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Online Appendices

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

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by

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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) provided 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 Table A.1. These studies generally use the “food away from home” (FAFH) component of data collected in selected metro areas for the US Bureau of Labor Statistics (BLS) Consumer Price Index. FAFH includes both full-service and limited-service restaurants. Seven locally based studies, summarized in Table A.2, 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 those 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: 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 coauthors, 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 used restaurant data from 1978–1995, a period with higher inflation and much less state-level minimum wage variation than has occurred since. This article found a price elasticity of about 0.07, but with varying degrees of statistical significance for different sample periods. For example, Aaronson reported 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" (2001:).

MacDonald and Aaronson's (2006) restaurant study examined the effects of the 1996–1997 federal and state increases. They found a minimum wage price elasticity of 0.041 (standard error of 0.006). In the most recent of Aaronson's studies, and the one that is usually cited as the most definitive in the price effects literature, Aaronson, French, and MacDonald (2008) drew upon store-level data for 1995–1997 for about 7 or 8 "meals" at about a dozen establishments in 88 areas, of which 82 are metropolitan areas. They found 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 found sizable positive effects on prices *before* the minimum wage takes effect. They interpreted this finding as an indication that firms anticipate a minimum wage increase and begin raising their prices in the months before the new floor is implemented. Because their data are bimonthly, interpreting the lead as an anticipation effect is plausible. Their specification includes only a single lead though, 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. did not examine whether heterogeneity among minimum wage states might be generating such bias. Moreover, using monthly data, MacDonald and Nilsson (2016) found that price increases occurred only in the month of minimum wage implementation.

A recent national panel study by 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 reported a price elasticity of 0.09 for two of the items (burgers and pizza), although one is marginally significant at the 10%

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 five 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) found only a partial pass-through. Their study used 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 six metro areas.[1] Unlike the previous studies, they clustered their standard errors. Their main finding indicated that about half of restaurant cost increases were passed through to consumers.

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

We turn next to the seven locally based estimates. Katz and Krueger (1992) found positive but imprecisely measured evidence of relative price increases at fast-food restaurants in Texas after a minimum wage increase. Card (1992) found 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: 51–55) found 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— found considerable price pass-throughs even with limited sample sizes. A study of the 26% increase in 2004 of San Francisco's minimum wage by Dube, Naidu, and Reich (2007) found a significant pass-through for fast-food restaurants, with an estimated price elasticity of 0.062; they found 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%, Colla, Dow, and Dube (2011) found that "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 was then .062.

In summary, although all seven of these local estimates were limited by small sample sizes, six of the seven found evidence of price pass-throughs and one found no price effect.

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[1] MacDonald and Nilsson (2016) found that the bimonthly data are not reliable for monthly interpretation. We therefore include in Table A.1 only their results with the monthly data.

Table A.1. 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	1990–1991 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	1978–1995 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	1986–1993 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	1996–1997 federal and 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	1996–1997 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 restaurants) e = 0.032, s.e.= 0.017 (FS restaurants)
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

Notes: BLS, Bureau of Labor Statistics; CPI, consumer price index; ACCRA, now known as C2ER, which is the Council for Community and Economic Research.

Table A.2. 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	1990–1991 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	1990–1991 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-food 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, Naidu, and Reich (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	2007–2009 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 Procedure

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.[2] 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 data set 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.[3] 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. Given that 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.[4]

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[2] 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.

[3] 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).

[4] In a national panel study, Aaronson (2001) did 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) suggested that minimum wage effects on restaurant pay and employment occur within the first two quarters of a policy increase. Aaronson, French, and MacDonald (2008) found that price increases are also highly concentrated in the first two quarters following an increase.[5]

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. Table B.1 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.[6] 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. We attempted to locate an up-to-date menu for every single restaurant in this universe.[7] As Table B.1 shows, in the first wave of collection we succeeded in identifying online

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[5] More precisely, they find 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.

[6] The Quarterly Census of Employment and Wages (QCEW) 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.

[7] 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.

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 website 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.[8] 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.[9] Restaurant prices were increasing at about 2.4% in 2013, so if some of the menus in this first wave were not up to date at the time of data collection, we may underestimate prices before the policy change. However, there is no obvious reason the timeliness of the posted menus in the first wave would vary between our treatment and control groups.[10]

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, Olive Garden, Papa John's Pizza (the 12th largest chain in the United States, as ranked by number of stores), Pizza Hut (the 3rd largest US chain), Red Lobster, Round Table Pizza, Sizzler, and Subway (the largest US chain). Some of the largest fast-food chains in Santa Clara County (such as McDonald's, Burger King, KFC, and In-N-Out Burger),

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[8] 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 article, but we use this method in an accompanying paper (Allegretto, Mallajosyula, and Reich forthcoming) to study price changes after a 36% minimum wage increase in Oakland, California. Cavallo (2015) used scraped data to study price stickiness in supermarkets; he provided a detailed account of scraping methods and showed that online and offline prices are highly correlated.

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

[10] 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.

however, do not provide online 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.[11] 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.[12] 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 at the end of November 2013.[13] 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 of those from inside San Jose and outside San Jose were comparable to the relative sizes of our subsamples for each area. That is, we could not detect a higher closure

[11] 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.

[12] 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.

[13] In both the first and 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 control groups.

rate due to the minimum wage increase (see Aaronson, French, and Sorkin 2015). 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 inputted every menu item for both waves into an Excel spreadsheet and then uploaded the data into STATA for our analysis.[14]

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.[15] Moreover, because 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% 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.

[14] 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, Mallajosyula, and Reich, forthcoming).
[15] Aaronson, French, and Sorkin (2015, table 2) found that restaurant entrants and exits both rose 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

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 Quarterly Census of Employment and Wages (QCEW). 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 data set provides exact addresses, allowing us to distinguish those inside San Jose from those outside San Jose. As Table B.2, panel A shows, the proportions in the two subsamples—San Jose and outside San Jose—are similar both for the universe and for our downloaded sample. For the universe and for our sample, the proportions of restaurants located outside San Jose are 56% and 63%, respectively. Thus, compared to the universe, our sample somewhat overweights restaurants outside San Jose. This overweighting, however, should not affect our difference-in-differences estimates.

Our *AFF* data set also includes three employment size bins: 1 to 7, 8 to 39, and 40 or more.[16] Table B.2, 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 2 x 2 x 3 matrix. The universe and sample distributions are similar across the three employment size bins.

[16] 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.

Given that we have the exact addresses of the restaurants, we are able to examine the spatial distributions of our restaurant for both our treatment and control groups. Using Google application programming interface (API), which allows communication with Google Maps, we obtained the latitude and longitude associated with each address. The spatial representation of the universe and the sample of restaurants is depicted in Figure B.1. 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 the treatment areas.[17] We also computed the distance of each restaurant to the San Jose border, which allows us to estimate price effects by distance of a restaurant to the San Jose border.[18]

In Table B.3, 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. The QCEW data that we used 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 both our inside– and outside–San Jose subsamples.

As Table B.3 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%.[19]

[17] 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.

[18] 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.

[19] Aaronson, French, and Sorkin (2015) reported very similar ratios.

These comparisons again support the representativeness of our sample, both within the treatment and the control areas.

The remainder of Table B.3 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 row in Table B.3 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 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. The density measure in our sample ranges from 0.6 to 87.0. Average density 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 B.3 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.

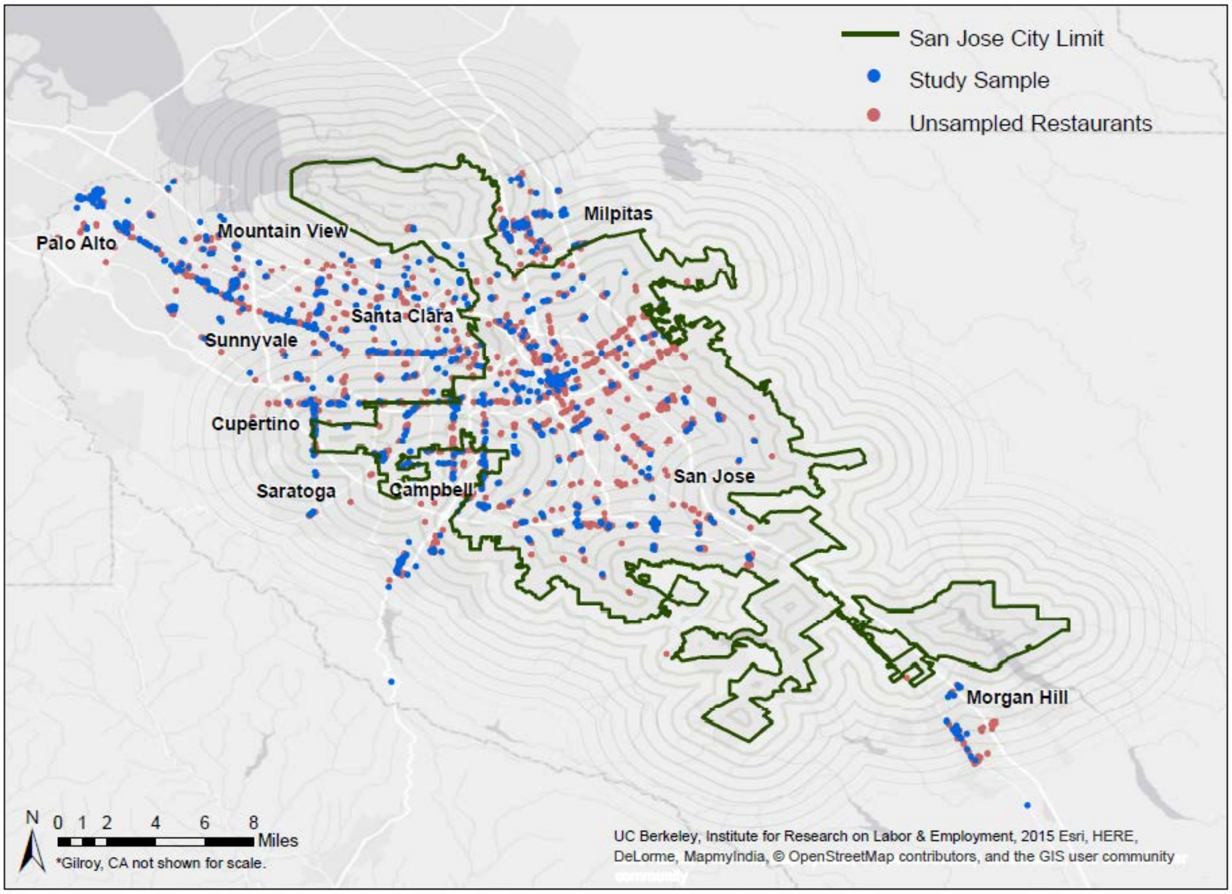
Although we do not have data on restaurant rents, we can examine residential rent trends. Between March 2013 and September 2013, when our second wave of price collection began, residential rents increased 1.25% more in Santa Clara City and Sunnyvale than they did in San

Jose.[20] Given that the duration of commercial leases is typically three to five years, compared to one 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.

[20] Residential rents obtained from Zillow, the online real estate database. See http://www.zillow.com/research/data/.

Figure B.1. Spatial Distribution of Restaurants in Santa Clara County: San Jose and Outside San Jose



Notes: As described in Table B.1, 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.

Table B.1. 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

Notes: [a]Food inspection list provided by Santa Clara County Public Health Department. [b]Restaurants 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, and so forth. [c]Includes only restaurants with store-specific menu prices posted online. [d]Excludes restaurants that closed, no longer had a website or online menu, or its online menu no longer listed prices. [e]Further 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.

Table B.2. All Santa Clara County Restaurants Compared to Our Sample

	Universe	Sample
A. Distribution		
Share inside San Jose	0.44	0.37
Number of observations	1,460	326
Share outside San Jose	0.56	0.63
Number of observations	1,825	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

Notes: This table compares the restaurant "universe" (*N* = 3,285) and the final sample (*N* = 884) as described in Table B.1. The restaurant "universe" was determined from the list of Active Food Facilities (AFF) in Santa Clara County, which was provided by the County's Department of Public Health. Our "sample" consists of restaurants for which we obtained both pre- and post-menus. [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.

Table B.3. 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%.

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.

Table C.1 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 those 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 Table C.1 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%) for the first quartile and declines to 40% for the fourth quartile. Outside San Jose, however, the share of restaurants with price increases exhibit a somewhat more uniform pattern, varying between 46% and 41%. 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 Table C.1 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% of the items; the shares drop to 26%, 24%, and 17% 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% in the first quartile to 13% 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.

Table C.1, 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% 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% 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.

Last, 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 Table C.1 and because previous research has often focused on these items. The results are shown in Table C.2. The overall elasticity for all three items pooled together is 0.050 (statistically significant at the 1% level), smaller than the 0.089 elasticity for restaurants in the smallest item quartile reported in Table C.1. However, in Table C.2 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. Given the larger standard errors, however, 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 were restaurants with smaller menus. Although 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.

Table C.1. Descriptive Statistics and Estimated Price Elasticities by Quartiles of the Number of Menu Items

	Quartile 1 (15–40 items)#	Quartile 2 (41–66 items)	Quartile 3 (67–105 items)	Quartile 4 (106–407 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% 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 website, but to obtain every individual item was beyond our resources. Two observations included a price for a buffet only. A robustness test in Table 6, specification (4), shows this trimming does not affect our main results. Significance levels: ***1%; **5%; *10%.

Table C.2. Estimated Price Elasticities for Three Main Dishes

	All 3 items	Individual items		
		Chicken	Pizza	Burger
San Jose	0.050***	0.048***	0.049	0.061
(se)	(0.017)	(0.015)	(0.060)	(0.055)
R^2	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 “Pizza.” "Pizza" and "Burger" are defined similarly. Categories are mutually exclusive.
Significance levels: ***1%; **5%; *10%.