ARE LOCAL MINIMUM WAGES ABSORBED BY PRICE INCREASES? ESTIMATES FROM INTERNET-BASED RESTAURANT MENUS

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The authors analyze 884 Internet-based restaurant menus from inside and outside San Jose, California, which they collected before and after the city implemented a 25% minimum wage increase in 2013. Their findings suggest that nearly all of the cost increase was passed through to consumers, as prices rose 1.45% on average. Minimum wage price elasticities averaged 0.058 for all restaurants and ranged from 0.044 to 0.109, depending on the type of restaurant. The authors' estimate of payroll cost increases net of turnover savings is consistent with these findings. Equally important, border effects for restaurants are smaller than is often conjectured. Price differences among restaurants that are one-half mile from either side of the policy border are not competed away, indicating that restaurant demand is spatially inelastic. These results imply that citywide minimum wage policies need not result in substantive negative employment effects nor shifts of economic activity to nearby areas.

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

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operating costs is about 30%, and about 33% of restaurant workers are paid within 10% 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 change with relatively small price increases, which in turn have relatively small effects on restaurant sales. This strategy, therefore, may dominate over responding to a minimum wage by reducing employment, which could reduce sales and profits to a greater extent.

Consequently, it may be 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 perplexing 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, and 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 from the San Jose, California, area, which we collected before and after the community implemented a 25% 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 the data allow us to identify chains as well. Our data include all menu items—the average restaurant menu consists of 75 individually priced items. Moreover, our data come directly from Internet-posted menus, whereas previous studies used reports from surveyed managers, volunteers, or surveyors visiting a restaurant.

Our article is the first to use Internet-based data to study restaurant price responses to a minimum wage increase. It is also the first 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 other 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%) 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% increase in the minimum wage is associated with a 0.58% increase in restaurant menu prices in San Jose. This price elasticity implies that restaurants responded to the 25% increase in minimum wage by increasing prices, on average, by 1.45%; furthermore, a 95% confidence interval rules out increases of more than 2.23%. 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.

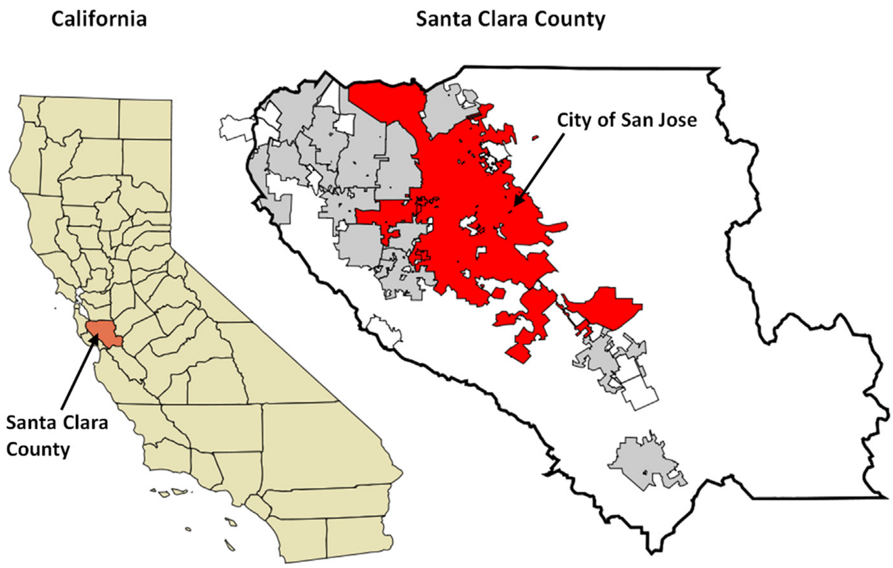
Economic and Policy Context

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% 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 has increased each January: to $10.15, $10.30, and $10.50 in 2014, 2015, and 2017, respectively. Early journalistic investigations (Brock 2014) suggested that the policy did not have negative employment effects. In November 2016, the San Jose City Council voted a phased increase in its minimum wage to $15 by 2019; this schedule is four years ahead of California's $15 phase-in to be fully implemented in 2023.

San Jose, the tenth largest city in the United States, has the highest median household income of the 25 most populous US cities. 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 in comparison 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

Figure 1. Santa Clara County within California, and San Jose City Limits within Santa Clara County



Source: Wiki Map, Accessed at https://commons.wikimedia.org/wiki/File:Santa_Clara_County_California_Incorporated_and_Unincorporated_areas_San_Jose_Highlighted.svg.
Notes: The area in white, for the map on the right, represents unincorporated Santa Clara County.

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 that 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 approximately 62% 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

[1]The 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 http://www.walkscore.com.

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 wage increases. Using the American Community Survey (ACS) place of work data, which identifies respondents by the location of their workplace, Reich estimated that 17.9% of workers who were employed in San Jose would receive pay increases because of the minimum wage policy. Using 12 months of Current Population Surveys Merged Outgoing Rotation Groups (MORG) data, which has better measures of hourly wages than does the ACS but only information on the respondents' place of residence, Reich estimated that 26.4% of the city's workers would receive increases.

According to Autor, Manning, and Smith (2016), each of the minimum wage policy changes (federal and state) between the mid-1980s and 2014 directly affected at most 7% of covered workers. By this metric, the San Jose policy 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 one 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, 2016); 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 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% 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 wages[3] (quarterly) and employment (monthly) in the

[2] An exception is Oakland, California, which implemented a one-time 36.1% increase in its minimum wage, from \$9 to \$12.25, on March 2, 2015. Reich, Jacobs, and Bernhardt (2014) estimated that 27% of Oakland's covered workers would receive pay increases.

[3] The 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.

Restaurant Industry (NAICS 722) and two of its subsectors: full-service (NAICS 722511) and limited-service (722513) restaurants. We employ 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. San Jose bills itself as the capital of Silicon Valley, yet much of the high-tech high-wage employment boom has taken place outside the city itself. Based on our 2010 to 2014 QCEW data set, 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% of the outside–San Jose wage. During this period, overall employment grew 3.61% per year in San Jose and 4.39% outside San Jose.

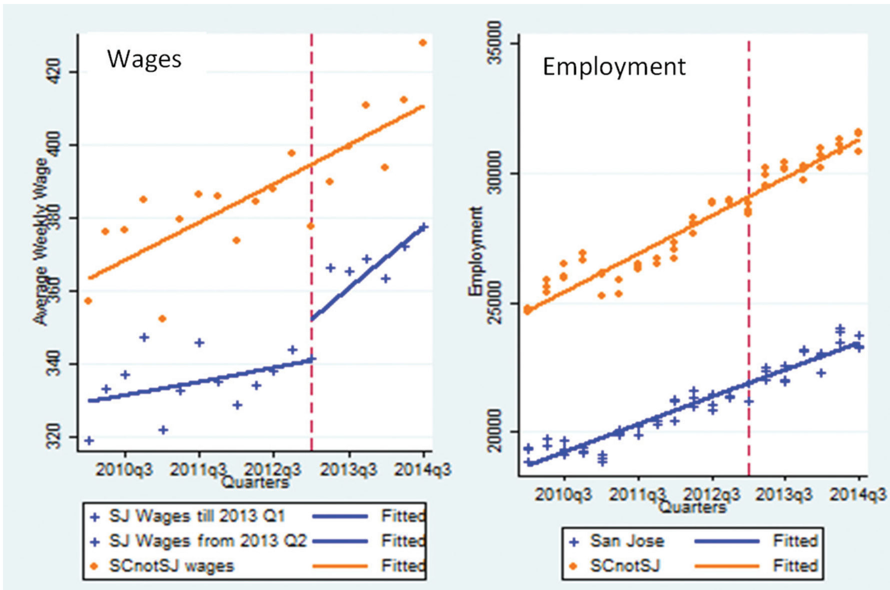
Given these differences, wage and employment trends in restaurants provide comparisons that are more pertinent to our study. We study restaurants because they are among the most intensive users of low-wage labor and account for more low-wage workers than any other major industry. In retail and accommodations, 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, with the comparable figure for outside San Jose at $394, about 10% higher. This difference 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%. Wage differences were greater among full-service restaurants: $400 in San Jose and $435 outside San Jose, a difference of 8%.[4]

Key questions are whether the treatment and the 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.

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

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



Sources: 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.

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% 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 the 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

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)
Number of observations		38 (quarterly)	114 (monthly)

Source: Quarterly Census of Employment and Wages (QCEW).
Notes: 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. 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%.

San Jose. We account for these slightly different pre-trends in our difference-in-differences calculation. 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-differences calculations, reported in Table 1. Although the number of observations is not large, we find a statistically significant (at the 10% 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, 2016). The somewhat smaller earnings effect in limited-service restaurants is surprising, given the relatively lower wages in this sector; however, the

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

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 ($p = 0.445$).

By 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 whereas 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.

Related Price Studies

A recent survey of the minimum wage literature by Neumark and Wascher contended that "the effect of a minimum wage increase on the overall price level is likely to be small" (2008: 248). Card and Krueger concluded that the data are "too imprecise to reach a more confident assessment about the effects of the minimum wage on restaurant prices" (1995: 148). Studies that focus on other mechanisms, such as employee turnover in restaurants (Batt, Lee, and Lakhani 2014; Dube et al. 2016), also neglected price changes as an adjustment mechanism. A recent survey of the minimum wage literature by Belman and Wolfson (2014: 383–92), however, concluded 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 (2001) obtained an estimated price elasticity of 0.037 for fast-food restaurants; Aaronson, French, and MacDonald (2008) obtained a statistically significant price elasticity of 0.074, also for fast-food restaurants.[6] All of these studies examined 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 data set and can estimate elasticities for a much larger range of restaurant characteristics. Moreover, national panel studies necessarily estimate an average effect across the United States. 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 policymakers.

[6]Aaronson (2001: 163) wrote that "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."

On the one hand, 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 et al. (2008), exhibit significant pre-trends, perhaps because of anticipation effects or because states with more inflation are more likely to 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 article is most related to the local studies of Card and Krueger (1994) and Dube et al. (2007) and to the national panel studies of Aaronson (2001) and Aaronson et al. (2008). Based on their own survey of restaurants in New Jersey and Pennsylvania, Card and Krueger found only mixed evidence that prices respond to minimum wage increases. Evaluating the effect of San Francisco's 28% increase (over two years for small-scale employers) in 2004, Dube et al. found significant positive price elasticities of 0.062 for limited-service restaurants and 0.018 for full-service restaurants (not significant).[8]

Restaurant Menu Sample: Collection and Representativeness

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 data set 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 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

[7]Allegretto, Dube, Reich, and Zipperer (2017) discussed the nonrandom character of states with higher minimum wages. Aaronson et al. (2008) found significant price effects in the quarter before a minimum wage increase. Unfortunately, they do not test for longer pre-trends.

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

[9]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. OpenTable 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 US 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) provided an early description of the growing prevalence of these services.

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.) Because 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) did not find price increases more than two months prior to implementation of a higher minimum wage.

Menu Collection Methods

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 comprised 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. We attempted to locate an up-to-date menu for every single restaurant in our universe.[11]

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

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

[11]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 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.

2013.[12] Our previous research (Dube et al. 2010) suggested that minimum wage effects on restaurant pay and employment occur within the first two quarters of a policy increase. Aaronson et al. (2008) found 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 inputted every menu item for both waves into an Excel spreadsheet and then uploaded the data into STATA for our analysis.

Sample Representativeness

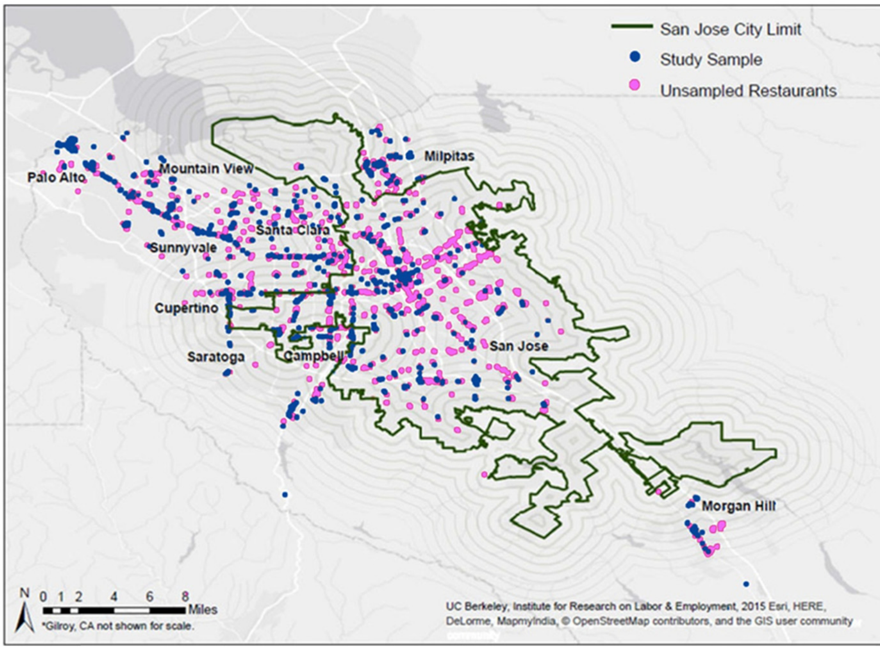
Our downloaded restaurants include treatment and control subsamples, hence, our results possess internal validity. That is, they will be informative for price effects of a minimum wage increase among the set of restaurants that have downloadable menus. We also want to know whether our results possess external validity: Do restaurants with downloadable menus differ in systematic ways, especially in pricing behavior, from restaurants that do not post their menus online? Although 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 QCEW. 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

[12]In both the first and the second wave, we collected data from individual restaurants in an order determined by a random number generator. This randomness ensured 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 the control groups.

[13]More precisely, Aaronson et al. (2008) found that 60% 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.

Figure 3. Spatial Distribution of Restaurants in Santa Clara County: San Jose and Outside San Jose



Notes: Sampling universe consists of 3,285 restaurants. Our final sample consists of 884 restaurants. The map compares the spatial distribution of restaurants that appear in our sample to those that do not.

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% are located within San Jose and 56% outside of San Jose. Comparatively, 37% of our restaurant sample is located inside San Jose's city boundaries and 63% are from the control area outside of San Jose (see online Appendix B for further discussion). Thus, compared to the AFF universe, our sample somewhat overweights restaurants outside San Jose. This overweighting, however, should not affect our difference-in-differences estimates.

Given that 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 application programming interfaces (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 line shows the boundary for the city of San Jose. The other major cities in Santa Clara County are listed on the map. The darker

Table 2. San Jose (Treatment Sample) Compared to Outside San Jose (Control Sample)

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

Notes: Standard deviations in parentheses. Standard errors of difference, clustered at the chain-level, in brackets.
[a]Chains are defined as restaurants with at least two locations in the study area.
[b]Restaurant 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.
Significance levels: ***1%; **5%; *10%.

dots represent our sample of restaurants, and the lighter dots represent restaurants that were not sampled. The map suggests that our sample is quite representative spatially within both the control and the treatment areas. We compute the distance between each restaurant and the San Jose border, which allows us to estimate price effects by distance of a restaurant to the San Jose border.[14]

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 AFF universe of all restaurants in Santa Clara County. The QCEW data that we used above to analyze earnings and employment effects, however, 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.

[14]Using Google API, we obtained the latitude and longitude associated with each address and computed the distance of each restaurant to the San Jose city 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.

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

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

We also computed a restaurant density measure. For each restaurant, this measure indicates how many other 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).[16] The density measure in our sample ranges from 0.6 to 87.0. Average density, reported in Table 2, is nearly 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 row 5 of Table 2 indicates, on average, restaurants in the control area are located 3.1 miles from the San Jose border, and 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, whereas the restaurants in the rest of Santa Clara County can be farther 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.

We do not have data on restaurant rents, but we can examine residential rent trends. Between March 2013 and September 2013, when our second

[15]Aaronson et al. (2015) reported very similar ratios.

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

wave of price collection began, residential rents increased 1.25% more in Santa Clara City and Sunnyvale than they did in San Jose, according to Zillow, an online real estate database. The duration of commercial leases is typically three to five years, compared to one year for residential leases, so 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. Given that 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, and so forth) 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 markup 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.

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. We use the estimated minimum wage elasticity of 0.208 for restaurants obtained by Allegretto, Dube, Reich, and Zipperer (2017).[18] The elasticity of *net* payroll costs then equals the earnings elasticity less cost savings because of reduced turnover. As in Reich, Jacobs, Bernhardt, and Perry (2015), we use a turnover cost offset of 15%, yielding a net payroll cost elasticity of 0.177. We then multiply 0.177 by 0.333, the labor share of operating costs in restaurants, to obtain 0.059 as the estimated elasticity of the cost pressure with respect to the minimum wage. Multiplying 0.059 by 25% (the size of the minimum

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

[18]The restaurant employment elasticity in this study is 0.002 and it is not statistically significant.

wage increase) yields an expected operating cost increase of 1.47%. If costs are fully passed to prices, restaurant prices would also increase by 1.47%.

Would a price increase of this magnitude substantially affect restaurant employment? Since the demand for restaurant meals is relatively inelastic (–0.71, according to Okrent and Alston 2012), a 1.47% price increase would reduce sales and employment by less than 1%. Moreover, the income effect of the higher minimum wage on the increase in purchasing power of low-wage workers is likely to stimulate restaurant sales and employment, so that the overall effect may be even smaller.[19]

Research Design

We employ a difference-in-differences strategy to estimate the price pass-through of the minimum wage increase in San Jose. Our main specifications estimate 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(pre-price) from log(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% increase in San Jose's minimum wage increase. Standard errors are clustered at the restaurant level. Our first specification and elasticity are then calculated as follows:

$$
\begin{gathered}
[\log(\text{post-price})_i - \log(\text{pre-price})_i] = \alpha + \beta(SJ)_i + \epsilon_i \\
E = \frac{e^{(\beta)} - 1}{0.25}
\end{gathered} \tag{1}
$$

The second specification separates the effect of the minimum wage change on prices in limited-service restaurants from that in 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 captures the main effect; the *FS* dummy is also interacted with *SJ* to parse out the additional effect in San Jose. The second equation and elasticities are as follows:

$$
\begin{gathered}
[\log(\text{post-price})_i - \log(\text{pre-price})_i] = \alpha + \beta_1(SJ)_i + \beta_2(FS)_i + \beta_3(SJxFS)_i + \epsilon_i \\
E_{LS} = \frac{e^{(\beta_1)} - 1}{0.25} \\
E_{FS} = \frac{\left(e^{(\beta_1)} - 1\right) + \left(e^{(\beta_3)} - 1\right)}{0.25}
\end{gathered} \tag{2}
$$

[19]This discussion ignores potential capital-labor substitution. Aaronson and Phelan (2017) found that technical change reduces demand for routine cognitive jobs, such as cashiers, but increases demand for routine manual jobs, such as in food preparation.

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.[20] Comparing rows 1 and 5 in Panel A, we see that average prices increased both for restaurants in San Jose and outside San Jose after the minimum wage increase—an increase from $9.71 to $9.96 in San Jose and from $10.44 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. Rows 3 and 7 in Panel A of Table 3 report that the average number of menu items is also similar between the treatment and the 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 the control restaurants—suggesting 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 both the treatment and the control areas added and deleted 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 six to nine months after the first. In what follows, we therefore report results for

[20]Also, 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).

Table 3. Prices and Menu Items: San Jose Compared to Outside San Jose

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

Notes: Standard deviations in parentheses. Standard errors of difference, clustered at the chain-level, in brackets.
[a]Average price of all items by restaurant.
[b]Excludes items in the pre-period that were not listed in the post-period; otherwise a balanced sample.
[c]Excludes items added in the post-period that were not listed in the pre-period.
[d]Proportion of restaurants in each category.
Significance levels: ***1%; **5%; *10%.

the balanced panel of data. The balanced panel also permits comparisons to previous minimum wage price studies.

Panel B of Table 3 displays the distribution of price responses for the balanced and unbalanced panels for the treatment and the 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 accounts for all items, including those that were removed or newly added in the second round.

After the minimum wage increase (including new and removed items), 46% of restaurants in San Jose increased prices, 14% did not change their

Table 4. Estimated Price Elasticities

	Specifications						
Controls	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
San Jose (SJ)	0.058***	0.072***	0.026	0.068***	0.051**	0.104***	0.055
	(0.016)	(0.026)	(0.017)	(0.026)	(0.022)	(0.028)	(0.037)
SJ × Full-service		–0.027					0.009
		(0.033)					(0.033)
SJ × Chain			0.082**				0.081**
			(0.034)				(0.038)
SJ × Number employed 8–39				–0.017			–0.021
				(0.032)			(0.033)
SJ × Number employed 40 +				–0.057			–0.084*
				(0.039)			(0.049)
SJ × Distance to border[a]					0.006		0.022
					(0.013)		(0.015)
SJ × Restaurant density[b]						–0.002**	–0.002**
						(0.001)	(0.001)
R^2	0.022	0.028	0.034	0.030	0.022	0.033	0.057
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. Standard error for the density coefficient is 0.0007.
[a]Distance to border measure ranges from 0.0 to 12.1.
[b]Restaurant density measure ranges from 0.6 to 87.0.
Significance levels: ***1%; **5%; *10%.

prices, and 39% decreased their average prices. The respective shares for the treatment area outside San Jose are 38%, 18%, and 44%. 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% 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% increase in San Jose's minimum wage by increasing prices, on average, by 1.45%—a 95% confidence interval rules out increases of more than 2.23%.

Specification (2) adds a main effect for *FS* restaurants and an interaction term (*SJ x FS*) to estimate the effects separately by sector (main effects are not reported in the table). 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 0.072 (statistically significant at the 1% 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 *SJ x FS*. The resulting estimated price elasticity for full-service restaurants is 0.044.[21] Using the STATA lincom command, we determine that the linear combination of the two effects is statistically significant at the 5% level.[22] 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) to (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) 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 the limited-service sectors, in our sample they are predominantly limited-service establishments. The estimated price elasticity for chains in Table 5 is 0.109 (significant at the 1% level); the price elasticity for non-chains is 0.026 (not statistically significant). The estimate for chains (0.109) is similar to the estimate for limited-service restaurants (0.072)—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 subsample of chains. The subsample 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 0.061 (significant at the 5% 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 0.068 (statistically significant at the 1% level); the elasticity for those with 8 to 39

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

[22]Because of limited sample size, some of the interaction terms reported in Table 4 are imprecisely estimated. As the coefficient on the interaction term *(SJ× FS)* is not statistically significant, we cannot rule out that the differential effects on full- and limited-service restaurants reflect random variation in the sample.

Table 5. Estimated Price Elasticities for All Categorical Variables

	Elasticities *(se)*
A. Overall	0.058***
	(0.016)
B. Sector	
Full-service	0.044**
	(0.020)
Limited-service	0.072***
	(0.026)
C. Chain analyses	
1. Indicator for chain using the whole sample	
Chain (at least two locations)	0.109***
	(0.030)
Non-chain	0.026
	(0.017)
2. Sample using only chains with outlets in both treatment and control areas	
Within-chain effect[a]	0.061**
	(0.027)
D. Number of employees	
1–7	0.068***
	(0.026)
8–39	0.050**
	(0.020)
40 or more	0.010
	(0.029)

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).
[a]The 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. Sample consists of 49 unique chains and a total of 202 restaurant observations.
Significance levels: ***1%; **5%; *10%.

workers is 0.050 (significant at the 5% level). The price effect (0.010) was not distinguishable from zero for restaurants with 40 or more workers.[23] Small restaurants apparently possess more pricing power than do 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]

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

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

Specifications (5) and (6) in Table 4 add two continuous measures, distance to the 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 marginal effect is small (0.006) and not statistically significant. The effect of the border (0.051 and significant at the 5% level) is similar to the overall effect (0.058) in specification (1). Specification (6) in Table 4 reports estimates using our restaurant density measure. The estimated elasticity for zero density, reported in the first row, is 0.104 (significant at the 1% level), a relatively large effect. Specification (6) also reports the additional price effect as restaurant density increases: –0.002 (significant at the 5% level). Price effects thus become smaller as restaurant density increases, perhaps attributable to greater competition spatially. At the mean density measure, which is 28.4, the price effect at the mean density equals [0.104 – (0.002 x 28.4)] = 0.047. This novel finding suggests that measured price elasticities are substantially affected by restaurant density.

Last, specification (7) in Table 4 includes all the controls simultaneously. The *San Jose* price elasticity now represents all the omitted dummy variable categories when distance and density measures are set at zero. Thus, 0.055 (first row, specification (7)) represents the elasticity for limited-service, nonchains, with 1 to 7 employees, with zero density, and zero distance to the border. 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 to four times larger and 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 United States 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 choose to relocate outside the city or not to locate within

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[25]Online 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).

it in the first place. By contrast, 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; Ater and Rigbi 2007) found substantial price differences among all the McDonald's outlets in the county. Thomadsen related these price differences to travel costs, and Ater and Rigbi related the price variation to the relative concentration of repeat customers, as 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] Given that none of these studies had high-frequency distance data, however, 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 United States. 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). The figure also suggests that prices of San Jose restaurants increased somewhat

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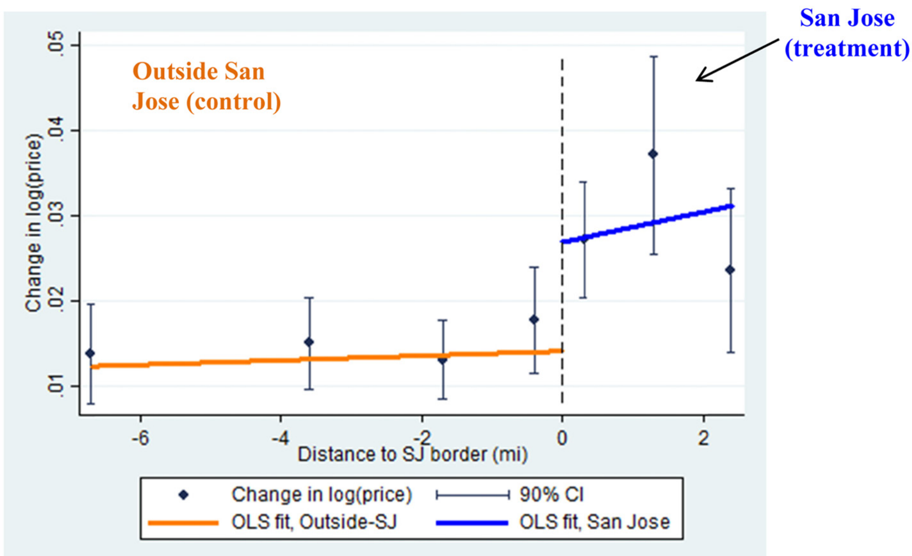
[26]For San Francisco, see Dube et al. (2007) as well as Dube, Kaplan, Reich, and Su (2006); for Santa Fe, see Potter (2006); and for all three cities, see Schmitt and Rosnick (2011).

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

Figure 4. Relative Price Changes by Distance to the San Jose Border



Notes: The dashed vertical line represents the San Jose border. The negative mile markers for 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.

less at the border than they did in the city's interior. Outside of San Jose, prices are only slightly higher near the border than they are farther away, and not significantly so. These findings indicate that price differences exist among restaurants that are less than one mile apart, consistent with market spatial areas of about 0.5 miles in radius. In other words, minimum wage cost 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 do not substantially affect our estimates.

Table 6. Robustness Tests: Elasticities by Sample and Restaurant Characteristics

	Sector			Number of employees		
Specification	*All restaurants*	*Full-service*	*Limited-service*	*1–7*	*8–39*	*40 or more*
(1)	0.058***	0.044**	0.072***	0.068***	0.050**	0.010
	(0.016)	(0.020)	(0.026)	(0.026)	(0.020)	(0.029)
(2)	0.052***	0.037*	0.069**	0.060**	0.055***	–0.024
	(0.017)	(0.020)	(0.028)	(0.027)	(0.020)	(0.023)
(3)	0.052***	0.036*	0.068**	0.060**	0.050***	–0.008
	(0.016)	(0.019)	(0.027)	(0.026)	(0.019)	(0.024)
(4)	0.052***	0.039**	0.065**	0.057**	0.056***	–0.006
	(0.016)	(0.019)	(0.027)	(0.026)	(0.019)	(0.026)
(5)	0.059***	0.045**	0.073***	0.069**	0.054**	–0.006
	(0.017)	(0.022)	(0.027)	(0.027)	(0.021)	(0.028)

Notes: Standard errors are in parentheses, and are clustered at the chain-level. Specifications are all at restaurant level, as follows:
(1) All observations.
(2) Excluding restaurants in the bottom 5% and top 5% of the distributions of menu items.
(3) Excluding restaurants in the bottom 5% of the distributions of menu.
(4) Excluding restaurants in the bottom 10% of menu items.
(5) Excluding restaurants in the top 5% of menu items.
Significance levels: ***1%; **5%; *10%.

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 state-mandated $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 hire more minimum wage workers than do most other businesses.

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 the city of 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 include prices on every menu item. Our Internet-based sample passes numerous tests of representativeness. This extensive data set allows for a rich analysis of how restaurants respond, through 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% increase in San Jose's minimum wage by increasing prices, on average, by 1.45%—a 95% confidence interval rules out increases of more than 2.23%. We find a range of statistically significant minimum wage price elasticities: 0.058 overall; 0.044 for full-service and 0.072 for limited-service restaurants; 0.109 for chains; 0.026 (not statistically significant) for non-chains; a within-chain effect of 0.061; and significant elasticities of 0.068 for restaurants with 1 to 7 employees and 0.050 among restaurants with 8 to 39 employees. Our estimated higher elasticities for limited-service restaurants compared to full-service restaurants are 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 0.109 for chains, which is consistent with the prevalence of limited-service restaurants among chains. Our estimated price elasticity for within chain-pairs is 0.061, which 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 by 25% in one fell swoop. Our study of border effects indicates that market spatial areas for restaurants are small, suggesting 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. (2017), county-based data on minimum wages indicated that most of the effects occur within the first two quarters. Longer-term effects, however, might occur in local minimum wages that we do not observe in statewide policies. For example, since workers are more mobile than firms are, 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.

More than two dozen US 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 will 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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