The Value of Competitor Information: Evidence from a Field Experiment

Hyunjin Kim*

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Abstract

Data on competitors have become increasingly accessible in recent years, raising the potential for firms to inform their decisions with a better understanding of the competitive environment. To what extent are firms aware of readily available information on key competitor decisions, and how does this information impact firms' strategic choices? I explore these questions through a field experiment in collaboration with Yelp across 3,218 businesses in the personal care industry, where treatment firms receive easily accessible information on their competitors' prices. At baseline, over 46% of firms are not aware of their competitors' prices. However, once firms receive this information, they are 17% more likely to change their prices, and do so by aligning their prices with competitor offerings. If competitor information is both decision-relevant and easily accessible, why had firms not invested in this information on their own? Evidence from interviews and a follow-up experiment across control firms suggests that managers appear to have underestimated the value of paying attention to competitor information. These findings suggest that managerial inattention may be a key barrier that leads firms to fail to realize gains from even readily accessible data.

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1 Introduction

Understanding the competitive environment is a central part of strategic decision-making, especially on key choices such as price, quality, and location. In recent years, it has become increasingly easier for firms to acquire data, not only on their customers or internal operations, but also their competitors and their decisions (e.g. Brynjolfsson and McElheran 2016, Einav and Levin 2014, Tambe 2014). For example, Amazon provides details on comparable products offered by other sellers, Expedia shows real-time pricing and amenity information for nearby hotels, and Yelp displays reviews of neighboring local businesses. This increased accessibility of competitor data raises the potential for firms to inform their decisions with a better understanding of the competitive environment (Seamans and Zhu 2013, Wang and Shaver 2014, Bennett and Pierce 2016).

However, while awareness of competitor decisions is often implicitly assumed, there is less research on how knowledgeable firms are of their competitors in practice – and how this information impacts their strategic choices. Well-known examples suggest that firms may lack knowledge about their competitors, even in settings where the costs of acquiring information appear to be low. Hotels fail to identify key competitors of similar price and size (Baum and Lant 2003, Li et al 2017). Large textile manufacturers are unaware of common management practices like having an uncluttered factory floor, despite their widespread adoption (Bloom et al 2013). While these examples suggest that firms may lack awareness in certain cases, they raise further questions: to what extent are firms aware of readily available information on key competitor decisions, and how does this information impact firms' strategic choices? This lack of competitor knowledge may have large implications for firm performance: firms may fail to respond to competition or miss out on opportunities for performance improvements.

In this paper, I provide large-scale evidence that firms may be unaware of key competitor decisions even when this information is easily accessible. Firms do not appear to lack awareness because competitor information is not decision-relevant: once firms receive this information, they change their decisions by better aligning them with competitor offerings. I find suggestive evidence that managerial inattention may drive firms' lack of awareness: managers believe that competitor information is important, but fail to pay attention because they believe they are already aware of it. As competitor data becomes increasingly accessible in the digital age, these findings highlight the role that attention may play in shaping the impact of digitization, and provide practical implications for when firms should invest in competitor intelligence and the barriers they may face in realizing gains from available data.

I empirically explore these questions using a field experiment across 3,218 businesses in the personal care industry. I focus on firms' pricing decisions, a central strategic lever in this industry that drives customer decisions.[1] I collaborate with Yelp to physically send canvassers to all 3,218 firms

[1] I analyze all consumer reviews on Yelp prior to the experiment for suggestive insights on the drivers of customer decisions. I use word2vec, a neural network that identifies words sharing common contexts by computing cosine similarity between a mean of the projection weight vectors of the words and for each word in the model. I find that pricing is one of the most frequently mentioned categories. 46% of all reviews include words related to pricing, 35% of reviews reference comparisons to competitors, 24% comment on cleanliness, and 17% of reviews comment on luxuriousness. Furthermore, analyzing reviews using a bag-of-words model (2- and 3-grams), I find that the most frequent phrases mention price and comparison to other salons, suggesting that customers are searching across salons along these dimensions.

for a standard marketing visit. Firms randomly assigned to treatment receive additional information during this visit on their relative price positioning compared to their 9 geographically closest competitors. This design enables me to tease apart the treatment effect of competitor information from the selection effect of firms that choose to invest in competitor intelligence, and ensure that randomly assigned treatment firms see the competitor information.

I run this experiment across personal care businesses that offer nail services, as this context enables precise identification of competitor knowledge and its impact across thousands of firms in hundreds of local markets with varying degrees of competition. A $9.8 billion market in the U.S., nail salons represent one of the largest local business verticals (IBIS 2019). This market is differentiated along pricing and quality, and exhibits much heterogeneity in size – from sole proprietorships to multinational chains with 800 establishments and over a million in revenues. Information on competitor prices is easily accessible in this market via phone calls or visits, enabling me to study why firms might lack competitor knowledge even when information is easily attainable.[2] Moreover, nail salons have simple strategy spaces, where price positioning is a central decision that is both measurable and comparable: every salon has a price for a regular manicure, which generally vary from $5 to $60 and serves as the base price for other services.[3] Measures of quality positioning can also be readily observed from the polish brands used, the cleanliness of the interior, and the luxuriousness of the décor. How these decisions are made resemble those of other retail businesses, as well as of small and medium enterprises (SMEs) more generally, which make up 99.7% of U.S. establishments, represent 46% of GDP, and are of policy importance in many countries.[4]

To measure the impact of competitor information, I obtain measures of firms' baseline knowledge of their competitors prior to treatment, and construct a panel data set of monthly prices and proxies of performance over 12 months. A team of approximately 50 data collectors make phone calls each month to all 3,218 businesses to obtain prices of regular manicures. They also physically visit businesses at baseline and endline to observe their polish brands, cleanliness, and luxuriousness as measures of their quality. To measure proxies of performance, I collect an indicator of availability for an appointment on the next day during a peak hour, as well as purchase intentions from the Yelp platform, which include calls to the business, page views, and map directions views. I also work with the city government of San Francisco to obtain data on business sales taxes.

At baseline, a large percentage of firms appear to lack competitor knowledge, including those that face higher levels of competition. When asked by canvassers who their primary competitors are and what prices they are charging prior to the information intervention, over 46% of treatment firms are

[2] Obtaining competitor prices that are provided as treatment takes less than 9 minutes of phone calls (less than a minute per competitor), and many managers state that they could easily obtain this information online or physically, suggesting that the acquisition costs are fairly low.

[3] More elaborate nail services (e.g. nail art or pedicure) are priced in proportion to the regular manicure price, such that two salons with approximately similar regular manicure prices will have approximately similar prices across their other services. This is often not the case in even other simple markets: for example, prices for a cup of coffee across cafés may not map to their price positioning, as cafés have differing sizes of cups, and some may have cheaper coffee but more expensive pastries.

[4] SMEs are defined by the U.S. Small Business Administration as firms with fewer than 500 workers. Firms with fewer than 100 workers account for 98% of employer firms, and firms with fewer than 20 workers make up 89%. SMEs represent 47% of employment and 46% of GDP. (https://sbecouncil.org/about-us/facts-and-data/).

not able to state specific competitors or their prices.[5] Consistent with this evidence, I also find a large dispersion of prices across firms that offer similar levels of quality, as well as discrepancies between firms' stated versus observed price-quality positions. Since many managers state that they can easily acquire information on competitor pricing, it may be that these measures are inflated, or that firms are unaware of this information simply because it is not decision-relevant. For example, it may be that other informative sources such as observing customers and residual market demand provide sufficient statistics for competitor information, especially in more competitive markets. Alternatively, it may be that firms that are unaware of competitor pricing rely on a large base of regular customers that shield them from competition.

However, once treatment firms receive this information, they change their pricing in ways that suggest that this information is valuable. Treated firms are 17% more likely to change their prices relative to control firms in the months following the canvasser visit. Over 19% of these firms show surprise and comment that they intend to change their prices based upon it, and an additional 18% actively engage with the information and ask follow-up questions – suggesting that these price changes are driven by the competitor information.

Rather than differentiating, firms increase alignment with their geographically nearest competitor's decisions, with those that were charging higher (lower) prices compared to their nearest competitors decreasing (increasing) prices. Firms that were over- or under-pricing relative to their quality also respond most to treatment, suggesting that these changes may be improvements. I find suggestive evidence consistent with the interpretation that receiving competitor information may be performance-enhancing: treatment firms observe 15% more calls, page views, and map directions views on Yelp, and 3% lower availability for an appointment the next day – which may be driven by passersby who can often see prices from the outside, or consumers searching on Yelp who can observe prices on the search results page. These performance effects do not appear to stem from firms' increased usage of the Yelp platform, and are driven mostly by firms that were over-pricing at baseline.[6]

Given this positive impact of easily accessible competitor information, the natural question is why firms had not previously invested in this information on their own. Treatment effects are larger for firms that face higher competition, as well as those without prior experience using demand-based promotions that indicate sophistication with pricing, suggesting that a lack of competition or capabilities to use the information may not fully explain firms' lack of knowledge.

Evidence from 25 interviews and a follow-up experiment across control firms suggests that inattention may have been an important factor, consistent with research on managerial attention (Ocasio 1997, Eggers and Kaplan 2009, Helfat and Peteraf 2015, Hanna, Mullainathan, and

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[5] This percentage excludes firms where managers were not willing to answer questions in general, appeared to brush off canvassers, or did not fully engage with questions that followed.

[6] I find little evidence of spillover effects, which I explore by surveying control firms on whether they heard about pricing information provided by Yelp after endline data collection, as well as by analyzing whether control firms in ZIP codes with a higher proportion of treated firms are more likely to change prices and observe lower purchase intentions. However, these performance effects are likely to at least partly capture business stealing, unless market demand is growing sufficiently over time. In terms of the main treatment effect on price change, any spillover effects would bias any estimate of a treatment effect downwards, as control firms also become more likely to change prices.

Schwartzstein 2014). Managers appear to underestimate the value of paying attention to this information, until they are triggered to explicitly reevaluate their knowledge. Managers that are randomly assigned to reassess their knowledge of competitors before being asked whether they are interested in receiving competitor information (for free) are more likely to sign up to receive it, compared to those who are asked first about their interest in competitor information.

In addition to the strategy literature on competitive interactions, this paper relates to several strands of literature. First, a variation of the concern about whether firms lack awareness of competitors is how firms apply readily available data to improve decision-making. Research on data-driven decision-making and information technology more broadly has shown that these investments are associated with higher firm performance but with differential gains across firms (Brynjolfsson, Hitt, and Kim 2011, Bloom et al 2012, Brynjolfsson and McElheran 2016, Hoffman, Kahn, and Li 2018, Bajari et al 2019). This paper unpacks how competitor information improves firm decisions, and provides evidence that despite its value and accessibility, firms may fail to attend to and use data.

Second, a large literature on firms' management practices has documented how firms' lack of knowledge and adoption of best practices may explain the dispersion in performance observed across firms (Bloom and Van Reenen 2007, Syverson 2011, Bloom et al 2013, Bruhn et al 2017). One puzzle raised by this literature is why firms lack knowledge of even commonly used best practices. This paper provides evidence on how widespread firms' lack of competitor knowledge may be even for key strategic decisions like pricing and in settings with low barriers to information and relatively high competition. The findings also provide suggestive evidence that behavioral factors like inattention may drive this lack of knowledge, consistent with an emerging literature on behavioral firms (DellaVigna and Gentzkow 2019, Kremer, Rao, and Schilbach 2019).

Lastly, a growing management literature on the cognitive underpinnings of strategy has proposed the importance of managerial capabilities for attention (Ocasio 1997, Eggers and Kaplan 2009, Helfat and Peteraf 2015). But problems in measurement and identification have made it hard to confirm how attention might impact firm strategy. This paper provides empirical evidence on how inattention might lead firms to overlook competitor information, and proposes that firms may become inattentive due to outdated information that leads them to be complacent to new information. Building on ideas proposed by Gavetti (2012), these findings suggest that even in competitive markets, managers may need to worry about inattention to the immediate competitive environment, and that attention may create opportunities for competitive advantage.

2 Setting

I study the personal care industry, which enables precise identification of firms' knowledge of competitor decisions and its impact across thousands of firms in hundreds of local markets with varying degrees of competition.

Case studies have long provided valuable insights to uncover empirical facts. Studies of hotels have yielded numerous insights on firm positioning, location choices, learning, and competitor perception (Baum and Haveman 1997, Baum and Ingram 1998, Chung and Kalnins 2001, Baum and

Lant 2003, Li et al 2017). Pizza stores offered evidence on how organizations acquire and transfer knowledge (Darr, Argote, and Epple 1995). Taxicab companies enabled a detailed study of coordination costs and organizational rigidity (Rawley 2010). Careful studies of fishing boats in India, pineapple farms in Kenya, local gas stations, and ready-mix concrete have provided detailed insights on issues as diverse as firm productivity, learning, and pricing (Conley and Udry 2010, Jensen 2006, Lewis 2008, Syverson 2004). In each of these papers, grounding the question in a case study of a particular industry helps identify precise measures of concepts and uncover new hypotheses or puzzles from the richness of the context.

However, finding a market to study whether and why firms might lack competitor knowledge and what its impact may be on strategic choices like price positioning is difficult, due to the many requirements it imposes. It requires a large number of firms across varying market conditions to statistically identify the extent to which the value of competitor information might vary across levels of market competition or firm attributes. Moreover, price positioning must be clear, measurable, and comparable across firms, which is challenging to find and often reduces the sample to an even smaller number of firms. For example, even in a relatively simple market like cafés, it is not straightforward to precisely measure firms' price positioning. Cafés vary in their menus with some items that are more expensive than others, and even a seemingly comparable item like a cup of coffee does not provide comparable measures across establishments due to its varying size and quality, both of which are challenging to consistently measure.[7] As a result, much prior research on positioning has been based on qualitative case studies of single organizations or limited by small sample sizes: 50 consulting firms in Semadeni (2006), 159 banks in Deephouse (1999), and 614 hotels in Baum and Haveman (1997).

After assessing many possible industries,[8] I chose to focus on personal care businesses that offer nail services, due to the extent to which I can isolate price positioning and how it changes. The market for nail salons is estimated to be approximately $9.8 billion in the U.S. (IBIS 2019). As a point of comparison, the nail salon industry is slightly larger than the men's clothing store market in the U.S., estimated at $8.5 billion, and slightly smaller than the egg production market, at $10.5 billion (IBIS 2019). While the nail salon market is fairly competitive and fragmented, large chains also exist. For example, Regal Nails has more than 800 salons across U.S., Canada, and Puerto Rico, with over $1.15 million in annual revenues. Many nail salons represent entrepreneurial endeavors, often founded by college-educated immigrants and women who pursue entrepreneurship as career alternatives (Nails Magazine 2015). A prominent example of an entrepreneurial salon is Miniluxe, a Boston-based chain of 25 salons, which recently received $23 million in venture capital investments.

The nail salon industry has a number of attributes that make it a compelling setting to study the impact of competitor information on firm pricing. First, nail salons represent the largest vertical among local businesses and compete locally, enabling a sample of thousands of firms across hundreds of local markets.[9] The large number of firms and local markets enables me to evaluate competitor

[7] More broadly, Archak et al 2011 illustrate how difficult it may be to isolate key features of products even in relatively simple markets like digital cameras.

[8] I analyzed industry verticals across drycleaners, florists, and restaurants based on market (and sample) size, comparability and observability of price positioning, and competitor information accessibility.

[9] Potentially as a result of the level of competition, nail salons have recently come under regulatory scrutiny for labor rights violations.

knowledge and the impact of competitor information across different firm attributes and degrees of market competition. Second, they have standardized, comparable, and observable measures of price and quality positioning. Every salon has a price for a regular manicure, which approximately represents its price positioning, as other services are priced proportionally to the regular manicure price. 99% of regular manicure prices vary from $5 to $65 depending on quality.[10] Quality can be observed using the salon's polish brands – which can vary from $9 to $70 per bottle at retail cost, as well as the cleanliness of the interior and the luxuriousness of the décor. These price and quality decisions and how they are made are generally similar to those of other retail businesses, as well as of small and medium enterprises (SMEs) more broadly, which make up a large percent of the economy.[11] Finally, information on competitor prices is easily accessible, enabling me to study why firms might lack competitor knowledge even when information is easily attainable. Many managers comment that they could easily obtain this information online or even physically, suggesting that the acquisition costs are fairly low. Nearly all firms in the sample are aware of Yelp, and most firms have a competitor within 0.5 miles that they pass by on their way to work. Furthermore, obtaining competitor prices provided as treatment takes less than one minute of phone calls per competitor.

Within this context, I partner with Yelp, an online platform that crowdsources listings and reviews of local businesses, to deliver the treatment information in a more natural manner. As of June 2018, Yelp listed over 4.6 million verified[12] businesses including restaurants, home services, beauty salons, and fitness centers, accumulating 163 million reviews and attracting 74 million unique desktop and 72 million mobile visitors on a monthly average basis (Yelp 2018). Yelp displays business listings with location information, which are continually sourced from Yelp's internal team, user reports, and partner acquisitions, and checked by an internal data quality team. Yelp also provides reviews and photos that detail business decisions, and tracks proxies of business performance, such as calls to the business, views of map directions to the business, and business pageviews. Furthermore, it has a free business dashboard for businesses to observe information about their reviews, where Yelp could in theory provide information about their competitive context.

I collaborate with Yelp by scaling up marketing efforts within the company that sent canvassers to physically visit local businesses. At the time of the experiment, Yelp was making marketing visits to a handful of businesses each year to inform them about how to update their information on Yelp's free business page. I scale up these efforts and layer an information intervention on top of the standard marketing visit for businesses assigned to treatment. This setting provides an advantage over online platform settings, by enabling information to be verifiably delivered.

[10] This range of manicure prices is observed across the entire set of 6,370 nail salons that I verified across the San Francisco Bay Area, New York City, Los Angeles, and Chicago.

[11] SMEs are defined by the U.S. Small Business Administration as firms with fewer than 500 workers, and represent 99.7% of all U.S. establishments. Firms with fewer than 100 workers account for 98% of employer firms, and firms with fewer than 20 workers make up 89%. SMEs represent 47% of employment and 46% of GDP. (https://sbecouncil.org/about-us/facts-and-data/).

[12] Verification means that the business claimed their free page on Yelp, verifying that the listing was a true business.

3 Experimental Design

To isolate the impact of competitor information, I run a field experiment across businesses in the personal care industry. All firms in the sample receive marketing visits from Yelp canvassers, during which treatment firms receive additional information on the prices of 9 geographically closest competitors. Canvassing visits result in a balanced experimental sample of 3,218 firms, which represent approximately 60% of each market across New York, Los Angeles, San Francisco, and Chicago. I observe low levels of attrition and non-compliance.

3.1 The competitor information intervention

All firms receive a marketing visit from a Yelp canvasser, and firms assigned to treatment receive additional information on competitor price positions during this visit. This information displays the relative price positions of their 9 geographically closest competitors, which canvassers explain based on a standardized script on which they are trained.

Within the experimental sample, all firms across control and treatment groups receive a physical visit from a Yelp canvasser. The canvasser provides a brochure with information on how to edit business details, add photos, and respond to reviews on Yelp's free business page (Appendix Figure A.1) and offers assistance with claiming their page. For businesses who have already claimed their Yelp page, the canvasser offers assistance with verifying the information or logging into the account. Firms also receive a standard marketing postcard with free Yelp advertising credits on the front and a blank canvas on the back (Appendix Figure A.1).

Businesses assigned to treatment additionally receive a personalized competitor pricing report on the back of the marketing postcard (Figure 1). The postcard displays the firm's regular manicure price compared to its nine geographically closest competitors.[13] It also lists the name of each competitor and the exact price it charges.[14] In order to further facilitate comprehension, the postcard displays the name of the business at the top with a summary description, which is algorithmically generated to take one of four versions: (1) You charge the lowest/highest price in the area. [If applicable: *n* businesses charge the same price.] (2) Most businesses nearby charge higher/lower prices than you. *n* businesses charge less/more. (3) Most businesses nearby charge the same or higher/lower prices as you. *n* businesses charge less/more. (4) Most/All businesses nearby charge the same price as you.

Every canvasser is trained using a standardized script. Team managers in the four cities and I trained each canvasser individually, guiding each canvasser through at least three hours of practice with the script and detailed data recording steps, followed by a few hours of canvassing visits together to confirm correct execution. A phone application records the canvasser's location and date stamp for

[13] The nine geographically closest competitors are determined using the full sample of verified businesses in the area, based on longitude and latitude coordinates. This means that information on businesses not in the experimental sample are included in these postcards.

[14] This image was extensively piloted prior to the experiment on nail salons in Boston (outside of the experimental sample) to ensure that business owners and managers could easily understand the information.

the business visit. Canvassers are instructed to follow up with a business up to three times if they are not able to speak with a manager or owner. If they are still unable to do so by the third visit, canvassers leave the brochure and postcard, and provide a contact number for any questions. They record descriptions of each interaction they have with businesses, such as whether they are able to speak with someone or asked to come back at another time.

Canvassers are not informed of the experiment or experimental conditions. Approximately two to five canvassers work in each metropolitan area at any given time. They are assigned to one form of canvassing (either control or treatment) to begin, and transition to the other canvassing type after a few weeks, with the explanation that Yelp is trying different ways to canvass. No canvasser performs both types of canvassing during the same period or switches more than once between canvassing types, in order to avoid the possibility that the canvasser may confuse the protocol.

3.2 Sample definition, randomization, and timing

To determine the eligible set of businesses for the experiment, all nail salon listings on Yelp across the San Francisco Bay Area, New York City, Los Angeles, and Chicago are verified via phone calls. Firms in the eligible set are randomly assigned to control or treatment, stratified on the metropolitan area, prior relationship with Yelp, and Yelp rating. Between June and November 2018, Yelp canvassers strive toward visiting all businesses in this set, sequencing visits by neighborhood such that a full neighborhood is finished out before moving to the next. Yelp canvassers reach 3,474 businesses, which results in an experimental sample of 3,218 firms.[15]

The San Francisco Bay Area, New York City, Los Angeles, and Chicago are chosen as the markets for intervention, based on (i) the presence of Yelp offices to leverage the canvassing effort; (ii) the number of nail salons in the area to allow for a sufficiently large sample; and (iii) coverage of Yelp to obtain robust data on businesses. I identify ZIP codes within these areas[16] and extract all nail salon listings on Yelp in these ZIP codes, which results in a set of 9,889 nail salons.

I call every business in this set and use Google Maps Streetview to confirm they are open, offering nail services, correctly located, and not a duplicate business. Any business that is not listed in Yelp's sales database is dropped (302 salons, or 3% of the extracted list), which serves as an additional screen to ensure the business is open and has the contact information required for data collection. I also drop any salons that are not physically located in one of the four markets (including mobile businesses), as well as businesses located inside airports. This process results in a sample of 6,370 nail salons across these areas.

Any salons with Yelp ratings of 1 to 2.5 stars (out of 5) are excluded, in order to maximize the likelihood of compliance to treatments.[17] This sample restriction is imposed because businesses with ratings lower than three stars are more likely to have antagonistic stances against Yelp, which can reduce the likelihood that the business complies to treatment by being receptive to a Yelp canvasser

[15] 256 were identified as duplicates or permanently closed by the time of visit.

[16] For the San Francisco Bay area, I identified ZIP codes in cities with more than 50,000 people across the greater Bay area.

[17] Treatment information on competitor pricing, as well as measures of competition, are not subject to this restriction. I take the full set of verified firms to determine the nearest competitors.

and any information that the canvasser delivers. To the extent that these lower-rated firms that are excluded are also less likely to know competitor information and to have set their prices conditioning on their competitors', the experimental sample may provide a stronger test for the impact of competitor information. This sample restriction results in an eligible set of 3,948 businesses, which represents 62% of the full set of salons.

The resulting eligible set of 3,948 businesses represents the goal that Yelp canvassers strive toward reaching, which is subject to a few constraints.[18] First, while all 3,948 businesses are verified to be open and unlikely to be a duplicate at the time of randomization in May 2018, canvassers may arrive at the business to discover that the business either no longer exists or is a duplicate of another listing. Second, Yelp has a fixed canvassing budget and timeline, by the end of which canvassing operations must terminate even if all 3,948 businesses have not yet been visited.

Businesses in the eligible set are assigned to experimental groups through a stratified randomization process using its metropolitan area, prior relationship with Yelp, and Yelp rating rounded to the nearest multiple of 0.5.[19] These variables are chosen based on a number of reasons. Metropolitan areas may have different dynamics of competition due to variation in business density as well as customer tastes, which could determine how the business responds to information on competitors. Prior relationship with Yelp, which defines whether a business has claimed its free business page on Yelp and/or previously advertised with Yelp, and prior Yelp rating are likely to be correlated with key firm attributes and determine the business's receptiveness to Yelp canvassers and any information that they might provide. Within each stratum, firms are randomly assigned to one of two experimental groups, control or treatment. 1,972 firms are assigned to treatment, and 1,976 firms are assigned to the control group (Figure 2).[20]

To ensure that the resulting experimental sample is approximately balanced in the timing of visits across experimental groups, canvassers are assigned to finish all visits across control and treatment firms within a neighborhood before moving on to their next neighborhoods.

Between June 18 and November 18 of 2018, canvassers reached 3,474 businesses. 256 are identified as duplicates or closed by the time that they visit, resulting in an experimental sample of 3,218 firms (Figure 3). All firms in Los Angeles and Chicago are reached, and most firms in New York and San Francisco are reached, excluding the farther out areas (Bronx and outer areas of Queens for New York and North Bay for San Francisco) (Appendix Figures A.2 and A.3).

3.3 Balance, attrition, and non-compliance

[18] Power calculations suggested that this sample size would be sufficient to detect standardized effect sizes of 0.09 for all treatment and control firms with 80% power.

[19] Stratified randomization ensures that treatment and control groups are similar not just in expectation, but also in practice in the sample along important observable dimensions. It can also improve precision to the extent that these variables explain the variation in the treatment of interest (Cox and Reid 2000, Duflo, Glennerster, and Kremer 2007).

[20] Stratified randomization was done using Stata.

Firms are well-balanced across experimental conditions. Control and treatment firms in the same neighborhood are visited approximately at the same time, but treatment firms appear to slightly lag behind control firms.[21] Non-compliance and attrition rates are low.

Table 1 shows summary statistics across all baseline characteristics of firms in the experimental sample.[22] The average baseline price is $13.88 and ranges from $5.00 to $60.00.[23] At the time of visit, data collectors observe an average of 4 employees and 4 customers, which range from 1 to 25 and 0 to 30, respectively. 75% of salons have availability between 4-5pm the next day.

Table 2 shows that across baseline variables, control and treatment firms are well-balanced. In two variables out of 16, control and treatment firms appear to be statistically different. The difference in luxuriousness is small and is likely explained by missing observations due to business closures at the time of data collector visits, but the timing of canvassing visits appears to be delayed among treatment firms by approximately 1.4 weeks. Given the importance of this variable, I control for the week of the canvassing visit in all specifications, and further explore this potential issue in robustness.

Non-compliance rates are low. Fewer than 2% of firms (58) are marked as non-compliant, which manifests in the form of firms rejecting any conversations with Yelp canvassers when they arrive at the business (Appendix Table A.1). In these cases, neither control nor treatment firms receive any information from the canvasser.

I observe similarly low levels of attrition. Attrition stems from both firm closures, which is unlikely to be influenced by treatment, as well as firms that cannot be reached after canvassing visits. Approximately 5% of firms in the sample permanently close during the 12-month period. 1% of firms (36) in the sample are unreachable for any data after canvassing visits. Neither type of attrition varies significantly across experimental groups.

4 Measuring firms' knowledge, positioning, and performance

I construct a data set of firm knowledge, price positioning relative to quality, and performance over a 12-month period between May 15, 2018, to September 15, 2019 (timeline shown in Appendix Figure A.4). Firms' prior knowledge of competitors is collected by Yelp canvassers who ask questions to treatment firms prior to providing treatment. Measures of firms' price positioning are collected via phone calls and physical visits to all businesses by data collectors at baseline and endline. Data from the Yelp platform, supplemented by city government tax records (to be received in summer 2020), provide proxies of firm performance. In order to ensure accuracy, canvassers and data collectors remain

[21] There was no one clear reason for this lag. One possible reason is that there were times where a canvasser had to take a break due to personal reasons or it took longer to fill a canvasser role, leading to odd numbers of canvassers, which may have driven idiosyncratic differences. Another reason is that anecdotally, treatment canvassers sometimes had a harder time speaking with the owner or manager, as they had to ask questions before providing information, and were asked to come back at a different time. Due to the importance of this variable, I control for the week that each firm was visited in all specifications.

[22] Data collectors were sometimes not able to visit the salon due to closure upon multiple tries, or due to security at reception, leading to varying numbers of observations across variables.

[23] Across the full set of verified salons, regular manicure prices range from $5 to $150.

blind to treatment assignment, and 5% of all hand-collected data is verified by an independent data collector, with any conflicts sent to a third data collector.

4.1 Measuring stated positions and knowledge of competitors

Firms' own descriptions of their positioning and knowledge of competitors are collected by Yelp canvassers during their visits. Treatment businesses are asked a set of questions before and after treatment. Prior to information delivery, canvassers ask, (1) "What do you think sets you apart from your competitors?" followed by (2) "Who do you consider as your primary competitors?" and (3) "What do you think they charge for a regular manicure?". Canvassers then deliver the competitor information treatment and ask, "Would you like to continue receiving this information?" to determine whether businesses find the information valuable. Canvassers record answers to these questions as close to verbatim as possible.

In order to ensure accuracy, canvassers remain blind to experimental assignment and hypotheses, and managers are not aware that they were being assessed as part of an experiment. Furthermore, canvassers' data entry and performance are monitored on a daily basis.

All answers are read and coded by two independent research assistants. Both research assistants first independently read a few hundred responses to understand potential categories of answers, and compare notes to arrive at a list of categories. They then individually assign each answer to one of the categories. Any conflicts are sent to a third research assistant to resolve.

4.2 Measuring price positioning relative to quality

Data on price positioning are collected by a team of ~50 data collectors who make calls and visits to businesses.[24] All data collectors are blind to experimental assignments, and are assigned to collect data on control and treatment businesses by neighborhood in order to ensure balance between experimental groups. To ensure data validity and accuracy, data collectors are given detailed scripts and evaluation rubrics, have a subset of their data validated by another independent data collector, and in the case of visits, take photos of menus, interiors, and exteriors to validate their coding. Their performance in terms of accuracy and productivity is tracked on a weekly basis, as well as their location and time of visit.

Price positioning is measured by the price of a regular manicure, collected via calls made to all businesses on a monthly basis between May 2018 and May 2019. Data collectors ask for the price of a regular manicure without taxes or cash discounts. In a subset of the months, prices of other services (pedicure, manicure and pedicure combination) are also collected.[25]

[24] Data collectors were undergraduates and Masters students recruited using job postings across every university in the four cities that were posted every 3-6 months. They were selected after an interview asking questions about data validity and collection methods. Over the course of the project, ~83 data collectors were hired.

[25] Data collectors also note whether the phone number is no longer in service, no one answers, nail services are no longer offered, business is permanently closed, or business refuses to provide prices over the phone. Due to these reasons, data collectors were not able to obtain a price every month for each salon, resulting in an unbalanced panel.

These pricing data are validated in two steps. First, the full list of salons is divided among data collectors, where 5% of the data are additionally allocated to another data collector as a quality check. Second, once all data collectors submit their data, any observations with a business closure or unreachable flag, conflict in prices or open status across two data collectors, or a mismatch between the name and identifier are reassigned to data collectors. This second step is repeated up to three times in each month.

Quality is measured by coding the level of nail polish brands used, the cleanliness of the interior, and the luxuriousness of the décor, observed via physical visits to each business at baseline (May – August 2018) and endline (May – September 2019). While reviews and photos on Yelp may potentially provide a subset of these data points for some businesses, they are collected at different points in time and missing for a large percentage of businesses in the sample, so physically visiting businesses to collect this data within a few months improves the collection of accurate and comparable measures.

In order to ensure standardization and accuracy of scoring, data collectors use an evaluation rubric to code quality metrics, and their coding is validated through a number of validation checks. For nail polish brands, data collectors are given a list of nail polish brands classified into low, medium, and high according to their retail price per bottle (low: below $10; medium: between $10-$20; high: above $20). They are instructed to select the highest level of polish brand they observe, as most firms use some proportion of the lowest-cost brands. They record any brands they observe that are not present on this list, which are then coded ex-post using their retail prices. For cleanliness and luxuriousness, data collectors are given a rubric of metrics to guide their coding, detailed in Table 3. Data collectors are also required to take photos of the interior, polish brands, menu, and exterior to ensure accuracy, and 5% of each data collector's photos are checked every week. Approximately 5% of firms are assigned to an additional independent data collector to validate quality measures.[26] Data collectors' accuracy and productivity are tracked on a weekly basis, and the data entry application records their location and time of visit.

During these visits, data collectors also collect additional data on businesses' opening hours, promotions, and the number of employees and customers at the time of the visit.

4.3 Measuring performance

Firm performance is measured using a variety of proxies: purchase intentions from the Yelp platform, next-day availability between 4-5pm via phone calls, and sales in one city as measured by San Francisco government's sales tax data.

My main proxies of performance are collected on the Yelp platform, which measures purchase intentions for each business based on consumer search patterns. I construct monthly measures of business performance, based on the number of unique views of the business page, the number of calls made to the business, and the number of views of map directions to the business – which prior studies have mapped to firm revenues (e.g. Luca 2016, Dai et al 2018). Changes in price or quality may lead these measures to increase through a few possible mechanisms. First, the search results page indicates

[26] Any data collectors above a threshold accuracy level was replaced immediately, but discrepancies were extremely rare, and only two data collectors were dismissed.

approximate price levels for each firm, and also highlight some review text that often elaborates on price or quality details. Second, many firms post their prices on windows and are viewable from the outside, and customers frequently walk in from the street. If changes in decisions lead more passersby to be interested in the firm, they may search for it on Yelp, increasing the firm's page views, and possibly call to confirm a detail without going in, which may increase its call volume.

While these proxies are available for all firms on a monthly basis, they have two key limitations in capturing effects on performance. First, they capture consumers' purchase intentions (particularly through the Yelp platform), and do not reflect actual sales. Second, while these measures may reflect demand among customers who search, they are not as likely to capture demand among regular customers.

To overcome these limitations, I complement these measures with additional proxies of performance. During monthly phone calls, data collectors ask if there is availability for an appointment the next day between 4-5pm[27], a peak hour for salons, and record a binary answer. This measure captures both searching customers as well as regular customers.

I also collect data from city government databases on business registration, licensing, and tax. Firm and owner attributes are extracted from city government databases on business registration and licensing data. I work with the government of San Francisco to analyze business sales data from tax records, which will be available in summer 2020 due to the tax cycle.

5 The landscape of firms' competitor knowledge and positioning

Baseline measures suggest that many firms may lack competitor knowledge, including those that face higher levels of competition. Over 46% of treatment firms are not able to state specific competitors and their prices prior to receiving information on competitor prices. Consistent with this evidence, firms' observed pricing positions display dispersion within each level of quality and exhibit discrepancies with firms' stated price-quality positions.

5.1 Baseline competitor knowledge

When asked by canvassers prior to treatment who they consider as primary competitors, 46% of firms are not able to state their primary competitors (Figure 4(a)). These firms respond that they do not know which businesses are their primary competitors, or that it has been a while since they looked at other businesses to be able to state specific competitors. Canvassers classify any answers that appear to be brush-offs as "did not answer" based on the firms' disinterest in answering follow-up questions or continuing the conversation, which constitutes 6% of responses.[28]

[27] In order to prevent any suspicion across salons, the specific time was changed on a monthly basis (e.g. 4pm in January, 4:45pm in February).

[28] This low brush-off rate may possibly be driven by the fact that Yelp was providing free assistance and information on these visits, as well as the general perception by many retail businesses that Yelp is important for their sales and may hold sway over their consumer ratings.

Among firms that are able to answer, the largest category of firms (21%) consider all salons nearby to be competitors (see Appendix Figure B.1 for further details on this category of responses). This lends credence to geographical distance being a key factor determining competitors, consistent with findings across other industries (Baum and Lant 2003). The geographic distance considered varies across salons: 55% state that nearby salons in walking or driving distance are competitors, 21% consider all salons in the neighborhood or city as competitors, 15% refer to salons on the same block, and 15% state salons within a few blocks from them. 16% of firms mention specific salons. 2% mention a type of salon (e.g. Japanese nail art salons). 9% of salons state that they have no competitors. Similarly, 58% of firms are not able to state the prices that their primary competitors charge (Figure 4(b)). 21% of firms state that they believe competitors charge similar prices, while 8% and 6% state more or less, respectively. 1% state that they do not care what competitor prices are.

Surprisingly, firms that are not aware of their primary competitors and their prices remain across those that face higher market competition. The level of competition is measured by the firm's distance from its geographically nearest competitor, as well as the baseline price dispersion across its geographically nearest 9 competitors, across the full set of verified salons in the cities beyond the experimental sample.[29] These set of measures are robust to adjusting for variation across cities such as density. Across both of these indicators, fewer firms in more competitive markets with closer nearby competitors and lower market price dispersion appear to lack knowledge of their competitors or their prices, as expected (Appendix Figures B.2 and B.3).[30] However, the difference in percentage between firms facing above and below median competition is not large, and a substantial percentage of firms across more competitive markets still display a lack of awareness. The lack of awareness also persists across firms with below and above median size (number of employees), age, and price points (Appendix Figures B.4 – B.6).

While these responses suggest that many firms may not be aware of their competitors even when facing higher levels of competition, they are based on stated responses, and may potentially overstate the percentage of firms that are not aware of primary competitors' positions. I explore additional evidence of baseline price positions to provide a more complete picture of the baseline landscape before analyzing experimental results on the impact of competitor information.[31]

5.2 Dispersion in baseline price positioning

Consistent with the interpretation that firms may lack knowledge of their competitors, firms display dispersion in their price positioning across the similar levels of quality. On average, firms with higher quality charge higher prices (Figure 5(a)). Quality represents a sum of the firm's polish brand

[29] The experimental sample excludes salons with 1-2.5 stars for Yelp ratings. However, both the treatment information and measures of competition are determined using the full sample of verified businesses in the area to identify the geographically closest competitors based on longitude and latitude coordinates.

[30] From this point onwards, I only show results for distance from the nearest competitor when referring to competition levels, but all results are robust to using the baseline price dispersion measure (which can be found in the appendix).

[31] I further explore measures of competitor knowledge using incentivized responses to questions on competitor knowledge at endline.

level, cleanliness, and luxuriousness, and ranges from 3 (lowest quality) to 11 (highest quality).[32] This positive correlation suggests that despite the inevitable noise present in the quality measures,[33] they capture some signal of offered quality, and is robust to using a standardized sum of polish brands, cleanliness, and luxuriousness, as well as each individual measure alone (Appendix Figure C.1 and C.2).

However, firms display a large dispersion in their pricing. Figure 5(b) plots the same figure as Figure 5(a), but shows every firm observation within each quality level sorted by price, along with the interquartile range. The coefficient of variation in price across all observations is 37.8%. Within each quality level, the coefficient of variation in price ranges from 22.2% to 47%. Strikingly, at $15 for a regular manicure, firms offer the entire range of quality. This dispersion persists when controlling for ZIP code fixed effects (Appendix Figure C.3). The largest dispersion in price positioning can be observed in the middle of the quality distribution, relative to those offering the lowest or highest levels of quality and price.[34] Consistent with results on baseline competitor knowledge, this dispersion remains across firms that face higher levels of competition (Appendix Figure C.4).

While consistent with widespread evidence of price dispersion across many other contexts such across general retail (Lach 2002), prescription drugs (Sorensen 2000), gasoline (Lewis 2008), as well as online consumer goods markets (Brynjolfsson and Smith 2000, Baye, Morgan, and Scholten 2004, Ellison et al 2018), this dispersion in prices may be explained at least in part by other firm attributes such as the level of customer service, the use of discounting from posted prices, as well as the noise present in quality measures.

5.3 Discrepancies between firms' observed and stated positions

Consistent with the interpretation that firms lack knowledge of their competitors and are dispersed in their positioning relative to other firms, many firms' observed positions do not match their stated positions. Firms provide varying descriptions of their positioning, which can be categorized into five broad types, loosely based on Porter's (1980) "generic strategies": low price, quality differentiation, horizontal differentiation, focus, and "stuck in the middle" (or according to firms' own descriptions, "nothing"). Figure 6 shows the descriptions that treatment firms provide of their positioning prior to treatment, prompted by the question, "What sets you apart from your competitors?".[35] The largest category of answers maps to quality differentiation: offering quality service and products (30%) or cleanliness (23%). The second largest category (13%) is "nothing", which includes answers like "we haven't looked at other salons, so we don't know," or "we offer the same services as other salons." The

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[32] As described in Section 4.2, polish brands range from 1 to 3 based on retail price per bottle, and cleanliness and luxuriousness are rated on a scale of 1 to 4.

[33] Noise may arise from variation in the date and time of the canvasser visit, as well as variation across canvassers – despite the measures taken using rubrics and data validation to increase accuracy. Furthermore, there may be measures of quality that are not captured in these, such as the level of customer service or friendliness.

[34] The same pattern can be observed when plotting by a standardized sum of each quality measure, or each individual measure of quality alone.

[35] As described in Section 4, each answer was coded by two independent research assistants. Any conflicts were sent to a third independent research assistant who resolved the conflict.

third largest category is low price (8%). Other answers loosely map to horizontal differentiation (e.g. service variety or location), and focus (e.g. specific customer segment or service specialty).

Although firms generally mention only a few types of positions, there remains much dispersion in positioning within each stated type. For example, when plotting observed price-quality positions for all firms that specify low price as their positioning, prices range from \$5 to \$18, and quality ranges from 3 to 8. This variation remains within neighborhoods. For example, in 10128, a ZIP code located in the Upper East Side in Manhattan, firms offer a range of prices, from \$9 to \$35, as well as a range of quality levels from 4 to 9. Even when focusing only on firms that offer quality differentiation within this ZIP code, much dispersion remains, with price levels from \$10 to \$30 and quality levels from 6 to 9.

6 Empirical strategy: identifying the value of competitor information

Baseline measures of competitor knowledge and price positioning suggest that firms may lack knowledge of their competitors. To more precisely evaluate this and the impact of competitor information, I analyze firm responses to the experimental treatment.

For all analyses, my base econometric specification leverages a difference-in-differences model to evaluate the difference in price changes after a canvassing visit across control and treatment firms.

Specifically, I run the following regression:

$$y_{iswt} = \beta_0 + \beta_1 Post_{iswt} * Treat_{isw} + \beta_2 Post_{iswt} + \beta_3 Treat_{isw} + \gamma_w + \delta_s + \eta_t + \varepsilon_{iswt} \tag{1}$$

where y_{iswt} is the outcome of interest for firm i in randomization strata s visited in week w, measured at month t. The primary outcome of interest is whether firms adjust their pricing, which is measured by a binary variable indicating whether a firm's regular manicure price in a given month is different from the price observed at baseline (May 2018). I decompose this price change into a price increase or decrease relative to baseline, and also examine percentage changes in price levels.

$Post_{iswt}$ is an indicator that takes value 1 for firms in either control or treatment starting the month they are visited by a Yelp canvasser until the end of the study and 0 otherwise. $Treat_{isw}$ is an indicator that takes value for 1 for firms assigned to treatment and 0 otherwise. γ_w controls for canvasser visit week fixed effects, δ_s controls for randomization strata fixed effects, and η_t controls for data collection survey month fixed effects. ε_{iswt} is an idiosyncratic error term. Since the unit of randomization is the firm, standard errors are clustered at the firm level (Abadie et al 2017).

β_1 identifies the treatment effect for treatment firms relative to control firms and is the main coefficient of interest. β_2 captures the passing of time and any effect of a canvasser visit across all firms, and β_3 identifies any pre-treatment differences between treatment and control firms. While fixed effects are not necessary for identification given that treatment is randomly assigned, I run this specification with and without fixed effects to account for any random differences across experimental groups.

7 The impact of competitor information on firm pricing

Once firms receive information on competitor prices, they change their pricing in ways that suggest that this information may be valuable. Treatment firms are 16.8% more likely to change their prices following the canvassing visit, relative to 17.3% of control firms that change their prices. At the time of the canvasser visit, 19% of firms mention that they plan to change their prices based on the competitor information they received, supporting the interpretation that the information drives these price changes. Firms change prices by both increasing and decreasing prices. Rather than differentiating from competitors, firms that were charging higher prices compared to their nearest competitor decrease their prices, while firms that were charging lower prices compared to their nearest competitor increase their prices. Firms that were over- or under-pricing relative to their quality compared to competitor offerings respond most to treatment.

7.1 Do treated firms change their pricing?

One reason why firms may lack knowledge of competitor decisions may be that they do not need to know it, if other informative sources such as observing customers and residual market demand offer sufficient statistics for competitor information. This may be the case especially in more competitive markets where strategic interaction may be limited. Consistent with this view, some popular management articles even advise managers to ignore competitors, with well-known executives like Jeff Bezos of Amazon and Larry Page of Google echoing this advice.[36] While this advice may be driven by potential concerns of distraction or hindrance to originality, underlying it is the suggestion that firms may be able to obtain functionally equivalent insights without paying close attention to competitor decisions.

If this were the case, the competitor information treatment should have little effect on treated firms' likelihood to change prices after canvasser visits, compared to control firms. To investigate whether treatment leads firms to be more likely to change their pricing, I first explore pricing patterns in this industry across time. Given seasonal variation in demand, firms display seasonality in when they change prices. They are more likely to use promotions in slower months (fall and winter)[37], and generally change menu prices at the end of the year between December to January. These patterns are reflected in Appendix Figure D.1, and are consistent with those documented in industry magazines and confirmed by salon managers and owners (Nails Magazine 2008, 2018).

Firms assigned to treatment show a higher likelihood of changing prices compared to control firms following the canvasser visit. Figure 7 plots the raw percentage of control versus treatment firms that

[36] In his 2019 letter to shareholders, Jeff Bezos stated that he believed it was important to obsess over customers, not competitors. Larry Page has been cited as saying "You don't want to be looking at your competitors."

[37] As discussed in later sections, 24.7% of firms use promotions of any kind, and 10.1% of firms use demand-based promotions (based on hours of week, days of week).

charge a different price compared to their baseline price in the spring of 2018,[38] in each month before and after the canvassing visit.[39] At the time of the canvassing visit, approximately 12% of firms have changed their prices relative to baseline, which mostly reflect firms that use promotions that may be captured at the time of the phone calls, as well as any firms that changed prices between baseline and the first month of data collection. At the time of the canvasser visit, there is little difference in the likelihood that a firm charges a different price from baseline between the control and treatment group, as expected by randomization and the balance of baseline variables. In the months following the canvasser visit, firms that are assigned to receive the competitor information treatment show a higher likelihood of changing prices by approximately 2-4 percentage points compared to control firms.

While these plots suggest that providing information on competitor positions leads firms to change their own price positioning, they do not isolate the precise effect of treatment. Estimating intention to treat effects using the econometric specification in Section 6 provides a more systematic analysis, addressing the unbalanced panel, noise from any small pre-treatment differences, and the slight delay of canvasser visits across treatment firms, which are reflected in the raw data. I now turn to these regression results.

Table 4 shows the intention to treat estimates of the competitor information on firms' likelihood of changing their price: treatment firms show a significantly higher likelihood of changing prices by 16.8% (3 percentage points) compared to control firms after the canvassing visit. Estimates of the treatment effect are stable across all specifications, which control for any pre-visit differences between control and treatment firms, the passing of time, and the week of the canvasser visit, with columns (2)-(4) additionally controlling for month and/or strata fixed effects to absorb noise from seasonality and location.[40] As shown in the last two rows of the table, 17.3% of control firms change their prices in the six to ten months following the canvasser visit. This effect encompasses not only changes in posted prices, but also any increased use of promotions that may be captured in data collection, although it likely under-captures the full extent of this channel.

Table 5 shows that treatment firms change their prices by both increasing and decreasing prices.[41] Column (1) shows that 3.6% of observations among control firms show a price decrease relative to

[38] To ensure accuracy in baseline prices, these were collected between early February and mid-May of 2018, in order to allow for multiple validations of each price.

[39] Each month begins in the 15^{th} of each month, in order to count months following canvasser visits, which began in June 18^{th}. The number of observations collected in each month vary, due to some firms not answering their phones or having closed. Due to the staggered timeline of visits across the 12 months of data collection, only firms that were visited in the first set of canvassing visits between June 15 and July 15 have observations 10 months after the canvassing visit. Similarly, only firms that were visited in the last set of canvassing visits between October 15 and November 15 have observations 4 months prior to the canvassing visit.

[40] Strata and month fixed effects are not necessary for identification given that treatment is randomly assigned, but help absorb noise. Given potential non-spurious imbalance between control and treatment groups in canvasser visit timing, I control for the week of the canvasser visit across all specifications. The estimate for "Treat" captures any pre-visit differences between control and treatment firms, which are small and statistically insignificant. The estimate for "Post" reflects control firms' likelihood of changing prices after the canvassing visit, but also captures a mechanical increase from the passing of time.

[41] For all results going forward, I report results from my base specification with canvasser visit week. Results are robust to adding strata and/or month fixed effects.

baseline in the months following the canvasser visit.[42] Treatment firms are 13.9% (0.5 percentage points) more likely to decrease their prices in the post-visit period, though the estimate is noisy. A larger percentage of firms increase their prices in the months following the canvasser visit, as shown in Column (2). Treatment firms are 16.8% (2.3 percentage points) more likely to increase their prices in the post-period, relative to 13.7% of observations among control firms. These changes result in a slight increase in price level among treatment firms of 2.3%, which represents an increase of approximately \$0.30 relative to the average price level among control firms of \$13.20 (Column 3).

During the canvasser visit, 19% of treatment firms show interest in the competitor information and indicate that they intend to change their prices, providing supportive evidence that the increased likelihood of treated firms to change prices may be at least partly driven by the competitor information treatment. Categorizing canvassers' notes on their visit shows a diversity of responses (Appendix Figure A.5). A majority (58%) of firms positively engage with Yelp canvassers, either showing active interest in the conversation or logging into their Yelp page. The 19% of firms who show interest in competitor information comment that they want to receive more pricing information over time or for their other services, show surprise in learning how their prices compare to their competitors, and indicate plans to change their pricing. For example, one note comments, "manager was surprised that her salon charges the lowest price in the area. She is thinking of raising her prices." Another salon owner expresses surprise that a nearby salon charged \$45 for a manicure, and notes that she will research what this salon offers to see how she might be able to also raise her prices. 16% of firms show no interest in Yelp or the pricing information.

These results suggest that information on competitor pricing leads firms to be more likely to change their own pricing decisions. However, it is difficult to tease apart whether this effect may be driven by the competitor information – and firms' lack of knowledge of it prior to treatment, or simply by increased salience of pricing. It is possible that increased salience may work through a similar channel, where it triggers firms to search for additional information about pricing in the market and decisions across their competitors. Yet, it could also be that salience leads firms to make changes to their pricing independently from competitor pricing, such as by deciding to make their end-of-year changes earlier than planned. To further unpack whether firms appear to change their pricing based on competitor information, I explore next how firms change their pricing in response to treatment.

7.2 How do firms change their pricing?

I explore heterogeneity in treatment effects to understand how firms change their pricing. While a large literature suggests that more information should at least weakly improve firm decisions (Blackwell 1953, Galbraith 1974, McAfee and Brynjolfsson 2012, Brynjolfsson and McElheran 2016), there is less insight on how information on competitor decisions might change firm decisions. Two alternatives appear to be possible.

[42] 3.6% of months among control firms reflect a price decrease, which does not mean that 3.6% of firms are persistently decreasing prices, but that 3.6% of the monthly observations show a price decrease, which may reflect the use of promotions.

First, the positioning view suggests that competitor information may result in more differentiated positioning, as industry analysis leads firms to arrive at more unique and distinctive positions compared to their competitors (Caves and Porter 1977, Porter 1980). Using competitor data to inform price positioning may similarly lead firms to move to a better position, which, within this context, would result in firms shifting both their price and quality decisions such that they end up being more spread out in their positioning.

However, firms may also align their decisions with their competitors. A strand of literature suggests that firms may match the decisions of their competitors for a variety of reasons: to economize on their search costs in the face of uncertainty, follow others who may have superior information, or maintain competitive parity from the view of consumers (DiMaggio and Powell 1983, Haveman 1993, Greve 1996, Henisz and Delios 2001, Lieberman and Asaba 2006). Within this context, firms may seek to adjust their pricing to match price-quality combinations offered by competitors to make consumers more comfortable with their offering, which could also be thought of as a class of managerial best practices, as firms that are initially mispricing or mispositioned move to the productivity frontier (Bloom and Van Reenen 2007, McKenzie and Woodruff 2017). This would suggest that when firms learn competitor information, they align their pricing with their own quality decisions relative to competitor offerings, increasing their prices if they charge lower prices compared to their competitors and decreasing prices if they charge higher prices compared to their competitors.

I find evidence consistent with this second interpretation that treatment firms increase or decrease prices to better align with the pricing of their nearest competitors. Figure 8(a) shows treatment effects on price change, price levels, price increase and decrease by firms' baseline price position relative to their geographically nearest competitor at baseline (details reported in Appendix Table E.1 Panel A). Firms with lower or higher baseline prices relative to their nearest competitor are more likely to change prices, compared to firms with the same baseline price relative to their nearest competitor. Firms with lower baseline prices are more likely to increase their price, while firms with higher baseline prices are more likely to decrease their price. This evidence is consistent with firms matching rather than differentiating from competitors, as has been suggested in qualitative studies of industries such as online news (Boczkowski 2010).

This matching behavior may be driven by firms that are mispriced or mispositioned. Consistent with this interpretation, competitor information appears to lead firms to better align their pricing to their quality decisions, with firms that were over- or under-pricing relative to their quality responding most to treatment. Figure 8(b) shows how treatment effects vary based on the baseline alignment between pricing and quality (details reported in Appendix Table E.1 Panel B).[43] The degree of misalignment in baseline decisions is measured by the absolute error from the best-fit line regressing baseline price on quality and ZIP code fixed effects, with firms farther away from the best-fit line having higher misalignment. Treatment firms with higher misalignment in their pricing relative to quality are more likely to change prices – both increasing and decreasing prices.

Appendix Figure E.1 reports additional heterogeneous treatment effects along other firm dimensions, including firm size, age, baseline price, scope, chain status, and firms' baseline pricing relative to their 9 nearest competitors summarized on the postcard.

[43] These results are robust to different specifications (e.g. continuous, tertile, or quartile measures of misalignment).

Together, these results provide evidence that some firms indeed may not have been aware of easily accessible competitor information, and that this information is decision-relevant. These findings are consistent with evidence from prior work that firms may be farther away from the optimum in practice (e.g. Bloom et al 2013, DellaVigna and Gentzkow 2019), and that digitization may not eliminate all frictions (e.g. Brynjolfsson and Smith 2000, Ellison et al 2018). Furthermore, they build on prior research suggesting that firms may have limited market knowledge due to various barriers (Porac et al 1989, Baum and Lant 2003, Kaplan and Eggers 2009), by showing that firms may lack competitor knowledge even when this information is easily accessible.

8 The impact of competitor information on performance

The findings so far suggest that many firms appear to lack awareness of a key competitor decision on pricing, and that once they are randomly provided with this information, they are more likely to change their own pricing to align more closely to their nearby competitors. In this section, I explore data on proxies of performance for some suggestive insights on whether these changes might be performance enhancing.

Treatment firms appear to see 15% higher number of calls, page views, and map direction views on Yelp, although sales tax data from the City of San Francisco may be able to provide a fuller picture of performance effects. These effects do not appear to be driven by firms' increased direct engagement with the Yelp platform, and are mostly driven by firms that were over-pricing at baseline.

8.1 Intention to treat estimates of competitor information on performance proxies

Columns (1)-(3) in Table 6 Panel A show that following canvasser visits, treatment firms ultimately receive 14.8% more calls, 14.6% more page views, and 14.5% more map directions views from customers on Yelp compared to control firms.[44] These gains appear to materialize for the median treatment firm, rather than shifting the full distribution (Appendix Figure F.1). Furthermore, gains appear to be driven more by firms that were over-pricing at baseline, who are more likely to respond to treatment by decreasing their prices (Appendix Figure F.2).

While these Yelp proxies of performance provide some suggestive evidence, they have at least two key limitations in capturing effects on performance. First, they capture consumers' purchase intentions and do not reflect actual sales. Second, while these measures may reflect demand among customers who search, they are not as likely to capture demand among regular customers. To fully explore the performance effects, I am obtaining sales tax data from the City of San Francisco, where the data relevant for the experimental time period (2019) will be available in summer 2020 due to the timeline of tax collection.

Additional measures provide suggestive supportive evidence. Back-of-the-envelope calculations mapping these purchase intentions to revenues suggest that treatment firms observe an increase in

[44] Due to restrictions in the data sharing agreement, I am not able to publicly share the base level of the number of calls, page views, or map directions views for the control firms.

revenues from these searchers relative to control firms. One concern that stems from measures of purchase intentions is that firms that are decreasing prices may attract more purchase intentions, but in fact reduce firm revenues. To investigate, I construct proxies of revenues using the price that firms charge each month and the number of purchase intentions observed. Interpreting these measures as revenues requires the assumption (1) that each purchase intention leads to a sale – which likely overestimates the effect especially in the case of page views, and (2) that every customer purchases a regular manicure and not any other services – which likely underestimates the effect. Therefore, these estimates are useful mostly as a directional guide, and appear to be positive (Appendix Table F.1). Additionally, prior studies estimate positive correlations between purchase intentions and revenues. Using revenue data from the Washington State Department of revenue, Dai et al 2018 found that a 10% increase in quarterly page views is correlated with a 3.3% increase in quarterly revenue.[45] Based on this estimate, a back-of-the-envelope calculation suggests that treatment firms observe 4.8% higher revenues compared to control firms from pageviews.

Furthermore, treatment firms appear to be less likely to have availability for an appointment during a peak hour the next day, suggesting that they may not be losing revenue from regular customers while increasing revenue from searchers. Consistent with the interpretation that treatment firms see higher performance, column (4) in Table 6 Panel A shows a 2.7% decrease in the likelihood of a next-day availability during a peak time (4-5pm) among treatment firms, relative to 77.2% of control firms that have availability, although the estimate is imprecise and not statistically significant.

While these results provide suggestive evidence that treatment results in improved performance, there are at least three reasons to be careful about their interpretation, which I am exploring in further work. First, none of these measures capture revenues or profits, but only proxies of them. Sales tax data from San Francisco that will be obtained in 2020 may provide further insights into this mapping. Second, there exists the possibility of spillover effects for performance, where treatment firms steal customers away from control firms. In early analysis of these effects leveraging the differential proportion of treated firms across local markets, I see limited evidence of spillovers and am further investigating robustness.[46] Third, the precise mechanisms through which performance might increase is unclear. Reasonable channels are through passersby and searchers on Yelp – as they either observe prices from outside the firm or become interested in the firm on the search results page that indicates price levels and often precise prices. However, these are only conjectures that are difficult to verify. To better understand what changes might have been made and how customers may have discovered changes made after treatment, I am exploring in ongoing analysis possible

[45] Using historical tax revenue data from 2015, Dai et al (2018) regress logged revenue change on logged change in page views, restaurant fixed effects, and quarterly dummies for a matched set of 835 restaurants, as a back-of-the-envelope calculation. Their estimate of the coefficient on change in pageviews is 32.54%, which was fairly precisely estimated (1% level) with standard errors clustered at the business level.

[46] I explore spillover effects by surveying control firms on whether they heard about pricing information provided by Yelp after endline data collection, as well as by analyzing whether control firms in ZIP codes with a higher proportion of treated firms are more likely to change prices and observe lower purchase intentions. While I find little evidence of spillovers, these performance effects are likely to at least partly capture business stealing, unless market demand is growing sufficiently over time. In terms of the main treatment effect on price change, any spillover effects would bias any estimate of a treatment effect downwards, as control firms also become more likely to change prices.

mechanisms, by analyzing Yelp ratings, processing review text, classifying uploaded photos, and analyzing changes in endline quality measures.

8.2 Do treatment firms increase their engagement on Yelp?

One potential mechanism through which treatment might result in higher performance is by motivating firms to increase their engagement with the Yelp platform, since treatment is delivered by Yelp canvassers. However, analyzing the effect of treatment on firms' engagement indicators suggests that treatment firms do not increase their engagement on Yelp compared to control firms.

Columns (1) to (3) in Table 6 Panel B show that in the months following the canvasser visit, treatment firms are not more likely than control firms to log in on Yelp, claim their Yelp page, or purchase advertising, as indicated by estimates that are close to zero with fairly large standard errors. The treatment effect on review comments in Column (5), which indicates firms' comments on reviews received from users, is also small and noisy. The estimate on direct responses is more precise, suggesting a 1.3% higher likelihood of treatment firms to send direct responses. However, this measure reflects an increase in customer interest more than business engagement metrics, as firms must first receive a request from a customer about a quote or an appointment to be able to send direct responses. These results suggest that observed performance effects do not appear to be driven by treatment firms' higher engagement with Yelp.

9 Why do firms lack knowledge of key competitor decisions?

Given that information on competitor prices appears to be both readily accessible and decision-relevant, the natural question is why many firms had not previously invested in this information on their own. I consider several possible explanations, such as limited competition reducing the value of competitor information and firms' lack of capabilities to use the information leading them to not invest. I find limited evidence that either can fully explain firms' lack of knowledge. Evidence from informal interviews and a follow-up experiment among control firms suggests that attentional costs may be an important factor, consistent with research on the importance of managerial attention. Managers appear to underestimate the value of paying attention to competitor information, until they are triggered to explicit reevaluate their knowledge.

9.1 Possible explanations

If readily available competitor information improves firm decisions, this poses a puzzle: why did firms not invest in this information on their own? To tease apart possible mechanisms driving why firms may fail to use readily available competitor information, I consider the following framework, where a firm chooses whether to pay attention to competitor information.

The firm should trade off its expected value from paying attention to competitor information, v, against the costs of doing so, c, and invest in competitor information if $v - c > 0$. In this setting, c

may include attentional costs from gathering competitor information or processing it, which may remain high even when information is readily available (Stigler 1961, Sims 2003, Gabaix 2014, Caplin and Dean 2015, Grennan and Swanson 2018). If v appears to be positive, but firms do not seem to be paying attention to this information, what might explain this puzzle? I consider three main categories of explanations for why this might be the case.

First, it may be that while v is on average positive, it varies heterogeneously across markets. In markets with low competition, competitor information may have lower value compared to the costs of processing the information, such that $\underline{v} - c < 0$. This would suggest that the competitor information treatment, by marginally lowering c, may lead those with $\underline{v} < v$ to change their prices.

Second, it may be that v varies heterogeneously across firms depending on their prior capabilities. Even when competitor information could be valuable, firms may suffer from other barriers to realizing its value, such as lower capabilities based on prior experience to take advantage of new information (Cohen and Levinthal 1990). This heterogeneity could equally be considered on the cost side, where firms without relevant capabilities incur higher information processing costs, with similar implications for findings. In this setting, firms that do not know how to interpret competitor prices may not able to process it in a way that improves their decisions. This would predict that treatment has no effect on firms that lack these capabilities, since the treatment does not change their v.

Third, managers may misestimate v, estimating a $\hat{v} < v$. A large literature on cognition and strategy has investigated how managers rely on cognitive filters, categories, and mental models, which may be incomplete or inaccurate (Simon 1955, Cyert and March 1963, Menon and Yao 2018). These biases could lead managers to overlook some competitors, or underestimate the value of paying attention to any competitors altogether (Porac et al 1989, Reger and Huff 1993, Baum and Lant 2003, Tripsas and Gavetti 2000, Kaplan, Murray, and Henderson 2003, Kaplan 2011). Recent approaches to cognition also suggest that differential cognitive abilities of managers, especially in this case in attention-related abilities, may lead to biased estimates of v (Hanna, Mullainathan, and Schwartzstein 2014, Helfat and Peteraf 2015, DellaVigna and Gentzkow 2017, Golman, Hagmann, and Loewenstein 2017).

9.2 Limited evidence of lack of competition or capabilities

I evaluate each explanation in turn, and find limited evidence that limited competition or a lack of capabilities to take advantage of the information can explain why firms might lack knowledge of easily accessible competitor information.

The first explanation suggests that one way to rationalize the high percentage of firms that lack competitor knowledge at baseline may be that unaware firms facing lower competition derive limited value from competitor information, and unaware firms facing higher competition use other sources of knowledge such as observing residual market demand, which serve as sufficient statistics. This explanation would suggest that providing competitor information should lead to price changes by firms in less competitive markets, who do not gain sufficient value from competitor information to incur the cost themselves but benefit from information being fully freely delivered.

I find limited support for this explanation. Appendix Table E.2 shows estimates of the treatment effect by the level of competition, as measured by the firm's distance from its nearest competitor.

Treatment firms that face lower levels of competition (indicated by farther distance from the nearest competitor and higher price dispersion among its nearest nine competitors) do not appear to be more likely to change their prices after the canvassing visit compared to control firms. In contrast, treatment firms facing above-median levels of competition show a ~3 percentage point higher likelihood of changing prices compared to control firms.[47] This result is further supported by evidence at baseline that firms facing lower competition do not appear to be substantially more dispersed in their pricing positions, as discussed in Section 1.5.2. This suggests that while higher levels of competition may not be sufficient to substantially raise firms' awareness of competitors, competitive forces may increase the value of competitor information and the likelihood that it triggers responses from firms.

The second explanation proposes that another reason why firms lack competitor knowledge may be that some are unable to take advantage of it. Prior research has documented the importance of relevant capabilities in being able to recognize the value of new information and apply it (Cohen and Levinthal 1990, Henderson and Cockburn 1994). In this case, firms without relevant pricing capabilities may not have the skills to take advantage of competitor information to improve their decisions, and thus not invest in acquiring the information. For example, firms may need a prior understanding of customer preferences across the market, or analytic skills to process optimal responses to many competitors, in order to use the information to their benefit (Dutta et al 2003, Zbaracki and Bergen 2010, Li et al 2017). Given that treatment firms appear to change their pricing in performance-enhancing ways on average, this explanation would suggest that firms that respond to treatment are mostly those with relevant capabilities, who may be adjusting earlier than they might have otherwise.

To explore this possibility, I code whether firms used promotions at baseline by identifying those that offer special demand-based promotions for regular manicures, pedicures, or packages.[48] 10.1% of firms offer promotions based on expectations of customer demand, such as slower times of day (before 3pm), days of the week (Monday to Wednesday), or months of the year (winter promotions). The use of these promotions may be linked to sophistication in pricing, as it indicates an understanding of the distribution of customer preferences and how they fluctuate. Conversations with managers and owners support this interpretation: they explain that they base these promotions on when they knew customer demand would slow. I also observe similar trends in the pricing data across control firms, where firms appear to be more likely to change prices in the winter months.

However, I find little supportive evidence that firms lack competitor knowledge due to their lack of relevant pricing capabilities to take advantage of the information. Treatment firms that did not use demand-based promotions at baseline appear to be more likely to respond to competitor information,

[47] This result that treatment firms that face higher levels of competition are more likely to respond is robust to using other cutoffs such as quartiles. This evidence raises the question: why do these firms survive? One explanation may be that I am observing short-run dynamics. Another explanation may be that there is some friction that limits competition. For example, quality firms may be capacity constrained, which reduces the strength of the selection mechanism in the market. My results likely do not generalize to perfectly competitive markets in the long run.

[48] Cash or credit card discounts are not included in this coding, as almost every firm uses these discounts. I also exclude promotions for new customers, repeat visits, and group- and birthday-based discounts, as these are also common and do not indicate sophistication with pricing based on knowledge of fluctuating customer demand. However, the results are robust to using this broader definition of promotions.

while treatment effect estimates are small and noisy for firms that used promotions at baseline (Appendix Table E.3).

9.3 Evidence of managerial inattention

Evidence from informal interviews suggests that attentional costs may have been an important factor. Managers appear to underestimate the value of this information because they hold outdated information that leads them to believe that they already know it. I further explore the extent to which this mechanism might explain why firms are not aware of competitor positions, by running a follow-up experiment across control firms.

Informal interviews

Informal interviews with salons provide suggestive evidence that managers may be inattentive to competitor information because outdated information they observed at an earlier point in time leads them to underestimate the value of acquiring information again. These interviews were conducted with 25 pilot salons, and lasted approximately 30 minutes to up to 2 hours.[49] Interviews were open-ended, but based on a common set of questions.

When asked whether they would find information on competitor prices valuable, managers answered that this information would not be useful, explaining that they were already aware of what competitors are doing. Some explained that they can easily observe this information themselves on Yelp, while others emphasized that they have “competitive prices.”

However, when asked to specify who their primary competitors are and what they were charging, most managers could not answer precisely, consistent with responses of treatment firms prior to receiving competitor information. Many managers explained that they were not sure exactly what the price points may be. One salon owner responded, “I thought I knew, but I guess it’s now been a few years since I’ve checked who our competitors are.” Another manager corroborated, “now that I’m trying to answer these questions, it must have been about ten years ago that I last looked at competitors’ prices.” These comments suggest that managers may fail to pay attention to competitor information, due to the belief that outdated information is more recent.

Once given treatment postcards with competitor prices, a few of the managers expressed surprise and stated they would change their prices. For example, one salon manager commented, “Wow, a lot has changed. I should think about how to change my prices. Maybe I can increase it by more than I planned -- I’ll keep it in mind at end of the year.” Treatment firms in the experiment echoed many of these comments, suggesting that inattention may be a potential mechanism that explains their lack of knowledge.

Evidence from a follow-up experiment among control firms

I run a follow-up experiment to explore this explanation for why firms might be inattentive. At endline (between May – August 2019), all firms are visited by data collectors and asked a series of

[49] These conversations were conducted with managers during piloting, across salons in Boston that were outside the experimental sample.

incentivized questions assessing their current knowledge of competitor positions: (1) "what salon is located closest to you?" (2) "what do you think they are charging for a regular manicure?" (3) "How do you think your price compares to your two nearest nail salons?". Once they finish answering all questions, they are provided with answers, based on data collected within the same week to ensure accuracy. If they answer all questions correctly, they receive a $10 Amazon gift card.

I randomly assign all 1,578 control firms to one of two experimental conditions, which vary in the sequence of asking managers if they are interested in signing up to receive information on competitors' pricing before or after answering the incentivized questions. Managers are shown a sample treatment postcard for a salon in a different city, and informed that this can be provided at no cost. Half of the control firms are assigned to be "Asked First" whether they would like to sign up to receive information on the prices of their nearest competitors, and then asked the incentivized questions assessing their knowledge. The other half of the control firms are assigned to be "Asked Last" whether they would like to sign up to receive competitor information, after reevaluating their knowledge by answering questions about their nearest competitors.

Randomizing the sequence of questions enables me to explore managers' demand for competitor information and whether they underestimate its value when they have not been prompted to reevaluate their knowledge. Data collectors record managers' answers to the three incentivized questions, their interest in signing up to receive competitor information, and their comments on follow-up questions on why they are (or are not) interested in signing up for the competitor information. These follow-up reasons can help explore the mechanisms driving managerial inattention, and unpack whether holding outdated information leads managers to underestimate the value of competitor information.

The experiment is currently ongoing, with approximately half of the control salons reached by data collectors.[50] Early results suggest that firms assigned to be asked first whether they are interested in signing up for competitor information before answering incentivized questions are less likely to show a demand for competitor information, consistent with the hypothesis that managers may be inattentive to competitor information until prompted to reassess their knowledge.

10 Conclusion

In this paper, I study the extent to which firms use readily accessible information on key competitor decisions, and how this information impacts firms' strategic choices. I find that despite the centrality of competitor awareness in strategy frameworks, a large percentage of firms appear to be unaware of competitor prices, a key strategic lever in this setting, even though this information is easily attainable. However, once firms receive this information, they are more likely to change their pricing decisions, suggesting that this information is decision-relevant and not obtained through other sources like observing customer demand. Firms change their decisions by aligning their pricing to their relative quality compared to competitor offerings, and these changes are associated with higher proxies of firm performance. I find suggestive evidence that a key factor that drives why firms may

[50] Conditional on being able to converse with 50% of my control salons, I should be sufficiently powered to detect a 10 percentage point difference in signup rates.

lack competitor knowledge is managerial inattention, fueled by outdated knowledge that makes managers underestimate the value of paying attention to new information.

This study focuses on the personal care industry, which has simple strategy spaces that enable precise empirical measurement and identification. As a result, these findings are likely to be most directly applicable to other small and medium enterprises with similar characteristics, which represents a large and important segment of the economy. However, the degree to which they may also apply to larger firms is an open question. Larger firms have far more resources to overcome attentional barriers, but also have more complex strategy spaces and many more dimensions beyond pricing that they could potentially be unaware of. While the specific lack of awareness on competitor pricing may not apply to other contexts, many examples suggest that managerial inattention on various dimensions is not limited to small firms or specific industries (Kaplan, Murray, and Henderson 2003, Eggers and Kaplan 2009), suggesting that it may be a mechanism that is present across many other contexts.

More broadly, data on competitors, consumers, and internal operations are becoming increasingly available across a number of different markets. One particularly relevant context is online platforms, where the design of information can impact the performance of firms on the platform, as well as the growth of the marketplace itself (Iansiti and Levien 2004, Parker and Van Alstyne 2005, Eisenmann 2007, Kapoor and Agarwal 2017, Piezunka, Katila, and Eisenhardt 2015, Rietveld, Schilling, and Bellavitis 2019). Many of these platforms are actively introducing information into their marketplaces, often in hopes of optimizing the supplier side of their marketplaces – such as businesses on Google that fail to update their advertising bids when doing so could increase revenues, or Airbnb hosts that fail to adjust their pricing even as demand grows (Airbnb 2017). These findings suggest that many firms – even across fairly competitive markets – may be farther away from the productivity frontier in their positioning than we may expect, and that relatively simple information interventions have the potential to help them improve their decisions. However, simply making information accessible may not be sufficient to change firm decisions. These findings highlight that as data become increasingly accessible in the digital economy, understanding how managers allocate attention and designing mechanisms to overcome issues of inattention may be increasingly important.

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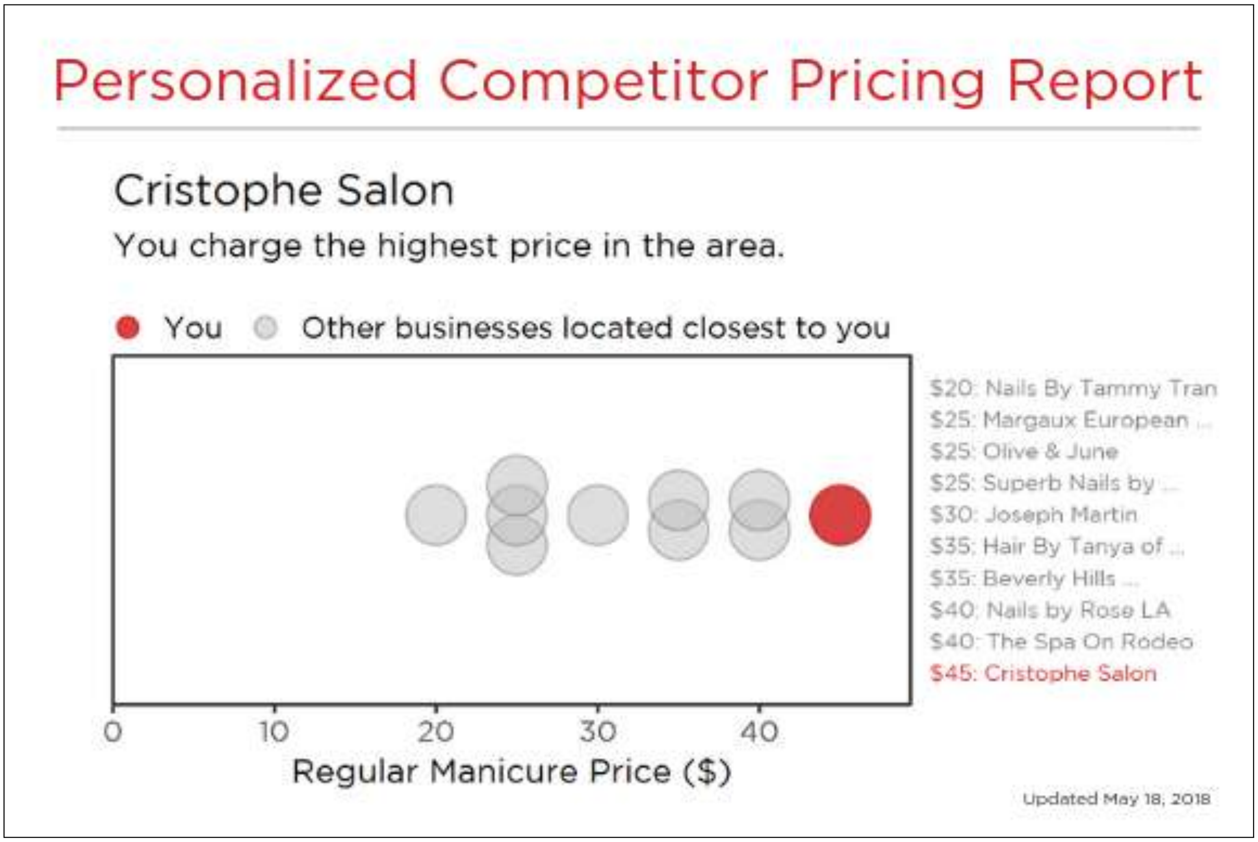
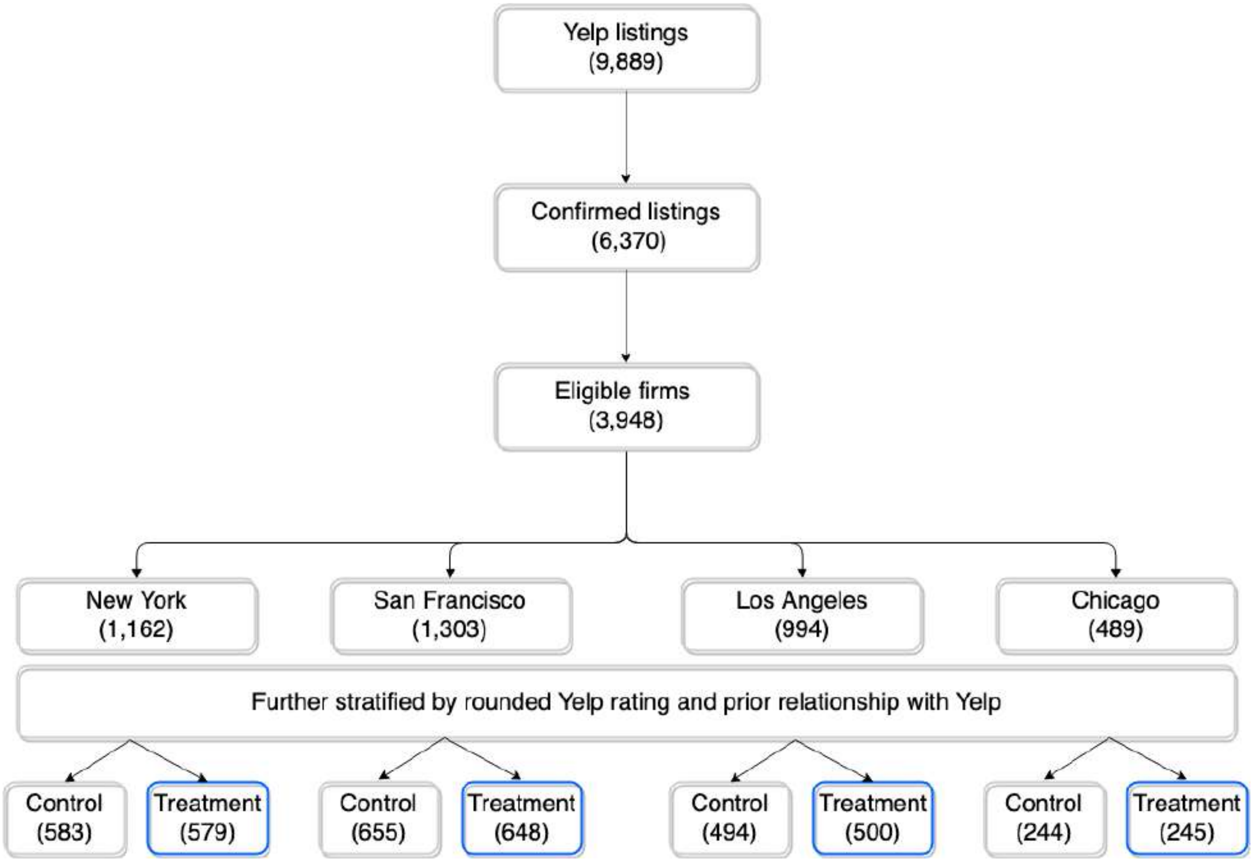
Figure 1: Sample treatment information



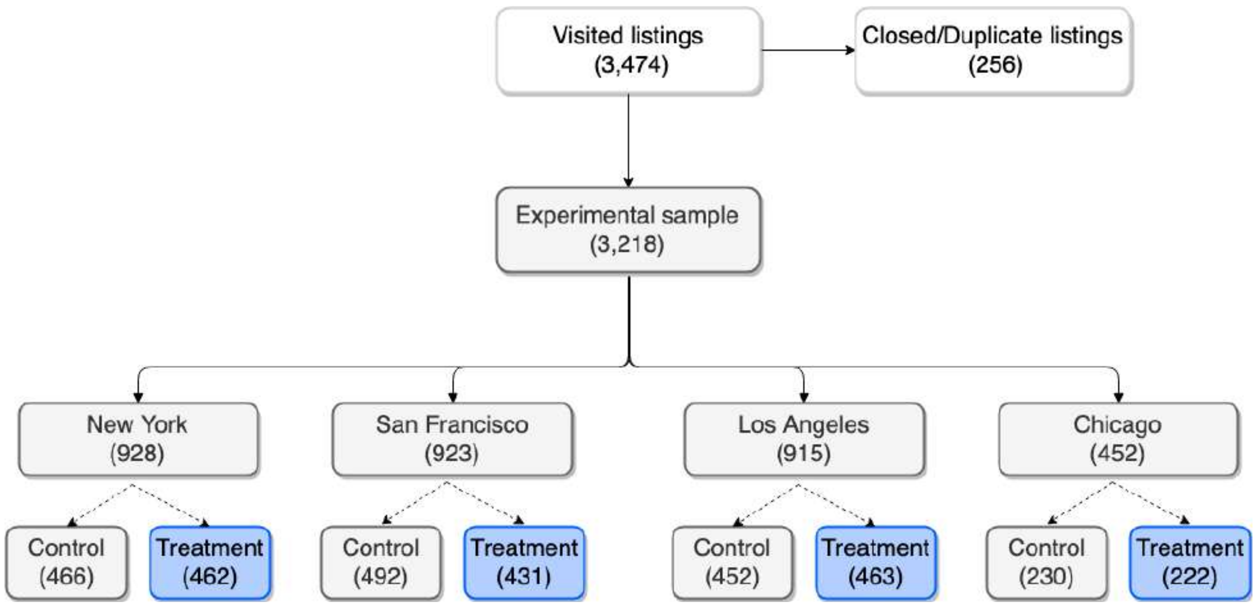
Notes: The back of the marketing postcard for treatment businesses includes a personalized competitor pricing report, a sample of which is shown above. The image shows the firm's regular manicure price compared to its nine geographically closest competitors. To the right of the postcard are the names of each competitor, along with the exact price it charges. The postcard displays the name of the business at the top with a line summarizing the firm's relative price positioning, which is algorithmically generated to take one of four versions: (1) You charge the lowest/highest price in the area. [If applicable: n businesses charge the same price.] (2) Most businesses nearby charge higher/lower prices than you. n businesses charge less/more. (3) Most businesses nearby charge the same or higher/lower prices as you. n businesses charge less/more. (4) Most/All businesses nearby charge the same price as you.

Figure 2: Randomization



Notes: This figure shows the sample definition and randomization map. To determine the set of eligible firms for the experiment, all nail salon listings on Yelp across the San Francisco Bay Area, New York City, Los Angeles, and Chicago are verified via phone calls and Google Streetview, which results in 6,370 confirmed firms. This set is further restricted by excluding any salons with Yelp ratings of 1 to 2.5 stars (out of 5), in order to maximize the likelihood of compliance to treatment. This sample restriction results in an eligible set of 3,948 businesses, which represents 62% of the verified set of firms and the goal Yelp canvassers strived toward reaching, subject to the canvassing budget and timeline. Firms are randomly assigned to control or treatment groups, stratified on its metropolitan area, prior relationship with Yelp, and Yelp rating rounded to the nearest multiple of 0.5.

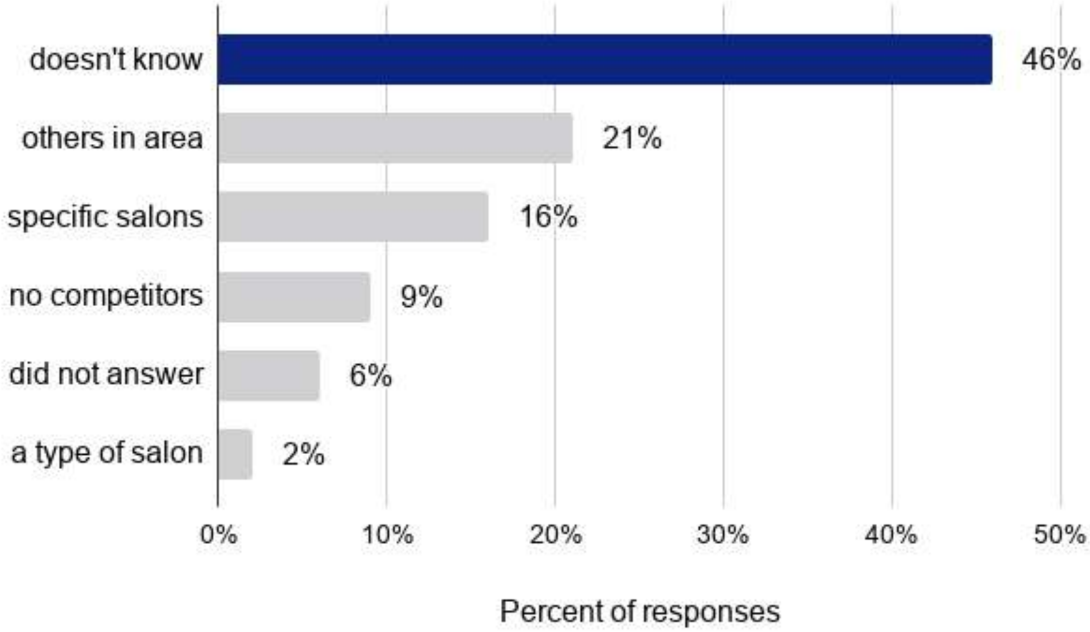
Figure 3: Experimental sample



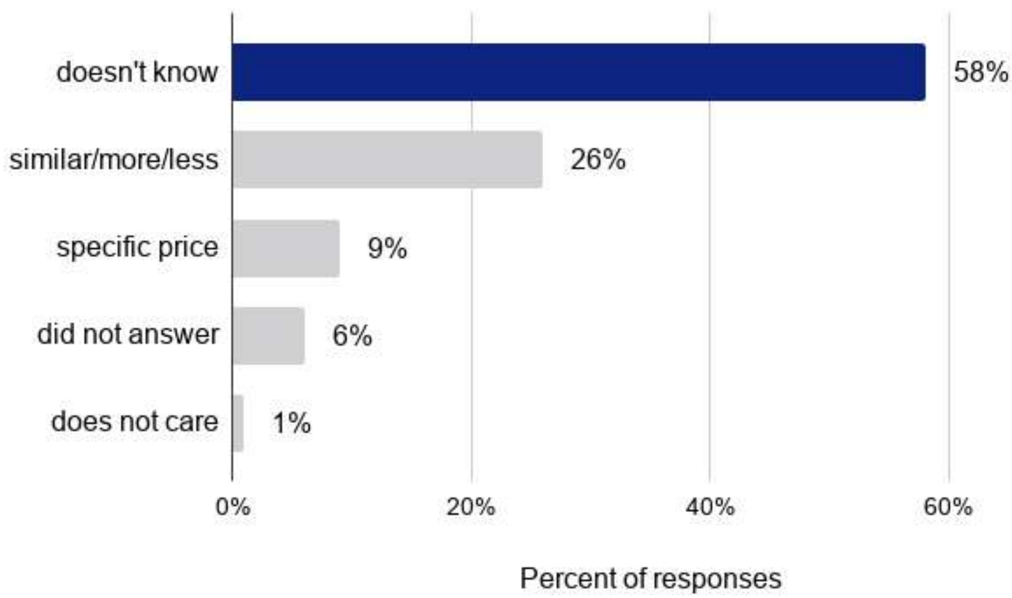
Notes: This figure shows the experimental sample, which results from visits canvassers are able to make among the eligible set within the canvassing timeline. Between June 18 and November 18 of 2018, canvassers are assigned to visit firms, where they are required to finish all visits across control and treatment firms within a neighborhood before moving on to the next neighborhood. Yelp canvassers reach 3,474 businesses. 256 are identified as duplicates or closed by the time that they visit, which results in an experimental sample of 3,218 firms. All firms in the eligible set in Los Angeles and Chicago are reached, and most firms in New York and the San Francisco Bay Area are reached (those that are not reached are in the farther out areas in the Bronx and Queens for New York and the North Bay for San Francisco, as shown in Appendix Figures A.1-2).

Figure 4: Firms' baseline knowledge of competitors

(a) Knowledge of primary competitors across treatment firms



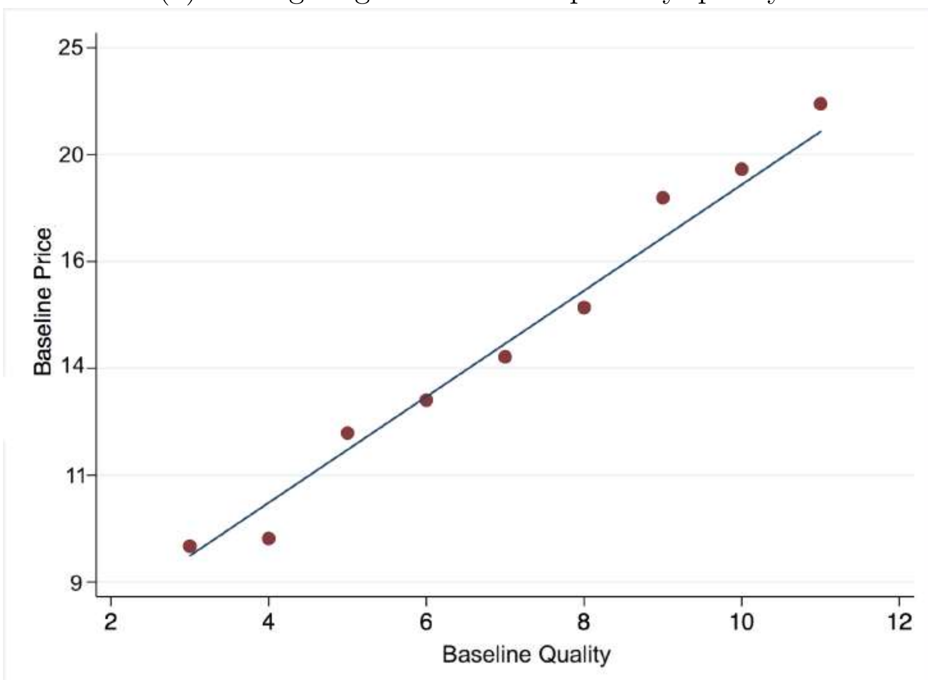
(b) Knowledge of competitor pricing across treatment firms



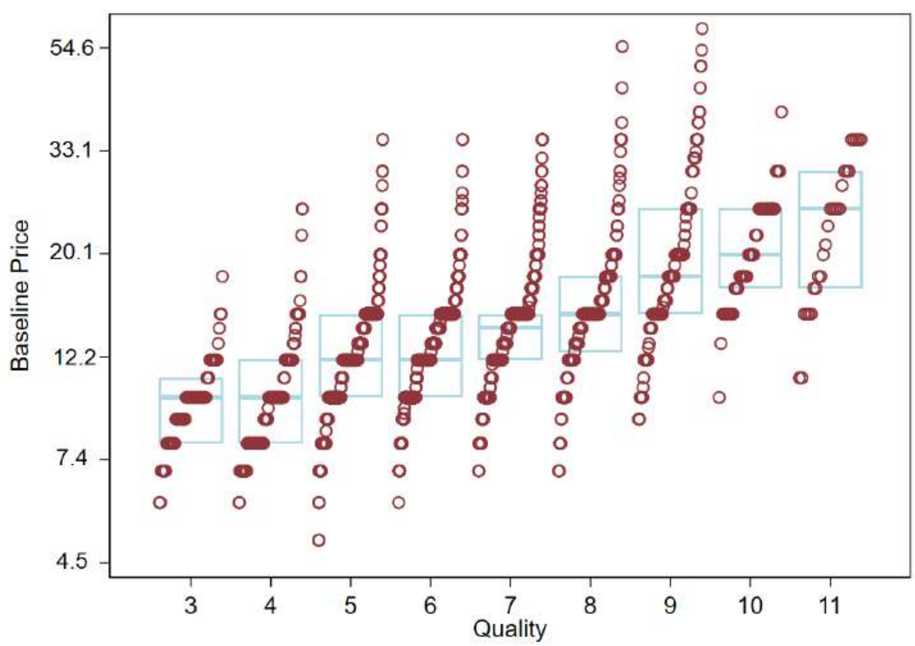
Notes: The top figure (a) shows the breakdown of responses to the question "who do you consider as your primary competitors?" across 1,383 (out of 1,578) treatment firms with whom Yelp canvassers were able to have a conversation to deliver pricing information. Any salons unwilling or too busy to answer the question, or disinterested in answering follow-up questions or continuing the conversation, were counted as "did not answer". The bottom figure (b) shows the breakdown of responses to the question "what do you think [your primary competitor(s)] charge for a regular manicure?" asked by Yelp canvassers to treatment firms.

Figure 5: Mapping price and quality decisions

(a) Average regular manicure price by quality

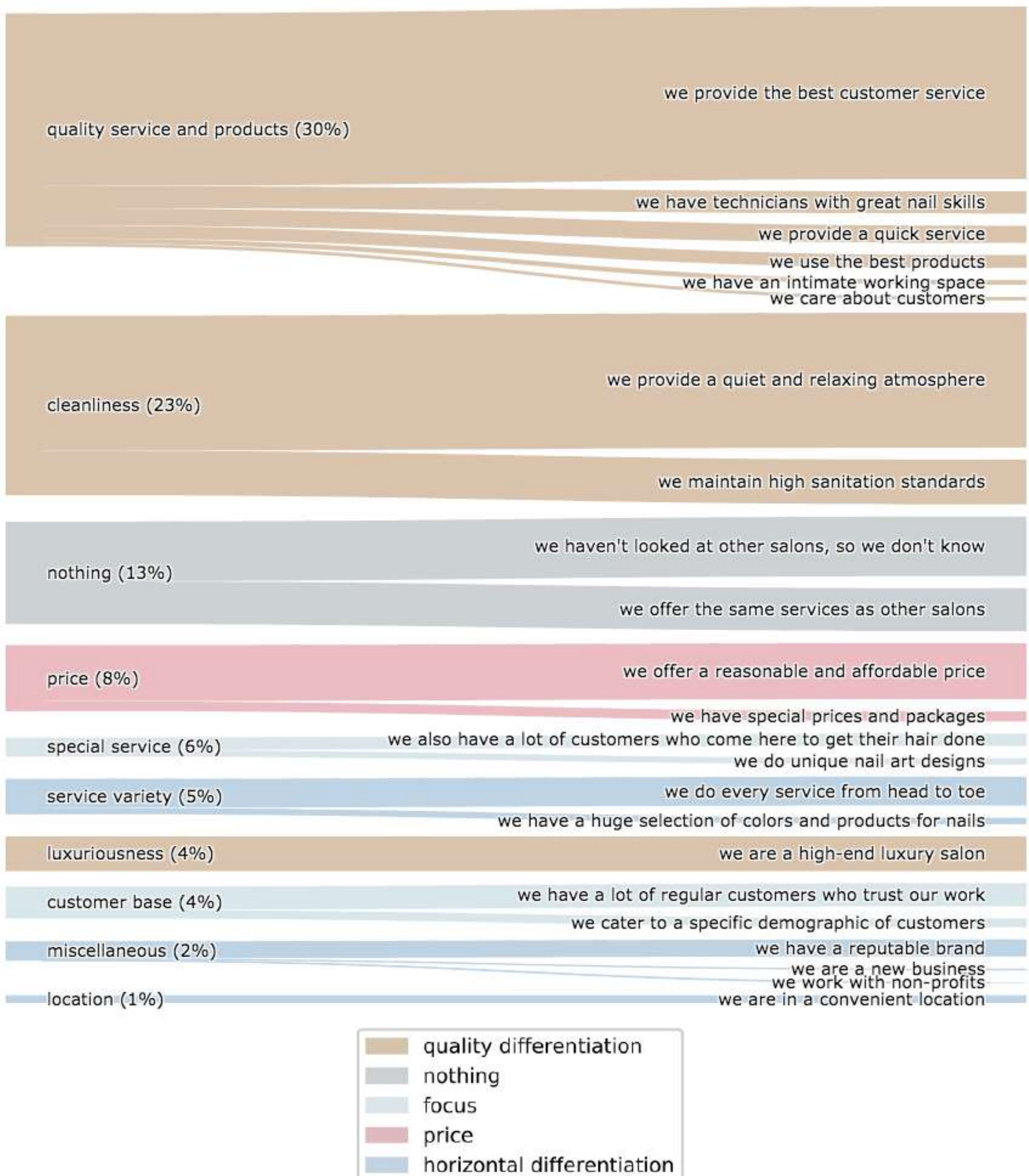


(b) Dispersion in firm pricing by quality



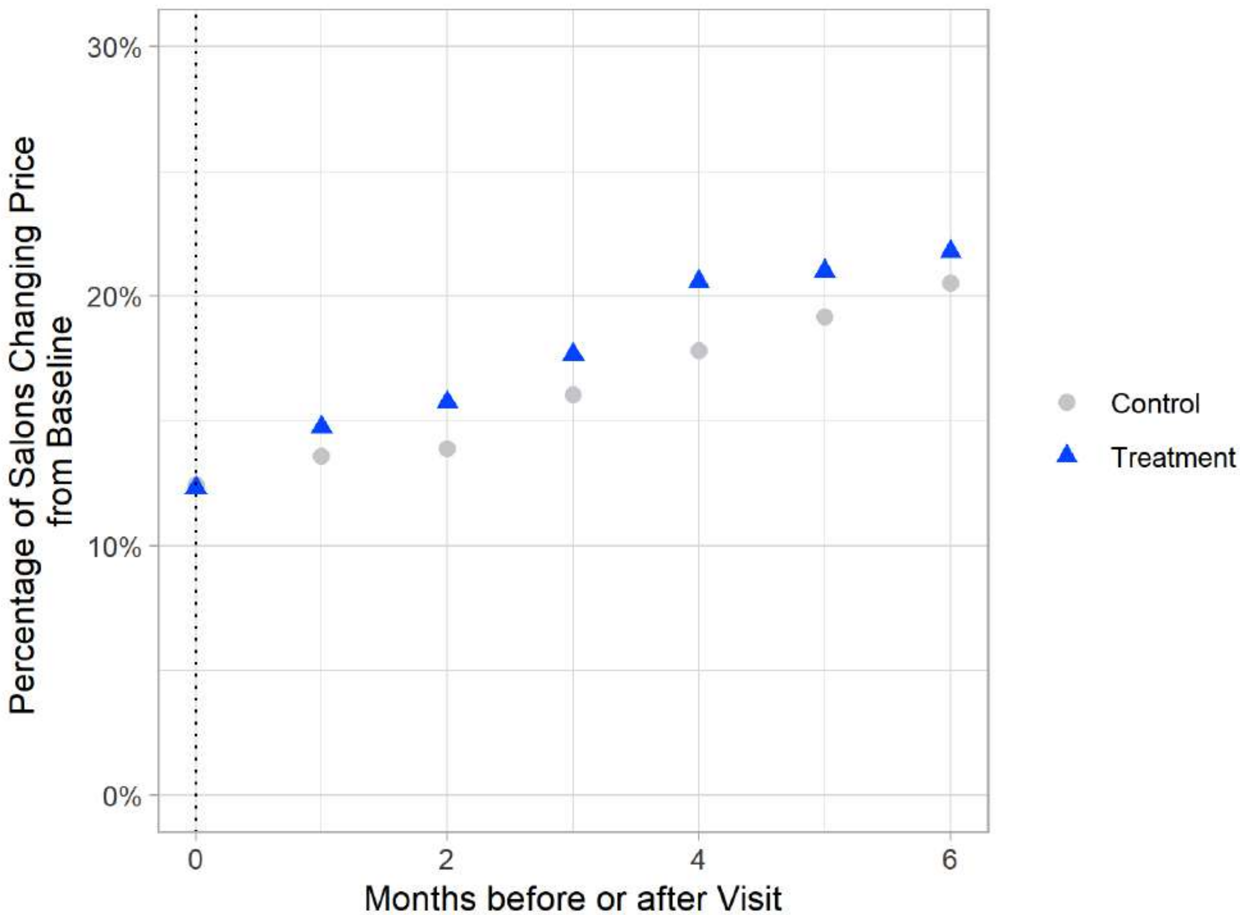
Notes: The top figure plots a binscatter of logged baseline price on baseline quality. The y-axis masks logged values of baseline price with price levels for ease of interpretation. Quality represents a sum of the firm's polish brand level, cleanliness, and luxuriousness, and ranges from 3 (lowest) to 11 (highest). This is robust to using a standardized sum of polish brands, cleanliness, and luxuriousness, as well as each individual measure alone. The bottom figure plots logged baseline price on baseline quality, showing every firm observation (represented by a red circle) within each quality level sorted by price, along with the interquartile range (in blue). The coefficient of variation in price across all observations is 37.8%. Within each quality level, the coefficient of variation in price ranges from 22.2% to 47%.

Figure 6: Firms' own descriptions of their positioning



Notes: This figure shows a diagram of the self-descriptions that treatment firms provide of their positioning prior to treatment, prompted by the question, "What sets you apart from your competitors?". Each response was coded into categories by two independent research assistants, with any discrepancies sent to a third research assistant. The largest category of responses is quality differentiation (59%), followed by nothing (14%), focus (10%), price (9%), and horizontal differentiation (8%).

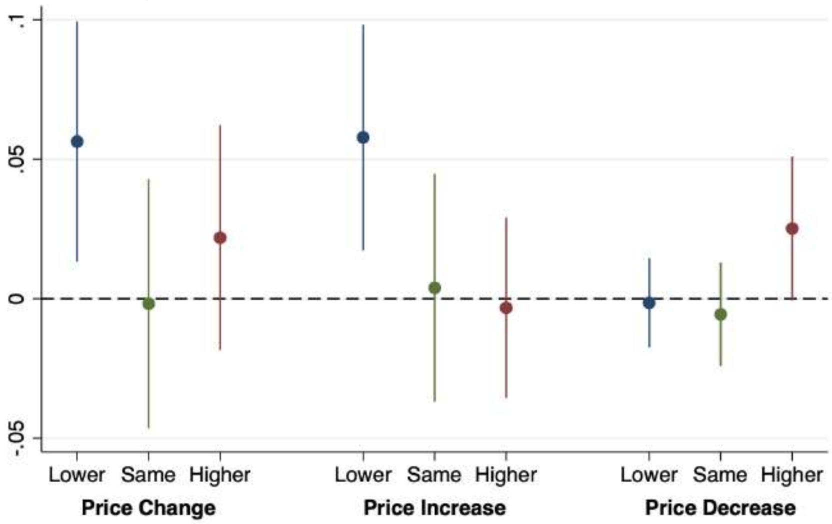
Figure 7: Percentage of firms with a different price relative to baseline (by elapsed month)



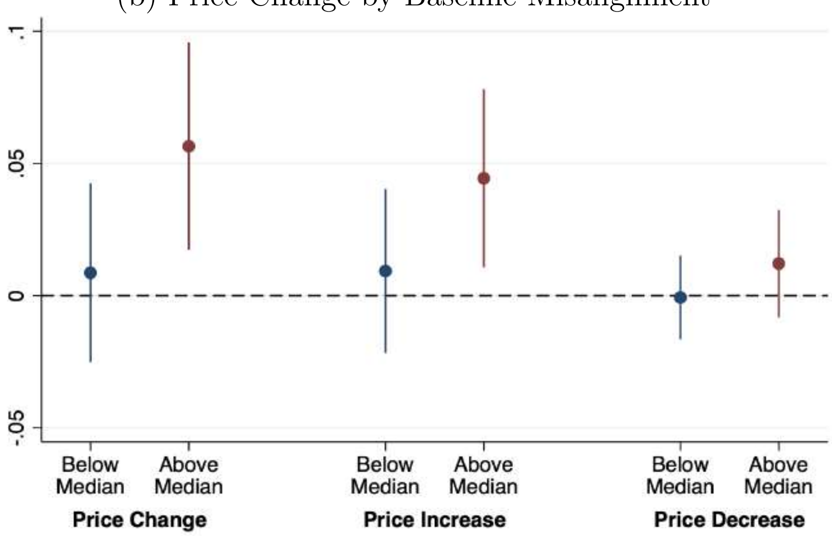
Notes: This figure plots the raw percentage of control versus treatment firms that charge a different price from their baseline price, by the number of months since the canvassing visit. Each month begins on the 15th of each calendar month in order to count months following the canvasser visit, which began on June 18, 2018. The figure displays outcomes across the 6 months for which most observations were collected, which varies due to the staggered timeline of visits across the 12 months of data collection (e.g. firms visited between October 15 - November 15 have only 5 months of post-visit data), as well as closures and firms not answering calls after multiple tries each month.

Figure 8: How firms change prices

(a) Price Change by Baseline Price Position from Nearest Competitor



(b) Price Change by Baseline Misalignment



Notes: Figure (a) plots estimates of treatment effects on price change, increase, and decrease, respectively (with 95% confidence intervals), by subsamples based on firms' baseline relative price positioning compared to their nearest competitor (whether the firm charged lower, same, or higher prices compared to its nearest competitor). Figure (b) shows estimates of treatment effects on price change, increase, and decrease by subsamples based on firms' baseline alignment in pricing and quality (measured by the absolute error from the best-fit line regressing baseline price on quality and ZIP code fixed effects). Observations are at the firm-month level, and all regressions control for any pre-visit differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. Standard errors are clustered at the firm level.

Table 1: Summary Statistics

	(1) All					
	mean	sd	min	p50	max	count
Baseline Price	13.88	5.24	5.00	13.00	60.00	3218
Baseline Number Of Employees	4.26	2.53	1.00	4.00	25.00	2923
Baseline Number Of Customers	3.75	3.23	0.00	3.00	30.00	2926
Baseline Total Hours Open Weekly	62.06	10.25	8.00	63.00	115.50	3073
Cleanliness1to4	2.65	0.70	1.00	3.00	4.00	2964
Luxuriousness1to4	2.41	0.73	1.00	2.00	4.00	2969
Polish Brand Level	1.12	0.37	1.00	1.00	3.00	3018
Price of Gel Manicure	29.32	8.06	10.00	28.00	105.00	2806
Baseline Number of Services (Scope)	2.09	1.24	0.00	2.00	7.00	3092
Baseline Yelp Rating	3.88	0.61	3.00	4.00	5.00	3142
Baseline Number of Yelp Reviews	69.01	84.68	0.00	41.00	1075.00	3218
Availability Next Day 4-5pm	0.75	0.27	0.00	0.86	1.00	3209
Baseline Average Daily Opening Hour	09:44	00:31	06:00	09:51	14:00	3075
Baseline Average Daily Closing Hour	19:14	00:50	13:04	19:04	23:25	3074
Yelp Canvass Week	33.66	5.33	24.00	34.00	44.00	3218
Number of Price Changes Pre-Visit	0.12	0.29	0.00	0.00	1.00	2609

Notes: This table provides summary statistics on all baseline characteristics of a salon, collected by data collectors via phone calls or physical visits to the business. Baseline price refers to the regular manicure price. Baseline number of employees and customers count the total number of employees and customers that are observed at the time of visit. Total hours open weekly counts the total number of hours that salons are open, based on their opening and closing times. Cleanliness and luxuriousness are coded on a scale of 1 to 4, detailed in Table 4. Polish brand level is coded on a scale of 1 to 3, based on the retail price of the most expensive nail polish brand observed. The number of services counts the total types of services that are offered by the firm (e.g. spa services, hair cuts, hair removal, make-up, tanning, and tattooes and piercings). Availability next-day is a binary variable collected by data collectors when inquiring for an appointment between 4-5pm, a peak hour for salon services. Yelp canvass week measures the week that canvassers visit each firm. The number of price changes pre-visit counts the total number of price changes between baseline and the canvasser visit.

Table 2: Balance of Baseline Variables Across Experimental Conditions

	Treatment Mean	Control Mean	Difference	(p-value)
Baseline Price	13.98	13.79	-0.19	(0.30)
Baseline Number Of Employees	4.31	4.22	-0.09	(0.31)
Baseline Number Of Customers	3.82	3.68	-0.13	(0.26)
Baseline Total Hours Open Weekly	62.23	61.89	-0.33	(0.37)
Cleanliness1to4	2.67	2.63	-0.04	(0.13)
Luxuriousness1to4	2.46	2.37	-0.10***	(0.00)
Polish Brand Level	1.12	1.12	-0.00	(0.74)
Price of Gel Manicure	29.35	29.29	-0.05	(0.86)
Baseline Number of Services (Scope)	2.11	2.08	-0.02	(0.59)
Baseline Yelp Rating	3.88	3.89	0.01	(0.49)
Baseline Number of Yelp Reviews	69.62	68.41	-1.21	(0.69)
Availability Next Day 4-5pm	0.75	0.75	-0.00	(0.95)
Baseline Average Daily Opening Hour	09:43	09:44	00:01	(0.40)
Baseline Average Daily Closing Hour	19:15	19:14	-00:01	(0.42)
Yelp Canvass Week	34.39	32.95	-1.44***	(0.00)
Number of Price Changes Pre-Visit	0.12	0.13	0.01	(0.32)
Observations	1578	1640	3218	

Notes: This table shows the balance of variables at baseline between control and treatment firms. Variables collected by physical visits (e.g. cleanliness and luxuriousness) are not available across the full sample (as reported in Table 1), as data collectors were unable to collect these measures if the business was closed at the time of visit or did not allow anyone without an appointment beyond the reception.

Table 3: Rubric to code cleanliness and luxuriousness

Instructions: Please rate the salon's cleanliness and luxuriousness, assigning the rating using the following guidelines. If you are in between categories and see any of what is listed for a lower rating, record the lower rating. If for any reason you cannot observe the salon interior, enter NA.

Cleanliness	
1	Grime on countertops and/or nail clippings on floors, technicians are wearing their own outside clothing and no gloves, technicians are reusing tools after each customer, pedicure bath is reused after a customer finishes
2	General disarray or grime on countertops and floors, technicians are wearing their own outside clothing and no gloves, technicians are using some disinfection (e.g. UV lighting machine), pedicure bath is washed with water after a customer finishes
3	Generally clean countertops and floors, technicians are wearing some type of uniform but may not be wearing gloves, technicians are using liquid disinfection, pedicure bath appears to be disinfected after a customer finishes
4	The floor and surfaces are spotless, technicians are wearing neat clothing and gloves, tools are disposable and/or salon has an autoclave, pedicure area is being disinfected for at least 10min after a customer finishes
Luxuriousness	
1	Small and cramped service area, no waiting area, no investment into decor (furniture, upholstery, or art) with stained walls and/or broken fixtures, no amenities provided
2	Small but comfortable service areas, some reception area even if small and not clearly separate from the rest of the salon, no broken fixtures or wall stains but little investment into decor, basic amenities (e.g. candy) may be provided
3	Spacious service area, small but separate reception area, some investment into decor (furniture, upholstery, or art), some amenities provided (e.g. water, disposable slippers, reading material)
4	Spacious and private or luxurious service area, security and/or spacious waiting area, high investment into decor (furniture, upholstery, or art), many amenities provided (e.g. drinks of choice, snacks, diversity of reading material, slippers/gowns)

Notes: This table shows the rubric that data collectors use to code cleanliness and luxuriousness. Data collectors are required to take accompanying photos of the interior, polish brands, menu, and exterior to validate their codings. 5% of each data collector's photos are checked every week.

Table 4: Price Changes Across Control and Treatment Firms

	(1) Price Change	(2) Price Change	(3) Price Change	(4) Price Change
Post * Treat	0.029**	0.028**	0.030**	0.030**
	(0.013)	(0.013)	(0.013)	(0.013)
Controls	Yes	Yes	Yes	Yes
Visit Week FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	Yes
Strata FE	No	No	Yes	Yes
Observations	30142	30142	29552	29552
Mean (control in months after visit)	0.173			
SD (control in months after visit)	0.378			

Notes: This table shows intention to treat estimates of the competitor information treatment on firms' likelihood of changing prices. Observations are at the firm-month level. The dependent variable is a binary indicator of whether the firm's regular manicure price in a given month is different from its baseline price. All regressions control for any baseline differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. Columns (2)-(4) additionally control for randomization strata fixed effects and/or month fixed effects. Standard errors are clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Directions of Price Changes Across Control and Treatment Firms

	(1) Price Decrease	(2) Price Increase	(3) ln(Price)
Post * Treat	0.005	0.023**	0.023***
	(0.006)	(0.011)	(0.009)
Controls	Yes	Yes	Yes
Visit Week FE	Yes	Yes	Yes
Observations	30142	30142	30142
Mean (control in months after visit)	0.036	0.137	2.580
SD (control in months after visit)	0.185	0.344	0.304

Notes: This table shows intention to treat estimates of the competitor information treatment on firms' likelihood of decreasing or increasing prices (columns 1 and 2), as well as price levels (column 3). Observations are at the firm-month level. Price decrease (increase) is a binary indicator of whether the firm's regular manicure price in a given month is lower (higher) than its baseline price. All regressions control for any baseline differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. Standard errors are clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Performance Across Control and Treatment Firms

Panel A: Proxies of Performance Across Control and Treatment Firms

	(1) ln(Calls)	(2) ln(Pageviews)	(3) ln(Map Directions Views)	(4) Next-day Availability
Post * Treat	0.148***	0.146***	0.145***	-0.027
	(0.042)	(0.039)	(0.040)	(0.018)
Controls	Yes	Yes	Yes	Yes
Visit Week FE	Yes	Yes	Yes	Yes
Observations	35398	35398	35398	25755
Mean (control)				0.772
SD (control)				0.420

Panel B: Platform Engagement Across Control and Treatment Firms

	(1) ln(Login Days)	(2) Account Claimed	(3) Advertising	(4) Responses	(5) ln(Comments)
Post * Treat	0.026	-0.002	0.006	0.013**	0.009
	(0.027)	(0.014)	(0.005)	(0.005)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes
Visit Week FE	Yes	Yes	Yes	Yes	Yes
Observations	35398	35398	35398	35398	35398

Notes: Panel A shows intention to treat estimates of the competitor information treatment on proxies of firm performance: calls to the business, number of pageviews, and number of map directions views on Yelp, as well as a binary indicator of availability for an appointment next day during a peak hour. Panel B shows intention to treat estimates of the competitor information treatment on firms' engagement with the Yelp platform. Dependent variables are the number of days a business logs in to Yelp (column 1), whether a business has claimed its page on Yelp (column 2), whether a business has purchased Yelp advertising (column 3), the number of responses the business has made to customer questions on quotes or appointments (column 4), and the number of comments the business has made on users' reviews (column 5). For both panels, observations are at the firm-month level. All regressions control for any baseline differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. Standard errors are clustered at the firm level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendices

A Experiment Details

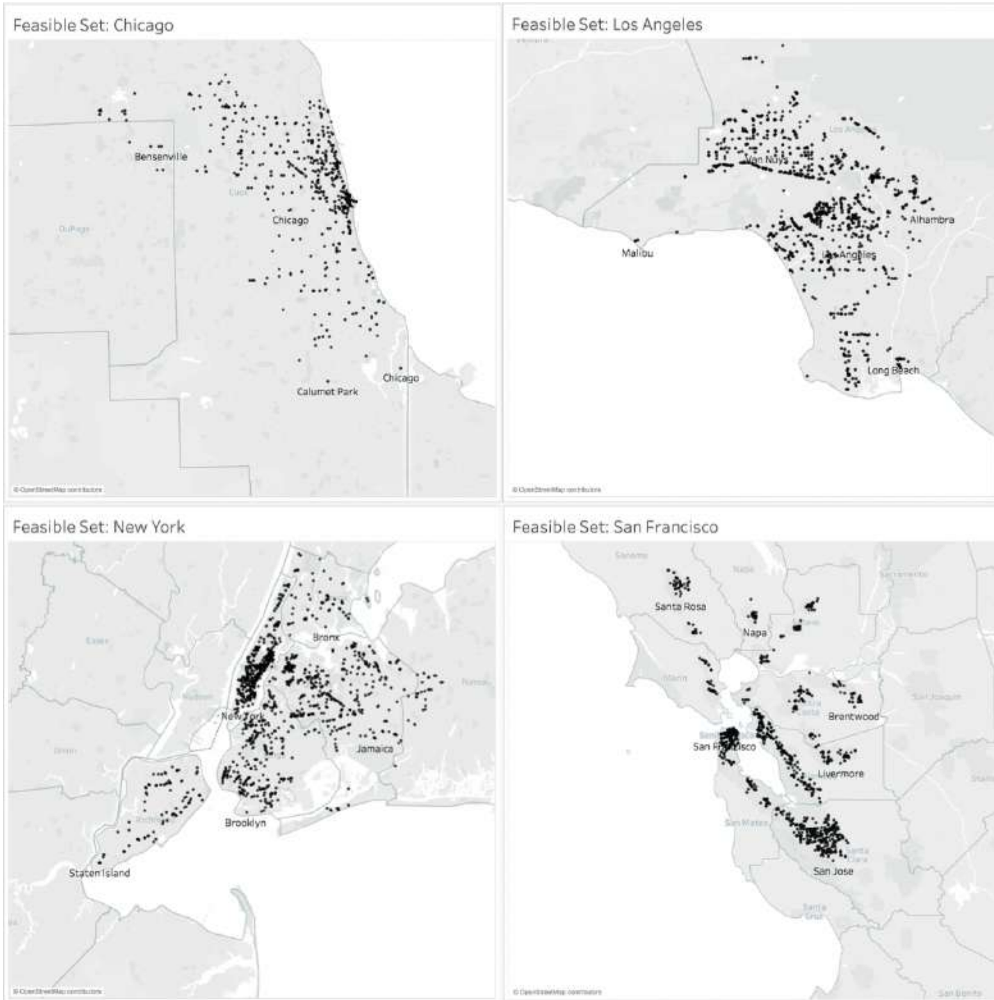
This appendix provides additional details on the experiment. Figure A.1 displays the standard marketing materials that all firms received, including those assigned to the control condition. Figure A.2 shows a map of all firms in the eligible set across each of the four cities, and Figure A.3 shows the subset of firms in the experimental sample. Table A.1 shows compliance and attrition across experimental conditions. Figure A.4 shows the timeline of data collection and experimental interventions.

Figure A.5 categorizes notes recorded by canvassers at the time of the treatment, which capture how firms responded to the informational intervention. These notes were categorized by two research assistants, and sent to a third research assistant in the case of conflicts.

Figure A.1: Brochure and postcard provided to all firms

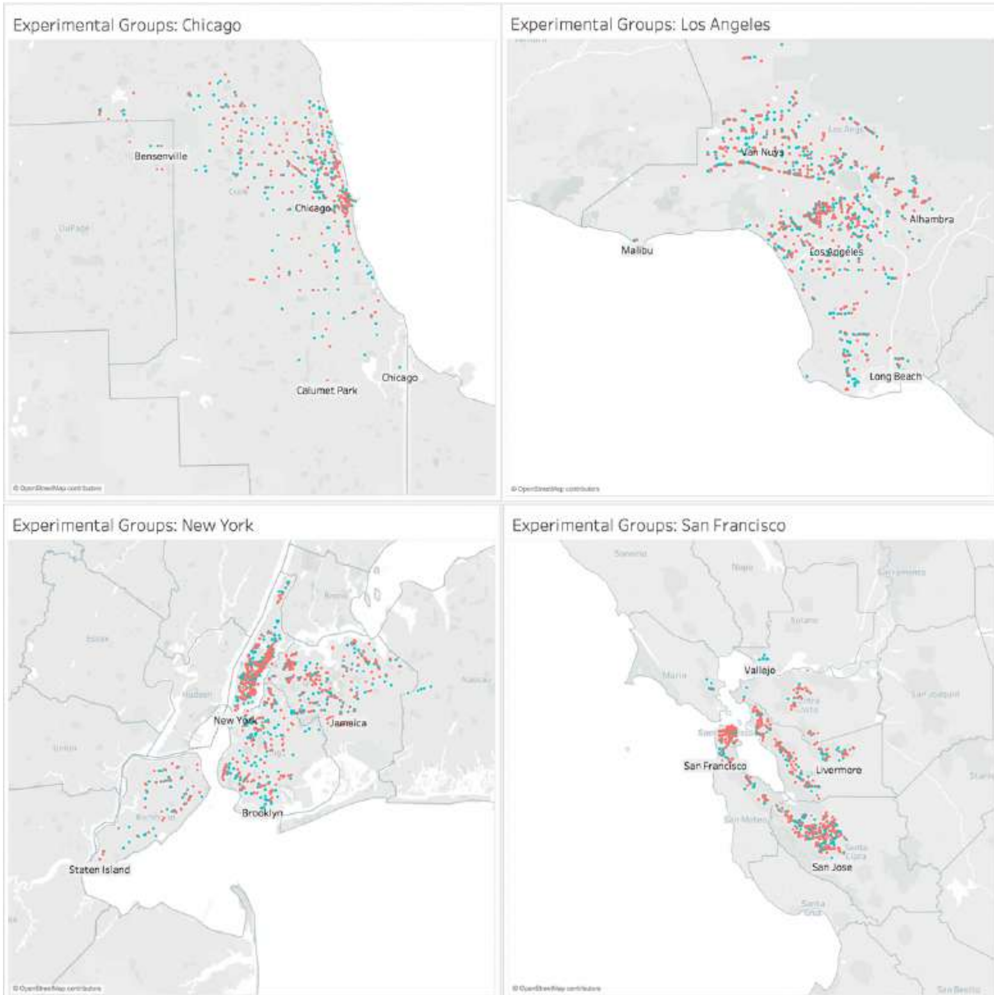
Notes: The top figure shows the brochure that Yelp canvassers provided to all businesses, which includes information on how to edit business details, add photos, and respond to reviews on Yelp's business page. The bottom figure shows a standard marketing postcard that Yelp additionally provided on their visits, which offers free Yelp advertising credits. The back of this postcard is blank for control businesses.

Figure A.2: Map of firms in the eligible set



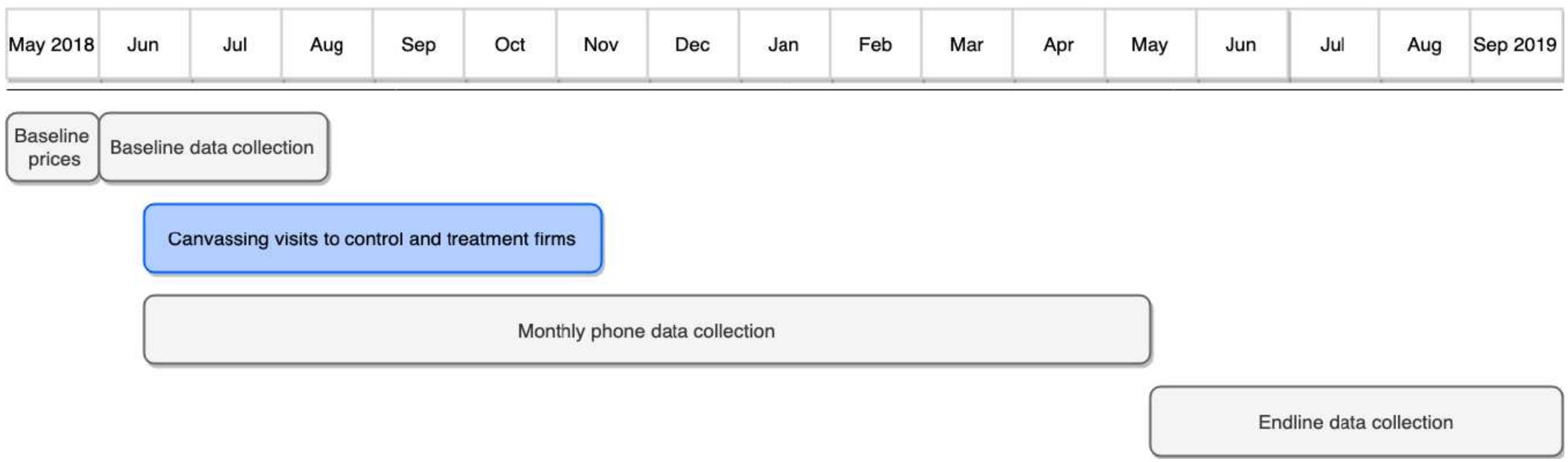
Notes: This map shows all firms in the eligible set across each of the four cities.

Figure A.3: Map of firms in the experimental sample



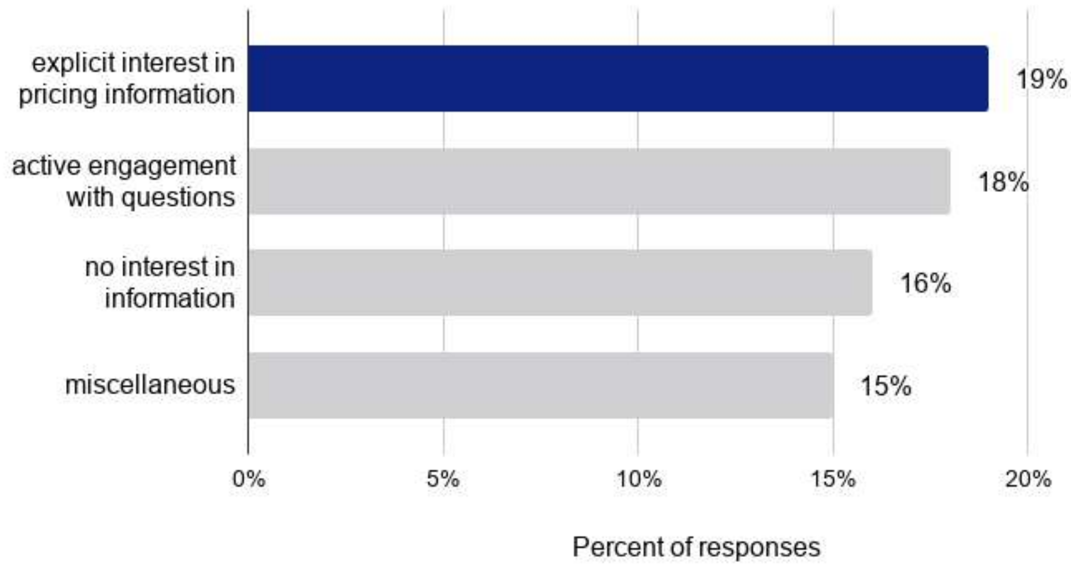
Notes: This map shows all firms in the experimental sample across each of the four cities. Control firms are in red, while treatment firms are in blue. Firms in the Bronx and outer Queens area are missing in New York, and firms in the outer North Bay area are missing for San Francisco, compared to the eligible set.

Figure A.4: Experimental Timeline



Notes: This figure shows the experimental timeline. Baseline prices are collected in May 2018, and continue to be collected on a monthly basis until May 2019. Baseline quality data are collected between June - August 2018, where it is staggered by neighborhoods to ensure that data are collected before canvassing visits. Endline data are collected between June and September 2019.

Figure A.5: Comments by Treatment Firms at the Time of Treatment



Notes: This figure shows the categories of responses across treatment firms, which were noted by canvassers that delivered the informational treatment. Canvassers recorded comments as close to verbatim as possible. Two research assistants later coded these comments into categories, with any conflicts sent to a third research assistant.

Table A.1: Compliance and attrition across experimental conditions

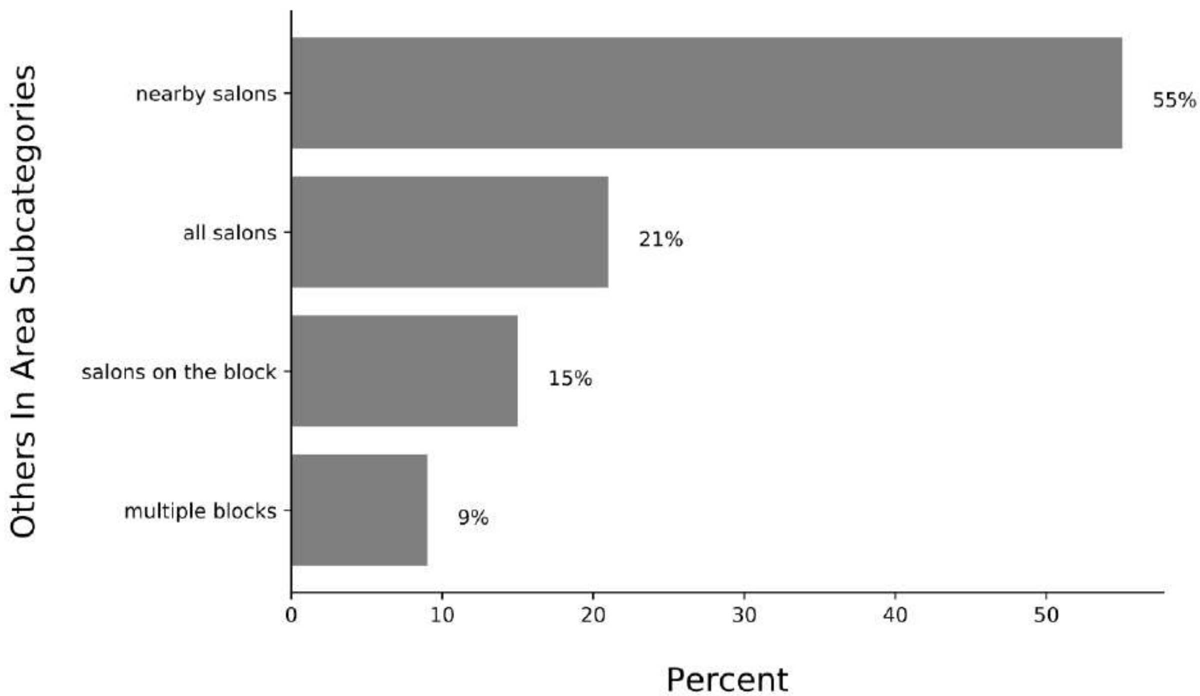
	(1) Treatment Number of Firms	(2) Treatment % of Firms	(3) Control Number of Firms	(4) Control % of Firms	(5) p-value
Non-compliance	25	1.58	33	2.01	0.36
Closed	88	5.58	73	4.45	0.14
No price data	20	1.27	16	0.98	0.43
Observations	1578	1578	1640	1640	3218

Notes: Non-compliance denotes firms that rejected any conversation with Yelp canvassers when they arrived. In these cases, the firm did not receive any information from the canvassers. "Closed" represents firms confirmed as closed or no longer offering nail services after the canvassing visit. "No price data" represents firms that were no longer reachable after the canvassing visit but not confirmed as closed or no longer offering nail services.

B Firms' baseline knowledge of competitors

This appendix shows further analysis of firms' baseline knowledge of competitors. Figure B.1 further disaggregates the responses of firms categorized into "others in area". Figure B.2-3 analyze how firms' baseline knowledge of competitors varies by the level of competition faced, measured by the firm's distance from the nearest competitor and the baseline price dispersion across its 9 nearest competitors. Figures B.4-6 show how firms' baseline competitor knowledge varies by whether they charge higher- or lower-end prices, as well as by age and size.

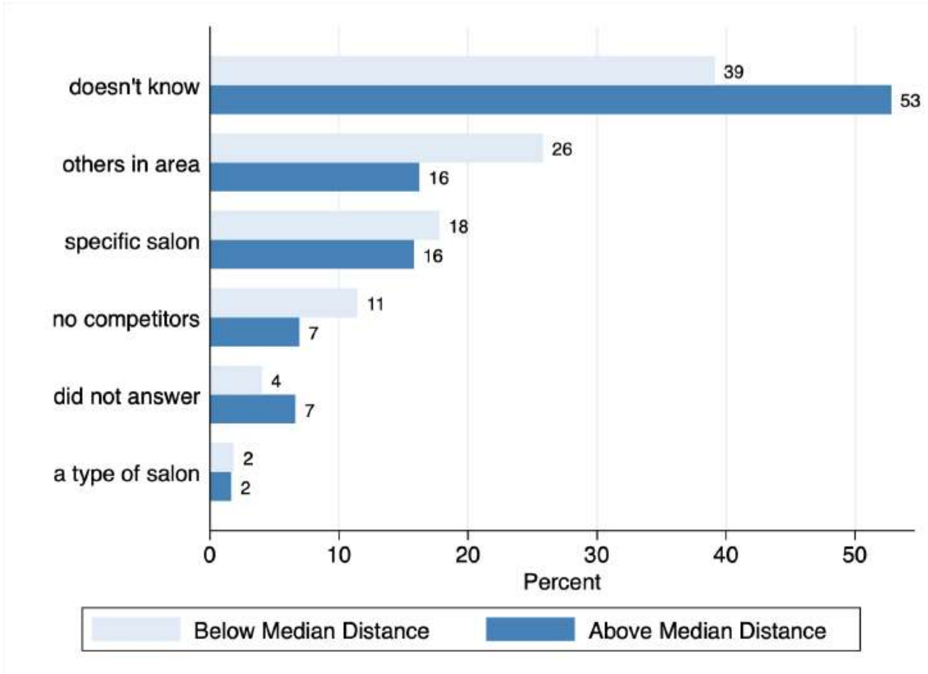
Figure B.1: Breakdown of responses categorized as "others in area" to describe competitors



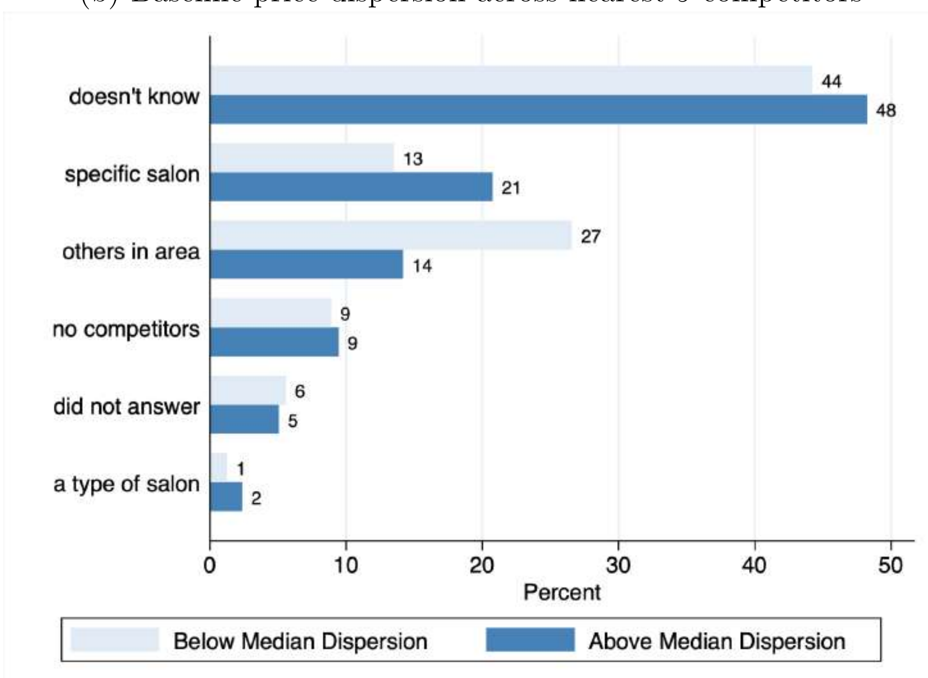
Notes: This figure shows the breakdown of 275 responses in "others in area", based on the four types of phrasing used to describe other competitors in the area: all salons in the area, nearby salons, salons on the block, and multiple blocks.

Figure B.2: Knowledge of primary competitors by level of competition

(a) Distance from nearest competitor



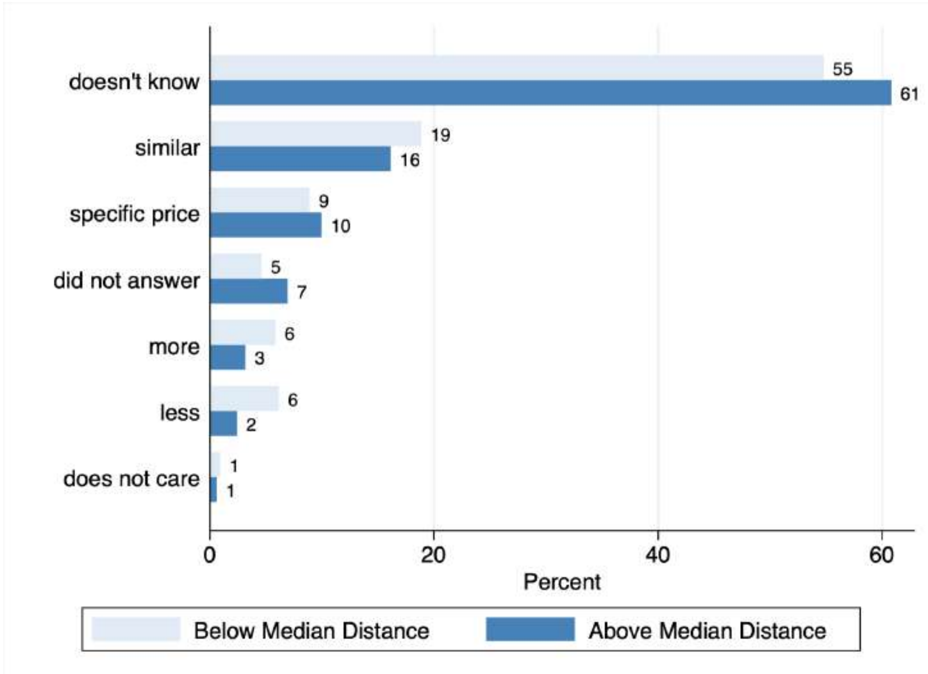
(b) Baseline price dispersion across nearest 9 competitors



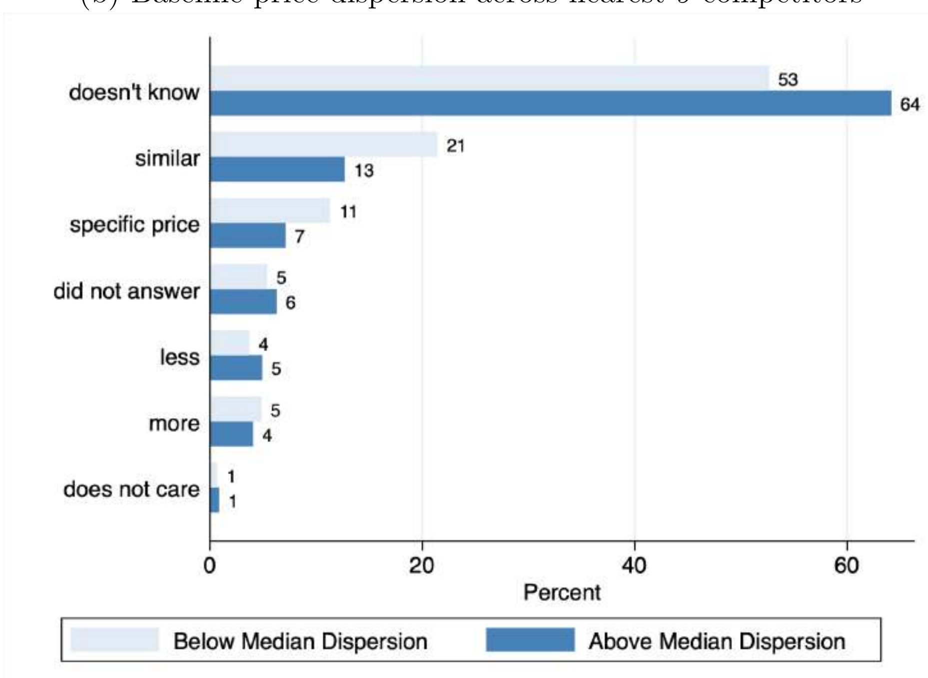
Notes: These figures break down firm responses reflecting their knowledge of competitors by two measures that proxy the level of competition. (a) uses the firm's distance from its nearest competitor as a measure of competition. (b) uses baseline price dispersion across its nearest 9 competitors as a measure of competition. For both of these measures, "below median" distance and dispersion map to higher levels of competition, as they suggest that competitors are closer by and less dispersed in prices.

Figure B.3: Knowledge of competitor pricing by level of competition

(a) Distance from nearest competitor



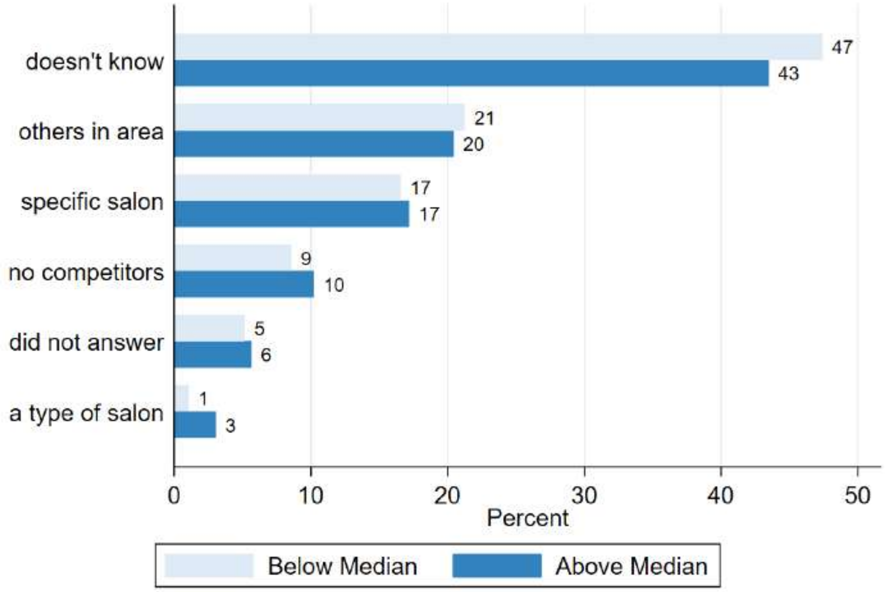
(b) Baseline price dispersion across nearest 9 competitors



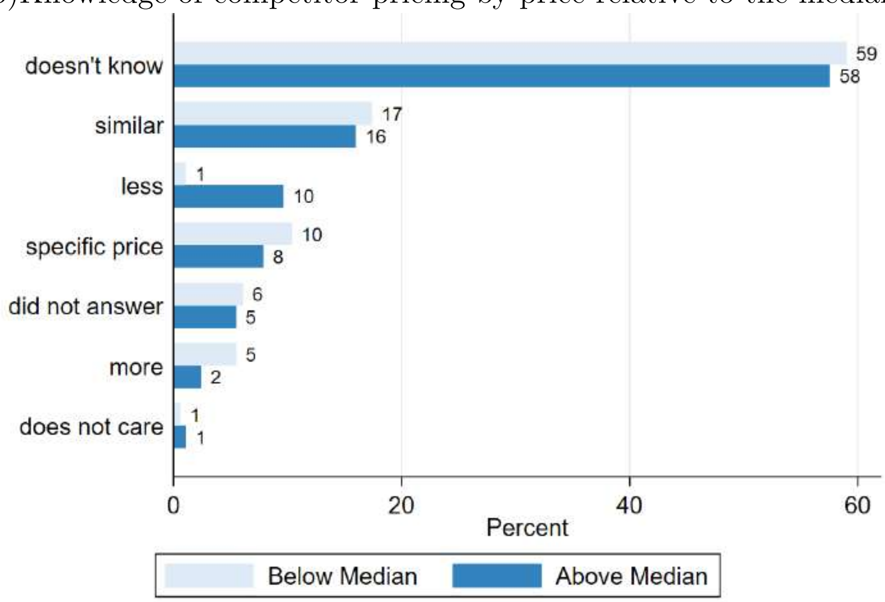
Notes: These figures break down firm responses reflecting their knowledge of competitor prices by two measures that proxy the level of competition. (a) uses the firm's distance from its nearest competitor as a measure of competition. (b) uses baseline price dispersion across its nearest 9 competitors as a measure of competition. For both of these measures, "below median" distance and dispersion map to higher levels of competition, as they suggest that competitors are closer by and less dispersed in prices.

Figure B.4: Knowledge of competitors across higher- and lower-end firms (relative to median price in ZIP code)

(a) Knowledge of primary competitors by price relative to the median



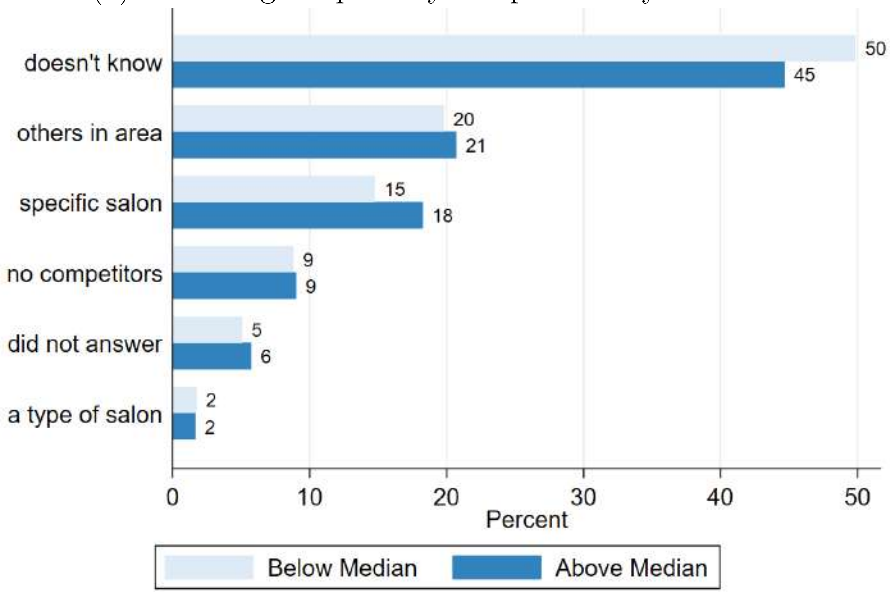
(b)Knowledge of competitor pricing by price relative to the median



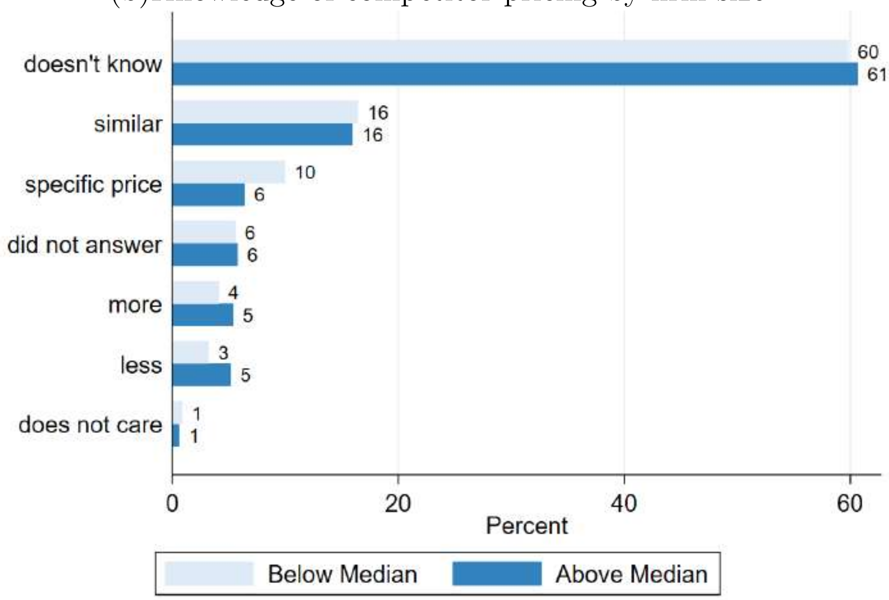
Notes: These figures break down firm responses reflecting their knowledge of competitors by whether the firms charged above- or below-median price in its ZIP code. (a) displays firms' stated knowledge of primary competitors, and (b) displays firms' stated knowledge on competitor prices.

Figure B.5: Knowledge of competitors by firm size

(a) Knowledge of primary competitors by firm size



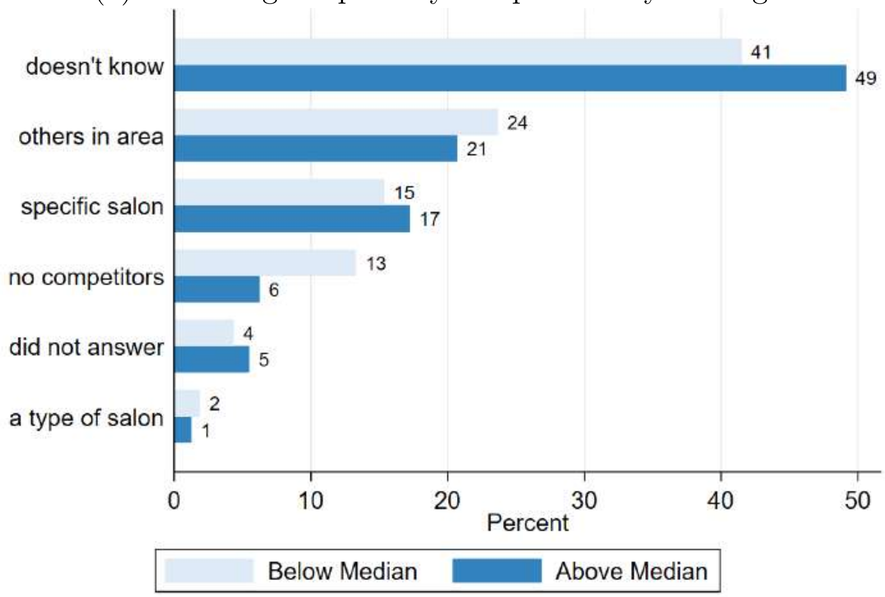
(b)Knowledge of competitor pricing by firm size



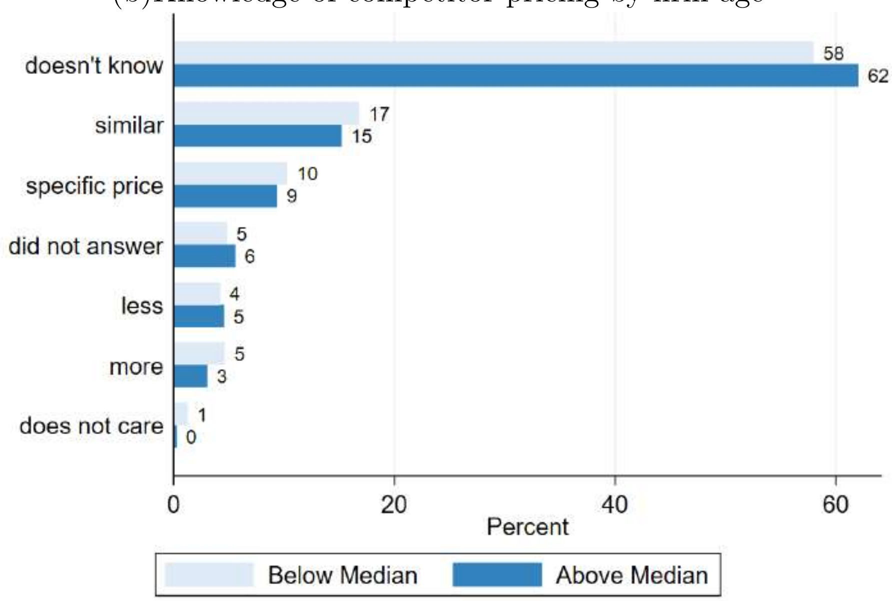
Notes: These figures break down firm responses reflecting their knowledge of competitors by the number of employees relative to the median size. (a) displays firms' stated knowledge of primary competitors, and (b) displays firms' stated knowledge on competitor prices.

Figure B.6: Knowledge of competitors by firm age

(a) Knowledge of primary competitors by firm age



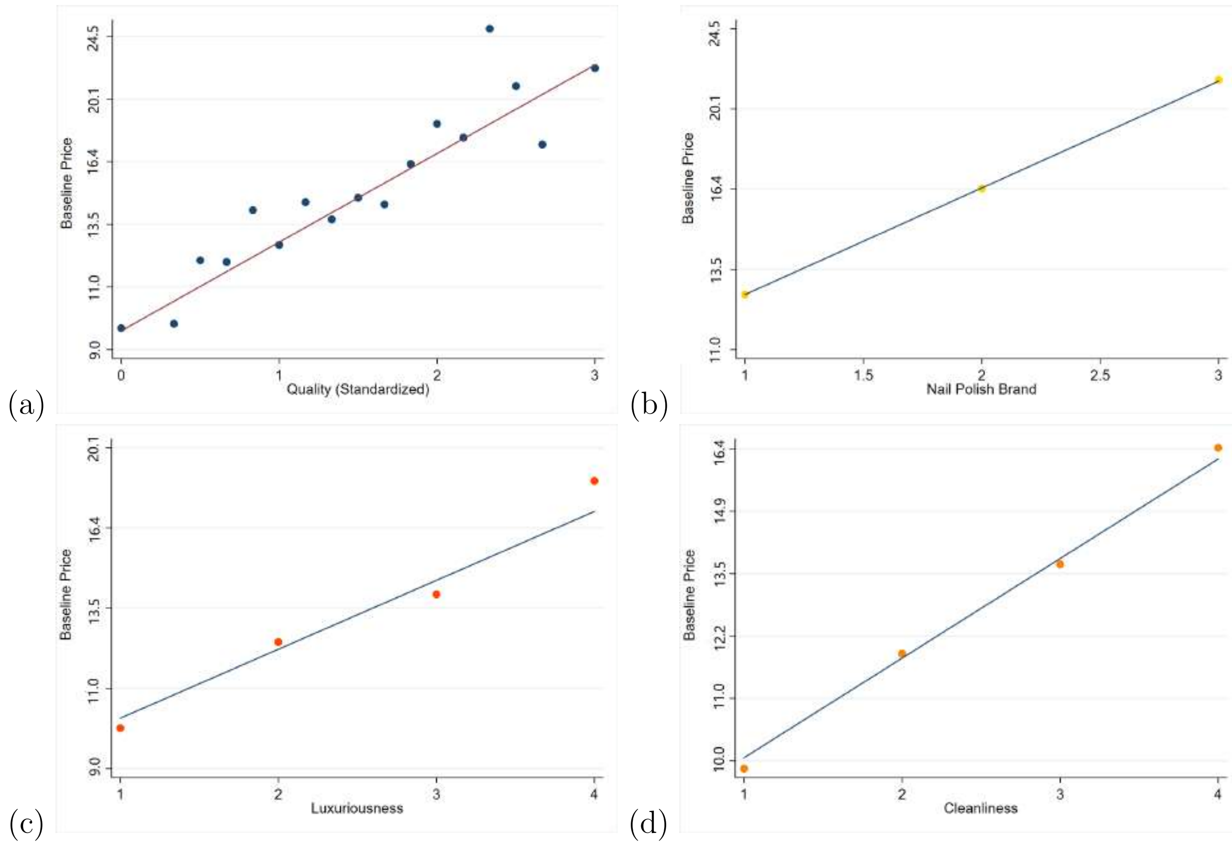
(b)Knowledge of competitor pricing by firm age



Notes: These figures break down firm responses reflecting their knowledge of competitors by the number of years they have been open relative to the median. (a) displays firms' stated knowledge of primary competitors, and (b) displays firms' stated knowledge on competitor prices.

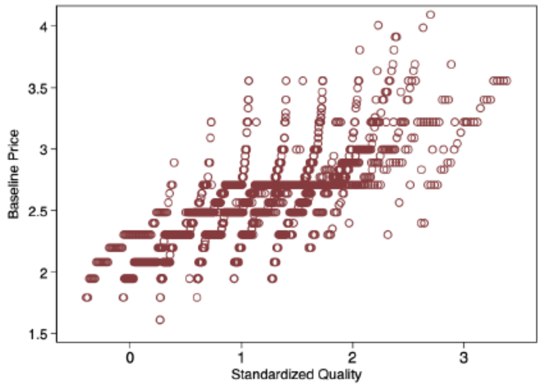
C Pricing patterns across quality measures

Figure C.1: Average price across quality measures

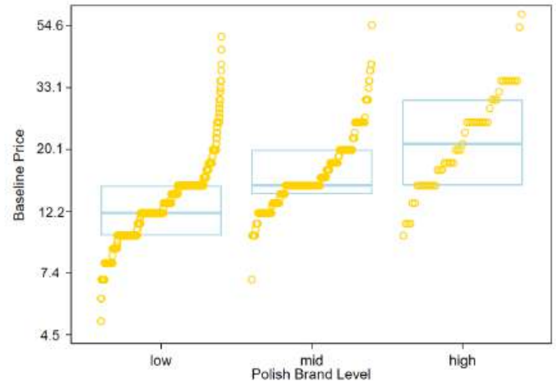


Notes: These figures plot the binscatter of logged baseline price on across measures of baseline quality. (a) plots a standardized measure of baseline quality (a standardized sum of polish brands, cleanliness, and luxuriousness), and (b)-(d) plot each individual measure alone. The y-axes mask logged values of baseline price with price levels for ease of interpretation.

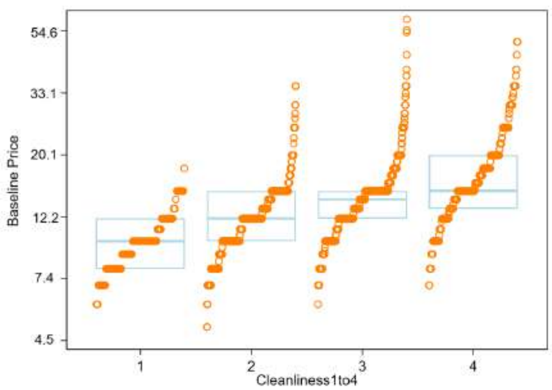
Figure C.2: Price dispersion across quality measures



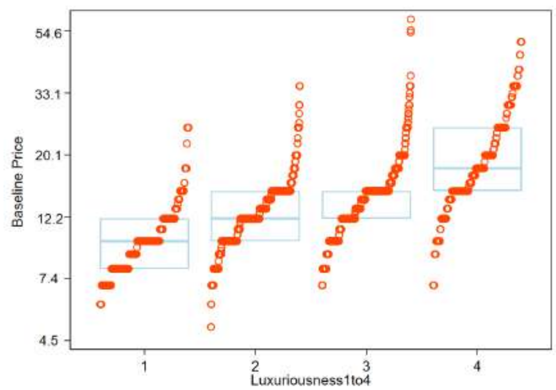
(a)



(b)



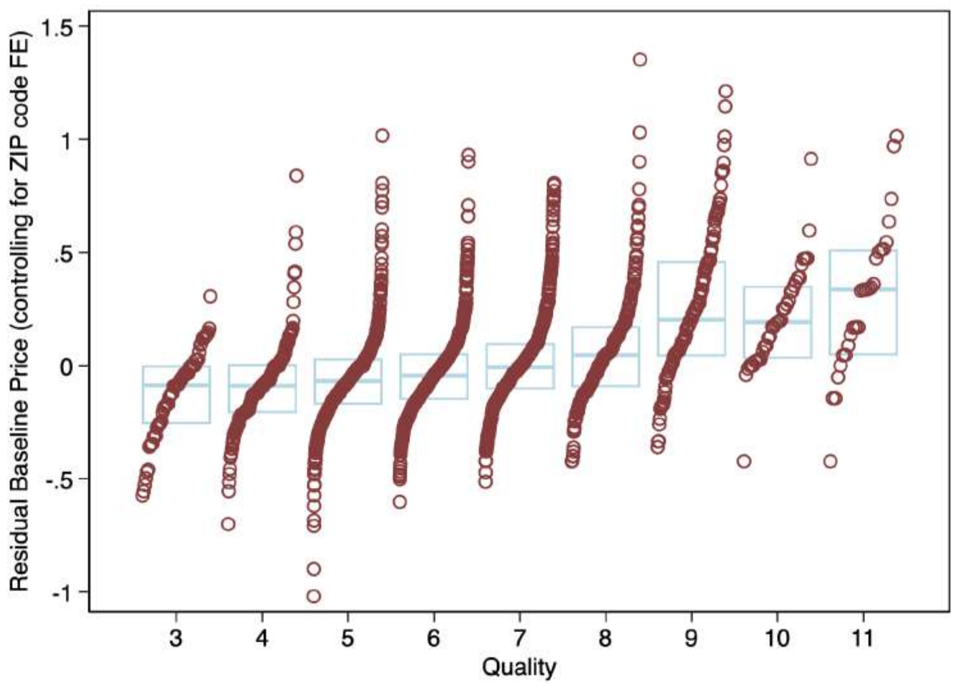
(c)



(d)

Notes: These figures plot logged baseline price on measures of baseline quality, showing every firm observation (represented by a circle) within each quality level sorted by price, along with the interquartile range. (a) plots the standardized sum of polish brands, cleanliness, and luxuriousness, and (b)-(d) plot each individual measure alone. The y-axes mask logged values of baseline price with price levels for ease of interpretation.

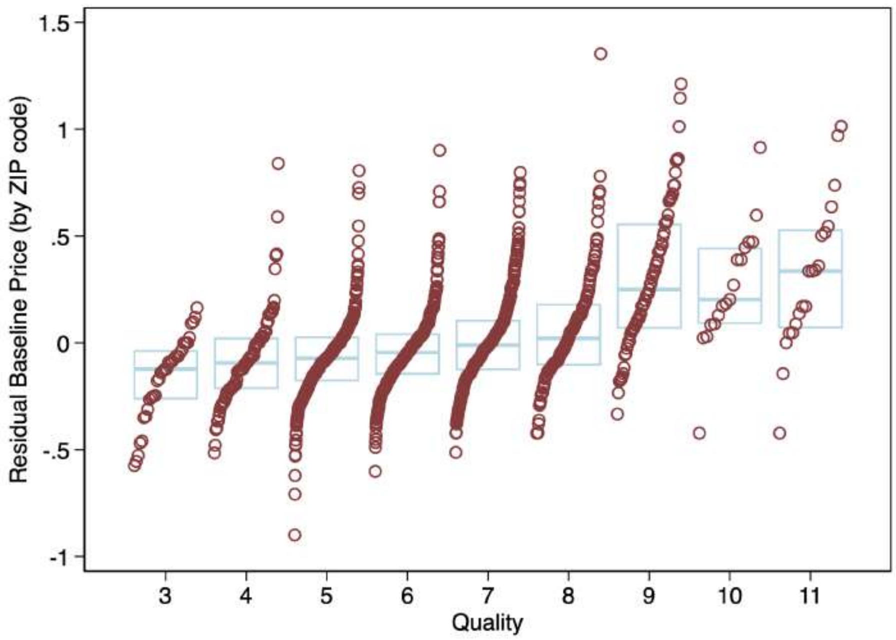
Figure C.3: Residual dispersion in firm pricing by quality level, controlling for ZIP code fixed effects



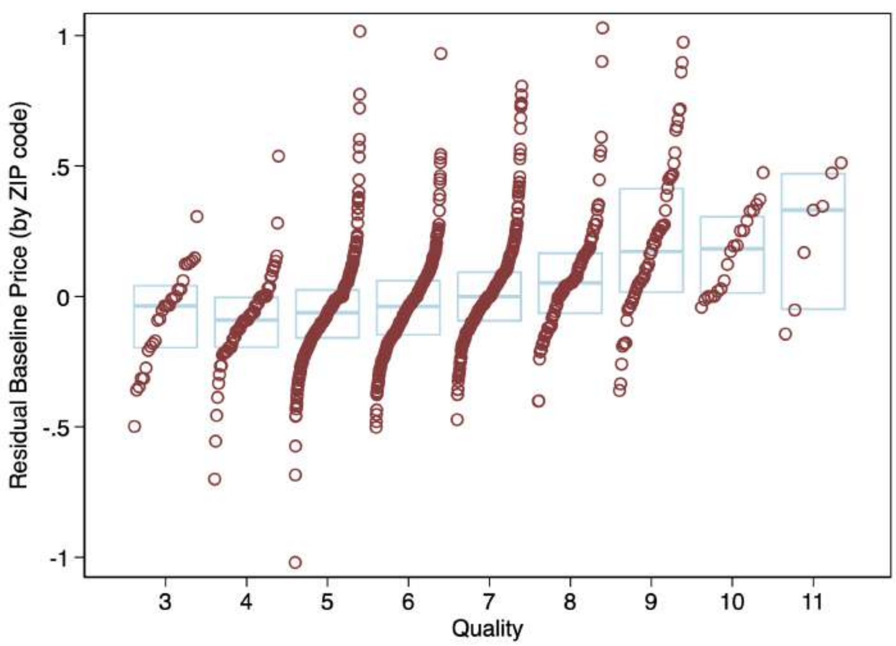
Notes: This figure plots a binscatter of residualized logged baseline price on baseline quality. The y-axis masks logged values of baseline price with price levels for ease of interpretation. Quality represents a sum of the firm's polish brand level, cleanliness, and luxuriousness, and ranges from 3 (lowest) to 11 (highest). This is robust to using a standardized sum of polish brands, cleanliness, and luxuriousness, as well as each individual measure alone.

Figure C.4: Dispersion in price-quality positions by level of competition

(a) Below median distance from nearest competitor



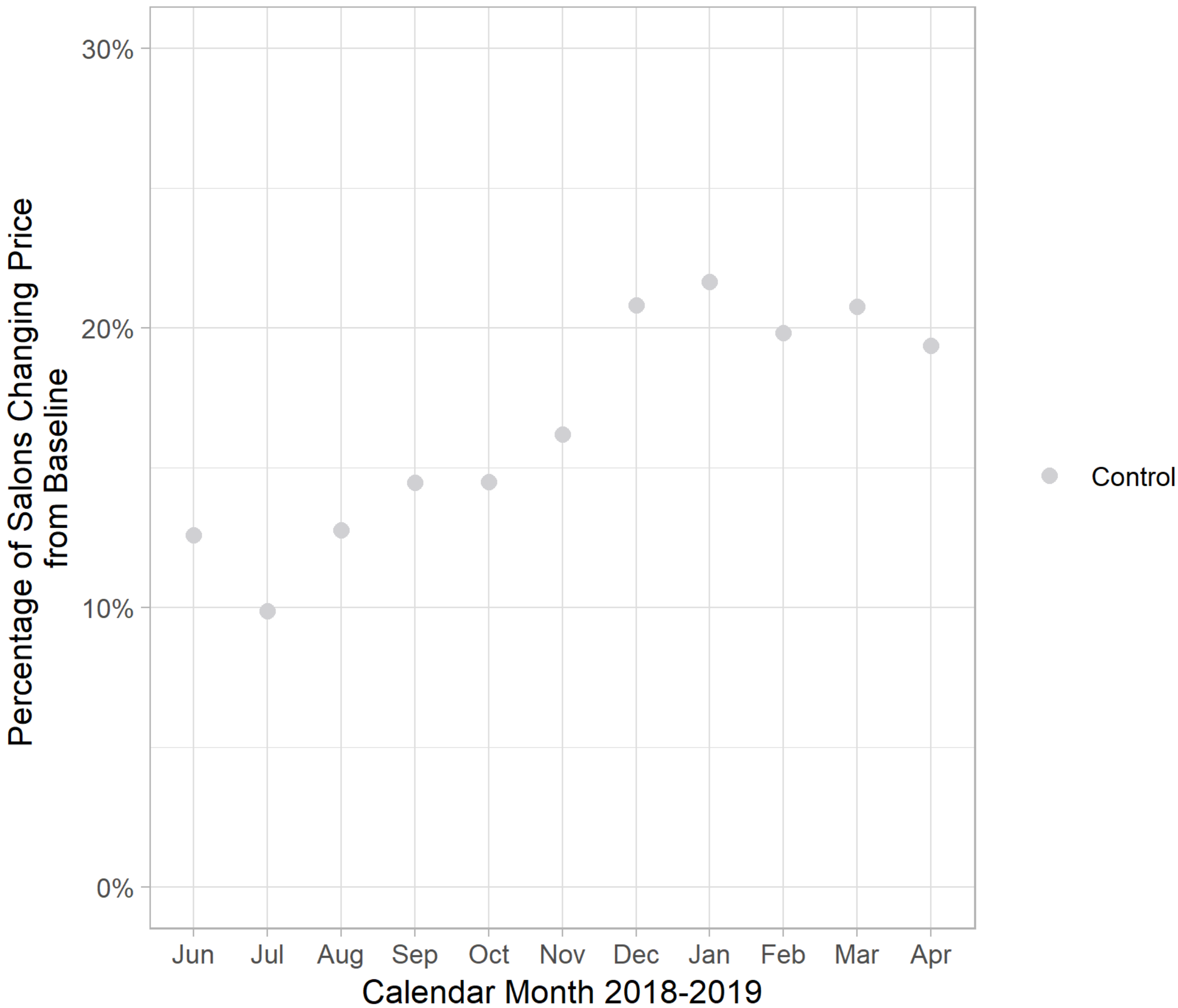
(b) Above median distance from nearest competitor



Notes: This figure separates Appendix Figure C.3 into below and above median distance from the nearest competitor to show the level of dispersion in price-quality positions by competition level.

D Timing of price changes

Figure D.1: Seasonality in price changes

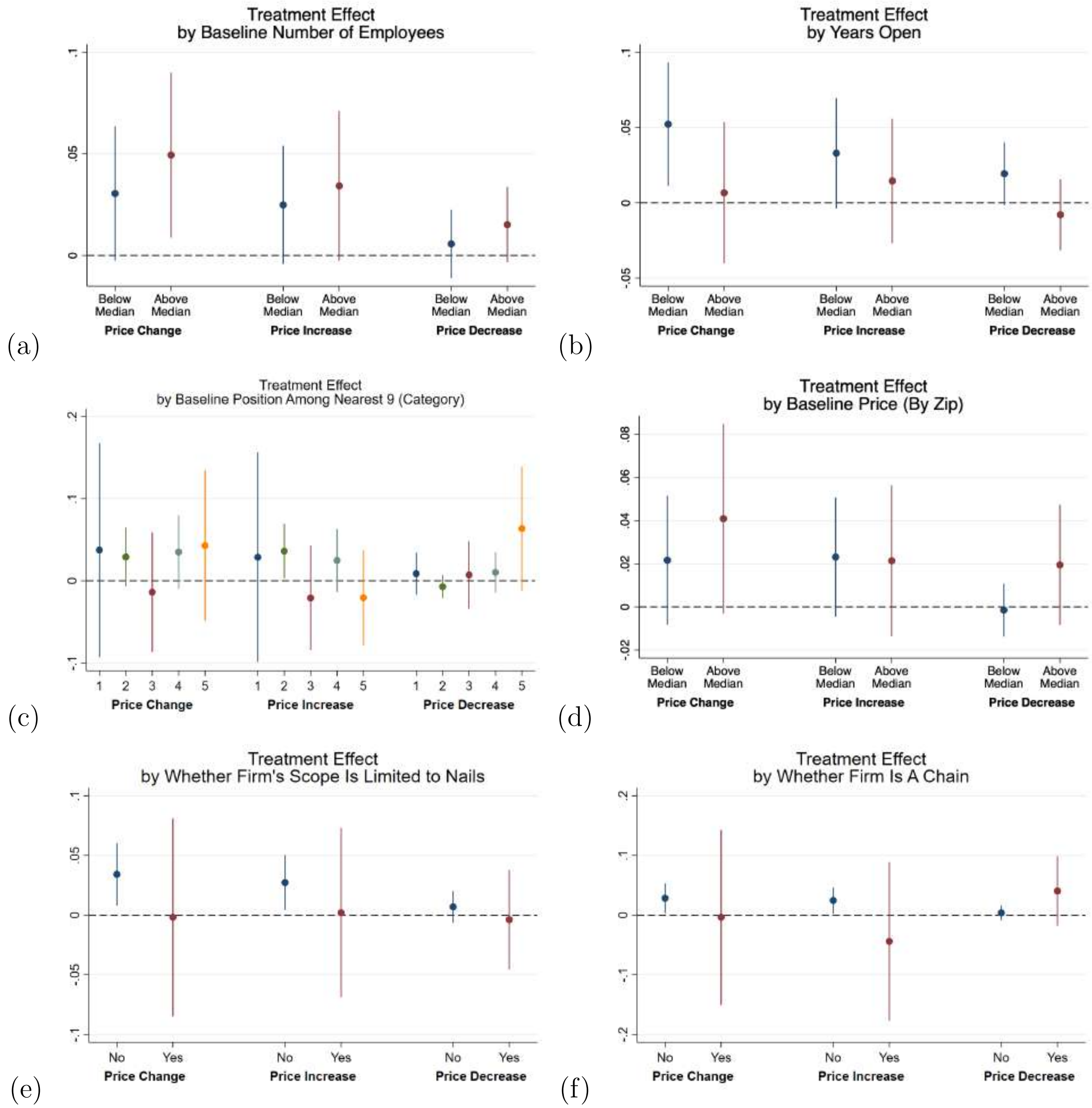


Notes: This figure plots the percentage of control firms with a different regular manicure price from their baseline price by calendar month. Firms appear to display seasonality in when they change prices, using more promotions in slower months (fall and winter) and changing menu prices at the end of the year. These patterns are consistent with those documented in industry magazines and confirmed by salon managers and owners.

E Heterogeneous treatment effects on price change

This appendix provides additional exploratory analyses on heterogeneous treatment effects, and reports the regression results in table form for the main dimensions in the paper.

Figure E.1: Treatment effects across subsamples



Notes: These figures plot estimates of treatment effects on price change, increase, and decrease, respectively (with 95% confidence intervals), by subsamples. Figure (c) examines subsamples by summary descriptions shown at the top of the firm's postcard, which were algorithmically generated. 1 represents "You charge the lowest price in the area," 2 represents "Most businesses nearby charger higher prices than you," 3 represents "Most/All businesses nearby charge the same prices as you," 4 represents "Most businesses nearby charge higher prices than you," and 5 represents "You charge the highest price in the area." For all regressions, observations are at the firm-month level, and control for any pre-visit differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. Standard errors are clustered at the firm level.

Table E.1: Heterogeneous Treatment Effects on Price Change

Panel A: Price Change Across Control and Treatment Firms by Baseline Price Position from Nearest Competitor

	Price Change			Price Increase			Price Decrease		
	(1) Lower Price	(2) Same Price	(3) Higher Price	(4) Lower Price	(5) Same Price	(6) Higher Price	(7) Lower Price	(8) Same Price	(9) Higher Price
Post * Treat	0.056**	-0.002	0.022	0.058***	0.004	-0.003	-0.001	-0.006	0.025*
	(0.022)	(0.023)	(0.021)	(0.021)	(0.021)	(0.016)	(0.008)	(0.009)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Visit Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11118	7302	11132	11118	7302	11132	11118	7302	11132
Mean (control)	0.177	0.159	0.178	0.158	0.141	0.114	0.019	0.017	0.064
SD (control)	0.382	0.365	0.382	0.365	0.348	0.318	0.136	0.130	0.245

Panel B: Price Change Across Control and Treatment Firms by Baseline Misalignment

	Price Change		Price Increase		Price Decrease	
	(1) Low Misalign	(2) High Misalign	(3) Low Misalign	(4) High Misalign	(5) Low Misalign	(6) High Misalign
Post * Treat	0.009	0.057***	0.009	0.044***	-0.001	0.012
	(0.017)	(0.020)	(0.016)	(0.017)	(0.008)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Visit Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14015	13663	14015	13663	14015	13663
Mean (control)	0.157	0.181	0.131	0.137	0.027	0.043
SD (control)	0.364	0.385	0.337	0.344	0.161	0.203

Notes: Panel A shows treatment effect estimates by subsamples based on firms' baseline relative price positioning compared to their nearest competitor (whether the firm charged lower, same, or higher prices compared to its nearest competitor). Observations are at the firm-month level. The dependent variable for columns (1)-(3) is price change, a binary indicator of whether the firm's regular manicure price in a given month is different from its baseline price. The dependent variable for columns (4)-(6) is price increase, and for columns (7)-(9) is price decrease – which are binary indicators of whether the firm's regular manicure price in a given month is higher or lower than its baseline price. All regressions control for any pre-visit differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. The last two rows show the mean and standard deviation of the dependent variable for control firms across post-canvasser visit months. Standard errors are clustered at the firm level. Panel B shows treatment effect estimates by subsamples based on firms' baseline alignment in pricing and quality (measured by the absolute error from the best-fit line regressing baseline price on quality and ZIP code fixed effects). Observations are at the firm-month level. The dependent variable for columns (1)-(2) is price change, a binary indicator of whether the firm's regular manicure price in a given month is different from its baseline price. The dependent variable for columns (3)-(4) is price increase, and for columns (5)-(6) is price decrease – which are binary indicators of whether the firm's regular manicure price in a given month is higher or lower than its baseline price. All regressions control for any pre-visit differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. The last two rows show the mean and standard deviation of the dependent variable for control firms across post-canvasser visit months. Standard errors are clustered at the firm level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table E.2: Price Changes Across Control and Treatment Firms by Distance from Nearest Competitor

	Price Change	
	(1) Below Median Distance	(2) Above Median Distance
Post * Treat	0.045**	0.011
	(0.018)	(0.018)
Controls	Yes	Yes
Visit Week FE	Yes	Yes
Observations	15050	15092
Mean (control in months after visit)	0.172	0.174
SD (control in months after visit)	0.377	0.379

Notes: This table shows treatment effect estimates by subsamples based on firms' distance from their nearest competitor as a proxy of the level of competition it faces (below median distance represents higher levels of competition). Observations are at the firm-month level. The dependent variable is price change, a binary indicator of whether the firm's regular manicure price in a given month is different from its baseline price. All regressions control for any pre-visit differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. The last two rows show the mean and standard deviation of the dependent variable for control firms in the subsample across post-canvasser visit months. Standard errors are clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01.

Table E.3: Price Changes Across Control and Treatment Firms by Baseline Use of Promotions

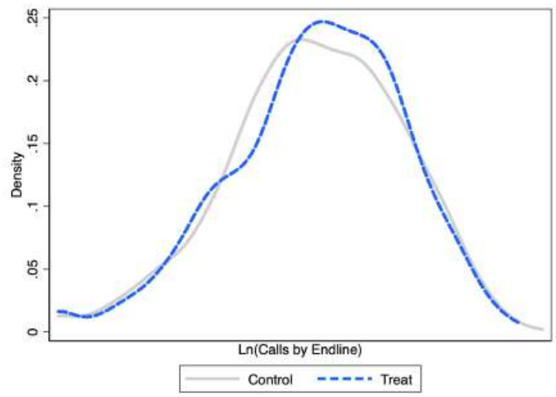
	Price Change from Baseline	
	(1) No Promotions	(2) Used Promotions
Post * Treat	0.032**	-0.002
	(0.013)	(0.045)
Controls	Yes	Yes
Visit Week FE	Yes	Yes
Observations	27010	3132
Mean (control in months after visit)	0.170	0.191
SD (control in months after visit)	0.376	0.394

Notes: This table shows treatment effect estimates by subsamples based on firms' baseline use of demand-based promotions as a proxy of their pricing capabilities. Observations are at the firm-month level. The dependent variable is price change, a binary indicator of whether the firm's regular manicure price in a given month is different from its baseline price. All regressions control for any pre-visit differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. The last two rows show the mean and standard deviation of the dependent variable for control firms in the subsample across post-canvasser visit months. Standard errors are clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01.

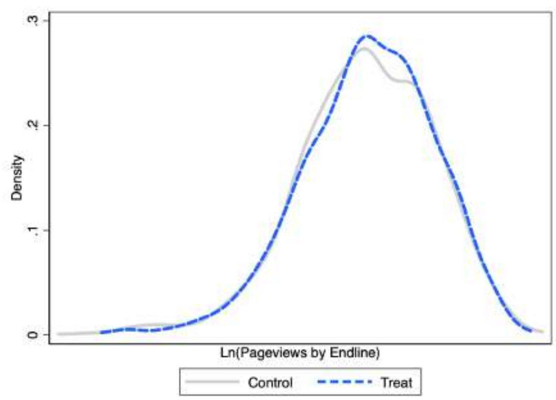
F Treatment effects on proxies of performance

Figure F.1: Distribution of firm performance

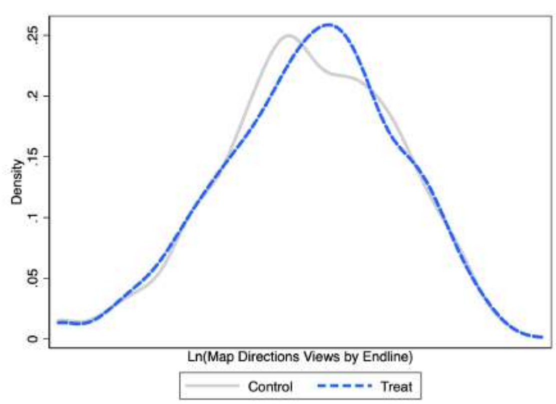
(a) Number of calls



(b) Number of page views

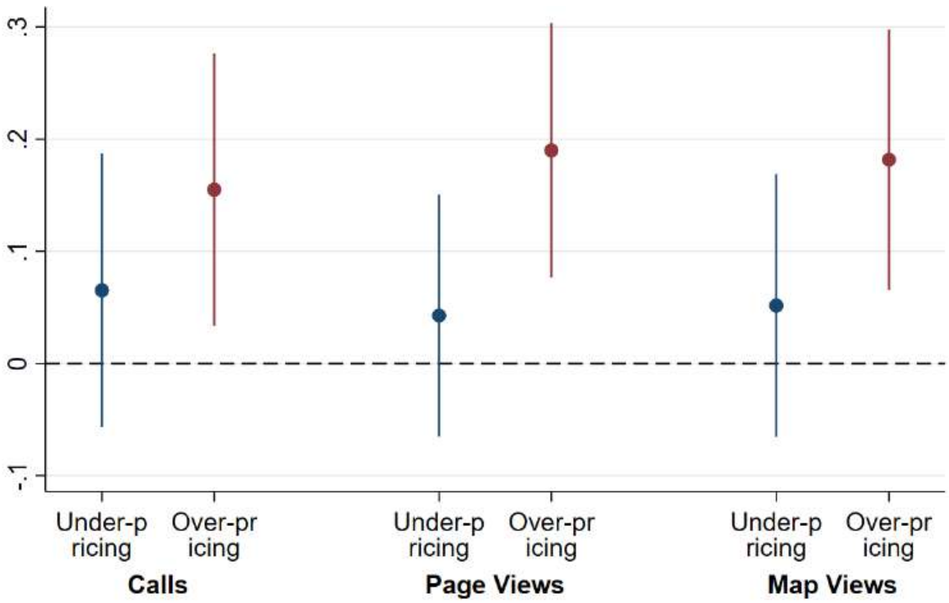


(c) Number of map directions views



Notes: These figures plot the distribution of the sum of calls, page views, and map directions views received between baseline and endline across control and treatment firms. Due to restrictions in the data sharing agreement, the levels of the number of calls, page views, or map directions views are masked.

Figure F.2: Performance effect by baseline over- or under-pricing



Notes: This figure plots estimates of treatment effects on logged calls, page views, and map directions views, respectively (with 95% confidence intervals), by whether the firm was under- or over-pricing at baseline. Under- or over-pricing was coded based on whether the firm was above or below the average price for its quality level.

Table F.1: Estimated Revenue Across Control and Treatment Firms

	(1) ln(Revenue Calls)	(2) ln(Revenue Pageviews)	(3) ln(Revenue Map Views)
Post * Treat	0.191***	0.162***	0.182***
	(0.070)	(0.046)	(0.068)
Controls	Yes	Yes	Yes
Visit Week FE	Yes	Yes	Yes
Observations	30142	30142	30142

Notes: This table shows intention to treat estimates of the competitor information treatment on estimated revenues based on Yelp purchase intentions. Dependent variables are constructed by multiplying the price firms charge each month and the number of purchase intentions (calls, pageviews, or map direction views) observed. Observations are at the firm-month level. All regressions control for any baseline differences between control and treatment groups, an indicator for months post-canvasser visits, and fixed effects for the week of the canvasser visit. Standard errors are clustered at the firm level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.