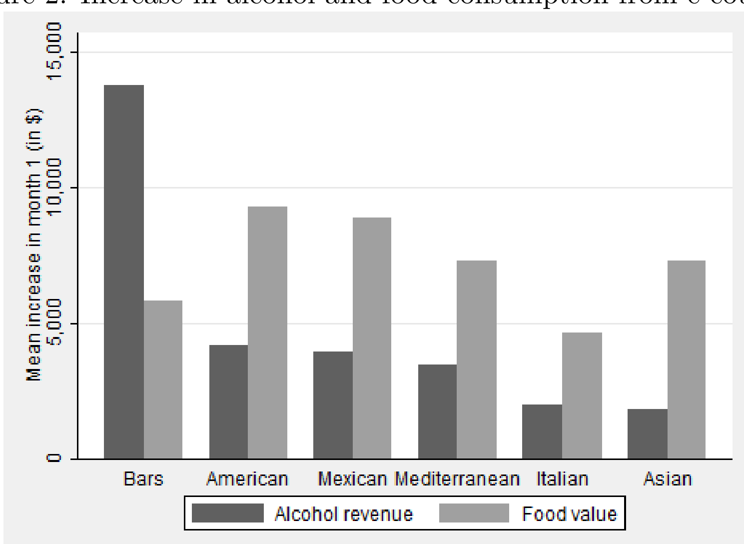

Figure 3: Percentage of e-coupon buyers who become new customers

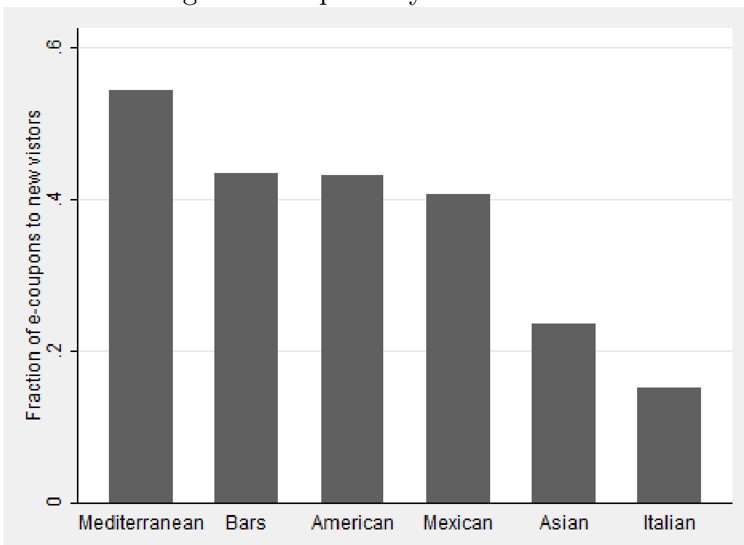

Figure 4: Changes in profits when offering e-coupons

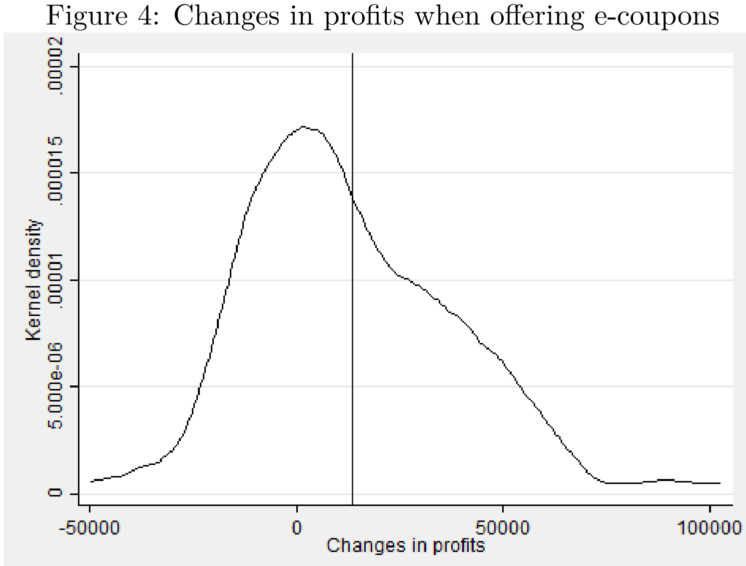

Figure 5: Changes in profits when offering e-coupons as λ varies

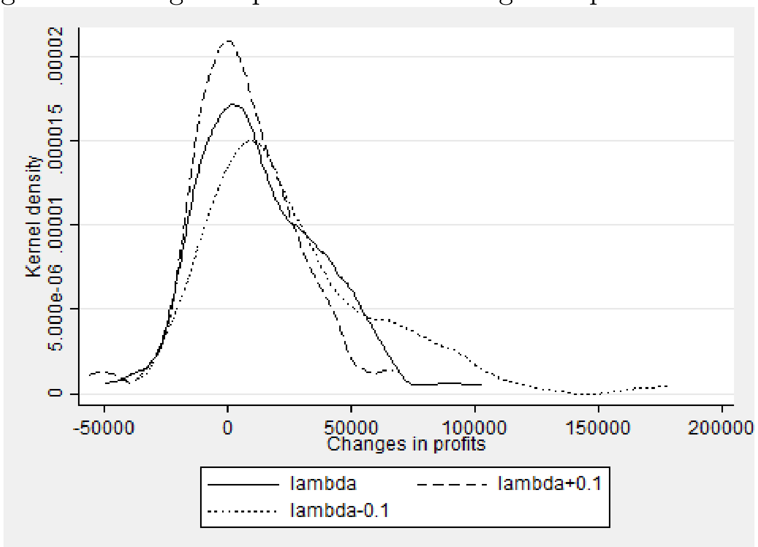

Figure 6: Percentage of e-coupon buyers who become new customers - lower λ