Electronic Markets and Geographic Competition among Small, Local Firms

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Abstract

We study the impact of electronic markets on small, boutique firms selling *presence* goods or services – goods or services which must be consumed at the selling firm's location. These firms have recently begun to compete on electronic markets by selling goods and services through local daily deal sites, such as Groupon and LivingSocial. Previous research has shown that electronic markets make transportation costs less relevant in determining competition among firms selling goods and services that can be consumed at the consumers' location. However, consumer transportation costs to the firm's location remain relevant for competition among those selling presence goods. Due to lack of data for such firms, it has been difficult to empirically examine the competition among them. We extract publicly available activity and spatial information from Groupon, LivingSocial, Google Maps, and Flickr to construct a unique panel dataset to study daily deals offered by restaurants and spa vendors in geographical clusters of concentration in 167 distinct cities. This dataset allows us to examine the effect of location on the competition vendors face in electronic markets. We find that as vendors in a particular geographical cluster participate in electronic markets, local competition increases and other vendors in that cluster join the electronic market and deepen discounts in response. However, vendors in other clusters in the same city remain relatively unaffected. We further analyze vendor ratings from Yelp and other infomediaries, to show that lesser known and low quality vendors utilize the advertising effect of electronic markets to increase their awareness among customers. We further test the moderating effect of horizontal and vertical differentiation among firms in geographical clusters on competition in electronic markets, using measures extracted from UrbanSpoon.com. We find that clusters having lower differentiation experience higher competitive effects of firms joining the electronic market. Our findings provide empirical validation of the analytical results in existing literature in an important and understudied context: competition among small businesses selling presence goods and services. Our results have implications for firms and electronic market platforms.

1.0 Introduction

Historically, the primary players in e-commerce have been large businesses attempting to reach a large, geographically dispersed audience through the expansive reach provided by the Internet. Small, boutique firms providing what we term *presence* goods or services, which require that the consumer be physically present *in a particular location or service area* to consume the good or service (for example, a restaurant for which a consumer must be present to consume a meal), did not typically engage in commerce online. Intuitively, this is because these firms serve a small, specific geographic area, and the investment required to engage in e-commerce was too high relative to the expected benefit. Recently, many services and platforms have emerged which enable these firms to have a more active engagement with customers over the Internet. Targeted search advertising based on region and other demographics; daily deal sites offering local deals, such as Groupon and LivingSocial; and emerging location-aware mobile "push" advertising are all examples of technologies which provide opportunities for these small, boutique firms to reach customers online, in addition to their traditional physical channels.

As these platforms lower barriers for small businesses in reaching customers online, it is important for these small businesses to understand the potential benefits and consequences of utilizing their services. On the one hand, they provide increased visibility and awareness which could drive increased demand, but on the other hand, they may erode margins, create operational strains, and attract less desirable customers. In this paper, we examine the effects of such electronic markets on competition between vendors. Specifically, we consider the impact on local competition among businesses offering similar goods or services within the same geographic area.

While some have argued that the Internet has made distance irrelevant (Cairncross 2001, Friedman 2007), it does not seem that this should hold for these small businesses. Because they provide *presence* goods or services requiring customers to be physically present for consumption, physical transportation costs will remain an important factor for consumers in choosing a particular vendor from which they will purchase. Advertising or selling through the Internet may increase awareness of a vendor outside its local geographic area, but due to transportation costs, few of the distant customers reached in this way will actually purchase from the vendor. The primary effect will be on customers within a local service area.

In pure physical commerce, transportation costs are a key factor (Hotelling 1929). The physical location of vendors creates disparate costs of travelling to one vendor or another for consumers, and these transportation costs moderates the competition among vendors in various locations. In pure electronic commerce, physical transportation costs as well as consumer search costs are lowered, and only differences in dimensions such as customer awareness and branding among retailers prevents near-perfect competition (Brynjolfsson and Smith 2000). In a dual channel market including both brick-and-mortar vendors as well as those that have a direct online channel, vendors with the direct channel may reach consumers without transportation costs, and search costs are lowered while choice sets are increased, increasing competition. Brick-and-mortar retailers survive because of disutility from use of the direct channel and costs related to potential lack of fit (Brynjolfsson et al. 2009, Forman et al. 2009).

Relative to this previous research, we examine a new question - how does utilization of a direct online sales channel by local vendors selling presence goods or services affect local competition? While presence goods or services may be purchased online, they must be consumed in a particular location. Therefore, transportation costs remain an important factor, with the primary effect of the online channel being a reduction in search costs. If an electronic market, such as Groupon, is effective in creating awareness about quality and fit of goods and services offered by the vendor, thereby reducing customers' search costs, then as vendors within a local geographic area engage with customers through the electronic market, competition will increase in a local service area surrounding these vendors, but not in distant areas. Other nearby vendors providing similar products or services will respond by also taking steps to engage with customers through the electronic market to remain competitive. We further expect that this effect will be moderated by the extent of differentiation in products offerings among vendors. Of course, if electronic markets do not influence consumer search costs, there may be no effect on competition. Thus, empirical studies are required to measure the ability of electronic markets to reduce consumer search costs. In this direction, our study empirically examines these effects of electronic markets on competition relative to the interplay between the reduction in search costs due to joining the electronic market (Bakos 1997) and the effects of transportation costs which limit the service areas of vendors (Hotelling 1929).

Examining competition among small vendors is challenging because of the difficulty in procuring appropriate data on such numerous and individually uninformative firms. However, studying these firms is important as small businesses make up nearly half of the US economy (U.S. Small Business Association 2014). We collect and combine data from several sources in order to create a unique dataset for analyzing the competition of small, local businesses in an electronic market. The primary electronic market we utilize for our study is Groupon, a popular provider of *daily deals* – vouchers which can be purchased at a deep discount and redeemed at local vendors for goods or services such as restaurants, spas, auto mechanics, and entertainment venues. Specifically, we collect data on all spa and restaurant daily deals offered in the US for a period of 39 months (July 1, 2011 through September 30, 2014). We also collect and analyze data from LivingSocial, Groupon's primary competitor. By performing a fine-grid search using the Google Maps API, we collect the locations of all spas and restaurants in every Groupon *division* (i.e. city or region served by Groupon and/or LivingSocial). Through an agglomerative clustering algorithm, we use locations of all spa and restaurant vendors to create clusters which describe the distribution of vendors within each division.

Combining data including the locations and details of restaurant and spa daily deals, we employ a dynamic panel model to examine the competitive reactions within these clusters to daily deal offerings by vendors selling similar goods and services in near geographic proximity. We find competitive responses to both the quantity and intensity of activity on the electronic market for both spas and restaurants. Specifically, an increase in the number of deals (discount amounts) offered in one period causes other vendors to offer more deals (deeper discounts) in response. However, these results only hold within a local area. The competitive response to nearby vendors is much larger than to those in the surrounding division as a whole. We further analyze the ratings of vendors from Yelp and other infomediaries to show that electronic markets primarily increase local competition among lesser known and low quality vendors, who offer deals to increase the awareness about their goods and services. Thus, we provide evidence for the underlying mechanism through which daily deals electronic markets influences local competition.

Further, for restaurant vendors in particular, we combine data collected from UrbanSpoon.com to imbue the distribution of restaurant vendors with specific consumer-perceived characteristics. Using this additional data, we find that the competitive effect is moderated by the degree of vendor differentiation in a local area, with areas of lower differentiation experiencing a greater competitive effect. This applies both to horizontal differentiation, which is represented by the concentration of cuisine types in the local area, as well as vertical differentiation, represented by the variation in prices among such vendors.

Our present work makes several contributions to the existing literature on the impact of electronic markets on competition. First, we examine the effect of electronic markets on local competition among vendors selling presence goods or services, distinct from previously studied effects of the Internet on competition in physical or electronic goods markets. We empirically demonstrate how analytical results from Bakos (1997), which describe the effect of electronic markets on competition, apply in a setting in which transportation costs play a significant role. Second, the nascent literature on daily deal markets has posited several possible underlying mechanisms by which these markets allow vendors to reach customers. We provide empirical evidence that the advertising effect of electronic markets is a dominant factor in the competition they drive. Third, we demonstrate the moderating role of vertical and horizontal differentiation on competition in an electronic market among small firms in a local geographic area. Fourth, we provide a novel approach for extracting relevant information from publicly available data and transforming it to analyze competition in a geographic area. Our approach of identifying the clusters of a vendor type in a geographic area using publicly available data may be used by academicians in future studies to examine the effect of a variety of factors on local competition, as well as by electronic market platform owners to predict the demand for deals in different geographic areas and accordingly allocate their marketing efforts more efficiently. Fifth, our study examines competition between small, boutique vendors, which typically may not be studied in such a large scale, due to issues in collecting data for a large number of small firms. We are not aware of any studies that examine such firms using objective economic data. Small businesses comprise 46% of private-sector output, and 48.5% of private-sector employment (U.S. Small Business Association 2014), and research on such a large, unstudied segment of the economy is valuable. As Internet usage becomes more ubiquitous and costs of interacting with customers online decrease, the importance of electronic markets to this business segment will grow, and should be studied. Our research provides implications for these small firms considering entrance into electronic markets.

2.0 Past Literature and Hypotheses Development

2.1 Search and Transportation Costs

Geographic competition in its simplest form is epitomized by the classic Hotelling model, in which customers experience different transportation costs in purchasing from competing firms (Hotelling 1929). Transportation costs, which may represent physical distance or other preferences, form the basis of consumer choice – if customers are aware of all vendors, prices, and qualities. This, however, may not be the case, and consumers must incur search costs to determine which vendor is the best fit. Hence, consumers face a trade-off between transportation costs (lack of fit) and search costs. A feature of electronic markets is that they serve to lower search costs (Bakos 1997). If online vendors can easily transport their goods or services directly to consumers, transportation costs are reduced as well. With reduced search and transportation costs and a large number of firms competing, competition may become intense due to the impact of the Internet, leading to low price dispersion and profits (Brynjolfsson and Smith 2000).

Several studies have empirically examined effects on competition from interplay of the Internet and geographic location. Blum and Goldfarb (2006) show that even if digital goods are available from vendors in various locations, consumers tend to transact with vendors who are closer to them. Brynjolfsson, Hu, and Rahman (2009) examine the competition between online and brick-and-mortar clothing retailers, finding that physical retailers in an area diminish online demand. Forman, Ghose, and Goldfarb (2009) also study competition between online and brick-and-mortar retailers, but of books, rather than clothing. They obtain panel data that allows them to examine the dynamics of competition as brick-and-mortar stores open in local areas, revealing the interplay of demand-side and supply-side factors. Janakiraman and Niraj (2011) show that geographic proximity creates social contagion which influences consumers' choices of brand, channel, and place in purchasing high-tech durable goods. Granados, Gupta, and Kauffman (2012) study differences in price elasticity in online and offline channels for air travel, finding online channels more price elastic. Pozzi (2013) examines the impact of supermarkets introducing online channels which reduce transportation costs, showing this allows capture of additional market share with little cannibalization – increasing demand through “business stealing” from brick-and-mortar competitors (Pozzi 2013, p. 580).

These empirical investigations share several common characteristics. First, they focus on the ability of the Internet and online channels to reduce transportation costs. Search costs may also be considered, but transportation costs play a central role. Second, they examine commodity goods that are virtually identical across the online and offline vendors from which consumers choose to purchase. Third, the literature has largely focused on the interplay between brick-and-mortar and online retailers, and typically not on the introduction of an online channel to a traditionally brick-and-mortar vendor. Of the studies mentioned above, only Pozzi (2013) studies the introduction of an online channel for an existing brick-and-mortar vendor, but still focuses on transportation costs and commodity goods. In contrast to existing empirical work in this area, we focus on brick-and-mortar vendors selling differentiated products. We examine the impact on competition created when certain of these vendors also sell goods or services through online channels. However, while the sale occurs online, the good or service still must be consumed at the vendor’s physical location, so transportation costs are unaffected. The benefit of the online channel is predominantly related to consumer search costs. Consider our setting of daily deal electronic market platforms. Consumers are uncertain about prices and qualities of product offerings from a large number of differentiated local firms. Such electronic market platforms provide information about available offerings, and even provide a low-cost way for consumers to experience the goods and services through discounted vouchers. This provides obvious benefits for customers by helping them determine fit and quality of various offerings (Hong and Pavlou 2014), but the impact on vendors is not as clear (Dholakia 2011).

Bakos (1997) shows that in differentiated markets, when customers’ costs of acquiring product information is high, the introduction of electronic markets will create pressure for competing sellers to increase discounts. The first seller to enter an electronic market will do so to capture buyer surplus, but this will increase competition in a prisoners’ dilemma, with other sellers also entering the market and increasing discounts. Based on this, we propose that when a seller offers a daily deal through the electronic market, other sellers will respond in kind by offering more deals with deeper discounts. But as these vendors sell presence goods and services, transportation costs will influence customer preferences for vendors (Hotelling 1929). Thus the competitive effect should be confined in a geographically concentrated area, as transportation costs will insulate distant vendors from the increased competition. That is, within a concentrated area, the response of competing vendors will be strong, but the effect will dissipate as distance increases. Based on this, we propose the following hypotheses:

Hypothesis 1a: As more (fewer) deals are offered through an electronic market in a geographic area in a given time period, the number of deals offered in the same geographic area in the subsequent period increases (decreases).

Hypothesis 1b: As deals with higher (lower) discount amounts are offered through an electronic market in a geographic area in a given time period, the discount amounts of deals offered in the same geographic area in the subsequent period increases (decreases).

Hypothesis 2a: As more (fewer) deals are offered through an electronic market in a geographic area in a given time period, the number of deals offered in other geographic areas in the same division in the subsequent period is unaffected or increases (decreases) by a smaller amount than within the original area.

Hypothesis 2b: As deals with higher (lower) discount amounts are offered through an electronic market in a geographic area in a given time period, the discount amounts of deals offered in other geographic areas in the same division in the subsequent period is unaffected or increases (decreases) by a smaller amount than within the original area.

2.2 Electronic Markets, Infomediaries, and Underlying Mechanisms of Competition

In discussing search costs, we adopt Bakos' (1997, p.1677) definition of "the cost incurred by the buyer to locate an appropriate seller and purchase a product". This is quite broad, and there are multiple mechanisms by which electronic markets may impact consumer search costs or otherwise allow vendors to reach them. In particular, Edelman et al. (Edelman et al. 2014) and Mejia et al. (2013, 2015) posit the specific mechanisms of price discrimination, advertising, and price promotion.[1]

First, to address price promotion, the analytical model provided by Edelman et al. (2014) suggests that this is only a possible outcome from daily deal services. They specifically show that there exists a discount amount that is profitable through a price discrimination mechanism *only if* the electronic market's share of voucher revenue is sufficiently small. With typical discounts and the daily deal site's share both around 50% (Dholakia 2010, Kumar and Rajan 2012), this leaves vendors with 25% of typical revenue for a voucher customer, making it unlikely that vendors offering daily deals find themselves in the region for profitable price discrimination. If so, this would mean restaurants and spas are typically operating at a 300% margin, just to break even with these price-sensitive customers transacting through daily deals.[2] In addition, just as with the price promotion effect discussed earlier, we would expect to see vendors offering repeat deals if they were primarily for price discrimination, which we largely do not.[3] As Kumar and Rajan (2012) show, there is an almost inevitable shortfall in short-term profits caused by selling daily deal vouchers at these types of discounts. In order to be profitable on the whole, there must be long-term customer acquisition through increased awareness of quality and fit – not simply price discrimination or promotion.

As for advertising and price promotion, these terms are somewhat ambiguous and to a degree intrinsically related. Therefore, in order to clarify our exposition, we adopt specific definitions and clarify the distinction between them as they will be used in this study. We define the *advertising effect* is that by which electronic markets provide increased awareness of the existence, quality, and fit of a vendor to consumers in order to improve long-term profits by creating repeat customers. The *price promotion* effect

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[1] We thank an anonymous reviewer for directing our attention to these valuable studies.

[2] To clarify, consider the example of a voucher for a meal worth $20. Typically such a voucher would sell for $10 on Groupon, and Groupon would keep $5 of the revenue. This means the vendor would receive $5 of revenue for a meal which typically sells for $20. In order for this to have a positive profit impact from a pure price discrimination perspective, the cost of providing the meal would have to be less than $5, meaning that the vendor's typical profit margin when selling the meal at full price is in excess of 300%.

[3] In our Groupon daily deals data collected over 39 months, 72% of all vendors offer only one deal, and 91% offer no more than three deals. We discuss the details of our data in section 3.

is the short-term increase in immediate sales through the deep price discounts offered. The mere inclusion of a vendor on an electronic market will contribute to the advertising effect, while the discounted voucher offered may contribute to either or both. The discounted voucher obviously may contribute to the price promotion effect, causing an increase in short-term demand as the vendor meets the reservation price of more consumers. However, it may also contribute to the advertising effect insofar as it helps to attract repeat customers by providing them with a low-cost, low-risk means to experience the vendor's quality and fit. For example, a newly opened vendor may offer a daily deal voucher with the goal of generating new repeat customers by raising awareness and allowing a low-cost trial of their product through the discounted voucher (advertising effect). Conversely, a more established vendor with excess capacity may offer a daily deal in an attempt to boost short-term sales by bringing in a large number of potentially one-time customers, possibly with the hope that they will spend beyond the value of their voucher (price promotion effect).

There are various online tools that consumers may use to help reduce their search costs. These tools can broadly be divided into two categories: 1) infomediaries and 2) electronic markets. Infomediaries such as Yelp aggregate information regarding vendors, which consumers may use to gain awareness and reduce uncertainty about vendor quality and fit. The word-of-mouth information available through these infomediaries has been shown to be effective in driving demand, especially for small, independent vendors (Goh et al. 2013, Lu and Lu 2013, Luca 2011). Electronic markets also offer awareness, as well as a vehicle for price promotion. Sites offering daily deals (originally referred to as group-buying deals) provide one example of such electronic markets. These sites have received some attention from researchers (Dholakia 2010, Edelman et al. 2014, Li 2016, Luo, Andrews, Song, et al. 2014, Mejia et al. 2015), although many open questions regarding their impact remain. Another example of electronic markets serving presence vendors would be location-aware mobile targeting platforms. These have become popular with the proliferation of connected mobile devices, and have been shown to be quite effective at inducing impulse purchasing (Andrews et al. 2016, Fang et al. 2015, Fong et al. 2015, Ghose et al. 2013, Luo et al. 2014).

The awareness of vendor quality and fit provided by the infomediaries can moderate the effect of electronic markets on local competition among vendors of presence goods. Vendors highly rated and well-known on other infomediaries have lower incentive to participate in an electronic market to create awareness about quality and fit. On the other hand, vendors not advertised on other infomediaries may have higher incentive to offer discount deals on an electronic market to advertise existence and offer customers a low cost and low risk opportunity to experience their goods or services and discover their quality and fit.

Previous studies on daily deals also suggest that the long-term advertising effect is more important in providing incentives for vendors to offer daily deals, and more indicative of deal success than the short term price promotion effect. In a small survey and qualitative study Dholakia (2010) finds that effectiveness in reaching new customers is a primary determinant of whether a daily deal will be profitable, and whether a vendor would consider offering other deals in the future. In a later study, he notes "the daily deal's success hinges on its ability to convert a significant proportion of the new customers that the deal brought in into repeat buyers who then return to repurchase from the business again and again at full price" (Dholakia 2012, p. 20). Kumar and Rajan (2012, p. 127) note that vendors offering daily deals "expect to attract new customers and in the process convert the new customers into regular customers" and that this is key to daily deal profitability. Shivendu and Zhang (2016) analytically show the motivation of vendors offering daily deals to reach uninformed consumers in order to improve their understanding of vendor quality and increase willingness to pay in subsequent periods. Based on these studies, and considering infomediaries to provide a substitute for advertising, creating awareness of quality and fit, we propose the following hypotheses:

Hypothesis 3a: The effect of electronic markets on competition among local vendors of presence goods as reflected by the volume of offered deals is moderated by the level of awareness provided by infomediaries: an increase in the proportion of vendors having a presence on one or more infomediaries results in a decrease in the volume of offered deals in the subsequent period.

Hypothesis 3b: The effect of electronic markets on competition among local vendors of presence goods as reflected by the magnitude of offered discounts is moderated by the level of awareness provided by infomediaries: an increase in the proportion of vendors having a presence on one or more infomediaries results in a decrease in the magnitude of offered discounts in the subsequent period.

2.3 Impact of Differentiation

Prior literature suggests that the competition among firms is moderated by their differentiation. (Hotelling 1929). Further, Shaked and Sutton (1982) demonstrate that differentiation among vendors reduces price competition. Zhelobodko et al. (2012) show that differentiation has an impact on competitive effects, and that this impact is moderated by a relative "love for variety" which changes the elasticity of substitution. Specifically related to electronic markets, Ba et al. (2007) show that online merchants use service and recognition differentiation to reduce competitive pressures. Based on these works, we expect that competition in local geographic areas with higher levels of vertical and horizontal differentiation will be less impacted vendors entering the electronic market. Therefore, we propose the following hypotheses:

Hypothesis 4a: The effect of electronic markets on competition among local vendors of presence goods as reflected by the volume of offered deals is moderated by the level of horizontal and vertical differentiation in their good and service offerings: areas having lower levels of differentiation should experience higher competitive effects.

Hypothesis 4b: The effect of electronic markets on competition among local vendors of presence goods as reflected by the magnitude of offered discounts is moderated by the level of horizontal and vertical differentiation in their good and service offerings: areas having lower levels of differentiation should experience higher competitive effects.

3.0 Data Construction

3.1 Electronic Market Platforms: Groupon and LivingSocial

We collected data on daily deals served by Groupon. Consumers subscribe to local daily deal emails provided by Groupon, which are distributed on a daily basis advertising available vouchers which may be purchased through the Groupon website. Vouchers commonly sell for a 50% discount relative to retail value. Groupon and the vendor split the revenues collected from the sale of vouchers (often 50/50, although the revenue split varies). Customers redeem purchased vouchers at the vendors' premises as if they were gift cards. Originally, Groupon was marketed as a group-buying platform, requiring a minimum number of sales before the deal became effective, however this mechanism was removed during 2012. This change does not affect our analysis, as virtually all minimum requirements were met, which is what led Groupon to cancel this policy (Bai et al. 2015).[4] This model allows brick-and-mortar vendors to sell their presence goods and services through an online channel.

For our analysis, we collected daily deals offered through Groupon over a 39 month period (7/1/2011–9/30/2014). We collected data for approximately 250,000 deals offered from vendors in 167 Groupon locations (called *divisions)* in North America, of which 152,574 deals from Groupon with redemption locations within the bounds of the divisions in our study.[5] To examine the effects of electronic markets on vendors of presence goods or services, we concentrate on only two types of deals: restaurant and spa/personal care. These two types comprise approximately 40% of all daily deals offered by Groupon and unambiguously represent presence goods or services that require customers to be physically present on vendors' premises or in a local service area for consumption. Of the deals collected, 36,052 were spa deals and 23,469 were restaurant deals. To ensure that outlier clusters[6] with few vendors and therefore minimal opportunity to run deals did not skew our results, we removed all observations in clusters in the bottom decile of vendor population collected from Google Maps, dropping the lower decile of clusters. For purposes of the differentiation results below, we remove observations in clusters with low data availability from UrbanSpoon, again removing the lower decile of clusters. Many of these removals overlap, and our results are robust to various choices of cutoffs for these removals. Our final set of observations contained 53,172 deals: 32,068 for spas, and 21,104 for restaurants. In addition, we also collected deals offered by LivingSocial in the same locations as those collected for Groupon. These deals were collected from 7/1/2011 – 12/31/2012. There were 87,619 deals in total: 16,120 restaurant-type 16,782 spa-type.[7]

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[4] We also performed our analysis only on data in 2013 and afterward, noting similar results to analysis performed on the entire dataset.

[5] The vast majority of deals without redemption locations were "Groupon Goods" deals, which are physical products shipped directly to the consumer. These are not relevant to our study, as they do not represent presence vendors.

[6] We deploy agglomerative clustering technique to identify geographical areas of local competition and call it clusters. The creation of these clusters is described in the next section.

[7] LivingSocial does not provide explicit deal categories as Groupon does. Instead, we had to assign deal categories manually. This was done in a two-step procedure. First, each deal vendor was matched to the Google Maps vendor data collected, based on latitude and longitude. In addition, to be considered a match, we required 90% overlap in the vendor name between LivingSocial and Google Maps. We identified matches for 32% of vendors. Based on these

3.2 Geographic Vendor Distribution and Characteristics

To examine the impact of daily deals on localized competition, we require a knowledge of the geographic distribution of vendors relative to those vendors offering daily deals. To obtain this, we used Flickr Shapefiles[8] to identify division boundaries and the Google Maps API[9] to collect information about the spatial distribution of vendors within a division. We use search terms *restaurant* for restaurant-type vendors, and *spa* and *massage* for spa-type vendors, and collect vendor locations using a fine grid search within the boundaries of each division (see Appendix A for a complete description of the collection methodology). 130,497 spa and 471,113 restaurant vendors were identified across all divisions from Google Maps in this way. The purpose of collecting these vendors is to determine the various local service areas in which consumers choose between vendors. Intuitively, based on transportation costs, consumers will typically limit their choice of vendor to those in a specific area that is nearby, rather than considering the entire division. For instance, a consumer in the Marina district of San Francisco is not likely to often visit restaurants and spas in Oceanview on the other side of the city. While customers may occasionally travel across a division for a deal, largely competition will be concentrated among vendors in specific local areas.

To identify these areas, we use an unsupervised agglomerative hierarchical clustering algorithm to classify all vendors of a type into groups based on geographic proximity. Distance is measured in the Euclidean sense using latitudes and longitudes for each vendor, with coordinates adjusted using great-circle distance calculations to account for the Earth's curvature (see the electronic companion for further details).

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matches, we identified a list of words which clearly delineated restaurant and spa vendors. We used this word list to identify further vendors of restaurant and spa type which were not matched to the Google Maps data (due to errors, slight differences in latitude/longitude or name, timing issues, etc.). Combining the matches based on Google Maps and keywords, in total 38% of vendors were identified as restaurant or spa, which is commensurate with the proportion of Groupon deals in these categories. In order to validate our categorization, we sampled 533 LivingSocial deals, which were manually coded by one of the authors and a research assistant with 100% agreement. Of these 533 deals, 177 were matched to Google Maps vendors, with 21 errors. 98 of the vendors were manually coded as restaurants, and 93 as spas. 12 of these vendors were not identified by the automated matching as spa or restaurant (false negatives), and 25 additional vendors were categorized as spa or restaurant, when in fact they were not (false positives). While the categorization is not perfect, we posit that it provides a sufficiently accurate signal of LivingSocial deal activity.

[8] http://code.flickr.net/2011/01/08/flickr-shapefiles-public-dataset-2-0/, last accessed 12/23/2015

[9] https://developers.google.com/maps/, last accessed 12/23/2015

Cluster agglomerations were determined using Ward's linkage method for minimizing total within-cluster variance (Ward 1963). Each cluster represents a consumer's typical choice set of vendors based on transportation costs. We specified the number of clusters for each division and category combination based on a monotonically increasing concave function of the number of vendors that exist in that division and category. The models presented below are based on functions creating between 4 and 10 clusters per division. We tested a variety of functions and resulting cluster sizes to determine robustness of our models (ranging up to a high end of 181 clusters in the largest division), with no qualitative change in results based on choice of cluster size within this range. We present results based on the function resulting in the smallest number of clusters tested, as this represents the most conservative model for determining parameter significance.

In order to measure the prior awareness of the vendors offering deals through Groupon, we additionally collected information from Yelp and other infomediaries which host reviews and ratings.[10] As of 1/1/2013, Groupon provides links to such infomediaries on all deal pages. For each vendor offering a deal through Groupon from 1/1/2013 – 9/30/2014, we collected the number of reviews and average ratings for each vendor. Of the 14,913 spa and 8,293 restaurant vendors offering deals in this period, 27% and 58% had at least one review on at least one infomediary site at the time the vendor offered the deal, respectively.

Finally, to measure the moderating effects of vertical and horizontal differentiation on the impact of electronic markets on local competition, we collect data regarding the types of cuisine and relative prices for restaurants in each division from UrbanSpoon, a popular restaurant review site.[11] For each division, we identify the corresponding area on UrbanSpoon and download all restaurant listings for that area. A total of 338,706 UrbanSpoon listings were collected within the divisions. Each listing includes the vendor's name,

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[10] The collected data includes the following infomediaries: Yelp, Google, UrbanSpoon, TripAdvisor, Yahoo, CitySearch, SpaFinder, OpenTable, Insider Pages, and Kudzu

[11] http://www.urbanspoon.com/, last accessed 5/21/2014, now https://www.zomato.com/ last accessed 12/23/2015

latitude, longitude, cuisine type, and relative price on a four-point scale. Based on location, we assign each listing to a cluster created from the Google Maps data.

For each cluster, we measure horizontal differentiation based on the distribution of restaurants across the 161 cuisine types assigned by UrbanSpoon[12]. We measure this distribution using the Herfindahl index (Herfindahl 1950), which measures market concentration. We group vendors by cuisine type and measure market share as the proportion of vendors offering that cuisine type in a particular cluster:

$$HHI_k = \sum_{q \epsilon Q} \left(\frac{x_{qk}}{\sum_{q \epsilon Q} (x_{qk})} \right)^2,$$

where Q is the set of all possible cuisine types, and x_{qk} the number of vendors of cuisine type q in cluster k. This measure will be higher in clusters with a higher concentration of certain cuisine types, signifying lower horizontal differentiation and more intense competition. Therefore, we expect that a higher Herfindahl index for a cluster will lead to a more intense effect of electronic markets on local competition.

To measure vertical differentiation, we use the price dispersion among vendors in a cluster, specifically the coefficient of variation (COV) of the prices (measured on a discreet four-point scale) for vendors in the cluster, σ_k^p / μ_k^p. The higher the coefficient of variation, the higher dispersion of prices, and less intense the competition. Therefore we expect that a lower coefficient of variation for a cluster will lead to more intense effect of electronic markets on local competition.

4.0 Econometric Model and Results

4.1 Data Description

Vendors compete for consumers' attention and patronage, and electronic markets offer a new platform for this competition. We are interested in measuring the effect electronic markets have on local competition. That is, does vendor participation in an electronic market spur competitive reactions? These

[12] To ensure that our results are not an artifact of the particular categorization scheme used by UrbanSpoon, and in particular, the fine granularity of distinctions in cuisine types, we re-performed our analysis using a more general set of 35 cuisine types created by combining similar types from UrbanSpoon. Our results were qualitatively unaffected by the scheme of cuisine categorization.

reactions may take many forms, of which many are unobservable to the researcher. But most commonly, competitive reactions to advertising and promotions occur in the same instrument (Steenkamp et al. 2005). Therefore, we measure competitive reaction by the quantity and intensity of daily deals offered by vendors in a local area. Specifically, we measure quantity as V_{ijkt}, the number of vendors in a category ($i \in \{restaurant, spa, etc.\}$), division ($j \in \{1, \dots, 167\}$), and cluster ($k \in \{1, \dots, K_{ij}\}$) who offer daily deals within a given time period t.[13] Similarly, we measure intensity as the mean discount percentage D_{ijkt} offered among these daily deals.[14] These measures represent the outcomes of our model.

The primary effect of interest is how prior activity on the electronic market prompts these competitive responses. Our objective is to compare the effects of prior *local* activity with the effects of prior activity that is more geographically dispersed in order to understand how competition is impacted by both nearby and further away activity. The quantity and intensity of nearby activity in the prior period is measured by autoregressive terms of the number of vendors offering deals in a given cluster, $V_{ijk(t-1)}$, and the mean discount offered, $D_{ijk(t-1)}$. The quantity and intensity of other geographically dispersed activity is measured by the number of vendors offering deals in the remainder of the division where the cluster resides, $V_{ij(-k)(t-1)}$, and the mean discount offered for these deals, $D_{ij(-k)(t-1)}$. If, as hypothesized, deals on electronic markets do increase geographically local competition, we should find that the quantity and intensity of deals of a specific type offered in a cluster in a period are positively correlated with the quantity and intensity of similar deals offered in the same cluster in the previous period but not with that of similar deals offered in other clusters of that division in the previous period.

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[13] In the results presented below, the time period is monthly. To ensure robustness to this choice, we additionally estimated our models using bi-monthly and quarterly time periods with qualitatively similar results.

[14] Many deals include multiple "options" with varying discount percentages. This is often an increasing volume discount (i.e. $5 for a voucher good for $10 of food, or $10 for a voucher good for $25 of food), but may represent differing products and services within the same deal. The measure used in the models presented is the mean (across all deals offered) of mean (across all options within a given deal) discounts. Alternatively, we used the mean of minimum discounts and mean of maximum discounts, noting qualitatively similar results.

Of course, there are other factors that influence the number of deals offered in any particular cluster in a given period. In addition to these main effects, we control for other covariates which might influence the dependent variables. First, the quantity and intensity of deals of a specific type (i.e. restaurant or spa) may be influenced by other types of deals offered. For instance, vendors may see competition from or want to capitalize on complementarity with other vendors in related categories who offer daily deals. To control for possible effects such as these, we include covariates for the number of vendors offering deals and their mean discount percentages, both in the same cluster as well as the division as a whole ($V_{(-i)jk(t-1)}$, $V_{(-i)j(t-1)}$, $D_{(-i)jk(t-1)}$, $D_{(-i)j(t-1)}$). Second, the quantity and intensity of deals offered may be influenced by the level of success achieved by prior deals. While success might be measured by the profit impact of the deals offered (Dholakia 2010, 2011, 2012), this information is largely unobservable to competitive vendors. The only information readily available relative to the success of a daily deal is the number of sales generated by the deal. To control for this information, we include a covariate for mean sales per deal offered in a particular category, division, and cluster in the prior period, $S_{ijk(t-1)}$.

We report the summary statistics for identified clusters in our data in Table 1. On average, each spa cluster generates 1.52 spa deals per month, but there is significant variation in the number of deals, with a standard deviation of 2.18. There are slightly fewer restaurant deals per month in each cluster (0.69 on average), but there is still significant variation (1.37 standard deviation). The median number of deals for restaurant clusters is 0, as there are a significant number of clusters which have no deals in some time periods. This is also the reason the mean discount amount and sales for restaurant deals are 0, as we coded discounts and sales to be 0 in the case of 0 deals offered, rather than counting these as missing data. The differentiation data for restaurants indicates that there is a high level of differentiation on both vertical and horizontal dimensions, with the mean price coefficient of variance at 0.45 and cuisine type Herfindahl index of 0.06. As we will show later, this has a significant effect on how competition is impacted.

Table 1. Summary Statistics and Variable Descriptions

		Restaurant			Spa		
Variable	Description	Median	Mean	Std Dev	Median	Mean	Std Dev
V_{ijkt}	Number of vendors offering deals in category i, division j, and cluster k during time period t	0.00	0.69	1.37	1.00	1.52	2.18
$V_{ij(-k)t}$	Number of vendors offering deals in category i, division j, and all clusters other than k during time period t	2.00	4.29	5.44	5.00	7.33	7.96
$V_{(-i)jkt}$	Number of vendors offering deals in all categories other than i in division j and cluster k during time period t	5.00	7.58	10.59	5.00	7.69	9.19
$V_{(-i)jt}$	Number of vendors offering deals in all categories other than i in all clusters in division j during time period t	37.00	55.90	61.48	32.00	45.61	42.74
D_{ijkt}	Mean discount amount for deals offered in i, j, k, t	0.00	0.18	0.24	0.52	0.35	0.30
$D_{ij(-k)t}$	Mean discount amount for deals offered in category i, division j, and all clusters other than k in time period t	0.50	0.39	0.21	0.59	0.53	0.20
$D_{(-i)jkt}$	Mean discount amount for deals offered in all categories other than i in division j and cluster k during time period t	0.57	0.49	0.24	0.57	0.54	0.18
$D_{(-i)jt}$	Mean discount amount for deals offered in all categories other than i in all clusters in division j in time period t	0.59	0.58	0.09	0.58	0.58	0.07
YP_{ijkt}	Proportion of vendors with at least one Yelp (or other) review who offer deals in i, j, k, t	0.67	0.58	0.44	0.00	0.22	0.33
YA_{ijkt}	Average Yelp rating of vendors with at least one Yelp (or other) review who offer deals in i, j, k, t	0.00	0.59	1.37	0.00	0.57	1.40
S_{ijkt}	Mean number of vouchers purchased per deal offered in in i, j, k, t	0.00	544.96	6304.08	4.00	225.77	797.75
HHI_k	Herfindahl index measuring concentration of cuisine types in cluster k	0.06	0.06	0.01	N/A	N/A	N/A
COV_k	Coefficient of variation for relative prices (on a 4-point scale) for vendors in cluster k	0.46	0.45	0.05	N/A	N/A	N/A

Table 2. Correlation matrices

Restaurants	V_{ijkt}	$V_{ij(-k)t}$	$V_{(-i)jkt}$	$V_{(-i)jt}$	D_{ijkt}	$D_{ij(-k)t}$	$D_{(-i)jkt}$	$D_{(-i)jt}$	YP_{ijkt}	YA_{ijkt}	S_{ijkt}	HHI_k	COV_k
V_{ijkt}	1.0000												
$V_{ij(-k)t}$	0.3555	1.0000											
$V_{(-i)jkt}$	0.4966	0.3737	1.0000										
$V_{(-i)jt}$	0.3527	0.6606	0.6879	1.0000									
D_{ijkt}	0.6744	0.2963	0.3226	0.2532	1.0000								
$D_{ij(-k)t}$	0.2119	0.4457	0.2177	0.3377	0.2537	1.0000							
$D_{(-i)jkt}$	0.1933	0.1866	0.2830	0.2502	0.2661	0.2184	1.0000						
$D_{(-i)jt}$	0.0776	0.1369	0.0968	0.1398	0.1041	0.2130	0.3351	1.0000					
YP_{ijkt}	0.0339	-0.0266	0.0446	0.0177	0.0298	-0.0138	0.0262	0.0702	1.0000				
YA_{ijkt}	0.2206	0.0214	0.1547	0.0735	0.0239	0.0137	0.0509	0.0773	0.8753	1.0000			
S_{ijkt}	0.0869	0.0695	0.0354	0.0311	0.1218	0.0441	0.0328	0.0165	-0.0676	-0.0307	1.0000		
HHI_k	-0.2999	-0.1983	-0.3378	-0.2875	-0.3192	-0.1803	-0.3440	-0.1242	0.0134	-0.0146	-0.0409	1.0000	
COV_k	0.1948	0.0373	0.1749	0.0995	0.1893	0.0602	0.1565	0.0259	0.0436	0.0919	0.0245	-0.3916	1.0000

Spas	V_{ijkt}	$V_{ij(-k)t}$	$V_{(-i)jkt}$	$V_{(-i)jt}$	D_{ijkt}	$D_{ij(-k)t}$	$D_{(-i)jkt}$	$D_{(-i)jt}$	YP_{ijkt}	YA_{ijkt}	S_{ijkt}
V_{ijkt}	1.0000										
$V_{ij(-k)t}$	0.3374	1.0000									
$V_{(-i)jkt}$	0.6584	0.2894	1.0000								
$V_{(-i)jt}$	0.3589	0.7317	0.5812	1.0000							
D_{ijkt}	0.5869	0.2535	0.3521	0.2432	1.0000						
$D_{ij(-k)t}$	0.1817	0.3934	0.1794	0.3419	0.2061	1.0000					
$D_{(-i)jkt}$	0.1778	0.1429	0.2176	0.1846	0.2514	0.1773	1.0000				
$D_{(-i)jt}$	0.0991	0.1644	0.0868	0.1330	0.1262	0.2470	0.4079	1.0000			
YP_{ijkt}	0.1256	0.1228	0.1832	0.1973	-0.0116	0.0878	0.0413	-0.0011	1.0000		
YA_{ijkt}	0.3983	0.2373	0.3380	0.3148	0.033	0.1502	0.0864	0.0415	0.8178	1.0000	
S_{ijkt}	0.1874	0.1483	0.1069	0.0860	0.2623	0.0923	0.0717	0.0416	0.0629	0.1708	1.0000

Correlations for all variables are reported in Table 2. The reported correlations are for the original untransformed, un-differenced data, and therefore a significant amount of correlation may be explained by time-invariant cluster-specific characteristics which are controlled for in the final models.

4.2 Econometric Specifications

We use specification (1) to examine the effect of prior period deals both inside and outside a competitive cluster on the quantity and intensity of deals in the current period after controlling for other observed and unobserved factors that may influence the offering of deals:

$$V_{ijkt} = \alpha_{ijk} + \beta_1 V_{ijk(t-1)} + \beta_2 V_{ij(-k)(t-1)} + \beta_3 V_{(-i)jk(t-1)} + \beta_4 V_{(-i)j(t-1)} + \beta_5 S_{ijk(t-1)} + \varepsilon_{ijkt}. \quad (1)$$

The term α_{ijk} denotes combined category-division-cluster fixed effects. In unreported tests, we additionally estimated our models including indicator variables for each time period to account for unobserved time-related effects, noting similar results.

In equation (1), the primary coefficient of interest β_1 represents the effect of the number of prior period deals in a given category, division, and cluster on the number of deals offered in that same category, division, and cluster in the current period, after also controlling for the intensity of similar deals offered in the same cluster in previous period and for deals in the other clusters of the same division in the previous period. A positive effect on this variable indicates that daily deals offered by vendors increase competition in a local area by inciting other vendors to respond competitively, offering deals of their own through the electronic market. Coefficient β_2, on the other hand, represents the effect of prior period deals offered in a category in all other clusters of the division on the deals offered in the same category in a particular cluster in the current period. If the electronic market promotes localized competition among these presence vendors, we should find a higher and more significant value for coefficient β_1 as compared to β_2.

Alone, it could be argued that this relationship may represent increasing awareness and adoption of the electronic market, or some other phenomenon aside from competition. Therefore in addition to examining the effects of the electronic market on the number of deals offered, we also test how the intensity of deals are impacted in the local area using specification (2):

$$D_{ijkt} = \alpha_{ijk} + \beta_1 D_{ijk(t-1)} + \beta_2 D_{ij(-k)(t-1)} + \beta_3 D_{(-i)jk(t-1)} + \beta_4 D_{(-i)j(t-1)} + \beta_5 S_{ijk(t-1)} + \varepsilon_{ijkt}. \quad (2)$$

Similar to the above, the primary coefficient of interest, β_1 represents the effect of the level of discounts offered for within-cluster deals in the prior period on the level of discount offered on within-cluster deals in the current period, while β_2 represents the effect of discount levels in the rest of the division on those within the cluster. A higher and more significant value for coefficient β_1 as compared to β_2 would signify a localized effect of the intensity of daily deals on competition.

We can take advantage of the panel nature of the data to remove time-invariant unobserved characteristics of individual clusters which would otherwise create issues for estimation. Typically this would be accomplished through a fixed-effects model using a within transformation. However, the autoregressive terms included in the model could introduce bias to these results. This is because the fixed-effects estimator is only consistent and unbiased under conditions of strict exogeneity of the regressors. That is, for each independent variable x, $E\left(x_{ijks}\varepsilon_{ijkt}\right) = 0$ for all combinations of time periods s and t (Wooldridge 2010). In Figure 1, it is apparent that this assumption does not hold in a model including lagged dependent variables as regressors, since each such lagged dependent variable is correlated with the error term from the previous time period (dashed lines). In addition, if errors are serially correlated, this in turn also causes contemporary endogeneity (solid lines).

$$\begin{aligned}
y_{ijk(t-1)} &= \beta y_{ijk(t-2)} + \cdots + \varepsilon_{ijk(t-1)} \\
y_{ijkt} &= \beta y_{ijk(t-1)} + \cdots + \varepsilon_{ijkt} \\
y_{ijk(t+1)} &= \beta y_{ijkt} + \cdots + \varepsilon_{ijk(t+1)}
\end{aligned}$$

Figure 1. Serial correlation and lack of strict exogeneity

In order to avoid these issues, we implement dynamic panel estimation using the generalized method of moments (Arellano and Bond 1991). This method utilizes further lags as instruments for the endogenous (i.e. not strictly exogenous) regressors in the model, which eliminates the endogeneity.[15] We utilize the one-step version of their estimator, as the two-step version is known to have a downward bias on the reported standard errors, inflating significance (Bond 2002). Additionally, we utilize robust standard errors which allow for heteroskedasticity and within-group correlation of error terms, as we expect errors to be related within vendor clusters. For the purposes of dynamic panel estimation, we treat the number of vendors offering deals and discount percentage offered for deals within a given cluster and category in the prior period as endogenous ($V_{ijk(t-1)}$ and $D_{ijk(t-1)}$). Our proposed model states that these variables are directly determined based on their own lagged values, which precludes their strict exogeneity. We assume that the per-deal sales, as well as the number of vendors and discount percentages for deals in other categories or clusters are exogenously determined, and treat them as such. In unreported tests, we assess the robustness of our model to this assumption by treating all covariates as endogenous, with similar results.

4.3 Estimation Results and Discussion

4.3.1 – Main Specification: The results of Models 1 and 2 are presented in Table 3 for restaurant vendors. We focus first on how the quantity of competitive response relates to the quantity of deals in the prior period, leaving out variables related to intensity. We find in Model 1 that vendors in a given cluster offer more deals in response to an increase in the number of vendors offering deals in the prior period in the same cluster ($V_{ijk(t-1)}$). There is also a statistically significant response to an increase in vendors offering deals in other clusters in the division ($V_{ij(-k)(t-1)}$), however the effect is significantly smaller than the within-cluster effect. This confirms that the electronic market for presence goods intensifies local competition (supports H1a), and that more distant competition is less affected (supports H2a).

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[15] We also jointly estimated our models using a vector autoregressive specification, in order to account for potential correlation between errors in Models 1 and 2. Additionally, we estimated Model 1 with additional controls for the average discount amounts ($D_{ijk(t-1)}, D_{ij(-k)(t-1)}, D_{(-i)jk(t-1)}, D_{(-i)j(t-1)}$) and Model 2 with additional controls for the number of deal offerings ($V_{ijk(t-1)}, V_{ij(-k)(t-1)}, V_{(-i)jk(t-1)}, V_{(-i)j(t-1)}$). All such models produced qualitatively similar results to the primary specification, confirming that correlations among such measures and error terms do not cause our results.

Table 3. Predicting number of restaurant vendors offering deals, V_{ijkt} (N = 25402)

	Model 1 (DV = V_{ijkt})		Model 2 (DV = D_{ijkt})	
Main Effects				
$V_{ijk(t-1)}$	0.0873	(0.0193)***		
$V_{ij(-k)(t-1)}$	0.0093	(0.0039)*		
$D_{ijk(t-1)}$			0.0345	(0.0097)***
$D_{ij(-k)(t-1)}$			0.0003	(0.0090)
Covariates				
$V_{(-i)jk(t-1)}$	0.0050	(0.0032)		
$V_{(-i)j(t-1)}$	0.0027	(0.0008)**		
$D_{(-i)jk(t-1)}$			-0.0195	(0.0072)**
$D_{(-i)j(t-1)}$			0.0288	(0.0128)*
$S_{ijk(t-1)}$	-0.0059	(0.0036)	-0.0013	(0.0008)
Z tests (H0: Zero correlation in first-differenced errors)				
Order 1	-16.88	***	-25.97	***
Order 2	2.76^{+}	**	3.95^{++}	***

$^{+}$ Controlling for an additional lag of the dependent variable brings the z score for order 2 error correlation to -1.45 with no difference in coefficient sign or significance

$^{++}$ Controlling for an additional lag of the dependent variable brings the z score for order 2 error correlation to -0.32 with no difference in coefficient sign or significance

***Significant at p < .001. **Significant at p < .01. *Significant at p < .05

The critical assumption that supports the consistency of the dynamic panel GMM estimator is a lack of serial correlation in errors beyond the first order (Arellano and Bond 1991). The first order correlation in such a model should be significantly negative, as can be seen by the z-statistic reported in Table 3. In Model 1, we do find significantly positive order 2 serial correlation in the errors of the model. In order to ensure that our model remains accurate despite the failed assumption of no serial correlation, we estimated the model with an additional lag of the dependent variable in order to make the model dynamically complete and remove the serial correlation. At this point the z-statistic for order 2 serial correlation became insignificant, with no difference in the sign or significance of any main effects or covariates. The sign and significance of the second lagged dependent variable was consistent with that of the first lag. For the remainder of the paper, it is noted for each order 2 test if additional lags were needed to remove serial correlation and how this affected (or did not affect) the model in question. Accepting that the model has no serial correlation provides confidence in the validity of the estimation.

Additionally, when using a GMM estimator, there is a potential for a large number of instruments to create bias in the model and inflate p-values (Roodman 2009). To ensure robustness against this bias, we estimated each of our models with multiple specifications limiting the number of lagged instruments per panel member (to as few as 2). Regardless of these limits, the models produced similar results.

Model 2 focuses specifically on how an increase in the mean discount percentage for deals offered impacts the level of discount offered in the subsequent period. Similar to how quantities of deals are influenced by those in the prior period, the positive and significant coefficient on $D_{ijk(t-1)}$ indicates that higher discounts offered through the electronic market for deals in a cluster lead to a further increase in discounts in the following period (supports H1b). However, the discounts in a given cluster are not influenced by previous discounts offered in other clusters of the same division (supports H2b).

Table 4. Predicting number of spa vendors offering deals, Vijkt (N = 17004)

	Model 1 (DV = V_{ijkt})		Model 2 (DV = D_{ijkt})	
Main Effects				
$V_{ijk(t-1)}$	0.1663	(0.0174)***		
$V_{ij(-k)(t-1)}$	0.0060	(0.0054)		
$D_{ijk(t-1)}$			0.0485	(0.0122)***
$D_{ij(-k)(t-1)}$			0.0383	(0.0153)*
Covariates				
$V_{(-i)jk(t-1)}$	0.0183	(0.0066)**		
$V_{(-i)j(t-1)}$	0.0054	(0.0017)**		
$D_{(-i)jk(t-1)}$			0.0322	(0.0159)*
$D_{(-i)j(t-1)}$			0.0444	(0.0325)
$S_{ijk(t-1)}$	-0.0915	(0.0241)***	-0.0266	(0.0070)***
Z tests (H0: Zero correlation in first-differenced errors)				
Order 1	-13.89	***	-21.59	***
Order 2	4.73[+]	***	2.74	**

[+] Controlling for an additional lag of the dependent variable brings the z score for order 2 error correlation to -1.73 with no difference in coefficient sign or significance

***Significant at p < .001. **Significant at p < .01. *Significant at p < .05

Next, we examine the competitive effects of the electronic market on spa-type vendors. Table 4 shows results of Models 1 and 2 for predicting the number of spas offering deals and the mean discount percentages offered, respectively. Similar to restaurants, both the quantity and intensity of spa deals in a cluster during a given period are positively related to those in the same cluster in the previous period (supports H1a, b). The quantity and intensity of deals offered outside a cluster again have either a much smaller or insignificant impact on those within the cluster in the subsequent period, as compared to the within-cluster effects (supports H2a, b).

To provide further evidence toward hypotheses H2a and H2b, we performed analysis using an alternative specification. Note there are a disparately large number of deals offered outside of any given cluster, as opposed to within. However, as the scale of deals increases, so does the scale of potential vendors, which should offset. In order to rule out concerns regarding scale, we also performed our analysis, replacing vendors in all other clusters (denoted by subscript -k) with only vendors in a matched cluster that is farthest away from the focal cluster (denoted by +k). Our results, available upon request, remain qualitatively unchanged with this specification, with the number of deals and discount amounts in distant locations having no effect, or a much smaller effect than those nearby (providing additional support for H2a, b).[16]

For both spas and restaurants, which represent vendors of presence goods and services, these results demonstrate that use of an electronic market increases local competition, both in quantity and intensity, to a much greater extent than it increases competition on a broader geographic scale. These results agree with our theory regarding the reduction of search costs allowed by the electronic market creating a more competitive environment, but with that competition limited by the transportation costs necessarily incurred by customers in order to consume the goods and services offered by these vendors. These transportation costs mean that vendors feel a much higher competitive pressure from those other vendors in close proximity, regardless of the expansive reach provided by the Internet and the electronic market.

4.3.2 – Robustness Checks for Alternative Explanations: Without a randomized or natural experiment, we acknowledge that some potential for endogeneity is unavoidable. To combat this, we have used GMM estimation of a dynamic panel model, which protects against endogenous patterns in deal offerings, by instrumentation of the previous period deals (lagged DV). Aside from this robust specification, we have performed several falsification tests to rule out alternative explanations for our results.

[16] We additionally tested alternative specifications using an inverse distance weighted value for quantity and intensity of deals outside of the focal cluster, as well as using median split, terciles, and quartiles to distinguish near and far clusters. Our results remain robust to each of these specifications.

Platform competition: It is possible that our observed results could be an outcome of competition among different electronic platforms like Groupon and LivingSocial in a local area.[17] For example if Groupon wins in some clusters (increase in Groupon deals) and loses in others (decrease in Groupon deals) to LivingSocial, this could cause the positive correlation we find in number of Groupon deals offered in consecutive periods. To account for platform competition, we collected data for LivingSocial deals offered in the same times and locations as Groupon deals in our dataset and conducted the following analyses.

Table 5. Restaurant results for LivingSocial and combined LivingSocial and Groupon Data (N=13,230)

	LivingSocial Only			
	Model 1		Model 2	
Main Effects				
$V_{ijk(t-1)}$	0.1410	(0.0396)***		
$V_{ij(-k)(t-1)}$	-0.0018	(0.00784)		
$D_{ijk(t-1)}$			0.1230	(0.0185)***
$D_{ij(-k)(t-1)}$			-0.00774	(0.0170)
Covariates				
$V_{(-i)jk(t-1)}$	0.0057	(0.0102)		
$V_{(-i)j(t-1)}$	-0.0063	(0.00343)*		
$D_{(-i)jk(t-1)}$			0.0027	(0.0102)
$D_{(-i)j(t-1)}$			0.0470	(0.0369)
$S_{ijk(t-1)}$	-0.0229	(0.0046)***	-0.0881	(0.0013)***
	Combined (Summed) LivingSocial and Groupon			
	Model 1		Model 2	
Main Effects				
$V_{ijk(t-1)}$	0.0975	(0.0588)*		
$V_{ij(-k)(t-1)}$	0.0060	(0.0063)		
$D_{ijk(t-1)}$			0.0633	(0.0127)***
$D_{ij(-k)(t-1)}$			0.0081	(0.0183)
Covariates				
$V_{(-i)jk(t-1)}$	0.00365	(0.0099)		
$V_{(-i)j(t-1)}$	-0.00252	(0.0016)		
$D_{(-i)jk(t-1)}$			0.0078	(0.0111)
$D_{(-i)j(t-1)}$			0.0366	(0.0370)
$S_{ijk(t-1)}$	-0.0280	(0.0009)***	-0.0042	(0.0001)***

[+]***Significant at p < .001. **Significant at p < .01. *Significant at p < .05

[17] We thank an anonymous reviewer for suggesting this possibility

Table 6. Spa results for LivingSocial and combined LivingSocial and Groupon Data (N=13,230)

	LivingSocial Only			
	Model 1		Model 2	
Main Effects				
$V_{ijk(t-1)}$	0.0819	(0.0261)***		
$V_{ij(-k)(t-1)}$	0.0095	(0.0063)		
$D_{ijk(t-1)}$			0.0528	(0.0190)***
$D_{ij(-k)(t-1)}$			-0.0054	(0.0215)
Covariates				
$V_{(-i)jk(t-1)}$	0.0336	(0.0128)***		
$V_{(-i)j(t-1)}$	0.0003	(0.0023)		
$D_{(-i)jk(t-1)}$			0.0083	(0.0140)
$D_{(-i)j(t-1)}$			-0.0171	(0.0478)
$S_{ijk(t-1)}$	-0.0749	(0.0164)***	-0.0207	(0.0044)***
	Combined (Summed) LivingSocial and Groupon			
	Model 1		Model 2	
Main Effects				
$V_{ijk(t-1)}$	0.0879	(0.0202)***		
$V_{ij(-k)(t-1)}$	-0.0130	(0.0051)**		
$D_{ijk(t-1)}$			0.0297	(0.0153)*
$D_{ij(-k)(t-1)}$			0.0301	(0.0220)
Covariates				
$V_{(-i)jk(t-1)}$	0.0155	(0.0083)*		
$V_{(-i)j(t-1)}$	0.0022	(0.0029)		
$D_{(-i)jk(t-1)}$			0.0093	(0.0135)
$D_{(-i)j(t-1)}$			0.0382	(0.0435)
$S_{ijk(t-1)}$	-0.0116	(0.0038)***	-0.0029	(0.0007)***

[+]***Significant at p < .001. **Significant at p < .01. *Significant at p < .05

First, we analyzed the LivingSocial deals alone just as we analyzed the Groupon deals, obtaining qualitatively similar results in this analysis as we obtained on Groupon data alone. The results of this analysis for restaurants and spa are reported in the top half of Tables 5 and 6, respectively. This provides additional support of our hypothesis that electronic markets (like Groupon and LivingSocial) promote local competition among vendors of presence goods due to their price promotion and awareness effect. This provides evidence that our results are generalizable to other electronic markets, and not specific to Groupon.

Second, we analyzed the combined deals of Groupon and LivingSocial in an area just as we analyzed Groupon deals alone. The results of this analysis for restaurants and spa are reported in the bottom half of Tables 5 and 6, respectively. We obtain qualitatively similar results in this analysis as we obtained on Groupon data alone. Just as with the Groupon analysis, we find positive and significant coefficients on

$V_{ijk(t-1)}$ and $D_{ijk(t-1)}$, meaning that as more combined deals (higher discounts in combined deals) are offered in a cluster in a given period, this will increase the number of combined deals (average discounts in combined deals) offered in the same cluster in the next period. If our results on Groupon data alone are driven by poaching and platform competition, then the increase in deals offered on Groupon should be offset by decrease in deals offered on LivingSocial and we should not observe these positive correlations on the combined data. Since we do observe the same positive correlations on the combined data, it shows that such platform competition is not driving our results.

Strategic Promotions: It is also possible that the systematic variation in deal volume and intensity that we observe are due to strategic detailing strategy of Groupon. For instance, if Groupon expands its business in specific areas over time, this may lead to increasing vendor participation in those areas.[18] To address this concern, we had extensive discussions with a member of Groupon's data science team responsible for planning and forecasting Groupon deals in the US. We learned that Groupon's strategy for following up on vendor leads focuses on previous voucher sales, which we include as a control in our primary specifications. Additionally, Groupon's team that interfaces with vendors normally targets all types of vendors in a division in a period. Based on this information, we have also estimated Models 1 and 2 with the number and discount level of all other types of deals in the same time period (bolded terms with coefficients β_3 and β_4 below. This controls for the possibility of higher overall promotion by Groupon:

$$V_{ijkt} = \alpha_{ijk} + \beta_1 V_{ijk(t-1)} + \beta_2 V_{ij(-k)(t-1)} + \beta_3 \boldsymbol{V}_{(-\boldsymbol{i})\boldsymbol{jkt}} + \beta_4 \boldsymbol{V}_{(-\boldsymbol{i})\boldsymbol{jt}} + \beta_5 s_{ijk(t-1)} + \varepsilon_{ijkt}. \quad (3)$$

$$D_{ijkt} = \alpha_{ijk} + \beta_1 D_{ijk(t-1)} + \beta_2 D_{ij(-k)(t-1)} + \beta_3 \boldsymbol{D}_{(-\boldsymbol{i})\boldsymbol{jkt}} + \beta_4 \boldsymbol{D}_{(-\boldsymbol{i})\boldsymbol{jt}} + \beta_5 S_{ijk(t-1)} + \varepsilon_{ijkt}. \quad (4)$$

The results of these estimates are given in Table 7. We find that our results remain unchanged, with coefficients on V_{ijkt} and D_{ijkt} still positive and significant. This provides evidence that our results are not due to increased promotions by the Groupon in an area. In addition to this analysis, we performed several additional analyses and falsification tests to provide evidence against this alternative explanation:

[18] We thank an anonymous reviewer for suggesting this possibility

- The results we report for both LivingSocial as well as the sum of Groupon and LivingSocial provide additional evidence against strategic behavior by Groupon driving our results. For these results to hold due to strategic behavior, both Groupon and LivingSocial would have to endogenously make similar strategic decisions, which is highly unlikely.
- There could be some exogenous factor causing both Groupon and LivingSocial to move similarly in some time periods, however the nature of the dynamic panel model GMM specification eliminates these external factors by instrumentation of the lagged dependent variable. For potential endogeneity to survive the instrumentation of this specification, platforms' strategies would have to be systematically and consistently coordinated over periods of several months throughout the 39-months represented by our data.
- We additionally estimate our models controlling for time fixed effects, finding our results to remain consistent.
- If all clusters are removed from the specification and the model is used to predict city-wide deal activity, we find no effect from one period to the next on the quantity and intensity of deals. For us to observe results at the cluster level but not at the division level due to systematic changes in sales effort, Groupon would have to systematically hold sales efforts for each category constant at a division level while also systematically increasing efforts for each category in certain hyper-local areas within the division consistently across the 167 divisions in our dataset.
- The number of sales representatives over time are detailed in Groupon's annual reports. As described in Appendix B in the electronic companion, we utilized these sales representative figures and performed simulations for alternative allocations of sales efforts across divisions based on the number of vendors offering deals. We find our results to be robust to specifications of our models controlling for these simulated sales effort allocations.
- The choice of variables measuring competition also helps in alleviating these concerns. We included two measures of competition among vendors. One is the number of deals offered (quantity), and the other is depth of discounts offered (intensity). While Groupon could focus efforts in an area to drum up more business (quantity), it is less likely that based on a platform strategy, Groupon could consistently, over a period of time, convince vendors to offer deepening discounts as well. This result, combined with that of the number of deals, strongly indicates a competitive response on behalf of vendors.
- Our results of positive correlations between deals in successive time periods not only mean that an increase in deals/discounts leads to a further increase in deals/discounts but also that a decrease in deals/discounts leads to a further decrease. So as vendors run fewer deals at less discounts, competitive pressures decline, leading to still fewer deals and less discounts. While increased Groupon deals in an area could be explained by the increased detailing (promotions) by Groupon, the decrease in number of deals/discounts in an area in a time period followed by further decrease suggests the explanation of a competitive response from vendors.

Because Groupon's strategy and sales effort is ultimately unobservable, and because we cannot perform a randomized experiment, it is impossible to unequivocally rule out all alternative explanations of our results. However, we these analyses combine to provide strong evidence against concerns of endogeneity due to platform strategy.

Table 7. Results controlling for contemporary deals in other categories

	Restaurant-Type Deals			
	Model 3		Model 4	
Main Effects				
$V_{ijk(t-1)}$	0.0829	(0.0183)***		
$V_{ij(-k)(t-1)}$	0.0124	(0.0038)***		
$D_{ijk(t-1)}$			0.0312	(0.0095)***
$D_{ij(-k)(t-1)}$			-0.0004	(0.0090)
Covariates				
$\mathbf{V_{(-i)jkt}}$	-0.0043	(0.0024)*		
$\mathbf{V_{(-i)jt}}$	0.0065	(0.0007)***		
$\mathbf{D_{(-i)jkt}}$			0.0692	(0.0074)***
$\mathbf{D_{(-i)jt}}$			-0.0115	(0.0125)
$S_{ijk(t-1)}$	-0.0006	(0.0004)*	-0.0001	(0.0001)
	Spa-Type Deals			
	Model 3		Model 4	
Main Effects				
$V_{ijk(t-1)}$	0.156	(0.0163)***		
$V_{ij(-k)(t-1)}$	0.0100	(0.0054)*		
$D_{ijk(t-1)}$			0.0482	(0.0122)***
$D_{ij(-k)(t-1)}$			0.0403	(0.0154)***
Covariates				
$\mathbf{V_{(-i)jkt}}$	0.0160	(0.0066)**		
$\mathbf{V_{(-i)jt}}$	0.0154	(0.0017)***		
$\mathbf{D_{(-i)jkt}}$			0.0866	(0.0165)***
$\mathbf{D_{(-i)jt}}$			0.0155	(0.0331)
$S_{ijk(t-1)}$	-0.0102	(0.0025)***	-0.0027	(0.0007)***

***Significant at $p < .001$. **Significant at $p < .01$. *Significant at $p < .05$

Our choice of variables measuring competition also helps in alleviating these concerns. We included two measures of competition among vendors. One is the number of deals offered (quantity), and the other is depth of discounts offered (intensity). While Groupon could focus efforts in an area to drum up more business (quantity), it is less likely that based on a platform strategy, Groupon could consistently, over a period of time, convince vendors to offer deepening discounts as well. This result, combined with that of the number of deals, strongly indicates a competitive response on behalf of vendors.

Finally, our results of positive correlations between deals in successive time periods not only mean that an increase in deals/discounts leads to a further increase in deals/discounts but also that a decrease in deals/discounts leads to a further decrease. So as vendors run fewer deals at less discounts, competitive pressures decline, leading to still fewer deals and less discounts. While increased Groupon deals in an area could be explained by the increased detailing (promotions) by Groupon, the decrease in number of deals/discounts in an area in a time period followed by further decrease suggests the explanation of a competitive response from vendors.

4.3.3 –Underlying Mechanisms for Competition: As discussed above, both the advertising and price promotion effects provide possible incentives for vendors to offer deals on electronic markets and thus could result in increased local competition. It is difficult to disentangle the individual effects of these two mechanisms on local competition based on the aggregate deals data. However, as noted, infomediaries such as Yelp also provide limited awareness of vendor quality and fit, providing an imperfect substitute for the advertising effect enabled by electronic markets such as Groupon. Therefore, we can measure the existing awareness about the vendors via infomediaries such as Yelp and examine how this impacts vendors' incentives to offer daily deals.

Table 8. Restaurant results controlling for Yelp and other intermediaries (N = 12,573)

	Model 1 (DV = V_{ijkt})			
	Model 1-YP		Model 1-YA	
Main Effects (Groupon)				
$V_{ijk(t-1)}$	0.4790	(0.0786)***	0.1170	(0.0508)*
$V_{ij(-k)(t-1)}$	-0.0036	(0.0061)	-0.0092	(0.0057)
Main Effects (Yelp)				
$YP_{ijk(t-1)}$	-0.8620	(0.0999)***		
$YA_{ijk(t-1)}$			-0.1900	(0.0186)***
Covariates				
$V_{(-i)jk(t-1)}$	0.0157	(0.0068)*	0.0141	(0.0066)*
$V_{(-i)j(t-1)}$	0.0028	(0.0012)*	0.0029	(0.0012)*
$S_{ijk(t-1)}$	-0.0017	(0.0011)	-0.0010	(0.0006)
	Model 2 (DV = D_{ijkt})			
	Model 2-YP		Model 2-YA	
Main Effects				
$D_{ijk(t-1)}$	0.3600	(0.0278)***	0.3830	(0.0293)***
$D_{ij(-k)(t-1)}$	-0.0346	(0.0104)***	-0.0329	(0.0104)**
Covariates				
$YP_{ijk(t-1)}$	-0.3400	(0.0145)***		
$YA_{ijk(t-1)}$			-0.0871	(0.0038)***
Covariates				
$D_{(-i)jk(t-1)}$	0.0033	(0.00622)	0.0040	(0.00621)
$D_{(-i)j(t-1)}$	0.0557	(0.0171)**	0.0560	(0.0173)**
$S_{ijk(t-1)}$	-0.0001	(0.0001)	-0.0001	(0.0001)

***Significant at p < .001. **Significant at p < .01. *Significant at p < .05

To determine the impact of prior awareness of vendors and their qualities on competition on electronic markets, we estimated Models 1 and 2 with the proportion of vendors offering deals in a given cluster who have at least one Yelp review (YP_{ijkt}) and the average Yelp rating across these vendors (YA_{ijkt}), separately, as independent variables.

Table 9. Spa results controlling for Yelp and other intermediaries (N = 9,988)

	Model 1 (DV = V_{ijkt})			
	Model 1-YP		Model 1-YA	
Main Effects (Groupon)				
$V_{ijk(t-1)}$	0.0858	(0.0299)***	0.1360	(0.0346)***
$V_{ij(-k)(t-1)}$	-0.0075	(0.0076)	-0.0091	(0.0080)
Main Effects (Yelp)				
$YP_{ijk(t-1)}$	-0.4030	(0.0771)***		
$YA_{ijk(t-1)}$			-0.1860	(0.0189)***
Covariates				
$V_{(-i)jk(t-1)}$	0.0165	(0.0093)	0.0171	(0.00941)
$V_{(-i)j(t-1)}$	0.0016	(0.0021)	0.0014	(0.00218)
$S_{ijk(t-1)}$	-0.0163	(0.0070)**	-0.0166	(0.0070)*
	Model 2 (DV = D_{ijkt})			
	Model 3-1		Model 3-2	
Main Effects (Groupon)				
$D_{ijk(t-1)}$	0.0352	(0.0170)*	0.0369	(0.0164)*
$D_{ij(-k)(t-1)}$	0.0131	(0.0182)	0.0103	(0.0143)
Main Effects (Yelp)				
$YP_{ijk(t-1)}$	-0.1210	(0.0145)***		
$YA_{ijk(t-1)}$			-0.0230	(0.00255)***
Covariates				
$D_{(-i)jk(t-1)}$	0.0021	(0.0157)	0.0004	(0.0113)
$D_{(-i)j(t-1)}$	0.0484	(0.0405)	0.0083	(0.0237)
$S_{ijk(t-1)}$	-0.0050	(0.0009)***	-0.0514	(0.0009)***

***Significant at p < .001. **Significant at p < .01. *Significant at p < .05

The results of these models are shown in Tables 8 and 9, which are consistent between restaurant- and spa-type vendors. We find that after controlling for prior awareness of vendors and their qualities through Yelp and other infomediaries, our primary results remain unchanged: the coefficients on $V_{ijk(t-1)}$ and $D_{ijk(t-1)}$ remain positive and significant. More interesting, we find the coefficients for $YP_{ijk(t-1)}$ to be negative and significant, meaning that as the proportion of vendors offering deals in period (*t*-1) that have at least one review on Yelp (or other infomediary) increases (support H3a), the number of deals and mean discount amount offered in period *t* decrease (support H3b). This shows that deals offered by vendors with lower (higher) baseline awareness provoke a higher (lower) competitive response from other vendors in the local area. We also find negative and significant coefficients for $YA_{ijk(t-1)}$, meaning that as the average ratings for vendors offering deals in t-1 increases, the number of deals and mean discount amount offered in period t decreases.

The above results indicate that competition responds more intensely to lesser known and lower ratings vendors offering deals. Along with the fact that we find the vast majority of vendors don't offer repeated deals in our 39 month study period, this implies that the advertising effect is the primary driver of the impact of electronic markets on competition among local presence vendors. However, we acknowledge that our present analysis is not able to precisely quantify the individual impact of the advertising and price promotion effects of electronic markets on local competition among presence vendors.

4.3.4 – Moderating Effects of Differentiation: Vendors in a local area may be differentiated in the type and quality of goods or services they provide. For restaurants, vendors may serve various types of cuisines, differentiating themselves horizontally, with customers of divergent tastes inherently preferring different vendors because of the cuisine types they offer. Alternatively, vendors may differentiate themselves vertically by offering varying qualities. For restaurants, this might distinguish a fast food restaurant from one serving gourmet quality food of the same cuisine type. Vendors differing on a horizontal dimension (i.e. serving different cuisine types) have less reason to compete with each other because, in large part, they serve different segments because of differences in fit with various consumers – some consumers prefer burgers, and some prefer sushi. Even those seeking variety might have a preference for a certain type of food on any given occasion. For vertical differentiation, consumers should have a uniform order of preference, but typically prices rise with quality as well, representing a trade-off. Some may prefer to pay fast food prices for fast food quality, while others prefer to spend more on gourmet cuisine. Again, the same customer over multiple opportunities may mix consumption between the two types, but often the choice set is constrained to a certain level of quality/price by occasion (e.g. high quality/price for an anniversary celebration, low quality/price for a weekday lunch). Therefore both horizontal and vertical differentiation should have a dampening effect on the competition stimulated by the presence of an electronic market. Specifically, clusters with higher horizontal or vertical differentiation among vendors should have lower competitive response to local vendor use of the electronic market.

To examine this question, we split our data into deciles based on the measures of horizontal and vertical differentiation defined above for restaurant vendors (Herfindahl index measuring concentration of cuisine types and coefficient of price variation, respectively). No data was available for spa-type vendors, and additionally the restaurant industry seems to have a significantly higher level of possible differentiation. For each of these deciles, we estimated models (1) and (2), in order to determine if there were any differences in the estimated coefficients representing the direct effects on quantity and intensity of competitive responses. The estimates for coefficient γ_1 from model (1) are plotted in the top two graphs in Figure 2, the left representing deciles of horizontal differentiation and the right representing vertical. Coefficient δ_1 from model (2) are similarly represented in the bottom two graphs. For each graph, there is an increasing trend in the coefficient values as differentiation decreases. Additionally, the shaded areas on each graph represent the 95% confidence intervals for these coefficients when the data is divided into terciles prior to running the models, with z-statistics for tests of their differences. The outer terciles for each model and differentiation type are significantly different at $p < 0.001$. The values for each of the main effect coefficients for these models are detailed in Table 10. These results show that the competitive response to activities in the electronic market, both in quantity and intensity, increase as horizontal and vertical differentiation decrease (supports H4a, b).

Table 10. Results by horizontal and vertical differentiation terciles

	Model 1 (DV = V_{ijkt})			
	Horizontal Differentiation		Vertical Differentiation	
Main Effect ($V_{ijk(t-1)}$)				
Top tercile	0.1784	(0.0501)***	0.2201	(0.0494)***
Middle tercile	0.4138	(0.0516)***	0.2745	(0.0861)**
Bottom tercile	0.6141	(0.0948)***	0.4556	(0.0857)***
	Model 2 (DV = D_{ijkt})			
	Horizontal Differentiation		Vertical Differentiation	
Main Effect ($D_{ijk(t-1)}$)				
Top tercile	0.1663	(0.0291)***	0.2036	(0.0311)***
Middle tercile	0.3863	(0.0492)***	0.2694	(0.0531)***
Bottom tercile	0.7431	(0.1137)***	0.5259	(0.0772)***

***Significant at $p < .001$. **Significant at $p < .01$. *Significant at $p < .05$

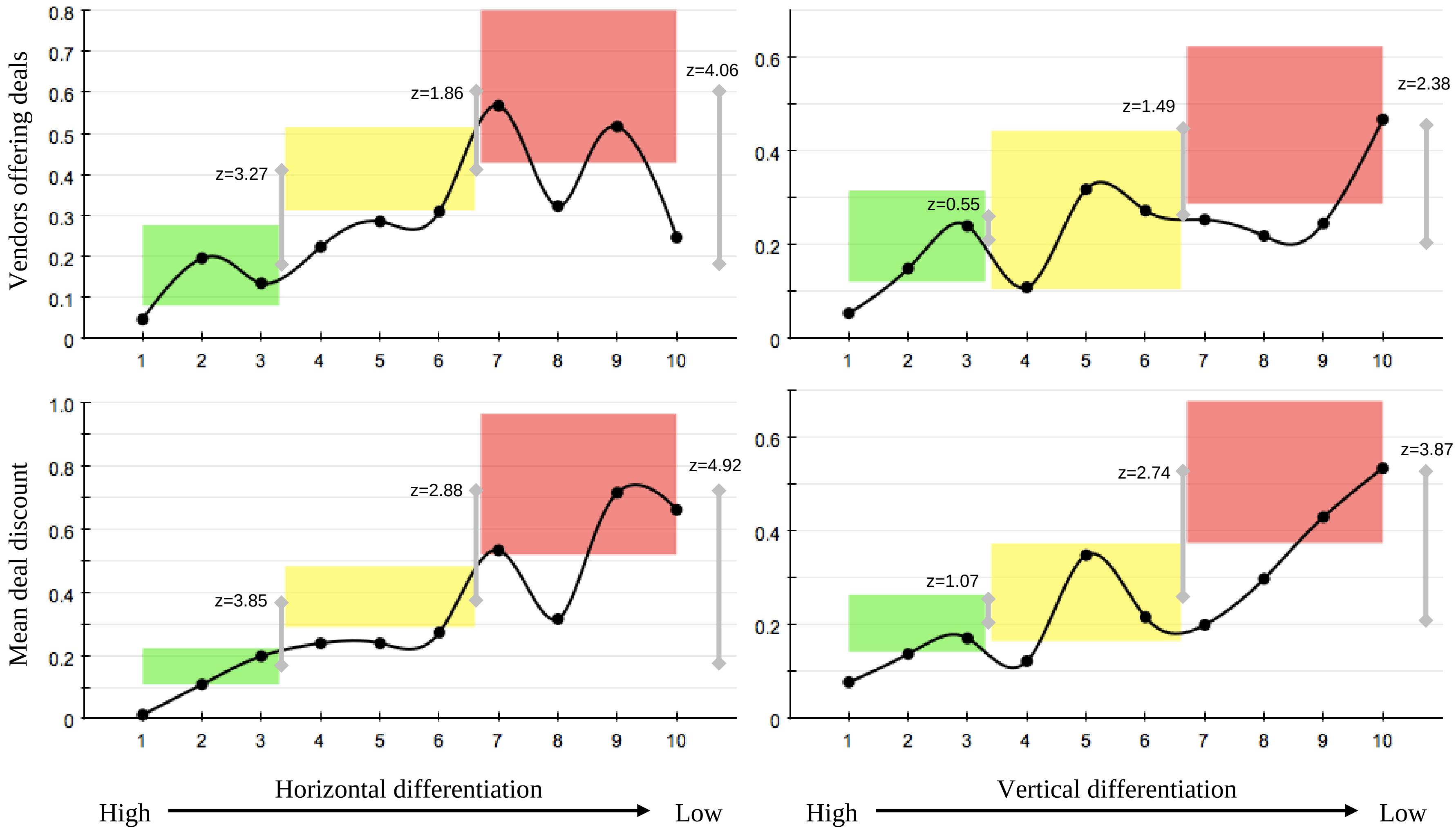

Figure 2. Results by differentiation deciles and terciles

5.0 Conclusion and Managerial Implications

In summary, we have found that usage of an electronic market by vendors of presence goods and services increases local competition among similar vendors, but does not promote competition on a broader geographic scale (unless at a much lower level). Specifically, both the quantity and intensity of deals offered through the electronic market by vendors in a given area increase based on both the quantity and intensity of deals offered by other vendors in the same area in prior periods. The effects from offerings of vendors in more distant areas in prior periods are much lower or insignificant. We also find these effects are largely driven by lesser known and lower quality vendors likely looking to increase awareness of the quality and fit of their goods and services in the minds of consumers. Both horizontal and vertical differentiation of vendors in the local area act as moderators of these effects, with areas having lower differentiation experiencing higher competitive responses to activity on the electronic market.

As large numbers of small, local, boutique firms begin to engage in electronic markets, it has become important to study the effects of this online engagement of customers on local competition. Previous studies empirically investigating the effects of the Internet on local competition have focused on large online firms competing against local vendors in markets selling commodity goods. In contrast, we offer a method of extracting and analyzing data from publicly available datasets to measure the competitive reaction of small vendors in geographical clusters. This allows us to examine small, local firms selling presence goods which join electronic markets to augment their original brick-and-mortar sales.

Our findings validate analytical studies such as Bakos (1997), which demonstrate that when information on product qualities is difficult to obtain, the introduction of electronic markets will increase competition in the form of price discounts. We validate these findings specifically in a setting in which transportation costs play a significant role. We also provide empirical evidence regarding the mechanism by which electronic markets impact competition. Several mechanisms have been proposed (Edelman et al. 2014, Kumar and Rajan 2012, Mejia et al. 2013, 2015), but we show the advertising effect is a dominant factor in the competitive responses of vendors. Finally, we validate studies such as those by Shaked and Sutton, as well as Zhelobodko et al. (1982, 2012), which show that differentiation should reduce competitive pressures. For each of these studies, we validate their results in the important and understudied context of small businesses selling presence goods and services.

Our work has managerial implications for electronic market platforms. We provide a novel method for collecting and analyzing publically available information regarding the competitive landscape of various categories of presence vendors in different geographies. This information, along with our approach for unsupervised clustering of vendors to identify local areas of competition, provides a valuable tool for electronic markets to analyze markets for their services. In addition to this methodology, the results of our models provide valuable insights which electronic markets may use to understand and respond to demand. Our findings show a positive correlation in quantity and intensity of deals in a local cluster in successive periods, and this correlation is moderated by the quality and awareness of vendors offering deals, as well as differentiation in service offerings in the cluster. This insight can be utilized by Groupon managers to efficiently allocate their sales and marketing efforts among different clusters in a city based on historical cluster-level data. To take advantage of competitive effects, managers should concentrate efforts in clusters with: 1) higher numbers of offered deals, 2) higher average discounts, 3) lower proportion of vendors offering deals with a Yelp presence (as well as lower Yelp ratings), and 4) lower horizontal and vertical differentiation in service offerings.[19]

Our findings also have important implications for small firms selling presence goods. Firms considering entering an electronic market should consider the competitive environment in which they

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[19] We provide the following two examples for restaurant-type vendors to demonstrate how data on vendors offering deals in a cluster in the present month can be utilized to efficiently allocate marketing effort.

- In the San Francisco division, over our 39 month study period, 4.3% of vendors in the cluster representing Downtown ran a deal through Groupon. This cluster has high differentiation, with cuisine type Herfindahl index of 0.0369 and price coefficient of variance of 0.4538. In contrast, the cluster representing Daly City (also an active part of the San Francisco division for Groupon) has significantly lower differentiation, with cuisine type Herfindahl index of 0.0448 and price coefficient of variance of 0.3878. In this cluster, 7.8% of vendors offered deals – almost double that of the higher differentiation Downtown.
- Within the Los Angeles division, in the cluster representing Central Los Angeles, 3 deals were offered by restaurant vendors in March 2013. Of these, only 1 vendor (33%) had a presence on Yelp. In April, 4 deals were offered, with none having presence on Yelp, and in May, 5 deals were offered. In contrast, in December 2013, 4 deals were offered, but all of these vendors had a presence on Yelp. In the next month, January 2014, only 1 deal was offered. Similarly in April 2014, 2 deals were offered, both with presence on Yelp, and in May, only 1 deal was offered.

operate and anticipate response from competing firms in their local service area, utilizing the same factors discussed above. Firms cannot expect nearby competitors to watch idly as they attract new customers through the reduction in search costs provided by electronic markets. These competitors will also join the platform, offering deeper discounts in response. However, this effect is largely limited to competitors within the local area, and is moderated by levels of awareness, quality, and differentiation among vendors.

We constructed a novel data set to examine a complex problem of spatial competition among small firms. However, our analysis is not without limitations, and opportunities exist for continued study in this area. Competition among such firms may be influenced by many factors unobserved in our data. Although we controlled such unobserved factors with the lagged endogenous variables in our dynamic panel model and many falsification tests, we cannot completely rule out the possibility of such unobserved factors affecting our coefficient estimates. In addition, we acknowledge that while we provide evidence regarding the underlying mechanisms by which electronic markets impact competition, it is not possible to precisely quantify the individual impacts of these mechanisms. Moreover, we examined the competition among only two types of vendors, spas and restaurants. It would be interesting to examine a larger variety of vendors classified by service type and then examine how competition in different classes are differentially affected by their geographical concentration. It would be interesting examine the probability of emergence of complementary deals in a geographical concentrated area. For example, restaurant vendors may offer more deals in areas where a higher concentration of deals related to entertainment activities are offered. Finally, our econometric model is designed for explanatory, rather than predictive purposes. A natural extension of this research would be to utilize the factors identified to create a predictive model for use in forecasting.

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Electronic Companion

Appendix A: Obtaining and managing geographic data

In order to examine the effect of daily deal offerings on local competition, a geographic distribution of vendors and vendor characteristics is required. To this end, we obtained data from Flickr, Google Maps and UrbanSpoon.

To obtain the distribution of vendors of a given type within each division (i.e. city or region served by Groupon), we performed a grid search using the Google Places API (https://developers.google.com/maps/, last accessed 12/23/2015). The API allows you to perform a search for places relevant to a particular keyword near a given location, specified by latitude and longitude. We divided each division into a grid of latitudinal and longitudinal increments of 0.001°. Because of the nature of latitudinal and longitudinal measurements, the actual distance between grid points varied. Because of the ellipsoid shape of the earth, a single degree of geodetic latitude accounts for between 110,574 meters (at the equator) and 111,694 meters (at the poles). As our study focused only on divisions within the US and Canada, the latitudes included range from 21° to 62°, for which single latitude distances measure between 110,717 meters and 111,446 meters (see http://msi.nga.mil/MSISiteContent/StaticFiles/Calculators/degree.html, last accessed 12/23/2015). Longitudinal distance varies more, as each longitude originates/terminates at the poles. Within our range of 21° to 62° latitude, distance between longitudes varies from 52,398 meters to 103,970 meters. With regard to the grid search, using 1/1000th of a degree means that each search was made within no more than 111.5 meters of the previous search (see Figure A1). Each search returns the 60 results nearest to the search location, so our collection method assumes that no more than 60 vendors will reside in any area of 12,433 square meters. To put it in perspective, this is less than one quarter of a standard block in Manhattan (http://greatergreaterwashington.org/post/6002/the-variety-of-american-grids/, last accessed 12/23/2015).

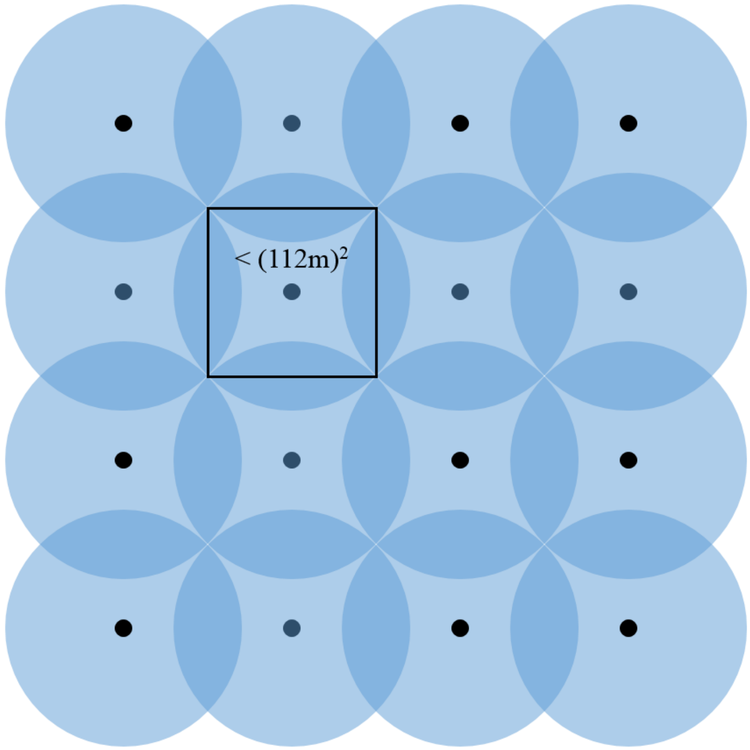

Figure A1: Grid collection method scale

However, for the 167 divisions in our data, this would amount to over 300 million Google Maps API calls, which is infeasible. To remedy this, we used an efficient collection approach which dynamically adjusted the grid search based on previous results found. For each search, our collection algorithm measured the distances from the current grid search location to each vendor returned. Since the Google Places API returns the set of all nearest vendors to the search point, we can eliminate search locations nearer to the original search point than the furthest search results. To be conservative, we calculated *m*, the distance from a given search point to the 10^{th} most distant vendor (out of 60 returned in each set), subtracted 0.005° from *m* and removed all remaining grid search locations nearer to the current search point than this vendor. Figure A2 illustrates this technique, with each grid point a potential search, and the light blue area defined by the radius $m - 0.005°$ representing the search points which were skipped because they were already covered by a previous search. In this manner, we eliminated over 99% of the grid search points in our matrix to reduce redundancy, while still ensuring that each search overlapped with the next to achieve full coverage for each division. With scripts running continuously, this allowed us to complete the data collection from Google Maps in just over two months, as opposed to several decades estimated for the complete grid search.

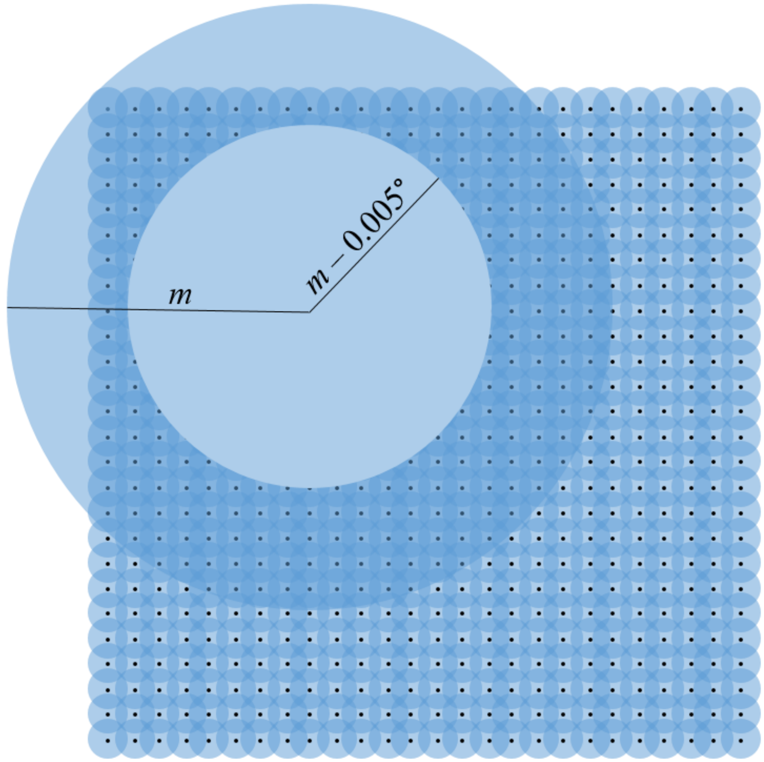

Figure A2: Dynamic grid collection approach

One further challenge to be met for collecting the vendor distributions is to identify bounds for each division which represent the area which Groupon serves, in order to obtain coverage for the relevant area while maintaining feasibility of collection. One option would be to define bounds to include all deals offered for that division. However, Groupon occasionally offers deals in a division that are redeemable at a faraway location (e.g. a deal offered in the Atlanta division but redeemable in New York), thus division boundaries cannot be determined in this way. Other defined boundaries such as official city or metropolitan area bounds are unsatisfactory as well. What is required is a definition of what a consumer would naturally consider the boundaries of a division. For this, we turn to a project undertaken by Flickr called *Shapefiles* (http://code.flickr.net/2011/01/08/flickr-shapefiles-public-dataset-2-0/, last accessed 12/23/2015). Millions of users upload photos to Flickr on a daily basis, tagged with meta-data including latitude, longitude, and user-input location. Flickr processed this meta-data to determine natural definitions for "regions" including cities and other areas representing Groupon divisions. After examining the boundaries for reasonableness, we adopted these definitions for boundaries in defining the scope of the grid search in each division. On average, the area for each division as determined by these boundaries was 67 kilometers by 69 kilometers. Additionally, we drop all deals offered in a division with redemption location outside this boundary, as they are irrelevant to the local competition we examine.

After collecting the information on vendor locations, we used agglomerative clustering with Euclidean distance measures and Ward's linkage technique to identify concentrations of vendors representing geographically competitive sets. In order to do this, we needed to standardize the measure of distance on the vertical (latitudinal) and horizontal (longitudinal) axes. As mentioned previously, in some cases, the distance between longitudinal degrees was less than half that between latitudinal degrees. Great-circle calculations are required to measure distances on a sphere, and there is no way to directly transform all coordinates in an area on a sphere so as to create consistent Euclidean distances between the points. Therefore, in order to create coordinates for clustering, we used a heuristic transformation in order to rescale the longitudinal coordinates to match the scale of the latitudinal coordinates. We chose the mid-point of each division, and used great-circle calculations to arrive at the ratio of longitudinal and latitudinal scales at that point. We then normalized the longitudinal coordinates using this ratio, such that a 1 degree change in adjusted longitude equates to the same distance as a 1 degree change in latitude. While approximate, this heuristic provides coordinates accurate to within 1% of actual normalized distances in the most extreme case of Anchorage, Alaska, and much closer in divisions at lower latitudes. Finally, coordinate values were further normalized using a [0,1] range transformation to ensure consistent treatment in clustering, regardless of division size or location.

UrbanSpoon data were collected from the "all restaurants" listings for each of the divisions studied. For the few divisions not directly matching an UrbanSpoon area, manual matching was performed by the authors. Rating, pricing, cuisine, and location information in the form of latitude and longitude were collected for each restaurant listed by automatically crawling all pages of data for each division. After collection, each UrbanSpoon observation was directly matched to a vendor collected from the Google Maps

API, and thus its information assigned to the cluster to which that vendor was assigned in the agglomerative clustering. If no exact match could be found, the UrbanSpoon observation was assigned to the cluster containing the nearest vendor by great circle distance.

Appendix B: Simulations to investigate the impact of Groupon's strategic sales effort allocation

Groupon reports the number of sales representatives deployed by quarter in its 2012 and 2013 annual reports (see Table B1 for detail). In the following analysis, by using the sales representative figures to simulate Groupon's sales effort as a control variable, we remove components related to the sales effort from the error, providing a cleaner estimation of the effects of competition.[20]

Table B1. Sales representatives reported by Groupon in 2012, 2013, and 2014 annual reports

Date	Sales Representatives
6/30/2011	990
9/30/2011	1004
12/31/2011	1062
3/31/2012	1194
6/30/2012	1139
9/30/2012	1230
12/31/2012	1151
3/31/2013	1287
6/30/2013	1209
9/30/2013	1357
12/31/2013	1421
12/31/2014	1369

We learned from our discussions with a representative from Groupon's data science team (also corroborated by verbiage in Groupon's annual report) that the vast majority of Groupon sales agents are located centrally in Chicago and they are assigned to contact the vendors of specific division(s) over phone from their Chicago office only. These assignments are neither done at the level of vendor categories, nor done at the level of hyper-local areas within divisions. Based on this information, in order to arrive at a better proxy for sales efforts at the division level, we simulated sales efforts based on A) the number of sales representatives reported at the national level for the period, B) the relative number of deals of all categories offered in a division in the previous period. We considered following two alternatives to arrive at a proxy for sales efforts at the division level.

(1) First, we considered that Groupon may assign their total sales force across divisions in proportion to the number of deals offered in divisions in prior periods. That is, the more deals offered in a division in period t-1, the more relative sales representatives allocated in period t. Thus, the simulated number of sales representatives in in division j in period t, $SimSEA_{ijt} = SR_t * (V_{j(t-1)} / V_{(t-1)})$, where

[20] Sales representatives are reported at the end of each quarter, the number is likely fluctuating in between quarters. To accommodate the possibility that this impacts our results, we estimated several alternative specifications. First, we shifted each reported number to the beginning of the reported month. Therefore $SA_t = 1194$ for March 2012, rather than $SA_t = 1062$. Second, we smoothed the SA_t observations by equally dividing the difference between two quarters and allocating among the interstitial months. For instance, $SA_t = 1106$ for January 2012 and $SA_t = 1150$ for February 2012. Third, we combined the first two approaches, both shifting and smoothing the figures. Finally, we estimated a model which considered observations for unreported months to be missing. The results are robust, with each of these specifications providing results that were qualitatively similar to those presented below.

SR_t is the total number of sales representatives nationally in period t, $V_{j(t-1)}$ is the number of deals offered in division j in period t-1, and $V_{(t-1)}$ is the total number of deals offered nationally in period t-1. The basic idea is that Groupon will assign more (less) sales force in divisions that had greater (smaller) number of deals in the past period.

(2) Second, we consider an opposing approach, in which Groupon assigns additional sales effort to divisions when sales fall short. Under this scheme, baseline sales efforts in a division may be allocated in a way that is proportional to division size, but adjusted in a way that is inversely proportional to the ratio of the number of deals offered in a division in t-1 to the mean value for the division across all periods. Thus, the simulated number of sales representative in in division j in period t, $SimSEB_{ijt} = Z * SR_t * (V_{j(mean)} / V_{(mean)}) / (V_{j(t-1)} / V_{j(mean)})$, where $V_{j(mean)}$ is the average monthly number of deals offered in division j over the 39 month period, $V_{(mean)}$ is the average monthly number of deals offered nationally over the 39 month period, and Z is a normalization factor to ensure that the sum of all allocated division sales representatives equals the total number of sales representatives available.

There may be other possible schemes that Groupon may use to allocate sales efforts. However, based on our knowledge of Groupon's operations and from our discussion with their data science team, we believe that if Groupon were to allocate their sales force dynamically, the above two proposed alternatives represent the most aggressive cases as far as providing alternative explanations for our results. That is, if controlling for simulated sales efforts under these two scenarios fails to alter our results, it seems unlikely that another allocation scheme would alter the results either. Tables B2, B3, B4, and B5 present the results of models including these simulated sales efforts as controls. Our primary results remain unaltered after controlling for these simulated sales efforts. We still find a positive and significant correlation in the quantity and intensity of deals offered within clusters from one period to the next. Thus, we find that our results are robust the possibility of Groupon making systematic allocation of their work force.

Table B2. Predicting restaurant deals with inclusion of simulated sales effort, $SimSEA_{ijt}$, proportional to prior period deals offered

	Model 1 (DV = V_{ijkt})		Model 2 (DV = D_{ijkt})	
Main Effects				
$V_{ijk(t-1)}$	0.1650	(0.0182)***		
$V_{ij(-k)(t-1)}$	0.0175	(0.0054)**		
$D_{ijk(t-1)}$			0.0496	(0.0132)***
$D_{ij(-k)(t-1)}$			0.0457	(0.0166)**
Covariates				
$V_{(-i)jk(t-1)}$	0.0168	(0.0078)*		
$V_{(-i)j(t-1)}$	0.0137	(0.0020)***		
$D_{(-i)jk(t-1)}$			0.0333	(0.0171)
$D_{(-i)j(t-1)}$			0.0450	(0.0332)
$S_{ijk(t-1)}$	-0.0076	(0.0022)***	-0.0026	(0.0007)***
$SimSEA_{ijt}$	-0.0717	(0.0084)***	-0.0013	(0.0007)

Table B3. Predicting spa deals with inclusion of simulated sales effort, $SimSEA_{ijt}$, proportional to prior period deals offered

	Model 1 (DV = V_{ijkt})		Model 2 (DV = D_{ijkt})	
Main Effects				
$V_{ijk(t-1)}$	0.0697	(0.0202)***		
$V_{ij(-k)(t-1)}$	0.0114	(0.0040)**		
$D_{ijk(t-1)}$			0.0417	(0.0102)***
$D_{ij(-k)(t-1)}$			0.0014	(0.0103)
Covariates				
$V_{(-i)jk(t-1)}$	0.0031	(0.0027)		
$V_{(-i)j(t-1)}$	0.0133	(0.0014)***		
$D_{(-i)jk(t-1)}$			-0.0182	(0.0078)*
$D_{(-i)j(t-1)}$			0.0263	(0.0131)*
$S_{ijk(t-1)}$	-0.0005	-0.0003	-0.0001	-0.0001
$SimSEA_{ijt}$	-0.0888	(0.0078)***	-0.0015	(0.0006)**

Table B4. Predicting restaurant deals with inclusion of simulated sales effort, $SimSEB_{ijt,}$ inversely proportional to prior period deals offered

	Model 1 (DV = V_{ijkt})		Model 2 (DV = D_{ijkt})	
Main Effects				
$V_{ijk(t-1)}$	0.1670	(0.0176)***		
$V_{ij(-k)(t-1)}$	0.0056	(0.0053)		
$D_{ijk(t-1)}$			0.0420	(0.0131)**
$D_{ij(-k)(t-1)}$			0.0340	(0.0171)*
Covariates				
$V_{(-i)jk(t-1)}$	0.0204	(0.0071)**		
$V_{(-i)j(t-1)}$	0.0050	(0.0018)**		
$D_{(-i)jk(t-1)}$			0.0260	(0.0175)
$D_{(-i)j(t-1)}$			0.0427	(0.0504)
$S_{ijk(t-1)}$	-0.0089	(0.0024)***	-0.0025	(0.0007)***
$SimSEB_{ijt}$	-0.0011	(0.0007)	-0.0007	(0.0002)**

Table B5. Predicting spa deals with inclusion of simulated sales effort, $SimSEB_{ijt,}$ inversely proportional to prior period deals offered

	Model 1 (DV = V_{ijkt})		Model 2 (DV = D_{ijkt})	
Main Effects				
$V_{ijk(t-1)}$	0.0909	(0.0202)***		
$V_{ij(-k)(t-1)}$	0.0093	(0.0041)*		
$D_{ijk(t-1)}$			0.0391	(0.0102)***
$D_{ij(-k)(t-1)}$			-0.00420	(0.0103)
Covariates				
$V_{(-i)jk(t-1)}$	0.00489	(0.0034)		
$V_{(-i)j(t-1)}$	0.0033	(0.0009)***		
$D_{(-i)jk(t-1)}$			-0.0238	(0.0080)**
$D_{(-i)j(t-1)}$			0.0177	(0.0323)
$S_{ijk(t-1)}$	-0.0006	-0.0004	-0.0001	-0.0001
$SimSEB_{ijt}$	0.0011	(0.0006)	-0.0003	(0.0001)*