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Samsun Knight
University of Toronto

Yakov Bart
Northeastern University

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GAP – Global Action for Policy Initiative

Address: 360 Huntington Ave.
Boston, MA, US

Email: gap@northeastern.edu

Web: https://cssh.northeastern.edu/gap/

The Effect of Minimum Wage Changes on Restaurants and the Service Elasticity of Demand

Samsun Knight, University of Toronto*

Yakov Bart, Northeastern University†

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Abstract

Using a panel of restaurant revenue and data on 55 local minimum wage increases, we present generalizable evidence of the effect of labor cost increases on restaurant demand. We estimate a distribution of effects with synthetic differences-in-differences and find a median restaurant revenue decline of 2.3% after a minimum wage hike, but with a wide dispersion. Attributing these effects to a mix of price increases and quality declines, we use this evidence to identify a structural model of restaurant demand in Los Angeles and provide novel estimates of the elasticity of demand to service quality and to price, respectively.

KEYWORDS: restaurants, demand elasticity, minimum wage, service quality, pricing

*samsundknight@gmail.com

†*y.bart@northeastern.edu

1 Introduction

Labor costs for restaurants have increased rapidly in recent years, presenting managers with compounding challenges. Beginning with the Covid-19 labor shortage, wages have been rising at a 30% higher rate than the pre-pandemic average and are continuing to rise at a historically fast clip today (Bureau of Labor Statistics 2023). In this environment, restaurant managers are confronted with either raising prices, reducing staff hours, accepting lower profits, or some combination of the above. The optimal adjustment policies for these managers relies crucially on how customers respond to marginal increases in price versus marginal declines in service quality.

Over the same period, dozens of cities, counties, and states across the US have taken to raising minimum wages regularly to compensate for the lack of adjustment in the federal minimum wage. This multitude of policy-induced variation in labor costs affords a rich opportunity to investigate the effect of restaurant labor cost changes with large-scale, rigorous evidence. Moreover, for policymakers considering such measures, understanding the impact of these minimum wage changes on businesses is of primary interest on its own, with the existing minimum wage literature offering unclear guidance on the final effect on business-relevant outcomes across differing contexts and differing research designs (Brummer, 2017; Harasztozi and Lindner, 2019).[1]

In this article, we present a novel set of estimates of the revenue effects on restaurants based on 55 city- and county-level minimum wage increases, producing new generalizable evidence on the effect of exogenous labor cost increases on business earnings. Then, to translate this reduced-form evidence into relevant economic parameters and decision-relevant elasticities, we match this evidence with a structural model to estimate the elasticity of restaurant demand to marginal price increases and to marginal service quality declines, respectively.

First, we use a panel dataset of store-level revenue for hundreds of thousands of

[1] Additionally, understanding how much flexibility businesses have in their response is determinative of whether policy may influence their behavior—a recent study of Hungary suggests that, depending on the industry, minimum wage increases that are associated with greater price pass-through also enjoy smaller disemployment effects (Harasztozi and Lindner 2019). If US restaurant businesses are choosing between different degrees of price increases versus reducing staff, implementations that encourage price adjustment or reduce price stickiness may have the potential to mitigate the employment impact of minimum wage hikes.

restaurants across the US, along with data on 55 sub-state-level minimum wage hikes, to estimate the effects of 55 local event studies between the years of 2019 and 2022.[2][3] We use the synthetic differences-in-differences approach of Arkhangelsky et al. (2021) to estimate event-study effects of each increase in a consistent manner across all of these contexts, using optimally reweighted control panels based on stores in the same state that do not receive a minimum wage increase.[4] We estimate a median decline in revenue of 2.3% and a mean decline of 2.1%, with a 20th percentile effect of a 6% decline and an 80th percentile effect of a 1% increase in revenue. This small density of point estimates above 1% corresponds with earlier positive revenue effects found in the literature; our full distribution of estimates nests this earlier positive revenue estimate from the literature, but allows us to understand it in the context of the far greater density of small negative revenue impact estimates for US restaurants (Harasztozi and Lindner 2019). By estimating all of these effects with a consistent methology, a national revenue dataset and singular estimation framework, we are able to produce generalizable evidence that ameliorates concerns about out-of-sample validity and publication bias and provides strong guidance for policymakers hoping to understand expected impacts of labor cost increases (and minimum wage increases more specifically) for US restaurants.

However, these revenue effects combine the effect of restaurant quantity demand changes and price changes and can be relatively hard to parse for immediate practical implications. While we show that the demand shifts occur primarily on the extensive margin of consumption, with revenue effects highly correlated with effects on the overall number of transactions, such shifts still don't identify the separate effects of price increases and quality declines resulting from staffing reductions.

Therefore, in a second step, we estimate a structural model of restaurant demand in order to unpack this reduced-form evidence into decision-relevant elasticities. To do

[2] Local minimum wage increases also affected tipped employees, both directly through increases in the minimum cash wage to tipped employees and indirectly through legal requirements that tipped employees still be paid minimum wage after adding their cash wage and tips (Henninger 2018).

[3] To address concerns about contemporaneous shocks from COVID-19 during this period, we additionally exclude hikes that coincide with major COVID lockdown periods, and use estimation windows focused in a relatively tight 6-month window on either side of the policy change. The distribution of results is very similar when restricting to only 2019 wage increases; for details, see Appendix A.

[4] As a final step, we also implement empirical Bayes shrinkage, following Kane and Staiger (2008) and Martin (2018), to account for noise across estimates in our distribution.

so, we focus on a case study of the July 2021 minimum wage increase in Los Angeles county, where we are able to combine our revenue panel with data on individual restaurant prices and Yelp ratings and estimate a full model that incorporates both of these dimensions. This matched panel allows us to translate our reduced-form evidence into novel elasticities for the separate channels of price increases and service quality declines.

We estimate this model in two stages. First, we complement our reduced-form evidence on revenues with a synthetic differences-in-differences estimate of the effect of the minimum wage increase on service quality as measured by Yelp ratings, inferring a significant 1%-2% decline in ratings after the minimum wage increase for restaurants in our final sample, and establish support for a 0.75% increase in prices by combining small-sample evidence and elasticity estimates from the literature. Then we fit our structural model using transparent moment conditions based on this reduced-form evidence, penalizing the model to match the observed revenue decline from these observed local price and service changes.[5] Combined with the micro evidence from our price and Yelp ratings time series, this allows us to transparently identify the elasticities of restaurant demand to marginal price increases and marginal service quality (Yelp rating) declines from our quasi-experimental reduced-form evidence.

From this exercise, we obtain point estimates of a high price elasticity of -1.56 and an even higher service-quality elasticity of 1.85, where changes in quality are measured in units of % changes in Yelp ratings.[6] The model fits the sample moments closely, successfully reproducing the observed shifts in revenue from the corresponding observed price and service shifts. That said, as we have a sample of only 538 Los Angeles restaurants fully matched across our three separate panels of price, revenue, and Yelp ratings, two-step block-bootstrapped confidence intervals for these elasticities using our full estimation procedure are wide and overlapping.

[5]We do not have price data for control areas to rigorously infer price effects of the minimum wage increase, but we show that literature estimates of the elasticity of restaurant menu price to minimum wage coincides with small-sample evidence for a roughly 0.8% relative price increase, based on a synthetic differences-in-differences estimate from a panel of city-level restaurant price data.

[6]This estimated price elasticity is somewhat smaller than the -2.99 elasticity found in prior work in the context of full-service restaurants (Okrent and Alston 2011). If prior work often observed cost-driven variation in prices that coincided with hours reductions or other cost saving measures, so price increases coincided with quality declines, this may have led to spuriously large estimated price elasticities in prior settings.

Taken at face-value, these point estimates suggest that unless managers expect a higher-than-1:1 ratio of cost savings to quality declines, restaurants may be better-served by passing labor cost increases onto consumers through price increases instead of shedding staff or otherwise sacrificing quality to save on expenses. That said, this relative difference in the point estimated elasticities is somewhat small, suggesting that restaurateurs may also be responsive to moderately sized policy nudges that reduce price stickiness or otherwise encourage adjustments along the price dimension instead, allowing policymakers to potentially induce differential employment responses through careful implementation choices.

1.1 Relation to Prior Literature

Within business and marketing literatures, this work most closely relates to earlier research on the price elasticity of demand and the importance of service in restaurant demand. This includes Owusu-Amankwah et al. (2017) and Andreyeva et al. (2010), who investigate the effect of price increases on restaurant demand, and Sulek and Hensley (2004), who use a survey-based approach to assess the importance of service on declared intentions to return to a restaurant a second time. To our knowledge, while price elasticities of restaurant demand have been previously studied, our estimate of the elasticity of restaurant demand to marginal declines in quality (as measured by Yelp ratings) is the first-of-its-kind in the empirical literature. The closest related studies are Anderson and McGruder (2011) and Luca (2012), which both investigated the effect of Yelp ratings with a regression-discontinuity design; but these papers studied the effect of different displayed Yelp ratings on restaurants of near-identical quality, in contrast to our study of restaurant quality itself.

The present work also contributes to the economics literature studying the impact of minimum wage increases on restaurant revenues. Most recently, Harasztosi and Lindner (2019) studied a large minimum wage increase in Hungary and found that most firms responded by raising prices rather than cutting jobs, with the increased labor costs passed onto consumers. In contrast, Brummund (2017) analyzed confidential data from a US restaurant chain and found evidence of declining revenues after minimum wage increases. Our current study contributes to this literature by estimating the effects of 55 local minimum wage increases on restaurant revenues in a consistent framework, finding a median revenue decline of 2.3%. With this, we able to nest both the positive revenue effects found by Harasztosi and Lindner (2019) and the negative effects found by Brummond (2017) within a broader distribution of predominantly negative impacts.

We also contribute to the body of economics research studying how minimum wage hikes impact restaurant pricing. Fougère et al. (2010) used individual price quotes from France to conclude there are significant effects of minimum wage increases on restaurant prices. Complementing this, Aaronson et al. (2008) found US restaurant prices rise following minimum wage increases, implying that models assuming perfect competition better match the data than those assuming monopsonistic labor markets. Ashenfelter and Jurajda (2021) investigate menu prices for McDonald's items, focusing on Value Meals in order to hold item attributes fixed across localities, and recover a price elasticity to minimum wage increases of 0.14. We build on this literature by not only estimating minimum wage effects on revenues, but also translating these into separate price and service quality elasticities of demand with a comprehensive structural model, which thereby micro-founds the price adjustment behavior observed in prior work.

Finally, we contribute to the larger labor economics literature on the effect of minimum wage hikes on restaurant employment. Different papers find sometimes conflicting employment effects of minimum wage increases in different settings, including the seminal Card and Krueger (1994) which studied fast food restaurants and found no reduction in employment, as well as Neumark and Wascher (2000), which investigated a similar event-study and did find negative employment effects. Among others, Giuliano (2013) using personnel records found no significant disemployment effects overall, but increases in teen relative wages raised their relative employment. Dube et al. (2010) studying contiguous counties across state borders found no employment effects. More recently, Aaronson et al. (2018) developed a model showing low-wage labor-intensive restaurants exit after minimum wage hikes but are gradually replaced by new entrants using more capital-intensive technologies, predicting growing disemployment over time through compositional changes. As a complement, our study measures the effect of abrupt minimum wage changes on service quality, as measured by Yelp ratings, allowing us to quantify labor adjustment effects on restaurant revenues and complete the picture from the standpoint of managerial decision-making.

The rest of this article is structured as follows. Section 2 describes the large-scale reduced form evidence of 55 exogenous labor cost increases—county and municipality minimum wage hikes—on local restaurant revenues. Subsection 2.1 describes the data for these studies; subsection 2.2 details the synthetic differences-in-differences empirical specification; and subsection 2.3 presents the reduced-form results. Section 3 describes the case study of Los Angeles' minimum wage hike of July 2021 and estimates a structural model to recover demand elasticities. Subsection 3.1 describes the additional data that we leverage for this case study; subsection 3.2 introduces complementary reduced-form evidence on minimum wage effects on log Yelp ratings and prices; and subsection 3.3 details the structural model and parameter estimates. Section 4 concludes.

2 Revenue Effects: Estimates from 55 Event Studies

We begin by presenting large-scale reduced-form evidence on the effect of exogenous labor cost increases—local minimum wage increases—on restaurant revenues.

2.1 Data: Revenue and Minimum Wage Increase Panels

Our primary data source for this exercise is SafeGraph Spend, a large-scale panel of monthly revenue for hundreds of thousands of physical stores. These data are aggregated from actual private credit- and debit-card transactions collected from a major US banking institution, matched to a panel of business locations across the United States, and provide monthly revenue time-series data for hundreds of thousands of business locations from 2019 to 2022, including both in-person purchases and online purchases routed through specific stores. Figure 1 visualizes the wide coverage of the restaurant locations across the United States in the SafeGraph Spend panel. SafeGraph provides documentation that its Spend data comes from a representative sample of the US population both across regions and demographics (SafeGraph 2023); in addition, to ensure that no potential unknown biases in the data generating process inform our estimates, we include extensive fixed effects in all of our empirical specifications. For the purposes of this study, we focus only on restaurants, as defined by the location NAICS code. The SafeGraph Spend panel also includes transaction count information in addition to its headline store-level revenue measure, which we use in extension analyses to demonstrate the degree to which observed revenue effects are driven by changes along the extensive versus intensive margin of consumption.

We then pair this revenue panel with a hand-collected dataset of minimum wage increases from 2019 to 2022. Gathered from online state policy announcements and other internet news sources by research assistants, these data consist of over one hundred minimum wage increases across the US. We restrict our attention to only local minimum wage increases, defined as city- and county-level minimum wage increases, so that we may construct weighted comparison groups using stores that belong to other areas in the same state that do not experience contemporaneous minimum wage increases. We further restrict consideration to only minimum wage increases that occur after January 2019 and prior to July 2022, so that we have enough data to estimate both a pre- and a post-period, and exclude minimum wage changes that were within 3 months of either the March 2020 COVID-19 lockdown period or the January 2021 COVID-19 spike and associated lockdowns. (The distribution of effects is extremely similar if we additionally restrict consideration only to 2019 minimum wage hikes, a setting that is completely insulated from any COVID-19-related bias, suggesting that any such bias is not a major driver of our findings; details presented in Appendix A.) After these restrictions, we end up with a final minimum wage dataset of 55 separate city- and county-level increases.[7]

Finally, we merge each of these minimum wage changes to the revenue panels to create 55 discrete datasets (one for each minimum wage increase) of minimum wage increase events and corresponding restaurant-level revenue data. Summary statistics for these data are presented in Table 1. In the top panel, we present the average summary statistics across all 55 matched event-study datasets, along with standard deviations of the summary statistics across event studies. In the bottom

[7]Note that some of these minimum wage increases include multiple minimum wage increases in the same locality, if multiple minimum wage increases were implemented in this period. However, no localities increased minimum wage floors multiple times in a single 12-month period; therefore, to both cleanly separate observations between different minimum wage increases and retain consistency across settings, in our estimation we focus on a relatively short window of 6 months prior and 6 months after the minimum wage increase. Further details are provided in the subsequent section.

panel, we present the summary statistics for our later structural case-study of the particular minimum wage increase in Los Angeles County in July 2021. In each of these state-level datasets, we define "treated" restaurants defined as those within the given locality that experienced a minimum wage increase and "control" restaurants as restaurants outside of the given locality that did not experience a contemporaneous minimum wage increase but that belong to the same state.

2.2 Empirical Specification

To consistently estimate the reduced-form effect of these minimum wage increases on restaurant revenue across these 55 localities, we rely on the synthetic differences-in-differences methodology of Arkhangelsky et al. (2021). This method optimally reweights control observations to match the averages of treatment observations in the pre-period and then estimates the effect of treatment by comparing the treated group to this reweighted control, allowing for consistent estimation of treatment effects even in the presence of differential pre-trends. Specifically, using the SynthDiD R package from Arkhangelsky et al. (2021), we estimate weights $\{\hat{\omega}_i\}$ to align the pre-exposure trends in restaurant spending between the treatment and control groups, as well as weights $\{\hat{\lambda}_t\}$ to balance pre-exposure and post-exposure periods; then we estimate

$$\left(\hat{\tau}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = argmin_{\tau,\mu,\alpha,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega}_i \hat{\lambda}_t \right\} \tag{1}$$

where Y_{it} is the outcome (log restaurant revenue), μ is a constant term, α_i is the unit fixed effect, β_t is the time fixed effect, and $W_{it} \in \{0,1\}$ is a binary variable that is 1 for treated and 0 otherwise, and $\hat{\tau}$ measures the average effect of treatment exposure. We use jackknife, again following Arkhangelsky et al. (2021) and using the SynthDiD R package, to estimate standard errors and 95% confidence intervals for $\hat{\tau}$.

With this approach, we are able to rigorously estimate effects from all 55 event studies, without modifying the procedure at all across settings. This allows us to infer estimates across a large variety of settings without any "researcher degrees of freedom" differing between studies, and enables us to present a broad distribution of estimates in a single article.[8]

2.3 Reduced-form Results: Revenue Effects

We present detailed synthetic differences-in-differences figures for three of our event studies in Figure 2, showing the pre-period and post-period trends for both treated groups and the optimally reweighted control for each example. In panel (a) we present the trends for our primary case study, the minimum wage increase in Los Angeles County in July 2021, while in panel (b) we present the trends for the minimum wage increase in Minneapolis in July 2019, and in panel (c) the trends for Santa Monica's minimum wage increase in January 2022.[9] In each case, the synthetic differences-in-differences procedure achieves a close fit between the treatment group and the reweighted control observations in the pre-period, even as spending fluctuates considerably with seasonality and other shifters. What occurs afterwards, however, varies considerably across settings: in the first two highlighted cases, Los Angeles County in July 2021 and Minneapolis in July 2019, revenue then declined by a highly significant 6% and 6.7%, respectively; but in the third highlighted case, Santa Monica in January 2022, revenue is statistically unchanged, with an insignificant increase of 1% after the advent of the minimum wage increase.

This variation is broadly representative of the wide spread of estimates across the full set of contexts studied. The full distribution of effects across all 55 local minimum wage event-studies is presented in Figure 3; the complete list of estimates and standard errors for every study is detailed in tables 2 and 3. To rigorously account for the fact

[8] That said, we are still restricted to investigating US cities and counties that introduced minimum wage increase policies, which tend be those with liberal-leaning area populations. We present these results as a step forward in generalizability of minimum wage effect findings, but caution that there may still be reasonable concerns about the representativeness of these estimates for settings that are very different from those that raise the minimum wage in these years, that are outside of the scope of this article to address.

[9] N.B. that the minimum wage increase of Los Angeles County in July 2021 was targeted towards establishments that employed 25 full-time employees or fewer. The Bureau of Labor Statistics reports that the average number of employees per establishment in the US restaurant industry was 16.1 in 2021. Given this, while we do not have sufficient employment data at the establishment level to determine which restaurants did or did not belong to this category, we expect that the large majority of restaurants in our data were directly affected (Bureau of Labor Statistics 2023). Moreover, any impact on the broader labor market for restaurant workers would be expected to indirectly affect all area restaurants; this result could thereby be interpreted as the gestalt impact of these direct and indirect effects.

that variance across our estimates is likely a combination of noise in the estimation and variance in the effect across contexts, we apply empirical Bayes shrinkage, as described in Kane and Staiger (2008) and Martin (2018), and shrink the distribution of estimates towards the mean estimate in proportion to their respective estimated noise levels, giving more weight to more precisely estimated effects and shrinking less precisely estimated effects closer to the effect distribution mean. Details of this procedure are presented in Appendix A. We find a median revenue decline of 2.3% and a mean revenue decline of 2.1% for area restaurants after a local minimum wage increase, but with a wide dispersion: the bottom 20% of estimates show declines of 6% or more, while the top 20% of estimates are non-negative.[10]

This high variance, while perhaps surprising, is in line with an earlier minimum wage literature that often finds a wide disparity of effects across different implementations and contexts, as noted in the literature review section. This study offers support for a truly wide variation in effects across contexts, suggesting that this observed range is not driven by different researcher choices with the data but arises even when the exact same estimation protocol is applied to a large number of contexts. This wide range also helps reconcile our negative average estimate with both the positive and negative point estimates found in earlier work between minimum wage and business revenue (Brummond, 2017; Harasztozi and Lindner, 2019). Our distribution suggests that positive revenue effects are not abnormal, presumably arising in contexts where minimum wage changes lead to price increases and with less-than-proportional demand declines; but these effects are nonetheless atypical, and policymakers and businesses are well-advised to expect that minimum wage increases will lead to revenue declines in the median case.

To determine whether these revenue effects are driven by extensive-margin consumption choices (whether to eat at a restaurant at all) or intensive-margin (how much to order), we then separately estimate event-study effects on the log of restaurant monthly transaction counts. Results of this regression for Los Angeles County in July 2021, side-by-side with the results for revenue, are presented in Figure 4. The effect trajectories are extremely similar, showing that the revenue effect appears to be driven in large part by changes in the overall number of transactions at restaurants.

[10] Prior to shrinkage, we see similar mean and median revenue declines of 2.3% for area restaurants after a local minimum wage increase.

Across event studies we find a similar phenomenon, with a large and highly significant correlation between log revenue effect estimates and log transaction effect estimates (Pearson's $r = 0.968$, p < 0.001).

Precisely interpreting these effects is still difficult, however, as top-level observed changes could arise from a variety of price and quantity shifts. For restaurants in particular, given that changes are driven by variable labor cost increases, one may reasonably expect that individual locations would adjust by some combination of cutting costs and raising menu prices. Adding to this puzzle, the distribution of observed effects τ only very noisily correlates with the size of the local minimum wage increase (measured in percent changes) with an insignificantly positive slope, suggesting that, if anything, revenue declines are smaller in areas with larger minimum wage increases. A scatterplot of τ and minimum wage increases is presented in Figure 5: the slope of the best-fit line is very slightly positive, meaning that revenue effects are less negative on average for larger minimum wage hikes, although the correlation is noisy and insignificantly different from zero.

To facilitate a more nuanced understanding of the underlying mechanisms of this overall revenue effect, we therefore turn to a single environment, the minimum wage increase in Los Angeles County in July 2021, where we are able to supplement our revenue data with establishment-level price and Yelp ratings panels.[11] Here, we can combine our reduced-form evidence with a structural model to parsimoniously decompose this overall revenue shift into separate effects of price increases and quality reductions, and produce novel estimates of the price elasticity and service quality elasticities of restaurant revenue.

3 Case Study: Los Angeles Restaurants

We first present details on our extended data and then present reduced-form results on the intermediate effects of minimum wage hikes on prices and Yelp ratings in this context. Then we fit a structural model with our micro data, estimated to precisely reproduce the overall observed revenue decline from such changes in price

[11] We focus on Los Angeles County in July 2021 as a plausibly representative case study for a major US city with an estimated effect close to the average of our distribution, and with a mid-summer implementation date especially unlikely to be confounded with major COVID-era events.

and Yelp ratings as we observe. This allows us to 1) transparently identify our model of restaurant demand from rigorous, quasi-experimental empirical evidence, and 2) to translate our reduced-form evidence into model-based elasticities, gleaning richer insights into economic fundamentals than would be possible from regression estimates alone.

3.1 Extended Data: Price and Yelp Ratings Panels

We hand-collected a price panel of restaurant menu prices for Los Angeles from 2019 to 2022 with the help of a large team of research assistants. The panel was built by going through every restaurant in every locality within Los Angeles County on an online menu aggregator website, as viewed through the Wayback Machine, to gather dated snapshots from which to construct an annual time series. We measure one price each of the entree, beverage, and appetizer categories for every restaurant and construct a price index by calculating the average within-dish ratio change from the first observation, using linear interpolation to approximate price adjustments between observations. Note that this price increase index is relative; because we don't observe portion sizes, we aren't able to measure absolute price differences.[12] This restaurant-level price time series should therefore be considered data on proportional price increases (Δp) rather than data on price (p) levels directly. (For more details on this interpolation, see Appendix A.) Because these data do not include restaurants from control areas, we supplement these data with city-level price index data from an online cost-of-living website to provide a comparison group for price changes when analyzing reduced-form price effects of the 2021 minimum wage increase.

We additionally constructed a time series of Yelp ratings for LA County and surrounding county restaurants using a scraper for the front-facing Yelp pages to capture the full universe of reviews for each restaurant, with dates and star ratings. We treat this panel of ratings as a dataset of noisy signals of underlying restaurant quality over time, and use this panel directly in our reduced-form estimates presented below. For final model estimation, we interpolate these ratings using LOESS smoothing to recombine these noisy measures into a continuous measure of the estimated underlying quality over time. For more details on this interpolation procedure and the final

[12] Such differences are absorbed in the store fixed effects in our final model.

matched dataset, see Appendix A.

Finally, we merge the store-level price panel, Yelp ratings panel, and revenue panel and achieve a match for a monthly panel of 538 restaurants in the Los Angeles County area, which forms our structural estimation dataset. Summary statistics are presented in Table 4.

3.2 Extended Reduced-form Results: Quality & Price Effects

In order to identify the structural model, we first establish empirical evidence on the separate effects of the minimum wage hike on restaurant prices and restaurant Yelp ratings using the same synthetic differences-in-differences approach as above for revenue effects. For details on the reduced-form methodology, see section 2.2.

Effects of 2021 Minimum Wage Hike on Log Yelp Ratings

We begin by inspecting the observed effects of the July 2021 Los Angeles County minimum wage hike on restaurant Yelp ratings. Due to the imbalance of our Yelp ratings panel and the requirement for synthetic differences-in-differences to have a balanced panel, we implement our analysis in three different ways, each of which returns a similar result of a significant 1%-2% decline in observed Yelp ratings for those in Los Angeles County affected by the minimum wage increase, compared to restaurants in surrounding counties.

In our baseline analysis, we aggregate our Yelp ratings data into 3-month averages for each restaurant and then perform synthetic differences-in-differences on every restaurant for which we having at least one observation in every 3-month period. This approach leads to a sample of 2404 restaurants from control areas and 9778 treated restaurants from Los Angeles County, spanning from the first quarter of 2020 to the last quarter of 2022. Results are presented in Figure 6. We find a significant decline of 1.05% (SE = 0.4%, p = 0.00996) in Yelp ratings for restaurants in Los Angeles County following the summer 2021 minimum wage increase. Extension results for alternative specifications are detailed in Appendix A. These include results from a synthetic differences-in-differences specification based on an annual panel of Yelp ratings between 2020 and 2022, allowing for the inclusion of more restaurants in the estimation sample; as well as results based on a simple two-way fixed effects specification with monthly treatment dummies, utilizing the full data sample but not the synthetic differences-in-differences rebalancing. In both of these alternative specifications, we find similar, slightly larger effects, corresponding to an approximately 2% decline in Yelp ratings for Los Angeles County restaurants after the implementation of the 2021 minimum wage increase.

This result stands in contrast to some prior research on the effect of minimum wage increases on restaurant service, namely Puranam et al. (2020), which found a positive effect of minimum wage increases on service in the case of a single local minimum wage increase, which the authors interpreted as arising from an employee morale effect of higher wages. This result is also much larger than can be explained by price increases in our data—while we present evidence in Appendix A that price increases are marginally significantly correlated with small Yelp rating declines in our estimation panel, the point estimates suggest that a 0.75% price increase would only lead to a 0.02% decline in Yelp ratings, or 0.05% at the upper end of the confidence interval.[13] We therefore interpret the observed 1.05% decline in Yelp ratings after the minimum wage increase as unlikely to driven by service quality reductions from morale or by price increases, and instead are likely driven by staff hours reductions or other cost saving measures.

Price Effects of 2021 Minimum Wage Hike

While we have a rich panel of price increases at the restaurant level for over 500 restaurants in the Los Angeles County area, we do not have such data for comparison areas to form a control group to similarly perform a rigorous differences-in-differences estimation of the effect of the 2021 minimum wage hike on restaurant prices. We therefore rely on estimates of the elasticity of restaurant prices to minimum wage increases from prior literature—namely Ashenfelter and Jurajda (2021), who estimate a price elasticity to minimum wage increases of 0.14. This estimate implies that the 5.3% minimum wage increase of July 2021 would causally lead to a 0.74% increase in restaurant prices.

We further validate this literature-based effect estimate with small-sample evi-

[13] Moreover, since we control for price increases in our logit model, even a larger price impact would not bias our elasticity estimates.

dence using a panel of city-level restaurant prices for a small panel of large cities in the US, using data gathered from an online cost-of-living calculator website, Numbeo.com. While this evidence is statistically insignificant, based on only N=84 observations, we present this as corroboration that this point elasticity from the literature is appropriate in our context. Specifically, we constructed an annual panel of McMeal prices from 2017 to 2022 for Atlanta, Austin, Birmingham, Boston, Dallas, Houston, Las Vegas, Miami, New York, Orlando, Philadelphia, Phoenix, and Salt Lake City, and Los Angeles (city), based on cities with at least 250,000 population with non-missing data in all years of our time window. Performing the same synthetic differences-in-differences procedure as we use in all our estimations above, we recover a point estimate of 0.08, or a 0.8% increase in prices in Los Angeles relative to other cities, closely in line with the imputed effect implied by the literature elasticities.[14] While this is not strong evidence on its own of the magnitude of the price increase in response to the July 2021 minimum wage increase in Los Angeles, we present this in combination with the literature-based projected effect of the minimum wage increase on restaurant prices from Ashenfelter and Jurajda (2021) to demonstrate that a 0.74% increase is a reasonable imputation for the price effect from this minimum wage increase.

3.3 Structural Model of Restaurant Demand

With this augmented dataset and reduced-form evidence in hand, we now estimate a structural model of restaurant demand for Los Angeles County restaurants between 2020 and 2022.

[14] The sample is insufficiently large to compute standard errors according to the standard methods associated with synthetic differences-in-differences and included in the SynthDiD R package.

Model

We rely on a simple restaurant-choice logit framework to model observed behavior.[15] Given reduced-form evidence that revenue effects are driven in this case by shifts along the extensive margin, in the choice to transact at a restaurant or not, we assume that every household in the vicinity[16] of our full matched sample of 538 Los Angeles County restaurants makes a choice each month to either eat at a single restaurant within our sample or not. This choice is modeled as a function of random utility based on restaurant relative prices, distance between household (tract) location and other tract-level controls, restaurant Yelp rating, and restaurant and time period fixed effects:

$$u_{ijt} = \alpha + \beta \Delta p_{jt} + \delta q_{jt} + \theta X_{ijt} + \gamma_j + \lambda_t + \varepsilon_{ijt} \tag{2}$$

where α measures the utility from staying home, β measures the utility impact of price increases over time, δ captures the effect of Yelp rating, θ captures the effect of a vector of controls including distance to the restaurant and demographic controls. γ_j and λ_t represent restaurant and time fixed effects, respectively.[17]

Moment Conditions and Identification

To estimate this model rigorously from our reduced-form evidence, we first introduce a moment condition based on our results from the plausibly exogenous shock of the minimum wage increase. Specifically, on the assumption that the overall revenue effect of the minimum wage increase can be decomposed into the revenue effect of restaurants raising prices and, separately, restaurants shedding staff and declining in quality, we require that our structural model exactly reproduce the observed revenue

[15] We use this simple model instead of a random coefficients model because of data limitations in our restaurant revenue panel, wherein we observe only the aggregate number of transactions at each restaurant and do not directly have data on the share of each household's visits that go to each choice in our choice set, limiting our ability to identify second-order features of demand. This simpler model, while limited in some respects, allows us to transparently estimate average elasticities that correspond to our data and reduced-form evidence.

[16] "Vicinity" is here defined as within 30km of any restaurant location in our sample, based on the maximum travel distance considered in previous studies of distance traveled to food establishments (Liu 2015).

[17] Note that we do not explicitly estimate γ_j and λ_t but instead absorb fixed effects using the method of alternating projections (Conlon and Gortmaker 2020).

decline from the observed levels of price increase and quality decline:

$$M_1 = \left(\Delta_{trans}(\Theta) - \hat{\Delta}_{trans}\right)^2 \tag{3}$$

where Δ_{trans} is the percentage decline in transactions resulting from a 1.8% decline in Yelp rating and a 0.74% increase in prices across all restaurants, and Θ is a given guess of model parameters $\Theta = \{\alpha, \beta, \delta, \theta\}$. (Note that we estimate 1.8% as the observed decline in Yelp ratings for the restaurants in our final matched sample; the earlier presented estimates used all restaurants in our Yelp sample, and found a similar, but slightly different, reduced-form point estimate.) We set $\hat{\Delta}_{trans} = -4.49\%$ based on $\hat{\tau}_{trans}$, our reduced-form synthetic differences-in-differences estimate for restaurant transactions for Los Angeles County in July 2021 in our final merged panel dataset.[18]

This moment condition identifies the combined level for price and quality elasticities. It does not, on its own, identify price and quality elasticities, since a continuous line of combinations of price and quality elasticities could produce any given observed revenue change, but it does pin down their combined magnitude at the observed levels using rigorous quasi-experimental evidence, ensuring that our model matches our reduced-form evidence within sample.

In order to estimate the remaining parameters and the relative magnitudes of price and quality elasticities, we rely on micro moments that match the observed numbers of transactions at every restaurant in our sample in each month, $\hat{trans}_{jt}$, to the expected numbers of transactions from our model for a given guess of parameters, $trans_{jt}(\Theta)$:

$$M_2 = \sum_{jt} \left(\hat{trans}_{jt} - trans_{jt}(\Theta)\right)^2 \tag{4}$$

where $trans_{jt}(\Theta)$ is modeled as the sum of expected visits to restaurant j in time t from every household h in the vicinity, given parameters Θ, under the conventional assumption of an extreme-value type I error distribution for ε_{ijt} [19]:

[18] Note that this $\hat{\tau}_{trans}$ is -4.49%, as compared to the $\hat{\tau}_{trans}$ of -5.05% in Table 3, because of the sample differences between the full panel and the much more restricted panel of restaurants that we are able to merge across all datasets. For our structural model estimation protocol, we estimate all of the above reduced-form effects that go into M_1 using our final merged panel to keep the data consistent across all stages.

[19] Note that households are observably identical within census tract, as we rely on tract character-

$$E(visit_{hjt}(\Theta)) = \frac{exp(\alpha + \beta\Delta p_{jt} + \delta q_{jt} + \theta X_{ijt} + \gamma_j + \lambda_t)}{\sum_{j'} exp(\alpha + \beta\Delta p_{j't} + \delta q_{j't} + \theta X_{ij't} + \gamma_{j'} + \lambda_t)} \tag{5}$$

$$trans_{jt}(\Theta) = \sum_h E(visit_{hjt}(\Theta)) \tag{6}$$

This micro moment condition M_2 identifies the control parameters from the covariance of restaurant transactions and nearby densities of tracts with higher or lower of each given attribute (net of the absorbed restaurant and time fixed effects). The moment condition also identifies the relative elasticities of revenue to price changes and to service quality changes: as our richly detailed data contain price change time series and service quality time series for each of our 538 restaurants, the relative correlation of each time series with observed transaction levels identifies the relative magnitude of each separate elasticity.

We then estimate model parameters to minimize the weighted average of these two moment conditions:

$$Loss(\Theta) = \Lambda \cdot M_1(\Theta) + M_2(\Theta) \tag{7}$$

where Λ controls the relative weight between moment conditions. We set Λ to be large in order to enforce a close match between reduced-form evidence and our model's predicted revenue effects of similar price increases and quality declines.[20] This forces the model to reproduce our observed reduced-form quasi-experimental evidence, and then to estimate the best-fit parameters for explaining the remaining micro variation that also reproduces these shifts. We estimate parameters to minimize this combined loss following the standard general method of moments (GMM) procedure of Newey and McFadden (1986) and McFadden (1989).

Parameter Estimates

Parameter estimates for Θ are presented in Table 5. In line with expectations, we find a negative effect of price increases, with a parameter estimate that implies a

istics to differentiate households, and so the above is modeled at the tract level and then multiplied by the population of the respective tract.

[20]Specifically, we set Λ heuristically at 10e5 as the smallest weight magnitude that enforces a near-exact match in estimated revenue effects.

-1.56 elasticity of restaurant revenue to price increases, and a positive effect of Yelp ratings, with an estimate that implies a 1.85 elasticity of restaurant revenue to quality increases as measured by percentage changes in Yelp rating. Our control variables also return point estimates that are in line with expectations, in particular with a negative relationship between travel distance and restaurant demand.

That said, standard errors based on twenty-five bootstrap draws are quite large, and almost all of our parameter estimates have 95% confidence intervals that broadly overlap with zero and with each other. We estimate these standard errors with block-bootstrap by drawing from replacement from the distribution of restaurants that we have matched data for, creating alternate bootstrapped samples of $N_{rest} = 538$. We then use these bootstrapped samples to estimate both our first-stage reduced-form effect estimates of revenue effects and Yelp rating effects to define M_1 for each bootstrap and then estimate our second-stage logit parameter estimates with these bootstrapped samples and bootstrap-specific moment conditions. This two-step bootstrap leads to wide confidence intervals, capturing the uncertainty both in our second-stage logit estimation and in our first-stage reduced-form estimates that we match in our GMM estimation procedure, so we do not have power to statistically reject the null hypotheses that our elasticities of revenue to service and price are not different from each other or from zero. Nonetheless, our point estimates provide a first-of-its-kind estimate of the elasticity of restaurant revenue to service reductions, and policymakers and business managers seeking to ground their assumptions about the relative revenue elasticities of service and price may find our point estimates informative for their decisionmaking.

Our point estimates also suggest that some of the variation in revenue effects across contexts may be driven by differential responses from restaurants. In light of the higher point estimate elasticity of restaurant revenue to quality changes, if restaurants are uncertain as to these specific elasticities when responding to labor cost increase, instances when restaurants relied more on price adjustments than employment shifts to protect profits could have led to lower declines in revenue. As the size of minimum wage changes does not explain the variation in revenue effects across event studies, it is plausible that such differences in restaurant responses may be a central mechanism behind the observed variation in effects across contexts.

4 Conclusion

Rising labor costs present a major challenge for restaurants, requiring difficult tradeoffs between raising prices, reducing staff, or accepting lower profits. Understanding how consumers respond to such adjustments is crucial for informing restaurant managers as well as policymakers considering minimum wage laws. In this article, we estimate the revenue impact of rising labor costs in the contexts of 55 local minimum wage hikes on restaurants across the US, producing novel, generalizable findings about the revenue impacts of labor cost increases, complemented by a case study of Los Angeles restaurants to separately identify price and service quality elasticities of restaurant revenue.

Our analysis of 55 minimum wage event studies finds a median revenue decline of 2.3% for restaurants, with a wide dispersion across contexts. Even after using empirical Bayes shrinkage to account for noise in each separate event study and shrink noisy estimates towards the effect population mean, we estimate a distribution of effects ranging from a 6% revenue decline at the 20th percentile to a 1% revenue increase at the 80th percentile. We further show that this variation in effects, if anything, covaries inversely with the size of the minimum wage increase, with larger declines noisily associated with smaller minimum wage hikes.

We then focus on the case study of Los Angeles' minimum wage increase in July 2021, where we are able to complement our revenue data with price and Yelp rating panels. We present reduced-form evidence that the July 2021 Los Angeles County minimum wage hike caused a 1%-2% decline in Yelp ratings and a 0.74% increase in prices for area restaurants, and then leverage this evidence to identify and estimate a structural model. With this model, we estimate high elasticities of restaurant revenue to price, at -1.56, and to service quality, at 1.85. While confidence intervals are wide, in contexts where the cost savings of service reductions are not disproportionately high, managers may be well-advised to raise prices instead of cutting staff in order to better protect profits. From the policymaker's perspective, the high elasticities across either dimension suggest restaurateurs may have some discretion in how they adjust to minimum wage increases and so small-to-moderate policy nudges may realistically expect to induce managers towards adjusting prices and away from adjusting employment levels.

That said, while this article moves forward our understanding of minimum wage and the relative importance of service quality and price in restaurant demand, more work remains to be done. Later research might expand the variety of studied labor cost shocks beyond minimum wage hikes to assess further generalizability. Larger restaurant samples with more granular data could also help tighten confidence intervals on elasticity estimates. Finally, investigating differential effects across restaurant segments and incorporating supply-side adjustments could further enrich understanding of how the restaurant industry responds to rising labor costs.

Understanding the drivers of restaurant demand is crucial for restaurant managers and for policymakers aiming to support them. The recent flurry of many local minimum wage increases affords researchers a novel opportunity to gather large-scale evidence on these demand drivers, and on the policies themselves as well.

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Appendix A:
Details on Reduced-Form Results

In this section, we present detailed results on the full set of event studies investigated in our reduced-form results. For each event study, we use synthetic differences-in-differences from Arkhangelsky et al. (2021) to estimate the effect of the minimum wage increase on restaurant revenue for the given locality (county or municipality) that hiked the minimum wage, with the synthetic control group based on restaurants in the same state that did not experience a contemporaneous minimum wage hike. We then employ empirical Bayes shrinkage, following Kane and Staiger (2008) and Martin (2018), to shrink the distribution of effect estimates towards the distribution's mean, to rigorously account for the fact that noisier and farther-from-the-mean estimates are more likely to be the result of statistical error.

Empirical Bayes Shrinkage Procedure

Empirical Bayes shrinkage corrects estimates from their naive values to a weighted combination of the effect estimate for event study e, $\hat{\tau}_e$ and the mean of the distribution of effect estimates $\mu_{\hat{\tau}}$. The shrinkage factor for each estimate, B_e, is determined by the effect distribution variance σ^2_{dist} and the variance of individual estimate, σ^2_e, according to the following statistical formula:

$$B_e = \frac{\sigma^2_{dist}}{\sigma^2_{dist} + \sigma^2_e} \tag{8}$$

We then compute our "shrunk" estimates as the weighted average between the distribution mean and the individual estimate, with the shrinkage factor B_e serving as the weight:

$$\hat{\tau}_{shrunk} = \hat{\tau} \cdot B_e + \mu_{\hat{\tau}} \cdot (1 - B_e) \tag{9}$$

From Martin (2018), this formula intuitively shrinks the estimate based on how much information is estimated to be contained in the individual estimate relative to the global average:[21]

> ...[i]f we have a lot of [data] for a[n event study], and the variance...for that [estimate is] low, we have $\sigma_e^2 \ll \sigma_{dist}^2$, so $B_e \approx 1$. When B_e is close to 1, we expect most of the contribution to come from the [estimate for the event study].
>
> On the other hand, if we have relatively little information on the [event study], $\sigma_e^2 \gg \sigma_{dist}^2$, so $B_e \approx 0$. This is where we would expect the global average to be important.

We recover $\mu_{\hat{\tau}}$ and σ_{dist}^2 from the empirical analogues of the estimated effect distribution. We use the estimated standard errors from the synthetic differences-in-differences procedure for each event study to recover σ_e^2.

Results for Each Event-Study

In tables 2 and 3, we present the full set of our estimates for all 55 local minimum wage increases inspected, including the revenue effect estimates post-empirical Bayes shrinkage, $\hat{\tau}_{shrunk}$, the raw revenue effect estimates pre-shrinkage, $\hat{\tau}$, and the estimates of the effect on the transaction count, $\hat{\tau}_{trans}$. The mean raw estimate prior to shrinkage is a -2.3% reduction; post-shrinkage, the mean point estimate is a -2.1% reduction. The mean point estimate among event studies with at least 5% statistical significance is slightly larger in magnitude, at -3.9% pre-shrinkage and -3.3% post-shrinkage. The correlation between revenue effects and transaction effects is large and highly significant with Pearson's $r = 0.968$, $p<0.001$.

Results for Only 2019

To ensure that our results are not biased by COVID-19, we inspect the more limited distribution of results unaffected by COVID and any associated lockdowns, excluding all hikes that occurred in 2020 or later. Results are presented in Figure 7. The distribution is highly similar, with a near-identical mean revenue decline of 2.3% and a median revenue decline of 1.7%. The 80th percentile effect is a 6.5% revenue decline

[21]Note that the quote is here adjusted so that their mathematical notation matches ours.

and the 20th percentile effect is a 0.7% revenue increase. This compares to a 2.3% median and 2.1% mean decline in the full distribution of effects including 2020 and later minimum wage increases, a 20th percentile effect of a 1% increase and an 80th percentile effect of a 6% decline.

Given the tight similarity between this restricted 2019 distribution and the full distribution of effects including COVID-19 era minimum wage hikes, we conclude that our results are unlikely to be driven by any sort of systematic COVID-19-related confounds—while this does not guarantee that no such bias exists, we present this as evidence against such systematic bias as a primary driver of our results.

Effect of Price Increases on Log Yelp Rating

To investigate the possibility that price increases themselves may explain our observed Yelp rating declines, we estimate a simple two-way fixed effects regression, using the data in our final estimation panel, of price increases on log Yelp ratings, with store fixed effects and date (monthly) fixed effects. Results are presented in Table 6. While we find a marginally significant negative effect of price increases on log Yelp ratings, with a p-value of 0.067, the point estimate is quite small in magnitude—we find that every 1% increase in price is associated with a 0.034% decrease in restaurant Yelp rating, or at most a 0.071% decrease at the upper end of the 95% confidence interval. This suggests that only a very small proportion of the observed 1%-2% decline in Yelp rating is likely to be due to any direct effect of price changes, and instead the lion's share of the effect is presumably from cost saving measures leading to quality declines.

Alternative Yelp Rating Effect Estimators

In this section, we present alternative specifications for estimating the effect of the Los Angeles County July 2021 minimum wage increase on local Yelp ratings of restaurants. Since synthetic differences-in-differences requires a balanced panel and Yelp rating observations are often sparse, there is a tradeoff between formatting the data to average ratings over a longer period window, and so include more restaurants with at least one observation per period, and averaging ratings over a shorter period window, including fewer restaurants but greater temporal precision—or using an alternative estimation method altogether. In Figure 6 in the main body of the article, we presented estimates based on a 3-month window and found significant evidence of a 1.05% decline in Yelp ratings, comparing 2404 control restaurants and 9778 treated restaurants.

In Figure 8 below, we present synthetic differences-in-differences results using an annualized panel of restaurants. We recover a point estimate of a 2.23% decline in Yelp ratings, comparing 6314 control restaurants and 22171 treatment restaurants. Based on this, our point estimate of 1.05% using a 3-month average panel is therefore a likely conservative estimate of the true effect of the minimum wage increase on Yelp ratings in local area restaurants. (Note that we use this annualized dataset when estimating the reduced-form effect of the minimum wage change on the restaurants in the final merged panel, which we use for defining M_1 in our structural model estimation; as there are already far fewer restaurants in our final merged panel, we use the annualized dataset approach to allow for more restaurants to be included in the sample and preserve statistical power.)

To ensure even further robustness, we also explore using a simple two-way fixed effects (TWFE) estimator that allows us to leverage the complete imbalanced panel with all observations included, and without averaging Yelp ratings into per-period means. Mathematically, we estimate

$$y_{it} = \delta_t + \gamma_i + \Delta_{LA,T} \cdot 1_{j \in LA, T=t} + \epsilon_{it} \tag{10}$$

where δ_t is a monthly fixed effect, γ_i is a store-level fixed effect, and $\Delta_{LA,t}$ captures the effect of belonging to Los Angeles County in period t. Inspecting the estimates of $\Delta_{LA,t}$ surrounding the period of the implementation of the minimum wage increase allows us to infer the effect of the minimum wage increase on log revenue $(y_i t)$ by comparing the difference in growth rates between LA County and non-LA County restaurants.

Results are presented in Figure 9. In this specification, we find some evidence of pre-period differences in the months directly preceding the minimum wage increase, which is why we rely on synthetic differences-in-differences as our primary specification. Nonetheless, we see a clear drop-off corresponding to the time of the minimum wage increase, with a point estimate very similar to that recovered in the synthetic differences-in-differences specifications, approximately 1%-2%. Comparing to the slightly positive pre-period average estimate of around 1%, the results are suggestive of a roughly 2%-3% overall decline. That said, given the pre-period differences in some months, we prefer the synthetic differences-in-differences estimates; we simply present these estimates to show that the effects are similar across estimators and data aggregation approaches.

Appendix B:
Details on Matched Panel for Model Estimation

In this section, we present details on the interim interpolation steps that we take to fill in missing observations in our final matched panel, as well as detailed summary data on this final model estimation dataset.

Relative price increase panel

Our raw data come from MenuPages.com, accessed using the Wayback Machine, which allows us to collect roughly annual snapshots of actual posted online menus for approximately 1000 restaurants in Los Angeles County. For each restaurant-time snapshot, our team of RAs collected the price and name of dish for 1 appetizer, 1 entree, and 1 beverage. Then, for each named dish, we compute the ratio of the price in a given period to the price in the very first observation for that restaurant. Finally, we average the ratio of price across dishes in every time period, and use linear interpolation to impute the plausible price-level increase in missing periods, assuming that such imputations are a reasonable guess given the lack of information on when the precise price increases occurred. For those restaurants where not all categories were available in all periods, we leave those data as missing and average based on the non-missing dish data. For restaurants where our first observation is after the first month in our matched panel, we back-fill the baseline ratio (1) to include earlier months. For restaurants where our final observation is before the last month in our matched panel, we forward-fill the final ratio to include subsequent months.

LOESS-smoothed Yelp rating panel

A greater challenge is presented by the irregularity of our Yelp rating panel. We observe Yelp ratings across the entire time period of our data at noisy intervals, with some months seeing multiple reviews for a given restaurant and some months without reviews, leading to a sparse and imbalanced Yelp rating panel over time. Moreover, Yelp ratings are already noisy measurements of the underlying quality of the restaurant, with individual biases and idiosyncratic events potentially shifting a given star rating in either direction for any given rating.

In order to infer a reasonable measure of underlying restaurant quality over time, we use a LOESS smoothing regression to construct an approximate estimate of each restaurant's quality in each month, given the observed empirical ratings data (Jacoby 2000).[22] Examples of the LOESS smoothed time series for two restaurants are presented in Figure 10. This allows us to use a single, coherent approach to create a steady moving average and also to interpolate across missing periods in a stable and efficient manner. We use the lowess smoother package from the statsmodels Python library, smoothed across daily observations of a moving 90-day average of Yelp ratings for each restaurant. As with the price panel, for restaurants for which the first observation is after the start of our data, we back-fill the first observed quality measure into prior dates, and for restaurants for which the last observation is before the end of our data, we forward-fill the last observed quality measure into subsequent dates.

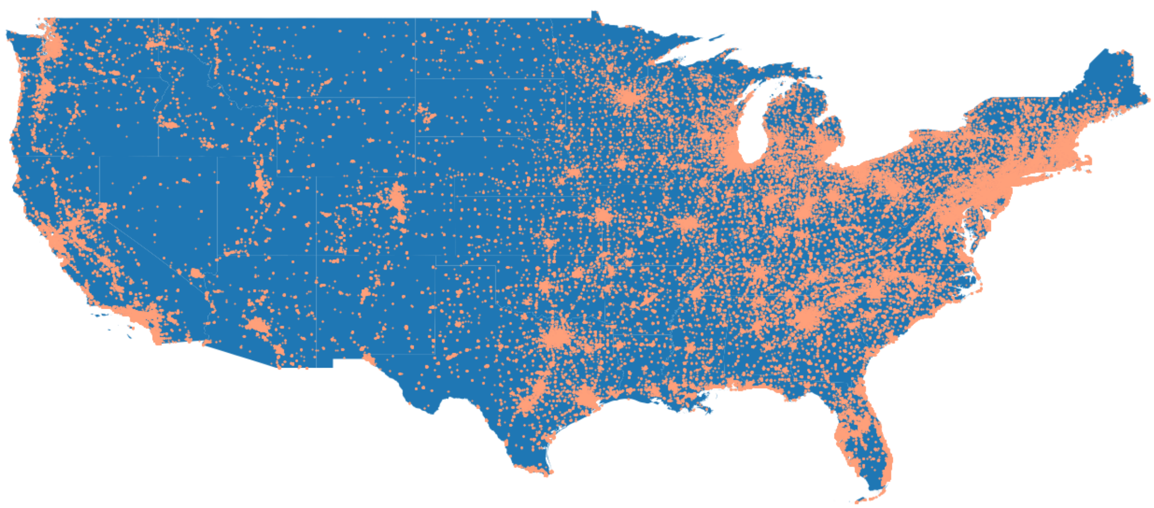
Final merged panel

We merge our revenue panel from SafeGraph Spend, our interpolated Yelp ratings dataset from our scraped Yelp.com data, and our hand-collected price data together based on a fuzzy match on geolocation and location name, achieving a final matched panel of 538 restaurants. Summary statistics for this final estimation dataset are presented in Table 4. In our final panel, we have 12,313 observations with non-missing data in all relevant fields (transactions are not always observed in every period for restaurants in SafeGraph Spend) which we then use in our above-described GMM procedure to implement our full two-step structural estimation. Note that we also use this merged panel for computing the reduced-form estimates in our first step that we match in our second step, to keep the sample consistent across both steps. In our block-bootstrap, we draw from replacement from this dataset at the restaurant level in order to compute model parameter standard errors.

[22]Note that we use the raw Yelp rating panel, either directly or averaged into 3-month or annual means, for all of our above reduced-form results. We only use this smoothing and interpolation for the structural model, where we wish to impute an estimated quantity for each time period to fill out our estimation panel.

List of Figures

Figure 1: SafeGraph Spend Restaurant Locations



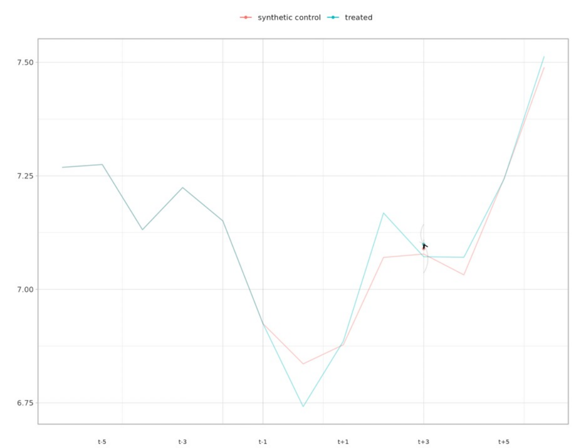
Notes: Distribution of physical restaurant locations across the continental US. Data from SafeGraph.

Figure 2: Effects of Minimum Wage Increases on Restaurant Revenue

(a) Los Angeles County, July 2021

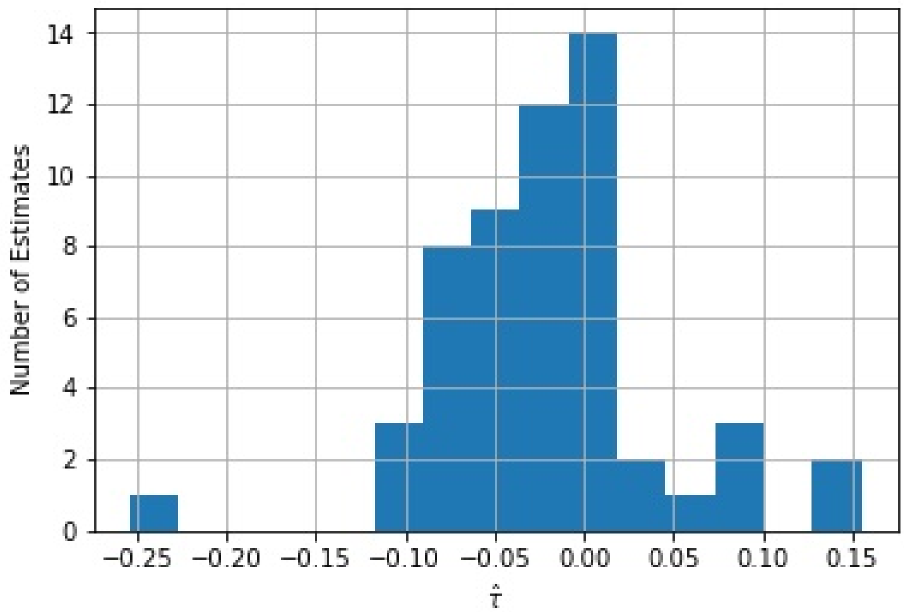
(b) Minneapolis, July 2019

(c) Santa Monica, January 2022



Notes: Effect of minimum wage increases on restaurant revenue based on synthetic differences-in-differences estimator for three example settings. X-axis shows relative time in months, y-axis shows log revenue. In each figure, red line describes the revenue path of synthetic control restaurants (based on the sample of restaurants in the same state, but in localities without a contemporaneous minimum wage increase) and the blue line describes the revenue path of restaurants that belonged to the described locality that raised minimum wage at time t. Panel (a) describes effects for Los Angeles County in July 2021, panel (b) describes effects for Minneapolis in July 2019, panel (c) describes effects for Santa Monica in January 2022. Precise numerical estimates presented in tables 2 and 3. Revenue data from SafeGraph Spend panel. Minimum age increases based on data hand-collected from online state webpages and policy announcements.

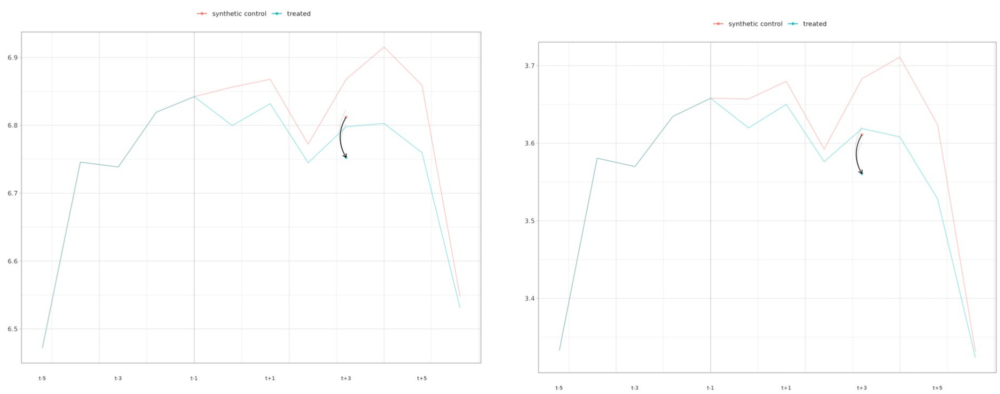
Figure 3: Distribution of Estimated Revenue Effects $\hat{\tau}$



Notes: Histogram of effects $\hat{\tau}$ of minimum wage increases on restaurant revenue based on synthetic differences-in-differences estimator. Precise numerical estimates presented in tables 2 and 3. Revenue data from SafeGraph Spend panel. Minimum age increases based on data hand-collected from online state webpages and policy announcements.

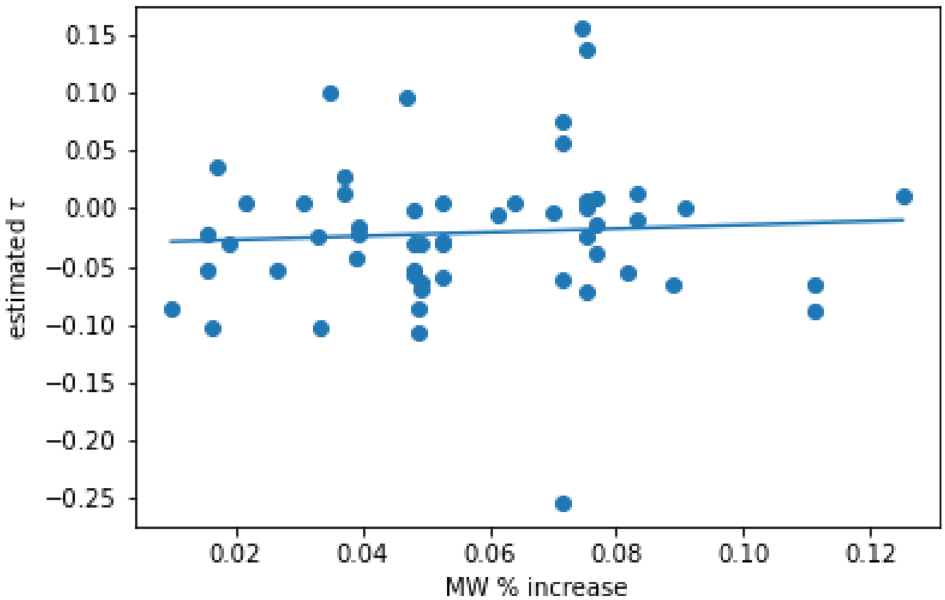
Figure 4: Effects of Minimum Wage Increases on Transactions vs. Revenue

(a) Log(Revenue) (b) Log(Transactions)



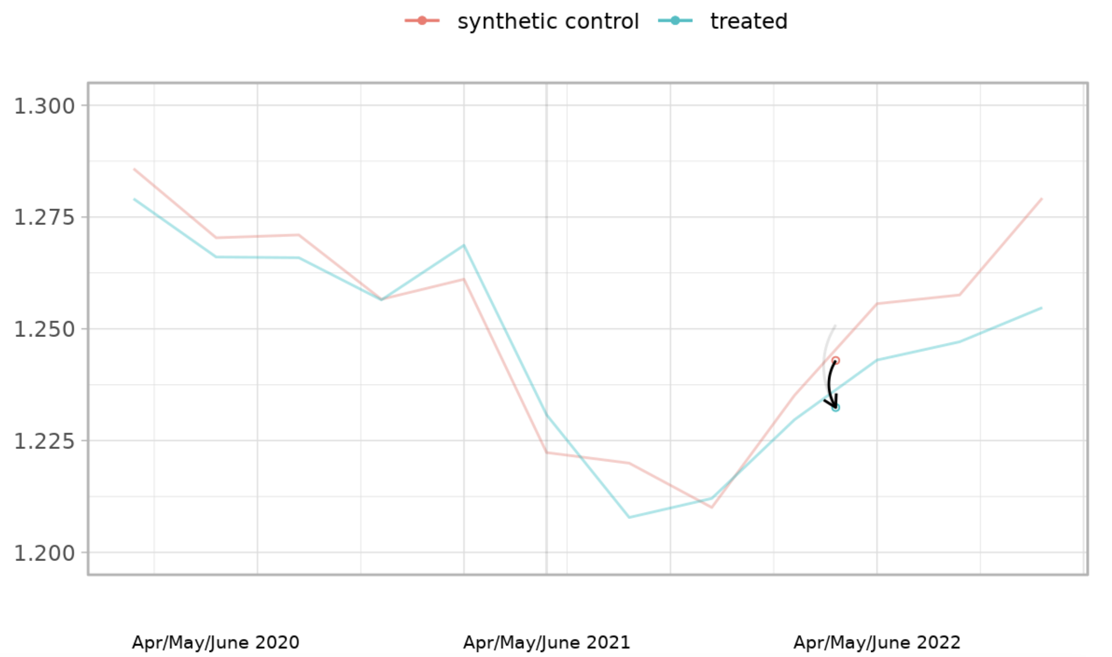
Notes: Effect of minimum wage increases on restaurant revenue and restaurant transactions based on synthetic differences-in-differences estimator of Los Angeles County minimum wage increase in July 2021. In each figure, red line describes the revenue path of synthetic control restaurants (based on the sample of restaurants in the same state, but in localities without a contemporaneous minimum wage increase) and the blue line describes the revenue path of restaurants that belonged to the described locality that raised minimum wage at time t. Panel (a) describes effects for restaurant revenue, panel (b) describes effects for restaurant transactions. Precise numerical estimates presented in tables 2 and 3. Revenue data from SafeGraph Spend panel. Minimum age increases based on data hand-collected from online state webpages and policy announcements.

Figure 5: Estimated Revenue Effects $\hat{\tau}$ vs. Size of MW Increase



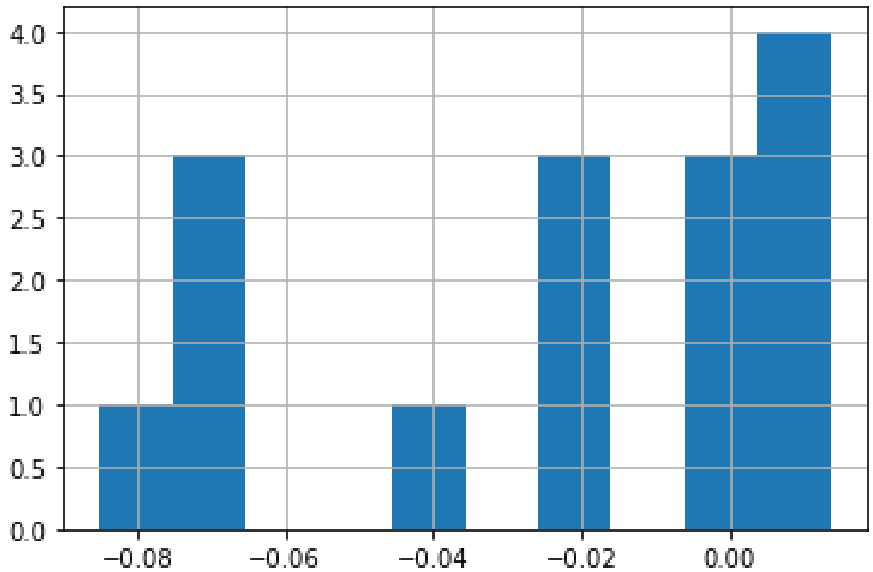
Notes: Scatterplot of effects $\hat{\tau}$ of minimum wage increases on restaurant revenue based on synthetic differences-in-differences estimator compared to the size of the corresponding minimum wage increase in % terms. Precise numerical estimates presented in tables 2 and 3. Revenue data from SafeGraph Spend panel. Minimum age increases based on data hand-collected from online state webpages and policy announcements.

Figure 6: Effect of Minimum Wage Increase on Log Yelp Ratings



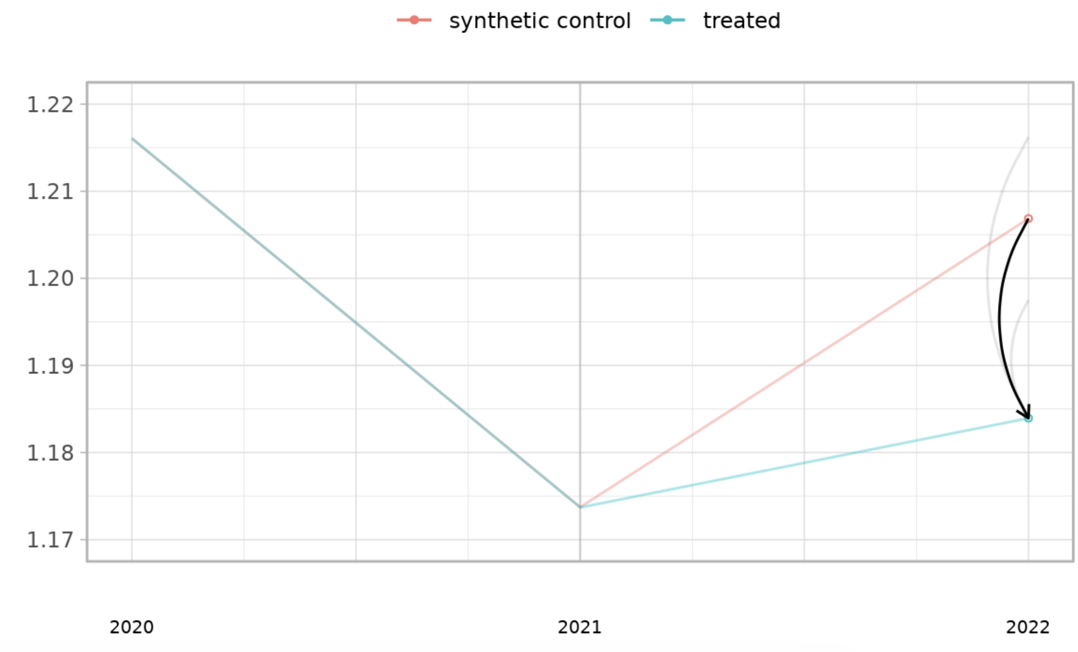
Notes: Effect of minimum wage increases on log restaurant Yelp Ratings based on synthetic differences-in-differences estimator for Los Angeles County in July 2021. Red line describes the ratings path of synthetic control restaurants (based on the sample of restaurants in the neighboring counties to Los Angeles County) and the blue line describes the ratings path of restaurants that belonged to Los Angeles County, which raised minimum wage at time t. Precise estimate of effect is 1.05% decline of treatment relative control in the post-increase period, with a standard error of 0.4%, significant at a 1% level. Revenue data from SafeGraph Spend panel, Yelp ratings data come from scraping from-facing Yelp website. Minimum age increases based on data hand-collected from online state webpages and policy announcements.

Figure 7: Distribution of Estimated Revenue Effects $\hat{\tau}$:
Only 2019



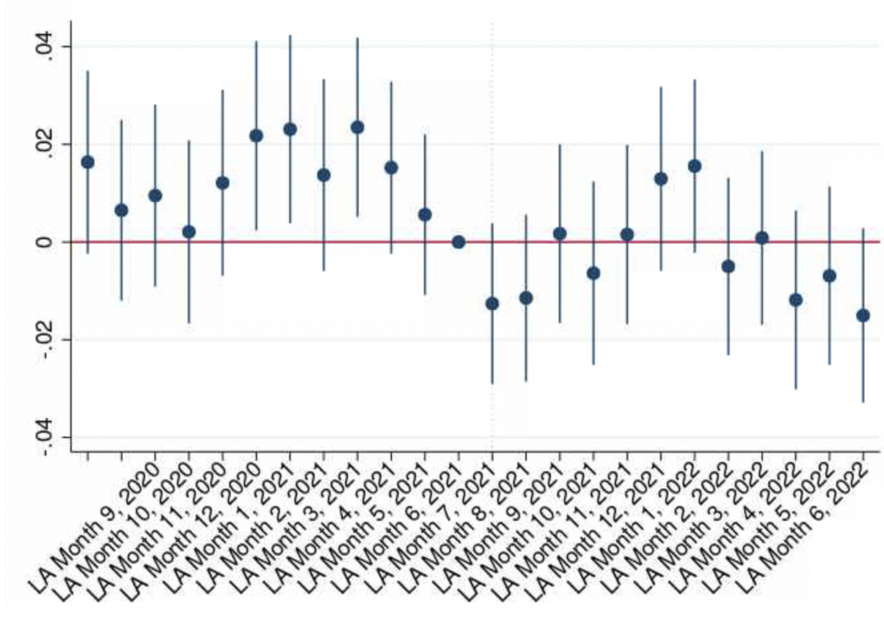
Notes: Histogram of effects $\hat{\tau}$ of minimum wage increases on restaurant revenue based on synthetic differences-in-differences estimator. Precise numerical estimates presented in tables 2 and 3. Revenue data from SafeGraph Spend panel. Minimum age increases based on data hand-collected from online state webpages and policy announcements. Restricted to only 2019 results.

Figure 8: Effect of Minimum Wage Increase on Log Yelp Ratings:
Annualized Panel



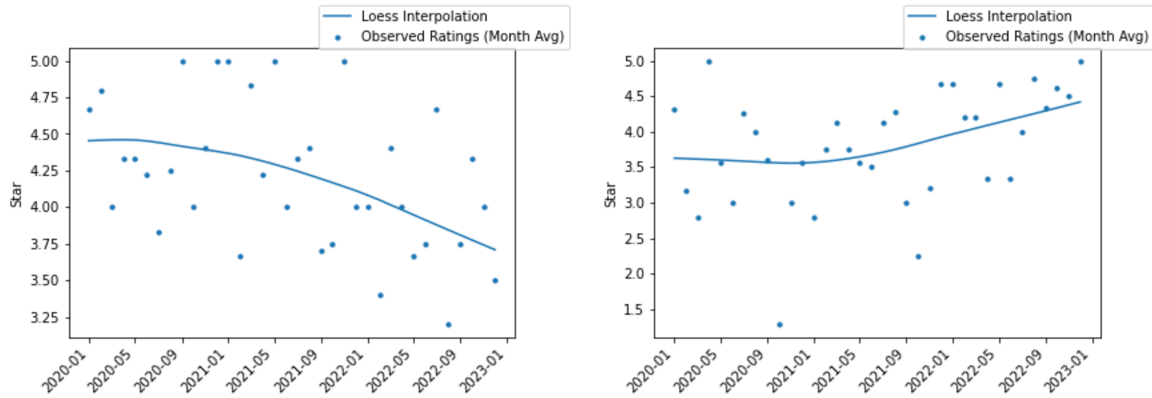
Notes: Effect of minimum wage increases on restaurant Yelp ratings based on synthetic differences-in-differences estimator for Los Angeles County in July 2021. Red line describes the ratings path of synthetic control restaurants (based on the sample of restaurants in the neighboring counties to Los Angeles County) and the blue line describes the ratings path of restaurants that belonged to Los Angeles County, which raised minimum wage at time t. Precise estimate of effect is 2.23% decline of treatment relative control in the post-increase period, with a standard error of 0.48%, significant at a 0.1% level. Revenue data from SafeGraph Spend panel, Yelp ratings data come from scraping from-facing Yelp website. Minimum age increases based on data hand-collected from online state webpages and policy announcements.

Figure 9: Effect of Minimum Wage Increase on Log Yelp Ratings: TWFE



Notes: Effect of minimum wage increases on restaurant Yelp ratings based on two-way fixed effect estimator for Los Angeles County in July 2021. Red line describes the ratings path of synthetic control restaurants (based on the sample of restaurants in the neighboring counties to Los Angeles County) and the blue line describes the ratings path of restaurants that belonged to Los Angeles County, which raised minimum wage at time t. Revenue data from SafeGraph Spend panel, Yelp ratings data come from scraping from-facing Yelp website. Minimum age increases based on data hand-collected from online state webpages and policy announcements.

Figure 10: LOESS-smoothed Interpolations of Yelp Ratings



Notes: Examples of restaurant Yelp rating time series scatterplots with associated smoothed LOESS curves. Smooth line shows the LOESS interpolated curve used in structural model estimation. Dots show the scatterplot of actual observed Yelp ratings, averaged to the monthly level. Yelp ratings data from scrape of front-facing webpage of Yelp.com.

List of Tables

Table 1: Summary Statistics

Average Statistics Across 55 Event-Study Datasets

	N Treated Restaurants	N Control Restaurants	Mean Monthly Revenue	Mean Monthly # Transactions	MW Increase (% Change)
Mean	917.4	19142.9	2968.2	141.2	5.3
SD	(1870.3)	(10247.8)	(1604.1)	(91.1)	(2.3)

Statistics for Los Angeles County, July 2021

N Treated Restaurants	N Control Restaurants	Mean Monthly Revenue	Mean Monthly # Transactions	MW Increase (% Change)
8080	23491	1876.9	79.6	5.0

Notes: The top panel provides average summary statistics for the 55 matched minimum wage event-study datasets, with each dataset including up to 6 months of pre-increase data and 6 months of post-increase data for every restaurant in the respective sample. The bottom panel provides summary statistics for the matched minimum wage event study dataset for the Los Angeles July 2021 minimum wage increase. "Treated" restaurants defined as restaurants within the given locality that experienced a minimum wage increase. "Control" restaurants defined as restaurants outside of the given locality but within the same state, and that did not experience a contemporaneous minimum wage increase. Standard deviations (measured across event study datasets) in parentheses. Restaurant revenue data from SafeGraph Spend.

Table 2: Event Study Results: 2019 and 2020

Year	**Month**	**Locality**	$\hat{\tau}$	**SE**	$\hat{\tau}_{shrunk}$	$\hat{\tau}_{trans}$
2019	7	Alameda	0.016	0.03	0.01	0.0014
2019	7	Berkeley	-0.021	0.02	-0.021	-0.0244
2019	7	Chicago	0.014*	0.007	0.014	0.0132
2019	7	Cook County	0.001	0.006	0.001	0.0062
2019	7	Emeryville	-0.046	0.03	-0.042	-0.0310
2019	7	Los Angeles County	0.0	0.004	0.0	0.0021
2019	7	Malibu	-0.082*	0.034	-0.072	-0.0830
2019	7	Milpitas	-0.071**	0.026	-0.066	-0.0689
2019	7	Minneapolis	-0.067***	0.015	-0.065	-0.0663
2019	7	Montgomery County	-0.004	0.011	-0.005	-0.0032
2019	7	Pasadena	0.009	0.017	0.007	0.0081
2019	7	Portland	-0.092***	0.024	-0.085	-0.0903
2019	7	San Francisco	-0.016	0.009	-0.017	-0.0152
2019	7	San Leandro	0.012	0.02	0.009	0.0110
2019	7	Santa Monica	-0.023	0.02	-0.023	-0.0234
2020	7	Alameda	-0.103**	0.036	-0.088	-0.1028
2020	7	Chicago	-0.039***	0.01	-0.039	-0.0387
2020	7	Cook County	-0.01	0.007	-0.01	-0.0098
2020	7	Emeryville	-0.025	0.085	-0.024	-0.0237
2020	7	Los Angeles County	0.005	0.007	0.005	0.0051
2020	7	Malibu	-0.038	0.087	-0.029	-0.0370
2020	7	Milpitas	-0.06	0.035	-0.053	-0.0597
2020	7	Minneapolis	-0.061	0.033	-0.054	-0.0605
2020	7	Montgomery County	-0.012	0.014	-0.013	-0.0118
2020	7	Pasadena	-0.032	0.032	-0.031	-0.0313
2020	7	San Francisco	0.007	0.017	0.006	0.0065
2020	7	San Leandro	-0.07*	0.034	-0.062	-0.0695

Notes: Effect of minimum wage increases on restaurant revenue based on synthetic differences-in-differences estimator for all studied settings in 2019 and 2020. τ_{shrunk} estimated using Empirical bayes shrinkage (Kane and Staiger 2008, Martin 2018). Revenue data from SafeGraph Spend panel. Minimum age increases based on data hand-collected from online state webpages and policy announcements. *** p $<$ 0.01, ** p $<$ 0.05, * p $<$ 0.1.

Table 3: Event Study Results: 2021 and 2022

Year	**Month**	**Locality**	$\hat{\tau}$	**SE**	$\hat{\tau}_{shrunk}$	$\hat{\tau}_{trans}$
2021	7	Berkeley	0.117***	0.031	0.096	0.1006
2021	7	Chicago	0.078***	0.01	0.076	0.0934
2021	7	Emeryville	0.081	0.064	0.036	0.0583
2021	7	Los Angeles County	-0.06***	0.005	-0.06	-0.0505
2021	7	Milpitas	-0.121***	0.036	-0.102	-0.1322
2021	7	Minneapolis	0.155***	0.025	0.137	0.1863
2021	7	Montgomery County	0.06***	0.012	0.058	0.0546
2021	7	San Francisco	-0.053***	0.013	-0.052	-0.0327
2022	1	Belmont	-0.039	0.089	-0.029	-0.0616
2022	1	Cupertino	0.024	0.079	-0.001	0.0655
2022	1	Denver	0.162***	0.015	0.155	0.1708
2022	1	El Cerrito	-0.188**	0.073	-0.106	-0.1671
2022	1	Flagstaff	-0.115***	0.028	-0.103	-0.0995
2022	1	Los Altos	-0.08	0.071	-0.052	-0.0035
2022	1	Mountain View	-0.032	0.046	-0.029	-0.0247
2022	1	Oakland	-0.093***	0.024	-0.086	-0.0845
2022	1	Palo Alto	-0.079*	0.034	-0.069	-0.078
2022	1	Portland	-0.0	0.033	-0.004	0.0107
2022	1	Redwood City	0.025	0.043	0.013	0.0352
2022	1	Richmond	0.013	0.041	0.004	-0.0342
2022	1	San Diego	-0.259***	-0.254	0.012	-0.2652
2022	1	San Jose	-0.06***	0.016	-0.058	-0.0695
2022	1	San Mateo	0.041	0.039	0.027	0.0229
2022	1	Santa Clara	-0.033	0.039	-0.031	-0.0431
2022	1	Santa Monica	0.01	0.027	0.006	0.0343
2022	1	Seattle	0.103***	0.012	0.1	0.1115
2022	1	Sunnyvale	-0.069*	0.028	-0.063	-0.0566
2022	4	Tucson	-0.021	0.017	-0.021	-0.0229

Notes: Effect of minimum wage increases on restaurant revenue based on synthetic differences-in-differences estimator for all studied settings in 2021 and 2022. τ_{shrunk} estimated using Empirical bayes shrinkage (Kane and Staiger 2008, Martin 2018). Revenue data from SafeGraph Spend panel. Minimum age increases based on data hand-collected from online state webpages and policy announcements. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Summary Statistics: Final Merged Panel

	Mean	SD
ΔPrice	0.046	0.088
Star Rating	3.704	0.894
Log(Transactions)	2.955	1.141
$N_{restaurants}$		538
$N_{observations}$		12313

Notes: Summary statistics for the final model estimation dataset, built by merging the price, Yelp, and revenue panels. Star rating interpolated with lowess, ΔPrice interpolated linearly. Restaurant revenue data from SafeGraph Spend, Yelp ratings data collected from Yelp.com, price data hand-collected from MenuPages.com and Internet Archive (Wayback Machine).

Table 5: Logit Restaurant-Choice Model Parameter Estimates

Parameter	**Estimate**
α (Constant term)	-11.437 (4.489)
β (ΔPrice coefficient)	-1.577 (9.885)
δ (Quality coefficient)	0.490 (1.601)
$\theta_{log(Distance)_{hj}}$	-1.048 (3.772)
$\theta_{log(MedianHHIncome)_h}$	-0.159 (2.457)
$\theta_{WhiteShare_h}$	-0.726 (2.780)
$\theta_{CollegeShare_h}$	-0.347 (2.607)
$\theta_{PopDensity_h}$	-0.074 (14.397)

Notes: Parameter estimates for random utility parameters in logit choice model described in equation 2 above. Restaurant and time fixed effects γ_j and λ_t not estimated, but absorbed prior to estimation using method of alternating projections (Conlon and Gortmaker 2020). Parameters estimated using GMM, based on moment conditions described above in equations 3, 4 and 7 (Newey and McFadden 1986). Price change data from hand-collected panel based on Internet Archive snapshots of MenuPages.com. Yelp ratings data collected from scraping Yelp.com front-facing pages for the universe of reviews, and then using loess interpolation to smoothly fill the time series for each restaurant. Restaurant-level revenue data from SafeGraph Spend. Demographic data from US Census Bureau.

Table 6: Effect of Price Increases on Yelp Rating

	Log(Star Rating)
$\beta_{\Delta p}$	-0.0342 (0.019)
λ_t	X
γ_j	X
N	12313
R^2	0.889

Notes: Regression of log restaurant Yelp rating against relative price increase index. Data based on final merged estimation sample. Yelp rating time series based on webscraped Yelp ratings from front-facing webpages, interpolated using loess. Price index based on hand-collected menu snapshots from MenuPages.com and Wayback Machine, and measures relative price increases over time for each restaurant, interpolated linearly across missing interim periods. Further details on interpolations available in Appendix B. Standard errors in parentheses.