Graduate Labor Economics

Lecture 10: The Minimum Wage: Part II

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The state of the debate

- New wave of minimum-wage increases
  - States and cities legislating a $15 minimum
  - And growing discussion of a $15 federal minimum
- New round of evaluations
  - Mix of old datasets and new datasets
  - New tools: synthetic control, interactive effects, bunching estimators
  - Bigger increases in the minimum wage

Jardim et al. (2017)

- The Seattle Minimum Wage Study
  - Analyzes an unusually high wage floor ...
  - ... with unusually rich data ...
  - ... and finds provocative results
- Up to now, we've mostly seen published articles
  - Final version of the analysis
  - Joint product of authors + referees/editors
- Today we're looking at a working paper
- Let's think like referees

The paper in a nutshell

Economic theory suggests that binding price floor policies, including minimum wages, should lead to a disequilibrium marked by excess supply and diminished demand. Previous empirical studies have questioned the extent to which this prediction holds in the labor market, with many estimates suggesting a negligible impact of higher minimum wages on employment. This paper, using rich administrative data on employment, earnings and hours in Washington State, re-examines this prediction in the context of Seattle's minimum wage increases from $9.47 to $11/hour in April 2015 and to $13/hour in January 2016. It reaches a markedly different conclusion: employment losses associated with Seattle's mandated wage increases are in fact large enough to have resulted in net reductions in payroll expenses—and total employee earnings—in the low-wage job market. The contrast between this conclusion and previous literature can be explained largely if not entirely by data limitations that we are able to circumvent in our analysis. Most importantly, much of the literature examines the impact of minimum wage policies in datasets that do not actually reveal wages, and thus can neither focus precisely on low-wage employment nor examine impacts of policies on wages themselves.

Under Seattle's June 2014 policy change:

Table 1: Minimum Wage Schedule in Seattle under the Seattle Minimum Wage Ordinance

	Large Employers[a]		Small Employers	
Effective Date	No benefits	With benefits[b]	No benefits or tips	Benefits or tips[c]
	Before Seattle Ordinance			
January 1, 2015	$9.47	$9.47	$9.47	$9.47
	After Ordinance			
April 1, 2015	$11.00	$11.00	$11.00	$10.00
January 1, 2016	$13.00	$12.50	$12.00	$10.50
January 1, 2017	$15.00[d]	$13.50	$13.00	$11.00
January 1, 2018		$15.00[e]	$14.00	$11.50
January 1, 2019			$15.00[f]	$12.00
January 1, 2020				$13.50
January 1, 2021				$15.00[g]

Jardim et al. (2017, Table 1)

Data

- Quarterly administrative payroll data, 2005–2016Q3
  - Employment, earnings, hours worked
  - Long pre-period, short post-period
  - Limited to Washington State
  - Same microdata that underlie the QCEW
- Only four states record hours: why does Washington?
  - UI eligibility depends on hours worked
  - Administrative data elements usually depend on administrative need
  - "[G]iven the statutory reporting requirement driven by benefits determination provisions, ESD considers the hours data reliable."
- Hourly wage $\equiv \frac{\text{quarterly earnings}}{\text{quarterly hours}}$
  - Can't distinguish standard hours vs. overtime

Administrative vs. survey data

- Some strengths of administrative employment data:
  - Full-count datasets
  - No non-response attrition
  - Minimal measurement error
  - Employer-employee links
  - (Sometimes) higher frequency
- Some weaknesses:
  - Sparse observables (here: no age, education, occupation)
  - Only observe those in formal employment
  - (Sometimes) don't observe entire household
  - Can't distinguish labor force exit from cross-state moves
- Lots of interest in linking administrative + survey data

Data limitations and sample restrictions

- Discard multi-site, multi-account firms
  - Why drop them?
  - 11% of firms, 38% of workers
  - Omitting could overstate or understate effects (survey evidence suggests the latter)
- Don't observe non-UI employment
  - The underground economy
  - Independent contractors (IRS 1099)

Sample exclusions: what's missing from this table?

Table 2: Characteristics of Included and Excluded Firms, Washington State

	Included in Analysis	Excluded from Analysis	Share Included
Number of Firms	123,180	14,917	89.2%
Number of Establishments (i.e., Sites)	140,451	Unknown	
Total Number of Employees	1,672,448	1,019,875	62.1%
Employees / Firm	14	68	
Employees / Establishment	12	Unknown	

Notes: Firms are defined as entities with unique federal tax Employer Identification Numbers. Statistics are computed for the average quarter between 2005.1 to 2016.3. "Excluded from Analysis" includes two categories of firms: (1) Multi-location firms (flagged as such in UI data), and (2) Single-location firms which operate statewide or whose location could not be determined.

Jardim et al. (2017, Table 2)

2018 revision adds some helpful detail

Table 2: Characteristics of Included and Excluded Firms, Washington State

	Included in Analysis	Excluded from Analysis: Multi-site businesses	Excluded from Analysis: Non-locatable single-site businesses	Excluded from Analysis: Total	Share Included
Number of Firms	123,132	1,345	12,277	13,622	90.04%
Number of Establishments (i.e., Sites)	126,248	Unknown	12,501	Unknown	
Total Number of Employees	1,676,653	767,348	240,237	1,007,585	62.46%
Number of Employees paid <$19/hour	715,808	325,320	87,395	412,715	63.43%
Employees / Firm	13	279	19	58	
St. Dev. of Employees / Firm	160	1610	328	706	
Employees / Establishment	13	Unknown	19	Unknown	
St. Dev. of Employees / Establishment	153	Unknown	282	Unknown	

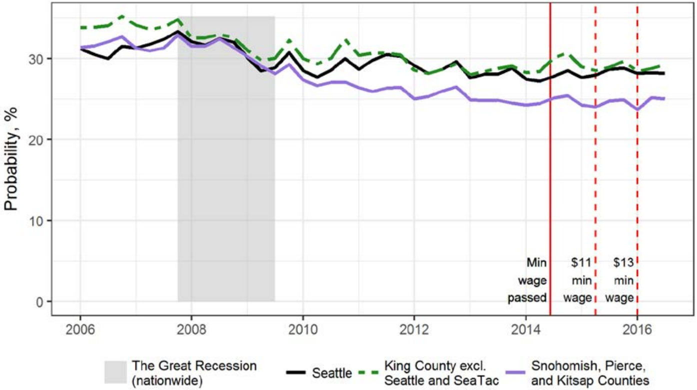
Notes: Firms are defined as entities with unique federal tax Employer Identification Numbers. Statistics are computed for the average quarter between 2005.1 and 2016.3. "Excluded from Analysis" includes two categories of firms: (1) Multi-location firms (flagged as such in UI data), and (2) Single-location firms which operate statewide or whose location could not be determined.

Jardim et al. (2018, Table 2)

2018 revision shows no increase in transitions to "non-locatable jobs"

Figure 1: Rates of Transition from Locatable to Non-Locatable Employment

Panel A. *P*(non-locatable job in t | locatable and paid under $19/hour in t-4, employed in WA in t) by initial location



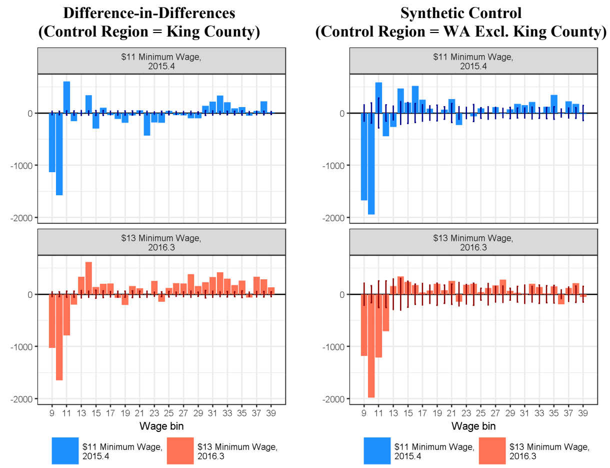
Jardim et al. (2018, Figure 1A)

Defining the low-wage sector

- Goal: partition labor market into low-wage/other sector
  - Prior studies: teenagers, restaurants
  - Jardim et al.: "Imagining a reaction function linking initial wages to post-increase wages, we aim to identify a fixed point above which there does not appear to be any impact—that is, the point where this reaction function strikes the 45-degree line."
- Challenge: which wage threshold to choose?
  - Cutoff too low: overstate decline in employment
  - Cutoff too high: dilute effects, lose precision

Finding the right cutoff (2017 version)

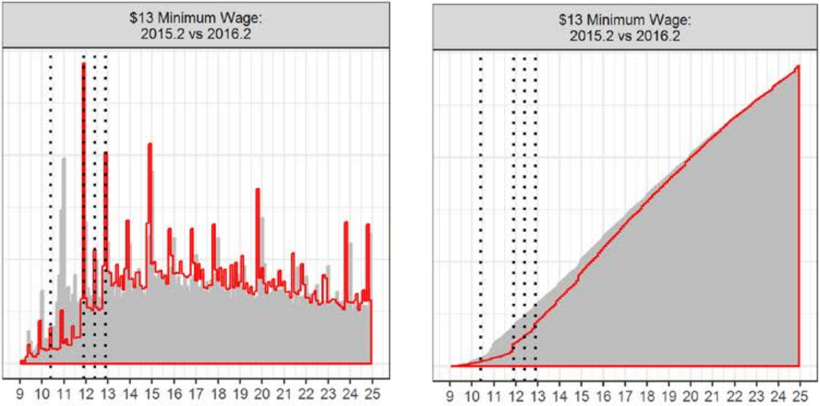
Figure 1: Finding a Reasonable Threshold – Effect on Quarterly Hours Worked (000s) Relative to Baseline Quarter (2014.2) for Those Paid Within Each Wage Bin



Notes: Point estimates (i.e., bars) and 50% confidence intervals centered around zero are shown.

Jardim et al. (2017, Figure 1)

Finding the right cutoff (2018 revision)



Jardim et al. (2018, Figure 2)

Choosing the right counterfactual (part 1: the simple stuff)

- Jardim et al. consider four counterfactuals
- First pass: difference-in-differences

$$\Delta Y_{rt} = \alpha_r + \psi_t + \sum_{q=1}^{9} \beta_q T_{rt} + \varepsilon_{rt}$$

- Define $\Delta Y_{rt} \equiv \frac{Y_{rt}}{Y_{r,t-4}} - 1$: why?
- Two control regions:
  - Seattle vs. King County
  - Seattle vs. other nearby counties
- Key assumption: parallel trends

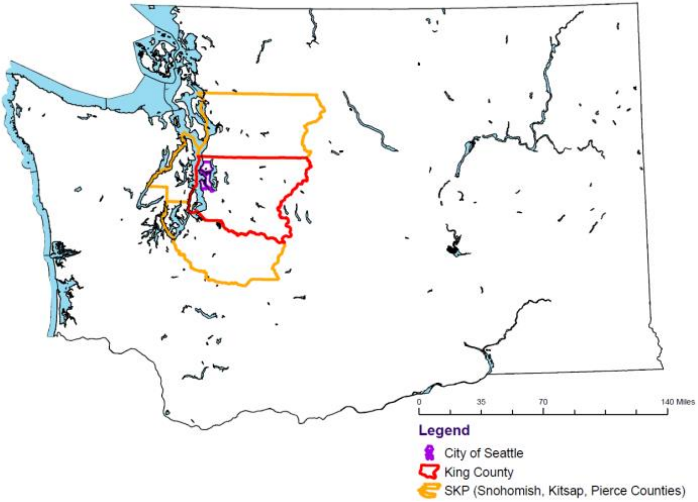
Choosing the right counterfactual (part 2: the fancy stuff)

- Generalization: unobserved factor model

$$\Delta Y_{rt} = \sum_{k=1}^{K} \lambda_{rk}\mu_{tk} + \sum_{q=1}^{9} \beta_q T_{rt} + \varepsilon_{rt}$$

- Idea: regions differ in sensitivity to aggregate shocks
  - The shocks are called "factors" (μ_{tk})
  - The region-specific sensitivities are "factor loadings" (λ_{rk})
  - Useful reference: Gobillon and Magnac (2016)
- Method 1: synthetic control
  - Construct "synthetic Seattle" as weighted avg. of other places
  - Choose weights to minimize pre-period forecast error
- Method 2: interactive fixed effects
  - Given choice of K, explicitly recover factors + factor loadings
  - Use a model-selection criterion to choose optimal K

The diff-in-diff control regions



Jardim et al. (2017, Figure 2B)

Synthetic control weights (for one particular outcome)

Appendix Table 2: PUMAs with positive weights chosen by Synthetic Control Estimator.

	PUMA ID	PUMA Name	Weight in Synthetic Control, %
A. Average Wages			
1	10503	Spokane County (East Central)--Greater Spokane Valley City PUMA	25.39
2	11702	Snohomish County (West Central)--Mukilteo & Everett (Southwest) Cities PUMA	19.29
3	11701	Snohomish County (Southwest)--Edmonds, Lynnwood & Mountlake Terrace Cities PUMA	15.22
4	11402	Thurston County (Outer) PUMA	10.08
5	10300	Chelan & Douglas Counties PUMA	9.86
6	10702	Benton County (East Central)--Kennewick & Richland (South) Cities PUMA	9.34
7	11502	Pierce County (Northwest)--Peninsula Region & Tacoma City (West) PUMA	5.30
8	11801	Kitsap County (North)--Bainbridge Island City & Silverdale PUMA	4.82
9	11505	Pierce County (North Central)--Tacoma (Port) & Bonney Lake (Northwest) Cities PUMA	0.69

Jardim et al. (2017, Appendix Table 2)

Evaluating alternative comparison regions

Table 4: Falsification Test: Pseudo-Effect of Placebo Law Passed 2012

Quarter	Quarters after (pseudo) Passage/ Enforcement	Difference-in-Differences between Seattle and: Outlying King County — Wage	Hours	Snohomish, Kitsap, and Pierce Counties — Wage	Hours	Synthetic Control: Washington excluding King County — Wage	Hours	Interactive Fixed Effects: Washington excluding King County — Wage	Hours
2012.3	1	0.001*	-0.044***	-0.003**	-0.014***	0.001	-0.014	-0.002	-0.012
		(0.001)	(0.004)	(0.002)	(0.006)	(0.003)	(0.015)	(0.003)	(0.013)
2012.4	2	-0.002***	-0.033***	-0.003*	-0.038***	0.001	-0.018	-0.001	-0.022
		(0.001)	(0.004)	(0.002)	(0.006)	(0.003)	(0.021)	(0.003)	(0.014)
2013.1	3	0.002***	-0.034***	0.001	-0.028***	0.001	-0.002	0.000	-0.017
		(0.001)	(0.004)	(0.002)	(0.006)	(0.003)	(0.020)	(0.003)	(0.038)
2013.2	4/1	0.003***	-0.022***	0.005***	-0.036***	0.001	0.004	0.001	-0.016
		(0.001)	(0.004)	(0.002)	(0.006)	(0.003)	(0.026)	(0.003)	(0.038)
2013.3	5/2	0.003***	-0.063***	-0.002	-0.063***	0.004	-0.006	-0.002	-0.024
		(0.001)	(0.007)	(0.003)	(0.012)	(0.005)	(0.022)	(0.004)	(0.041)
2013.4	6/3	0.003**	-0.069***	-0.006*	-0.095***	0.006	-0.009	0.000	-0.034
		(0.001)	(0.007)	(0.003)	(0.012)	(0.004)	(0.033)	(0.004)	(0.049)
2014.1	7/4	0.003**	-0.031***	0.001	-0.047***	0.005	0.028	-0.001	-0.008
		(0.001)	(0.007)	(0.003)	(0.012)	(0.004)	(0.029)	(0.004)	(0.053)
2014.2	8/5	0.006***	-0.031***	0.004	-0.059***	0.008***	0.014	0.003	-0.024
		(0.001)	(0.007)	(0.003)	(0.012)	(0.004)	(0.031)	(0.004)	(0.055)
2014.3	9/6	0.004**	-0.046***	-0.001	-0.073***	0.010*	0.013	0.000	-0.019
		(0.002)	(0.011)	(0.005)	(0.017)	(0.005)	(0.031)	(0.005)	(0.081)
Average		0.003	-0.041	0.000	-0.050	0.004	0.001	0.000	-0.019
Obs.		68	68	68	68	1,530	1,530	1,530	1,530

Jardim et al. (2017, Table 4)

Wages go up . . .

Table 5: Main Results: Effect on Wages

Quarter	Quarters after Passage/ Enforcement	Synthetic Control	Interactive FE
2014.3	1	0.003 (0.003)	0.003 (0.003)
2014.4	2	0.003 (0.003)	0.006** (0.003)
2015.1	3	0.005 (0.004)	0.007*** (0.003)
2015.2	4/1	0.014*** (0.004)	0.014*** (0.003)
2015.3	5/2	0.019*** (0.005)	0.019*** (0.004)
2015.4	6/3	0.018*** (0.004)	0.018*** (0.004)
2016.1	7/4	0.031*** (0.005)	0.028*** (0.005)
2016.2	8/5	0.033*** (0.006)	0.029*** (0.005)
2016.3	9/6	0.036*** (0.007)	0.031*** (0.006)

Jardim et al. (2017, Table 5)

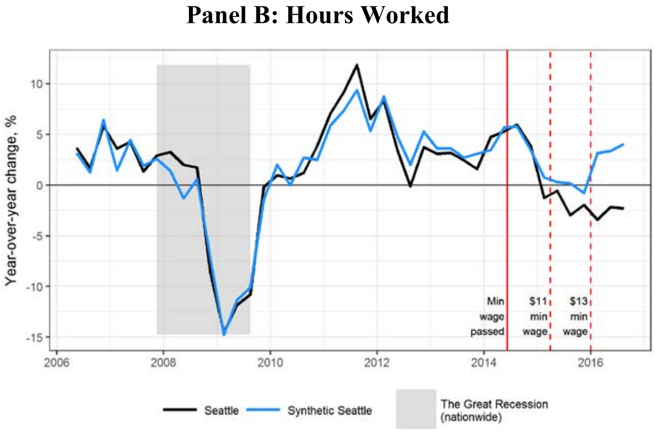
. . . and employment goes down

Table 6: Main Results: Effect on Employment

	Quarters since	Hours		Jobs	
Quarter	Passage/ Enforcement	SC	IFE	SC	IFE
2014.3	1	0.008	0.004	0.004	-0.006
		(0.018)	(0.013)	(0.017)	(0.015)
2014.4	2	0.003	-0.001	-0.010	-0.023
		(0.018)	(0.013)	(0.021)	(0.015)
2015.1	3	-0.023	-0.018	0.000	-0.013
		(0.018)	(0.013)	(0.023)	(0.015)
2015.2	4/1	-0.013	-0.014	-0.014	-0.032**
		(0.019)	(0.014)	(0.019)	(0.015)
2015.3	5/2	-0.034	-0.022	-0.019	-0.035*
		(0.025)	(0.020)	(0.021)	(0.021)
2015.4	6/3	-0.021	-0.009	-0.045	-0.048***
		(0.033)	(0.019)	(0.029)	(0.020)
2016.1	7/4	-0.106***	-0.090***	-0.051*	-0.053***
		(0.031)	(0.024)	(0.028)	(0.021)
2016.2	8/5	-0.087***	-0.079***	-0.052*	-0.083***
		(0.031)	(0.027)	(0.028)	(0.020)
2016.3	9/6	-0.102***	-0.100***	-0.063*	-0.106***
		(0.042)	(0.034)	(0.036)	(0.024)

Jardim et al. (2017, Table 6)

Seattle hours fall relative to Synthetic Seattle (2018 revision)



Jardim et al. (2018, Figure 5B)

Payroll doesn't rise, and maybe falls

Table 7: Main Results: Effect on Payroll

Quarter	Quarters since passage/ enforcement	Synthetic Control	Interactive Fixed Effects
2014.3	1	0.011 (0.018)	0.010 (0.013)
2014.4	2	0.008 (0.018)	0.003 (0.013)
2015.1	3	-0.016 (0.019)	-0.014 (0.014)
2015.2	4/1	0.002 (0.019)	0.002 (0.014)
2015.3	5/2	-0.013 (0.025)	0.004 (0.020)
2015.4	6/3	-0.002 (0.034)	0.011 (0.019)
2016.1	7/4	-0.076*** (0.034)	-0.054* (0.029)
2016.2	8/5	-0.053 (0.032)	-0.040 (0.031)
2016.3	9/6	-0.065 (0.044)	-0.060 (0.038)

Jardim et al. (2017, Table 7)

A non-linear response?

Table 8: Estimates of the Elasticity of Labor Demand with respect to Minimum Wages

Quarter	Quarters after Passage/ Enforcement	Denominator is synthetic control estimated wage effect		Denominator is statutory increase in minimum wage	
		Point Estimate	95% Conf. Int.	Point Estimate	95% Conf. Int.
2015.2	4/1	-0.97	(-3.75, 1.81)	-0.08	(-0.32, 0.15)
2015.3	5/2	-1.80	(-4.49, 0.90)	-0.21	(-0.51, 0.09)
2015.4	6/3	-1.16	(-4.81, 2.50)	-0.13	(-0.53, 0.27)
2016.1	7/4	-3.46	(-5.87, -1.04)	-0.28	(-0.45, -0.12)
2016.2	8/5	-2.66	(-4.79, -0.54)	-0.23	(-0.40, -0.07)
2016.3	9/6	-2.82	(-5.38, -0.27)	-0.27	(-0.50, -0.05)

Notes: Estimates for all jobs paying < \$19 in all industries, where the control region is defined as the state of Washington excluding King County. % Δ Min. Wage is defined as (\$11 - \$9.47)/\$9.47 for quarters 1-3 after enforcement, and as (\$13 - \$9.47)/\$9.47 for quarters 4-6 after enforcement.

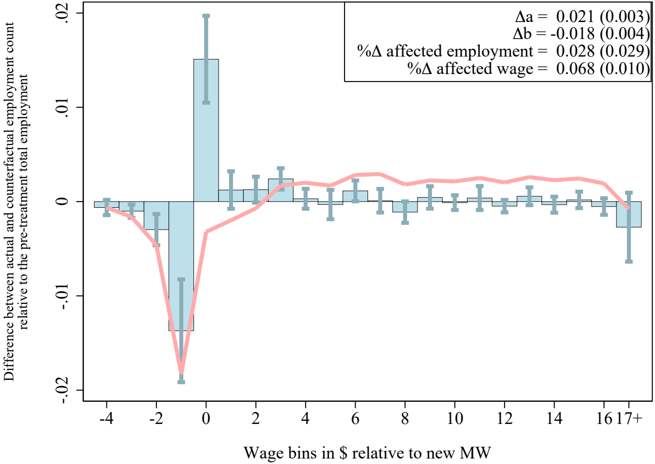
Jardim et al. (2017, Table 8)

What explains these big disemployment effects?

- Is the result right?
    - Is Seattle "outside the convex hull" of the donor regions?
    - Does employment shift into the suburbs?
    - Does employment shift into multi-site/multi-account firms?
    - Does employment shift into informality?
- If the result is right, why are the effects so big?
    - Maybe it's a fluke: "$n = 1$"
    - Maybe it's the data: past studies couldn't look at low-wage jobs
    - Maybe it's non-linearity: Seattle's minimum is unusually high

Cengiz et al. (2019): pooling 138 minimum-wage changes

Figure 2: Impact of Minimum Wages on the the Wage Distribution



Cengiz, Dube, Lindner, and Zipperer (2019), Figure 2