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Publication Date

2016-11-01



IRLE WORKING PAPER
#124-15
November 2016

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Cite as: Sylvia Allegretto and Michael Reich (2016). "Are Local Minimum Wages Absorbed by Price Increases? Estimates from Internet-based Restaurant Menus". IRLE Working Paper No. 124-15.
<http://www.irlle.berkeley.edu/files/2015/Are-Local-Minimum-Wages-Absorbed-by-Price-Increases.pdf>

November 21, 2016

Are Local Minimum Wages Absorbed by Price Increases? Estimates from Internet-based Restaurant Menus

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ABSTRACT

We analyze 844 Internet-based restaurant menus that we collected before and after San Jose, CA implemented a 25 percent minimum wage increase in 2013. Our estimated minimum-wage price elasticities are: 0.058 for restaurants as a whole, 0.083 for limited-service restaurants, 0.040 for full-service restaurants, 0.077 for small restaurants, 0.039 for mid-sized restaurants, 0.098 for chains and 0.062 within chain-pairs. These estimates are very similar to our estimate of payroll costs increases net of turnover savings, implying that nearly all of the minimum wage increase is passed through to consumers. Equally important, price differences among restaurants 0.5 miles from either side of the policy border are not competed away, indicating that restaurant demand is spatially inelastic. Border effects for restaurants are therefore smaller than is often conjectured. These results imply that citywide minimum wage policies need not result in substantive negative employment effects or shifts of economic activity to nearby areas.

JEL codes: J2, J3, J4, J8

Key words: minimum, wages, prices, restaurants, menus, elasticities

We are indebted to Megan Collins, Zachary Goldman, Harsha Mallajosyula, Carl Nadler, Chris Stern and Dan Thompson for assistance in the collection and analysis of the Internet-based data and to the California Employment Development Department for providing us with special data runs for the city of San Jose. A team of students helped to digitize all the pre- and post-menus. We especially thank Matilda Hale along with Eric Bloss, James Geluso, Yeena Lee, Sarah Martin-Anderson, Joshua Netter, Jonathan Ngan and Consuelo Velasquez for their assistance. We are grateful to Dale Belman, Gabriel Chodorow-Reich, Arindrajit Dube, David Graham-Squire, Claire Montialoux and Ben Zipperer for their excellent suggestions. This study was supported by research funds from the University of California and a grant from the Ford Foundation.

We investigate the extent to which businesses increase their prices in order to adjust to higher payroll costs associated with local minimum wage increases. Price effects are to be expected, in proportion to the magnitude of an industry's low-wage labor in operating costs and the sensitivity of industry product demand to price. In restaurants the direct labor share of operating costs is about 30 percent and about 33 percent of restaurant workers are paid within 10 percent of the minimum wage (Dube, Lester and Reich 2010). At the same time, output demand for restaurants is relatively price inelastic: -0.71 (Okrent and Alston 2012). Consequently, the restaurant industry can absorb labor cost increases from a minimum wage with relatively small price increases, which in turn have relatively small effects on restaurant sales. This strategy therefore may dominate responding to a minimum wage by reducing employment, which may reduce sales and profits to a greater extent.

It is therefore surprising that the causal effects of minimum wages on prices have received very little attention from scholars, especially compared to the very large literature on employment effects. In part, this lack of attention reflects a surprising view that price effects of minimum wages are relatively unimportant or difficult to measure precisely. Also, previous national studies of price effects generally have focused on a few menu items collected from secondary data sources with a small number of restaurants per city, while previous local price studies have been based on even smaller samples. Reviews of these studies report mixed findings.

We add to this literature by analyzing a large sample of Internet-based restaurant menu data that we collected before and after San Jose implemented a 25 percent minimum wage increase in March 2013. Our sample includes 884 limited-service (fast food) and full-service restaurants located both inside and outside of San Jose, and allows us to identify chains as well. Our data also includes all menu items—the average restaurant menu consists of 75 individually priced items. Moreover, our data comes directly from Internet-posted menus, while previous studies used reports from surveyed managers, volunteers, or surveyors visiting a restaurant.

Our paper is the first to use Internet-based data to study restaurant price responses to a minimum wage increase. It is also the first paper to analyze the price effects of a citywide minimum wage policy on the city's competitiveness: we can investigate whether affected firms near the city's border restrain price increases in order to compete with nearby firms near the

order side of the border, whether firms just outside the border raise their prices, and whether such effects dissipate with distance from the border.

We use a local quasi-experimental design that exploits the implementation of a citywide minimum wage in San Jose, California and the emergence of online data as a source of information about restaurant menus. The San Jose case holds special interest because a relatively large (25 percent) minimum wage increase was implemented at a single point in time, because San Jose is bordered by other urbanized areas, and because our analysis of wage and employment data suggest that the policy affected wages but not employment. We compare fast-food and full-service restaurants, chains with independents and restaurants by employee size. We are also able to examine whether price effects are related to distance to the San Jose border and to the density of restaurants in a given radius.

Our results indicate a statistically significant minimum wage price elasticity of 0.058 for the overall restaurant industry—meaning a 10 percent increase in the minimum wage is associated with a 0.58 percent increase in restaurant menu prices in San Jose. This price elasticity implies that restaurants responded to the 25 percent increase minimum wage by increasing prices, on average, by 1.45 percent; furthermore, a 95 percent confidence interval rules out increases of more than 2.23 percent. This estimated price elasticity is very similar to our estimated cost pressures, net of turnover cost savings, among San Jose restaurants. In other words, our results indicate a substantial price pass-through for the restaurant industry overall. Our results also indicate a price discontinuity within 0.5 miles of San Jose’s border, challenging the suggestion that local minimum wages disadvantage a city’s economic competitiveness.

Economic and policy context

In November 2012, San Jose voters passed a citywide minimum wage ballot item (Measure D) that increased the city’s wage floor from the state’s \$8 minimum to \$10. The impetus for a citywide minimum wage originated with San Jose State University sociology students, who worked with community leaders to place the measure on the ballot. Measure D was highly contested, with considerable opposition from restaurant interests, half of the city council and also the mayor. Opponents cited substantial job destruction, especially at the city’s borders, and much higher consumer prices as the main likely negative effects. Nonetheless, the ballot measure received 59 percent of the vote and went into effect on March 11, 2013. The

ballot measure specified annual subsequent increases, to be determined by the regional consumer price index. As a result, the minimum wage increased to \$10.15 on January 1, 2014 and to \$10.30 on January 1, 2015. Early journalistic investigations (Brock 2014) suggested that the policy did not have negative employment effects. In September 2015, the San Jose City Council voted unanimously to study a phased increase in its minimum wage to \$15; six surrounding cities also voted to explore means to coordinate such increases in the entire region.

San Jose, the tenth largest city in the U.S., has the highest median household income of the 25 most populous cities in the U.S. On its municipal website, San Jose describes itself as the “Capital of Silicon Valley.” Like many other booming cities, its income has become more unequally distributed in recent decades. In particular, the relative pay of workers in low-wage industries—such as restaurants—has been falling relative to those in the prosperous higher-wage technology sectors.

Figure 1 provides two maps of the area under study. The first map situates Santa Clara County within California. The second map situates the City of San Jose within Santa Clara County. San Jose (marked in red) is located entirely within Santa Clara County and abuts on three sides the urbanized portion (marked in gray) of the county. Some of the city’s borders are basically straight lines drawn on a map; others relate to natural geographical boundaries. The white portion of the map on the right denotes unincorporated areas of the county, of which large parts are state parks and/or mountainous rural regions. The map thus provides a visual guide to the minimum wage treatment area—inside the boundaries of San Jose (the red area), and to our control area—the other cities in Santa Clara County (the gray area).

Santa Clara County includes a number of smaller incorporated cities which constitute our control area: Campbell, Coyote, Cupertino, Gilroy, Hollister, part of Livermore, Los Altos, Los Gatos, Milpitas, Morgan Hill, Mountain View, Palo Alto, Santa Clara, San Martin, Saratoga and Sunnyvale. Employment in San Jose constitutes about 62 percent of employment in Santa Clara County. Thus, San Jose is the major city of a larger localized labor market.

Population densities in San Jose and in its bordering cities are similar and typical of California cities, with small downtowns composed of city block grids and larger areas that are suburban in layout. Restaurants outside the downtown areas tend to locate on strip malls, with

automobiles as the predominant method of customer access.¹ As a result, restaurants may be more likely to advertise than to rely on neighborhood walk-ins, as would be the case in highly dense cities such as San Francisco or New York.

In a prospective study, Reich (2012) used two different data sets to estimate a range for the proportion of San Jose workers who would receive increases. Using the American Community Survey place of work data, which identifies respondents by the location of their workplace, Reich estimated that 17.9 percent of workers who were employed in San Jose would receive pay increases because of the minimum wage policy. Using twelve months of CPS MORG data, which has better measures of hourly wages than the ACS, but only information on the respondents' place of residence, Reich estimated that 26.4 percent of the city's workers would get increases.

According to Autor, Manning and Smith (2015), each of the federal and state minimum wage policy changes between the mid-1980s and 2014 directly affected at most seven percent of covered workers. By this metric, the San Jose increase constitutes a much larger increase. Cities that have enacted increases to \$15 are phasing in those increases over a number of years; consequently smaller fractions of workers will receive increases at any point in time.²

Effects of the San Jose minimum wage increase on earnings and employment

Beginning with Card and Krueger (1994), economists have studied minimum wage effects by comparing nearby areas, such as adjacent counties. Examples include Dube, Naidu and Reich (2007); Dube, Lester and Reich (2010, 2015); Addison, Blackburn and Cotti (2014); and Aaronson, French and Sorkin (2015). For citywide minimum wages, it is informative to compare effects in adjacent areas within the same county or metro area. This approach is especially appropriate for testing effects at the city's border and the rate at which border effects dissipate with distance.

Following this approach, we use Quarterly Census of Employment and Wages (QCEW) data to compare restaurant wage and employment trends in the City of San Jose to those in the

¹The real estate industry compiles walkability scores for most cities. Walk scores range from 0 when all errands are car-dependent to 100 when daily errands do not require a car. San Jose's walk score is 48, compared to 55 for Santa Clara County as a whole, 64 for Los Angeles, 69 for Oakland and 84 for San Francisco. See www.walkscore.com.

²An exception is Oakland, CA, which implemented a one-time 36.1 percent increase in its minimum wage, from \$9 to \$12.25, on March 2, 2015. Reich et al. (2014) estimated that 27 percent of Oakland's covered workers would get pay increases.

urbanized adjoining areas of Santa Clara County. To exclude recession years, our sample begins in 2010q1 and ends in 2014q3, the most recent data available to us. The sample thus spans 19 quarters. The QCEW, which covers approximately 97 percent of all nonfarm jobs, provides a near-census of county-level payroll data with monthly employment and quarterly earnings information. Our variables of interest are average weekly wages³ (quarterly) and employment (monthly) in the Restaurant Industry (NAICS 722) and two of its sub-sectors: full-service (NAICS 722511) and limited-service (722513) restaurants. We use public-use QCEW data for Santa Clara County and special QCEW runs conducted for us by the state Employment Development Department (EDD) to construct our data. EDD provided us with QCEW data separately for San Jose. We then subtract data on San Jose from publicly available data on all of Santa Clara County to obtain QCEW data for our treatment area, San Jose, and our control area, the rest of Santa Clara County net of San Jose.

We first examine whether the urban areas of Santa Clara County that surround San Jose (hereafter referred to as outside-San Jose) make a good control group for the city. This is not self-evident. While San Jose bills itself as the capital of Silicon Valley, much of the high-tech high-wage employment boom has taken place outside the city itself. Based on our 2010-2014 QCEW dataset, private sector weekly wages averaged \$1,510 in San Jose and \$2,140 in the rest of Santa Clara County; the average San Jose wage was thus 70.6 percent of the outside-San Jose wage. During this period, overall employment grew 3.61 percent per year in San Jose and 4.39 percent outside-San Jose.

Wage differences in restaurants and trends in unemployment rates thus provide comparisons that are more pertinent to our study. We study restaurants because they are among the most intensive users of low-wage labor and account for more low-wage workers than any other major industry. In retail and accommodations, the next two largest users, wages are somewhat higher, and the proportions of labor costs in overall operating costs are much lower. Previous studies thus suggest that restaurants are the only major industry with detectable price effects (Neumark and Wascher 2008).

Weekly wages from the QCEW in San Jose restaurants averaged \$361 in 2013, while the comparable figure for outside-San Jose was \$394, about 10 percent higher. This difference

³The QCEW weekly wages are defined as the ratio of total wages (quarterly) to average monthly employment (quarterly) and dividing the result by 13 weeks (per quarter). This measure does not take into account changes in weeks worked or hours worked per week.

mainly reflects the higher concentration of limited-service restaurants in San Jose. Thus weekly wages in limited-service restaurants in San Jose averaged \$312 in 2013; the comparable figure for outside-San Jose was \$319, a difference of only 2 percent. Wage differences were greater among full-service restaurants: \$400 in San Jose and \$435 outside-San Jose, a difference of 8 percent.⁴ Both areas experienced parallel trends in unemployment. The unemployment rate in the County fell from 11.1 percent in 2010 to 7.2 in 2013 and 5.4 in 2014, as reported by the California Employment Development Department; the comparable rates in San Jose were 11.3, 7.6 and 5.8, respectively.

A key question is whether the treatment and control group exhibit parallel trends before the treatment and whether we can detect a treatment effect. Figure 2 displays pre- and post-trends in wages and employment in the treatment group—restaurants in San Jose, and in the control group—restaurants “outside-San Jose.” These data are for full- and limited-service restaurants combined. Recall that the minimum wage rose from \$8 to \$10 in March of 2013—denoted by the dotted-vertical line in Figure 2—and then rose to \$10.15 in January of 2014, in line with the increase of the local consumer price index.

The left panel of Figure 2 shows that average weekly wages in the control group (the top line) rose steadily, and at the same rate, before and after the \$2 increase in San Jose’s minimum wage. This panel also shows that wages were lower and rose less rapidly in San Jose (bottom line) than in the control group before the new minimum wage was implemented. At the time of implementation, however, average wages in San Jose rose discontinuously—by about \$20 per week—and continued to increase more rapidly than before the implementation. A Chow Test confirms a statistically significant (at the 1 percent level) structural break in San Jose’s wages post-minimum wage increase—as is clearly depicted in Figure 2. No such break is detected for wages outside-San Jose.

The right panel of Figure 2 displays the employment trends in both the treatment (bottom line) and control (top line) areas. Combined employment for full- and limited-service restaurants before implementation grew slightly faster in the control area than in San Jose, reflecting the faster growth of overall employment in the rest of Santa Clara County relative to San Jose. These slightly different pre-trends are taken into account in our difference-in-differences calculation.

⁴California does not have a tip credit. Consequently, earnings (including tips) in full-service restaurants are higher than in limited-service restaurants.

Note that neither of the two employment trend lines shows a break at the time of implementation. Instead, growth in restaurant employment in San Jose and outside-San Jose occurs at the same rate as before implementation. Chow Tests did not indicate statistically significant structural breaks.⁵

Figure 2 also provides insights on the effect of the statewide minimum wage increase from \$8 to \$9 on July 1, 2014. The final observation in our sample is for 2014q3, when the treatment and control group in effect switch identities. As the left panel shows, and as one would expect, the wage outside San Jose rose substantially in 2014q3, while the wage inside San Jose rose just slightly. The right panel of Figure 2 shows that employment barely budged in both areas.

This visual summary of the data in Figure 2 is confirmed by our difference-in difference calculations, reported in Table 1. Although the number of observations is not large, we find a statistically significant (at the 10 percent level) wage elasticity of 0.145 for full-service restaurants. We obtain an estimated wage elasticity of 0.086 (not significant) among limited-service restaurants and a wage elasticity of 0.150 (not significant) for food services as a whole. The point estimates for earnings effects among full-service restaurants are similar to those in previous studies (Dube, Lester and Reich 2010, 2015). The somewhat smaller earnings effect in limited-service restaurants is surprising, given the relatively lower wages in this sector; however, the estimate is imprecise because of the limited sample size. Indeed, a Chow test indicates that the difference between the two estimates is statistically not significant ($p = 0.445$).

In contrast, the employment elasticities from monthly data in Table 1 are very small and none are statistically significantly different from zero. The estimated employment elasticities are 0.006 for full-service restaurants, -0.024 for limited-service restaurants, and -0.008 for all food services. These results should not be taken as definitive, given that standard errors are large in small samples. Nonetheless, they provide suggestive evidence that the San Jose minimum wage did not result in substantial disemployment in San Jose restaurants while it did provide a boost in wages. This finding supports the likelihood that restaurants absorbed some of the additional payroll costs through mechanisms such as price increases.

⁵Separate graphs for full-service and limited-service restaurants (not shown) indicate similar patterns within each sector.

Related price studies

A recent survey of the minimum wage literature by Neumark and Wascher (2008) contends that “the effect of a minimum wage increase on the overall price level is likely to be small” (p. 248). Card and Krueger (1995) conclude that the data are “too imprecise to reach a more confident assessment about the effects of the minimum wage on restaurant prices” (p. 148). Studies that focus on other mechanisms, such as employee turnover in restaurants (Dube, Lester and Reich 2015; Batt et al. 2014) also neglect price changes as an adjustment mechanism. However, a recent survey of the minimum wage literature by Belman and Wolfson (2014, pp. 383-92) concludes that minimum wage increases generally do increase prices.

A small number of papers examine the relationship between state and federal minimum wages and prices. These studies divide into national panel studies and local studies (see online Appendix A for a more detailed review). Using national panel data, Aaronson obtains an estimated price elasticity of 0.037 for fast-food restaurants, while Aaronson, French and MacDonald obtain a statistically significant price elasticity of 0.074, also for fast-food restaurants.⁶ All of these studies examine a very small number of menu items per restaurant and much smaller increases in minimum wages. Relative to these studies, we have a much larger dataset and can estimate elasticities for a much larger range of restaurant characteristics. Moreover, national panel studies necessarily estimate an average effect across the U.S. But current policy activity is more concentrated among state and local policy entities. Consequently, an Internet-based local case study that is replicable in other localities offers a new approach that is more informative for state and local policy makers.

National panel studies of price effects have the advantage of encompassing data from multiple areas and multiple points in time. On the other hand, some panel data on price increases, such as in Aaronson, French and McDonald (2008) exhibit significant pre-trends, perhaps because of anticipation effects or because states with more inflation are more likely to

⁶Aaronson 2001, p. 163: “...excluding the high-inflation period of 1978–1982 reduces the pass through estimate to 0.051 (0.020) when city- and time-fixed effects are included and 0.037 (0.021) with a full set of price and employment controls.

raise the nominal level of their minimum wage.⁷ Panel data may therefore be biased toward finding positive price effects.

Local studies with nearby comparisons provide an alternative method for studying price effects of minimum wages. Our paper is most related to the local studies of Card and Krueger (1994) and Dube, Naidu and Reich (2007), and the national panel studies of Aaronson (2001) and Aaronson, French and MacDonald (2008). Based on their own survey of restaurants in New Jersey and Pennsylvania, Card and Krueger find only mixed evidence that prices respond to minimum wage increases. Evaluating the effect of San Francisco's 28 percent increase (over two years for small employers) in 2004, Dube, Naidu and Reich find significant positive price elasticities of 0.062 for limited-service restaurants and 0.018 for full-service restaurants (not significant).⁸

Our paper is also related to the "Billion Prices Project" at MIT which scrapes global price data daily from large supermarkets and retailers, also draws upon Internet-based data. They do not, however, include any information on restaurant menu prices.

Restaurant menu data collection

Our data represent a novel and large sample of restaurant menus downloaded directly from posted online menus. As far as we know, ours is the first study to demonstrate that *online* restaurant menus provide a suitable dataset to study minimum wage price effects. An increasing number of restaurants are posting and updating their menus online, despite the costs of doing so. Posting provides consumers with additional information and permits individual restaurants to participate in networked online reservation, ordering, delivery, and evaluation services.⁹ Such services have multiplied in recent years, to the point that many restaurants regard an online presence as a mandatory component of their marketing plans. The San Jose case is especially

⁷Allegretto, Dube, Reich and Zipperer (2015) discuss the non-random character of states with higher minimum wages. Aaronson, French and MacDonald (2008) find significant price effects in the quarter before a minimum wage increase. Unfortunately, they do not test for longer pre-trends.

⁸Although the San Francisco results are very similar to ours in this paper for San Jose, local price elasticities are likely to vary with the proportion of workers who receive pay increases.

⁹AllMenus.com lists 255,000 restaurant menus nationwide and claims 5 million visitors per month (<http://www.allmenus.com/contact-us/>). By September 2015, Allmenus.com listed menus for 1,120 San Jose area restaurants (<http://www.allmenus.com/ca/san-jose/>) and 170 delivery restaurants. Open Table and SeatMe are examples of widely-used online reservation systems; GrubHub.com, which acquired Allmenus.com in 2011, provides remote ordering and delivery for 35,000 restaurants in 900 U.S. cities (<http://get.grubhub.com/>). Yelp and UrbanSpoon are but two examples of well-known websites that provide restaurant ratings using consumer reviews. McLaughlin (2010) provides an early description of the growing prevalence of these services.

opportune for using Internet-based data if Silicon Valley area restaurants are more likely to be early adopters of the technology. By eliminating the need for survey respondents to recall price and sales data, the online method may reduce measurement error and provide tighter confidence intervals for the estimated effect. Moreover, we collected data on all menu items, not just a few dishes, as was the standard in previous research.¹⁰

We initiated the first wave of data collection at the end of November 2012, soon after the ballot measure passed, and completed collection of the first wave in early January 2013, well before the policy's March 11, 2013 implementation date. (Online Appendix B provides a detailed description of our data collection methods and checks on the representativeness of our data.) Since individual businesses face limits in raising prices relative to competitors, we would not expect significant anticipation effects to occur more than two months before the implementation date. Indeed, Aaronson (2001) does not find price increases more than two months prior to implementation of a higher minimum wage.

As our first step we acquired a list of all *Active Food Facilities* (AFF) in Santa Clara County from the County's Department of Public Health. The Department maintains such a list because it is mandated to inspect all food facilities for compliance with health and sanitary conditions. The AFF list included 5,747 facilities, including the name, street address, city, zip code, and phone number, as well as size bins for employment at each facility. After editing the list to identify restaurants that fell within the 722511 and 722513 NAICS codes for restaurants we were left with 3,285 limited- and full-service restaurants—these effectively constitute our “sampling universe.”

For the first wave of data collection we succeeded in identifying online websites and downloaded menus from 1,211 of these restaurants, or about one-third of our restaurant sample. Importantly, we attempted to locate an up-to-date menu for every single restaurant in the universe.¹¹

¹⁰We are not aware of any other dataset that provides such a comprehensive number of restaurant menu items. Large datasets are now available for retail prices. Nakamura (2008) uses Nielsen scanner data from 7,000 large supermarkets to study retail price variation. This dataset contains observations on 100 individual products, while the Consumer Price Index research retail database contains only seven price quotes per item per month. See also Nakamura and Steinsson 2008.

¹¹We searched AllMenus.com, a website service that posts actual restaurant menus provided by restaurants, as well as each restaurant's website, if it had one. Restaurant owners periodically update their menus on AllMenus.com, but we were unable to identify the date of their most recent upload. We therefore also examined the restaurant's website and used its menu whenever possible. We did not use Yelp.com or other consumer-created restaurant guides, as the menus on those sites are posted by consumers and may be unreliable.

We began collecting the second wave of post-treatment menus, drawing from the same restaurants for which we obtained menus in the first wave, in September 2013—six months after the minimum wage went into effect—and we concluded collecting the second-wave data at the end of November 2013.¹² Our previous research (Dube, Lester and Reich 2010) suggests that minimum wage effects on restaurant pay and employment occur within the first two quarters of a policy increase. Aaronson, French and MacDonald (2008) find that price increases are also highly concentrated in the first two quarters following an increase.¹³ As in any panel survey, some attrition occurred in the second wave. In both waves, we kept detailed records of our process and attempts at menu collection. In the end, our balanced (two-wave) panel consists of 884 total downloaded menu pairs of which 326 were from inside San Jose (treatment area) and 558 were from outside of San Jose (control area).

In contrast to our expectations, the digitization of the menus required highly labor-intensive methods. Each menu was saved as a PDF—basically an electronic image of the menu. We expected to use off-the-shelf software that could accurately compare the prices on the pre- and post-menu pictures. As it turned out, and despite consultation with a variety of software experts, we were unable to obtain a software package that met our accuracy standards. As a result, for each menu, we manually input every menu item for both waves into an Excel spreadsheet and then uploaded the data into STATA for our analysis.

Representativeness of our sample

Since our downloaded restaurants include treatment and control sub-samples, our results possess internal validity. That is, they will be informative for price effects of a minimum wage increase among the set of restaurants that have downloadable menus. We also want to know whether our results possess external validity: Do restaurants with downloadable menus differ in systematic ways, especially in pricing behavior, from restaurants that do not post their menus online? While we cannot determine external validity definitively, we can compare our restaurant

¹²In both the first and second wave, we collected data from individual restaurants in an order determined by a random number generator. This randomness insured against correlation between the time of data collection and other characteristics, such as the name of the restaurant. Seasonal differences between the timing of the first and second waves do not affect our results, as seasonality should have similar effects in both the treatment and control groups.

¹³More precisely, they find that 60 percent of the price increases occur in the first two months after a minimum wage increase, with the remainder occurring in the next two months and in the two months preceding the policy change.

universe and our downloaded sample along a number of dimensions: by size, by location patterns inside and outside San Jose, and by the proportion of limited-service and full-service restaurants. When possible, we also compare our sample to data on restaurant characteristics from the Quarterly Census of Employment and Wages. In online Appendix B we show in more detail that the universe and the downloaded restaurant menu sample are quite similar along these dimensions. Here we present the most salient points from that analysis.

To check the representativeness of our sample, we compared our file of all Santa Clara County restaurants from the AFF list (N=3,285) to our restaurant sample obtained from acquiring downloaded menus from San Jose and outside-San Jose (N=884). The restaurant proportions for treatment and control are similar across the AFF universe list and our downloaded sample. From the AFF list, 44 percent are located within San Jose and 56 percent outside of San Jose. Comparatively, 37 percent of our restaurant sample is located inside San Jose's city boundaries and 63 percent are from the control area outside of San Jose (see Appendix B for further discussion). Thus, compared to the AFF universe, our sample somewhat over-weights restaurants outside-San Jose. This over-weighting, however, should not affect our difference-in-difference estimates

Since we have the exact addresses of the restaurants, we are able to examine the spatial distributions of all the restaurants on the AFF list—distinguishing between those that ended up in our sample and those that did not. This spatial analysis also depicts the representation of restaurants across our treatment and control areas. Using Google API, which allows communication with Google Maps, we obtained the latitude and longitude associated with each address. The spatial representation of the universe and sample of restaurants is depicted in Figure 3. The solid black line shows the boundary of San Jose. The other major cities in Santa Clara County are listed on the map. The darker circles represent our sample of restaurants, while the lighter dots represent restaurants that were not sampled. The map suggests that our sample is quite representative spatially within both the control and treatment areas. We also computed the distance of each restaurant to the San Jose border, which also allows us to estimate price effects by distance of a restaurant to the San Jose border.¹⁴

¹⁴Using Google API, we obtained the latitude and longitude associated with each address and computed the distance of each restaurant to the San Jose border. We then obtained the exact San Jose city border polygon from the Census TIGER database of "places" and ran the function "Near_Dist" from ArcGIS on the polygon for the San Jose

In Table 2 we look at the distribution and the representativeness of our treatment and control samples, separately for the full- and limited-service sectors. Each restaurant in our sample was researched and individually coded into one of these two sectors. Unfortunately, the labor-intensive nature of this process precluded sector identification for the “un-sampled” restaurants in our universe of all restaurants in Santa Clara County. However, the QCEW data that we used above to analyze earnings and employment effects are disaggregated by full- and limited-service sectors. We can therefore compare the distribution of full- and limited-service restaurants in the near-census QCEW data to the distribution of full- and limited-service restaurants in our sample.

As Table 2 indicates, 57 percent of the sampled restaurants in San Jose are full-service, while 43 percent are limited-service establishments. QCEW data (not shown in the table) indicate that 54 percent and 46 percent of restaurants in San Jose are in the full- and limited-service sectors, respectively. A somewhat larger share of restaurants outside-San Jose are full-service (65 percent) and a smaller share are limited-service (35 percent). The respective QCEW figures for the control area are 60 percent and 40 percent.¹⁵ These comparisons again support the representativeness of our sample, both within the treatment and control areas.

The remainder of Table 2 moves from analyzing the representativeness of our treatment and control samples to a descriptive analysis that compares the San Jose and control area samples along other dimensions. The third line in Table 2 reports how many sampled restaurants are chains. Chains account for 40 percent of the sampled restaurants in San Jose and 29 percent outside-San Jose.

We also computed a ‘restaurant density’ measure. For each restaurant, this measure indicates how many restaurants are located nearby. Density is measured by the number of restaurants that fall within a given radius of each restaurant; the density value for each restaurant is weighted by the inverse of its distance from the center of the search radius (nearer point features have a stronger weight). We then fit a smooth continuous surface over the sampled points to show interpolated values for any possible point within the radius.¹⁶ The density

border and the geocoded data. This method returned a vector of distances to the San Jose border for every address, giving us a continuous distance variable that ranges from 0.0 to 12.1 miles.

¹⁵Aaronson, French and Sorkin (2015) report very similar ratios.

¹⁶We then fit a smooth continuous surface over the sampled points to show interpolated values for any possible point within the radius.

measure in our sample ranges from 0.6 to 87.0. Average density is 29.0 in San Jose and 28.0 for restaurants outside-San Jose; the small difference is not statistically significant.

Using restaurant addresses we are also able to measure each restaurant's distance to the San Jose border. Distances range from 0 to 12.1 miles. As line 5 of Table 2 indicates, on average, restaurants in the control area are located 3.1 miles from the San Jose border while restaurants inside San Jose are on average 1.35 miles away. These differences are expected, since restaurants inside San Jose are surrounded by the city's border, while the restaurants in the rest of Santa Clara County can be further away.

One threat to our identification of minimum wage price elasticities using inside and outside San Jose samples concerns differential trends in rent expenses and franchise fees. These costs together make up a substantial portion of restaurant operating costs, approximately equal to that of payroll. If, for example, rents were rising faster in San Jose than outside-San Jose, and if rent costs are passed forward to consumers, then our attribution of greater price increases in San Jose to minimum wage changes might be overstated.

While we do not have data on restaurant rents, we can examine residential rent trends. Between March 2013 and September 2013, when our second wave of price collection began, residential rents increased 1.25 percent more in Santa Clara City and Sunnyvale than in San Jose, according to Zillow. Since the duration of commercial leases is typically 3-5 years, compared to 1 year for residential leases, commercial rent trends are likely to lag residential rent trends. We conclude that differential trends in commercial rents are not likely to have substantial effects on our results.

Our focus on prices ignores another potential adjustment margin: portion size. Changes in portion sizes are often conjectured, but we lack data on how common they are. Since an unobserved portion size reduction is equivalent to an unobserved effective price increase, we might be underestimating price effects if portion adjustments are heterogeneous across treatment and control. Of course, portion size reductions constitute an adjustment mechanism that does not negatively affect worker well-being.

Economic theory of minimum wage effects on costs and prices

How much would we expect a minimum wage to increase prices? We begin with the widely-used Dixit-Stiglitz monopolistic competition pricing model. Monopolistic competition is

especially applicable to the restaurant industry, given its differentiation of restaurants by ethnicity (Italian, French, Mexican, Peruvian, Chinese, Thai, Mediterranean, etc.) as well as by full-service versus limited-service. In the Dixit-Stiglitz price-formation model, price increases in the short run are determined by changes in operating costs, plus a mark-up for profits.¹⁷ Changes in operating costs are determined by the increase in payroll costs and the proportion of labor costs to operating costs. The increase in payroll costs in turn depends upon the fraction of workers earning below the new minimum wage, the average wage increase they will receive, and wage increases received by workers just above the new minimum wage because of “ripple effects.”

Cost pressures

We calculate here the overall minimum wage-related cost pressure, building on the pricing model above. The gross payroll elasticity is simply the minimum wage earnings elasticity, assuming that employment was not affected by the minimum wage increase, as we showed in Table 1. The elasticity of net payroll costs in turn equals the earnings elasticity less cost savings because of reduced turnover. In turn, the elasticity of the cost pressure with respect to the minimum wage equals the elasticity of net payroll costs with respect to the minimum wage multiplied by the ratio of net payroll costs to operating costs.

To implement this calculation, we use two different estimates of the minimum wage earnings elasticity, an employee turnover savings estimate from Dube, Lester and Reich (2015) and Reich et al. (2015) the fact that labor costs in restaurants constitute about one-third of operating costs (Aaronson 2001). Table 1 shows an earnings elasticity estimate of 0.125 for full-service and limited-service restaurants combined. Thus, the elasticity of gross payroll costs with respect to the minimum wage is also 0.125. The net payroll increase equals the gross payroll increase less the turnover savings, which amount to 15 percent of gross payroll costs. The elasticity of net payroll costs is therefore 85 percent of 0.125, or 0.106. To obtain the operating cost pressure elasticity, we then multiply the net payroll increase elasticity by the one-third labor share of operating costs. This calculation yields a cost pressure elasticity of 0.035. In other

¹⁷In the longer run, with new entrants, the profit share can become much smaller. However, that possibility is beyond our analysis here.

words, a 10 percent increase in the minimum wage raises operating costs by 0.35 percent.¹⁸ However, as we previously noted, our earnings elasticity estimates for San Jose are imprecisely estimated because of the small number of QCEW data points in our sample.

Our second, and preferred, estimated minimum wage elasticity comes from Allegretto, Dube, Reich and Zipperer (2015). This study uses a much larger sample and more controls and obtains a highly significant estimated minimum wage earnings elasticity of 0.208 for restaurants.¹⁹ Using this estimate and the same method of calculation, we obtain a cost pressure elasticity of about 0.059.

Our two cost pressure estimates are thus 0.035 and 0.059. Price increases of these magnitudes are consistent with no substantial negative employment effect. Since the demand for restaurant meals is relatively inelastic (-0.71, according to Okrent and Alston 2012), a price increase will have a smaller negative effect on sales and employment. Moreover, as the Reich et al. (2015) study of a \$15 minimum wage in Los Angeles found, the increase in purchasing power of low-wage workers will have a small positive effect on sales and employment of about the same magnitude.²⁰

Research design

We employ a difference-in-differences strategy to estimate the price pass-through of the minimum wage increase in San Jose. Our most basic model estimates the effects of the minimum wage on mean menu price for each restaurant. The independent variable is the change in average restaurant prices calculated by subtracting $\log(\text{pre-price})$ from $\log(\text{post-price})$, where i refers to each restaurant. SJ is a dummy indicator that is equal to 1 if the restaurant is in San Jose; 0 if outside-San Jose. E is the calculation of the elasticity from the estimated coefficient (β) and the 0.25 denominator represents the 25 percent increase in San Jose's minimum wage increase. Standard errors are clustered at the restaurant level. Our first specification and elasticity are then:

$$[\log(\text{post-price})_i - \log(\text{pre-price})_i] = \alpha + \beta(SJ)_i + \epsilon_i \quad (1)$$

¹⁸Expected price effects can differ by type of restaurant and size of restaurant as well as in other dimensions. We discuss these differences below.

¹⁹The restaurant employment elasticity in this study is .002 and not significant.

²⁰This discussion ignores potential capital-labor substitution. Aaronson and Phelan (2015) find that technical change reduces demand for routine jobs, such as cashiers, but increases demand for less-routine jobs, such as in food preparation.

$$E = \frac{e^{(\beta)} - 1}{0.25}$$

The second specification separates the effect of the minimum wage change on prices in limited-service restaurants from that of full-service restaurants. The notations in specification (2) follow those in (1) with the addition of FS , which denotes a dummy variable equal to 1 if the restaurant is full-service and 0 if it is limited-service; this dummy is interacted with SJ . The second equation and elasticities are as follows:

$$[\log(\text{post-price})_i - \log(\text{pre-price})_i] = \alpha + \beta_1(SJ)_i + \beta_2(SJ \times FS)_i + \epsilon_i \quad (2)$$

$$E_{LS} = \frac{e^{(\beta_1)} - 1}{0.25}$$

$$E_{FS} = \frac{(e^{(\beta_1)} - 1) - (e^{(\beta_2)} - 1)}{0.25}$$

We build a set of regression specifications based on those above. We first separately add controls as sets of dummy variables or individual continuous variables regarding restaurant characteristics and interact them with the SJ dummy to isolate the treatment effect. Thus, as discussed, specification (2) incorporates a limited- versus full-service indicator; specification (3) incorporates a dummy identifying “chains,” defined in this case as restaurants with two or more locations; specification (4) incorporates a set of dummy variables on three employee size bins; specification (5) includes a continuous control for distance to the San Jose border; specification (6) incorporates a continuous measure of restaurant density for each observation; and, finally specification (7) controls for all of the above simultaneously.

Main price results

Table 3 summarizes descriptive statistics for San Jose and outside-San Jose, both before and after the minimum wage increase. Panel A reports that, on average, prices outside-San Jose (\$10.44) before the policy change were a bit higher than inside San Jose (\$9.71)—although the 73 cents difference is not statistically significant.²¹ Comparing lines 1 and 5 in Panel A, we see that average prices increased both for restaurants in San Jose and outside-San Jose after the

²¹Also, the standard deviation of the average menu price outside-San Jose, prior to the minimum wage hike is larger than inside San Jose (not shown in Table 3).

minimum wage increase—an increase from \$9.71 to \$9.96 in San Jose and from \$10.45 to \$10.63 outside-San Jose.

We also examined the extent to which restaurants added or dropped individual items before and after the policy changes. Lines 3 and 7 in Panel A of Table 3 report that the average number of menu items is also similar between treatment and control—both before the minimum wage increase and after. The number of items before the minimum wage increase averaged 71.2 in San Jose and 74.8 outside-San Jose; after the policy went into effect, these averages were 72.9 and 77.1, respectively. These patterns indicate the net change in the number of menu items was very similar between the treatment and control restaurants—indicating that restaurants alter menus for many reasons. Moreover, the differences in average prices when either including or excluding menu items added or dropped between the two periods was very small. None of the differences reported in Panel A were statistically significant.

Table 3 reports that restaurants in the treatment and control areas both add and delete items at similar rates. Consequently, it is not easy to determine whether removing or adding items represents a response to minimum wage policy or to other factors, such as the availability of seasonal food items. Recall that the second wave of data collection occurred nine months after the first. In what follows we therefore report results for the balanced panel of data. The balanced panel also permits comparisons to previous minimum wage price studies.

The bottom panel of Table 3 displays the distribution of price responses for the balanced and unbalanced panels for the treatment and control areas. We use a balanced panel to denote the sample of menu items that appear both before and after the policy change. The unbalanced panel includes all items, including those that we removed or were new.

After the minimum wage increase (including new and removed items), 46 percent of restaurants in San Jose increased prices, 14 percent did not change their prices, and 39 percent decreased their average prices. The respective shares for the treatment area outside-SJ are 38 percent, 18 percent, and 44 percent. The share of restaurants with a price increase is 8 percentage-points higher in San Jose compared to the control and the difference is statistically significant.

We move next to Table 4, which reports the estimated elasticities from the difference-in-differences models discussed in the previous section. As noted above, specification (1) incorporates an indicator variable on San Jose. The estimated price elasticity is 0.058 (significant

at the 1 percent level) and denotes the overall price elasticity without any other controls. This elasticity estimate implies that restaurant owners in San Jose responded to the 25 percent increase in San Jose's minimum wage by increasing prices, on average, by 1.45 percent—a 95 percent confidence interval rules out increases of more than 2.23 percent.

Specification (2) adds an interaction term (*SJxFS*) to estimate the effects separately by sector. The interpretation of the regression results in Table 4 that control for a set of dummy variables (specifications (2) through (4)) is as follows. Using specification (2) as an example, the price elasticity in the first row for 'San Jose' represents the dummy indicator that was omitted from the regression—in this case the dummy on limited-service restaurants. Thus the elasticity for limited-service establishment is 0.083 (statistically significant at the 1 percent level). The elasticity for full-service restaurants is obtained from the combination of the '*San Jose*' effect (otherwise the limited-service elasticity) and the additional effect from the interaction term '*SJxFS*'. The resulting estimated price elasticity for full-service restaurants is 0.040.²² Using the STATA *lincom* command we determine that the linear combination of the two effects is statistically significant at the 5 percent level. The lower price elasticity among full-service restaurants is consistent with the higher wages paid in that sector, compared to those in limited-service restaurants, as well as to a higher price elasticity of demand for full-service restaurants relative to limited-service restaurants (Okrent and Alston 2012).

For ease of interpretation, Table 5 reports the elasticities for all the indicator variables from specifications (1)-(4) and subsequent linear combinations calculated by using the regression results from Table 4 together with the *lincom* command as described above.

As with specification (2), specifications (3) and (4) also incorporate sets of dummy variables. Specification (3) in Table 4 isolates price effects for chain and non-chains. Recall that our broad definition of chain is any restaurant with two or more locations. Although chain restaurants may be located in either the full-service or limited-service sectors, in our sample they are predominantly limited-service establishments. The estimated price elasticity for chains in Table 4 is 0.098 (significant at the 1 percent level); the price elasticity for non-chains is 0.030 (significant at the 10 percent level). The estimate for chains (0.098) is similar to the estimate for

²²Using different data and methods, McDonald and Aaronson (2006) also report higher price elasticities among limited-service restaurants than full-service restaurants: 0.16 and 0.04, respectively. However, the spread between the two is much greater than in our results.

limited-service restaurants (0.082)—consistent with the observation that the restaurant chains in our sample are predominantly limited-service establishments.

In Table 5, Panel C we also provide an estimated elasticity for a sub-sample of chains. The sub-sample includes restaurants that have at least one outlet in San Jose and one outside-San Jose (there may be more in either location) and consists of 49 unique chains and 202 total restaurants. The estimated price elasticity of 0.062 (significant at the 5 percent level) represents the pooled within-chain price effect—which represents more of an apples-to-apples comparison.

Next we report how price elasticities vary by the number of employees. Generally, as Table 5, Panel D reports, restaurants with a smaller number of workers increased their average prices more than restaurants with more workers. The estimated elasticity for restaurants with 1 to 7 workers is 0.077 (statistically significant at the 1 percent level); the elasticity for those with 8 to 39 workers is 0.039 (significant at the 5 percent level). The price effect (0.008) was not distinguishable from zero for restaurants with 40 or more workers.²³ Small restaurants apparently possess more pricing power than larger restaurants.

To some extent, these price differences by number of employees reflect differences between limited-service and full-service restaurants. The distribution across the three employee size bins (not shown in the table) is 0.64, 0.34 and 0.02 for limited-service restaurants and 0.49, 0.39 and 0.12 for full-service restaurants, by small, medium and large, respectively. To the extent that the number of employees is a proxy for restaurant size, limited-service restaurants are, on average, smaller than full-service restaurants.²⁴

Specifications (5) and (6) in Table 4 add two continuous measures, distance to border and restaurant density, respectively, while specification (7) incorporates all the controls into one regression. Specification (5) estimates whether price effects differ by distance to the San Jose border. The estimate is small (0.007) and not statistically significant. Specification (6) in Table 4 reports estimates using our restaurant density measure. The estimated elasticity for zero density, reported in the first row, is 0.098 (significant at the 1 percent level), a relatively large effect. Specification (6) also reports the additional price effect as restaurant density increases: -0.001 (significant at the 5 percent level). Price effects thus become smaller as restaurant density

²³The distribution of the three employee bins shows that only 8.5 percent of restaurants belong to the largest bin. The small sample size for this bin—29 in San Jose and 46 outside-SJ—likely makes the estimates for this bin imprecise.

²⁴These differential price responses by employee size may also reflect a correlation with the number of menu items which we address in online Appendix C.

increases, perhaps due to greater competition spatially. At the mean density measure, which is 28.4, the price effect at the mean density equals $[0.098 - (0.001 \times 28.4)] = 0.068$. This novel finding suggests that measured price elasticities are substantially affected by restaurant density.

Lastly, specification (7) in Table 4 includes all the controls simultaneously. The *San Jose* price elasticity now represents all the omitted dummy variable categories and distance and density measures set at zero. Thus, 0.068 (first row, specification (7)) represents the elasticity for limited-service, non-chains with 1 to 7 employees with zero density and zero distance to the border. The qualitative results for the controls are similar to those from the isolated specifications for each: elasticities with negative (positive) signs mean the effects are less (more) for those controls versus their omitted dummy variable counterparts. The interpretation is the same as described above for the continuous variables on density and distance to the border. The density effect is the same and remains statistically significant. The coefficient on distance is now about three times larger, but remains statistically not significant.²⁵

Border effects

A key question for citywide minimum wage policies concerns whether affected firms in the city will face increased competition from firms outside the city's borders. In 2014 and 2015 alone, 29 cities in the U.S. established local minimum wages and many more are considering doing so. Quite a few of these cities are geographically very small. The question of border effects is thus of particular relevance.

Border effects arise if firms inside the treatment city want to raise their prices in response to payroll increases, but feel constrained by the fear of losing business to their competitors outside the city limit. As a result, some businesses may want to relocate outside the city or not to locate within it in the first place. On the other hand, local market spatial areas for some businesses—such as restaurants—may be too small to face competition outside the treatment area. Two studies of price differences among fast-food restaurants in Santa Clara County (Thomadsen 2005, and Ater and Rigbi 2007) find substantial price differences among all the McDonalds outlets in the county. Thomadsen relates these price differences to travel costs, while Ater and Rigbi relate the price variation to the relative concentration of repeat customers, as

²⁵Online Appendix C presents additional descriptive analyses and elasticity estimates based on the number of menu items and for three main dishes (chicken, pizza and burgers).

measured by distance to local freeways. In either case, the implication is that product markets contain spatial frictions that limit the extent of competition.

Border issues have been studied in the three cities that established local minimum wages in the 1990s: San Francisco, Santa Fe and Washington, DC. Thorough studies of these cities did not detect negative employment effects or the relocation of retail stores to other areas.²⁶ However, since none of these studies had high-frequency distance data, they may have missed local effects near their borders.

The local density of restaurants within the same chain provides some insight on the relevant geographic size of the local market. Firms want to locate near their competitors, but not too near their own outlets, for fear of cannibalizing their own sales. According to their company websites, McDonald's has 32 stores within San Jose and Burger King has 18. These two chains have the highest number of burger outlets in the U.S. By comparison, the entire city of San Jose encompasses 180 square miles, some of which are parks or otherwise unavailable for commercial development. If 32 (18) stores were located equidistantly from each other in a circle that measured 180 square miles, the distance between them would be the square root of 180 divided by 32 (18), or about 0.4 (0.7) miles. Given the actual shape of San Jose, the average distance between stores would be slightly lower. These location patterns suggest that the local market spatial area for fast food burger chains probably lies between 0.3 and 0.6 miles.²⁷

We estimate border effects with our data using two metrics—price differences very close to the border and the dissipation of border effects with distance from the border. Figure 4 illustrates relative price effects by distance to the border. The figure displays the fitted lines of price difference on distance, separately, for San Jose and outside-San Jose. Since observations in San Jose are surrounded by the city's border, distances to the border are smaller compared to the distance for the average restaurants located in the remainder of Santa Clara County.

The two fitted lines in Figure 4 suggest a price discontinuity at the border, consistent with our regression results in Table 4, specification (5). It also suggests that prices of San Jose restaurants increased somewhat less at the border than in the city's interior. Outside of San Jose, prices are only slightly higher near the border than farther away, and not significantly so. These findings indicate that price differences exist among restaurants that are less than one mile apart,

²⁶For San Francisco, see Dube, Naidu and Reich (2007) as well as Dube, Kaplan, Reich and Su (2006); for Santa Fe, see Potter (2006) and for all three cities, see Schmitt and Rosnick (2011).

²⁷Subway has 50 stores within San Jose, indicating that its spatial market area is much smaller.

consistent with market spatial areas of about 0.5 miles in radius. In other words, minimum wage costs differentials at the municipal border do not prevent restaurants in the treatment group from raising their prices, despite often-stated concerns in citywide minimum wage policy debates.

Robustness tests

Our robustness tests check how our results vary with the number of menu items. Restaurants with very large menus are more likely to contain more items that are not top sellers; raising the prices of these items may be unnecessary for such restaurants. Since our measure of restaurant price increases simply averages the item-level increases, our measure may underestimate price increases for restaurants with a large number of menu items. The correct solution would be to weight the items by their popularity among customers. We do not, however, have any data on the weights of each item in the market basket of restaurant sales. In our main results, we simply weight each item equally. We have experimented with weighting each restaurant observation by the inverse of the number of menu items and also directly with the number of menu items. These experiments did not substantially affect our estimates.

We use another approach—trimming our sample in various ways to test our main results for robustness. Some very small menus are actually incomplete. In a few cases, we were able to obtain base prices for different sizes of pizza (i.e. small, medium and/or large) but we did not obtain prices for all topping combinations; in some other cases, we obtained only a single buffet price. Some of our largest menus may include instances in which our assistants incorrectly combined several menus, for example breakfast and lunch, into one observation. To address these potential biases we implement several trimming procedures, ranked by the number of menu items, to alter our sample.

These robustness tests are displayed in Table 6 by sector and by number of employee bins. As indicated by the results in the table, the estimates do not change much whether these data are trimmed at the bottom only—specifications (3) and (4), at the top only—specification (5), or at both ends—specification (2). We conclude that the estimated elasticities are quite stable regardless of the trimming method.

Concluding remarks

On November 6, 2012 voters in San Jose passed a minimum wage ordinance that increased the city's wage floor from California's \$8 to \$10. The ordinance was implemented on March 11, 2013. This policy change provides the opportunity to use a quasi-local experimental design to assess the price pass-through resulting from the wage floor increase. If a price effect were to be found, it would be at restaurants, as restaurants are heavy users of minimum wage workers.

We first analyze QCEW data from 2010q1 through 2014q3 to estimate wage and employment effects. Second, using a unique set of primary data on 884 pre- and post-menu pairs for San Jose (treatment) and outside-San Jose (control), we estimate price effects.

We detect a statistically significant increase in wages for the combined limited- and full-service sector in San Jose at the time (quarter) of the minimum wage increase, but no such structural break in wages in the rest of Santa Clara County. We also do not detect a structural break in restaurant employment in San Jose or for the rest of Santa Clara County. These wage and employment trends are further confirmed by difference-in differences estimates. This finding of wage increases but no detectable employment effects motivates our analysis of whether restaurants absorbed the payroll cost increases through price increases.

We employ a new technique to collect data for our price pass-through analysis: downloading menus directly from individual restaurant websites or menu outlets such as AllMenus and GrubHub. Our sample consists of 884 restaurants and our data includes prices on every menu item. Our Internet-based sample passes numerous tests of representativeness. This extensive dataset allows for a rich analysis of how restaurants respond, via menu prices, to an increase in the minimum wage.

We use a difference-in-differences research design to empirically analyze the price elasticity of the minimum wage increase on restaurant menu prices. In general, our overall estimated elasticity of 0.058 implies that restaurant owners in San Jose responded to the 25 percent increase in San Jose's minimum wage by increasing prices, on average, by 1.45 percent—a 95 percent confidence interval rules out increases of more than 2.23 percent. We find a range of statistically significant minimum wage price elasticities: 0.058 overall; 0.040 for full-service and 0.083 for limited-service restaurants; 0.098 and 0.030 for chains and non-chains, respectively; a within-chain effect of 0.062; and elasticities of 0.077 for restaurants with 1 to 7

employees and 0.039 among restaurants with 8 to 39 employees. Our estimated higher elasticities for limited-service restaurants compared to full-service restaurants is consistent with evidence indicating that wages are somewhat higher in the full-service sector and that demand for limited-service restaurants is more price inelastic than for full-service restaurants. Our highest estimated price elasticity is 0.098 for chains; consistent with the prevalence of limited-service restaurants among chains. Our estimated price elasticity for within chain-pairs is 0.62 is especially salient given that it is derived from homogenous chains.

Our estimated price elasticities fall with restaurants that have larger workforces, suggesting the presence of more adjustment margins among larger businesses. In a novel finding, price increases were less where restaurants face greater local competition—as estimated using a restaurant density measure.

Our overall estimated price elasticity of 0.058 is nearly identical to our preferred estimate of cost pressure elasticity (0.059). This result indicates that minimum wages are largely absorbed by price increases, as well as by turnover cost savings, even when the minimum wage increases in one swoop by 25 percent. Our study of border effects indicates that market spatial areas for restaurants are small, indicating that a citywide minimum wage does not negatively affect restaurants very close to the city's border.

Our price data extend only six months after the implementation of the policy. According to Allegretto et al. (2015), county-based data on minimum wages indicate that most of the effects occur within the first two quarters. However, longer term effects might occur in local minimum wages that we do not observe in statewide policies. For example, since workers are more mobile than firms, over time wages might be bid up near the border in the neighboring cities. This wage spillover could also affect prices there. The subsequent increases of the California minimum wage to \$9 in July 2014 and to \$10 in January 2016 preclude studying long run effects of the 2013 San Jose increase. Nonetheless, further research that looks at longer term effects would shed light on this question.

Over two dozen U.S. cities, including San Jose, have adopted or are actively discussing even larger minimum wage increases, in both absolute and percentage terms. These policies will generate substantial cost pressures in a broad range of industries and raise border effect issues. Future research will determine whether price increases continue to be the primary mechanism through which minimum wages are absorbed.

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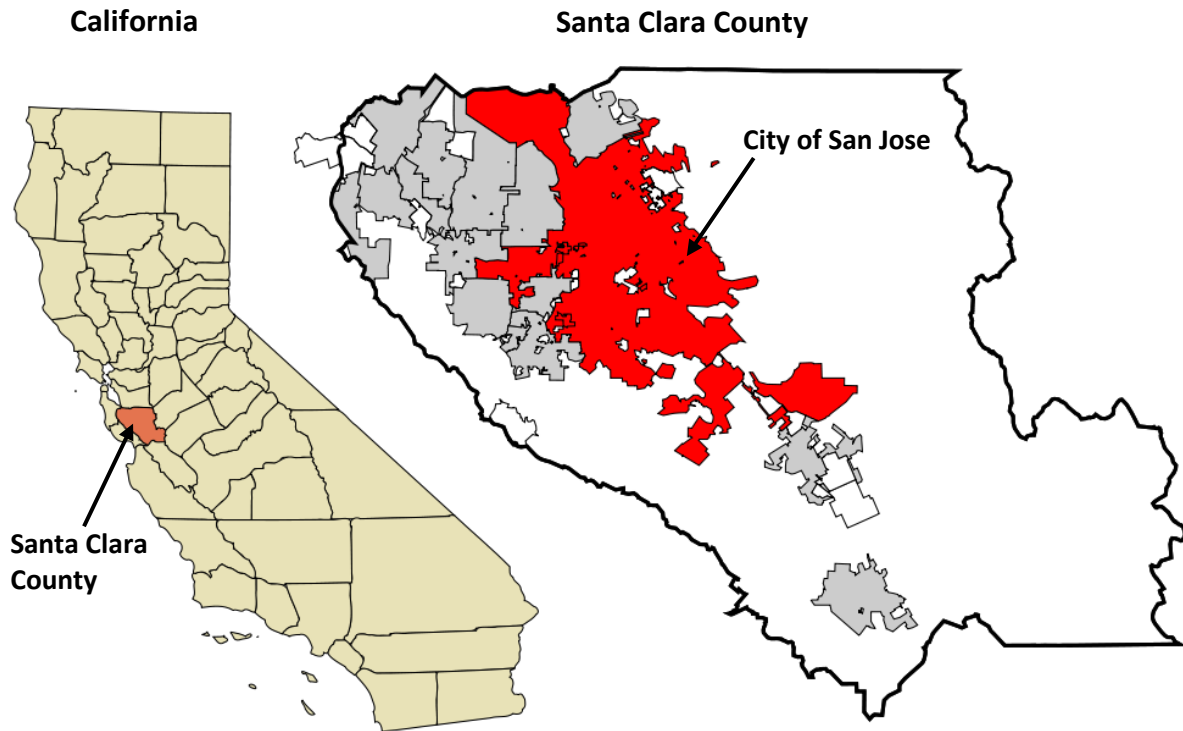
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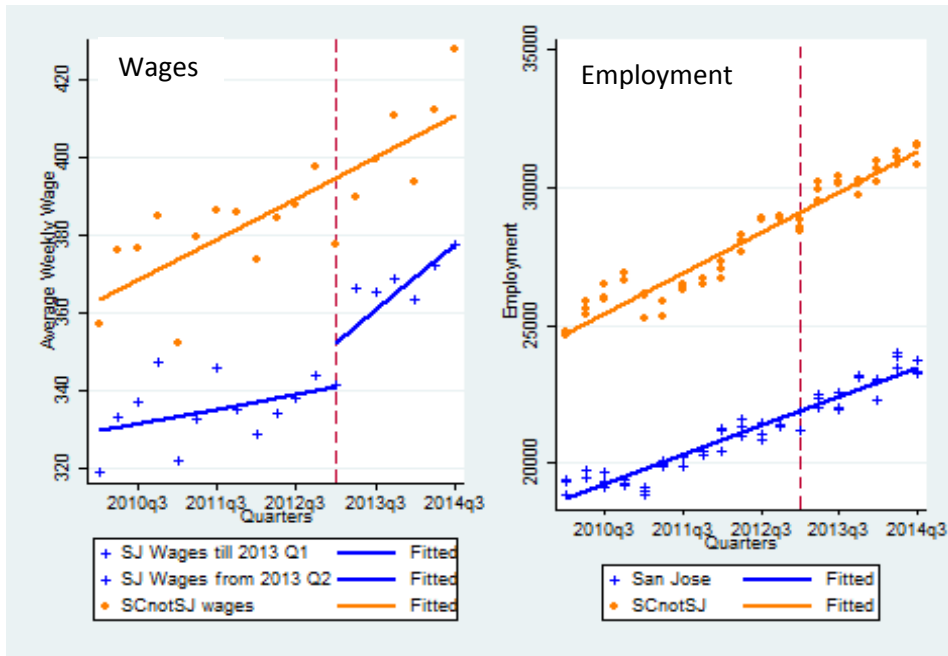
Figure 1. Santa Clara County within California and San Jose city limits within Santa Clara County



Source: Wiki Map

https://commons.wikimedia.org/wiki/File:Santa_Clara_County_California_Incorporated_and_Unincorporated_areas_San_Jose_Highlighted.svg. The area in white, on the right hand side map, represents unincorporated Santa Clara County.

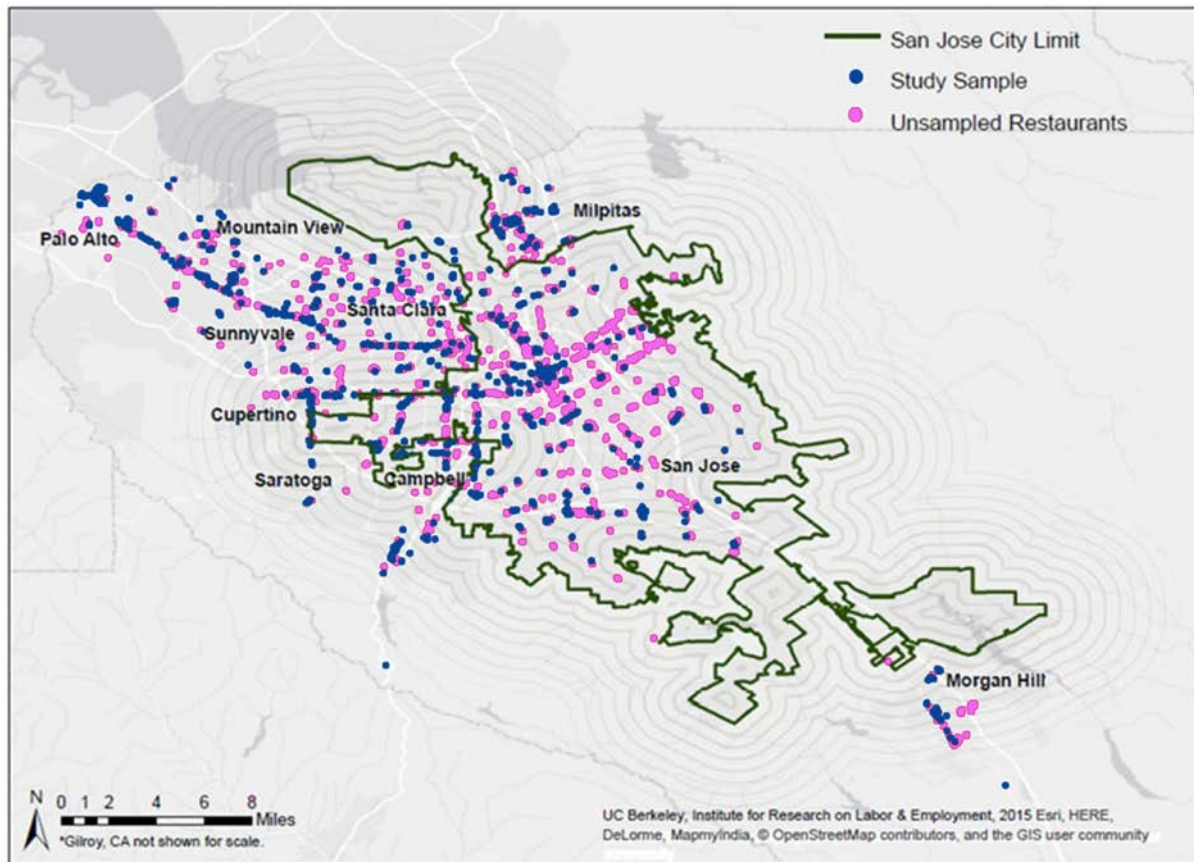
Figure 2. Test for structural breaks in wage and employment trends for San Jose and outside-San Jose: QCEW full- and limited-service restaurants combined.



Source: Quarterly Census of Employment and Wages (QCEW), 2010q1-2014q3. Combined data on full- and limited-service restaurants; NAICS codes 722511 and 722513, respectively.

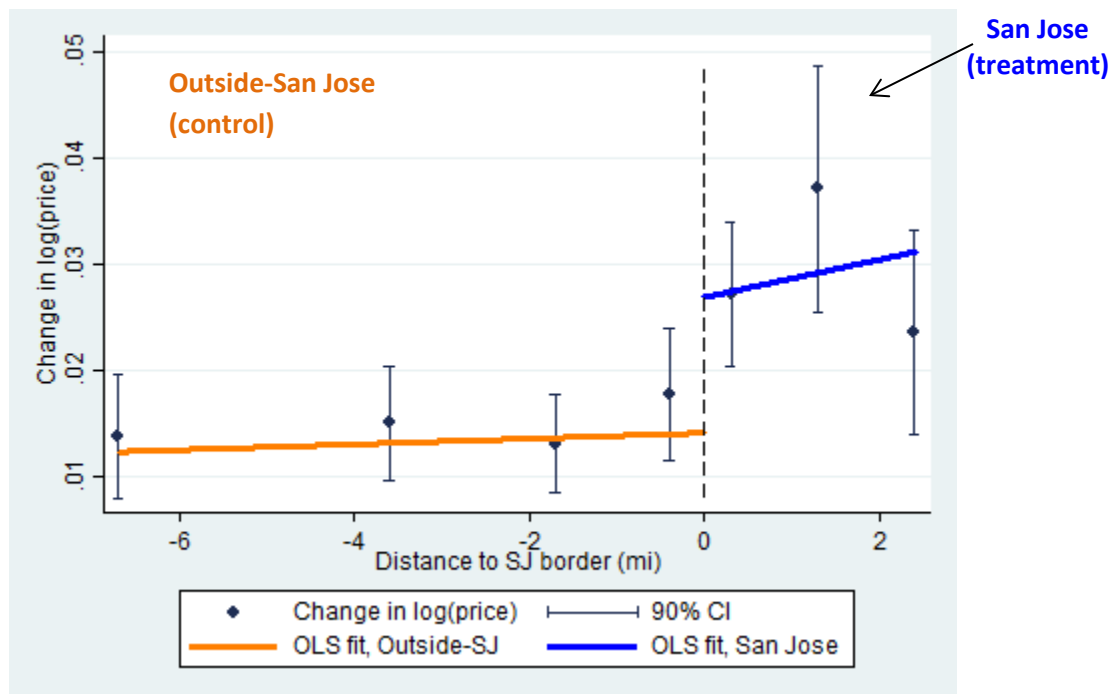
Notes: Wages(employment) are the average weekly wages(average employment level) for each quarter(month) for a given sector in San Jose and the rest of Santa Clara County outside of San Jose (denoted by ‘SCnotSJ’ in the legend). A statistically significant structural break was measured only for average wages in San Jose at the time of the minimum wage increase from \$8 to \$10 in 2013Q1. The last observation in each panel, for 2014q3, includes the quarter after the state minimum wage increased from \$8 to \$9. As noted in the text, wages rose substantially outside San Jose but not inside, in response, while employment barely budged in either area.

Figure 3. Spatial distribution of restaurants in Santa Clara County: San Jose and outside-San Jose



Notes: The sampling universe consists of 3,285 restaurants. Our final sample consists of 844 restaurants. The map compares the spatial distribution of restaurants that appear in our sample to those that do not.

Figure 4. Relative price changes by distance to the San Jose border



Notes: The large dashed vertical line represents the San Jose border. The negative mile markers outside-San Jose represent actual positive miles from the San Jose border. Using our restaurant sample, we report relative price differences by distance to the San Jose border by estimating a fitted line of price difference on distance, separately, for the treatment and the control areas.

Table 1. Wage and employment elasticities using QCEW data

Sector		Wages	Employment
Restaurant industry	η	0.150	-0.008
	se	(0.097)	(0.077)
Full- and limited-service	η	0.125	-0.024
	se	(0.086)	(0.067)
Full-service only	η	0.145*	0.006
	se	(0.085)	(0.066)
Limited-service only	η	0.086	-0.024
	se	(0.111)	(0.135)
N of observations		38 (quarterly)	114 (monthly)

Source: The Quarterly Census of Employment and Wages (QCEW) data spans 38 quarters (2010q1-2014q3) and provides a near census of county-level payroll data on employment and earnings. Wages (employment) are the average weekly wages (average employment level) for each quarter (month) for a given sector in San Jose and outside of San Jose.

Notes: The broad category of Restaurant Industry (NAICS 722) includes: special food services, food service contractors, caterers, mobile food services, drinking places, cafeterias, buffets, snack and non-alcoholic beverages and full-service (NAICS 722511) and limited-service (NAICS 722513) restaurants. Significance levels: ***1%, **5%, *10%.

Table 2. San Jose (treatment sample) compared to outside-San Jose (control sample)

	San Jose	Outside-SJ	Difference
Restaurant characteristics			
Share of full-service restaurants	0.57 (0.50)	0.65 (0.48)	-0.083** [0.03]
Share of limited-service restaurants	0.43 (0.50)	0.35 (0.48)	0.083** [0.03]
Share of chain restaurants ^a	0.40 (0.49)	0.29 (0.45)	0.113*** [0.03]
Average restaurant density ^b	28.96 (23.82)	28.09 (15.85)	0.869 [1.52]
Average distance to San Jose border (miles)	1.35 (0.91)	3.10 (2.59)	-1.743*** [0.11]
Number of observations	326	558	884

Notes: ^aChains are defined as restaurants with at least two locations in the study area. ^bRestaurant density is based on kernel density analysis and "Silverman's Rule of Thumb," which calculates a magnitude per unit area from point or polyline features using a kernel function to fit a smoothly tapered surface to each point or polyline and ranges from 0.6 to 87.0. Distance to border ranges from 0.0 to 12.1. Standard deviations in parentheses. Standard errors of difference, clustered at the chain-level, in brackets. Significance levels: ***1%, **5%, *10%.

Table 3. Prices and menu items: San Jose compared to outside-San Jose

Variable Name	San Jose	Outside-SJ	Difference
A. Average characteristics of prices and items			
Price before MW increase ^a	9.71 (4.74)	10.44 (8.22)	-0.73 [0.47]
Price before MW increase excluding removed items ^b	9.69 (4.72)	10.40 (8.02)	-0.70 [0.46]
Number of items before MW increase	71.23 (59.30)	74.79 (56.38)	-3.56 [4.00]
Number of items removed after MW increase	5.33 (11.00)	4.86 (10.90)	0.47 [0.74]
Price after MW increase ^a	9.96 (4.82)	10.63 (8.59)	-0.67 [0.49]
Price after MW increase excluding new items ^c	9.97 (4.87)	10.57 (8.38)	-0.60 [0.48]
Number of items after MW increase	72.95 (60.05)	77.06 (58.55)	-4.11 [4.11]
Number of new items after MW increase	7.06 (15.71)	7.13 (16.73)	-0.07 [1.09]
B. Distribution of price responses^d			
Price responses (including new and removed items)			
Price increases	0.46 (0.50)	0.38 (0.49)	0.08** [0.04]
No change in prices	0.14 (0.35)	0.18 (0.38)	-0.03 [0.03]
Price decreases	0.39 (0.49)	0.44 (0.50)	-0.05 [0.04]
Price responses (excluding new and removed items)			
Price increases	0.51 (0.50)	0.43 (0.50)	0.08** [0.04]
No change in prices	0.05 (0.21)	0.08 (0.27)	-0.03* [0.02]
Price decreases	0.45 (0.50)	0.49 (0.50)	-0.04 [0.04]
N	326	558	884

Notes: ^aAverage price of all items by restaurant. ^bExcludes items in the pre-period that were not listed in the post-period; otherwise a balanced sample. ^cExcludes items added in the post-period that were not listed in the pre-period. ^dProportion of restaurants in each category. Standard deviations in parentheses. Standard errors of difference, clustered at the chain-level, in brackets. Significance levels: ***1%, **5%, *10%.

Table 4. Estimated price elasticities

Controls	Specifications						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
San Jose (SJ)	0.058*** (0.016)	0.083*** (0.027)	0.030* (0.016)	0.077*** (0.024)	0.048** (0.020)	0.098*** (0.026)	0.068** (0.032)
SJ X Full-service		-0.043 (0.033)					-0.013 (0.029)
SJ X Chain			0.068** (0.034)				0.064* (0.035)
SJ X Number employed 8-39				-0.038 (0.029)			-0.037 (0.029)
SJ X Number employed 40+				-0.069** (0.033)			-0.081* (0.043)
SJ X Distance to border ^a					0.007 (0.013)		0.023 (0.015)
SJ X Restaurant density ^b						-0.001** (0.000)	-0.001** (0.001)
R2	0.022	0.027	0.033	0.028	0.022	0.033	0.053
Number of clusters (restaurant chains)	699	699	699	698	699	699	698
Number of menu pairs	884	884	884	880	884	884	880

Notes: Standard errors, clustered at the chain level, in parentheses. Estimated coefficients were transformed into elasticities by dividing by 0.25. Specifications (4) and (7) dropped observations with missing employment size bins (4 in San Jose and 4 outside-San Jose). Including observations with missing employment size bins did not significantly change the results. The standard error for the density coefficient is 0.0006. ^aDistance to border measure ranges from 0.0 to 12.1. Restaurant density measure ranges from 0.6 to 87.0. Significance levels: ***1%, **5%, *10%.

Table 5. Estimated price elasticities for all categorical variables

	Elasticities (se)
A. Overall	0.058*** (0.016)
B. Sector	
Full-service	0.040** (0.019)
Limited-service	0.083*** (0.027)
C. Chain analyses	
1. Indicator for chain using the whole sample	
Chain (at least two locations)	0.098*** (0.030)
Non-chain	0.030* (0.016)
2. Sample using only chains with outlets in both the treatment and control areas	
Within-chain effect ^a	0.062** (0.029)
D. Number of employees	
1 to 7	0.077*** (0.024)
8 to 39	0.039* (0.020)
40 or more	0.008 (0.025)

Notes: Standard errors, clustered at the chain level, in parentheses. All estimated elasticities are from regressions in Table 4 (except the within-chain estimate): sector elasticities from specification (2); chain elasticities from specification (3); and elasticities by number of employee bins from specification (4). ^aThe within-chain estimate is from a subsample of data on chains that have at least one outlet in both San Jose and outside-San Jose. The sample consists of 49 unique chains and a total of 202 restaurant observations. Significance levels: ***1%, **5%, *10%.

Table 6. Robustness tests

Specification	Sector			Number of employees		
	All restaurants	Full-service	Limited-service	1 to 7	8 to 39	40 or more
(1)	0.058*** (0.016)	0.040** (0.019)	0.083*** (0.027)	0.077*** (0.024)	0.039* (0.020)	0.008 (0.025)
(2)	0.052*** (0.017)	0.033* (0.019)	0.078*** (0.028)	0.071*** (0.025)	0.040** (0.020)	-0.015 (0.020)
(3)	0.052*** (0.016)	0.032* (0.018)	0.078*** (0.028)	0.071*** (0.025)	0.038** (0.019)	-0.011 (0.018)
(4)	0.052*** (0.016)	0.033* (0.018)	0.079*** (0.027)	0.066*** (0.024)	0.046** (0.019)	-0.011 (0.019)
(5)	0.059*** (0.017)	0.041** (0.021)	0.082*** (0.027)	0.078*** (0.025)	0.041* (0.021)	0.006 (0.027)

Notes: Specifications are as follows: (1) Restaurant level, all observations.

(2) Restaurant level, excluding restaurants in the bottom 5% and top 5% of the distributions of menu items.

(3) Restaurant level, excluding restaurants in the bottom 5% of the distributions of menu.

(4) Restaurant level, bottom 10% of the distributions of menu items dropped.

(5) Restaurant level, excluding restaurants in the top 5% of the distributions of menu items.

Standard errors are in parentheses, and are clustered at the chain-level. Significance levels: ***1%, **5%, *10%.

Appendix A

Previous price studies

We review here the existing studies that have used a credible research design to estimate the causal effects of minimum wages on prices in restaurants. Lemos (2008) provides an older and broader survey, including studies that focus on effects on the overall price level. In our view, causal identification in such studies is not credible, as minimum wage workers are concentrated in a small number of service sectors—especially, restaurants, retail, hotels and accommodations. It seems unlikely that spillovers from these sectors would affect prices in say, manufacturing or construction.

The credible studies of the price effects of minimum wages have mainly examined price effects on restaurants and used either national panel data or local case studies. Seven studies use national panel data and are summarized in Appendix Table A1. These studies generally use the “food away from home” (FAFH) component of data collected in selected metro areas for the BLS Consumer Price Index. FAFH includes both full-service and limited service restaurants. Seven locally-based studies, summarized in Appendix Table A2, examine prices of a few main items in restaurants. These studies are local in that they use data within a state or near the border between two states or between two counties. Their sample sizes are much smaller than in the national studies. All but one of these local studies examines limited-service restaurants only.

The national studies have found positive price elasticities. Using cross-sectional state data, Card and Krueger (1995, pp. 143-48) could not reject a zero price-pass-through in response to the 1990 and 1991 federal minimum wage increases. Three papers by Aaronson and his co-authors, published in 2001, 2006 and 2008 also use a national panel approach. These papers all use store-level and aggregated restaurant price data from the Consumer Price Index and progressively more credible econometric methods. However, none of them cluster standard errors, suggesting that their estimates may be less precise than they report.

Aaronson (2001) contains two different studies. One uses restaurant data from 1978-95, a period with higher inflation and much less state-level minimum wage variation than has occurred since. This paper finds a price elasticity of about 0.07, but with varying degrees of statistical significance for different sample periods. For example, Aaronson (2001) reports that "... excluding the late 1970s and early 1980s reduces the sum of coefficients to the point of not being statistically significant. Therefore, the high-inflation late 1970s and early 1980s, in part, drives

the significant pass-through results in the United States and Canada. The ability of restaurant firms to pass through minimum wage increases may have declined in the intervening years."

MacDonald and Aaronson's (2006) restaurant study examined the effects of the 1996-97 federal and state increases. They find a minimum wage price elasticity of 0.041 (standard error of 0.006). In the most recent of these studies, and the one that is usually cited as the most definitive in the price effects literature, Aaronson, French and MacDonald (2008) draw upon store-level data for 1995-97 for about 7 or 8 "meals" at about a dozen establishments in 88 areas, of which 82 are metropolitan areas. They find a price elasticity of 0.155 (standard error of 0.028) among limited-service restaurants, an elasticity of .032 (standard error 0.017) among full-service restaurants, and an overall elasticity of 0.071 (standard error 0.014). Using data from 1979 to 1997, Aaronson et al.'s robustness tests show that local demand shocks do not affect their results.

Aaronson et al. (2008) also find sizable positive effects on prices *before* the minimum wage takes effect. They interpret this finding as indicating that firms anticipate a minimum wage increase and begin raising their price in the months before the new floor is implemented. Since their data are bimonthly, interpreting the lead as an anticipation effect is plausible. However, their specification includes only a single lead, making it difficult to determine whether the price increase occurred in one or two months before the minimum wage implementation—or sometime earlier. It seems unlikely that all restaurants will increase their prices well before their competitors are required to do so. Their lead results may therefore indicate pre-trends that may bias their results, as is the case for the canonical two-way fixed-effect specification for employment effects. Aaronson et al. do not examine whether heterogeneity among minimum wage states might be generating such bias. Moreover, using monthly data, MacDonald and Nilsson (2016) find that price increases occurred only in the month of minimum wage implementation.

A recent national panel study, Basker and Khan (2013), updates and improves upon Aaronson (2001) by using city-level data from 1993-2012 for three fast-food items and including a control for city-specific linear trends. Basker and Khan report a price elasticity of 0.09 for two of the items (Burgers and Pizza), although one is marginally significant at the 10 percent level and a negative but very imprecise elasticity for the third (Chicken). Basker and Khan's data were collected by volunteers recruited at local Chambers of Commerce, cover only 5 to 10 restaurants per participating city, and contain only two or three menu items per restaurant.

In contrast to the finding that restaurant costs are entirely passed through, MacDonald and Nilsson (2016) find only a partial pass-through. Their study uses BLS data collected at some point between 1978 and 2015 for the CPI on a bimonthly basis in 28 metro areas and on monthly data in 6 metro areas.²⁸ Unlike the previous studies, they cluster their standards errors. Their main finding indicates that about half of restaurant cost increases are passed through to consumers.

In summary, all seven of these national studies find positive minimum wage price effects, albeit of varying amounts and robustness.

We turn next to the seven locally-based estimates. Katz and Krueger (1992) find positive but imprecisely-measured evidence of relative price increases at fast-food restaurants in Texas after a minimum wage increase. Card (1992) finds that fast-food prices and a food-away-from-home price index rose at similar rates in California and in comparison areas after California raised its minimum wage in 1988. Card and Krueger (1995, pp. 51-55) find positive evidence of price pass-throughs for fast food restaurants in their New Jersey-Pennsylvania data.

Three more recent local estimates—all of San Francisco— find considerable price pass-throughs even with limited sample sizes. A study of the 26 percent increase in 2004 of San Francisco's minimum wage by Dube, Naidu and Reich (2007) finds a significant pass-through for fast-food restaurants, with an estimated price elasticity of 0.062; they find a smaller and imprecisely measured pass-through for full-service restaurants. In their study of the 2008 health spending mandate in San Francisco, which was equivalent to a minimum wage increase of 16 percent, Colla, Dow and Dube (2011) find: "about 25 percent of surveyed restaurants imposed customer surcharges, with the median surcharge being 4 percent of the bill." The implied minimum wage price elasticity is then .062. In summary, although all of these seven local estimates were limited by small sample sizes, six of the seven find evidence of price pass-throughs and one finds no price effect.

²⁸ MacDonald and Nilsson find that the bimonthly data are not reliable for monthly interpretation. We therefore include in Table A1 only their results with the monthly data.

Appendix Table A1: Impact of minimum wage increases on fast-food prices – National level studies

Study	Sample and data	Policy changes	Point estimate, standard error
1. Card and Krueger (1995)	N=1,392 (29 cities) Food away from home BLS CPI 1989-1992	1990-91 federal increases from \$3.35 to \$4.25 27% increase	e = 0.060, s.e.= 0.04
2. Aaronson (2001)	N=4,486 (27 cities) Food away from home BLS CPI 1978-1995	1978-95 federal and state increases from \$2.65 to \$4.25 at federal level 60% increase at federal level	e = 0.056, s.e.= 0.017
3. Aaronson (2001)	N=3,085 (542 cities) Hamburger, Fried Chicken, Pizza ACCRA 1986-1993	1986-93 federal and state increases from \$3.35 to \$4.25 at federal level 27% increase at federal level	e = 0.155, s.e.= 0.053 (Hamburger) e = 0.162, s.e.= 0.062 (Fried Chicken) e = 0.009, s.e.= 0.064 (Pizza)
4. MacDonald and Aaronson (2006)	N=68,887 (88 metro and urban areas) Food away from home BLS CPI 1995-1997	1996-97 federal & state increases in 13 states from \$4.25 to \$5.15 at federal level 21% increase at federal level	e = 0.041, s.e.= 0.006
5. Aaronson, French and MacDonald (2008)	N=71,077 (88 Primary Sampling Units) Food away from home, 7-8 items/restaurant BLS CPI 1986-1993	1996-97 federal increases from \$4.25 to \$5.15 at federal level 21% increase at federal level	e = 0.071, s.e.= 0.014 (all restaurants) e = 0.155, s.e.= 0.028 (LS rest.) e = 0.032, s.e.= 0.017 (FS rest.)
6. Basker and Khan. (2013)	N=17,888 (284 cities in 48 states) Burgers, Chicken, Pizza C2ER (formerly ACCRA) 1993-2012	1993-2012 federal and state increases	e = 0.094, s.e.= 0.023 (Burger) e = 0.049, s.e.= 0.062 (Chicken) e = 0.094, s.e.= 0.0329 (Pizza)
7. MacDonald and Nilsson (2016)	N=1,852 (6 metro areas) Food away from home BLS CPI 1978-2015 monthly data	1978-2015 federal, state and city increases	e = 0.039, s.e. = 0.010

Appendix Table A2: Impact of minimum wage increases on fast-food prices – Local level studies

Studies	Sample and data	Policy changes	Point estimate, standard error
1. Katz and Krueger (1992)	N=266 (fast-food restaurants in TX) Full meal Employer survey	1990-91 federal increase from \$3.35 to \$4.25 27% increase	e = 0.010, s.e.= 0.006 (Burger) e = 0.009, s.e.= 0.007 (Chicken)
2. Card and Krueger (1994)	N=315 (fast-food restaurants in NJ & PA) Full meal Employer survey	1992 New Jersey increase from \$4.25 to \$5.05 19% increase	e = 0.063, s.e.= 0.089
3. Spriggs and Klein (1994)	N=75 (fast-food restaurants in MS) 8 items per restaurant. Employer survey	1990-91 federal increases from \$3.35 (1989) to \$4.25 (April 1991) 27% increase	e = 0.279, s.e.= 0.839
4. Dube, Naidu and Reich (2007)	N= 125 (fast-ood restaurants in San Francisco and East Bay) Most popular menu item Employer survey	2004 increase \$6.75 to \$8.50 26% increase	e = 0.062, s.e.= 0.028
5. Dube A., Naidu S. and Reich M. (2007)	N= 149 (full-service restaurants in San Francisco and East Bay) Most popular menu item Employer survey	2004 increase \$6.75 to \$8.50 26% increase	e = 0.018, s.e.= 0.030
6. Colla, Dow and Dube (2011)	N=217 (restaurants in San Francisco) Surcharge on meals Employer survey	2008 SF Health Care Security Ordinance 13% to 19% increases	e = .062 significant at 5% level
7. Hirsch., Kaufman and Zelenska (2011)	N= 81 (Georgia and Alabama) most popular menu item Employer survey	2007-09 federal increases from \$5.15 to \$7.25 41% increase in nominal terms	10.9% increase in prices over 3 years, significant at 5% level

Appendix B

Restaurant menu data collection

Relative to previous studies, our data represent a novel *and* large sample of local restaurant menus downloaded directly from posted online menus. An increasing number of restaurants are posting and updating their menus online, despite the costs of doing so. Posting provides consumers with additional information and permits individual restaurants to participate in networked online reservation, ordering, delivery, and evaluation services.²⁹ Such services have multiplied in recent years, to the point that many restaurants regard an online presence as a mandatory component of their marketing plans. The San Jose case is especially opportune for using Internet-based data insofar as Silicon Valley area restaurants are more likely to be early adopters of the technology. As far as we know, ours is the first study to demonstrate that *online* restaurant menus provide a suitable dataset to study minimum wage price effects. By eliminating the need for survey respondents to recall price and sales data, the online method may reduce measurement error and provide tighter confidence intervals for the effect size. Moreover, we collected data on all menu items, not just a few dishes, as was the standard in previous research.³⁰ We therefore can examine whether price changes are related to the salience of individual items in the overall menu and to the number of items on a menu.

We initiated the first wave of data collection at the end of November 2012, soon after the ballot measure passed, and completed collection of the first wave in early January 2013, well before the policy's March 11, 2013 implementation date. Since individual businesses face limits in raising prices relative to competitors, we would not expect significant anticipation effects to occur more than two months before the implementation date.³¹

²⁹ AllMenus.com lists 255,000 restaurant menus nationwide and claims 5 million visitors per month (<http://www.allmenus.com/contact-us/>). By September 2015, Allmenus.com listed menus for 1,120 San Jose area restaurants (<http://www.allmenus.com/ca/san-jose/>) and 170 delivery restaurants. Open Table and SeatMe are examples of widely-used online reservation systems; GrubHub.com, which acquired Allmenus.com in 2011, provides remote ordering and delivery for 35,000 restaurants in 900 U.S. cities (<http://get.grubhub.com/>). Yelp and UrbanSpoon are but two examples of well-known websites that provide restaurant ratings using consumer reviews. McLaughlin (2010) provides an early description of the growing prevalence of these services.

³⁰ We are not aware of any other dataset that provides such a comprehensive number of restaurant menu items. Large datasets are now available for retail prices. Nakamura (2008) uses Nielsen scanner data from 7,000 large supermarkets to study retail price variation. This dataset contains observations on 100 individual products, while the Consumer Price Index research retail database contains only seven price quotes per item per month. See also Nakamura and Steinsson 2008.

³¹ In a national panel study, Aaronson (2001) does not find price increases more than two months prior to implementation of a higher minimum wage.

In our second wave, initiated six months after implementation, we collected menus for the same restaurants. Our previous research (Dube, Lester and Reich 2010) suggests that minimum wage effects on restaurant pay and employment occur within the first two quarters of a policy increase. Aaronson, French and MacDonald (2008) find that price increases are also highly concentrated in the first two quarters following an increase.³²

As our first step we acquired a list of all *Active Food Facilities (AFF)* in Santa Clara County from the County's Department of Public Health. The Department maintains such a list because it is mandated to inspect all food facilities for compliance with health and sanitary conditions. The *AFF* list included 5,747 facilities, including the name, street address, city, zip code, and phone number, as well as size bins for employment at each facility. After deleting supermarkets, grocery stores, soup kitchens, coffee bars, juice bars and ice cream stores, as well as cafeterias in institutions, such as hospitals and schools, and caterers and other non-restaurant entities, we were left with 3,285 limited- and full-service restaurants that would be classified within the 722511 and 722513 NAICS codes for restaurants. Appendix Table B1 provides the details of our sampling process.

These 3,285 restaurants constitute our 'sampling universe'—each of these restaurants met the NAICS definition of a full- or limited-service establishment. Each restaurant was further coded as a chain or non-chain restaurant and also identified as a full- or limited-service establishment.³³ These distinctions enable us to estimate separate effects for each of these binary categories.

The first wave of data collection involved obtaining online menus from our pared-down sampling universe. Importantly, we attempted to locate an up-to-date menu for every single restaurant in this universe.³⁴ As Appendix Table B1 shows, in the first wave of collection we

³² More precisely, they find that 60 percent of the price increases occur in the first two months after a minimum wage increase, with the remainder occurring in the next two months and in the two months preceding the policy change.

³³ The Quarterly Census of Employment and Wages website reports 1,540 full-service and 1,149 limited-service restaurants (2,699 in total) in Santa Clara County for 2012q4. However, NAICS code 7222 is now labeled as Limited-service eating places; the previous definition was limited-service restaurants. We suspect that much of the difference between the number of restaurants in our sampling frame (3,285) and the 2,699 in the QCEW reflects the juice, ice cream and similar establishments that we removed from our sample. A special tabulation conducted for us by the California Employment Development Department found 1,206 restaurants that were located inside San Jose.

³⁴ We searched AllMenus.com, a website service that posts actual restaurant menus provided by restaurants, as well as each restaurant's website, if it had one. Restaurant owners periodically update their menus on AllMenus.com, but we were unable to identify the date of their most recent upload. We therefore also examined the restaurant's website

succeeded in identifying online websites and we were able to download menus from 1,211 of these restaurants, or about one-third of our restaurant sample. This one-third rate reflects how widespread having an online presence had already become as a competitive element in the restaurant industry. This presence includes both the ability to make online reservations for full-service restaurants and the capacity for online ordering of take-out food items among both full-service and limited-service establishments.

If we were not able to download a menu, we called the restaurant to determine whether it was still open. We also coded whether these restaurants did not have a web site with a menu, or whether its online menu did not include price information. Each menu was saved in PDF format and saved with a restaurant ID number and address in the title.

Some of the menus were obtained from online ordering websites, such as GrubHub (a subsidiary of AllMenus.com); thus these advertised prices were binding.³⁵ We checked whether menus that were posted online but not associated with direct ordering were up to date. To do so, we called a random sample from our collected menus and checked prices for the first three items on the collected menu to see if they were accurate. We found little discrepancy in prices.³⁶ Since restaurant prices were increasing at about 2.4 percent in 2013, if some of the menus in this first wave were not to date at the time of data collection, we may under-estimate prices before the policy change. However, there is no obvious reason why the timeliness of the posted menus in the first wave would vary between our treatment and control groups.³⁷

Another sampling issue concerns chains. We have data on 112 restaurant chains in our sample, including Applebee's, Boston Market, California Pizza Kitchen, Chevy's, Chipotle, Domino's Pizza, Five Guys Burgers, Olive Garden, Papa John's Pizza (the 12th largest chain in the U.S., as ranked by number of stores), Pizza Hut (the 3rd largest U.S. chain), Red Lobster, Round Table Pizza, Sizzler, and Subway (the largest U.S. chain). However, some of the largest

and used its menu whenever possible. We did not use Yelp.com or other consumer-created restaurant guides, as the menus on those sites are posted by consumers and may be unreliable.

³⁵ Scraping data from menu websites such as GrubHub provides another strategy for obtaining Internet-based data on restaurant prices. We encountered technical difficulties in our scraping attempts for this paper, but we use this method in an accompanying paper (Allegretto, Mallajosyula and Reich forthcoming), to study price changes after a 36 percent minimum wage increase in Oakland, CA. Cavallo (2015) uses scraped data to study price stickiness in supermarkets; he provides a detailed account of scraping methods and shows that online and offline prices are highly correlated.

³⁶ Informal interviews with restaurant owners suggest that they update their online restaurant menus in frequencies that range from two weeks to six months.

³⁷ The policy may have induced more timely updates of menu prices in the treatment area compared to the control area, affecting our second-wave data.

fast food chains in Santa Clara County (such as McDonald's, Burger King, KFC and In-n-Out Burger) do not provide on-line menus with store-specific prices. McDonald's, for example, post their menu prices only on in-store electronic menu boards; no paper or online menu is available. Thus, we were not able to get menu prices for many of the largest chains.

To address this issue we examined cross-sectional data on two of the largest California chains: McDonald's and In-N-Out Burgers. We determined that McDonald's Big Mac burger prices across 40 cities in 33 states showed a correlation of 0.48 with state minimum wages.³⁸ We also determined through store visits across California and online data that price and starting wages at In-N-Out Burger showed a similar correlation.³⁹ This pattern, which was similar to those we find in our pre- and post-sample of chains that do post their restaurant menus, suggests that the omission of restaurants that do not post prices online from our sample does not necessarily bias our results. Below we report further tests on the representativeness of our treatment and control samples.

We began collecting the second wave of post-treatment menus in September 2013—six months after the minimum wage went into effect—and we concluded collecting the second-wave data at the end of November 2013.⁴⁰ Successful menu downloads were once again saved as PDFs. In the second wave, we again coded if and when the menus were collected and made extensive notes on each attempt. If the download was unsuccessful, the reason was also noted, such as 'no menu online,' 'menu without prices,' or 'out of business.'

As in any panel survey, some attrition occurred in the second wave. Our balanced (two-wave) panel consists of 884 downloaded menu pairs, compared to 1,211 menus in the first wave, a difference of 327. About half of the attrition involved incomplete or corrupted data—such as an unreadable PDF—in the first wave. Of the remainder, we could confirm that about 25 had closed or moved and the rest no longer had a website or downloadable menu. Of the restaurants that closed, the proportions from San Jose and outside-San Jose were comparable to the relative sizes

³⁸ Big Mac prices are from <http://www.nerdwallet.com/blog/cities/economics/quarter-pounder-index-most-least-expensive-cities/>. The underlying data come from ACCRA.

³⁹ The popular In-n-Out Burger chain (304 locations in the western United States) posts its starting wage online for each store location. We visited and photographed menu prices posted at In-n-Out restaurants around the state.

⁴⁰ In both the first and second wave, we collected data from individual restaurants in an order determined by a random number generator. This randomness insured against correlation between the time of data collection and other characteristics, such as the name of the restaurant. Seasonal differences between the timing of the first and second waves do not affect our results, as seasonality should have similar effects in both the treatment and control groups.

of our subsamples for each area. That is, we could not detect a higher closure rate due to the minimum wage increase (see Aaronson, French and Sorkin 2015). However, the sample size of identified closures is very small. We were unable to obtain data on restaurants that had opened after the first wave of data collection, as the Santa Clara County Department of Public Health could not provide us with an updated list of food facilities.

For the second wave, we also telephoned a subsample of restaurants to determine whether their online menus were up to date. The proportions that were up to date were high and similar in both treatment and control areas, suggesting that we were not underestimating price changes due to the minimum wage.

In contrast to our expectations, the digitization of the menus required highly labor-intensive methods. Each menu was saved as a PDF—basically an electronic image of the menu. We expected to use off-the-shelf software that could accurately compare the prices on the pre- and post-menu pictures. As it turned out, and despite consultation with a variety of software experts, we were unable to obtain a software package that met our accuracy standards. As a result, for each menu, we manually input every menu item for both waves into an Excel spreadsheet and then uploaded the data into STATA for our analysis.⁴¹

We did not attempt to sample new entrants in our second wave, as we could only track new entrants into the set of restaurants with an Internet presence. We would not be able to determine whether such restaurants were new entrants into the industry or pre-existing restaurants that joined the growing fraction of restaurants with an Internet presence.⁴² Moreover, since we were not contemplating a third wave of data collection, data on new entrants would not be informative of price changes. As mentioned, our sample includes 884 restaurants with both pre- and post-downloaded menus. Thus we were able to sample 25.7 percent of the restaurants from our universe of 3,285 restaurants. On average, each menu contains about 75 items. We also analyze individual entrees to better situate our research in relation to much of the previous literature; our data include 7,291 observations of chicken dishes, 899 for hamburger dishes and 644 for pizzas.

⁴¹ These constraints made it impractical for us to conduct further follow-up survey waves, unlike our subsequent study using scraped data for Oakland and its environs (Allegretto, Mallosojuya and Reich, forthcoming).

⁴² Aaronson, French and Sorkin (2015, Table 2) find that restaurant entrants and exits both rise after a minimum wage increase. Their entry elasticities are 1.37 for limited-service restaurants and 0.14 for full-service restaurants.

Representativeness of our sample

Since our downloaded restaurants include treatment and control sub-samples, our results possess internal validity. That is, they will be informative for price effects of a minimum wage increase among the set of restaurants that have downloadable menus. We also want to know whether our results possess external validity: Do restaurants with downloadable menus differ in systematic ways, especially in pricing behavior, from restaurants that do not post their menus online? While we cannot determine external validity definitively, we can compare our restaurant universe and our downloaded sample along a number of dimensions: by size, by location patterns inside and outside San Jose, and by the proportion of limited-service and full-service restaurants. When possible, we also compare our sample to data on restaurant characteristics from the Quarterly Census of Employment and Wages. We show in this section that the universe and the downloaded restaurant menu sample are quite similar along these dimensions.

As mentioned, to check the representativeness of our sample, we compared our file of all Santa Clara County restaurants (N=3,285) to our downloaded restaurants for San Jose and outside-San Jose (N=884). The file of all restaurants provided in the Santa Clara County Department of Public Health's dataset provides exact addresses, allowing us to distinguish those inside San Jose from those outside San Jose. As Appendix Table B2, Panel A shows, the proportions in the two sub-samples—San Jose and outside-SJ—are similar both for the universe and our downloaded sample. For the universe and our sample, the proportions of restaurants located outside-San Jose are 56 percent and 63 percent, respectively. Thus, compared to the universe, our sample somewhat over-weights restaurants outside-San Jose. This over-weighting, however, should not affect our difference-in-difference estimates.

Our *AFF* dataset also includes three employment size bins: 1-7, 8-39, and 40 or more.⁴³ Appendix Table B2, Panel B displays the proportion of restaurants in each of the three size bins for our restaurant universe and for our sampled restaurants, disaggregated by the San Jose and outside-San Jose subsamples: a 2x2x3 matrix. The universe and sample distributions are similar across the three employment size bins.

⁴³ We recalculated the bin sizes in the original data to reflect total employee head count. Santa Clara County data instructions ask managers for a count of total employee hours worked on a typical day. The reported data provide bins for calculated full-time equivalent employees. We converted the bin sizes to total employment by using BLS national averages of hours per week employees in restaurants and our previous counts of the proportion of workers who are part-time in restaurants.

Since we have the exact addresses of the restaurants, we are able to examine the spatial distributions of our restaurant for both our treatment and controls groups. Using Google API, which allows communication with Google Maps, we obtained the latitude and longitude associated with each address. The spatial representation of the universe and sample of restaurants is depicted in Appendix Figure B1. The solid black line shows the boundary of San Jose. The other major cities in Santa Clara County are listed on the map. The darker circles represent our sample of restaurants, while the lighter dots represent restaurants that were not sampled. The map suggests that our sample is quite representative spatially in both the control and treatment areas.⁴⁴ We also computed the distance of each restaurant to the San Jose border, which also allows us to estimate price effects by distance of a restaurant to the San Jose border.⁴⁵

In Appendix Table B3 we look at the distribution and the representativeness of our treatment and control samples, separately for the full- and limited-service sectors. Each restaurant in our sample was researched and individually coded into one of these two sectors. Unfortunately, the labor-intensive nature of this process precluded sector identification for the “un-sampled” restaurants in our ‘universe’ of all restaurants in Santa Clara County. However, the QCEW data that we used in Section 3 to analyze earnings and employment effects, are disaggregated by full- and limited-service sectors. We can therefore compare the distribution of full- and limited-service restaurants in the near-census QCEW data to the distribution of full- and limited-service restaurants in both our inside- and outside-San Jose sub-samples.

As Appendix Table B3 indicates, 57 percent of the sampled restaurants in San Jose are full-service, while 43 percent are limited-service establishments. QCEW data (not shown in the table) indicate that 54 percent and 46 percent of restaurants in San Jose are in the full- and limited-service sectors, respectively. A somewhat larger share of restaurants outside-San Jose are full-service (65 percent) and a smaller share are limited-service (35 percent). The respective QCEW figures for the control area are 60 percent and 40 percent.⁴⁶ These comparisons again support the representativeness of our sample, both within the treatment and control areas

⁴⁴ A more detailed map, not included here, shows that many of the restaurants are located on a number of major avenues that stretch in and out of San Jose proper or that lie on the city’s border.

⁴⁵ Using Google API, we obtained the latitude and longitude associated with each address and computed the distance of each restaurant to the San Jose border. We then obtained the exact San Jose city border polygon from the Census TIGER database of “places” and ran the function “Near_Dist” from ArcGIS on the polygon for the San Jose border and the geocoded data. This method returned a vector of distances to the San Jose border for every address, giving us a continuous distance variable that ranges from 0.0 to 12.1 miles.

⁴⁶ Aaronson, French and Sorkin (2015) report very similar ratios.

The remainder of Appendix Table B3 moves from analyzing the representativeness of our treatment and control samples to a descriptive analysis that compares the San Jose and control area samples along other dimensions. The third line in Appendix Table B3 reports how many sampled restaurants are chains. Chains account for 40 percent of the sampled restaurants in San Jose and 29 percent outside-San Jose.

We also computed a ‘restaurant density’ measure. For each restaurant, this measure indicates how many restaurants are located nearby. Density is measured by the number of restaurants that fall within a given radius of each restaurant; the density value for each restaurant is weighted by the inverse of its distance from the center of the search radius (nearer point features have a stronger weight). We then fit a smooth continuous surface over the sampled points to show interpolated values for any possible point within the radius.⁴⁷ The density measure in our sample ranges from 0.6 to 87.0. Average density is 29.0 in San Jose and 28.0 for restaurants outside-San Jose; the small difference is not statistically significant.

Using restaurant addresses we are also able to measure each restaurant’s distance to the San Jose border. Distances range from 0 to 12.1 miles. As line 5 of Appendix Table B3 indicates, on average, restaurants in the control area are located 3.1 miles from the San Jose border while restaurants inside San Jose are on average 1.35 miles away. These differences are expected, since restaurants inside San Jose are surrounded by the city’s border, while the restaurants in the rest of Santa Clara County can be further away.

One threat to our identification of minimum wage price elasticities using inside and outside San Jose samples concerns differential trends in rent expenses and franchise fees. These costs together make up a substantial portion of restaurant operating costs, approximately equal to that of payroll. If, for example, rents were rising faster in San Jose than outside-San Jose, and if rent costs are passed forward to consumers, then our attribution of greater price increases in San Jose to minimum wage changes might be overstated.

While we do not have data on restaurant rents, we can examine residential rent trends. Between March 2013 and September 2013, when our second wave of price collection began, residential rents increased 1.25 percent more in Santa Clara City and Sunnyvale than in San

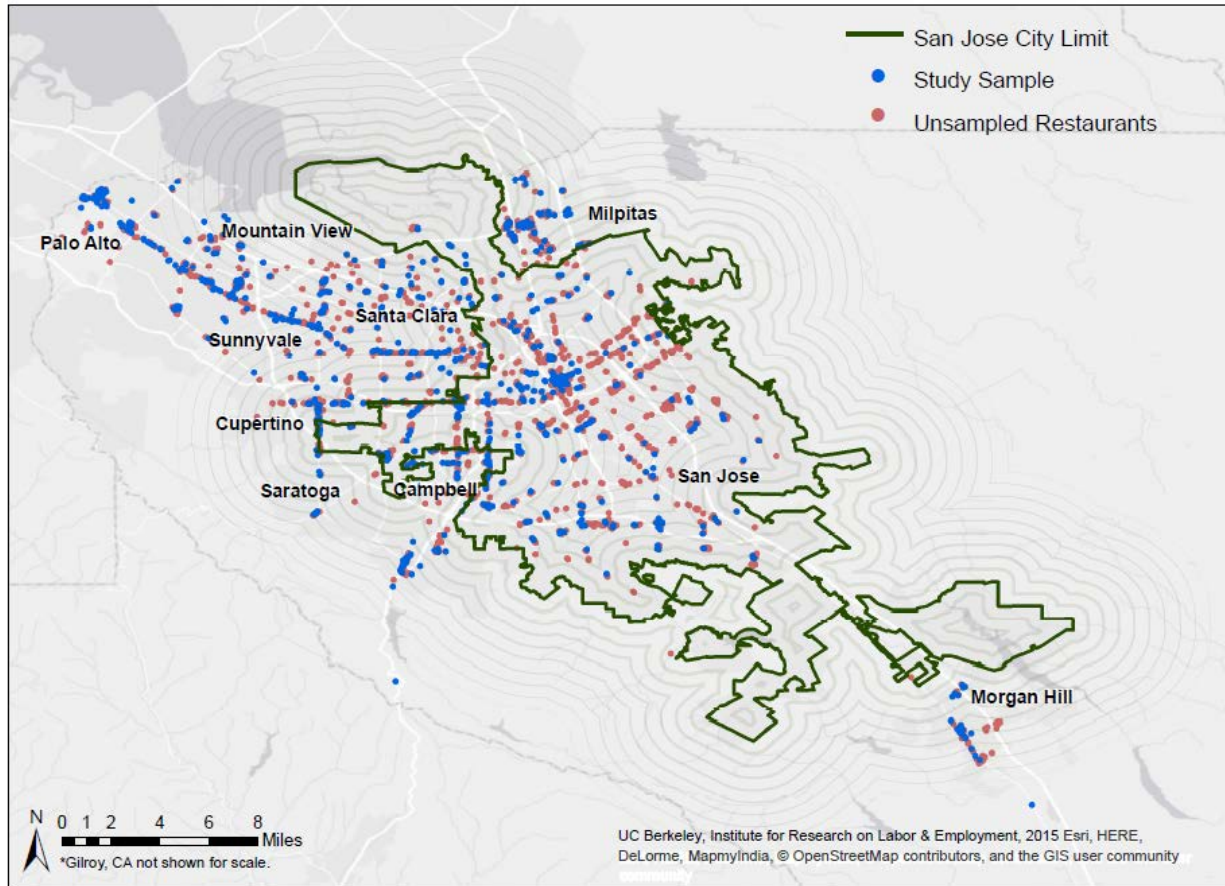
⁴⁷ We then fit a smooth continuous surface over the sampled points to show interpolated values for any possible point within the radius.

Jose.⁴⁸ Since the duration of commercial leases is typically 3-5 years, compared to 1 year for residential leases, commercial rent trends are likely to lag residential rent trends. We conclude that differential trends in commercial rents are not likely to have substantial effects on our results.

Our focus on prices ignores another potential adjustment margin: portion size. Changes in portion sizes are often conjectured, but we lack data on how common they are. Since an unobserved portion size reduction is equivalent to an unobserved effective price increase, we might be underestimating price effects. Of course, portion size reductions constitute an adjustment mechanism that does not negatively affect worker well-being.

⁴⁸ Residential rents obtained from Zillow: <http://www.zillow.com/research/data/>

Appendix Figure B1. Spatial distribution of restaurants in Santa Clara County: San Jose and outside-San Jose



Notes: As described in Appendix Table B1, the sampling universe consists of 3,285 restaurants. Our final sample consists of 844 restaurants. The map compares the spatial distribution of restaurants that appear in our sample to those that do not.

Appendix Table B1. Construction of online menu sample

Sample construction	N
Santa Clara County active food facilities ^a	5,747
Screen for NAICS-defined full- and limited-service restaurants ^b	3,285
Restaurants with online menus—first wave ^c	1,211
Restaurants with online menus—second wave ^d	1,009
Final sample of restaurants with menu- pairs ^e	884

Source: ^aFood inspection list provided by Santa Clara County Public Health Department.

Notes: ^bRestaurants are stores that sell food that is prepared on site, they are open to the general public, and food vending is their primary purpose. This definition excludes school and office cafeterias, grocery stores, cafes serving drinks only, take-and-bake pizza establishments, dance clubs, airports, retirement communities, sports arenas, etc. ^cIncludes only restaurants with store-specific menu prices posted online. ^dExcludes restaurants that closed, no longer had a website or online menu, or its online menu no longer listed prices. ^eFurther attrition after double-checking sample: includes unreadable menus, the menu was not location-specific or had not been updated since first-wave collection; the menu had no prices; the restaurant did not fit the universe definition.

Appendix Table B2. All Santa Clara County restaurants compared to our sample

	Universe	Sample
A. Distribution		
Share inside San Jose	0.44	0.37
Number of observations	1460	326
Share outside-San Jose	0.56	0.63
Number of observations	1825	558
B. Distribution by employment size bins^a		
Inside San Jose		
1-7 ^b	0.63	0.58
8-39	0.31	0.33
40+	0.07	0.09
Outside-San Jose		
1-7	0.56	0.52
8-39	0.37	0.39
40+	0.07	0.08

Source: This table compares the restaurant 'universe' (N=3,285) and the final sample (N=884) as described in Appendix Table B1. The restaurant 'universe' was determined from the list of Active Food Facilities (*AFF*) in Santa Clara County and provided by the County's Department of Public Health. Our 'sample' consists of restaurants for which we obtained both pre- and post-menus.

Notes: ^a Excludes four observations with missing employee bins. ^b The number of employees was based on reported full-time equivalent employee bins as reported in the *AFF* list. Using Bureau of Labor Statistics reports, we assumed 40% of restaurant workers are part-time, full-timers work 34 hours per week and part-timers work 20 hours per week.

Appendix Table B3. San Jose (treatment sample) compared to outside-San Jose (control sample)

	San Jose	Outside-SJ	Difference
Restaurant characteristics			
Share of full-service restaurants	0.57 (0.50)	0.65 (0.48)	-0.083** [0.03]
Share of limited-service restaurants	0.43 (0.50)	0.35 (0.48)	0.083** [0.03]
Share of chain restaurants ^a	0.40 (0.49)	0.29 (0.45)	0.113*** [0.03]
Average restaurant density ^b	28.96 (23.82)	28.09 (15.85)	0.869 [1.52]
Average distance to San Jose border (miles)	1.35 (0.91)	3.10 (2.59)	-1.743*** [0.11]
Number of observations	326	558	884

Notes: ^aChains are defined as restaurants with at least two locations in the study area. ^bRestaurant density is based on kernel density analysis and "Silverman's Rule of Thumb," which calculates a magnitude per unit area from point or polyline features using a kernel function to fit a smoothly tapered surface to each point or polyline and ranges from 0.6 to 87.0. Distance to border ranges from 0.0 to 12.1. Standard deviations in parentheses. Standard errors of difference, clustered at the chain-level, in brackets. Significance levels: ***1%, **5%, *10%.

Appendix C

Robustness tests and additional price elasticity estimates

In this appendix, we examine how our price elasticity estimates vary with the number of items in a restaurant's menu. Our main analysis uses an unweighted average price of the items for each restaurant, subtracting the pre- from the post-price by restaurant to get the average price change. Ideally, we would like to weight the individual menu items by their importance in each restaurant's sales, but such data are not available.

Instead, we examine here whether restaurants change prices differently based on the number of items on their menus (menu size). Smaller menus may mean more prices increase for a larger share of items—just by dint of menu size—and thus a propensity to have a greater average price change. Price increases may also vary with the popularity of a small number of individual items. We employ a variety of weighting schemes to examine whether menu size affects our price effect estimates. We find that our results are generally unaffected no matter what weighting scheme we use.

Appendix Table C1 analyzes restaurants by the number of items per menu, arranged by quartiles. Panel A shows that restaurants with more than the average number of menu items are somewhat more likely to be located outside of San Jose than are restaurants with below the average number of menu items. This difference likely represents the higher proportion of limited-service restaurants in San Jose relative to outside-San Jose. As one would expect, the average number of menu items among limited-service restaurants—55—is smaller than the average among full-service restaurants—95 (not shown in the table).

Panel B of Appendix Table C1 reports the share of restaurants with price increases, by quartiles of the number of items per menu, separately for the treatment and the control groups. The share of San Jose restaurants with price increases is highest (63 percent) for the first quartile and declines to 40 percent for the fourth quartile. Outside-San Jose, however, the share of restaurants with price increases exhibit a somewhat more uniform pattern, varying between 46 percent and 41 percent. These patterns suggest that restaurant price increases are concentrated among a limited number of items, which is consistent with our previous finding that price increases are greater in limited-service restaurants than in full-service restaurants.

To explore this question further, Panel C of Appendix Table C1 reports by quartiles the share of items within each restaurant with price increases. Among San Jose restaurants with

menu item counts in the first quartile, prices increased for 45 percent of the items; the shares drop to 26 percent, 24 percent and 17 percent for the second, third and fourth quartiles, respectively. Restaurants in San Jose with smaller menus (40 items or less) were both more likely to increase prices and to increase prices for a larger share of individual items, compared to restaurants with more than 40 items. For the outside-San Jose restaurant sample, the shares are again much smaller across quartiles: ranging from 27 percent in the first quartile to 13 percent in the fourth quartile. Among restaurants with a small number of menu items, prices are changed for most items. Among restaurants with larger menus, only some menu item prices were increased.

Appendix Table C1, Panel D reports estimated price elasticities by quartiles of the number of menu items. The smallest item quartile exhibits the largest estimated price effect (0.090), statistically significant at the 1 percent level. Elasticity estimates for the other three quartiles are much smaller. Only the 0.033 estimate for the fourth quartile is statistically significant—at the 10 percent level. Chow tests indicate that the two estimates differ statistically. These elasticities further support the contention that only some item prices are increased after a minimum wage increase.

Lastly, our analysis examines three individual items: chicken (N=7,291), pizza (N=644) and burgers (N=899). The categories are mutually exclusive (e.g. a chicken pizza was labeled a pizza). We examine these specific dishes to explore further the patterns in Appendix Table C1 and because previous research has often focused on these items. The results are shown in Appendix Table C2. The overall elasticity for all three items pooled together is 0.050 (statistically significant at the 1 percent level), smaller than the 0.089 elasticity for restaurants in the smallest item quartile reported in Appendix Table C1. However, in Appendix Table C2 the only statistically significant individual price elasticity is 0.048, for a chicken dish. The standard errors for pizza and burgers are quite large, likely because of the smaller sample sizes. Their elasticity point estimates may still be informative: 0.049 for pizza and 0.061 for burgers. Apparently, while minimum wage-related price increases are concentrated among restaurants with a small number of menu items, they are not as concentrated among chicken, pizza and burger dishes. However, given the larger standard errors we would not place much weight on this result. Nonetheless, these estimates are also lower than the findings in previous research.

These results permit two main conclusions. First, restaurants with a larger number of menu items were less likely to increase the prices of all their items than restaurants with smaller menus. While this finding may not seem surprising, it is novel and of importance for construction of price indices and for understanding how prices vary with external business conditions. Second, the number of items in a restaurant menu does not materially affect a restaurant's average price increase. This result is surprising and a subject for additional research.

Appendix Table C1. Descriptive statistics and estimated price elasticities by quartiles of the number of menu items

	Quartile 1 (15 to 40 items)*	Quartile 2 (41 to 66 items)	Quartile 3 (67 to 105 items)	Quartile 4 (106 to 407 items)
A. Number of restaurants	206	200	199	198
San Jose	84	75	68	67
Outside-San Jose	122	125	131	131
B. Share of restaurants with price increases	0.53	0.48	0.46	0.40
San Jose	0.63	0.55	0.44	0.40
Outside-San Jose	0.46	0.43	0.47	0.41
C. Share of items with price increases	0.35	0.22	0.21	0.15
San Jose	0.45	0.26	0.24	0.17
Outside-San Jose	0.27	0.20	0.20	0.13
D. Estimated price effect				
Elasticity	0.090**	0.025	0.045	0.033*
Standard error	(0.036)	(0.029)	(0.036)	(0.019)

Notes: *Excludes observations for restaurant menus with less than 15 items (N=81), which is 9.2 percent of the total sample. These were incomplete menus; most were pizza restaurants that displayed only the price for a specific pizza size. In these instances prices of other menu items were obtainable from the restaurant's interactive web site, but to obtain every individual item was beyond our resources. Two observations included a price for a buffet only. A robustness test from Table 10, specification (4) shows this trimming does not affect our main results. Significance levels: ***1%, **5%, *10%.

Appendix Table C2. Estimated price elasticities for three main dishes

	All 3 items	Individual items		
		Chicken	Pizza	Burger
San Jose (se)	0.050*** (0.017)	0.048*** (0.015)	0.049 (0.060)	0.061 (0.055)
R2	0.010	0.011	0.005	0.010
Number of clusters (restaurant chains)	610	587	109	170
Number of items	8,834	7,291	644	899

Notes: Standard errors, clustered at the chain-level, in parentheses. Estimated coefficients are transformed into elasticities by dividing by 0.25. "Chicken" includes all items with the word 'chicken' in the name of the item except 'chicken pizza,' which is considered a 'Pizza'. "Pizza" and "Burger" are defined similarly. Categories are mutually exclusive. Significance levels: ***1%, **5%, *10%.