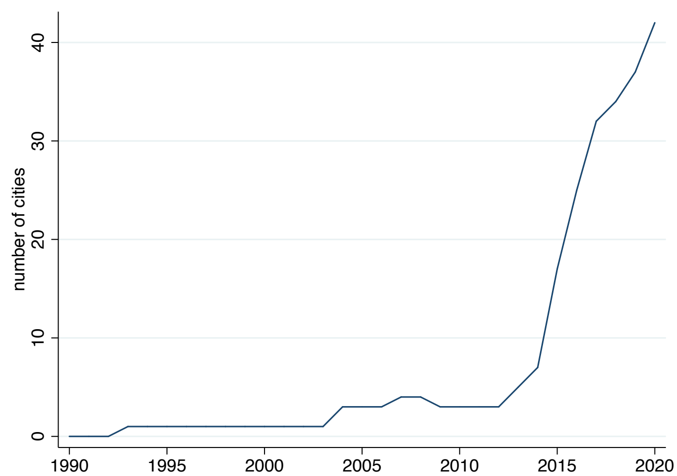
ONLINE APPENDIX

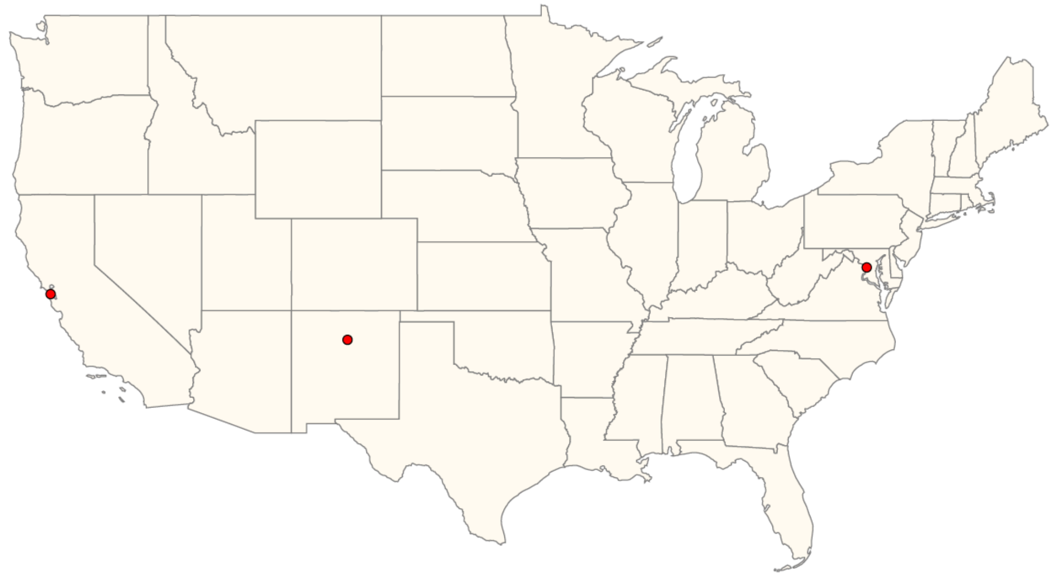
A. Additional Tables and Figures

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

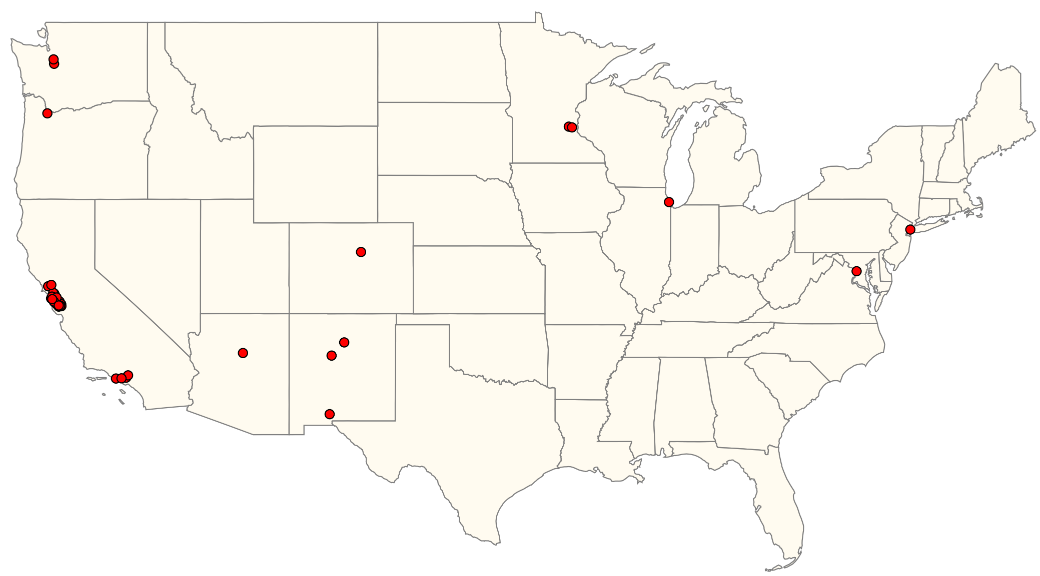


Notes: The figure shows the number of cities having minimum wages above the state-level one in each year between 1990 and 2020.

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.

Table A.2: Cities with Minimum Wage in 2020

Cities	MW in 2020	Planned nominal MW in 2022	Kaitz index
1. Seattle, WA	16.39	17.19	0.57
2. SeaTac*, WA	16.34	16.79	0.67
3. Emeryville, CA	16.30	17.92	0.65
4. Sunnyvale, CA	16.05	17.05	0.39
5. Mountain View, CA	16.05	17.05	0.34
6. Berkeley, CA	15.59	17.15	0.60
7. San Francisco, CA	15.59	17.05	0.45
8. Santa Clara, CA	15.40	15.85	0.43
9. Palo Alto, CA	15.40	15.85	0.33
10. Los Altos, CA	15.40	16.40	0.33
11. Redwood, CA	15.38	15.87	0.42
12. San Mateo, CA	15.38	16.32	0.39
13. El Cerrito, CA	15.37	16.31	0.64
14. Cupertino, CA	15.35	16.35	0.27
15. San Jose, CA	15.25	16.20	0.56
16. South San Francisco, CA	15.00	15.90	0.53
17. Richmond, CA	15.00	16.40	0.75
18. Petaluma, CA	15.00	15.90	0.62
19. Milpitas, CA	15.00	16.50	0.50
20. Menlo Park, CA	15.00	15.90	0.48
21. Belmont, CA	15.00	16.41	0.40

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Cities	MW in 2020	Planned nominal MW in 2022	Kaitz index
22. New York, NY	15.00	15.00	0.66
23. Pasadena, CA	14.25	14.94	0.63
24. Los Angeles, CA	14.25	15.72	0.75
25. Santa Monica, CA	14.25	15.36	0.44
26. Malibu, CA	14.25	15.72	0.36
27. Oakland, CA	14.14	15.01	0.56
28. Washington, DC	14.00	14.50	0.48
29. San Leandro, CA	14.00	15.00	0.52
30. Daly, CA	13.75	14.60	0.57
31. Sonoma, CA	13.50	16.00	0.60
32. Fremont, CA	13.50	15.92	0.36
33. Alameda, CA	13.50	15.48	0.50
34. Flagstaff, AZ	13.00	15.50	0.81
35. Chicago, IL	13.00	13.60	0.65
36. Denver, CO	12.85	15.87	0.58
37. St. Paul, MN	12.50	15.00	0.66
38. Portland, OR	12.50	14.75	0.56
39. Minneapolis, MN	12.25	15.00	0.61
40. Santa Fe, NM	11.80	12.65	0.62
41. Las Cruces, NM	10.25	10.70	0.80
42. Albuquerque, NM	9.35	9.60	0.55

Notes: Kaitz index is the minimum wage divided by the median wage. The median wages of all workers is calculated from the 2018 wave of the American Community Survey and it is 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.*

B. Data Summary

The city-level and state-level minimum wage information comes from various sources. For city-level minimum wages, we rely on Vaghul and Zipperer (2019), 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 (2019) 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 (UC Census Bureau, 2018a). 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 (UC Census Bureau, 2018b). 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 (Bureau of Economic Analysis, 2017). 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 [-0.57,0.53]	Computed using wage and employment estimates. CI obtained using the delta method

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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, Naidu, Reich (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

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Paper	City	Outcome	Wage	Note
Moe, Parrott, Lathrop (2019) – full service restaurants	New York City	Wage	0.09 [0.03,0.16]	Figure 9. Standard error is obtained using Randomization Inference. For each control city with no minimum wages, we take the difference between the city's wage growth and the average wage growth in the other 11 cities in the control. To obtain 90th percentile confidence intervals we multiply the standard deviation of this difference by 1.645.
		Employment	0.03 [-0.16,0.22]	Figure 8. Standard error is obtained using Randomization Inference. For each control city with no minimum wages, we take the difference between the city's employment growth and the average employment growth in the other 11 cities in the control. To obtain 90th percentile confidence intervals we multiply the standard deviation of this difference by 1.645.
		Elasticity	0.29 [-1.74,2.32]	Computed using wage and employment estimates. CI obtained using the delta method.
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 $\Delta\overline{\mathrm{w}}$ (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 $\overline{\mathrm{w}}_{-1}$, we can rewrite the above expression as:

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

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., $\Delta\overline{\mathrm{w}}/\overline{w}_{-1}$. 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.[1]

[1] 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**	0.000	0.000	-0.001
	(0.004)	(0.003)	(0.003)	(0.003)
Employment ≥ $20	0.015***	0.009*	0.004	0.004
	(0.006)	(0.005)	(0.005)	(0.004)
Own-wage elasticity (employment <$20)	-1.102**	0.058	0.089	-0.116
	(0.545)	(0.400)	(0.400)	(0.379)
Controls:				
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.

F. Data Access and Construction

Here we provide access instructions and location details of the sources used to build our datasets contained in the replication kit. As described in the readme.txt file, the following groups of datasets are used:

- Summary and PUMS files from the 2012, 2013, 2017 and 2018 American Community Survey:
    - Summary files (US Census Bureau, 2018a): Downloaded for every state, year and sequence. The sequence numbers needed are: 3 and 115 in 2012; 3 and 107 in 2012; 3 and 103 in 2017; 3 and 103 in 2018. For example, to get the sequence number 3 file for Alabama in 2012, one should go to https://www2.census.gov/programs-surveys/acs/summary_file/2018/data/1_year_seq_by_state/Alabama/20181al0003000.zip , download the file and extract e20181al0003000.txt. All other files are accessed in a similar way changing year, sequence and state in the path provided.

    - PUMS files (US Census Bureau, 2018b): Downloaded for every year. For example, to get data for 2018, one should go to https://www2.census.gov/programs-surveys/acs/data/pums/2018/1-Year/csv_pus.zip , download the file and extract psam_pusa.csv and psam_pusb.csv. All other files are accessed in a similar way changing year in the path provided.

- Crosswalks between different geographical units: Obtained using the application Geocorr 2014 from Missouri Census Data Center (2014). This application allows the user to retrieve correspondences between geographical units of different levels. In our case, we get relations between cities and PUMAs and counties and PUMAs. For example, to get the information on the share of each city in Alabama contained in each PUMA, one should go to https://mcdc.missouri.edu/applications/geocorr2014.html , select "Alabama" as state, select "Place (City, Town, Village, CDP, etc.)" from 2014 source geography, "PUMA" from 2012 target geography and then click "Run request". This generates a file from where we select the cities of interest. This process must be repeated for every state (or groups of few states, more than that may produce server errors) in order to create the final file. Similarly, for the case of counties, the same process must be repeated selecting "County" instead of "Place (City, Town, Village, CDP, etc.)" from the 2014 source geographies.

- City Minimum Wages 1993-2020: We build these datasets combining three main data sources:
    - Vaghul and Zipperer (2019): One should go to https://github.com/benzipperer/historicalminwage/releases/download/v1.2.0/mw_substate_excel.zip , download and extract mw_substate_annual.xlsx.
    - UC Berkeley Labor Center (2020): Obtained directly from https://laborcenter.berkeley.edu/wp-content/uploads/2020/10/UCB-Labor-Center-city-min-wage-inventory.xlsx
    - Economic Policy Institute (2020): Obtained from the "Minimum Wage Tracker" available at https://www.epi.org/minimum-wage-tracker/. This source provides a map with information on city minimum wages by state. For example, to get data for California, one should click on California and then select the city of interest under "Areas with different minimum wages". This process must be repeated for all cities in all states.
- State Minimum Wages 2012-2018 and 2020: We build these datasets combining two main data sources:
    - Vaghul and Zipperer (2019): One should go to https://github.com/benzipperer/historicalminwage/releases/download/v1.2.0/mw_state_excel.zip , download and extract mw_state_annual.xlsx.
    - Economic Policy Institute (2020): Obtained from the "Minimum Wage Tracker" available at https://www.epi.org/minimum-wage-tracker/. This source provides a map with information on state minimum wages. For example, to get data for California, one should just click on California. This process must be repeated for all states.
- Votes information from 2016 election: Obtained from McGovern (2016), available at https://github.com/tonmcg/US_County_Level_Election_Results_08-20/blob/master/2016_US_County_Level_Presidential_Results.csv
- Cost of living: Regional Price Parities (RPP) at the MSA level (Bureau of Economic Analysis, 2017). One should go to https://apps.bea.gov/iTable/iTable.cfm?reqid=70&step=1&acrdn=8 , click on "Regional Price Parities (RPP)", then "MARPP – Regional Price Parities by MSA". Select "all areas" and "RPPs: all items", year "2017" and download the file produced. Finally, to get the index for every city of interest one needs to match each city with its MSA (information on the MSA for a given city can be found, for example, on www.citypopulation.de).

- Geographical coordinates: Obtained from Picard and Stepner (2015). The files can be downloaded from http://fmwww.bc.edu/repec/bocode/g/geo2xy_us_coor.dta and http://fmwww.bc.edu/repec/bocode/g/geo2xy_us_data.dta
- State abbreviations: Obtained from US Census Bureau (2020). One should go to https://www.census.gov/library/reference/code-lists/ansi/ansi-codes-for-states.html and click on "FIPS Codes for the States and District of Columbia".
- Wage and employment growth 2013-2018 in 13 US cities: Obtained from Figures 8 and 9, full-service restaurants in Moe, Parrott, Lathrop (2019).

References

Bureau of Economic Analysis. “Regional Price Parities, MSA level” (2017) Accessed at https://apps.bea.gov/iTable/iTable.cfm?reqid=70&step=1&acrdn=8

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/tonmcg/US_County_Level_Election_Results_08-20/blob/master/2016_US_County_Level_Presidential_Results.csv

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

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)

Picard, Robert and Michael Stepner. “GEO2XY: Stata module to convert latitude and longitude to xy using map projections” (2015) Accessed at https://ideas.repec.org/c/boc/bocode/s457990.html

UC Berkeley Labor Center. “Inventory of US City and County Minimum Wage Ordinances”, (2020). Accessed at https://laborcenter.berkeley.edu/wp-content/uploads/2020/10/UCB-Labor-Center-city-min-wage-inventory.xlsx

US Census Bureau. “American Community Survey – 1 year Summary Files 2012, 2013, 2017, 2018” (2018a) Accessed at https://www2.census.gov/programs-surveys/acs/summary_file/

US Census Bureau. “American Community Survey – 1 year Public Use Microdata Samples 2012, 2013, 2017, 2018” (2018b) Accessed at https://www2.census.gov/programs-surveys/acs/data/pums/

US Census Bureau. “FIPS Codes for the States and District of Columbia” (2020) Accessed at https://www.census.gov/library/reference/code-lists/ansi/ansi-codes-for-states.html

Vaghul, Kavya, and Ben Zipperer. "Historical state and sub-state minimum wage data." Version 1.2.0 , (2019) Accessed at https://github.com/benzipperer/historicalminwage/releases/tag/v1.2.0