Many Channels of Adjustment to a Higher Minimum Wage: Evidence from Restaurant Reviews

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Abstract

Minimum wage changes may induce many responses by affected establishments in addition to, or instead of, changes in employment. Some of these channels are difficult to detect directly or simultaneously with conventional data and methods. Using natural language processing methods on millions of restaurant reviews, this paper examines the impacts of minimum wage changes on prices, friendliness, hygiene, portion sizes, and wait times. I find evidence of a rise in prices and improvements in staff friendliness with higher wages. While there is some weak evidence for deteriorating hygiene standards, there are no detectable impacts on portion sizes or wait times. Overall, these changes are associated with a small but significant drop in restaurant ratings.

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1 Introduction

Although nearly all research on firms' responses to higher minimum wages focuses on changes in employment, firms employing low wage workers can make adjustments along several margins. In this paper, I use review data for restaurants and employ natural language processing methods to simultaneously examine many margins empirically, including some that are difficult to detect with conventional data and methods. I also examine the net impact of minimum wage changes on restaurant quality as proxied by the ratings associated with these reviews to try and understand the net effects of the adjustments restaurants make on the "value" of their product.

The debate on the employment effects of minimum wage changes has led to a vast literature (see Dube, 2019; Neumark, 2019, for recent discussions). Schmitt (2015) reviews the employment debate and focuses on other adjustment channels that may reconcile some of the differences in the literature. He considers alternative channels that could arise from assuming a competitive model, an institutional model or a dynamic monsopsony framework, reviewing other research work that studies each of these in greater detail. Apart from a reduction in employment, competitive models suggest that higher minimum wages can be passed on through higher prices to consumers, reductions in fringe benefits, or reductions in worker training, though the empirical evidence on this is mixed (Belman and Wolfson, 2014). Institutional models do not assume that firms are operating at peak efficiency and allow for other adjustments, such as greater managerial efforts, reliance on productivity enhancing activities, the efficiency wage effect, and the mitigating effects that result from the improved spending power of low-wage workers. Another suggested channel is an upgrade in skill level of workforce in response to the minimum wage. The dynamic monopsony model suggests an increase in employment and reduced turnover as a possible consequence of higher minimum wages.

Most literature on the effects of higher minimum wages on employment focuses exclusively on this margin, and indirectly appeals to some of the above alternative adjustment channels as potential explanations for small or null effects. Among the recent papers that focus on other channels, many only examine a single adjustment mechanism. Thus, while there is now considerable collective evidence on some of these alternative channels (prices, for instance), there is less on others, since these may be difficult to study using typical labor market or firm level data, especially simultaneously.

The minimum wage literature often focuses on restaurants or food services because they rely heavily on minimum wage workers and employ a significant share of these workers. Restaurants also have fairly complex production technology with several potential margins to adjust, making this an interesting sector to study multiple margins of adjustment. Advances in text analysis methods mean that reviews of restaurants may be an informative source to detect responses to higher minimum wages. In this paper, I use natural language processing methods on review texts to provide further evidence on the adjustments that can be reliably detected through reviews. Specifically, I examine impacts on prices, friendliness, hygiene, portion sizes, wait times and staff training.

Another contribution of this paper is to study the impact of higher minimum wages on the overall customer experience as proxied by ratings. [1] Studying various adjustments together with ratings helps us better understand the broad implications of minimum wage changes, and the mechanisms underlying the net impacts on this useful summary measure. Since the different adjustments restaurants could make in response to minimum wage increases may have countervailing effects on ratings for service-oriented establishments, the overall effect is theoretically ambiguous, but empirically testable. For instance, if employment falls, the retained employees may have to handle larger workloads and deal with additional tasks where they are less productive. Alternatively, a higher wage for workers, *ceteris paribus*, may motivate them to work harder and exert more effort which would reflect in the actions

[1] Ratings may also be an important outcome to examine because recent research suggests that they can impact revenues and reservations of restaurants. For instance, Luca (2011) finds that a one star increase in restaurant ratings increase revenues by 5 to 9 percent, an effect driven mainly by independent restaurants. Anderson and Magruder (2012) find that a half-star increase in Yelp ratings causes restaurants to fill reservations more frequently.

of customer facing personnel in service-oriented establishments. This efficiency wage effect may lead to higher ratings.[2] Additionally, employers could cut costs which may be reflected in poorer quality of food or service, or lower hygiene standards. Higher menu prices could lower ratings holding everything else constant.

I use data from over 16 million reviews of about 370,000 establishments across 18 metropolitan areas in the United States and Canada. Combining natural language processing methods with difference-in-difference techniques for identification, I find evidence of a rise in prices and improvements in staff friendliness with higher wages. I find weaker evidence for deteriorating hygiene, and no significant effects for portion sizes or wait times. An estimate of price elasticity recovered from review texts of 0.05 is in line with recent literature on the topic, and lends support to the competitive model. However, improvements in staff friendliness may indicate efficiency wage effects or changes by managers to improve operational efficiency that is more in line with institutional models. The findings on improved friendliness and null impacts on wait times are corroborated by interviews with managers surveyed in Hirsch et al. (2015), where they indicated the importance of maintaining speedy customer service and improving performance standards in response to higher wages. However, managers also indicated cross-training of employees as a cost saving measure, which may be consistent with the evidence of deteriorating standards of hygiene found here, and elsewhere in the literature (Chakrabarti et al., 2020). Finally, I find evidence that higher minimum wages are associated with a drop in ratings of restaurants and other food-service establishments.[3]

Aside from these specific conclusions, the methods I develop and implement demonstrate that unstructured natural language found in review data analyzed with computational linguistics methods may be informative in examining the response of firms to minimum wage changes as well as other policies. Gentzkow et al. (2019) provide an excellent introduction on

[2]For instance, Reich et al. (2005) find that in response to living wage policies implemented at the San Francisco Airport in 1999, employers surveyed were more likely to report an improvement in overall work performance, morale, absenteeism, and disciplinary issues.

[3]As a useful placebo check, I find no impact on ratings of other (non-restaurant) establishments that presumably have fewer minimum wage workers on the payroll.

the potential of text as data for use in economic research. In their review of applications and methods they conclude that "virtually all of the methods applied to date, including those we would label as sophisticated or on the frontier, are based on fitting predictive models to simple counts of text features. Richer representations, such as word embeddings, and linguistic models that draw on natural language processing tools have seen tremendous success elsewhere, and we see great potential for their application in economics." (pp. 569). The text analysis in my paper relies on one such word embedding technique - Word2Vec (Mikolov et al., 2013), to better capture the meaning of words and the relationships between them. Words in the text of reviews and the adjustment mechanisms are represented as vectors in a space where similar words (and their combinations) are co-located. [4] To account for the syntactical richness of natural language used in reviews, the outcomes that capture the adjustments studied in this paper are based on similarity scores that rely on models which account for this. To verify that these outcomes capture the concepts meaningfully, I use validation techniques detailed in Section 4.2, making use of the ratings associated with the reviews or the "$" sign (a proxy for price range) associated with the business.

The rest of this paper is organized as follows. Section 2 provides a brief overview of recent work on the impact of minimum wages on non-employment margins, especially those that use digital data. Section 3 describes the data and provides some descriptive statistics. Section 4 provides details on the identification strategy as well as the construction and validation of the text-based outcomes. Section 5 presents the results, and Section 6 concludes by placing the findings in the context of the channels of adjustments literature.

[4] A recent application of these methods can be found in Burn et al. (2019) who study the relationship between ageist language in job ads and hiring discrimination.

2 Brief review of related literature

While there is limited evidence on some of the adjustments studied here, this paper also supplements findings from recent work on others. [5] The one margin aside from employment on which there is fairly extensive evidence is prices, where some degree of pass-through is documented. Aaronson et al. (2008) use panel of store-level restaurant prices as well as aggregated Consumer Price Index data to document price increases in response to federal minimum wage hikes. Allegretto and Reich (2018) find that almost all of the minimum wage increase was passed on through higher prices when San Jose increased its minimum wage in 2013. Using firm level price index data from Hungary, Harasztosi and Lindner (2019) find that three-fourths of a large minimum wage increase was passed on to consumers. Turning to other margins that are harder to measure, work by Chakrabarti et al. (2020) suggests that minimum wage hikes are associated with lower hygiene levels in restaurants due to a possible increase in the task demands on the retained staff. Using a difference-in-difference framework with Seattle restaurants as treated and those in New York City as controls, they find that a \$0.10 increase in real minimum wage is associated with a 11.45% increase in total health violation scores.

Recent work has started to rely on digital data in creative ways to further our understanding of the impacts of minimum wage increases. Luca and Luca (2019) use Yelp data for the San Francisco Bay area and conclude that restaurants with lower ratings are closer to the margin of exit, and are disproportionately driven out of business by increases in the minimum wage. Direct evidence on the impact of minimum wages on ratings is rare. A working paper by Crain (2018) uses a scraped dataset of online menu items and restaurant quality for restaurants across three states (New York, Massachusetts and New Jersey) to estimate the price and quality responses to minimum wage increases in 2017. The author finds higher pass-through in prices among smaller firms, and significant changes in restaurant quality,

[5] Clemens (2021) focuses on the relevance of non-employment margins and is an excellent review of the recent work that explores these margins.

with quality declining among low quality restaurants and increases for high quality ones. The author relies mainly Grubhub, with a secondary dataset from Yelp. Using the former dataset to examine the quality results further, the author finds that changes in quality are driven by changes in order accuracy and timeliness of deliveries as opposed to food quality. These ratings could reflect different adjustments than those captured in this paper using text reviews largely based on customer experience in person. The other margins captured in the text analysis in my paper also help in the interpretation of the ratings responses found here and elsewhere in the literature. The data used in this paper allow me to exploit several minimum wage changes since the establishment of Yelp.com (2004) across 18 metropolitan areas in the United States and Canada. Other non-restaurant establishments less affected by minimum wage changes serve as a useful placebo check. Moreover, since reviews are linked to businesses and users using identifiers, I use both business fixed effects and business-user pair fixed effects to assess impact on ratings, which can help address concerns of compositional changes driving the results. The large sample of review texts also enables a text analysis with greater precision, and is critical for studying the multiple margins of response.

3 Data and Descriptive Statistics

I use datasets released by Yelp for use by researchers. [6] The data released in 2020 and 2021 together contain information on nearly 370,000 businesses across eighteen major metropolitan areas in two countries (United States and Canada) with information from nearly 17 million reviews written by over 3.9 million users. The data include businesses that have had at least 3 reviews older than 14 days and only includes the Yelp recommended reviews. [7] The eighteen metropolitan areas include fourteen in the United States: Las Vegas (NV), Pittsburgh (PA),

[6] This data is made available under the annual Yelp data challenge and has been used in several research papers. The data are updated for each iteration of the challenge.

[7] Yelp recommended reviews are about 75% of the total reviews and excludes reviews that their algorithm detects as biased, fake or unreliable based on user characteristics (`https://www.yelp-support.com/article/Why-would-a-review-not-be-recommended?l=en_US`). Luca and Zervas (2016) provide evidence that this alogirthm does a good job in identifying fake reviews by validating these with sting operations conducted by Yelp starting in 2012.

Phoenix (AZ), Charlotte (NC and SC), Cleveland (OH), Madison (WI), Champaign (IL), Boulder (CO), Orlando (FL), Atlanta (GA), Boston (MA), Columbus (OH), Portland (OR), Austin (TX) and four in Canada, namely, Toronto (ON), Calgary (AB), Montreal (QC), and Vancouver (BC). Aside from average ratings, establishment level information includes hours of operation, street address, geographic coordinates, number of reviews and various attributes like type of business, cuisine for restaurants, parking availability and others. The review level data has individual review texts, associated rating from 1 to 5, the date of the review, and individual dummies for whether the review was useful, funny or cool. Finally, the user-level data has the user id, first name, number of reviews, the average rating they give, date of first review, their friend lists, number of fans, number of useful, funny or cool votes they received and so on. I link this review data with both the users and businesses using identifiers. Integrated information provided in this format by Yelp on businesses, reviews and users has advantages over scraped data which is typically unable to link all this information. For instance, this allows me to add not just business fixed effects, but also user fixed effects, or business-user pair fixed effects for more credible identification that accounts for compositional changes. Essentially, the identification here relies on the same user reviewing the same restaurant at different minimum wage levels.

The critical component of the data from the point of view of this study, is the exact time and date on which the review was written. This means each review can be associated with with a particular minimum wage level in that state at that time. Since the data contain the entire set of reviews for the included businesses, the reviews begin as early as October 2004 (when Yelp was founded) until December 2019. [8] This means that several minimum wage changes across these eighteen metro areas can be exploited. The primary sources for the minimum wage data were the Department of Labor [9] for the fourteen U.S. metro areas and the Government of Canada webpage[10] for the four metro areas in Canada. Appendix

[8] The data for 2020 is only available for 8 metropolitan areas, and is dropped from the analysis to restrict attention to the period unaffected by the COVID-19 pandemic.

[9] `https://www.dol.gov/whd/state/stateMinWageHis.htm`

[10] `http://srv116.services.gc.ca/dimt-wid/sm-mw/rpt2.aspx`

Tables A.1 and A.2 provides details of the minimum wage levels over the relevant time period (2004-2019) for these cities. While the tables list a single minimum wage for a given year for simplicity, in the analysis I exploit the exact month that minimum wage changes came into effect. [11]

Table 1 provides some descriptive statistics for the data. The final data used in this analysis drops less than 0.03 percent of observations from the raw data, excluding only those that did not belong to the 18 metropolitan areas, because of data entry errors and observations where the business, user and review files did not merge perfectly. The average number of reviews for a business is 43, and 79% of businesses in the data are classified as open. Using the attributes of businesses, I classified about 149,244 businesses as restaurants or related to the food-service industry more generally. While restaurants make up about 40% of the total businesses, they account for over 71% of all reviews written. [12] The second panel of the table provides information user characteristics. On average, each user has written about 18 reviews in total.

4 Methods

4.1 Identification Strategy

I use a difference-in-difference (DID) strategy to estimate the causal effects of minimum wage hikes. To keep the identification strategy transparent, the main analysis focuses on the time period 2011-2019 and a single large minimum wage hike in Phoenix, Arizona in 2017. The Arizona minimum wage was increased by nearly 25%, from \$8.05 to \$10.00 per hour. This analysis also relies on using the seven metro areas that serve as "pure" controls

[11] For this I use David Neumark's Minimum Wage Dataset available at `http://www.economics.uci.edu/~dneumark/datasets.html`

[12] The most popular non-food related categories of businesses in the data are Shopping, Beauty & Spas, Home Services, Health & Medical, Automotive, Local Services, Active Life, Hair Salons, Auto Repair, Nail Salons, Event Planning & Services, Hotels & Travel, Fashion, Real Estate, Doctors, Professional Services, Pets, Arts & Entertainment, Home & Garden, Financial Services, Fitness & Instruction, Dentists and so on.

or a "never-treated" group. This mitigates some of the issues generated by staggered roll out designs (Callaway and SantAnna, 2020; Sun and Abraham, 2020). These are Las Vegas, Champaign, Charlotte, Pittsburgh, Madison, Austin and Atlanta. Appendix Figure A.1 shows the (annual) average weekly wage in the food service industry for these metropolitan statistical areas over this period using the Quarterly Census of Employment and Wages (QCEW) data. The figure clearly demonstrates the impact of this minimum wage change on average wages of workers in this industry. [13] The baseline specification for the DID analysis is the following:

$$Y_{rjst} = \beta * Treat_s * Post_t + \mu_j + \eta_t + \epsilon_{rjst} \quad (1)$$

In equation (1), Y_{rjst} represents an outcome ("star" rating between 1 to 5 or an outcome that represents the closesness of the review text to an adjustment mechanism; defined in the section below) for review r for business j in state s at time t. μ_j and η_t represent business and time fixed effects. I extend this difference-in-differences model to an event study design in which I estimate treatment effects by year (equation (2) below). The event study design not only allows us to trace out the time pattern of the minimum wage impacts on Phoenix establishments after 2017, but also helps us assess the validity of the parallel trends assumption by estimating differences between outcomes in each year prior to minimum wage hike (relative to 2016, the omitted year). I also supplement this DID analysis (including event study designs) with a synthetic control approach.

$$Y_{rjst} = \sum_{\substack{t=2011 \\ t \neq 2016}}^{2019} \beta_t * (Treat_s * D_t) + \mu_j + \eta_t + \epsilon_{rjst} \quad (2)$$

In supplementary analysis, I use reviews from all 18 metropolitan areas from 2004-2019

[13]Arizona's minimum wage for tipped workers also increased commensurately from \$5.05 to \$7 am hour in 2017. Even and Macpherson (2014) study the impacts of changes in the tipped minimum on full service restaurants and find reductions in employment in the full-service restaurant industry and tipped workers. In Appendix Figure A.2, I provide average weekly wages from the QCEW data for workers for workers in Arizona and the control states for both limited service and full service restaurants. Wages appeared to increase for workers in both categories (QCEW data includes tips). In this paper, I focus on all restaurants in the review data, and do not make a distinction between the two.

using two-way fixed effects panel regressions with a continuous minimum wage variable to estimate equations of the form:

$$Y_{rjst} = \beta * MW_{st} + \mu_j + \eta_t + \epsilon_{rjst} \tag{3}$$

4.2 Constructing and validating the text-based outcomes

Here, I describe the procedure I use to detect restaurant's adjustment mechanisms from the language of review texts. Figure A.4 shows the empirical distribution of the number of words in each of the 11.3 million reviews for restaurants in the entire data. The mean number of words is 105, while the median is 75. The first step in text processing was to remove the frequently used stop words (such as "of", "a", "the", "and", "to", "in" ,"for"). I then used a word2Vec model where each word is represented as a vector (of dimension 300) in a vector space. This model was first trained on the Google news corpus. Using this model, one can calculate the semantic similarity scores between words, such that words that appear more often together in similar contexts have higher similarity scores. Cosine similarity scores between two vectors representations can range from a value of -1 to 1, where scores closer to 1 indicate a high similarity and scores closer to -1 implies that the words are unrelated (unlikely to appear in similar contexts). Based on this model, I calculate the cosine similarity score between each word in a review and a word (or phrase) that represents a particular adjustment mechanism of interest. As an example, the notion of how expensive a restaurant is can be expressed in various ways. Words with high cosine similarity scores with the word "expensive" include impractical, fancier, onerous, uneconomical, pricy, pricey and so on. Using these scores helps account for the various ways in which language can be used to express a particular concept, as opposed to searching for particular words. The choice of phrases that represent the adjustment mechanisms of interest is informed by looking at token or tri-gram (three-word phrase) frequencies of how these these are typically referred to in review language. The list of words and phrases that represent each mechanism is given below:

- Prices: “Expensive”, “Cheap”
- Efficiency Wage: “Friendly”, “Rude”
- Hygiene: “Clean”, “Dirty”
- Portion Sizes: “Large” + “Portion”, “Small” + “Portion” [14]
- Wait Times: “Wait” + “Long” + “Time”, “Wait” + “Short” + “Time”
- Training: “Well” + “Trained”, “Poorly” + “Trained”

First, I calculate the cosine similarity scores for each token (or word) in a given review and each of the vector representations in the list above. Therefore, for each review, I obtain a distribution of scores. For example, if a review consists of 100 words (after removing stop words) I calculate the cosine similarity score between each of these words and the word (vector) “expensive”. The next step is to recover the 95^{th} percentile of cosine similarity score as the building block of the outcome we will examine. I look at higher percentiles within a review in order to capture the words (and associated scores) in the review that are more likely to be related to the adjustment mechanism, on average.

To validate that these cosine similarity scores are informative, as a first example, I provide a figure that relates the 95^{th} percentile of the cosine similarity score from the distribution of words within a review and the word “friendly”. Since each review is also associated with a customer rating from either one-star up to five-stars, we can plot the distribution *across* reviews (of the 95^{th} percentile score *within* each review) for each of these rating levels. This is shown in the top panel of Figure A.5. It is evident that reviews with five stars had the highest scores (right-most), and those with progressively lower ratings are shifted to the left, in the order that we would expect. This is also reflected in the vertical lines, that show the mean values for these distributions. In the bottom panel of the figure, I show the analogous

[14] Note that the vector space in which words are represented allows for an internally consistent arithmetic. This means that mathematical operations can be done in a way that preserves the meanings of words. For instance, the vector that results from “king” - “man” +“woman” will be close to “queen” in this vector space.

figure with similarities with the word "rude". As expected, the order of the distributions is now reversed, with the one-star review distribution with the greatest semantic similarity scores, and the five-star distribution with the least similarity.

It is important to note that lower values indicate of cosine similarity implies that the terms are unrelated as opposed to opposites. To create a single, continuous summary measure that captures the closeness of a review text to an adjustment mechanism such that low values are related to one end of the mechanism (lower prices, rudeness, poor hygiene) and high values indicate the other (higher prices, friendliness, cleanliness), I use the (standardized) distance between these scores for each review. Thus, the outcome for each review r is defined for the six adjustment mechanisms as follows:

$$Y_r^{Price} = \Theta(CS(\text{“}Expensive\text{”}, Token_r)) - \Theta(CS(\text{“}Cheap\text{”}, Token_r))$$

$$Y_r^{Efficiency} = \Theta(CS(\text{“}Friendly\text{”}, Token_r)) - \Theta(CS(\text{“}Rude\text{”}, Token_r))$$

$$Y_r^{Hygiene} = \Theta(CS(\text{“}Dirty\text{”}, Token_r)) - \Theta(CS(\text{“}Clean\text{”}, Token_r))$$

$$Y_r^{Portion} = \Theta(CS(\text{“}Small\ portion\text{”}, Token_r)) - \Theta(CS(\text{“}Large\ portion\text{”}, Token_r))$$

$$Y_r^{Waiting} = \Theta(CS(\text{“}Wait\ long\ time\text{”}, Token_r)) - \Theta(CS(\text{“}wait\ short\ time\text{”}, Token_r))$$

$$Y_r^{Training} = \Theta(CS(\text{“}Well\ trained\text{”}, Token_r)) - \Theta(CS(\text{“}Poorly\ trained\text{”}, Token_r))$$

, where Θ represents the 95^{th} percentile of the distribution of CS scores *within* a review. In Figure A.6, I present the final (standardized) outcome that captures efficiency wage effects (friendliness or rudeness of staff) and its relationship to review ratings. Appendix Figure A.7 shows hygiene, training, and wait time outcome histograms (validated with review stars) and price adjustments (validated with Yelp $ signs). As further validation of the information contained in these outcomes, I provide the actual review texts for a random sample of 100 reviews drawn from within the first percentile and above the ninety-ninth percentile for each of the outcome variables in an online appendix. [15]

Finally, even though we have picked the 95^{th} percentile value of the cosine similarity scores *within* a review to construct an outcome, most reviews will not be informative about many adjustment mechanisms especially considering average review length. Therefore, instead of only looking at mean impacts using ordinary least squares, I also consider impacts on higher percentiles *across* reviews by employing quantile regressions. I calculate the difference-in-difference estimates for the twenty vigintiles [16] of the outcome distribution by estimating a modified version of equation (1) where $Post_t = 1$ for 2017 and $Post_t = 0$ for 2016.

5 Results

5.1 Ratings

Before turning to the text of reviews to test for evidence of various adjustment mechanisms, I first briefly examine the impact of minimum wages on ratings. Ratings here serve as a proxy or summary measure for overall quality of service. While some potential adjustments such as higher prices or lower hygiene could impact ratings negatively others such as improvements in operational efficiency or efficiency wage effects could lead to higher ratings.

I focus on the impact of the minimum wage hike in Arizona that came into effect in 2017 on ratings. The 2017 Arizona minimum wage rise was one of the largest in our data for the United States from \$8.05 to \$10.00. Since this was a recent minimum wage hike in the Phoenix metropolitan area, there is a considerable amount of data in terms of number of establishments and associated reviews. The comparison states of Nevada, Illinois, North and South Carolina, Pennsylvania, Wisconsin, Georgia and Texas had constant minimum wages throughout this period. Figure 1 shows the annual average ratings using reviews from restaurants in the top panel. First, it is evident from the top panel that since 2012 average

[15] Link to Online Appendix.

[16] The twenty vigintiles refer to the fifth to ninety-fifth percentiles in intervals of five.

restaurant ratings were on the rise. Second, while Phoenix establishments had higher ratings throughout, trends looked quite similar to the comparison areas until the minimum wage hike in 2017. Ratings in Phoenix declined in 2017, and fell below the average ratings of restaurants in the control group. The latter continued to rise in line with previous trends.[17]

To estimate the impact on ratings formally, I use a simple difference-in-difference (DID) framework in Equation (1), where $Treat = 1$ for Phoenix, Arizona and 0 for control areas. $Post$ takes a value of 0 for 2011 to 2016 and 1 for 2017 to 2019. The DID coefficient of interest is β. All specifications include year and month fixed effects to account for overall time trends affecting all establishments (including seasonal variation). Table 2 shows that the DID coefficient is negative and significant. To account for possible compositional changes in the restaurants being reviewed, columns 2 includes business fixed effects to effectively exploit the within-establishment variation. Results are similar with this restriction. Column 3 further adds business-user pair fixed effects.[18] The nearly two dollar increase in minimum wage in Arizona was associated with a 0.03 to 0.04 "stars" reduction in average ratings for restaurants, relative to the control states. [19] The results are robust to only including a single pre (2016) and post (2017) year, as well as using only a single neighboring state (Nevada) as a control.

Event study estimates for restaurants are presented in the bottom panel of 1, where we see that the parallel trends appear to be satisfied, even accounting for alternative levels of clustering standard errors. As a robustness check, I also employ a synthetic control approach (Abadie et al., 2010) that matches on pre-trends of average annual ratings for restaurants since 2011. Figure A.11 presents the results for restaurants. This figure is very similar to the top panel of Figure 1, and encouragingly I find that the method assigns the largest weights

[17] In contrast to this, Appendix Figure A.3 shows that trends continued to be similar through 2017 in the for treated and control states for all other (non-food) establishments, which serves as a useful placebo check.

[18] This restriction means identification relies on a very small subset of reviews which makes the estimate somewhat imprecise (p=0.11)

[19] The results for placebo establishments corresponding to the specifications in Table 2 are presented in Appendix Table A.3. For these (non-food service) establishments, the coefficients are not significant and close to zero.

(0.488 and 0.123) to the two most geographically proximate control regions of Austin, Texas and Las Vegas, Nevada, respectively. Wisconsin, Pennsylvania, North Carolina, Georgia, South Carolina and Illinois are all assigned weights less than 0.1 (in descending order).

Finally, in Table 3, I present results from estimating Equation (3) where the coefficient of interest represents the rating change associated with a one dollar change in minimum wage. This specification utilizes all the minimum wage changes for 18 metro areas since 2004. The table confirms that a higher minimum wage is associated with a significant drop in ratings for restaurants. Column 2 introduces Business-User pair fixed effects and reinforces this result, even though identification relies on a much smaller subset of reviews.

5.2 Restaurant Prices

The first text-based outcome I consider is to examine price adjustments to minimum wages using restaurant review texts. I do this using two approaches. The first searches the text of reviews for an explicit mention of numeric dollar prices and recovers numbers following the "$" symbol. The advantage of this numeric approach is that I can estimate the elasticity of prices faced by the consumers with respect to minimum wages which is easily interpreted and can be placed in the context of the existing literature. An important caveat here is that identification relies on the reviews that explicitly mentioned a dollar amount (about 10 percent of reviews). The second approach uses the outcome based on the semantic similarity of the review text to the word "expensive" relative to the word "cheap". This approach was outlined in detail in section 4.2 above for all the adjustment mechanisms I explore in this paper. This has the benefit of using all reviews in the data.

As a check on whether the extracted prices are sensible and informative, Appendix Figure A.8 shows how the average extracted dollar prices from reviews correspond to Yelp's "$" signs for the restaurant that was reviewed. These average prices are about $9,$17, $31 and $41 for the four categories in increasing order of expensiveness. The event study figure for extracted (log) prices is shown in Figure 2. The Arizona minimum wage hike appeared to raise prices for Phoenix restaurants relative to the controls.

Table 4 presents the results from a panel regression of log prices on the log of minimum wages, using the same baseline specifications as in Table 3 where we use all the data since 2004 (limited to the 14 U.S. metro areas). [20] For the specification with only business fixed effects (column 1), the minimum wage price elasticity is about 0.05 and statistically significant. Thus a 10 % increase in minimum wage leads to a 0.5 % rise in the prices, as experienced and mentioned by consumers. This is in line with other estimates of price elasticity in the literature (Allegreto and Reich , 2018). Adding business-user pair fixed effects (column 3) limits the variation in the sample further to repeat reviewers for restaurants that mentioned prices explicitly. I find that the estimates are still positive though no longer significant. [21]

Next, we can explore price adjustments using the language based outcome. As mentioned at the end of Section 4.2 above, I present the DID estimates for the language based outcomes at various quantiles of the distribution in column 1 of Table 5. Looking at higher percentiles of the outcome focuses on the reviews most likely to mention language highly correlated with price adjustments, I find some evidence of a higher propensity for language associated with "expensive" (relative to "cheap") for Phoenix, though these are imprecisely estimated. Overall, looking at the evidence from both of these approaches, it does appear that there is an increase in prices in Phoenix restaurants after the minimum wage hike relative to the control MSAs.

5.3 Friendliness and Training Outcomes

In this section, I examine whether higher minimum wages are associated with improvements in staff friendliness or training that would be reflected in reviews. First, I explore whether higher wages could leads to better service through improvements in staff friendliness. Once again, I present the DID estimates for these language based outcomes at the higher quantiles

[20] I exclude Canada from the analysis that relies on extracting prices following the US $ symbol

[21] Appendix Table A.5 shows that for other (placebo) establishments the elasticity is not significant in either specification.

of the distribution. For staff friendliness (relative to rudeness), these results are presented in column 2 of Table 5. I find evidence of a significant improvement in this outcome at higher percentiles in Phoenix after the minimum wage rise relative to the pure control regions. This is especially true of reviews at the 90th and 95th percentile of this outcome, which are likely the most informative in capturing the adjustment mechanism. The results in support of changes in training are somewhat weaker but consistent with an improvement. These are presented in Column 4 of Table 5.

5.4 Hygiene

To the study the association between minimum wages and overall levels of hygiene, we consider the text based outcome that takes on higher values when reviews are associated more closely with worse hygiene, based on higher semantic similarities with the word "dirty" relative to "clean". Column 3 of Table 5 shows the difference-in-difference estimate for this outcome at the 95th, 90th and 85th percentile. The 95th percentile has the largest estimate, which is significant at the 10% level. This would imply that the most informative reviews about this adjustment mechanism experienced a larger increase in Phoenix after the minimum wage rise relative to the control areas, indicating worsening hygiene levels.

5.5 Wait Times and Portion Sizes

Analogous to the case of price adjustments, I approach wait times in two different ways. The first is to extract wait times from text using any numeric mention of wait times preceding the word "minutes". [22] The event-study presented in Figure A.10 does not provide strong evidence of lack of clear pre-trends or a significant change in wait times after the minimum wage change. The language based outcome on wait times constructed as a standardized measure based on mentions of long relative to short wait times also does not appear to show

[22] This extraction can also be validated by looking at average wait times across Yelp $ signs in Appendix Figure A.9.

clear effects. This is true even for the most informative reviews at higher percentiles of the outcome (column 5 of Table 5). From the point of view of customers, therefore, there appears to be no detectable changes in wait times.

The last column of Table 5 presents the results for the change in the outcome on portion sizes at the top three vigintiles of the outcome distribution. Recall that higher values of this outcome are associated with smaller portion sizes. I find no clear evidence that restaurants in Arizona changed their portion sizes significantly in response to the minimum wage change, relative to restaurants in the control areas.

6 Conclusion

Restaurants and other food service industry establishments can adjust to changes in minimum wages in many different ways. Combining natural language processing with differences-in-differences methods for identification, this paper examined the impact of minimum wage changes on prices, staff friendliness, hygiene, training, wait times and portion sizes. I find evidence of improvements in staff friendliness, higher prices and deteriorating hygiene. Extracting prices from text of reviews indicates that a 10 percent increase in minimum wage increases prices by 0.5 percent. I find no discernible impacts on portion sizes or wait times.

It is important to place these findings in the context of the small but growing literature on alternative channels of adjustment, which typically relies on very different methods and data. To further explore the small effects of a federal minimum wage hikes between 2007-2009 on employment and hours worked Hirsch et al. (2015) surveyed of 66 store managers to examine alternative channels of adjustments. In response to how they would adjust to minimum wage changes, managers cited the importance of improving performance standards, hiring more experienced workers, and maintaining speedy customer service. Since enhanced operational efficiency requires more training and not less, very few managers actually reported decrease in training as a cost saving response. My findings on an improvement in staff friendliness are in line with the "institutional" model of the labor market. It is conceivable that the improved friendliness reflects increased performance standards. This finding is also consistent with the efficiency wage theory that predicts greater work effort by workers either by increasing the cost of losing a job, or through the reciprocity effect of the "gift" of higher wages. Aside from discouraging over-time work, interviews with managers in Hirsch et al. (2015) also revealed that cross training workers is an important tool to improve operating efficiency. My finding of a decline in cleanliness may reflect this, and is also consistent with Chakrabarti et al. (2020), who cite increased task demands on retained staff as a possible explanation. The fact that I do not find any impacts on wait-times is also consistent with managerial priorities on maintaining the speed of customer service. On the issue of training, Schmitt (2015) hypothesizes that "one reason that the research has not identified clear effects of the minimum wage on training may be that some employers may respond to a higher wage floor by increasing training for low-wage workers in order to raise their productivity to a level commensurate with their new, higher earnings." (pp. 569). In this paper, the text analysis of review language on training indicates that customers did not detect declines in training, and if anything may have observed some improvements, though this language could be correlated with friendliness and it would be difficult to disentangle these two effects further. Therefore, while I do find some evidence in support of institutional models overall, the increase in prices observed is also consistent competitive model of labor markets.

Finally, the net impact of the changes on ratings is negative, though small in magnitude. A dollar increase in minimum wage is associated with a fall in ratings of 0.01 to 0.02 off a base of approximately 3.8 out of 5 (about 0.5 %). These negative impact on ratings are robust to the inclusion of business fixed effects and business-user fixed effects, as well to clustering at the zipcode, state or business level. While these effects may seem small, they can have still have more serious implications for a large number of restaurants, especially because of the way summary ratings are displayed on the Yelp page of businesses. Recall that even though ratings by users can take values from 1 to 5, the main page for the restaurant summarizes the average ratings in half-star intervals. Since a 3.24 average would be rounded to 3, and a 3.26 would be rounded to 3.5, even a small shift in response can have implications for firms. Both Luca (2011) and Anderson and Magruder (2012) have used these rounding thresholds in RD designs, and found significant impacts of ratings on revenues and reservations. Thus, these costs may be important as ratings are being seen as increasingly valuable signals of restaurant quality by consumers.

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Tables

Table 1: Descriptive Statistics for Businesses, User and Reviews

Businesses		
	Mean	S.D
Business Rating	3.59	(0.99)
Number of Reviews	43.47	(126.52)
Open	0.79	(0.41)
Restaurant Dummy	0.40	(0.49)
N	369,844	
Users		
	Mean	S.D
User Reviews	17.82	(61.59)
Average rating given	3.64	(1.19)
Elite Dummy	0.03	(0.17)
N	3,901,337	
Reviews		
	Mean	S.D
Rating	3.72	(1.47)
N	*16,653,518*	

Table 2: Ratings Impact for Restaurants: DID Specification

	(1)	(2)	(3)
Post X Treatment	-0.037**	-0.026**	-0.035
	(0.015)	(0.012)	(0.024)
Constant	3.764***	3.768***	3.696***
	(0.017)	(0.002)	(0.003)
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Business FE	No	Yes	No
Bus-User FE	No	No	Yes
N	5567805	5567130	337599

AZ treated, NV IL NC SC PA WI TX GA Controls. SE clustered at zipcode.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Ratings Impact for Restaurants: Panel Regressions

	(1)	(2)
Min Wage	-0.007**	-0.022***
	(0.003)	(0.006)
Constant	3.802***	3.875***
	(0.028)	(0.053)
Month FE	Yes	Yes
Year FE	Yes	Yes
Business FE	Yes	No
Bus-User FE	No	Yes
N	11371172	691204
R-Square	0.19	0.75
Adj. R-Square	0.18	0.54

Restaurant reviews for all 18 metropolitan areas. SE clustered at zipcode.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Panel Regressions of Log Prices on Log of MW for Restaurants

	(1)	(2)
Ln(MW)	0.047^{*}	0.190
	(0.028)	(0.134)
Constant	2.262^{***}	1.902^{***}
	(0.059)	(0.281)
Month FE	Yes	Yes
Year FE	Yes	Yes
Business FE	Yes	No
Bus-User FE	No	Yes
N	995152	31384
R-Square	0.34	0.84
Adj. R-Square	0.29	0.70

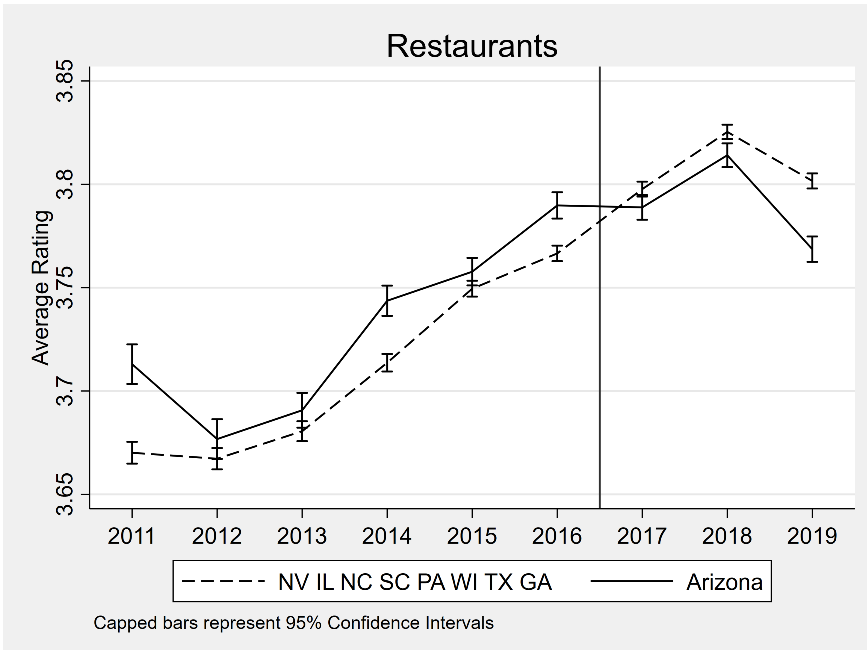
Sample restricted to restaurant reviews where dollar prices mentioned explicitly.
SE clustered at zipcode.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: DID Results for Text-Based Outcomes - 95th, 90th and 85th Percentiles

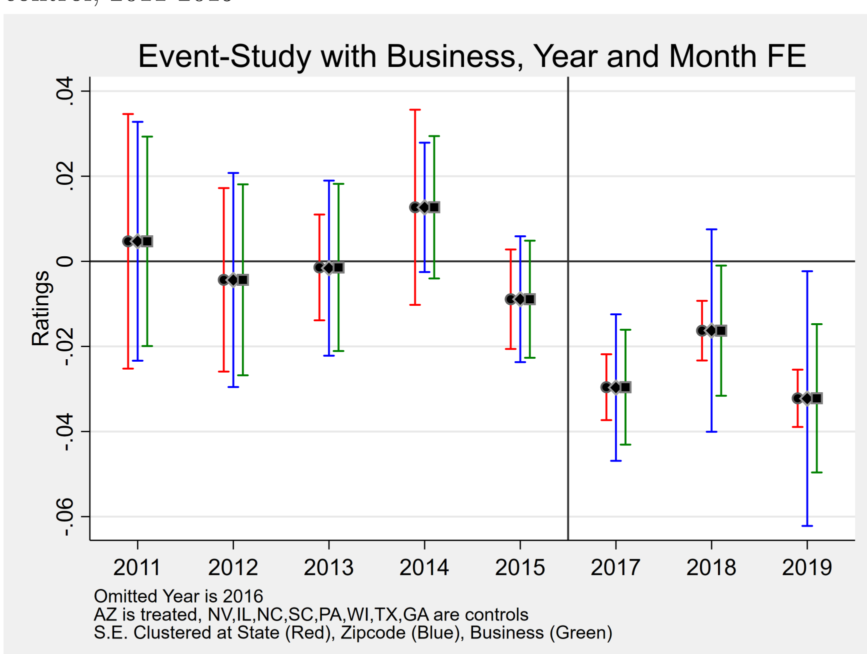
	Price	Friendliness	Hygiene	Training	Wait Times	Portion Sizes
DID at 95th	0.009	0.017***	0.015*	0.008	0.005	0.001
	(0.008)	(0.006)	(0.009)	(0.014)	(0.008)	(0.009)
DID at 90th	0.006	0.008*	0.008	0.010	0.001	0.001
	(0.006)	(0.004)	(0.005)	(0.006)	(.003)	(0.006)
DID at 85th	0.007	0.006	0.003	-0.000	0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.006)	(0.003)	(0.006)
N			1599733			

AZ is treated, NV, IL, NC, SC, PA, WI, TX, GA are controls
Robust standard errors in parenthesis
* $p < 0.10$,** $p < 0.05$,***$p < 0.01$

Figures



(a) Annual average ratings for restaurant reviews in Phoenix, AZ and control, 2011-2019



(b) Event-Study Plot for Impact on Restaurant Ratings

Figure 1: Ratings associated with restaurant reviews

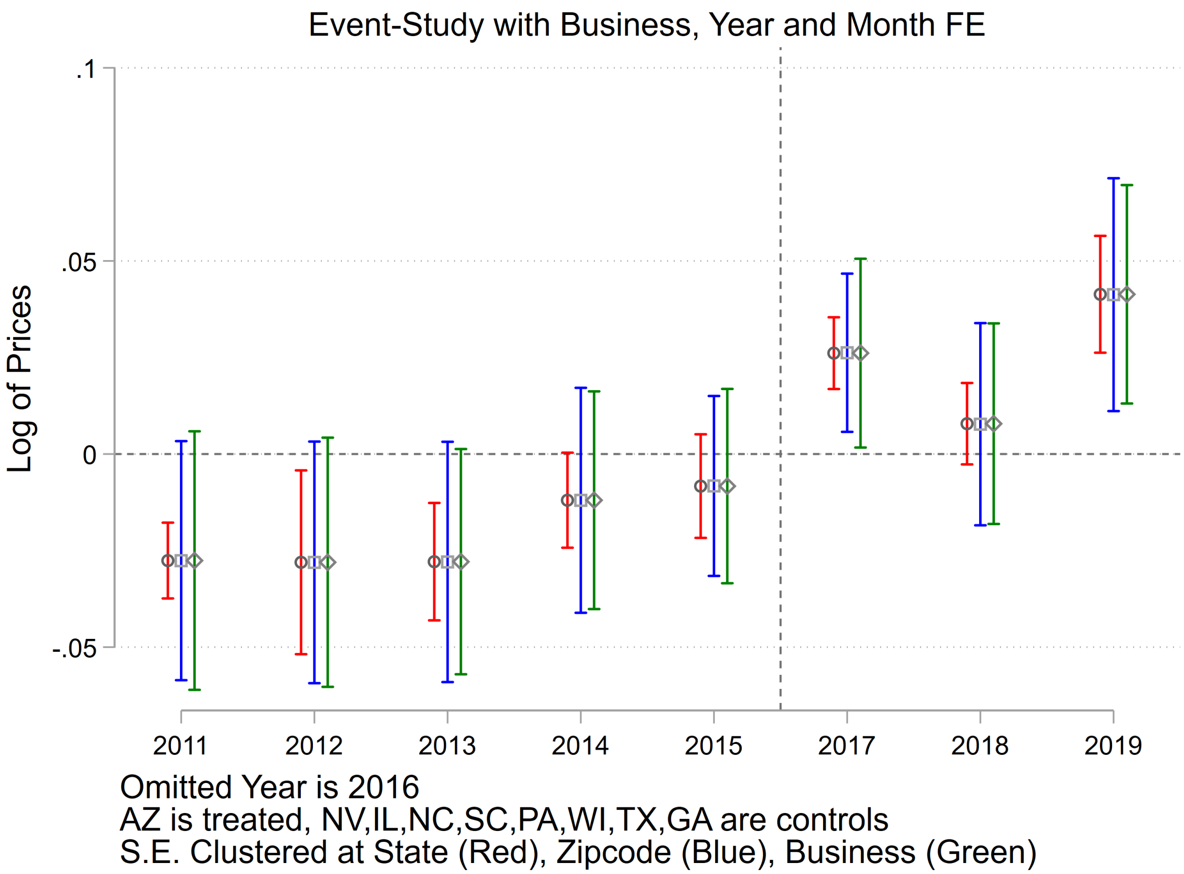


Figure 2: Event Study Plot for Impact on Log of Prices

A Appendix Tables and Figures

Table A.1: Minimum Wages for the U.S States in data 2004-2019 in USD

	AZ Phoenix	IL Champaign	NC Charlotte	SC	NV Las Vegas	OH Cleveland-Columbus	PA Pittsburgh	WI Madison	CO Boulder	FL Orlando	GA Atlanta	MA Boston	OR Portland	TX Austin
2004	5.15	5.50	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.75	7.05	5.15
2005	5.15	6.50	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.15	5.15	6.75	7.25	5.15
2006	5.15	6.50	5.15	5.15	5.15	5.15	5.15	5.70	5.15	6.40	5.15	6.75	7.50	5.15
2007	6.75	7.50	6.15	5.85	6.15	6.85	6.25	6.50	6.85	6.67	5.15	7.50	7.80	5.15
2008	6.90	7.75	6.15	6.55	6.33	7.00	7.15	6.50	1.02	6.79	5.85	8.00	7.95	5.85
2009	7.25	8.00	6.55	7.25	6.85	7.30	7.15	6.50	7.28	7.21	6.55	8.00	8.40	6.55
2010	7.25	8.25	7.25	7.25	7.55	7.30	7.25	7.25	7.24	7.25	7.25	8.00	8.50	7.25
2011	7.35	8.25	7.25	7.25	8.25	7.40	7.25	7.25	7.36	7.31	7.25	8.00	8.80	7.25
2012	7.65	8.25	7.25	7.25	8.25	7.70	7.25	7.25	7.64	7.67	7.25	8.00	8.95	7.25
2013	7.80	8.25	7.25	7.25	8.25	7.85	7.25	7.25	7.78	7.79	7.25	8.00	9.10	7.25
2014	7.90	8.25	7.25	7.25	8.25	7.95	7.25	7.25	8.00	7.93	7.25	8.00	9.25	7.25
2015	8.05	8.25	7.25	7.25	8.25	8.10	7.25	7.25	8.23	8.05	7.25	9.00	9.25	7.25
2016	8.05	8.25	7.25	7.25	8.25	8.10	7.25	7.25	8.31	8.05	7.25	10.00	9.75	7.25
2017	10.00	8.25	7.25	7.25	8.25	8.15	7.25	7.25	9.30	8.10	7.25	11.00	10.25	7.25
2018	10.50	8.25	7.25	7.25	8.25	8.30	7.25	7.25	10.20	8.25	7.25	11.00	10.75	7.25
2019	11.00	8.25	7.25	7.25	8.25	8.55	7.25	7.25	11.10	8.46	7.25	12.00	11.25	7.25

Table A.2: Minimum Wages for the relevant Canadaian Provinces in the Data 2004-2019 in CAD

	AB Calgary	ON Toronto	QC Montreal	BC Vancouver
2004	7.50	7.50	7.50	8.00
2005	7.50	7.50	7.60	8.00
2006	7.50	7.75	7.75	8.00
2007	8.00	8.00	8.00	8.00
2008	8.40	8.75	8.50	8.00
2009	8.80	9.50	8.50	8.00
2010	8.80	10.25	9.50	8.00
2011	9.40	10.25	9.65	8.00
2012	9.75	10.25	9.90	8.75
2013	9.95	10.25	10.15	9.50
2014	10.20	11.00	10.35	10.25
2015	11.20	11.25	10.55	10.45
2016	12.20	11.40	10.75	10.85
2017	13.60	11.60	11.25	11.35
2018	15.00	14.00	12.00	12.65
2019	15.00	14.00	12.50	13.85

Table A.3: Ratings Impact for Other (Placebo) Establishments: DID Specification

	(1)	(2)	(3)
Post X Treatment	0.008	-0.002	-0.027
	(0.015)	(0.009)	(0.025)
Constant	3.697***	3.685***	3.285***
	(0.024)	(0.002)	(0.005)
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Business FE	No	Yes	No
Bus-User FE	No	No	Yes
N	2732913	2732310	206730

AZ treated, NV IL NC SC PA WI TX GA Controls. SE clustered at zipcode.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Ratings Impact for Other (Placebo) Establishments: Panel Regressions

	(1)	(2)
Min Wage	-0.003	0.007
	(0.003)	(0.011)
Constant	3.686***	3.238***
	(0.025)	(0.097)
N	4628958	336064
R-Square	0.33	0.84
Adj. R-Square	0.30	0.70

Other (non-food) reviews for all 18 metropolitan areas. SE clustered at zipcode.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Panel Regressions of Log Prices on Log of MW for Other (Placebo) Establishments

	(1)	(2)
Ln(MW)	-0.023	-0.086
	(0.037)	(0.287)
Constant	3.029***	3.222***
	(0.077)	(0.610)
N	320502	11764
R-Square	0.40	0.88
Adj. R-Square	0.29	0.76

Sample restricted to other (non-food establishment) reviews where dollar prices mentioned explicity.

SE clustered at zipcode.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

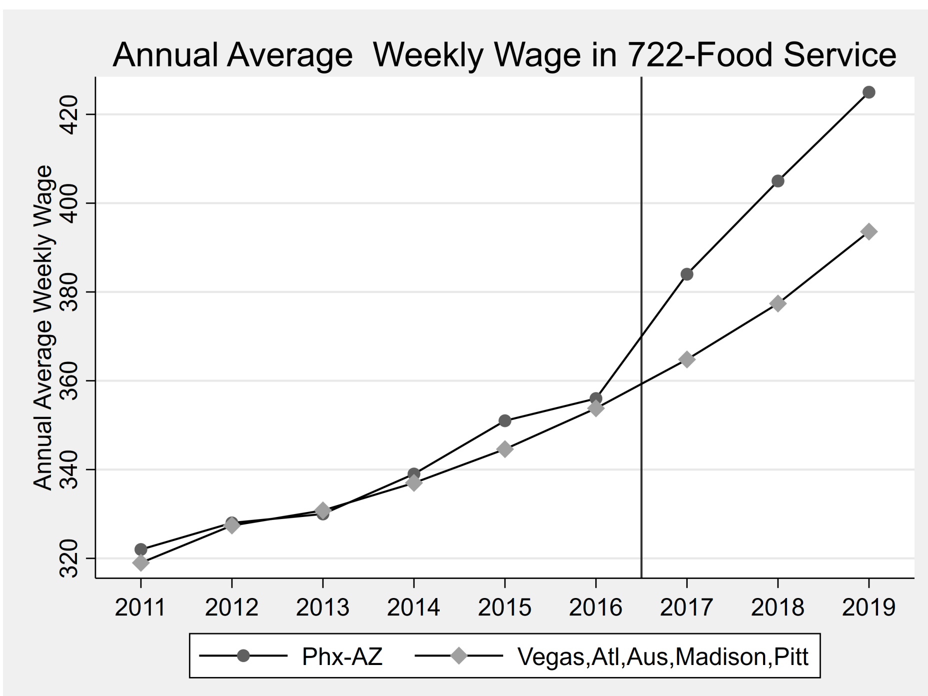
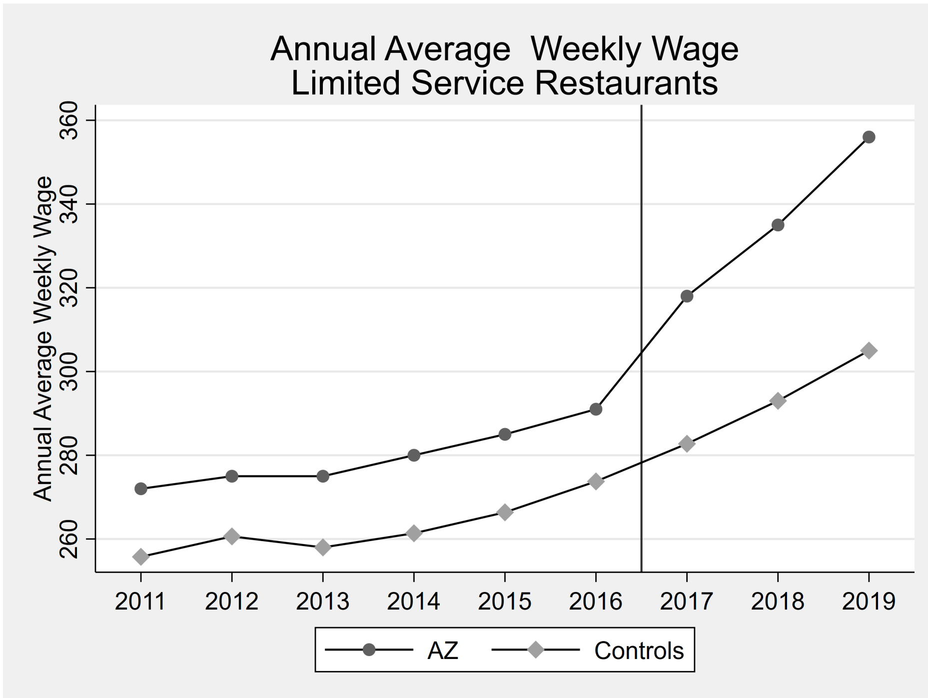
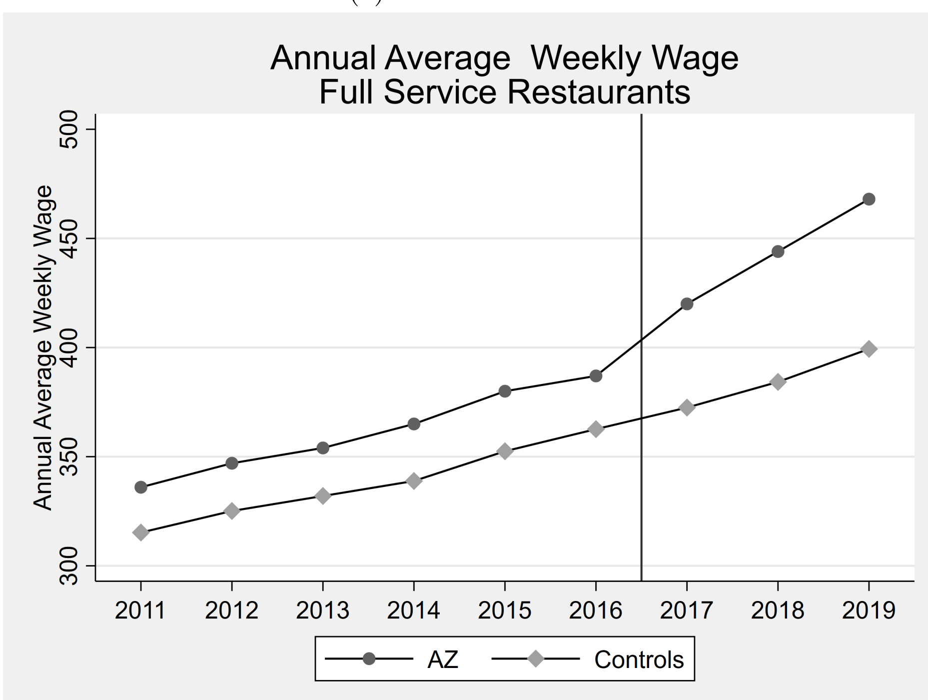


Figure A.1: Average Annual Weekly Wages in Food Service (QCEW Data)



(a) Limited Service



(b) Full Service

Figure A.2: Annual Average Wages in Restaurants (QCEW), Treated (AZ) and Control States

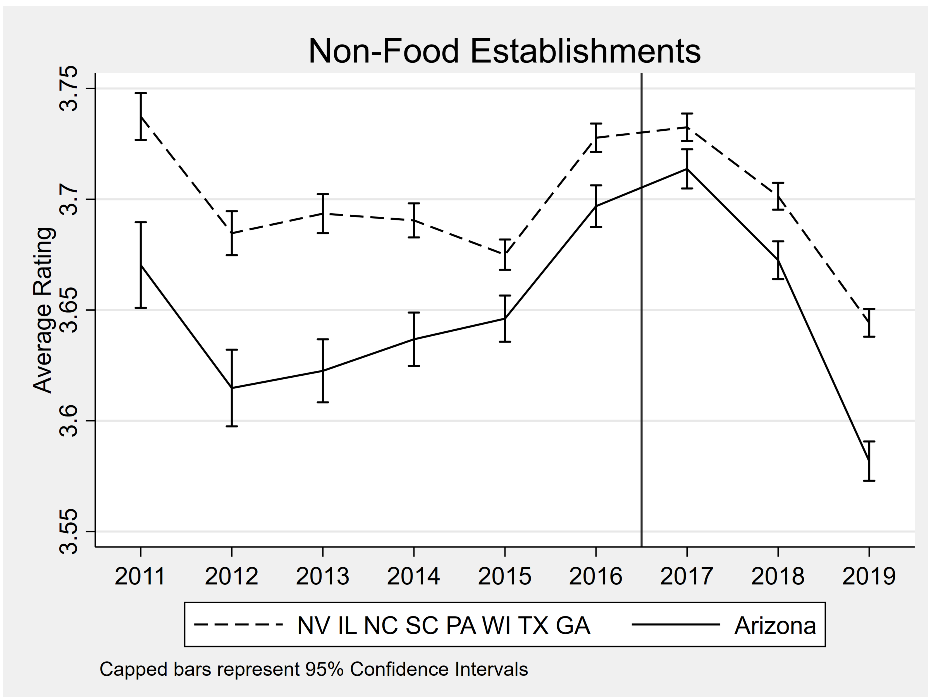


Figure A.3: Annual average ratings for placebo establishment reviews in Phoenix, AZ and control, 2011-2019

A.1 Descriptive Statistics for Text Analysis Outcomes

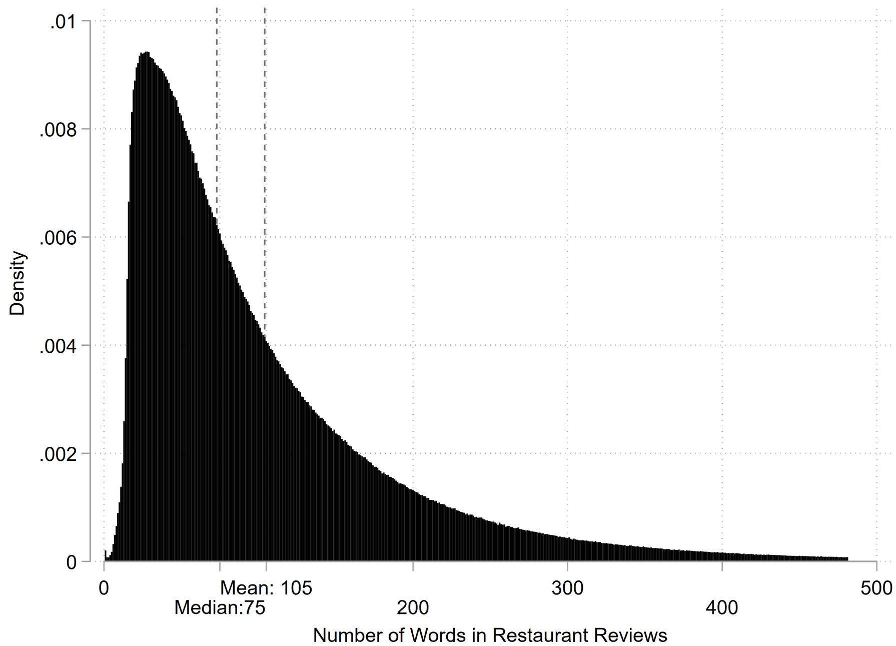
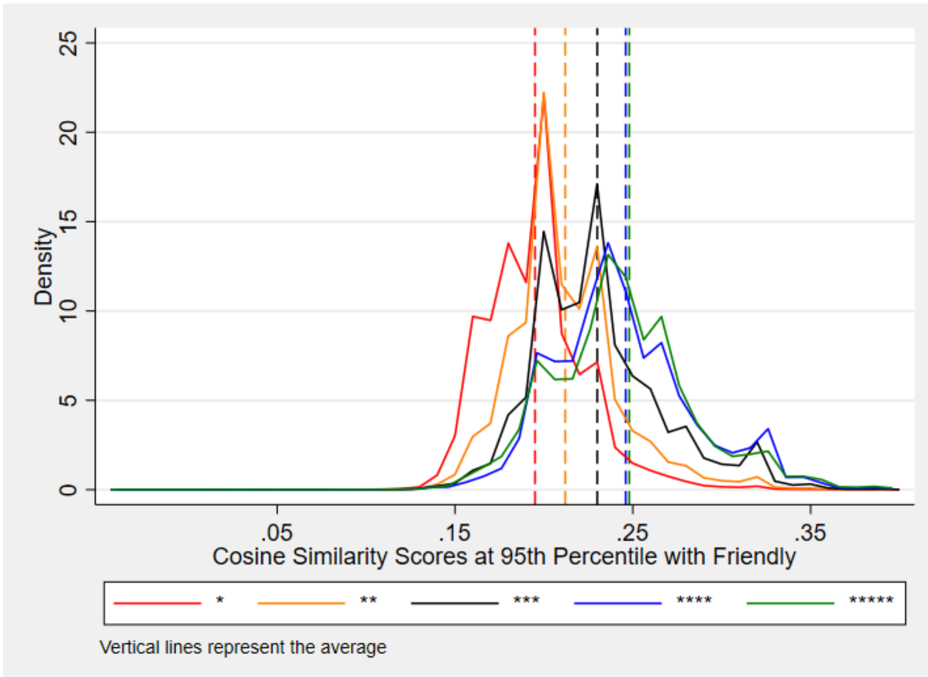
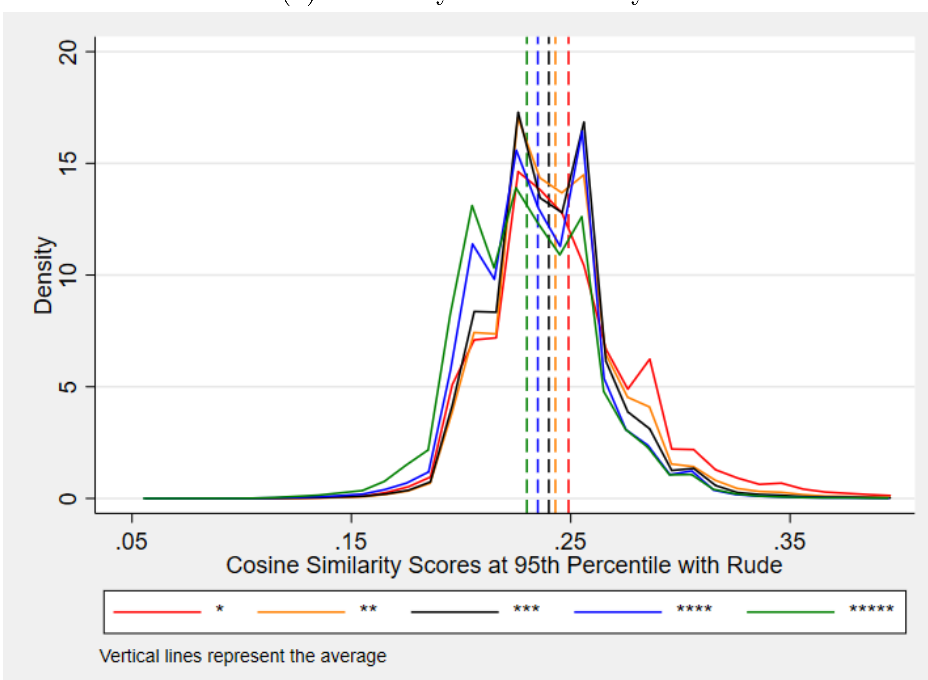


Figure A.4: Histogram of Word Counts in Review Texts for restaurants



(a) Similarity with "Friendly"



(b) Similarity with "Rude"

Figure A.5: Distribution of Cosine Similarity Scores, by Review Ratings (Stars)

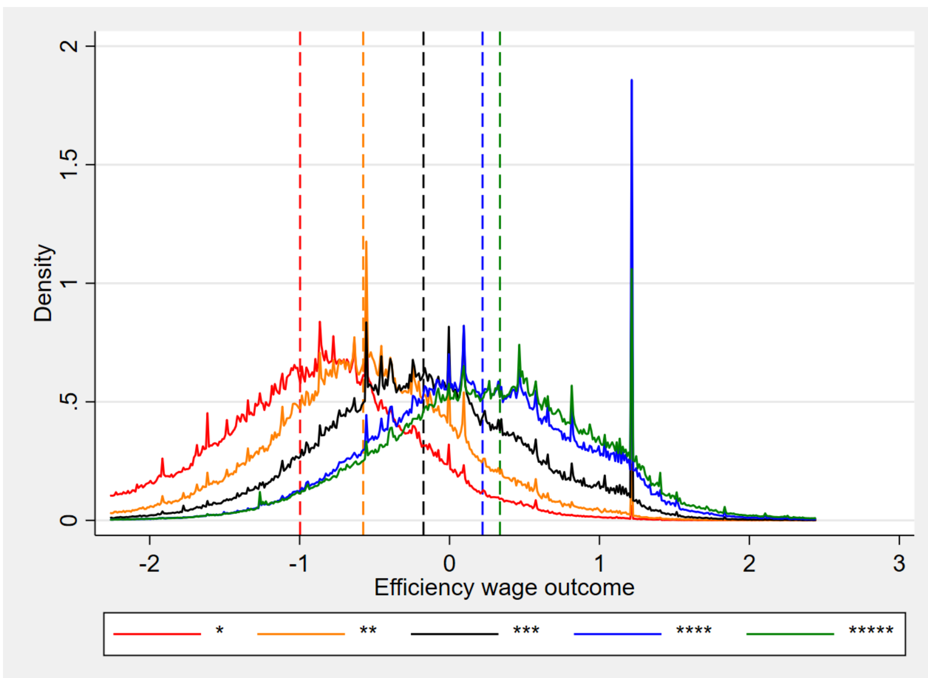
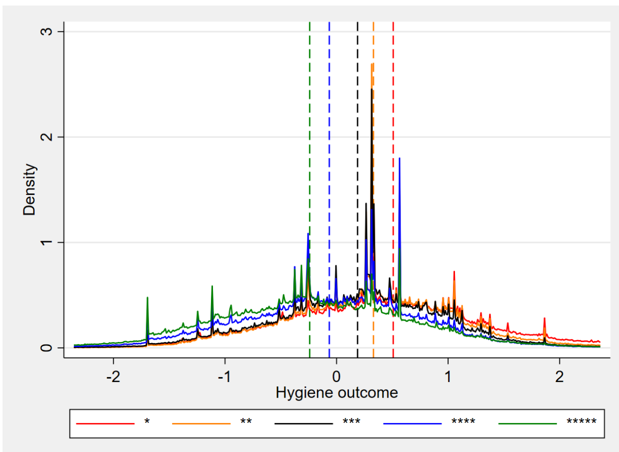
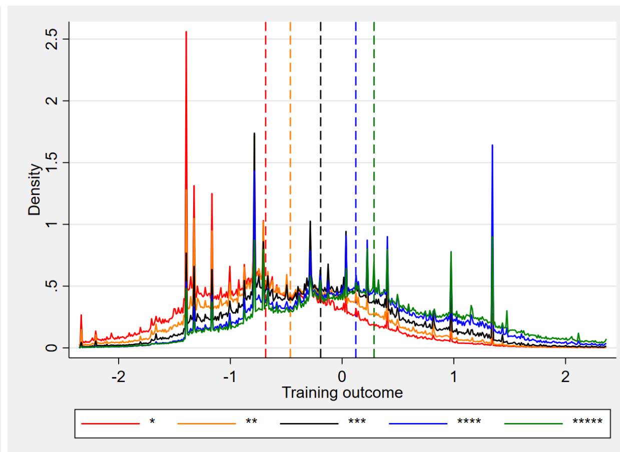


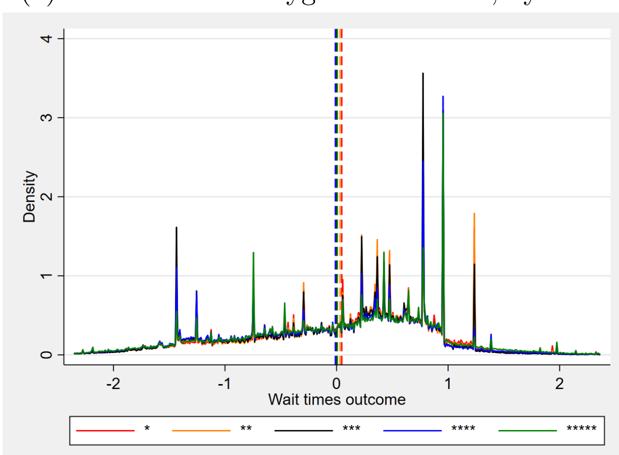
Figure A.6: Distribution of Efficiency Wage Outcome, by Review Ratings (Stars)



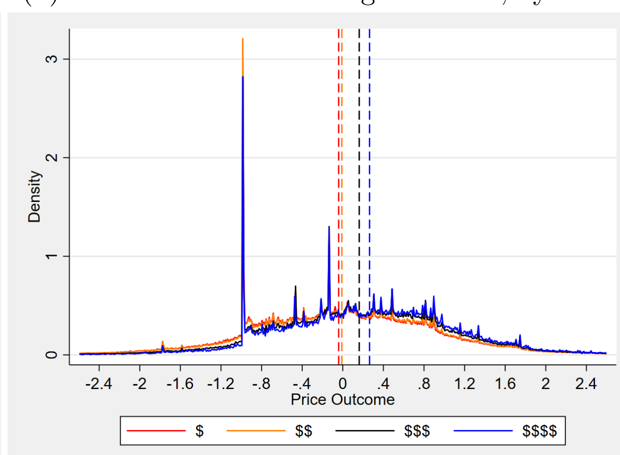
(a) Distribution of Hygiene Outcome, by stars



(b) Distribution of Training Outcome, by stars



(c) Distribution of wait-time Outcome, by stars



(d) Distribution of Price Outcome, by Yelp $ signs

Figure A.7: Outcome distributions

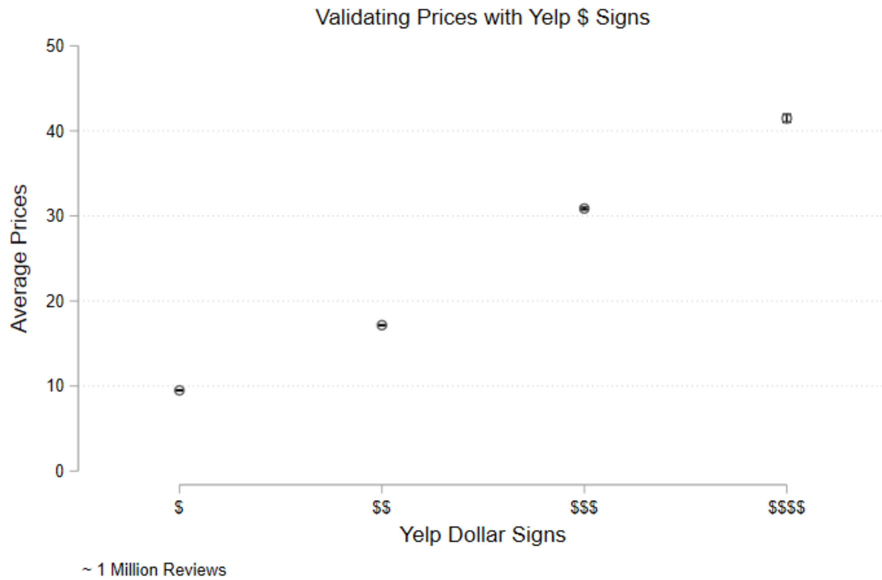


Figure A.8: Average Extracted Dollar Prices by Yelp "$" Signs

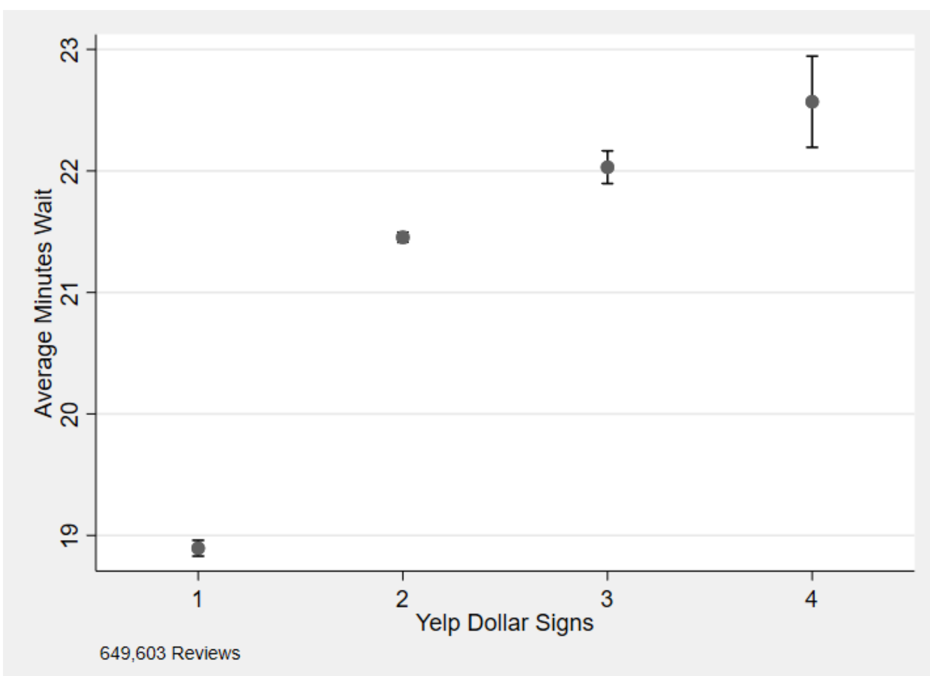


Figure A.9: Average Extracted minute wait times by Yelp "$" Signs

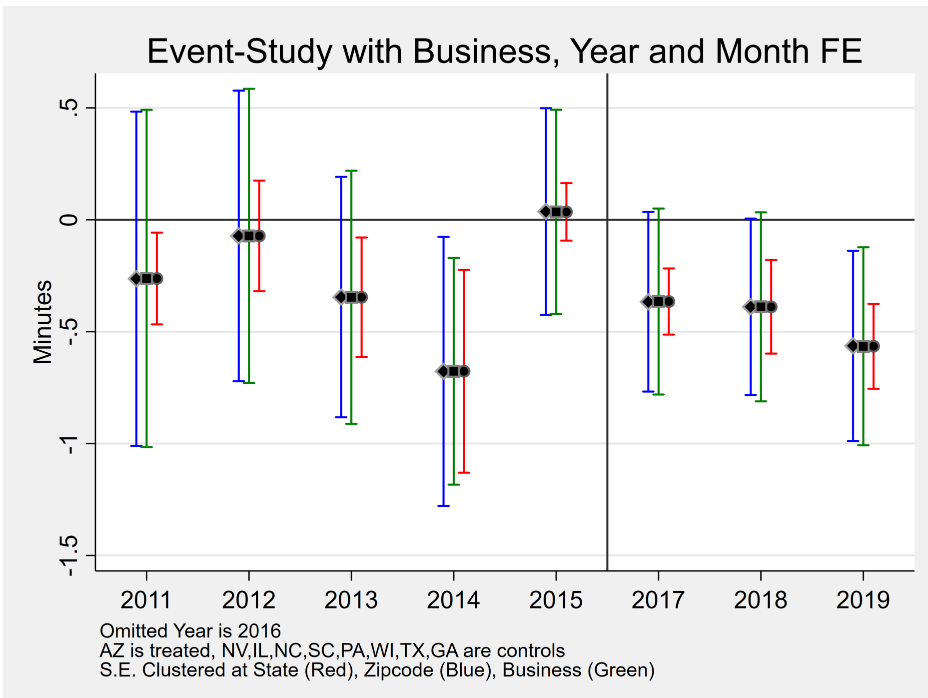


Figure A.10: Wait Times (in minutes)

A.2 Robustness Checks

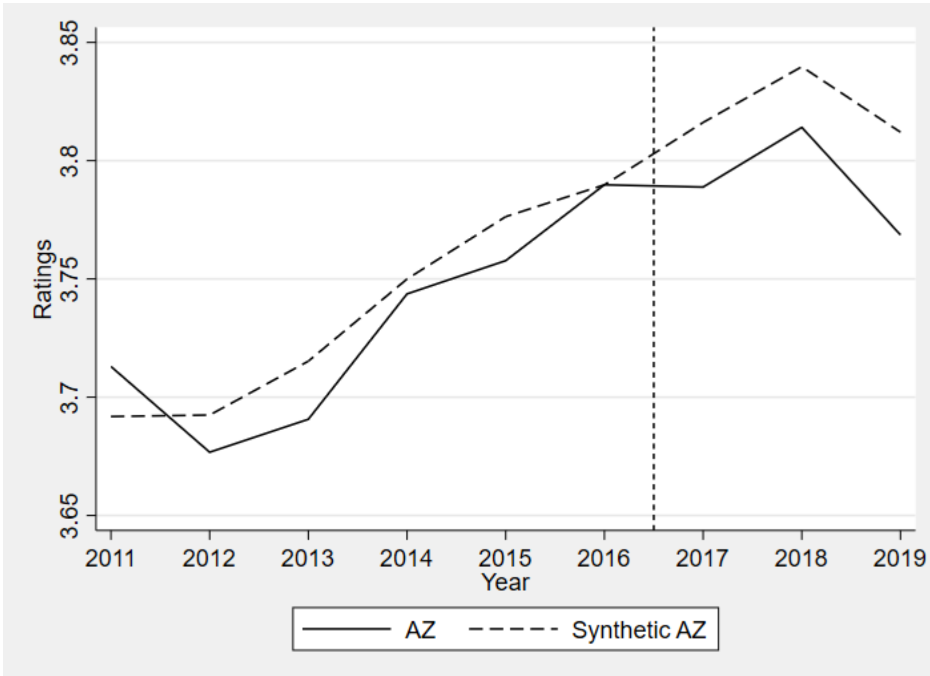


Figure A.11: Synthetic Control for Impact on Restaurant Ratings