Seattle's Local Minimum Wage and Earnings Inequality

Mark C. Long
University of Washington
marklong@uw.edu

Keywords
Minimum Wage, Local Policy, Inequality

JEL Codes
J31, J38, H79

Abstract:
During the past six years, a wave of local minimum wage laws passed in the United States with policymakers and advocates framing the policy as a means of reducing income inequality. This report evaluates whether one of the first of these efforts, Seattle's $15 minimum wage ordinance, lowered inequality of earnings of workers in the city. I find that inequality among workers who earned less than the city's median wage was modestly reduced, yet overall earnings inequality substantially increased during the period in which the ordinance was phased in, likely for reasons unrelated to the minimum wage law.

Introduction

There is widespread concern about the growth in income inequality in the United States (Piketty and Saez 2003; Piketty, Saez, and Zucman 2018; CBO 2018; Fixler, Gindelsky, and Johnson 2019; Auten and Splinter 2019) and stagnation in earnings at the bottom of the distribution (Piketty, Saez, and Zucman 2018). Between 1980 and 2014, pre-tax income fell 25% for those in the bottom fifth of the income distribution (Piketty, Saez, and Zucman 2018). These concerns were accelerated by the Great Recession and the Occupy Wall Street protest movement, "sparking a national worker-led movement to raise the minimum wage to $15 an hour" (Levitin 2015). Momentum in these causes were seen in cities where rising housing costs coupled with stagnant lower wages were increasingly making living unaffordable for less-skilled workers.

On March 27th, 2014, a highly attended public "Income Inequality Symposium" was assembled by Seattle Mayor Ed Murray and featured a full day of speakers, including myself. The Symposium was billed as "part of the public engagement process being employed by the Income Inequality Advisory Committee which is charged with delivering to the Mayor a set of actionable recommendations to raising the minimum wage in Seattle by the end of April 2014" (Murray 2014). One of the "three primary goals for the Symposium" was to "(e)stablish Seattle as a national leader in developing strategies to address income inequality" (Murray 2014).

During the following month, Seattle's city council approved the establishment of a local minimum wage, the largest in the U.S. to that date. Beginning on April 1st, 2015, for large employers that did not pay benefits, the top minimum wage in the city became $11 and rose to $13 in 2016 and $15 in 2017, thereafter indexed to account for inflation, with slower rates of phase in to $15 for smaller employers and larger employers that paid benefits (Seattle Office of Labor Standards, no date). Over fifty cities and counties enacted local minimum wages during the years 2014 to 2019, including Chicago, Los Angeles, Minneapolis, Oakland, San Diego, San Francisco, San Jose, and Washington D.C. (UC Berkeley Labor Center 2019).

This paper answers the following question: Did Seattle's minimum wage ordinance cause a reduction in earning inequality among the city's workers? I first evaluate effects on earnings inequality among workers paid below the City's median wage, followed by an analysis of earnings inequality among all workers. As I demonstrate, there are changes as the very top-end of the earnings distribution that are unlikely to be due to the minimum wage ordinance.

Seattle's Wage Distribution

The Minimum Wage Study at the University of Washington was contracted by the City of Seattle to conduct an evaluation of the effects of the city's minimum wage ordinance. To conduct this research, our team obtained quarterly Unemployment Insurance (UI) administrative records on all Washington workers covered by the UI system from the State of Washington's Employment Security Department for the period of 2005q1 to 2017q2.[1] These records contain the workers' quarterly earnings and hours. By taking the ratio of earnings to hours, we compute the worker's realized wage. Further, these data include the address of the employer, which permit us to place the location of work inside or outside of the City of Seattle for most employers. A detailed discussion of data and limitations is included in the Appendix.

Figure 1 shows the distribution of wages among workers whose employer was in Seattle. Note that the y-axis is shown in natural log terms. The median wage in the city was \$26.42 at the time of passage in 2014q2 and rose 17%, in inflation-adjusted dollars, to \$30.91 by 2017q2. The 10th percentile wage rose faster, by 25%, from \$11.72 to \$14.65. This convergence between the 10th percentile and median wage is what one would expect to see as the direct effect of the minimum wage law, and this result is consistent with prior research on state and federal minimum wage law increases (Autor, Manning, and Smith 2016) as well as the findings in my team's other analyses of the impact of the Seattle minimum wage (Jardim et al. 2017, 2018, 2020). Yet, note that, as shown in Figure 1, wages at the top end of the distribution increased even more rapidly. At the 99th percentile, wages rose 49%, from \$227 to \$338, during this period.

The observed contraction in inequality in the bottom half of the wage distribution might not indicate a decline in *earnings* inequality if the gain in the hourly wage rate is offset by a decline in hours worked. Indeed, my team's prior research has found a decline in aggregate hours worked at wages below \$19 (Jardim et al. 2017, 2020). Consequently, to understand the impact of the minimum wage on inequality it is necessary to evaluate the impact on the distribution of earnings.

---

[1] In November of 2017, voters in the state of Washington passed Initiative 1433, which will raise the state's minimum wage from \$9.47 to \$13.50 by 2020. Given passage of this new statewide law, which will affect the "control" group in this analysis, I limit this analysis to the period through 2017q2.

Measuring Earnings Inequality

I measure earnings inequality in two ways. First, I compute the Gini Index (Gini 1955), which is perhaps the most used measure of inequality. The Gini Index ranges from a low of zero (corresponding to perfect equality of earnings) to one (which would occur if one person received all of the earnings). Second, I compute the Atkinson Index (Atkinson 1979) with the inequality aversion parameter, ε, set equal to 1. The Atkinson Index also ranges from zero to one. If we assume that individual utility (or wellbeing) is a linear function of the natural log of earnings (for which Stevenson and Wolfers (2013) provide evidence), and assume that social welfare (i.e., the measure of collective wellbeing that a central planner would ideally maximize) is utilitarian (Bentham 1789) and given by the mean of individual utilities, then the Atkinson Index with $\varepsilon=1$ has the nice interpretation: it measures the proportional cost of inequality (Atkinson 1979; Jenkins 2006). That is, under these assumptions, the Atkinson Index shows the extent by which aggregate earnings could be reduced while maintaining the current level of social welfare by distributing the remaining aggregate earnings equally.

The pre-policy Atkinson index values of around 0.40 (Appendix Table 1) suggest a sub-optimal distribution in earnings. That is, 40% of aggregate earnings could be eliminated and the remainder redistributed without effecting the amount of aggregate social welfare in Seattle.[2]

Given the strong seasonality in earnings (Figure 1), particularly for higher wage workers who often receive holiday bonuses in the fourth quarter of each year, I seasonally adjust the Gini and Atkinson indices by computing deviations from pre-policy quarterly means (Appendix Table 1) and evaluate impacts on these adjusted values.

Impact Estimates

To derive causal estimates of the effect of Seattle's minimum wage on these measures, I construct a counterfactual estimate of what would have likely happened in Seattle in the absence of the policy change and compare this counterfactual to the observed outcomes in Seattle. Derivation of this counterfactual (i.e., "Synthetic Seattle") is described by Figure 2, with a detailed discussion of methods included in the Appendix.

---

[2] Of course, this computation only holds under the unrealistic assumption of no labor demand or supply response to taxation and redistribution.

The solid black line in Figure 2A shows the demeaned Gini Index for Seattle workers whose wage was below the median in their region. The thin gray lines show the demeaned Gini Indexes for forty other Public Use Micro Areas (PUMAs) in Washington, excluding Seattle's King County. Using the synthetic control method (Abadie, Diamond, Hainmueller 2010), I produce a weighted average of these forty PUMAs shown by the dashed gold line. The gap between Seattle and Synthetic Seattle in the post-policy quarters yields the estimate of the causal effect of the policy.

In Seattle and PUMAs statewide, inequality of earnings among lower paid workers was trending downwards pre-policy, and this downward trend continued after passage. There is only a modest difference between Seattle's and Synthetic Seattle's demeaned Gini Indexes in the post-policy period for below-median-wage workers, suggesting a small effect of the policy on earnings inequality.

In Figure 2B, I show the causal impact estimates for Seattle, i.e. the gap between Seattle and Synthetic Seattle from Figure 2A. To assess the statistical significance of these impact estimates, I construct a "placebo-in-space" test (Abadie, Diamond, Hainmueller 2010) whereby fictitious policies are assigned to each of the 2,994 other sets of 5 contiguous PUMAs in Washington outside King County. [3] The range of these 2,994 estimates is shown by the thin light blue lines. A *p*-value corresponding to a two-tailed test of the null hypothesis that the treatment effect is zero is derived by computing the share of occurrences in which the absolute value of the estimated effect in Seattle is greater than the absolute values of the 2,994 placebo estimates. As shown in Table 1, the impact estimates on the Gini Index for below-median wage workers are mostly not statistically significant at the two-tailed, 5% level, with the largest estimate being -0.011 (2016q4), relative to a pre-policy base of 0.352 (for 4th quarters during 2005 to 2013). Thus, I conclude that the minimum wage had either a modest or zero effect on earnings inequality among employed workers earning less than the median wage.

In Figures 2C and 2D of Figure 1, I repeat this analysis for all workers. The demeaned Gini Index for Seattle workers was fairly level in the years 2005 to 2015, but jumped upwards during the first quarter of 2016, coincident with the increase in Seattle's top minimum wage to $13, and the impact estimates are large and statistically significant in 5 of the final 6 quarters (Table 1).

---

[3] Note that Seattle is composed of 5 contiguous PUMAs.

The impacts on the Atkinson Indexes mirror the effects on the Gini Indexes (as shown in Table 1 and Appendix Figure 1), suggesting that inequality in earnings across all workers jumped upwards beginning in 2016q1, while there was modest, sporadically significant reductions in the Gini and Atkinson indexes for earnings of workers paid less than the median wage.

Discussion

There are several possible explanations for the large increase in inequality for all workers in 2016 and 2017. It could indicate "labor-labor substitution" from low-skilled to high-skilled workers who are now relatively more valued by their employers (Neumark and Wascher 1995; Aaronson and Phelan 2019). Additionally, reduced turnover (Jardim et al. 2018, 2020), more motivated low-skilled workers, and/or labor-capital substitution (Aaronson and Phelan 2019) yielding firm-level productivity gains could benefit the earnings of high-skilled workers.

A more likely explanation would be a contemporaneous, but unrelated, shock to demand for very high-skilled labor. Figure 3 plots earnings at the 99th, 95th, 90th, 75th, and 50th percentiles divided by their means in the year prior to passage of the ordinance. During the years before the ordinance was passed, earnings at the top of the Seattle earnings distribution were growing slightly faster than at the median of the earnings distribution, indicating a slight widening of inequality of earnings above the median during this pre-policy period. After passage, this trend continued and accelerated with the 99th percentile racing away from the other percentiles during the last six quarters studied. By 2017q2, earnings at the 99th percentile were more than 60% above its pre-policy level. Since the 99th percentile was growing much faster than the 90th percentile, it would be hard to argue that this event was *due* to the minimum wage ordinance.[4]

---

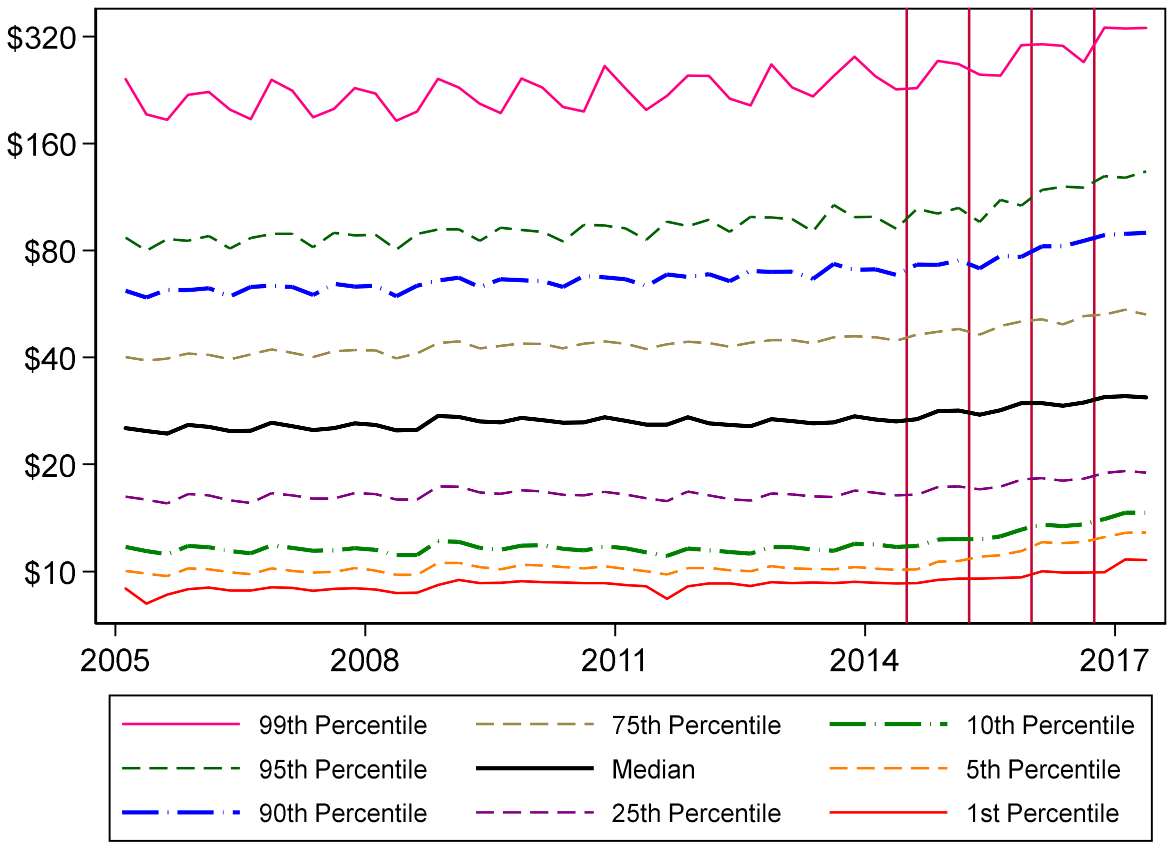
[4] Growth in employment at Amazon.com, Inc.'s corporate headquarters in Seattle is a plausible explanation for this pattern. However, our data-sharing agreement with the State of Washington precludes an analysis of a single company. As shown in Appendix Figure 2, publicly available data suggests very strong growth in compensation of Amazon's employees during 2016 and 2017; Amazon's stock-based compensation expenses reported to the Security and Exchange Commission in quarterly and annual filings shows rapid growth of such compensation during these same quarters. However, it is not possible with publicly available records to obtain information on other forms of employee compensation, nor to restrict the analysis to just Amazon's employees in Seattle.

Conclusions

The evidence presented in this report suggests that Seattle's minimum wage did little to offset widening inequality of earnings among workers in the city. These results suggest that local minimum wage laws are not likely to substantially reduce earnings inequality. While wage gaps are likely to diminish, as mandated by law, the ability of firms to substitute away from low-skilled workers may offset wage gains, leaving earnings inequality unchanged. Moreover, the results in this report pertain to earnings inequality of those employed and thus do not include any additional increase in inequality produced by a reduction in the number of employed low-skilled workers.

Whether these results generalize to other cities and in other times is not clear. It is important to note that these results hold during a time when the U.S. economy was strong and Seattle was booming. Given the current recession brought on by the COVID-19 pandemic, similar results may not hold for other city's enacting such laws today.

Figure 1. Seattle's Wage Distribution

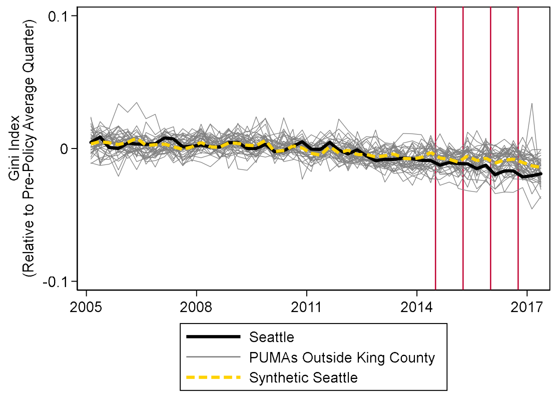


Notes: From left to right, the four vertical lines reflect the initiation of the following four policy regimes: (1) Seattle minimum wage ordinance passed, but not yet in force; (2) top minimum wage in Seattle = \$11; (3) top minimum wage in Seattle = \$13; and (4) increase in state's minimum wage passed by voter initiative in November and to begin in January, 2017 and top minimum wage in Seattle to be \$15 in January.

Figure 2. Effect of the Seattle Minimum Wage on the Gini Index of Earnings Inequality

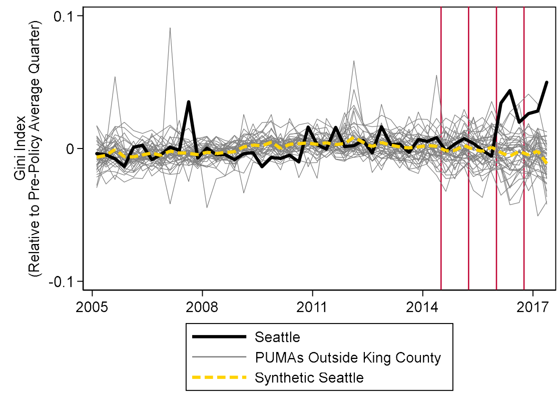
A

Time Series of Gini Index in Seattle and Comparison Regions, Below Median Wage Workers



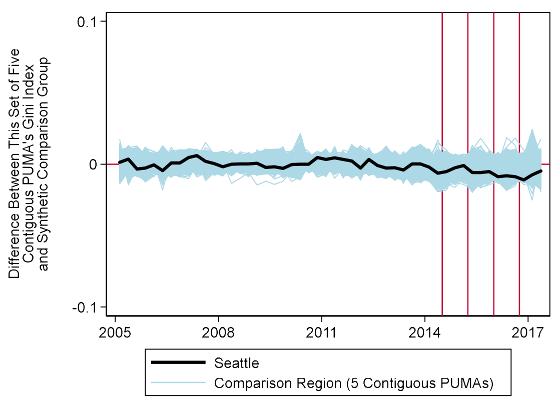
C

Time Series of Gini Index in Seattle and Comparison Regions, All Workers



B

Impact Estimate for Gini Index in Seattle and Placebo Estimates for Comparison Regions, Below Median Wage Workers



D

Impact Estimate for Gini Index in Seattle and Placebo Estimates for Comparison Regions, All Workers

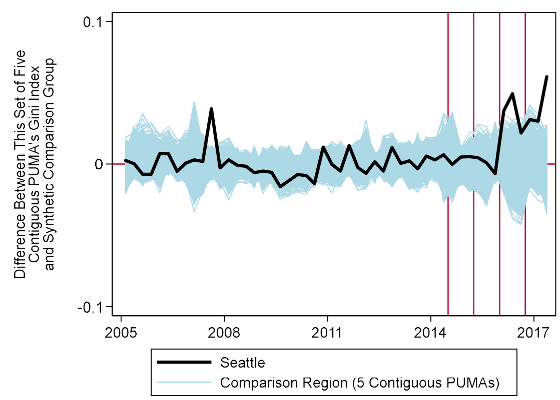
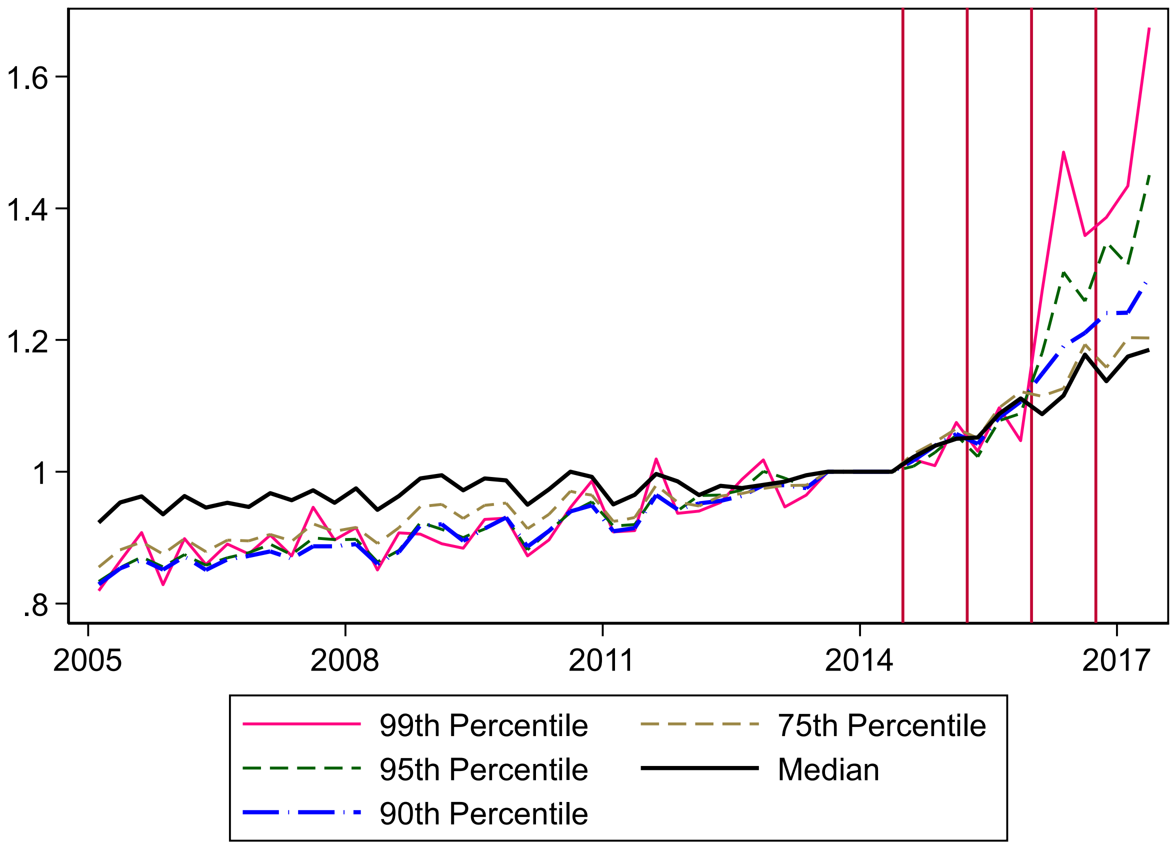


Figure 3. Growth in Earnings for Seattle's Workers Paid Median Earnings or Higher



Notes: Each series is divided by its mean in the same quarter during the year before passage of the Seattle minimum wage ordinance.

Table 1: Estimated Impact of the Seattle Minimum Wage on Inequality

Quarter	Quarters After Passage / Enforcement	Top Minimum Wage in Seattle	Below Median Wage Workers' Earnings Inequality: Gini Index	Below Median Wage Workers' Earnings Inequality: Atkinson Index	All Workers' Earnings Inequality: Gini Index	All Workers' Earnings Inequality: Atkinson Index
2014.3	1 / .	.	-0.005	-0.007	0.000	-0.004
			[0.324]	[0.354]	[0.990]	[0.736]
2014.4	2 / .	.	-0.003	-0.003	0.005	0.004
			[0.445]	[0.538]	[0.359]	[0.701]
2015.1	3 / .	.	-0.001	0.001	0.005	0.004
			[0.786]	[0.812]	[0.409]	[0.398]
2015.2	1-Apr	$11	-0.006	-0.004	0.004	0.003
			[0.241]	[0.474]	[0.582]	[0.781]
2015.3	2-May	$11	-0.006	**-0.011**	0.001	-0.004
			[0.219]	[0.050]	[0.940]	[0.725]
2015.4	3-Jun	$11	-0.005	-0.006	-0.007	-0.008
			[0.186]	[0.316]	[0.334]	[0.451]
2016.1	4-Jul	$13	**-0.009**	-0.009	**0.037**	**0.036**
			[0.031]	[0.324]	[0.000]	[0.000]
2016.2	5-Aug	$13	-0.008	**-0.008**	**0.049**	**0.048**
			[0.142]	[0.016]	[0.000]	[0.006]
2016.3	6-Sep	$13	-0.009	-0.012	0.022	0.019
			[0.053]	[0.188]	[0.056]	[0.244]
2016.4	7-Oct	$13	**-0.011**	**-0.011**	**0.031**	0.029
			[0.010]	[0.099]	[0.004]	[0.099]
2017.1	8-Nov	$15	-0.008	-0.011	**0.030**	0.027
			[0.321]	[0.317]	[0.001]	[0.076]
2017.2	9-Dec	$15	-0.005	-0.003	**0.061**	**0.060**
			[0.311]	[0.681]	[0.000]	[0.000]

Notes: Bracketed values show the two-tailed p-values. Bolded coefficients have p-values ≤ 0.050.

References:

Aaronson, D., and B.J. Phelan, "Wage Shocks and the Technological Substitution of Low-wage Jobs," *The Economic Journal* 129:617 (2019), 1–34.

Abadie, A., A. Diamond, J. Hainmueller, "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program," *Journal of the American Statistical Association* 105:490 (2010), 493-505.

Atkinson, A.B., "On the measurement of inequality," *Journal of Economic Theory* 2 (1979), 244-63.

Auten, G., and D. Splinter, "Top 1 Percent Income Shares: Comparing Estimates Using Tax Data," *AEA Papers and Proceedings* 109 (2019), 307-11.

Autor, D. H., A. Manning, and C. L. Smith, "The Contribution of the Minimum Wage to US Wage Inequality over Three Decades: A Reassessment," *American Economic Journal: Applied Economics* 8:1 (2016), 58-99.

Bentham, J., *An Introduction to the Principles of Morals and Legislation* (T. Payne, and Son, London, England, 1789).

Congressional Budget Office (CBO), "The Distribution of Household Income, 2015" (2018), https://www.cbo.gov/system/files/2018-11/54646-Distribution_of_Household_Income_2015_0.pdf.

Fixler, D., M. Gindelsky, and D. Johnson, "Improving the Measure of the Distribution of Personal Income," *AEA Papers and Proceedings* 109 (2019), 302-06.

Gini, C. "Variabilità e mutabilità" in Memorie di Metodologica Statistica (E. Pizetti and T. Salvemini, Eds., Libreria Eredi Virgilio Veschi, Rome, Italy, 1955).

Jardim, E., M.C. Long, R. Plotnick, E. van Inwegan, and J. Vigdor, H. Wething, "Minimum Wage Increases, Wages and Low-Wage Employment: Evidence from Seattle," *National Bureau of Economics Research Working Paper* No. 23532 (2017).

Jardim, E., M.C. Long, R. Plotnick, E. van Inwegen, and J. Vigdor, H. Wething, “Minimum Wage Increases and Individual Employment Trajectories,” *National Bureau of Economics Research Working Paper* No. 25182 (2018).

Jardim, E., M.C. Long, R. Plotnick, E. van Inwegen, and J. Vigdor, H. Wething, “Minimum Wage Increases and Low-Wage Employment: Evidence from Seattle,” *American Economic Journal: Economic Policy* (Conditionally Accepted) (2020).

Jenkins, S.P., “Estimation and interpretation of measures of inequality, poverty, and social welfare using Stata,” Presentation at North American Stata Users' Group Meeting (2006) http://econpapers.repec.org/paper/bocasug06/16.htm.

Levitin, M., “The Triumph of Occupy Wall Street,” *The Atlantic* (June 2015), https://www.theatlantic.com/politics/archive/2015/06/the-triumph-of-occupy-wall-street/395408/.

Murray, E., “Murray announces additional details on Income Inequality Symposium” (March 24, 2014), http://murray.seattle.gov/murray-announces-additional-details-on-income-inequality-symposium/.

Neumark, D., and W. Wascher, “The Effects of Minimum Wages on Teenage Employment and Enrollment: Evidence from Matched CPS Surveys.” *National Bureau of Economics Research Working Paper* No. 5092 (1995).

Piketty, T., and E. Saez, “Income Inequality in the United States, 1913–1998,” *Quarterly Journal of Economics* 118:1 (2003), 1–39.

Piketty, T., E. Saez, and G. Zucman, “Distributional National Accounts: Methods and Estimates for the United States,” *Quarterly Journal of Economics* 133:2 (2018), 553-609.

Seattle Office of Labor Standards, “Seattle’s Minimum Wage” (no date) http://www.seattle.gov/Documents/Departments/LaborStandards/OLS-MW-multiyearChart2020_Final2.pdf.

Stevenson, B., and J. Wolfers, “Subjective Well-Being and Income: Is There Any Evidence of Satiation?,” *American Economic Review* 103:3 (2013), 598-604.

UC Berkeley Labor Center, “Inventory of US City and County Minimum Wage Ordinances” (2019), http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/.

Acknowledgments: Excellent research assistance was provided by Ellie Terry. This research was conducted as part of the Minimum Wage Study (MWS). The author would like to acknowledge the contributions of the other MWS investigators, Scott Allard, Heather Hill, Jennifer Otten, Robert Plotnick, Jennifer Romich, and Jake Vigdor. **Funding:** I am grateful for funding from the City of Seattle, the Laura and John Arnold Foundation, the Russell Sage Foundation, the Harry Bridges Center for Labor Studies, the West Coast Poverty Center, Washington Center for Equitable Growth, and the Economic Self-Sufficiency Policy Research Institute. The MWS also receives computing resources from the Center for Studies in Demography and Ecology at the University of Washington (Eunice Kennedy Shriver National Institute of Child Health and Human Development research infrastructure grant, R24HD042828). The contents of this report are solely the responsibility of the author and does not necessarily represent the official views of any funder. **Author contributions:** Conceptualization, methodology, analysis, and writing were conducted solely by the author with comments and suggestions by Terry, Ekaterina Jardim, and MWS investigators. **Competing interests:** The author declares no competing interests. **Data and materials availability:** Access to the data may be obtained through application to the State of Washington's Employment Security Department. Statistical code for any researcher who wishes to reproduce or extend the analysis is available from the author.

Appendix: Data and Methods

Data

Data were obtained by the Minimum Wage Study at the University of Washington from the State of Washington's Employment Security Department. These data are at the worker-quarter-employer level for each quarter between the first quarter of 2005 and the second quarter of 2017 and include all jobs in Washington that are covered by the Unemployment Insurance system. These data do not include self-employed workers (e.g., Uber drivers). The dataset begins with 169,926,627 worker-quarter-employer observations.

I drop 3,730,445 observations from employers in industries where it is know that hours and earnings data are unreliable and/or inconsistently recorded, including "Private Households" (North American Industry Classification System (NAICS) code 814) and "Services for the Elderly and Persons with Disabilities" (NAICS code 624120). I then drop 3,527,365 worker-quarter-employer observations where the worker has zero or missing hours recorded or zero or missing earnings recorded in the quarter for any employer. Such data, which is likely faulty, would, if included, result in erroneous values for the worker's derived wage rate. Of the remaining 162,668,817 observations, the Public Use Microdata Area (PUMA) can be identified for 156,732,206 observations by geocoding the employer's address.

Employers that have multiple locations of work in Washington have the option of reporting employment by separate location (e.g,. a particular gas station) or reporting all employment at a central location (e.g., the gas company's state headquarters). If the employment is reported at a central location, then it is not possible to determine whether the worker is subject to the minimum wage law in Seattle, which only covers work done in the city limits. Consequently, I drop 45,849,501 worker-quarter-employer observations for workers that had any earnings in the quarter at a non-locatable, multi-location employer in a particular quarter, unless the main PUMA location (defined below) of the worker's employment in a quarter can be unequivocally identified using only locatable employers. My team's previous work (Jardim et al. 2017, 2020), suggests that the effects of the Seattle minimum wage law on employment were likely to have been similar in locatable and non-locatable firms.

I collapse the remaining worker-quarter-employer observations to the worker-quarter-PUMA level, thereby computing the sum of earnings and hours within each worker-quarter-PUMA. I then identify the main PUMA location as the PUMA whose employers pay the most earnings to the worker in that quarter. If this procedure results in a tie, the main PUMA location is defined as the PUMA whose employers supply the most hours of work among those PUMAs that pay the most earnings. If this procedure still results in a tie, I select randomly from the tied PUMAs. I then collapse the data to the worker-quarter level, computing the sum of earnings and hours within each worker-quarter. The analytical dataset contains 105,672,075 worker-quarter observations. Of these, 16,938,647 worker-quarter observations were in one of Seattle's five PUMAs, and these observations are used to generate Figure 1.

Methods

Synthetic Seattle draws on data from worker-quarter observations that are located in one of Washington's PUMAs that lie outside of King County. These forty PUMAs contain 63,681,569 worker-quarter observations. The portions of King County that surrounds Seattle are not used to identify Seattle's counterfactual as wages and employment in these areas were plausibly affected by Seattle's minimum wage. This outlying King County buffer area contains 22,498,825 worker-quarter observations. Finally, 5,877,653 worker-quarter observations are not used as the PUMA for the main location of work could not be determined (e.g., employer's address was missing or could not be geocoded).

Nominal dollar amounts are adjusted for inflation using the U.S. Bureau of Labor Statistics' Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W) with the second quarter of 2015 as the base. The CPI-W is used by the State of Washington and the City of Seattle to index the state's and the city's minimum wages, respectively.

The Gini Index for each region by quarter (e.g., as shown in Figure 2) was computed using the "fastgini" Stata command (Sajaia 2007). To obtain a Gini Index, one first obtains a Lorenz Curve, which plots the cumulative earnings of workers who have been sorted from the lowest to the highest earner. A 45-degree line captures the cumulative share of workers below worker i. The Gini Index equals one minus the share of the area below the 45-degree line that is below the Lorenz Curve. If earnings are equal across workers, then the Lorenz Curve will be the same as the 45-degree line and the Gini Index will equal 0. If all earnings are received by one worker, then there will be no area under the Lorenz curve and the Gini Index will equal 1. While popular, there are known limitations of the Gini Index. For example, Deininger and Squire note that, "(o)ne disadvantage of any aggregate measure of inequality such as the Gini index is that there is no unique mapping between changes in the index and the underlying income distribution; redistribution from the top to the middle class may be associated with the same change in the aggregate indicator as an increase in the share of income received by the bottom quintile at the expense of the middle class" (Deininger and Squire 1996).

The Atkinson Index, in contrast, explicitly accounts for where redistribution occurs in the income distribution. Let social welfare be equal to the average of individual utilities: $\frac{1}{N}\sum_{i=1}^{N} U(y_i)$ for workers i=1 to N. Let y_E be defined as the level of earnings such that if that level were distributed equally across workers, it would yield the same level of social welfare as the current distribution of earnings. That is, y_E yields the following equality: $\frac{1}{N}\sum_{i=1}^{N} U(y_E) = \frac{1}{N}\sum_{i=1}^{N} U(y_i)$. Atkinson's measure of inequality, which is a function of the social planner's inequality aversion, ε, is given by the following $A_\varepsilon = 1 - y_E/\mu$, where μ is the mean earnings of workers. Put differently, the Atkinson Index measures the extent to which mean earnings are "wasted" in that they are not adding to social welfare given inequality in distribution. Assuming that the social planner's inequality aversion is such that ε=1, or equivalently, assuming that the social planner equally weighs workers' utilities and those utilities are given by a linear function of the natural log of earnings (as supported by within and cross-country data (Stevenson and Wolfers 2013)), then the Atkinson Index becomes $A_1 = 1 - e^{\frac{1}{N}\sum_{i=1}^{N} ln(y_i/\mu)}$ (Jenkins 2006). The Atkinson Index is computed by the author's own coding of this equation.

The resulting values of the Gini and Atkinson indexes are "demeaned" by taking the difference between the raw index and the corresponding quarter's pre-policy mean as shown in Appendix Table 1. For example, all first quarter Gini indexes are demeaned by deducting 0.487.

To obtain causal impact estimates, I employ the synthetic control method of Abadie, Diamond, and Hainmueller (2010) using the "synth" Stata command (Abadie, Diamond, and Hainmueller 2011). Let G_{t0} represent the demeaned Gini index in quarter t for Seattle (i.e., region 0). The synthetic control method derives a counterfactual estimate for Seattle using a weighted average of the values of $G_{t1}, G_{t2} \dots, G_{t40}$ for the forty Washington PUMAs outside of King County. The estimated effect of the minimum wage for post-passage quarters t = 1 to 12, $\hat{\beta}_t$, is computed as follows: $\hat{\beta}_t = G_{t0} - \sum_{r=1}^{40} w_r G_{tr}$, where w_r is the weight assigned to region r and $\sum_{r=1}^{40} w_r = 1$. To identify the weights, I follow the approach used in my team's prior research on the Seattle minimum wage (Jardim et al. 2017, 2018, 2020) whereby the weights are found by minimizing forecasting error in the pre-passage period: $\min_{w_r} \sum_{t=-37}^{0} (G_{t0} - \sum_{r=1}^{40} w_r G_{tr})^2$, subject to the constraints $\sum_r w_r = 1$ and $w_r \geq 0$ for all r.

As described in the manuscript, inference is based on a "placebo-in-space" test (Abadie, Diamond, Hainmueller 2010). This test is based on the 2,994 possible combinations of five contiguous PUMAs in Washington outside of King County. Contiguous sets are chosen as local employment shocks can have spillovers to adjacent PUMAs. Thus, by using sets of contiguous PUMAs, I allow the identification of "statistically significant" changes in Seattle's indexes of inequality to account for spurious local events that have clustered effects. The smallest possible resulting p-value for each impact estimate is 1/2,994 = 0.0003.

Appendix References:

Abadie, A., A. Diamond, and J. Hainmueller, "SYNTH: Stata module to implement Synthetic Control Methods for Comparative Case Studies" (2011), https://econpapers.repec.org/software/bocbocode/s457334.htm.

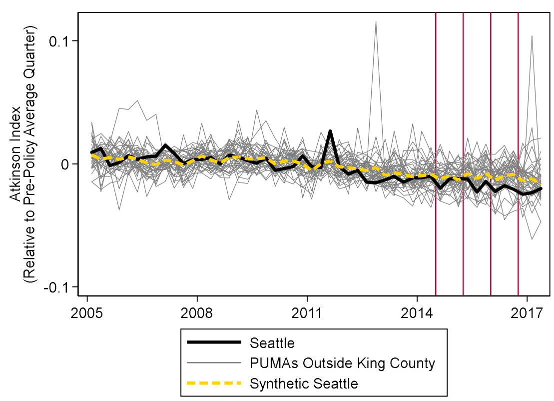
Deininger, K., and L. Squire, "A New Data Set Measuring Income Inequality," *The World Bank Economic Review*, 10:3 (1996), 65-91.

Sajaia, Z. "FASTGINI: Stata module to calculate Gini coefficient with jackknife standard errors" (2007), https://econpapers.repec.org/software/bocbocode/s456814.htm.

Appendix Figure 1. Effect of the Seattle Minimum Wage on the Atkinson Index of Earnings Inequality

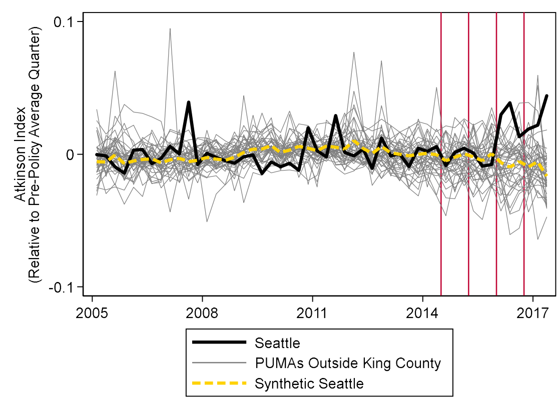
A

Time Series of Atkinson Index in Seattle and Comparison Regions, Below Median Wage Workers



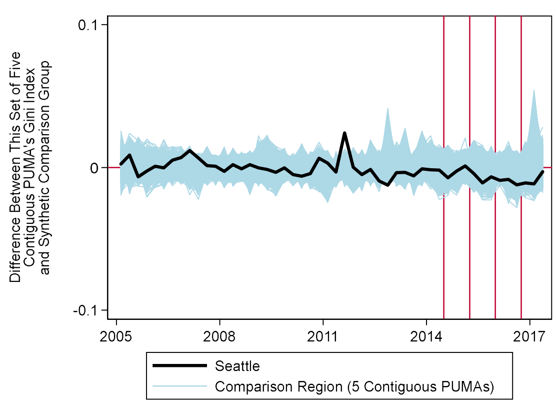
B

Time Series of Atkinson Index in Seattle and Comparison Regions, All Workers



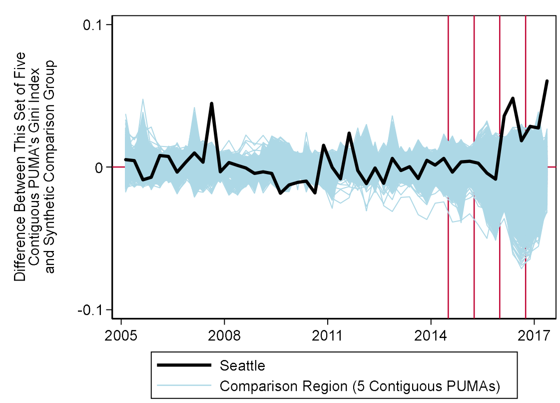
C

Impact Estimate for Atkinson Index in Seattle and Placebo Estimates for Comparison Regions, Below Median Wage Workers

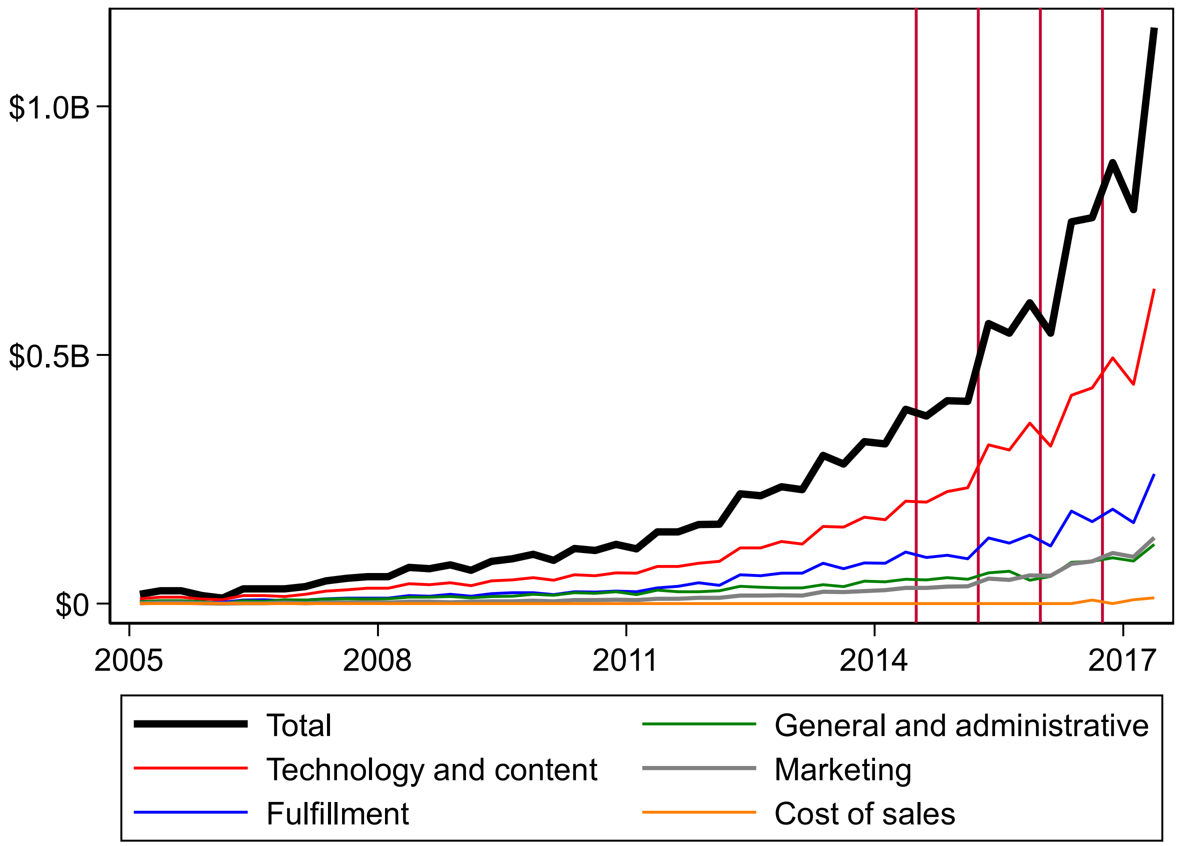


D

Impact Estimate for Atkinson Index in Seattle and Placebo Estimates for Comparison Regions, All Workers



Appendix Figure 2: Stock-Based Compensation Expenses at Amazon.com, Inc.



Notes: Data are taken from form 10-Q (quarterly) and 10-K (annual) filings to the Securities and Exchange Commission, available at https://www.sec.gov/edgar/searchedgar/companysearch.html.

Appendix Table 1: Seasonal Variation in Seattle's Levels of Inequality Prior to Passage of the Seattle Minimum Wage Ordinance

Quarters	Below Median Wage Workers' Earnings Inequality		All Workers' Earnings Inequality	
	Gini Index	Atkinson Index	Gini Index	Atkinson Index
1st Quarters of 2005-14	0.351	0.302	0.487	0.412
2nd Quarters of 2005-14	0.354	0.307	0.469	0.396
3rd Quarters of 2005-13	0.361	0.311	0.478	0.406
4th Quarters of 2005-13	0.352	0.303	0.490	0.417