Received: 2 April 2021 | Accepted: 28 October 2021

DOI: 10.1111/ecin.13053

ORIGINAL ARTICLE

Economic Inquiry

Seattle's local minimum wage and earnings inequality

Mark C. Long

Evans School of Public Policy and Governance, University of Washington, Seattle, Washington, USA

Correspondence
Mark C. Long, Evans School of Public Policy and Governance, University of Washington, Seattle, WA 98195, USA.
Email: marklong@uw.edu

Funding information
City of Seattle; Laura and John Arnold Foundation; Russell Sage Foundation; Harry Bridges Center for Labor Studies; West Coast Poverty Center; Washington Center for Equitable Growth; Economic Self-Sufficiency Policy Research Institute; University of Washington; Eunice Kennedy Shriver National Institute of Child Health and Human Development, Grant/Award Number: R24HD042828

Abstract

During the past 6 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.

KEYWORDS
inequality, local policy, minimum wage

JEL CLASSIFICATION
J31, J38, H79

1 | INTRODUCTION

There is widespread concern about the growth in income inequality in the United States (Auten & Splinter, 2019; Congressional Budget Office, 2018; Fixler et al., 2019; Piketty & Saez, 2003; Piketty et al., 2018) and stagnation in earnings at the bottom of the distribution (Piketty et al., 2018). Between 1980 and 2014, pre-tax income fell 25% for those in the bottom fifth of the income distribution (Piketty et al., 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 27, 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).

Abbreviations: CBO, Congressional Budget Office; CPI-W, Consumer Price Index for Urban Wage Earners and Clerical Workers; D.C., District of Columbia; MWS, University of Washington's Minimum Wage Study; NAICS, North American Industry Classification System; PUMAs, Public Use Micro Areas; UC, University of California; UI, Unemployment Insurance; US, United States.

Managing Editor: Glen Waddell

During the following month, Seattle's city council approved the establishment of a local minimum wage, the largest in the United States to that date. Beginning on April 1, 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 50 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 DC (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.

2 | SEATTLE'S WAGE DISTRIBUTION

The MWS 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 A.)

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 et al., 2016) as well as the findings in other analyses of the impact of the Seattle minimum wage (Jardim

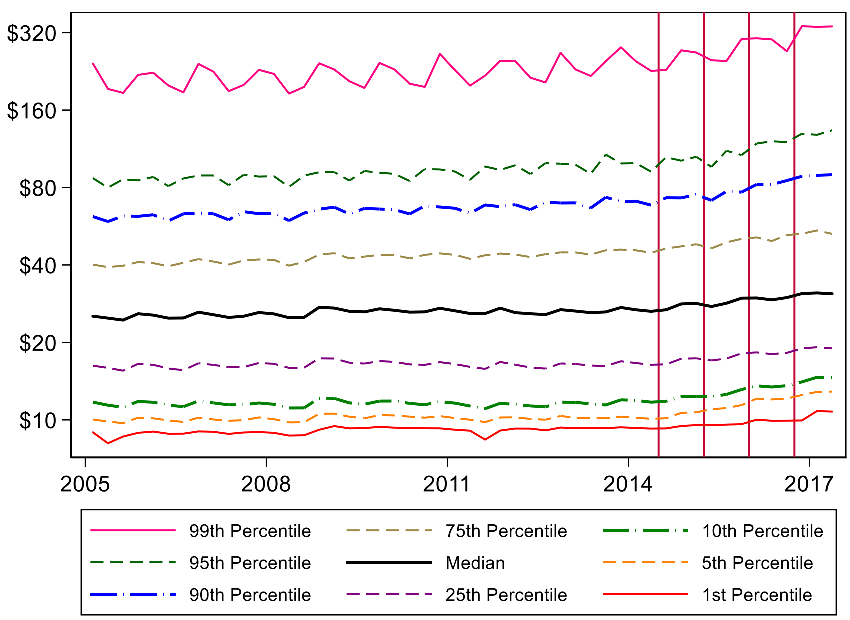

FIGURE 1 Seattle's wage distribution. From left to right, the four vertical lines reflect the initiation of the following four policy regimes: (1) Seattle minimum wage ordinance passed, but not yet in force; (2) top minimum wage in Seattle = $11; (3) top minimum wage in Seattle = $13; and (4) increase 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

et al., 2017, 2018, Forthcoming). 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, prior research has found a decline in aggregate hours worked at wages below $19 (Jardim et al., 2017, Forthcoming).[2] Consequently, to understand the impact of the minimum wage on inequality, it is necessary to evaluate the impact on the distribution of earnings.

3 | MEASURING EARNINGS INEQUALITY

I measure earnings inequality in two ways. First, I compute the Gini Index (Gini, 1912), 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 & 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 .40 (Table 1, Panel A) 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.[3]

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 (Table 1, Panel A) and evaluate impacts on these adjusted values.

4 | SIMULATED IMPACT (*CETERIS PARIBUS*)

Prior to estimating the causal impacts of the law, it is useful to get a sense of what magnitude effect we might expect to see if there were no changes in labor demand and supply and no cascading effects on wages for workers earning above the minimum wage. From conversations with city leaders engaged with planning and promoting the passage of the law, I heard a frequently expressed belief that there would be no changes in demand for labor in response to the law. Thus, using this assumption held by policy leaders, we can estimate the impact on the Gini and Atkinson indices by simply replacing actual earnings with simulated earnings = max[actual earnings, minimum wage × actual hours worked] and computing the inequality indices with the new, simulated earnings for quarters prior to the laws' passage. The simulation for a $13 minimum wage is shown in Panel B of Table 1. In Panel C of Table 1, I show the difference in the indices between the simulated earnings (Panel B) and the actual earnings (Panel A). I find that, *ceteris paribus*, a $13 minimum wage would lower the Gini index by an average of .016 (down 4.6% from the pre-policy average) for below-median wage workers and .007 (−1.4%) for all workers, and correspondingly lower the Atkinson index by .025 (−8.1%) for below-median wage workers and .016 (−3.9%) for all workers. The same exercise for a $15 minimum wage is shown in Panels D and E of Table 1. I find that, *ceteris paribus*, a $15 minimum wage would lower the Gini index by an average of .030 (−8.3%) for below-median wage workers and .013 (−2.7%) for all workers, and correspondingly lower the Atkinson index by .038 (−12.5%) for below-median wage workers and .027 (−6.6%) for all workers. Thus, even if there are no adverse endogenous labor market responses, we should not expect to see very large reductions in earnings inequality in Seattle as a result of the $15-per-hour minimum wage law.

For the interested reader, Table A1 extends this simulation to consider the simulated impacts of a $20 and a $25 minimum wage on earnings inequality. *Ceteris paribus*, the Gini index for all workers would fall by an average of .037 (−7.7%) with a $20 minimum wage and .067 (−13.9%) with a $25 minimum wage.

TABLE 1 Seasonal variation in Seattle's levels of inequality prior to passage of the Seattle minimum wage ordinance and simulated impact of a $15 minimum wage, *ceteris paribus*

	Quarters	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
Panel A: Actual earnings	First quarters of 2005–2014	.351	.302	.487	.412
	Second quarters of 2005–2014	.354	.307	.469	.396
	Third quarters of 2005–2013	.361	.311	.479	.407
	Fourth quarters of 2005–2013	.352	.303	.491	.417
	Average	.355	.306	.482	.408
Panel B: Simulated earnings with $13 per hour. Minimum wage, *ceteris paribus*	First quarters of 2005–2014	.336	.279	.481	.397
	Second quarters of 2005–2014	.337	.281	.462	.379
	Third quarters of 2005–2013	.343	.284	.472	.390
	Fourth quarters of 2005–2013	.337	.280	.485	.403
	Average	.338	.281	.475	.392
Panel C: Difference between panels B and A	First quarters of 2005–2014	−.015	−.023	−.006	−.015
	Second quarters of 2005–2014	−.017	−.026	−.007	−.017
	Third quarters of 2005–2013	−.018	−.027	−.007	−.017
	Fourth quarters of 2005–2013	−.015	−.024	−.006	−.014
	Average	−.016	−.025	−.007	−.016
	Percentage change	−4.6%	−8.1%	−1.4%	−3.9%
Panel D: Simulated earnings with $15 per hour. Minimum wage, *ceteris paribus*	First quarters of 2005–2014	.323	.266	.475	.387
	Second quarters of 2005–2014	.324	.268	.456	.368
	Third quarters of 2005–2013	.330	.271	.465	.378
	Fourth quarters of 2005–2013	.324	.267	.479	.392
	Average	.325	.268	.469	.381
Panel E: Difference between panels D and A	First quarters of 2005–2014	−.028	−.036	−.012	−.026
	Second quarters of 2005–2014	−.030	−.040	−.014	−.029
	Third quarters of 2005–2013	−.031	−.041	−.014	−.029
	Fourth quarters of 2005–2013	−.028	−.037	−.012	−.025
	Average	−.030	−.038	−.013	−.027
	Percentage change	−8.3%	−12.5%	−2.7%	−6.6%

Note that we should be cautious in comparing these simulated results to the actual impacts. First, note that Seattle's minimum wage was phased in slower for smaller employers and employers paying benefits. When Seattle's top minimum wage was $13, this rate only applied to large firms (those with more than 500 employees worldwide) that did not pay benefits. For large firms paying benefits, the minimum wage was $12.50 during this period. For small firms, the minimum wage during this period was $12 if no benefits were paid and workers did not receive tips or $12 in total compensation inclusive of tips and benefits taken up by the employee. Thus, we might expect the simulation of an across-the-board $13 minimum wage to exceed the actual effect for Seattle when the top minimum wage is $13. The available UI data do not record benefits nor total worldwide employees; thus, I cannot simulate Seattle's exact policy. On the other hand, the Seattle Minimum Wage Study (2016) report that some firms misunderstood the phase-in of the $15 minimum wage and immediately raised their wages to $15 rather than following the city's schedule. To the extent that such behavior was common, the simulation might underestimate the impact of the "$13" minimum wage.

I now turn to evaluate the actual impacts, inclusive of any changes in labor demand, labor supply, and cascading impacts on wages above the minimum wage.

5 | IMPACT ESTIMATES

To derive causal estimates of the effect of Seattle's minimum wage on earnings inequality, 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. 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 40 other Public Use Micro Areas (PUMAs) in Washington, excluding Seattle's King County. Using the synthetic control method (Abadie et al., 2010), I produce a weighted average of these 40 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. (An extended discussion of methods is included in the Appendix A.)

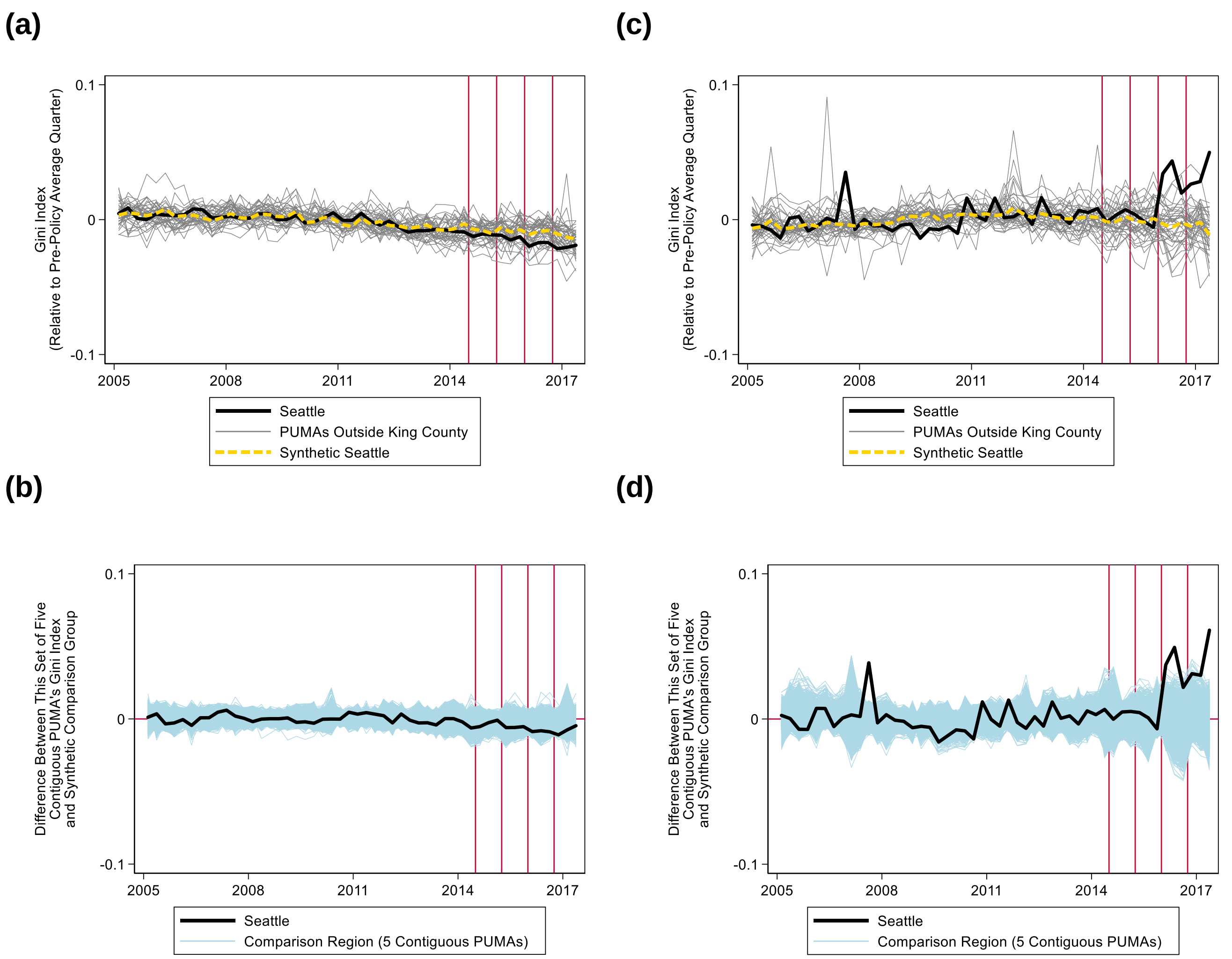

FIGURE 2 Effect of the Seattle minimum wage on the Gini index of earnings inequality. (a) Time series of Gini index in Seattle and comparison regions, below median wage workers. (b) Impact estimate for Gini index in Seattle and placebo estimates for comparison regions, below median wage workers. (c) Time series of Gini index in Seattle and comparison regions, all workers. (d) Impact estimate for Gini index in Seattle and placebo estimates for comparison regions, all workers

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, that is, 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 et al., 2010) whereby fictitious policies are assigned to each of the 2994 other sets of five contiguous PUMAs in Washington outside King County.[4] The range of these 2994 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 2994 placebo estimates. As shown in Table 2, 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 −.011 (2016q4), relative to a pre-policy base of .352 (for fourth quarters during 2005 to 2013).[5] Thus, I conclude that Seattle's minimum wage had either a modest or zero effect on earnings inequality among employed workers earning less than the median wage.

TABLE 2 Estimated impact of the Seattle minimum wage on inequality

			Below median wage worker's earnings inequality		All workers' earnings inequality	
Quarter	**Quarters after passage/ enforcement**	**Top min. wage in Seattle**	**Gini index**	**Atkinson index**	**Gini index**	**Atkinson index**
2014.3	1/-	-	−.005	−.007	.000	−.004
			[.324]	[.354]	[.990]	[.736]
2014.4	2/-	-	−.003	−.003	.005	.004
			[.445]	[.538]	[.359]	[.701]
2015.1	3/-	-	−.001	.001	.005	.004
			[.786]	[.812]	[.409]	[.398]
2015.2	4/1	$11	−.006	−.004	.004	.003
			[.241]	[.474]	[.582]	[.781]
2015.3	5/2	$11	−.006	**−.011**	.001	−.004
			[.219]	[.050]	[.940]	[.725]
2015.4	6/3	$11	−.005	−.006	−.007	−.008
			[.186]	[.316]	[.334]	[.451]
2016.1	7/4	$13	**−.009**	−.009	**.037**	**.036**
			[.031]	[.324]	[.000]	[.000]
2016.2	8/5	$13	−.008	**−.008**	**.049**	**.048**
			[.142]	[.016]	[.000]	[.006]
2016.3	9/6	$13	−.009	−.012	.022	.019
			[.053]	[.188]	[.056]	[.244]
2016.4	10/7	$13	**−.011**	**−.011**	**.031**	.029
			[.010]	[.099]	[.004]	[.099]
2017.1	11/8	$15	−.008	−.011	**.030**	.027
			[.321]	[.317]	[.001]	[.076]
2017.2	12/9	$15	−.005	−.003	**.061**	**.060**
			[.311]	[.681]	[.000]	[.000]

Note: Bracketed values show the two-tailed p-values. Bolded coefficients have p-values $\leq$ .05.

In Figure 2c,d, 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 five of the final six quarters (Table 2).

The impacts on the Atkinson Indexes mirror the effects on the Gini Indexes (as shown in Table 2 and Figure A1), suggesting that inequality in earnings across all workers jumped upwards beginning in 2016q1, while there were modest, sporadically significant reductions in the Gini and Atkinson indexes for earnings of workers paid less than the median wage.

To examine these impacts in greater detail, Figure 3 shows the impact results for workers paid below the 10th, 20th, …, and 90th percentiles, and for all workers. Table A2 shows these results in tabular form, including standard errors, where the results for workers paid below the median (column 5) and all workers (column 10) repeat the estimates previously shown in Table 2. The estimated impacts are statistically insignificant for workers with wages below the 10th percentile, negative and significant for workers with wages below the 20th, 30th, and 40th percentiles for most quarters during 2016 (i.e., when the top minimum wage was $13), and positive and significant for workers with wages below the 80th and 90th percentiles and for all workers for most quarters beginning with 2016.1.

6 | 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 (Aaronson & Phelan, 2019; Neumark & Wascher, 1995). Additionally, reduced turnover (Jardim et al., 2018, Forthcoming), more motivated low-skilled workers, and/or labor-capital substitution (Aaronson & 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 4 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

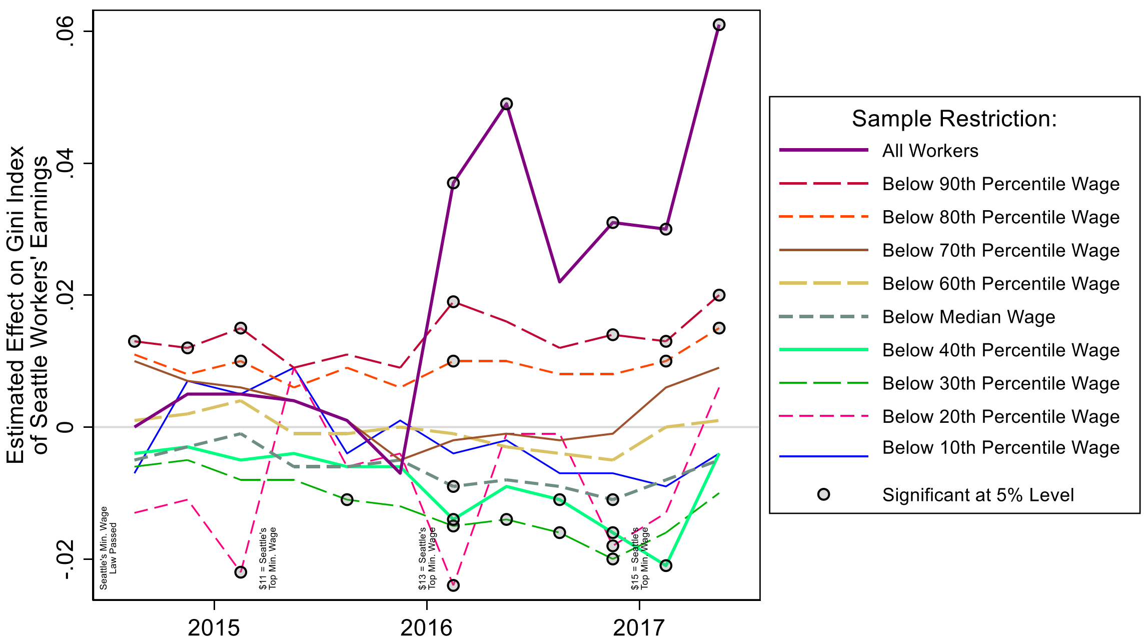

FIGURE 3 Estimated impact of the Seattle minimum wage on the Gini index of earnings inequality for workers with wages below the *X*th percentile

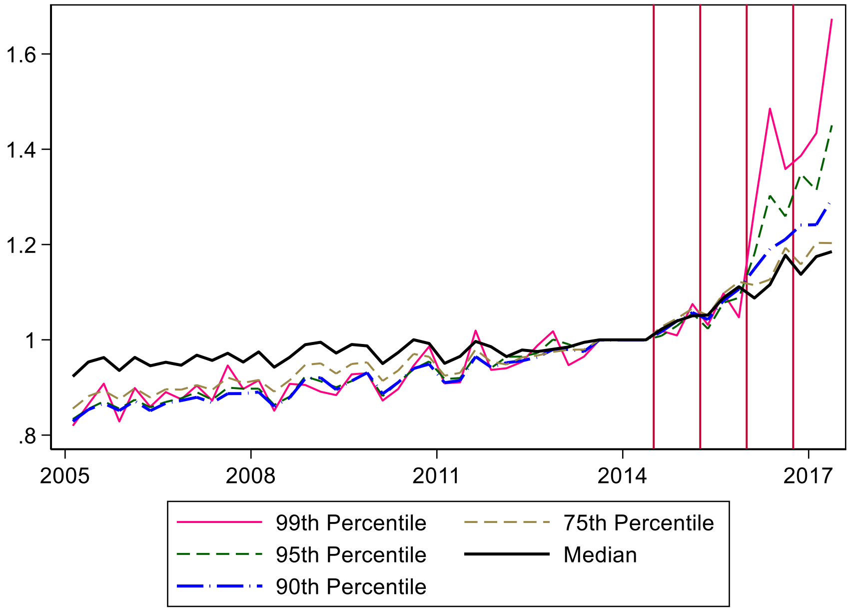

FIGURE 4 Growth in earnings for Seattle's workers paid median earnings or higher. Each series is divided by its mean in the same quarter during the year before the passage of the Seattle minimum wage ordinance

much faster than the 90th percentile, it would be hard to argue that this event was *due* to the minimum wage ordinance.[6]

7 | 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. The impact estimates as well as the simulation 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 US economy was strong and Seattle was booming. Similar results may not hold for other city's enacting such laws.

ACKNOWLEDGMENTS

Excellent research assistance was provided by Ellie Terry. This research was conducted as part of the University of Washington's 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. 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.

CONFLICT OF INTEREST

The author declares no competing interests.

AUTHOR CONTRIBUTIONS

Conceptualization, methodology, analysis, and writing were conducted solely by the author with comments and suggestions by Terry, Ekaterina Jardim, and MWS investigators.

ORCID

Mark C. Long https://orcid.org/0000-0001-5500-9967

ENDNOTES

[1] In November of 2016, voters in the state of Washington passed Initiative 1433, which raised the state's minimum wage from $9.47 (2016) to $11 (2017), ramping up to $13.50 in 2020. Given passage of this new statewide law, which evaluates impacts through 2017q2, note that the "control" group is affected in the latter quarters.

[2] When Seattle's top minimum wage increased to $13, for those employed in jobs earning less than $19, Jardim et al. estimate that wages increased 3% while hours declined 7%, yielding a 4% reduction in the total amount paid to workers in these jobs. Yet, those who were employed in Seattle in low-wage jobs before the minimum wage increased fared better. For Seattle workers earning less than $11 per hour in the winter of 2015, Jardim et al. estimate that the $13 minimum wage caused wages to rise $1.37, hours to fall by 11 h per quarter, yielding a net increase in earnings of $153 per quarter. Of this gain in earnings, all of it can be attributable to those with more labor-market experience; earnings increased $296 per quarter for above median experience workers while falling $2 per quarter for those with below median experience. Finally, Jardim et al. find that Seattle saw a decline in low-wage labor market entrants (which contributed to the aggregate reduction in low-wage job payroll) and a reduction in turnover in low-wage jobs. These papers did not explicitly measure earnings inequality, although their findings of a small increase in earnings for those who were employed at baseline is consistent with the finding in this paper of a small decrease in inequality of earnings among those who are employed.

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

[4] Note that Seattle is composed of five contiguous Public Use Micro Areas.

[5] The largest estimated effect, −.011, is roughly two-thirds of the size of the simulated .016 reduction in the Gini Index for below-median wage workers given an across-the-board $13 minimum wage (Table 1). The difference between the actual estimated effect and the simulated effect may be due to a combination of reductions in labor demand (or supply) and the fact that Seattle's top minimum wage of $13 only applied to large firms that did not pay benefits.

[6] 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 Figure A2, 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.

REFERENCES

Aaronson, D. & Phelan, B.J. (2019) Wage shocks and the technological substitution of low-wage jobs. *The Economic Journal*, 129(617), 1–34.

Abadie, A., Diamond, A. & Hainmueller, J. (2010) Synthetic control methods for comparative case studies: estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105(490), 493–505.

Atkinson, A.B. (1979) On the measurement of inequality. *Journal of Economic Theory*, 2, 244–263.

Auten, G. & Splinter, D. (2019) Top 1 percent income shares: comparing estimates using tax data. *AEA Papers and Proceedings*, 109, 307–311.

Autor, D.H., Manning, A. & Smith, C.L. (2016) The contribution of the minimum wage to US wage inequality over three decades: a reassessment. *American Economic Journal: Applied Economics*, 8(1), 58–99.

Bentham, J. (1789) *An introduction to the principles of morals and legislation*. London: T. Payne and Son.

Congressional Budget Office. (2018) *The distribution of household income, 2015*. Available from: https://www.cbo.gov/system/files/2018-11/54646-Distribution_of_Household_Income_2015_0.pdf [Accessed 15th November 2021].

Fixler, D., Gindelsky, M. & Johnson, D. (2019) Improving the measure of the distribution of personal income. *AEA Papers and Proceedings*, 109, 302–306.

Gini, C. (1912). *Variabilità e mutabilità. Contributo allo Studio delle Distribuzioni e delle Relazioni Statistiche*. Bologna: Paolo Cuppini.

Jardim, E., Long, M.C., Plotnick, R., van Inwegen, E., Vigdor, J. & Wething, H. (2017) *Minimum wage increases, wages and low-wage employment: evidence from Seattle*. National Bureau of Economics Research Working Paper No. 23532.

Jardim, E., Long, M.C., Plotnick, R., van Inwegen, E., Vigdor, J. & Wething, H. (2018) *Minimum wage increases and individual employment trajectories*. National Bureau of Economics Research Working Paper No. 25182.

Jardim, E., Long, M.C., Plotnick, R., van Inwegen, E., Vigdor, J. & Wething, H. (Forthcoming) *Minimum wage increases and low-wage employment: evidence from Seattle*. American Economic Journal: Economic Policy.

Jenkins, S.P. (2006) *Estimation and interpretation of measures of inequality, poverty, and social welfare using Stata*. Presentation at North American Stata Users' Group Meeting. Available from: http://econpapers.repec.org/paper/bocasug06/16.htm [Accessed 15th November 2021].

Levitin, M. (2015) The triumph of occupy Wall Street. *The Atlantic*, 10 June. Available from: https://www.theatlantic.com/politics/archive/2015/06/the-triumph-of-occupy-wall-street/395408/ [Accessed 15th November 2021].

Murray, E. (2014) *Murray announces additional details on Income Inequality Symposium*. Available from: http://murray.seattle.gov/murray-announces-additional-details-on-income-inequality-symposium/ [Accessed 15th November 2021].

Neumark, D. & Wascher, W. (1995) *The effects of minimum wages on teenage employment and enrollment: evidence from matched CPS surveys*. National Bureau of Economics Research Working Paper No. 5092.

Piketty, T. & Saez, E. (2003) Income inequality in the United States, 1913–1998. *Quarterly Journal of Economics*, 118(1), 1–41.

Piketty, T., Saez, E. & Zucman, G. (2018) Distributional national accounts: methods and estimates for the United States. *Quarterly Journal of Economics*, 133(2), 553–609.

Seattle Minimum Wage Study. (2016) *Report on baseline employer survey and worker interviews*. University of Washington, Seattle. Report commissioned by the Seattle City Council.

Seattle Office of Labor Standards. (no date) *Seattle's minimum wage*. Available from: http://www.seattle.gov/Documents/Departments/LaborStandards/OLS-MW-multiyearChart2020_Final2.pdf [Accessed 15th November 2021].

Stevenson, B. & Wolfers, J. (2013) Subjective well-being and income: is there any evidence of satiation? *American Economic Review*, 103(3), 598–604.

UC Berkeley Labor Center. (2019) *Inventory of US city and county minimum wage ordinances*. Available from: http://laborcenter.berkeley.edu/minimum-wage-living-wage-resources/inventory-of-us-city-and-county-minimum-wage-ordinances/ [Accessed 15th November 2021].

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Long, M.C. (2021) Seattle's local minimum wage and earnings inequality. *Economic Inquiry*, 1–15. Available from: https://doi.org/10.1111/ecin.13053

APPENDIX A

A1 | Data and methods

A1.1 | 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 624,120). 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, Forthcoming) suggests that the effects of the Seattle minimum wage law on employment were likely to have been similar in locatable and non-locatable firms.

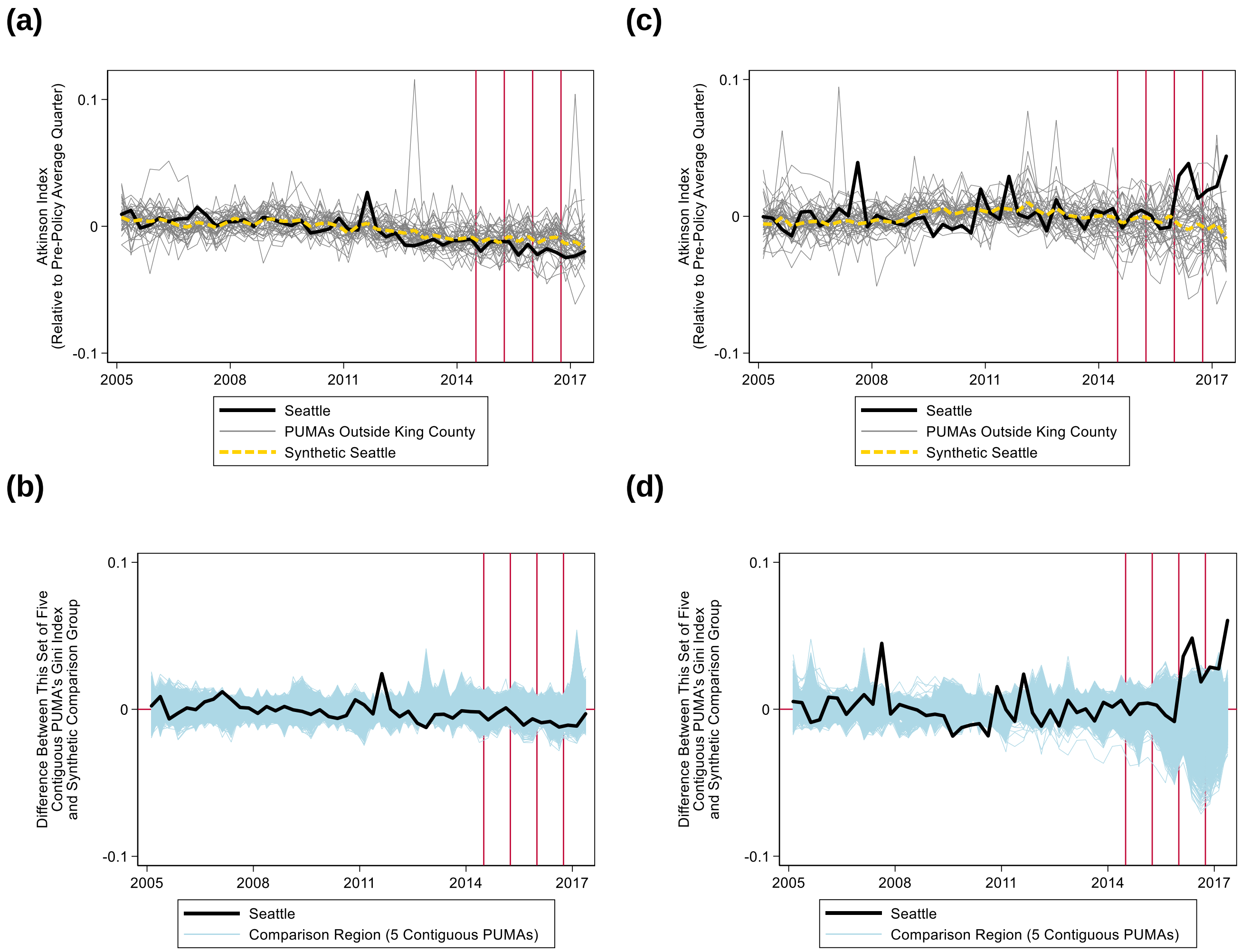

FIGURE A1 Effect of the Seattle minimum wage on the Atkinson index of earnings inequality. (a) Time series of Atkinson index in Seattle and comparison regions, below median wage workers. (b) Impact estimate for Atkinson index in Seattle and placebo estimates for comparison regions, below median wage workers. (c) Time series of Atkinson index in Seattle and comparison regions, all workers. (d) Impact estimate for Atkinson index in Seattle and placebo estimates for comparison regions, all workers

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.

A1.2 | 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 40 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).

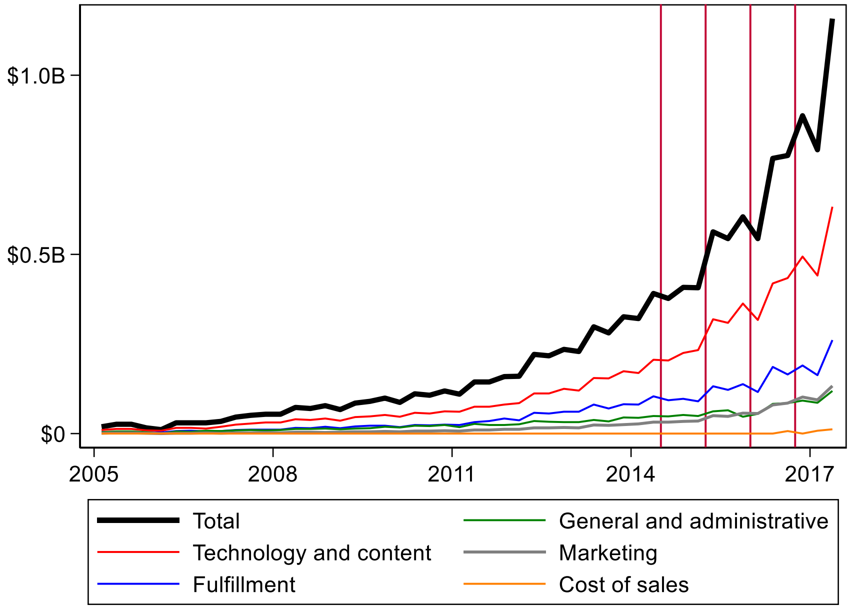

FIGURE A2 Stock-based compensation expenses at Amazon.com, Inc. Data are taken from form 10-Q (quarterly) and 10-K (annual) filings to the Securities and Exchange Commission. Available from: https://www.sec.gov/edgar/searchedgar/companysearch.html

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 & 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 $\varepsilon = 1$, 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 & Wolfers, 2013]), then the Atkinson Index becomes $A_1 = 1 - e^{1/N\sum_{i=1}^{N}\ln(y_i/\mu)}$ (Jenkins, 2006). The Atkinson Index is computed by the author's own coding of this equation.

TABLE A1 Simulated impact of a \$20 and \$25 minimum wage, *ceteris paribus*

	Quarters	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
Panel A: Actual earnings	First quarters of 2005–2014	.351	.302	.487	.412
	Second quarters of 2005–2014	.354	.307	.469	.396
	Third quarters of 2005–2013	.361	.311	.479	.407
	Fourth quarters of 2005–2013	.352	.303	.491	.417
	Average	.355	.306	.482	.408
Panel B: Simulated earnings with \$20 per hour. Minimum wage, *ceteris paribus*	First quarters of 2005–2014	.294	.243	.451	.355
	Second quarters of 2005–2014	.295	.245	.430	.335
	Third quarters of 2005–2013	.302	.249	.439	.346
	Fourth quarters of 2005–2013	.295	.243	.456	.362
	Average	.296	.245	.444	.350
Panel C: Difference between panels B and A	First quarters of 2005–2014	−.057	−.059	−.036	−.057
	Second quarters of 2005–2014	−.059	−.062	−.039	−.061
	Third quarters of 2005–2013	−.059	−.062	−.040	−.061
	Fourth quarters of 2005–2013	−.057	−.060	−.035	−.055
	Average	−.058	−.061	−.038	−.059
	Percentage change	−16.4%	−19.9%	−7.8%	−14.3%
Panel D: Simulated earnings with \$25 per hour. Minimum wage, *ceteris paribus*	First quarter of 2005–2014	.284	.236	.421	.325
	Second quarter of 2005–2014	.287	.307	.399	.305
	Third quarters of 2005–2013	.294	.244	.408	.315
	Fourth quarters of 2005–2013	.284	.236	.427	.332
	Average	.287	.256	.414	.319
Panel E: Difference between panels D and A	First quarters of 2005–2014	−.067	−.066	−.066	−.088
	Second quarters of 2005–2014	−.067	.000	−.070	−.092
	Third quarters of 2005–2013	−.067	−.068	−.071	−.092
	Fourth quarters of 2005–2013	−.068	−.067	−.064	−.086
	Average	−.067	−.050	−.068	−.089
	Percentage change	−19.0%	−16.4%	−14.1%	−21.8%

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 Table A1. For example, all first quarter Gini indexes are demeaned by deducting .487.

To obtain causal impact estimates, I employ the synthetic control method of Abadie et al. (2010) using the "synth" Stata command (Abadie et al., 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 $G_{t1}, G_{t2} \ldots, G_{t40}$ for the 40 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 prior research on the Seattle minimum

TABLE A2 Estimated impact of the Seattle minimum wage on the Gini index of earnings inequality for workers with wages below the *X*th percentile

Quarter	Quarters after passage/ enforcement	Top min. wage in Seattle	(1) Below 10th pct. wage	(2) Below 20th pct. wage	(3) Below 30th pct. wage	(4) Below 40th pct. wage	(5) Below median wage	(6) Below 60th pct. wage	(7) Below 70th pct. wage	(8) Below 80th pct. wage	(9) Below 90th pct. wage	(10) All
2014.3	1/-	-	−.007	−.013	−.006	−.004	−.005	.001	.010	.011	**.013**	.000
			[.621]	[.131]	[.325]	[.528]	[.324]	[.826]	[.067]	[.078]	[.022]	[.990]
2014.4	2/-	-	.007	−.011	−.005	−.003	−.003	.002	.007	.008	**.012**	.005
			[.448]	[.155]	[.292]	[.419]	[.445]	[.626]	[.160]	[.137]	[.024]	[.359]
2015.1	3/-	-	.005	**−.022**	−.008	−.005	−.001	.004	.006	**.010**	**.015**	.005
			[.488]	[.025]	[.082]	[.162]	[.786]	[.271]	[.120]	[.009]	[.003]	[.409]
2015.2	4/1	$11	.009	.009	−.008	−.004	−.006	−.001	.004	.006	.009	.004
			[.347]	[.310]	[.130]	[.399]	[.241]	[.911]	[.512]	[.314]	[.281]	[.582]
2015.3	5/2	$11	−.004	−.006	**−.011**	−.006	−.006	−.001	.001	.009	.011	.001
			[.764]	[.422]	[.011]	[.311]	[.219]	[.875]	[.860]	[.216]	[.142]	[.940]
2015.4	6/3	$11	.001	−.004	−.012	−.006	−.005	.000	−.005	.006	.009	−.007
			[.885]	[.489]	[.078]	[.258]	[.186]	[.947]	[.398]	[.128]	[.093]	[.334]
2016.1	7/4	$13	−.004	**−.024**	**−.015**	**−.014**	**−.009**	−.001	−.002	**.010**	**.019**	**.037**
			[.595]	[.003]	[.001]	[.001]	[.031]	[.729]	[.767]	[.030]	[.002]	[.000]
2016.2	8/5	$13	−.002	−.001	**−.014**	−.009	−.008	−.003	−.001	.010	.016	**.049**
			[.838]	[.876]	[.005]	[.126]	[.142]	[.545]	[.917]	[.253]	[.057]	[.000]
2016.3	9/6	$13	−.007	−.001	**−.016**	**−.011**	−.009	−.004	−.002	.008	.012	.022
			[.701]	[.878]	[.019]	[.008]	[.053]	[.406]	[.726]	[.245]	[.170]	[.056]
2016.4	10/7	$13	−.007	**−.018**	**−.020**	**−.016**	**−.011**	−.005	−.001	.008	**.014**	**.031**
			[.413]	[.003]	[.000]	[.000]	[.010]	[.224]	[.875]	[.078]	[.045]	[.004]
2017.1	11/8	$15	−.009	−.013	−.016	**−.021**	−.008	.000	.006	**.010**	**.013**	**.030**
			[.426]	[.212]	[.091]	[.034]	[.321]	[.982]	[.258]	[.022]	[.031]	[.001]
2017.2	12/9	$15	−.004	.006	−.010	−.004	−.005	.001	.009	**.015**	**.020**	**.061**
			[.678]	[.535]	[.066]	[.451]	[.311]	[.749]	[.092]	[.003]	[.037]	[.000]

Note: Bracketed values show the two-tailed *p*-values. Bolded coefficients have *p*-values ≤ .05.

wage (Jardim et al., 2017, 2018, Forthcoming) whereby the weights are found by minimizing forecasting error in the pre-passage period: $\min_{w_r}\sum_{t=-37}^{0}\left(G_{t0}-\sum_{r=1}^{40}w_rG_{tr}\right)^2$, 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 et al., 2010). This test is based on the 2994 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 1/2994 = .0003.

APPENDIX B

B1 | References

Abadie, A., Diamond, A. & Hainmueller, J. (2011) *SYNTH: stata module to implement synthetic control methods for comparative case studies*. Available from: https://econpapers.repec.org/software/bocbocode/s457334.htm [Accessed 15th November 2021].

Deininger, K. & Squire, L. (1996) A new data set measuring income inequality. *The World Bank Economic Review*, 10(3), 65–91.

Sajaia, Z. (2007) *FASTGINI: stata module to calculate Gini coefficient with jackknife standard errors*. Available from: https://econpapers.repec.org/software/bocbocode/s456814.htm [Accessed 15th November 2021].