

CITY LIMITS: WHAT DO LOCAL-AREA MINIMUM
WAGES DO?

Arindrajit Dube
Attila S. Lindner

WORKING PAPER 27928

NBER WORKING PAPER SERIES

CITY LIMITS: WHAT DO LOCAL-AREA MINIMUM WAGES DO?

Arindrajit Dube
Attila S. Lindner

Working Paper 27928
<http://www.nber.org/papers/w27928>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2020, Revised November 2020

We thank Pat Kline, Enrico Moretti and Michael Reich for useful suggestions. We are grateful to Jon Piqueras for outstanding research assistance. Lindner acknowledges financial support from the Economic and Social Research Council (new investigator grant, ES/T008474/1). Dube acknowledges financial support from the Russell Sage Foundation. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2020 by Arindrajit Dube and Attila S. Lindner. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

City Limits: What do Local-Area Minimum Wages Do?

Arindrajit Dube and Attila S. Lindner

NBER Working Paper No. 27928

October 2020, Revised November 2020

JEL No. J01,J18,J2,J23,J3,J31,J38,J8,J88

ABSTRACT

Cities are increasingly setting their own minimum wages, and this trend has accelerated sharply in recent years. While in 2010 there were only three cities with their own minimum wages exceeding the state or federal standard, by 2020 there were 42. This new phenomenon raises the question: is it desirable to have city-level variation in minimum wage policies? We discuss the main trade-offs emerging from local variation in minimum wage policies and evaluate their empirical relevance. First, we document what type of cities raise minimum wages and we discuss how these characteristics can potentially impact the effectiveness of city-level minimum wage policies. Second, we summarize the evolving evidence on city-level minimum wage changes and provide some new evidence of our own. Early evidence suggests that the impact of the policy on wages and employment to date has been broadly similar to the evidence on state and federal-level minimum wage changes. Overall, city-level minimum wages seem to be able to tailor the policy to local economic environment without imposing substantial distortions in allocation of labor and businesses across locations.

Arindrajit Dube

Department of Economics

University of Massachusetts

Crotty Hall

412 N. Pleasant Street

Amherst, MA 01002

and NBER

adube@econs.umass.edu

Attila S. Lindner

Department of Economics

University College London

30 Gordon Street

London

WC1H 0AX

United Kingdom

and CERS-HAS, IZA and IFS

a.lindner@ucl.ac.uk

To date, 42 cities in the United States have instituted minimum wages above the state or federal level. Of these cities, 22 have a minimum wage that is \$15 per hour or more—including San Francisco, Seattle, Los Angeles, and Washington DC—a level that seemed unthinkable just a few years ago. Moreover, advocates for city-wide minimum wages have played an important role both by changing wages in some of the largest and most dense labor markets in the United States, and by re-shaping the policy terrain more broadly. In these campaigns, advocates for a higher minimum wage first shifted their focus from state and federal government to city councils, mayors, and voters (via ballot initiatives). Subsequently, legislatures in states like California and Washington responded to the city-wide minimum wages by passing large state-wide increases of their own. In contrast, other state legislatures passed laws pre-empting a city-wide minimum wage mandate.¹

The growing number of cities with minimum wages naturally raises the question: is local variation in minimum wage policies a good idea? Most of the extensive minimum wage literature to date has focused on state or federal-level changes, but city-level minimum wage changes can have potentially different implications than changes that affect a state or the whole country. For instance, city boundaries are porous, and for many businesses it might be easy to relocate to a few miles outside of the city boundaries. This distortion may also be present to some extent for state-level minimum wages, but it could be much larger for minimum wage changes that are restricted to cities. On the other hand, local variation in minimum wages can better tailor the policy to local circumstances. For example, the level of minimum wage that might raise concerns about unintended consequences in rural areas in California may not bind at all in San Francisco or Los Angeles, given the generally higher wages in those cities.

To evaluate these trade-offs, we begin with some descriptive evidence on the evolution of city-level minimum wage policies. We examine what type of cities have instituted minimum wages, and discuss how these characteristics can potentially impact the effectiveness of city-level minimum wage policies. In the next part of the paper, we summarize the evolving evidence on city-level minimum wage changes and provide some new evidence of our own. By combining the existing evidence from cities, with some additional insights obtained from the literature on state and federal level changes, we provide an overall (if tentative) evaluation on what city-level minimum wages do. The weight of evidence suggests that city mandates (especially in larger cities) have been successful in raising wages in the bottom quartile of the wage distribution, with limited impact on employment prospects for low-wage workers. But the evidence base is still limited, and for this reason we identify some key areas where further research can be particularly helpful.

¹ While we mainly focus here on US evidence, city or local minimum wages are also present in other countries. There are 15 countries (besides the US) with some type of geographical differentiation in minimum wages: Bangladesh, China, India, Indonesia, Japan, Pakistan, Philippines, Vietnam, Portugal, Switzerland, Burundi, Canada, Malawi, Tanzania and Kenya. Among these Bangladesh, China, India, Indonesia, Burundi and Kenya have city-level minimum wages. Pakistan has a different minimum wage in Islamabad Capital Territory, which is federal territory (like DC). Portugal has different minimum wage for (archipelagos) Azores and Madeira. Malawi's minimum wage differentiates between urban versus rural. Tanzania's minimum wage differentiates between mainland and (archipelago) Zanzibar. The rest of countries have state/province variation. Switzerland has two cantons (Jura and Neuchatel) with minimum wage and the canton of Geneva just passed a law to introduce one. Therefore, around 6-10 countries have city minimum wages depending on the definition (Tijdens and van Klaveren, 2019).

Some Basic Facts

The first city-level minimum wage in the United States was instituted in 1993 in Washington, DC. However, city-level minimum wages remained a rather rare phenomenon until about seven years ago. To be sure, there were some isolated attempts and even some successes starting at the turn of the century. In 2002, New Orleans attempted to raise the minimum wage by \$1 above the federal standard when a majority of voters supported it on a ballot initiative, but the state of Louisiana barred local governments from setting the minimum wage. In 2004, San Francisco and Santa Fe successfully introduced local minimum wage ordinances. Both of these cities were located in states that already had minimum wages above the federal level, but these cities decided to go further. In San Francisco's case, the policy came out of a ballot initiative backed by more than 60 percent of the voters.

By 2010, only these three cities had city-level minimum wage. Yet ten years later, city-level minimum wages had spread to 42 major cities, including New York, Chicago, Los Angeles, Seattle, Denver, and Minneapolis. Today city-level minimum wage policies cover almost 8% of the U.S. workforce. However, these 42 cities with their own minimum wages are all located in only nine states, showing significant regional concentration. Moreover, of these 42 cities, 29 are located in California, and in turn, 24 of these are cities in the San Francisco Bay Area.

This shift to cities as a focus of efforts to raise the minimum wage is not the result of any major changes in the legal environment. In general, cities can pass laws on specific issues for which they have explicit permission from the state, but they can pass laws within a broader category of issues, as long as they are not specifically pre-empted by state or federal laws. Instead, the recent increase in city-level minimum wages seems to reflect two developments: first, the federal minimum wage has been stagnant over the past decade; and second, even when state legislatures have enacted a higher minimum wage, it has often been below the level desired in certain high-wage, high cost-of-living cities (Rapoport, 2016). These two developments pushed minimum wage advocates to move their efforts to the local level. Beginning in 2012, a coalition of unions—especially the Service Employees International Union—and progressive advocates helped launch the “Fight for Fifteen” movement. In November 2012, groups of workers from many fast food chains walked off their jobs in New York City, demanding a minimum of \$15/hour and other workplace rights. The momentum spread nationally. In 2014, SeaTac and then Seattle successfully passed ordinances mandating city-wide minimums. Other cities followed, building on these early successes and from having a national-level organizing infrastructure in place.

However, it is important to remember that states ultimately have the power to decide whether cities can institute their own minimum wage policies (Briffault, 2018). As mentioned earlier, pre-emption legislation in Louisiana barred New Orleans from setting its own minimum wage in 2002. As another example, St. Louis, Missouri, approved a minimum wage increase in 2015, which went into effect in 2017 following nearly two years of litigation. However, the state quickly passed a new law pre-empting cities in Missouri from setting minimum wages. As a consequence, the higher St. Louis minimum wage was in effect for only three months. By 2018, 28 US states had

pre-emption legislations in place, banning city-level minimum wages within their jurisdiction (EPI 2018).²

There are also some counties with minimum wages above the state level, although these counties typically either contain or adjoin a city with a higher minimum wage. Examples include Cook County in Illinois, which encompasses the city of Chicago; Montgomery County and Prince George's County in Maryland, which adjoin Washington, DC; Los Angeles County in California, which includes the city of Los Angeles, and Bernalillo County in New Mexico, which includes the city of Albuquerque. The state of New York also set a separate minimum wage for "downstate" counties near New York City (Nassau, Suffolk, and Westchester counties) and Oregon has introduced a three-tiered minimum wage where the wage floor varies across rural, non-rural, and Portland metro counties. In this paper, we will focus on city-level minimum wages. However, we suspect that these county-level minimum wage changes are likely to have similar implications.

In most cases, these city-level minimum wages cover nearly all low-wage workers working within the city limits. A notable exception is the city of SeaTac in Washington state, where only workers in the hospitality and transport sector are bound by the law (the law notably excludes the SeaTac international airport, the largest employer in the city). There are also some cities with separate minimum wages for tipped workers (as in New York City). Finally, in many cases the local ordinance allows for small businesses to set somewhat lower wages.

The top panel of Table 1 shows the 10 largest cities with local minimum wage ordinances. The three largest U.S. cities—New York, Los Angeles, and Chicago—all had city-level minimum wages in place as of January 2020. Among the top 10 largest cities with their own minimum wages, four have a minimum wage that is at least \$15 per hour and two other large cities are scheduled to pass the \$15 per hour threshold by 2022. Currently, the highest state-level minimum wage is in Washington state at \$13.5/hour; in contrast, six of the ten largest cities with minimums have levels exceeding \$13.5/hour. At the same time, large cities also tend to be areas where wages are generally higher for everyone, and this should be taken into account when assessing the level of the minimum wage.

To better gauge the bite of the city minimum wages, we calculate the median wage for each city using the latest wave of American Community Survey, and look at the ratio of the minimum wage to median wage—the so called Kaitz index. The (unweighted) average Kaitz index in the largest ten cities is around 0.58. This average is substantially higher than the average state-level Kaitz index, which is 0.48. This implies that the top 10 largest cities introducing minimum wages went substantially further in their minimum wage policies than the average US state, even after accounting for differences in the overall wage levels.

The bottom panel of Table 1 reports the 10 cities with the highest nominal minimum wages. The two highest nominal minimum wage cities—Seattle and SeaTac—are both located in Washington state, while the rest of cities that made the list are all in the San Francisco Bay Area. The top 10

² One of these is Oregon, which does not allow city-level minimum wages; however, in 2016, the Oregon legislature established a three-tiered minimum wage plan. The highest minimum wage tier established a wage floor for the Portland Urban Growth Boundary. This is effectively a Portland city-level minimum wage, which we include in our analysis below.

highest nominal minimum wage cities are on average small (average population is around 230,000). Among the three cities that have a long tradition of minimum wages—Washington D.C., Santa Fe, San Francisco—only San Francisco is in the top 10 list for cities with the highest minimum wage.

Table 1: Some Cities With Minimum Wages

Cities	Population	Minimum Wage in 2020	Kaitz Index	Planned Nominal Minimum Wage in 2022
Panel A: Largest Population Cities With Minimum Wages Above the State Level				
1. New York City	8,398,748	15.00	0.66	15.00
2. Los Angeles	3,990,469	14.25	0.75	15.72
3. Chicago	2,705,988	13.00	0.65	13.60
4. San Jose	1,030,119	15.25	0.56	16.20
5. San Francisco	883,305	15.59	0.45	17.05
6. Seattle	744,949	16.39	0.57	17.19
7. Denver	716,492	12.85	0.58	15.87
8. Washington, D.C.	702,455	14.00	0.48	14.50
9. Portland	652,573	12.50	0.56	14.75
10. Albuquerque	560,234	9.35	0.55	9.60
Mean of top 10				
Unweighted	2,038,533	13.82	0.58	14.95
Pop weighted		14.33	0.64	15.04
Panel B: Highest City-Level Minimum Wages (Nominal Minimum Wage in 2020):				
1. Seattle	74,4949	16.39	0.57	17.19
2. SeaTac*	28,925	16.34	0.67	16.79
3. Emeryville	11,724	16.30	0.65	17.92
4. Mountain View	83,377	16.05	0.34	17.05
5. Sunnyvale	15,3175	16.05	0.39	17.05
6. Berkeley	121,654	15.59	0.60	17.15
7. San Francisco	883,305	15.59	0.45	17.05
8. Los Altos	30,588	15.40	0.33	16.40
9. Palo Alto	66,655	15.40	0.33	15.85
10. Santa Clara	129,489	15.40	0.43	15.85
Mean of top 10				
Unweighted	225,384	15.85	0.48	16.83
Pop weighted		15.89	0.49	16.98

Notes: Kaitz index is the minimum wage divided by the median wage. The median wages of all workers are calculated from the 2018 wave of the American Community Survey and are measured in 2020 dollar value.

** Minimum wage only applies to transportation and hospitality workers within SeaTac city. We report the city level Kaitz index, where we calculate the industry share weighted average of the minimum to median wage.*

All of the cities in Panel B of Table 1 have minimum wages exceeding \$15/hour, but these cities also have generally high wages. As a result, in some cases the Kaitz index is rather modest: for example, cities of Los Altos and Palo Alto in the Bay Area have a Kaitz index of only 0.33—which is lower than the current Kaitz index of the federal minimum wage of 0.37. The average Kaitz index among the top 10 highest nominal minimum wage cities is 0.48, which is the same as the average Kaitz index among the US states. This highlights that top-line nominal minimum wage numbers can provide a misleading picture of how local minimum wage policies may affect a local economy.

Table 2 summarizes the basic characteristics of all 42 cities with minimum wages as of January 2020. We calculate city-level characteristics using the 2018 American Community Survey, the most recent data available. The first two columns, report statistics for cities with minimum wages. The first column shows population weighted averages for cities with less than 100,000 residents, while column two shows the statistics for cities with more than 100,000 residents as of 2018. For comparison, in column 3 we report the same statistics for all US cities with at least 100,000 residents, but no city-wide minimum wages.

Table 2: Basic Characteristics of Cities With and Without Minimum Wages

	(1)	(2)	(3)
	Cities with MW		Cities without a MW
	Pop < 100k	Pop > 100k	Pop > 100k
Number of cities	20	22	249
Population (in thousand)	55.2	1034.4	266.9
Nominal MW in 2020	14.57	14.27	9.44
Planned MW by 2022	15.71	15.07	
Mean wage	42.31	31.42	24.58
Median wage	31.26	22.47	18.04
Cost of living index (RPP)	122.9	117.1	100.2
MW to mean wage	0.36	0.45	0.38
MW to median wage	0.50	0.63	0.52
Share Democrats	0.73	0.76	0.55
College share	0.47	0.38	0.30
Unemployment rate	3.84	5.61	5.45
Industry shares:			
Restaurants	0.06	0.07	0.08
Retail	0.09	0.09	0.11
Manufacturing	0.09	0.06	0.08
Construction	0.05	0.05	0.06
Health and social care	0.12	0.14	0.13
Professional services	0.15	0.11	0.07

Notes: Own calculations based on the 2018 American Community Survey. Cost of living index is the MSA level RPP measured in 2017. The share of democrats in the 2016 presidential election is obtained from McGovern (2016). Each row (except the one on population) reports population weighted averages.

As expected, the nominal minimum wage is substantially higher in the cities with minimum wage (columns 1-2), than in the cities where only the state or the federal minimum wage applies (column 3). The difference in the nominal level of the minimum wage is substantial—around \$5 (or 50 percent). However, minimum wage cities also have around 25-75 percent larger average and median wages than other cities. As a result, the economic bite of the policy is substantially smaller than the headline nominal numbers would indicate. For smaller cities, the minimum-to-median-wage ratio is very similar to other cities without any minimum wage (0.50 in column 1 vs. 0.52 in column 3). The difference in the minimum-to-median-wage ratio is sizable if we compare larger cities with and without city-wide minimums (0.63 in column 2 versus 0.52 in column 3). Furthermore, the cost of living is also much higher in minimum wage cities; using the regional price parities measured at the level of metropolitan statistical areas (MSAs), we estimate that minimum wage cities have around 16 percent higher cost of living.³ Accounting for cost of living suggests that the real value of the minimum wages in larger cities with ordinances is around 25-30 percent larger than in cities without.

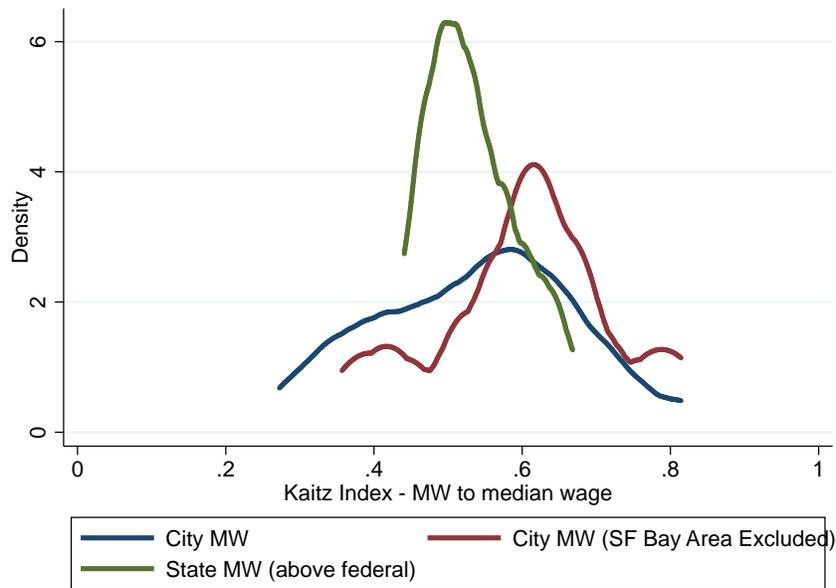
Table 2 also highlights that in cities with minimum wages, the population has higher levels of education, and workers are more likely to be employed in high-paying industries such as professional services. Furthermore, and not surprisingly, cities with minimum wages are more likely to lean Democrat: in the 2016 presidential election, for example, 76 percent of the cities with their own minimum wage voted for Democrats, while in other larger cities without minimum wage the vote share was only 55 percent. Finally, the local unemployment rate seems to be very similar between cities with and without minimums, at least for cities with a population exceeding 100,000.

City-level minimum wages are above state-level minimum wages, but the cities with higher minimum wages also tend to have median wages above the state level. Figure 1 shows the distribution of the Kaitz index (ratio of minimum to median wage) for cities with minimum wages as well as the comparable distribution of state-level minimums. For the states, we only consider minimum wages when they are above the federal level. Many cities (shown by the blue line) went beyond the highest state-level Kaitz: they had higher levels of minimum wages even after differences in the median wage across locations are taken into account. On the other hand, there are many high-wage cities where the Kaitz index is quite low even with the higher nominal minimum wages. The figure shows that the Kaitz index is more dispersed for cities than for states.

If we exclude the cities in the San Francisco Bay Area with their high levels of median wages (as shown in Table 2 above), then dispersion in the city-level Kaitz indices is more comparable to the state-level one, though the average value of the Kaitz index is considerably higher in cities. Notably, the Kaitz index exceeds 0.65 in a substantial portion of cities, which it essentially never does at the state level.

³ Note that the differences in cost of living are at the 1 metropolitan statistical areas (MSAs) level and not at the city-level. That is why the differences in median and average wages are substantially larger than the differences in cost of living. This also implies that we may be underestimating the differences in cost of living across cities.

Figure 1: Distribution of Kaitz Index for U.S. Cities and States



Notes: The figure shows the distribution of Kaitz index (minimum wage to median wage) for cities with minimum wages (blue and red line) and for all U.S. states where a minimum wage above the federal one applied (green line).

To summarize, cities passing minimum wages are typically large, with higher overall wages and cost of living. However, even after accounting for these differences, the city-wide minimum wages appear to have pushed the wage standards to be more binding than they would have from state-level policies alone.

Arguments Concerning City-Level Minimum Wages

The prevalence of city minimum wages naturally raises the question: is the growing variation in local-level minimum wages desirable? Here, we review some of the main arguments concerning minimum wages in general and consider how they apply in the context of city-level minimum wages. To do so, we assess the trade-offs that emerge for any place-based policies (Kline and Moretti, 2014). In the next section, we consider the empirical evidence for these arguments.

First, one of the oldest arguments for a minimum wage is that someone who works full-time should be able to afford the basic cost of living. However, there are large differences in costs of living across the United States (Albouy, 2009). As Table 2 showed, the cities that have enacted city-wide minimum wages had, on average, a 17 percent higher cost of living as measured by the regional price parity index (at the level of metropolitan statistical areas) than other cities. A local-level

minimum wage can be adjusted to take into account that workers with the same nominal wage are substantially “poorer” in locations with high costs of living.

Second, local variation in minimum wages may serve to redistribute resources from higher-income consumers to lower-wage workers. A body of empirical studies suggests that minimum wages are passed on to consumers via higher output prices (Lemos, 2008; MaCurdy, 2015; Harasztosi and Lindner, 2019). Because most minimum wage workers are employed in local non-tradable sectors (like restaurants or retail stores), this redistribution mainly takes place among local consumers and local minimum wage workers. As shown in Table 2, cities with minimum wages have a larger share of high-educated workers, a larger share of workforce in the professional services sector, and therefore a higher income consumer base. In these types of cities, redistribution from local high-income consumers to local low-wage workers may be more desirable.⁴

Third, another justification for minimum wages in general is that if employers have market power in the labor market, and they create a wedge between the marginal product of labor and wages, then minimum wages can potentially push wages and employment closer to the competitive equilibrium. However, the level of employer market power varies by local areas. Azar et al. (2019) find that labor market concentration in the general merchandise sector varies considerably across locations, and that the employment response to the minimum wages is linked to this variation.

Fourth, the minimum wage may shift the composition of local jobs. Harasztosi and Lindner (2019) and Cengiz et al. (2019) document considerable negative effects of state-level or country-level minimum wages on jobs in the tradable sector. Aaronson and Phelan (2019) find a drop in cognitive routine occupations after minimum wage hikes, while Lordan and Neumark (2018) document a drop in automatable jobs. However, in practice, such considerations do not seem to play a major role in the current discussion on city-level minimum wages. As shown in Table 2, the share of non-tradable sectors such as restaurants and retail or the share of tradable jobs such as manufacturing are similar in cities with and without minimum wages.

Fifth, a central concern expressed about the minimum wage is that it could reduce employment, either by causing employers to reduce the number of employees or by causing them to move out of the jurisdiction where the higher minimum wage applies. These employment and wage responses for localized minimum wage changes may differ from state or federal-level ones. After all, city boundaries are more porous than state boundaries. Businesses can simply move a few miles away to avoid minimum wage changes. Workers can seek higher wages or better employment opportunities by changing their commuting patterns. In general, given the density of highways in commuting zones, labor mobility is much greater across cities than across states. As a result, it is important to directly assess the effect of the minimum wage on both employment and business reallocation across city boundaries. However, it is also important to consider whether a reallocation of businesses and jobs from some high wage cities to outside their boundaries is necessarily bad from the public perspective (Albouy, 2009). If a higher minimum wage does,

⁴ Diamond (2016) shows that high skilled workers do not just get higher wage premium in some cities, but they also enjoy higher amenities. This would provide an additional reason to redistribute resources from high skilled workers to lower skilled ones in those cities.

indeed, lead to reallocation, the creation of new jobs outside of the urban core may help relatively disadvantaged areas outside city limits.

Finally, variation in minimum wages across cities can better reflect citizens' preferences (Tiebout, 1956). Residents of some cities prefer higher minimum wages even if the policy is accompanied by various trade-offs. Table 2 highlights considerable differences between the electorates in cities with and without minimum wages in terms of supporting major political parties. Recent survey evidence by Simonovits and Payson (2020) highlights that there is a strong correlation between city-level preferences and the prevailing minimum wage.

Evidence on the Impact of City-Level Minimum Wages

There is an extensive literature studying the impact of state and federal level minimum wage changes, but the existing evidence on city-level minimum wage laws is limited. Here, we consider the evidence (or sometimes the lack of evidence) on the effect of city-level minimum wages.

Estimates for Employment and Wages

Three studies provided evidence on the early wave of city minimum wages. Dube et al. (2007) study the effect of introducing the minimum wage in San Francisco in 2004 using two waves of a survey of restaurants and using aggregate level data from Quarterly Census of Employment and Wages. They use a difference-in-differences approach using a variety of control groups, including firms outside of San Francisco, smaller firms unaffected by the wage mandate within San Francisco, and higher wage firms within San Francisco. They find that the policy increased worker pay and compressed wage inequality, but did not create any detectable employment loss among affected restaurants. Potter (2006) focuses on the other early example of the city-level minimum wage changes: Santa Fe, New Mexico. Based primarily on comparisons with patterns in Albuquerque (about 60 miles away), Potter shows that the 65 percent increase in the minimum wage in 2004 did not have a negative impact on employment—if anything, Santa Fe actually did better than Albuquerque.

Schmitt and Rosnick (2011) study the impact of the minimum wage in three cities using firm-level administrative data from Quarterly Census of Employment and Wages: San Francisco, Santa Fe and Washington, DC. They find that average earnings increased in San Francisco and Santa Fe, but not in Washington, DC. They, too, use a difference-in-differences approach using alternative control groups (similar to Dube et al. (2007)). Their estimates on employment vary considerably across specifications, making it difficult to draw a definitive conclusion. Nonetheless, the estimates are clustered around zero—suggesting that the impact on employment was likely limited.

This early consensus on the effects of city-level minimum wage changes has been challenged recently by an influential study from Seattle. Jardim et al. (2017) study the introduction of the Seattle Minimum Wage Ordinance, which raised the minimum wage from \$9.47 to \$13 per hour in 2016. The study makes an important improvement relative to existing evidence as it utilizes high-quality administrative data on hourly wages. The paper documents a dramatic drop in the number of jobs below \$25/hour in Seattle relative to the other areas in Washington state. Their point estimates on employment elasticity with respect to own wage (in a competitive model, this

is the elasticity of labor demand)—is -2.18. Such an elasticity is outside of the range of existing estimates in the literature exploiting state or country-level variation in the minimum wage (see Figure 4B of Dube (2019)) and suggests that the policy did considerable harm to low-wage workers in Seattle.

The Seattle study received considerable attention. Jardim et al. (2017) used a credible empirical strategy that created a synthetic control for Seattle from other cities in Washington, and combined it with a unique administrative data on hourly wages. Nevertheless, there are some features of the Seattle experiment that should lead us to a cautious interpretation of the findings. First, it turned out that the Seattle labor market evolved quite differently than the cities in the comparison group around the time of the introduction of the local ordinance, with a substantial increase in the number of jobs and wages especially at the top of the wage distribution in Seattle. Because it is unlikely that the minimum wage has a substantial impact on jobs at the top of the wage distribution,⁵ such divergence between Seattle and the comparison group suggests that other shocks also affected the Seattle labor market around the policy change. Indeed, the “Seattle boom” might have shifted the whole wage distribution, in a way that led low-wage jobs to disappear at the same time as more high wage jobs were created. While the authors are careful in constructing a control group, given the generally greater wage growth in major cities during this period, it may just not be feasible to construct a counterfactual using places in Washington state outside of Seattle (which is the data the authors are using).

Furthermore, in a follow-up paper, Jardim et al. (2018) examine the employment trajectories of workers with jobs before the introduction of the minimum wage. The employment estimates for that subgroup are substantially lower: the implied employment elasticity with respect to own wage is 0.03 and the confidence intervals rule out even moderate-sized disemployment effects.⁶ While these estimates do not take into account the potential for a drop in new entrants to the labor market, they are also less affected by the overall shift of the wage distribution. As a result, it is unclear whether these estimates are biased upward or downward.

In a study on the impact of city-level minimum wages on employment in the restaurant sector in six large cities, Allegretto et al. (2018) use data from the Quarterly Census of Employment and Wages aggregated at the county-by-industry level. While their analysis is based on less rich data than the Seattle study by Jardim et al. (2017), they can use all counties without minimum wages to find the best comparison group. Given that the cities with minimum wages are quite unique, it may be important to go outside of a given state (like Washington) to find a better comparison group. Allegretto et al. (2018) find considerable increases in wages and modest, statistically insignificant, disemployment effects. Interestingly, Allegretto et al. also study the

⁵ The neoclassical model does predict that low-skilled workers will be replaced by high-skilled ones in response to the minimum wage. However, because the share of minimum wage workers in total production is low, we expect limited effects on the upper tail employment under reasonable values of labor-labor substitution (for details, see Cengiz et al. (2019), Appendix B). Therefore, the overall increase in employment (relative to the synthetic control) suggests that other major shocks were also in action around the time of the reform.

⁶ Jardim et al. (2018) report separate estimates on the effect of the minimum wage on total hours and on employment. We focus here on the head count estimates as those are more comparable to the existing literature. Jardim et al. (2018) find a significant drop in total hours, which amplifies the negative consequences of minimum wage changes. We discuss the change in hours results below.

employment changes in Seattle and find no indication for negative disemployment effects in the restaurant sector.⁷

Table 3 summarizes some key estimates in the literature on the impact of the city-level minimum wages on own wages and employment. Because it is hard to interpret the findings on employment in absence of any wage responses to the policy, we only report estimates with statistically significant effects of the minimum wage on wages. Column 5 reports the employment elasticity with respect to own wage.

Table 3 highlights that the employment elasticity estimates are centered around zero, which suggests that city-level minimum wages have no discernible effect on employment. Out of the 11 estimates, 7 have positive point estimates and 4 have negative sign for employment. Only two point estimates have an own-wage employment elasticity less than minus one, thereby implying that the total wage bill collected by low wage workers falls after the policy change as a result of job losses. Nevertheless, individual estimates are quite noisy even if we consider the 90 percent confidence intervals. Only two estimates can rule out that the employment is unaffected by the policy: Jardim et al. (2017) aggregate-level one finds a statistically significant negative employment effect, while Allegretto et al. (2018) in Oakland finds a statistically significant positive estimate on employment. Six estimates in the literature can rule out large negative employment effects (employment elasticity is less than -1) and four estimates can rule out medium-sized negative employment responses (employment elasticity is less than -0.4).

⁷ Jardim et al. (2017) also provide separate estimates for restaurants. Similarly to Allegretto et al. (2018), they confirm that the overall number of jobs did not fall in the restaurant sector. Nevertheless, they find some drop in employment for jobs below \$25 per hour. In addition, Nadler et al. (2019) show that small industry-wide employment elasticities are inconsistent with highly elastic labor demand for low-wage workers, given plausible elasticities of substitution across skill groups.

Table 3: Existing Estimates on City-level Minimum Wage Changes

Paper	City	Wage	Employment	Own-Wage Elasticity
Allegretto et al. (2018) - restaurants	Average of 6 cities	0.02 [0.01,0.03]	-0.01 [-0.02,0.01]	-0.23 [-0.78,0.32]
	Oakland	0.10 [0.06,0.14]	0.07 [0.03,0.11]	0.71 [0.20,1.22]
	San Francisco	0.06 [0.04,0.09]	0.01 [-0.05,0.07]	0.14 [-0.83,1.11]
	San Jose	0.11 [0.06,0.15]	0.00 [-0.06,0.06]	-0.02 [-0.5,0.53]
	Seattle	0.04 [0.02,0.07]	0.01 [-0.05,0.07]	0.20 [-1.16,1.57]
Dube, Naidu, Reich (2007) - restaurants	San Francisco	0.14 [0.06,0.22]	0.04 [-0.12,0.2]	0.29 [-0.34,0.91]
Jardim et al. (2017, 2018) - jobs below \$19	Seattle, worker level	0.15 [0.14,0.17]	0.01 [-0.01,0.02]	0.03 [-0.04,0.11]
	Seattle, aggregate level	0.03 [0.03,0.03]	-0.07 [-0.14,-0.01]	-2.18 [-4.14,-0.22]
Moe, Parrott, Lathrop (2019) - full service restaurants	New York City	0.10 [n.a.]	0.02 [n.a.]	0.25 [n.a.]
Schmitt and Rosnick (2011) -fast food	San Francisco	0.10 [0.05,0.14]	0.00 [-0.33,0.34]	0.03 [-3.45,3.5]
	Santa Fe	0.07 [0.02,0.12]	-0.08 [-0.29,0.13]	-1.20 [-4.36,1.96]

Notes: We report the estimated impact of city-level minimum wages on wages (column 3), on employment (column 4), and on employment elasticity with respect to own wage – the labor demand elasticity in the competitive model. We only report estimates where positive wage effects have been detected in the data. When the elasticity with respect to own wage was not directly reported (Allegretto et al., 2018; Dube et al., 2007, Jardim et al., 2017, 2018), we calculated the elasticity by dividing the employment effect with the wage effect. The corresponding standard errors were calculated by using the delta method. All estimates report the 90th percent confidence intervals. Moe, Parrott, Lathrop (2019) do not report standard errors.

Therefore, the evidence on city-level minimum wages is consistent with the growing body of evidence suggesting that moderate levels of minimum wage increases have a relatively small employment effect on the affected workers (Cengiz, Dube, Lindner and Zipperer, 2019; Belman and Wolfson, 2014). At the same time, it is important to point out that there is sizable uncertainty

around the existing estimates. There is plenty of room for additional research to glean important information on this question.

Overall Impact of City-Wide Minimum Wages

Almost all studies on the impact of city-level minimum wage changes focus on a particular city and a particular minimum wage hike. Nevertheless, inference based on one particular case study is inherently difficult. Furthermore, estimates based on any single experiment may be easily contaminated by other shocks, as seemed potentially true in the case of the Seattle study.

The Allegretto et al. (2018) study mentioned a moment ago is an exception to the single-city approach, because it reports event-study estimates exploiting six prominent minimum wage hikes. But many more city-level minimum wage changes could be used for identification. In fact, studies on the combined evaluation of city-level minimum wage changes are noticeably missing. This is in stark contrast to the literature on state-level minimum wage changes which moved some years ago from a case-by-case analysis (as in the seminal work of Card and Krueger (1994)) to combined evaluation of many state-level minimum wage shocks (e.g. Neumark and Wascher, 1992; Dube, Lester and Reich, 2010; Cengiz et al., 2019). Moreover, Allegretto et al. (2018) only look at restaurants, and therefore cannot fully resolve the concerns raised by Jardim et al. (2017).

Here we make a first effort at filling this hole in the literature by providing an overall assessment of the city-level minimum wage changes instituted as of 2018. We have three specific objectives. First, we wish to evaluate the full set of major cities instituting or raising the city-wide minimums during the recent period. Second, we wish to consider the *overall* impact of these policies on low-wage jobs in the spirit of Cengiz et al. (2019) and Jardim et al. (2017), as opposed to focusing on particular sectors or groups. Third, having shown how selective the minimum wage cities are, we wish to address concerns about invalid counterfactuals by comparing these cities with other large cities with similar characteristics that did not raise their minimum pay standard.

For this exercise, we use the American Community Survey between 2012 and 2018 that has data on wages and employment at the city-level. This dataset provides the geographic granularity needed to hone in on specific cities, something not feasible with other publicly available datasets. We start with a sample of all cities with a population of at least 100,000 in 2018 (last year of our sample). This leave us with 21 cities with minimum wage changes.

We estimate the following regression using ACS samples from 2012, 2013, 2017 and 2018:

$$y_{ct} = \beta_0 + \beta_1(Treat_c \times Post_t) + \beta_2(X_{c,2012} \times Post_t) + \mu_c + \tau_t + e_{ct} \quad (1)$$

The left-hand variable y_{ct} is the main outcome of interest—for us, either wage percentile or employment—at city c at time t , $Treat_c$ is a dummy variable for cities with minimum wage as of 2018, $Post_t$ is a dummy for years 2017 and 2018, μ_c are city fixed effects (thus adjusting for time-invariant unobserved heterogeneity), and τ_t control for year effects.

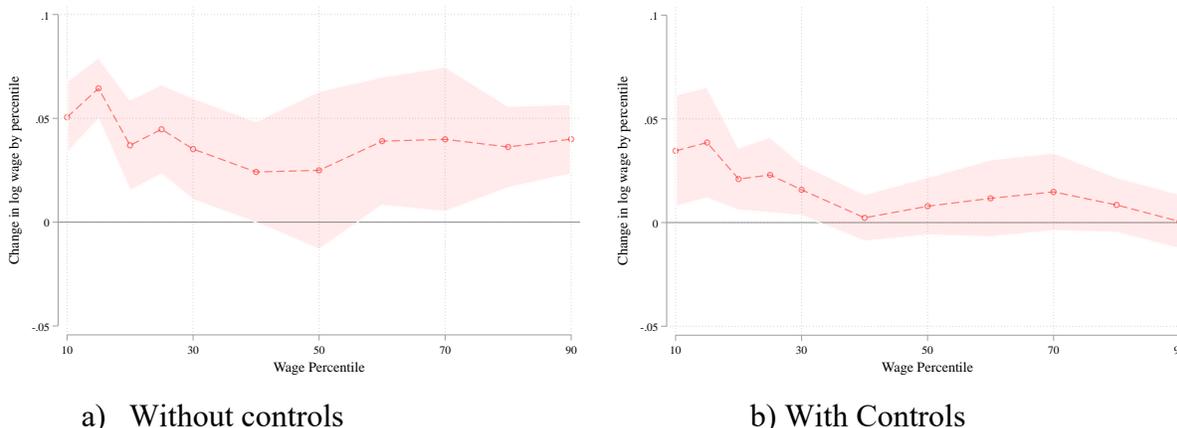
Of course, a central issue in the minimum wage literature arises because jurisdictions which enact a higher minimum wage are not chosen exogenously or at random. Given that we expect differences between cities that introduced minimum wages and those that did not, we control for

the interaction of a dummy for *Post* with a set of 2012 covariates $X_{c,2012}$ on cost of living, employment to population ratio, average wage, the 10th, 25th, 50th, 75th and 90th wage percentiles, shares of employment below wage cutoffs (\$15, \$20, \$25, \$30, \$50), and sectoral shares measured at the one-digit level. As we will see below, controlling for pre-treatment city characteristics produces much more sensible results on the upper tail of the wage distribution, which can be considered a key falsification test for both wage and employment effects (as discussed in Autor, Manning and Smith (2016); Cengiz et al. (2019)). We weight the regressions by population of the city and cluster the standard errors at the state level.

Figure 2 studies the contribution of city minimum wages to inequality in spirit of Autor, Manning and Smith (2016). We report the estimated β_1 coefficient from the regression where the outcome variable is various percentiles of income measured in log hourly wages. We compute hourly wages as (annual) salary income divided by hours per week times number of weeks worked.⁸

Panel a) in Figure 2 shows the estimates without controlling for the covariates $X_{c,2012}$ in the regression. As expected, there is a clear increase in wages at the bottom of the wage distribution in cities with minimum wages relative to the cities without minimum wages. However, wages *also* increase significantly for all percentiles (including the very top) throughout the wage distribution. Because minimum wages are unlikely to have much effect on wages at the very top, the no controls results here highlight that comparing cities with and without minimum wages can lead to misleading results. Instead, a plausible interpretation would be that cities experiencing wage growth across the income distribution may be more likely to enact their own minimum wage laws.

Figure 2: City-Level Minimum Wages and Inequality



Notes: This figure shows the change in log wages for each wage percentile from our regression analysis (see equation 1) exploiting 21 city-level minimum wage changes between 2012-2018. The shadowed area shows, for each percentile, the 95 percent confidence intervals around the estimate. Panel a) shows the estimates with time and city fixed effects but without controlling for the set of 2012 covariates interacted with the post dummy. Panel b) controls for 2012 values of cost of living, employment to population ratio, average wage, wage percentiles, shares of employment below wage cutoffs, and 1-digit level sectoral shares. Results are weighted by the population size of the city. For detailed regression results, see the online Appendix available at the JEP website with this paper.

⁸ The specific variables that we use from the American Community Survey are: “Salary income in the last 12 months”; “Usual hours worked per week in the last 12 months”; “Weeks worked during the last 12 months”. Given that the weeks variable is intervalled (6 categories), we take the midpoint of each interval in all categories but the last one (50 to 52 weeks) where we assign a value of 52.

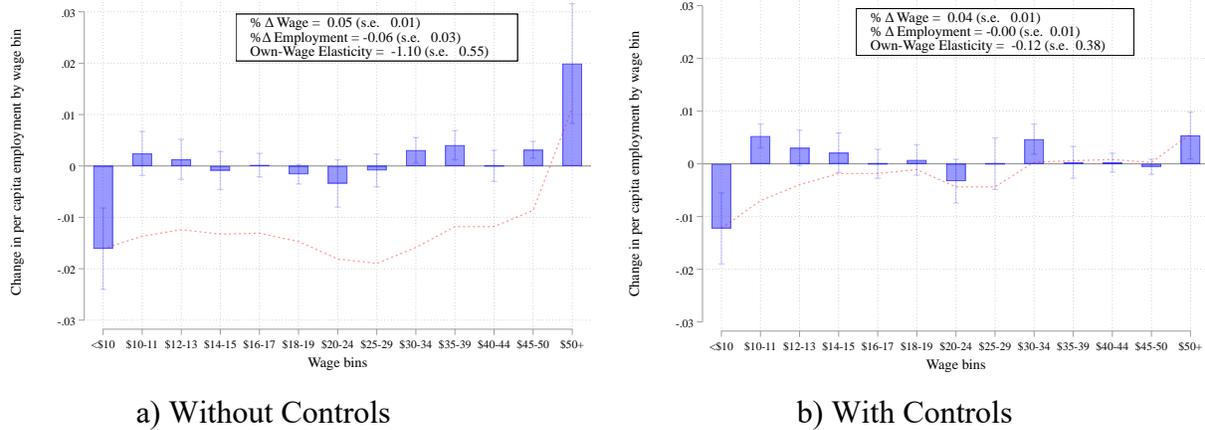
The second panel in Figure 2 controls for baseline differences in cities with minimum wage. The results with controls show a clear change at the bottom of the wage distribution that fades out around the 30th percentile of the wage distribution. Such spillover effects are broadly similar to the estimates in Autor, Manning and Smith (2016) who find a similar pattern for state-level minimum wage changes.

The evidence is consistent with a belief that that the city-level minimum wages affect workers' pay at the bottom of the wage distribution and have compressed wage inequality. However, the magnitude seems modest. If we estimate the same regression using the log of the minimum wage as an outcome variable, we find that the minimum wages increased by 23 percent (with a standard error of 1.6 percent) more in cities with minimum wage throughout this period. This increase is substantially larger than the roughly 4 percent increase in wages at the bottom of the distribution. This discrepancy likely reflects the increasing tightness across all labor markets during this period additionally led to wage growth even in cities that did not increase the minimum wage. These two factors likely limited how binding these minimum wage changes were, and thereby attenuated the inequality-reducing impact of the city minimum wage policies.

Did cities that adopted a minimum wage experience both wage growth and weaker job growth at the bottom of the wage distribution? We assess the employment effects of the minimum wage with the distributional approach developed in Cengiz et al. (2019), which divides the wage distribution into a set of "bins". By studying the effect of the minimum wage on employment for each wage "bin" separately, we can potentially calculate missing number of jobs at the bottom of the wage distribution and compare it to an excess number of jobs higher up the wage distribution.⁹ The approach also allows us to study the changes in the upper part of the wage distribution. Large changes there would suggest that the estimates of how a higher city-level minimum wage affects employment are potentially contaminated by other shocks.

⁹ This approach is also closely related to the Jardim et al. (2017) aggregate estimate, where they consider changes in employment below thresholds (e.g., \$19/hour). This allows us to consider how similar the findings are when we pool across multiple minimum wage events, and also when we use other large cities as controls (instead of rural and suburban Washington state).

Figure 3
City-Level Minimum Wages and Employment Changes



Notes: The figure shows the bin-by-bin employment changes from our regression analysis (see equation 1) exploiting 21 city-level minimum wage changes between 2012-2018. The blue bars show, for each wage bin, the estimated average employment change in that bin relative to the total employment in the city in 2012. The error bars show the 95 percent confidence intervals. The red line shows the running sum of employment changes up to the wage bin it corresponds to. Panel a) shows the estimates with time and city fixed effects but without controlling for the set of 2012 covariates interacted with the post dummy. Panel b) controls for 2012 values of cost of living, employment to population ratio, average wage, wage percentiles, shares of employment below wage cutoffs, and 1-digit level sectoral shares. Results are weighted by the population size of the city. For detailed regression results, see the online Appendix available at the JEP website with this paper.

Panel a) in Figure 3 shows the bin-by-bin employment estimates from our earlier regression equation without controls. There is a clear drop in employment at the bottom of the wage distribution (jobs under \$10) in cities with minimum wage, which is in line with a binding minimum wage policy. In addition, there is no apparent increase in the number of jobs higher up in the wage distribution, except at the very top where there is a large increase in the number of jobs. The missing number of jobs under \$10 only recovers once jobs above \$50/hour are incorporated. In fact, overall employment increased in cities with minimum wage, even if at the bottom of the wage distribution there are large job losses. When we consider jobs up to \$20/hour, Panel a) suggests that wages for this group of workers rose by around 5 percent while their employment fell by around 6 percent. The implied disemployment is quite pronounced: the estimated own-wage employment elasticity of -1.10 is statistically significant at the 95 percent confidence level.¹⁰

¹⁰ We calculate the percentage change in employment and wages as in Cengiz et al. (2019). In particular, the percentage change in affected employment is the change in employment below \$19 (relative to pre-treatment total employment) divided by the (sample average) share of workforce below the new minimum wage. To calculate the wage changes, we use equation 2 in Cengiz et al. (2019); see the Online Appendix for details. It is worth mentioning that Jardim et al. (2017) calculate the employment elasticity somewhat differently: they divide the percentage change in employment below \$19 by the percentage change in average wage below \$19. This approach dilutes the wage effects, since the change in wages of the workers close to the \$13 minimum wage is compared to higher wage workers earning just below \$20. As a result, the Jardim et al. (2017) estimates overstate the employment elasticity. If we calculate the

However, the story is very different when we control for the differences in baseline characteristics across cities. In Panel b), Figure 3 shows that once we control for observable baseline differences, the dramatic change in the upper part of the wage distribution disappears. We continue to find that cities with minimum wages have some missing jobs under \$10 per hour, but once we control for the baseline characteristics, we find that excess number of jobs emerge at jobs between \$11-\$19 per hour. The upper part of the wage distribution is more or less stable at higher part of the wage distribution, which is consistent with a relatively low impact of the minimum wage at that part of the wage distribution. Our estimates suggest that affected workers experienced a 4 percent additional wage gain, but the employment changes were negligible. The implied employment elasticity with respect to wage is -0.12. The 90 percent confidence interval rules out own-wage employment elasticities more negative than -0.75 (including the point estimate of -1.1 from the specifications without controls). These estimates are quite similar to the overall minimum wage literature to date. For example, the median own-wage employment elasticity in the literature is around -0.17, while it is around -0.04 when restricting attention to broad-based groups (Dube, 2019). At the same time, the confidence interval here also rules out some other prominent negative estimates from the minimum wage literature. Importantly, the aggregate own-wage employment elasticity of -2.18 in the Jardim et al. (2017) study of Seattle lies far outside of our confidence interval.

Indeed, the differences between the two panels in Figure 3 can help shed light on the controversy surrounding the Seattle minimum wage studies. The findings in Panel a) are strikingly similar to the aggregate-level findings in Jardim et al. (2020, see Appendix Figure 7). In Seattle, too, there was an apparent drop in jobs below the new minimum wage and those jobs did not recover if only jobs below a certain threshold (say, \$20, \$25 or \$30 per hour) are considered. Nevertheless, similar to our results here, Jardim et al. (2020) find an overall increase in jobs in Seattle that mainly came from an unusual job creation above \$50. These employment patterns are observed even though Jardim et al. (2020) are careful to construct a synthetic control; however, as we pointed out before, all of their control areas come from Washington state. The raw-vs.-control comparisons in Figures 2 and 3 document that the cities with minimum wage are often unique in terms of economic structure, cost of livings, and wage and employment growth trends, and in general, it might be difficult to find comparable cities within a state with similar characteristics.

The analysis here shows that the inclusion of the full set of controls produces much better-behaved findings when it comes to the upper tail falsification tests, while also suggesting relatively modest impacts on affected employment. However, the results here suggest that the parallel trends assumption appears to hold only conditional on covariates, highlighting the systematic differences between cities with and without minimum wages. This is different from the findings from state level policies, where state-level estimates are not sensitive to exclusion of additional controls for time-varying heterogeneity (see Cengiz et al., 2019). This naturally raises the question: how sensitive are these results to the particular set of controls included here? In the online Appendix, we show that the estimates are very similar when controlling for a small number of city characteristics chosen using a data-driven procedure, the double-selection post-LASSO proposed by Belloni et al. (2014). In particular—and as discussed above—treated cities had much higher

employment elasticity using their approach we get -1.65 (s.e. 0.84), qualitatively similar to their estimate for Seattle of -2.18.

share of workers in professional services in the pre-treatment period, and not accounting for this particular difference seems to impart a large amount of bias.

As always in the minimum-wage literature, the key to assessing the effects of the minimum wage is to find a credible comparison group, and the selectivity of cities makes this a more difficult challenge than at the state level. However, the existing evidence, including the results presented here, does not indicate that city-wide minimum wages differ substantially from state-level ones in terms of wage and employment responses. Besides the effect of city-level minimum wages on inequality, wages and employment, it is worth considering evidence on other aspects of these minimum wage policies—which we do in the remainder of this section.

Geographic Reallocation

Businesses may be able to avoid city-level minimum wages by shifting their production outside city boundaries. Such a shift in employment would create wage and employment spillovers in neighbouring cities and counties. However, we are not aware of any studies that directly assess the presence of such spillover effects in the city minimum wage context.

If the effect of the minimum wage spills over to its own suburbs, but not to nearby cities, we would expect that the wage effects are smaller in the own-suburb estimates and the employment effects are larger than the estimates on nearby cities. There is no such tendency found in Schmitt and Rosnick (2011). Furthermore, the fact that much of the existing estimates of the effect of a city-level minimum wage on employment are centered around zero suggests that business reallocation must be limited. However, more precise documentation by future researchers on when such spillovers occur and how large they are would be useful.

Firm Entry and Exit

At least in theory, city-level minimum wage policies could affect the rates of firm entry and exit. The existing evidence on firm's closure is inconclusive. Dube, Naidu and Reich (2007) do not detect any increase in the rate of business closure. On the other hand, Jardim and van Inwegen (2019) find that the Seattle Minimum Wage Ordinance accelerated exit of firms with a higher share of low-wage jobs. Luca and Luca (2018) exploit Yelp data to show that the exit rate of firms increased in response to the minimum wage, especially for those firms providing low quality services (measured by low Yelp ratings on the website). Such increase in business exit rate might reflect within-city reallocation of workers from lower-paying, lower-quality firms to higher-paying, higher-quality ones—a channel that is found to be important in responding to the introduction of the minimum wage in Germany (Dustmann et al., 2020).

The evidence on firm entry in the context of city-level minimum wages is even more limited. Jardim and van Inwegen (2019) find no effect on city-level minimum wage policies on the overall rate of business entry, though they document a change in the composition of the entering firms towards less labor-intensive businesses.

Hours Worked and Other Benefits

Even if a city-level minimum wage policy does not affect the overall number of jobs, it might potentially affect hours worked or other employment benefits. In their analysis of the Seattle

data, Jardim et al. (2017) find a substantial decrease in hours worked for jobs below \$19 per hour. As discussed above, it is unclear whether the drop in hours reflects the shift of the wage distribution discussed above or the genuine effect of the minimum wage. Looking at earlier evidence, and contrary to the findings in Seattle, Dube, Naidu and Reich (2007) find (if anything) a positive effect of a city-level minimum wage on hours worked.

The discrepancy between these two studies may be explained, at least in part, by the different data sources used in the analysis. Jardim et al. (2017) exploit administrative data on hours, while Dube, Naidu and Reich (2007) rely on survey data. It is possible that some firms avoid compliance to the minimum wage by underreporting hours, a practice that was found to be important in Germany (see Caliendo et al., 2018). Such underreporting might affect the results based on administrative data sets, but not the results based on survey data. Dube, Naidu, and Reich (2007) also study whether the impact of a pay increase resulting from a higher city-level minimum wage is offset by cutting non-cash benefit. They find no indication for cutting health insurance benefits and document an increase in the proportion of workers receiving tips.

Output Prices

A key channel of absorption of minimum wages is passing prices through to consumers. However, if the city-level minimum wage only applies to a subset of an integrated metro-area-wide product market, price pass-through may be difficult. On the other hand, if the demand for products is tightly linked to locations within the city itself, it may be possible for prices to exhibit sharp differences near city boundaries. Additionally, as we have argued, cities raising minimum wages tend to have residents with higher incomes and these consumers may be more willing and able to absorb an increase in prices of minimum wage intensive services and goods.

The empirical findings on this front are varied. Dube, Naidu, and Reich (2007) find that output prices increase especially for the fast food sector, particularly when comparing firms within versus outside of San Francisco. On the other hand, Jardim and Inwegen (2019) study the effect of the minimum wage on output prices in Seattle and find somewhat inconclusive evidence. Perhaps the most persuasive evidence on price responses comes from Allegretto and Reich (2018) who study the impact of the San Jose minimum wage change on Internet-based restaurant menus inside and outside of the city boundaries. Allegretto and Reich (2018) find clear and positive price effects in response to the minimum wage that are consistent with the large body of evidence on state-level minimum wage changes. What is particularly telling is that they document a sharp drop on output prices just a mile from the San Jose city boundary. Therefore, otherwise similar restaurants operating within a few miles of each other—but facing differential shocks to labor costs—seem able to set different consumer prices. This suggests a very sharp segmentation of certain markets, even when the boundary is as porous as it is between San Jose and adjacent smaller cities like Sunnyvale and Milpitas. Overall, the sharp reduction in prices indicates that spillover effects of a city-wide minimum wage policy are limited even in the context of the San Francisco Bay Area with highly interlinked cities.

Worker Turnover

Minimum wage policies can affect labor market flows. In models of a frictional labor market where employers have some wage-setting power, a higher minimum wage can lead to a reduction in worker turnover at the bottom of the wage distribution: essentially, a higher minimum

wage improves the relative quality of the lowest-paying jobs and increases retention (Portugal and Cardoso, 2006; Dube, Lester, and Reich, 2016). In turn, the decrease in turnover can lead to potential cost savings that can help to explain how a higher minimum wage is absorbed by employers without a substantial drop in employment.

Such a mechanism seems to play some role in the context of city-level minimum wages. Dube, Naidu, and Reich (2007) find an increase in worker tenure for a typical worker in the context of the San Francisco minimum wage increase, though they do not detect a reduction in overall separation rate. Jardim et al. (2018) find statistically significant reductions in separations following the Seattle minimum wage changes. Overall, the evidence from city minimum wages offers a qualified similarity to the broader literature suggesting reduced worker turnover is likely to be one of the channels of adjustment.

Conclusion

A growing number of cities have recently instituted their own minimum wages above the state or the federal one recently. Local variation in minimum wages allows to better tailor the policy to the local economic and political environment. At the same time, city-level minimum wages might be more distortionary as relocating businesses outside of city boundaries may be easier than relocating outside of the state or the country. While the literature on city-level minimum wages is still at an early stage, existing evidence does not indicate that the employment and wage responses differ substantially from the responses to state-level changes. Overall, the weight of the evidence is consistent with these policies having moderately raised wages at the bottom without a large change in employment probabilities. Much of the adjustment seems to have been similar to state and federal-level increases: through higher consumer prices, which in this case is mostly borne by middle and higher income consumers, and through some reductions in labor turnover costs. But considerable uncertainty surrounds some of these estimates, and more research is needed.

We expect a growing number of case studies will emerge soon concerning the impact of the policy in large cities such as Los Angeles and Minneapolis. Nevertheless, the literature can also benefit from exploiting combined analysis of the city-level minimum wage changes.

The new minimum wage literature started from studying the effect of a particular minimum wage increase in New Jersey, by looking at employment in the fast food industry with a comparison across the state border to Pennsylvania (Card and Krueger 1994). After the recent rapid expansion in the number of city-level minimum wages, economic research now has the ability to exploit hundreds of minimum wage increases. Data limitations pose some real challenges, but we see much value of exploiting more than single events to identify the effect of the policy. Our analysis presented in this paper provides an initial attempt at such a synthetic analysis; we hope to see much more. One additional point merits a mention: while use of state-specific administrative data can be of great help if there are credible control groups present within the state, the costs of relying on one state may exceed the benefits if proper control groups are not available. Furthermore, there is scope to learn from use of widely available public-use data (like the Quarterly Census of Employment and Wages or the American Community Survey). This is similar to the conclusion reached in Cengiz et al. (2019) who showed that wage data from the Current Population Survey

had comparable accuracy in many cases as hourly wage data from administrative sources. We think a similar lesson may apply to the city-wide context as well, at least for some questions.

Finally, surprisingly little research has been devoted to some important aspects of city-wide minimum wages. Direct evidence on business reallocation across city boundaries seems potentially important to assess the key trade-off emerging from introducing local variation in the policy. It would be also valuable to study the welfare implications arising from the potential reallocation of business from the core of a city to the more disadvantaged areas. Additional evidence on rental and housing prices would also help to understand the welfare implications of minimum wage policies. We hope these gaps in the literature will be filled in the next wave of research on city-level minimum wages.

Acknowledgements

We thank Pat Kline, Enrico Moretti, and Michael Reich for useful suggestions. We are grateful to Jon Piqueras for outstanding research assistance. Lindner acknowledges financial support from the Economic and Social Research Council (new investigator grant, ES/T008474/1) and from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement Number 949995). Dube acknowledges financial support from the Russell Sage Foundation. Dube and Lindner acknowledge financial support from the Arnold Foundation.

References

Aaronson, Daniel, and Brian J Phelan. "Wage Shocks and the Technological Substitution of Low-Wage Jobs". *The Economic Journal* 129, no. 617 (2019): 1-34.

Albouy, David. "The Unequal Geographic Burden of Federal Taxation". *Journal of Political Economy* 117, no. 4 (2009): 635-667.

Allegretto, Sylvia, Anna Godoey, Carl Nadler, and Michael Reich. "The New Wave of Local Minimum Wage Policies: Evidence from Six Cities." *CWED Policy Report* (2018).

Allegretto, Sylvia, and Michael Reich. "Are Local Minimum Wages Absorbed by Price Increases? Estimates from Internet-Based Restaurant Menus." *ILR Review* 71, no. 1 (2018): 35-63.

Autor, David H., Alan Manning, and Christopher L. Smith. "The Contribution of the Minimum Wage to US Wage Inequality Over Three Decades: A Reassessment." *American Economic Journal: Applied Economics* 8, no. 1 (2016): 58-99.

Azar, José, Ioana Marinescu, and Marshall Steinbaum. "Measuring Labor Market Power Two Ways". *AEA Papers and Proceedings* 109 (2019): 317-321.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. "High-Dimensional Methods and Inference on Structural and Treatment Effects." *Journal of Economic Perspectives* 28, no. 2 (2014): 29-50.

Belman, Dale, and Paul J. Wolfson. "What Does the Minimum Wage Do?" *WE Upjohn Institute*, 2014.

Briffault, Richard. "The Challenge of the New Preemption". *Columbia Public Law Research Paper* No. 14-580 (2018).

Caliendo, Marco, Alexandra Fedorets, Malte Preuss, Carsten Schröder, and Linda Wittbrodt. "The Short-Run Employment Effects of the German Minimum Wage Reform." *Labour Economics* 53 (2018): 46-62.

Card, David and Alan B. Krueger. "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania". *The American Economic Review* 84, No. 4 (1994): 772-793.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. "The Effect of Minimum Wages On Low-Wage Jobs". *The Quarterly Journal of Economics* 134, No. 3 (2019): 1405-1454.

Diamond, Rebecca. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000". *American Economic Review* 106, No. 3 (2016): 479-524.

Dube, Arindrajit. "Impacts of minimum wages: review of the international evidence", HM Treasury Report, (2019) https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/844350/impacts_of_minimum_wages_review_of_the_international_evidence_Arindrajit_Dube_web.pdf

Dube, Arindrajit, Suresh Naidu, and Michael Reich. "The Economic Effects of a Citywide Minimum Wage." *ILR Review* 60, No. 4 (2007): 522–43.

Dube, Arindrajit, T. William Lester, and Michael Reich. "Minimum Wage Effects across State Borders: Estimates Using Contiguous Counties." *The Review of Economics and Statistics* 92, No. 4 (2010): 945-964.

Dube, Arindrajit, T. William Lester, and Michael Reich. "Minimum Wage Shocks, Employment Flows, and Labor Market Frictions", *Journal of Labor Economics*, 2016, vol. 34, issue 3, 663 - 704

Dustmann, Christian, Attila Lindner, Uta Schönberg, Matthias Umkehrer, and Philipp Vom Berge. "Reallocation Effects of the Minimum Wage: Evidence from Germany". mimeo, 2020.

Economic Policy Institute (EPI). "Worker Rights Preemption in The U.S. A Map of the Campaign to Suppress Worker Rights in The States", 2018. <https://www.epi.org/preemption-map/>.

Fajgelbaum, Pablo D, Eduardo Morales, Juan Carlos Suárez Serrato, and Owen Zidar. "State Taxes and Spatial Misallocation". *The Review of Economic Studies* 86, No. 1 (2019): 333–376.

Harasztsosi, Peter, and Attila Lindner. "Who Pays for the Minimum Wage?". *American Economic Review* 109, No. 8 (2019): 2693-2727.

Kline, Patrick, and Enrico Moretti. "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs", (2014), *Annual Review of Economics*, 6:1, 629-662

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Emma Van Inwegen, Jacob Vigdor, and Hilary Wething. "Minimum Wage Increases, Wages, and Low-Wage Employment: Evidence from Seattle". No. w23532. National Bureau of Economic Research, 2017.

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Emma Van Inwegen, Jacob Vigdor, and Hilary Wething. "Minimum Wage Increases and Individual Employment Trajectories". No. w25182. National Bureau of Economic Research, 2018.

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Emma van Inwegen, Jacob Vigdor, and Hilary Wething. "Minimum Wage Increases and Low-Wage Employment: Evidence from Seattle". (2020)

Jardim, Ekaterina, and Emma Van Inwegen. "Payroll, Revenue, and Labor Demand Effects of the Minimum Wage". No. 19-298. Upjohn Institute Working Paper, 2019.

Lemos, Sara. "A Survey of the Effects of the Minimum Wage on Prices." *Journal of Economic Surveys* 22, no. 1 (2008): 187-212.

Lordan, Grace, and David Neumark. "People Versus Machines: The Impact of Minimum Wages on Automatable Jobs". *Labour Economics* 52 (2018): 40-53.

Luca, Dara Lee, and Michael Luca. "Survival of the Fittest: The Impact of the Minimum Wage on Firm Exit". No. w25806. National Bureau of Economic Research, (2019).

MaCurdy, Thomas. "How Effective Is the Minimum Wage at Supporting the Poor?". *Journal of Political Economy* 123, No. 2 (2015): 497-545.

McGovern Tony. "United States General Election Presidential Results by County from 2008 to 2016", (2016).
https://github.com/tonmcg/US_County_Level_Election_Results_08-16

Moe, Lina, James Parrott, and Yannet Lathrop. "New York City's \$15 Minimum Wage and Restaurant Employment and Earnings", New York City, NY: New York City Affairs at the New School and the National Employment Law Project (2019)

Nadler, Carl, Sylvia A. Allegretto, Anna Godøy and Michael Reich. "Are Local Minimum Wages Too High?" *IRLE Working Paper* #102-19, 2019.

Neumark, David, and William Wascher. "Employment Effects of Minimum and Subminimum Wages: Panel Data on State Minimum Wage Laws." *ILR Review* 46, no. 1 (1992): 55-81.

Neumark, David, and William L. Wascher. "Minimum wages". MIT press, 2008.

Portugal, Pedro, and Ana Rute Cardoso. "Disentangling the Minimum Wage Puzzle: An Analysis of Worker Accessions and Separations." *Journal of the European Economic Association* 4, no. 5 (2006): 988-1013.

Potter, Nicholas. "Measuring the Employment Impacts of the Living Wage Ordinance Santa Fe, New Mexico." University of New Mexico, Bureau of Business and Economic Research. (2006).

Rapoport, Abby. "Blue Cities, Red States". *The American Prospect*, (2016). <https://prospect.org/economy/blue-cities-battle-red-states/>.

Reich, Michael, Ken Jacobs, Annette Bernhardt, and Ian Perry "The Proposed Minimum Wage Law for Los Angeles: Economic Impacts and Policy Options." Briefing Paper. Center on Wage and Employment Dynamics, UC Berkeley: Institute for Research on Labor and Employment. (2015) Accessed at <http://irle.berkeley.edu/files/2015/The-ProposedMinimum-Wage-Law-for-Los-Angeles.pdf> (January 11, 2017).

Schmitt, John, and David Rosnick. "The Wage and Employment Impact of Minimum-Wage Laws in Three Cities." Center for Economic and Policy Research. (2011).

Simonovits, Gábor, and Julia Payson, "Locally Controlled Minimum Wages Are No Closer to Public Preferences", mimeo, (2020)

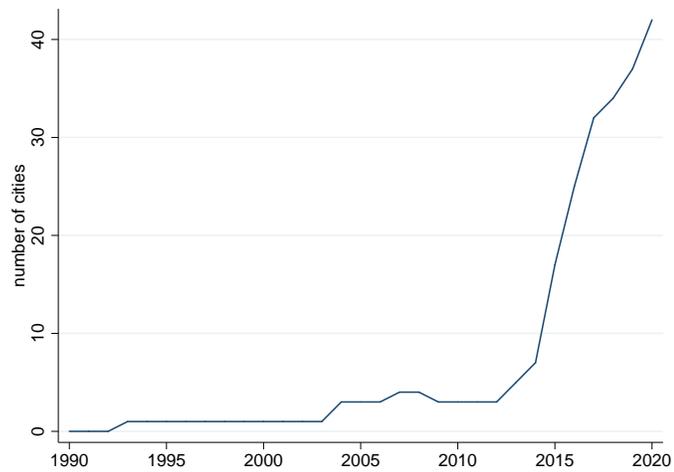
Tiebout, Charles M. "A Pure Theory of Local Expenditures". *Journal of Political Economy* 64, No. 5 (1956): 416-424.

Tijdens, K.G. & van Klaveren, M. "Understanding the Drivers of Minimum Wage-Setting: An Analysis of 146 countries." (2019) ILO's 6th RDW Conference in Geneva, 8-10 July 2019

ONLINE APPENDIX

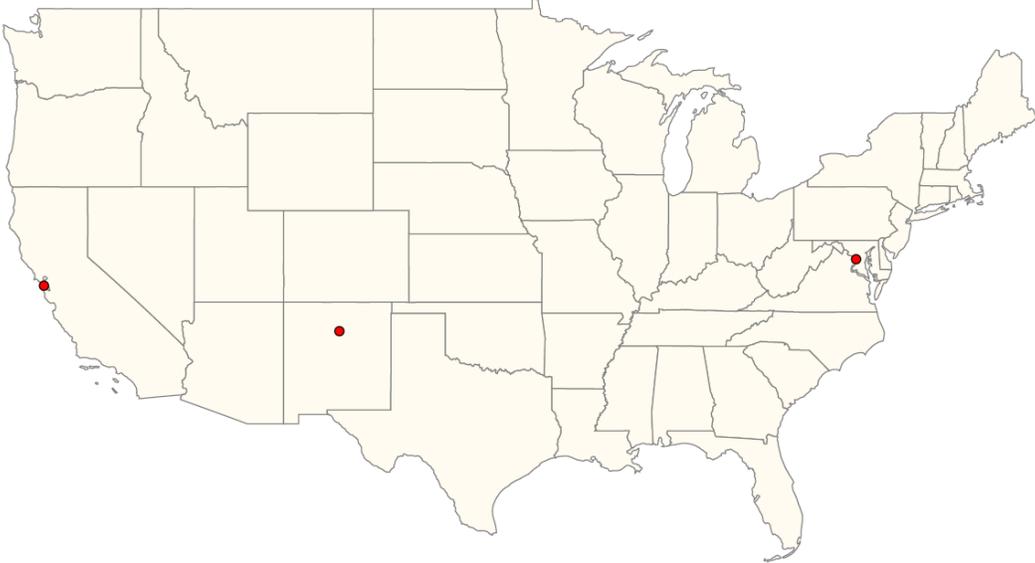
A. Additional Tables and Figures

Figure A.1: The Number of City-level Minimum Wage Changes Over Time

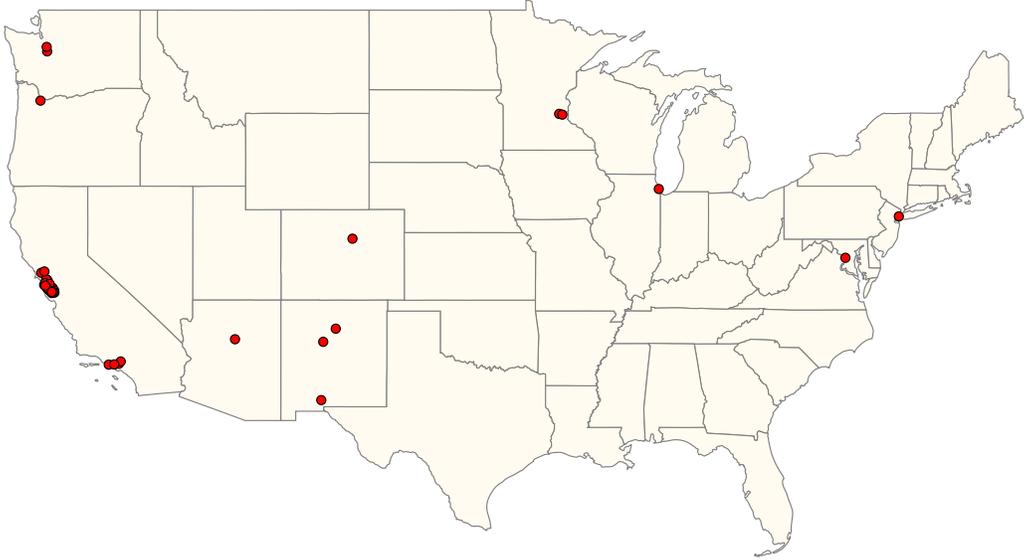


Notes: The figure shows the number of cities having minimum wages above the state-level one in each year between 1990 and 2020.

Figure A.2: City-level Minimum Wages Across the United States



(a) 2010



(b) 2020

Notes: The figure shows the cities having minimum wages above the state-level one in 2010 and in 2020.

Table A.1: Basic Characteristics of Cities with and without Minimum Wages – Unweighted by Population

	(1)	(2)	(3)
	Cities with MW		Cities without a MW
	Pop < 100k	Pop > 100k	Pop > 100k
Number of cities	20	22	249
Population (in thousand)	55.2	1034.4	266.9
Nominal MW in 2020	14.74	13.92	9.79
Planned MW by 2022	15.94	15.16	
Mean wage	42.58	33.92	24.63
Median wage	31.10	25.17	18.38
Cost of living index (RPI)	123.5	117.1	101.2
MW to mean wage	0.36	0.42	0.40
MW to median wage	0.50	0.57	0.53
Share Democrats	0.73	0.73	0.54
College share	0.46	0.44	0.30
Unemployment rate	3.94	4.81	5.30
Industry shares			
Restaurants	0.06	0.07	0.08
Retail	0.09	0.09	0.11
Manufacturing	0.09	0.08	0.09
Construction	0.05	0.05	0.06
Health and social care	0.11	0.12	0.14
Professional services	0.14	0.14	0.07

Notes: This table reports the statistics reported in Table 2, but without population weights.

Own calculations based on the 2018 American Community Survey. Cost of living index is the MSA level RPP measured in 2017. The share of democrats in the 2016 presidential election comes from Tony McGovern's website.

B. Data

The city-level and state-level minimum wage information comes from various sources. For city-level minimum wages, we rely on Vaghul and Zipperer (2016), UC Berkeley Labor Center (2020), EPI (2020) and the specific local ordinances of each city. For state-level minimum wages, we rely on Vaghul and Zipperer (2016) and EPI (2020). Minimum wages refer to the ones in effect at the end of the year. A notable exception is New York City, which usually changes minimum wages on 31st of December, where we report the minimum wage as if it were instituted in the following year. For the planned minimum wages in 2022, we use either the nominal values when stated in the ordinance or obtain them following the city indexation rules. For indexation we use the average growth rate in regional CPI between 2014 and 2019.

The main dataset used for the analysis is the American Community Survey (ACS) 1-Year Public Use Microdata Sample (PUMS) files of United States Population Records for 2012, 2013, 2017 and 2018. This data source contains individual-level information and we exploit its most detailed unit of geography which is the Public Use Microdata Area (PUMA) of residence. In order to get statistics at the city level, we weight by the population shares of each city in each PUMA which are obtained from Missouri Census Data Center (2014). We complement this with other ACS aggregate variables at the city level, namely employment and population, which are obtained from the ACS 1-Year Summary Files. For cities with less than 65,000 inhabitants, the aggregate information is obtained from the ACS 5-Year Summary Files.

The mean and median wage at the city level are constructed using the ACS variables WAGP (annual earnings), WKW (annual weeks worked), WKHP (annual usual hours worked). Given that WKHP is discrete, we take the mean value of each category except for the highest one where we assume 52 weeks worked for everyone reporting 50 to 52 weeks. We winsorize the wage variable (1 and 99 percentiles). Comparison of our ACS variables at the city level with their counterparts at the MSA level from the Occupation Employment Statistics (OES) yields a correlation of around 0.67. In order to compute bin-by-bin employment, we deflate wages using the US city average CPI from the Bureau of Labor Statistics.

In addition, we also consider variables regarding cost of living and electoral outcomes from other sources. For cost of living we use Regional Price Parities (RPP) data at the MSA level, which is obtained from the Bureau of Economic Analysis (BEA). Regarding political outcomes, we use the share of people voting for the Democratic party in the 2016 election, which we take from McGovern (2016). This information is at the county level, so we construct our city level statistics weighting by the share of each city in each county from Missouri Census Data Center (2014).

C Existing Estimates From the Literature in Table 3

In Table 3 we report estimates on city-level minimum wage changes from the extant literature. The following table summarizes the key sources of the estimates. In some cases, we had to calculate the own-wage elasticity as it was not directly reported. In those cases, we calculate the standard errors using the delta method and we assume that the non-diagonal elements of the variance-covariance matrix are zero.

Paper	City	Outcome	Wage	Note
Allegretto et al. (2018) - restaurants	Average of 6 cities	Wage	0.02 [0.01,0.03]	Table 4, col 3. CI clustering at city/county level
		Employment	-0.01 [-0.02,0.01]	Table 4, col 6. CI clustering at city/county level
		Elasticity	-0.23 [-0.78,0.32]	Computed using wage and employment estimates. CI obtained using the delta method
	Oakland	Wage	0.10 [0.06,0.14]	Table 5, col 3
		Employment	0.07 [0.03,0.11]	Table 5, col 3
		Elasticity	0.71 [0.20,1.22]	Computed using wage and employment estimates. CI obtained using the delta method
	San Francisco	Wage	0.06 [0.04,0.09]	Table 5, col 4
		Employment	0.01 [-0.05,0.07]	Table 5, col 4
		Elasticity	0.14 [-0.83,1.11]	Computed using wage and employment estimates. CI obtained using the delta method
	San Jose	Wage	0.11 [0.06,0.15]	Table 5, col 5
		Employment	0.00 [-0.06,0.06]	Table 5, col 5
		Elasticity	-0.02 [-0.5,0.53]	Computed using wage and employment estimates. CI obtained using the delta method

...continued from the previous page

Paper	City	Outcome	Wage	Note
Allegretto et al. (2018) - restaurants	Seattle	Wage	0.04 [0.02,0.07]	Table 5, col 6
		Employment	0.01 [-0.05,0.07]	Table 5, col 6
		Elasticity	0.20 [-1.16,1.57]	Computed using wage and employment estimates. CI obtained using the delta method
Dube, Reich, Suresh (2007) - restaurants	San Francisco	Wage	0.14 [0.06,0.22]	Table 2, col 1. Divide estimate by pretreatment mean in Table 1, col 1. CI computed from reported SE.
		Employment	0.04 [-0.12,0.2]	Table 7, col 1. CI computed from reported SE.
		Elasticity	0.29 [-0.34,0.91]	Computed using wage and employment estimates. CI obtained using the delta method
Jardim et al. (2017, 2018) - jobs below \$19	Seattle, worker level	Wage	0.15 [0.14,0.17]	2018 WP, Table 5, col 7 (Divide DDD estimate by pretreatment mean in Table 5, col 1). CI computed from reported SE.
		Employment	0.01 [-0.01,0.02]	2018 WP, Table 6, col 7 (DDD estimate). CI computed from reported SE.
		Elasticity	0.03 [-0.04,0.11]	Computed using wage and employment estimates. CI obtained using the delta method
	Seattle, aggregate level	Wage	0.03 [0.03,0.03]	2017 WP, Table 5, col 1 (2016.3). CI computed from reported p-value.
		Employment	-0.07 [-0.14,-0.01]	2017 WP, Table 6, col 3 (2016.3). CI computed from reported p-value.
		Elasticity	-2.18 [-4.14,-0.22]	Computed using wage and employment estimates. CI obtained using the delta method

...continued from the previous page

Paper	City	Outcome	Wage	Note
Schmitt and Rosnick (2011) -fast food	San Francisco	Wage	0.10 [0.05,0.14]	Table 4, cols 1, 2 and 3 (three years). Computed by averaging the point estimates and standard errors over the three specifications.
		Employment	0.00 [-0.33,0.34]	Table 4, cols 1, 2 and 3 (three years). Computed by averaging the point estimates and standard errors over the three specifications.
		Elasticity	0.03 [-3.45,3.5]	Table 4, cols 1, 2 and 3 (three years). CI obtained using the delta method
	Santa Fe	Wage	0.07 [0.02,0.12]	Table 4, col 5 (three years)
		Employment	-0.08 [-0.29,0.13]	Table 4, col 5 (three years)
		Elasticity	-1.20 [-4.36,1.96]	Table 4, col 5 (three years). CI obtained using the delta method

D. Calculation of Wage Effects

We follow the approach developed in Cengiz et al. (2019) to calculate the wage effects for workers likely affected by the policy. In particular, the percentage change in wages of affected workers is defined as:

$$\% \Delta w = \frac{\% \Delta wb - \% \Delta e}{1 - \% \Delta e} = \left(\frac{b_{-1}}{wb_{-1}} \right) \left(\frac{wb_{-1} + \Delta wb}{b_{-1} + \Delta e} \right)$$

Here Δwb is the change in wage bill under \$20/hour, Δe is change in employment under \$20/hour, wb_{-1} is the wage bill under the new minimum wage in 2012, while b_{-1} is employment below the new minimum wage in 2012. All of these are in per-capita terms.

This expression can equivalently be calculated using changes in the conditional average wage $\Delta \bar{w}$ (i.e., the change in the average wage conditional on earning under \$20/hour) and changes in employment. Denoting employment below \$20 in 2012 as e_{-1} and the conditional average wage under \$20 in 2012 as \bar{w}_{-1} , we can rewrite the above expression as:

$$\% \Delta w = \left(\frac{b_{-1}}{wb_{-1}} \right) \left(\frac{wb_{-1} + \Delta \bar{w}(e_{-1} + \Delta e) + \Delta e \cdot \bar{w}_{-1}}{b_{-1} + \Delta e} \right)$$

This is the expression we estimate in the paper. We separately estimate regressions with the conditional wage and employment effect as outcomes; we calculate standard errors using the delta method (`suest` command in Stata). The above expression also highlights that it is insufficient to simply consider the percentage change in the conditional wage below \$20, i.e., $\Delta \bar{w} / \bar{w}_{-1}$. This is because we are adding many potentially unaffected, higher wage workers earning below \$20, and we need to account for this dilution effect. For example, in our sample, the change in conditional wage under \$20 is around 2% while our estimates for the affected wage is around 4%. By using information about the location of the minimum wage relative to \$20, our approach accounts for this dilution.¹¹

¹¹ Jardim et al. (2017) define the wage effect as the change in the conditional wage under \$19. This is likely to understate the wage effect for affected workers for reasons described above.

E. Choice of Controls and Specifications in Estimation of Employment Effects.

Our preferred specification controls for a wide set of baseline (pre-treatment) city characteristics including college share, wage percentiles, employment counts per capita by wage bins, 1-digit industrial composition, and cost-of-living. As discussed in the main paper, inclusion of these controls eliminates the spurious “upper tail” effects on employment which provides important validation for the specification. Moreover, after accounting for these differences we find that there is little impact of city minimum wages on low-wage jobs, while there is a clear increase in low-wage pay. We take this to suggest it is very important to account for systematic differences between cities with and without minimum wages in order to draw conclusions about causal effects of the policies. Moreover, inclusion of these controls does not somehow throw out “too much variation” in minimum wages to be able to detect an impact; inclusion of controls actually increases precision via soaking up error variance.

At the same time, given the large set of controls included, a natural question is whether the findings are being driven by all of these possible factors, or whether a lower dimensional set of controls produces similar findings. Substantively, it is also interesting to better understand which of the differences between the two sets of cities really drives the bias in this case.

To unpack these questions, here we show how the estimates are impacted by alternative sets of controls. We show estimates from four specifications using alternative sets of controls. In all cases, we report the treatment effect (percentage point change) on employment per capita (1) below \$20 (“affected employment”), (2) at or above \$20 (“upper tail employment”) as well as the implied own-wage elasticity (OWE) for affected employment.

Column 1 shows the impact for the simple two-way fixed effects specification with no additional controls. The estimates suggest a sizable reduction in affected employment (-0.009 with an implied OWE of -1.102) but an even larger increase in upper-tail employment (0.015) which is implausible. In contrast, column 4 shows the estimates from the full set of controls on pre-treatment characteristics interacted with post, where the impact on affected employment (-0.001 with an

implied OWE of -0.116) and upper tail employment (0.004) are both small and not distinguishable from zero. As it turns out, there are some key differences between the two sets of cities which are critical to control for. In column 2, we show the estimates with a single additional covariate – the share of employment in professional services in the pre-treatment period (2012), interacted with the post-treatment dummy. As we documented in Table 2 in the main paper, this is the key sectoral difference between the cities with and without a minimum wage. Inclusion of this one variable substantially reduces the upper tail estimate from 0.15 to 0.009, and entirely erases the estimated affected employment loss from -0.009 to 0.000. The implied OWE falls in magnitude to 0.058. This highlights that minimum wage cities are more specialized towards high wage sectors and were also likely to experience generally greater wage growth over this period which can lead to a bias when counting changes in jobs below \$20.

However, the choice of any single variable naturally raises the question: what would have happened if we had picked different variables, or combination of variables? To approach the problem in a more systematic manner, we use the Double-Selection/Post-Lasso method of picking controls in column (3), which is a data-driven way of choosing covariates. The basic idea is that if the conditional independence assumption holds under the full set of available covariates, but there are many more such covariates than ones that “matter” (i.e. the true CIA is on a sparse set of controls), we can use regularization to hone in on the relevant covariates. As shown in Belloni et al. (2014), one appealing way is to find covariates that “matter” either for predicting the treatment (city minimum wages), or the outcome (affected employment), and using the L1 norm of Lasso to search for a sparse set of such predictors. When we apply the double selection criteria, we end up selecting a total of 12 covariates, which are the 2012 values of: college share, cost of living, EPOP, 7 industry shares, employment share below \$10/hour, and the 90th percentile wage. We find that this data driven approach of covariate selection produces no upper tail effects (even though we weren’t actually trying to predict that per-se, so this is a valid falsification test), and suggests an OWE of 0.09 (s.e. = 0.400), which is quite similar (though slightly less precise) than our baseline specification with full set of controls.

Overall, the totality set of evidence strongly suggests that inability to control for key features of minimum wage cities can produce serious challenges in drawing causal inference. And once we

apply standard tools like controlling for pre-treatment labor market characteristics (either using an expansive approach, or a data-driven approach like double-selection) we find that city minimum wages to date largely raised wages and the bottom without harming employment prospects.

Table D.1. Impact of City Minimum Wages on Affected and Upper Tail Employment – Alternative Specifications

	(1)	(2)	(3)	(4)
Employment <\$20	-0.009** (0.004)	0.000 (0.003)	0.000 (0.003)	-0.001 (0.003)
Employment ≥ \$20	0.015*** (0.006)	0.009* (0.005)	0.004 (0.005)	0.004 (0.004)
Own-wage elasticity (employment <\$20)	-1.102** (0.545)	0.058 (0.400)	0.089 (0.400)	-0.116 (0.379)
<i>Controls:</i>				
None	Y			
Prof service share control		Y		
DSPL controls			Y	
All controls				Y

Notes: The table shows employment changes from our regression analysis (see equation 1) exploiting 21 city-level minimum wage changes between 2012-2018. The estimated average employment changes are shown for under \$20 and \$20 and above bins, relative to the employment in the city in 2012. Column 1 shows the estimates with time and city fixed effects but without controlling for the set of 2012 covariates interacted with post dummy. Column 2 additionally controls for professional and business service employment share in 2012 interacted with the post dummy. Column 4 controls for 2012 values of cost of living, employment to population ratio, average wage, wage percentiles, shares of employment below wage cutoffs, and 1-digit level sectoral shares, all interacted with the post dummy. Column 3 controls for 2012 values of controls picked by the Double-Selection/Post-Lasso procedure, interacted with post dummy. Results are weighted by the population size of the city. Standard errors are clustered by city.

References

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. "The Effect of Minimum Wages On Low-Wage Jobs". *The Quarterly Journal of Economics* 134, No. 3 (2019): 1405-1454.

Economic Policy Institute. "Minimum Wage Tracker", (2020). Accessed at <https://www.epi.org/minimum-wage-tracker/>

Jardim, Ekaterina, Mark C. Long, Robert Plotnick, Emma Van Inwegen, Jacob Vigdor, and Hilary Wething. "Minimum Wage Increases, Wages, and Low-Wage Employment: Evidence from Seattle". No. w23532. National Bureau of Economic Research, 2017.

McGovern Tony. "United States General Election Presidential Results by County from 2008 to 2016", (2016). Accessed at https://github.com/tonmcbg/US_County_Level_Election_Results_08-16

Missouri Census Data Center. "Geocorr 2014: Geographic Correspondence Engine" (2014). Accessed at <http://mcdc.missouri.edu/applications/geocorr2014.html>

UC Berkeley Center for Labor Research and Education. "Inventory of US City and County Minimum Wage Ordinances", (2020). Accessed at <http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/>

Vaghul, Kavya, and Ben Zipperer. "Historical state and sub-state minimum wage data." *Washington Center for Equitable Growth Working Paper* 90716 (2016).