Does regional variation in wage levels identify the effects of a national minimum wage?

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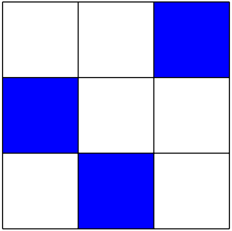
Identifying minimum wage effects



Minimum wage increases in blue states

Identifying minimum wage effects

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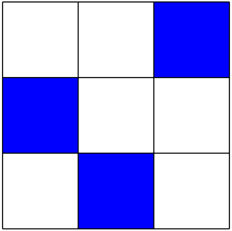
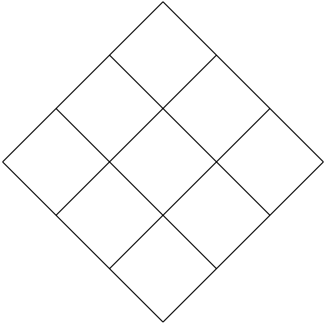
Minimum wage increases in blue states

Identifying minimum wage effects

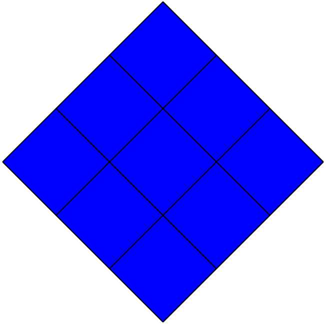


$$y_{r,t} = \alpha_r + \delta_t + \beta T_r \cdot \mathbf{1}\{t \geq 1\} + \epsilon_{r,t}$$

A national change in the minimum wage?

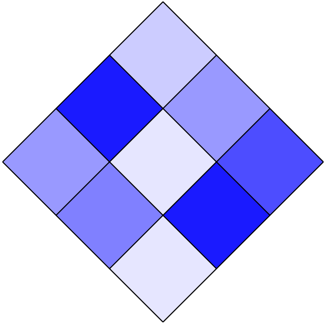


A national change in the minimum wage?



$$y_{r,t} = \alpha_r + \delta_t + \beta T_r \cdot \mathbf{1}\{t \geq 1\} + \epsilon_{r,t}$$

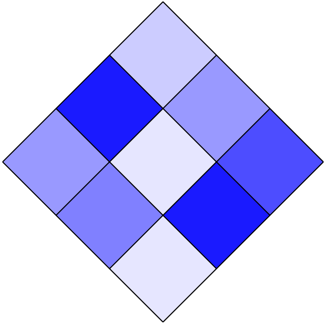
The fraction affected design



$$y_{r,t} = \alpha_r + \delta_t + \beta FA_r \cdot \mathbf{1}\{t \geq 1\} + \epsilon_{r,t}$$

- Card (1992)
- Bailey, DiNardo and Stuart (2021); Dustmann et al. (2021, using *Gap*)

The effective minimum wage design



$$y_{r,t} = \alpha_r + \delta_t + \beta \left[mw_t - w_{50,r,t}\right] + \gamma \left[mw_t - w_{50,r,t}\right]^2 + \epsilon_{r,t}$$

- Lee (1999); *older stuff like Neumark and Wascher (1992)*
- Bosch and Manacorda (2010); Engbom and Moser (2022)

This paper

Does regional variation in wage levels identify the effects of a national minimum wage?

- Evaluate identification assumptions of both designs

This paper

Does regional variation in wage levels identify the effects of a national minimum wage?

- Evaluate identification assumptions of both designs

Findings for the **effective minimum wage design:**

- Identification assumptions of Lee (1999) are crucial, but hard to satisfy without region-specific minimum wages
- If regional variation is available: IV strategies a la Autor, Manning, and Smith (2016) are preferable

This paper

Does regional variation in wage levels identify the effects of a national minimum wage?

- Evaluate identification assumptions of both designs

Findings for the **fraction affected/gap designs:**

- Parallel trend violations can come from unexpected places like e.g., skill-biased technical change
- Pre-trends checks useful, but should be implemented with care
- May be sensitive to functional form assumptions

Outline

1. **Setup**
2. Effective minimum wage design
3. Fraction affected/gap designs
4. Conclusion

The data-generating process

$$\mathbf{y}_{r,t} = f\left(mw_t, \boldsymbol{\theta}_{r,t}\right)$$

- $r \in \{1, \ldots, R\}$ are regions, $t \in \{0, 1\}$ is time
- $\mathbf{y}_{r,t}$: vector of outcomes, e.g., employment to population ratio and quantiles of the log wage distribution
- f given by an economic model
- $mw_1 > mw_0$
- $\boldsymbol{\theta}_{r,t}$: Region-time-specific parameters

The data-generating process

$$\mathbf{y}_{r,t} = f\left(mw_t, \boldsymbol{\theta}_{r,t}\right)$$

What this rules out:

- Regional spillovers due to e.g. migration: Cadena (2014)
- Short vs. long effects of minimum wages: Sorkin (2015), Hurst et al. (2022), Vogel (2023)
- Bias caused by measurement error in region-level statistics: Autor, Manning, and Smith (2016)
- Diff-in-diffs with staggered treatment: de Chaisemartin and D'Haultfoeuille (2020)

The causal effect of interest

$$\mathbf{y}_{r,t} = f\left(mw_t, \boldsymbol{\theta}_{r,t}\right)$$

$$\mathbf{ATE}_0 = \frac{1}{R}\sum_r f\left(mw_1, \theta_{r,0}\right) - \mathbf{y}_{r,0}$$

$$\mathbf{ATE}_1 = \frac{1}{R}\sum_r \mathbf{y}_{r,1} - f\left(mw_0, \theta_{r,1}\right)$$

$$\mathbf{ATE} = \frac{\mathbf{ATE}_0 + \mathbf{ATE}_1}{2}$$

Outline

1. Setup
2. **Effective minimum wage design**
3. Fraction affected/gap designs
4. Conclusion

Effective minimum wage design

Baseline specification for measuring *wage spillover effects*:

$$w_{q,r,t} - w_{0.5,r,t} = \alpha_{q,r} + \delta_{q,t} + \beta_q \left[mw_t - w_{0.5,r,t}\right] + \gamma_q \left[mw_t - w_{0.5,r,t}\right]^2 + \epsilon_{q,r,t}$$

- $w_{q,r,t}$: quantile q of log wage distribution in r, t
- Each q is a separate regression ▸ Figure from AMS

$$\widehat{ATE}_q = \frac{1}{R}\sum_r \Big\{ \hat{\beta}_q \left[(mw_1 - w_{0.5,r,1}) - (mw_0 - w_{0.5,r,0})\right] + \hat{\gamma}_q \left[(mw_1 - w_{0.5,r,1})^2 - (mw_0 - w_{0.5,r,0})^2\right] \Big\}$$

Effective minimum wage design

Also used for employment to population ratio (e.g., Engbom and Moser, 2022):

$$emp_{r,t} = \alpha_r + \delta_t + \beta \left[mw_t - w_{0.5,r,t}\right] + \gamma \left[mw_t - w_{0.5,r,t}\right]^2 + \epsilon_{r,t}$$

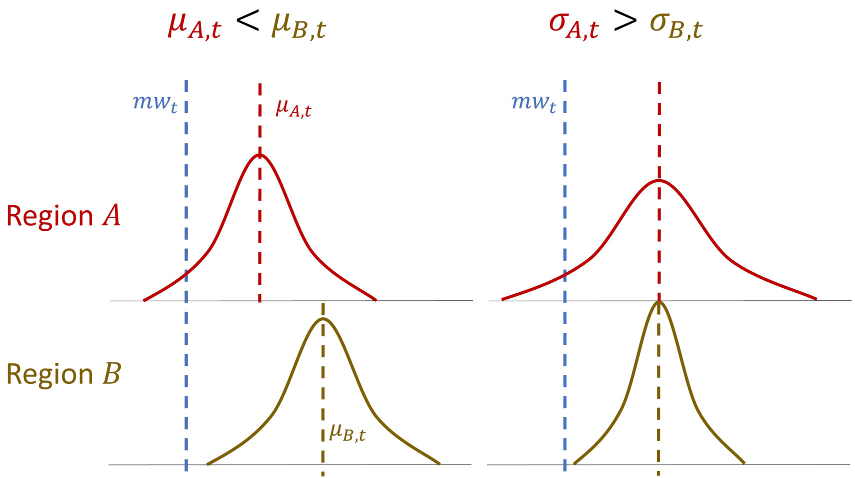
Lee's (1999) semiparametric model

CDF of *latent* log wages has the form:

$$F_t\left(\frac{w - \mu_{r,t}}{\sigma_{r,t}}\right) \qquad \text{with } F_t(0) = 0.5$$

- $\mu_{r,t}$ is the location (or *centrality*) parameter
- $\sigma_{r,t}$ is the *dispersion* parameter

Location (centrality) and dispersion



Lee's (1999) identification assumptions

CDF of *latent* log wages has the form:

$$F_t\left(\frac{w-\mu_{r,t}}{\sigma_{r,t}}\right) \qquad \text{with } F_t(0) = 0.5$$

- **Assumption 1:** $w_{0.5,r,t} \approx \mu_{r,t}$
- **Assumption 2:** $\mu_{r,t}$ and $\sigma_{r,t}$ are uncorrelated conditional on t

Building intuition with a linear model

The *economic* model is:

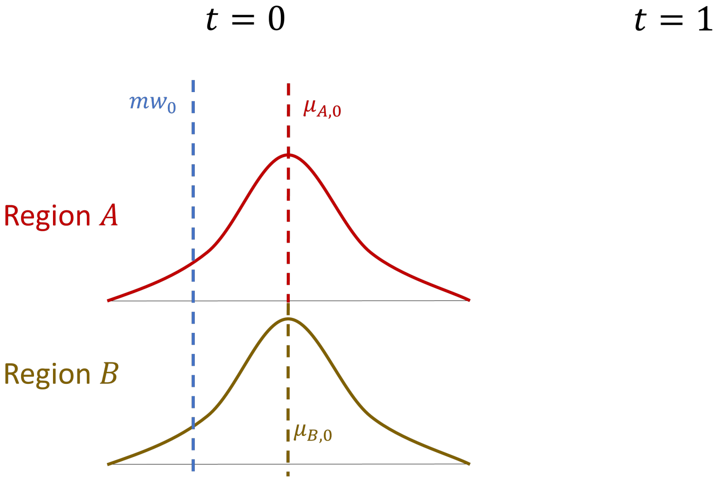
$$y_{q,r,t} = \alpha_{q,r} + \delta_{q,t} + \beta_q \left[mw_t - \mu_{r,t} \right] + \epsilon_{q,r,t}$$

We're interested in β_q. Taking differences:

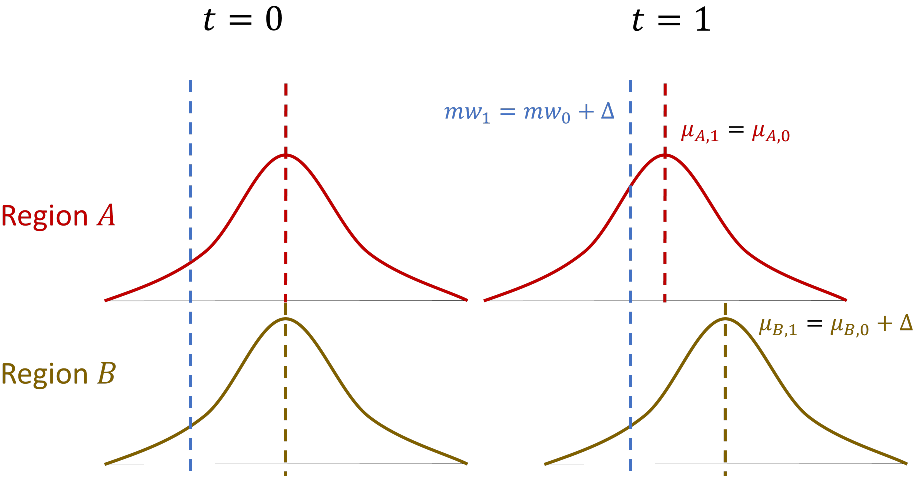
$$\begin{aligned} y_{q,r,1} - y_{q,r,0} &= (\delta_{q,1} - \delta_{q,0}) + \beta_q \left[(mw_1 - \mu_{r,1}) - (mw_0 - \mu_{r,0}) \right] \\ &\qquad + (\epsilon_{q,r,1} - \epsilon_{q,r,0}) \\ &= \rho_q + \beta_q \left[-(\mu_{r,1} - \mu_{r,0}) \right] + \upsilon_{q,r} \end{aligned}$$

Key source of variation: shocks to location parameter.

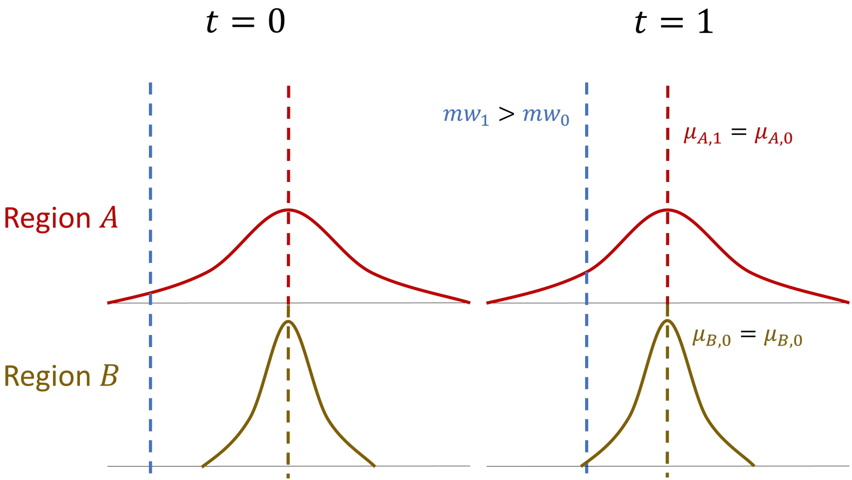
The ideal scenario: A is treated, B is not



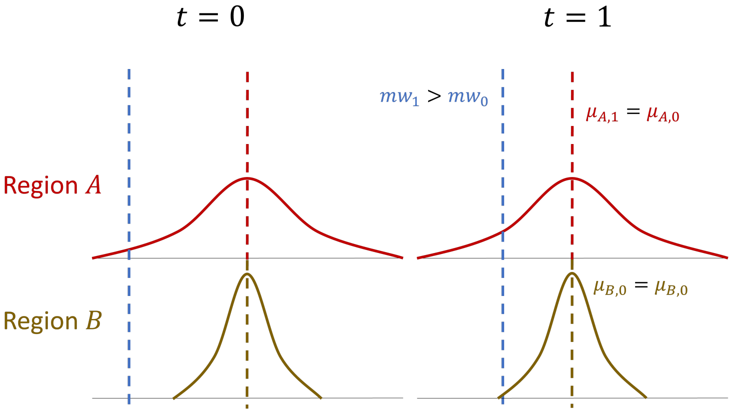
The ideal scenario: A is treated, B is not



Alternative scenario: no idiosyncratic shocks

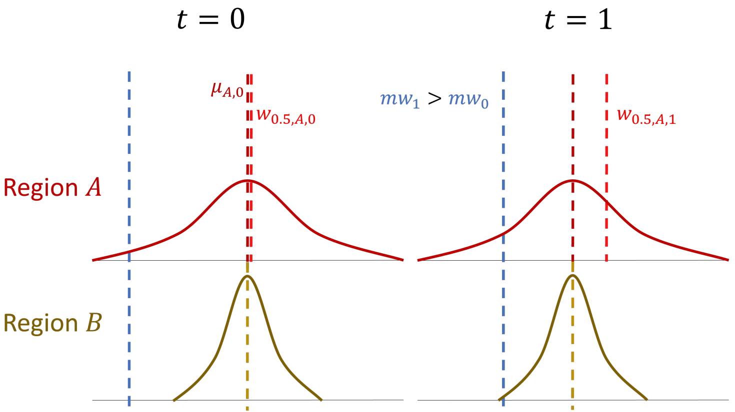


If we could observe $\mu_{r,t}$: no variation



Economic model: $\Delta y_{q,r} = \rho_q + \beta_q \left[-(\mu_{r,1} - \mu_{r,0})\right] + \upsilon_{q,r}$

Min. wage effects on median: bad variation



Statistical model: $\Delta y_{q,r} = \rho_q + \beta_q \left[-(w_{0.5,r,1} - w_{0.5,r,0}) \right] + \upsilon_{q,r}$

Issue #1: Correlated measurement error

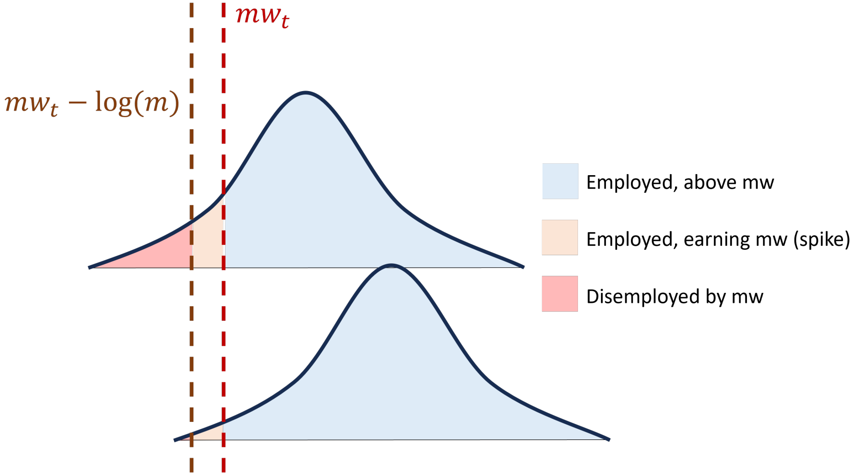
- Causal effects on median wage likely to be correlated with effects on other quantiles and on employment
- Problem exists even if average effect on median wage is zero
- Is it quantitatively relevant?

Simulations: the Normal-markdown model

- Latent log wages are Normal
- Vector $\boldsymbol{\theta}_r = [\mu_{r,0}, \sigma_{r,0}, \mu_{r,1}, \sigma_{r,1}]$ drawn from multivariate Normal calibrated to match data from the US CPS
  - Regions are states
  - Years are 1989 and 2004
  - Construct different scenarios. For example:
    - Shut down differences in dispersion: $\sigma_{r,t} = \bar{\sigma}_t$
    - Allow dispersion in $\sigma_{r,t}$, but make it uncorrelated with $\mu_{r,t}$

Minimum wage in the Normal-markdown model

Markdown parameter $m = 0.7$



Log min. wage increases by 0.2

Averages across 5,000 simulations, 50 regions in each simulation.

Panel A has $\sigma_{r,t} = \bar{\sigma}_t$ and $Corr(\mu_{r,0}, \mu_{r,1}) = 0.89$

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel A: Regions differ only in location parameter				
True average causal effect	-0.010	0.019	0.006	-0.004
Effective min. wage	-0.010	0.019	0.006	-0.004
	(0.001)	(0.002)	(0.000)	(0.000)

Log min. wage increases by 0.2

Averages across 5,000 simulations, 50 regions in each simulation.

Model imposes $Corr(\mu_{r,t}, \sigma_{r,t}) = 0$.

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel B: Regions differ in location and dispersion				
True average causal effect	-0.010	0.020	0.006	-0.004
Effective min. wage	-0.007	0.033	0.014	-0.023
	(0.004)	(0.023)	(0.013)	(0.028)

Larger minimum wage hike (0.4 vs. 0.2)

Averages across 5,000 simulations, 50 regions in each simulation.

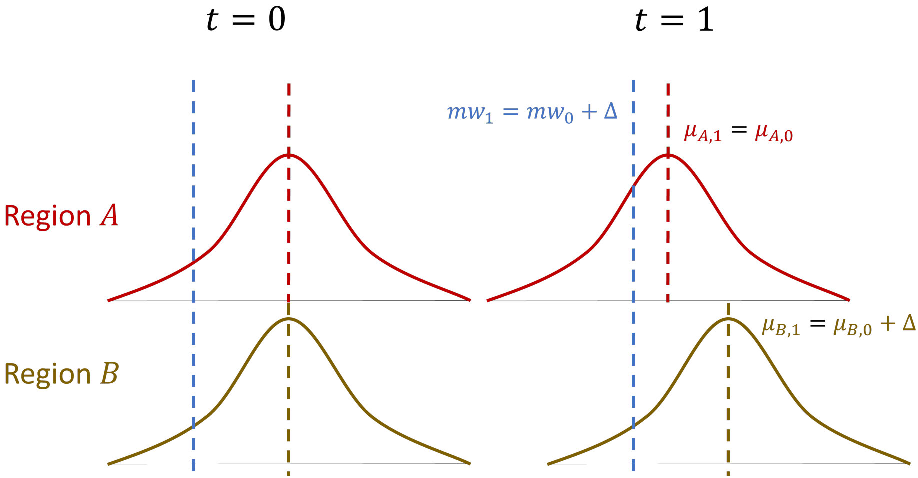
	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel C: As above, but larger increase in min. wage				
True average causal effect	-0.032	0.078	0.017	-0.012
Effective min. wage	-0.013	0.115	0.045	-0.079
	(0.015)	(0.040)	(0.023)	(0.053)

More heterogeneity in dispersion parameters

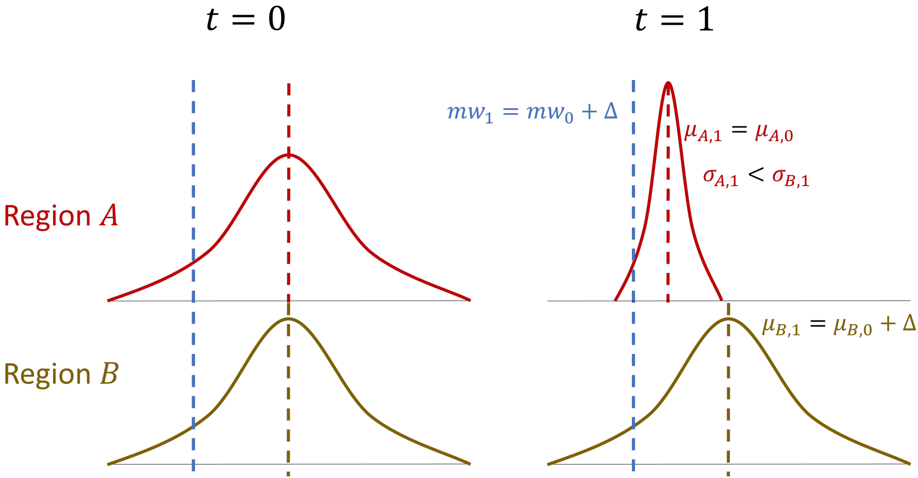
Averages across 5,000 simulations, 50 regions in each simulation.

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel D: St. dev. of dispersion is 50% larger				
True average causal effect	-0.010	0.020	0.006	-0.004
Effective min. wage	-0.003	0.050	0.025	-0.047
	(0.006)	(0.033)	(0.020)	(0.041)

Issue #2: Correlation between $\mu_{r,t}$ and $\sigma_{r,t}$



Issue #2: Correlation between $\mu_{r,t}$ and $\sigma_{r,t}$



Issue #2: Correlation between $\mu_{r,t}$ and $\sigma_{r,t}$

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel B: Contemporaneous correlation of 0.076				
True average causal effect	-0.010	0.020	0.006	-0.004
Effective min. wage	-0.002	0.076	0.040	-0.075
	(0.004)	(0.021)	(0.012)	(0.026)

Correlation between mean log wage and std. dev. of log wage at state level:

- 0.076 in 1989
- 0.264 in 2004

Issue #2: Correlation between $\mu_{r,t}$ and $\sigma_{r,t}$

Should we expect such correlations to occur?

- Regional differences in workforce composition
  - E.g., Lemieux (2006): there's more wage dispersion in more higher-wage education-experience cells
- Differences in endowments affecting industrial composition may also affect both wage levels and wage dispersion

Can we fix the problem with appropriate controls?

- Options: control for worker composition, regional trends...
- Only helps if *residual variation* in $\mu_{r,t}$ is uncorrelated with $\sigma_{r,t}$.

Lee (1999) argues *fewer* controls can be better:

"*... the reduced identifying variation resulting from eliminating the "permanent" state effects may magnify biases due to misspecification, in the same way biases stemming from measurement error in the independent variable are magnified when true variation in the independent variable is reduced.*"

- In simulations: estimator without region fixed effects works well for wage spillover effects, but not for employment.

Other specifications and diagnostics

1. Removing time fixed effects? **No.** ▸ Table
2. Using higher quantiles as the deflator? **No.** ▸ Table
3. IV strategy by Autor, Manning, and Smith (2016)? ▸ Table
    - **Yes**, but only feasible with state-level minimum wages.
    - Version with two, rather than three instruments may be better.
4. Diagnosing with upper tail spillovers?
    - Subject to false positives and false negatives. ▸ Why?
5. Are those problems specific to the Normal-markdown DGP?
    - **No**; paper includes exercises with the ▸ Canonical CES Model or the one from ▸ Haanwinckel (2023).

Taking stock

If you have exogenous variation in region-level minimum wages:

- Use instrumental variables approaches to isolate that variation

If you don't:

- Use the median as deflator and include time fixed effects
- The argument for identification should be:
  1. Is there a structural shock that shifts location $\mu_{r,t}$, but not dispersion $\sigma_{r,t}$ or latent employment (conditional on controls?)
  2. Is that good variation large enough to offset biases caused by the imperfect measurement of location?

Outline

1. Setup
2. Effective minimum wage design
3. **Fraction affected/gap designs**
4. Conclusion

Fraction affected and Gap designs

Definition: Fraction Affected | Fraction Affected Illustration | Definition: Gap measure

Issues:

1. Misspecification biases Details
2. Regression to the mean Details
3. Common trends in the dispersion of latent wages Details

Outline

1. Setup
2. Effective minimum wage design
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4. **Conclusion**

Conclusion

Contribution: pointing out potential pitfalls.

What if there is no regional variation in minimum wage laws, and neither of those between-region designs are recommended?

- Within-region comparisons of affected vs. non-affected firms or workers
- Structural approaches

Thanks!

OLS estimates for the US, 1972-2012 ◂ Back

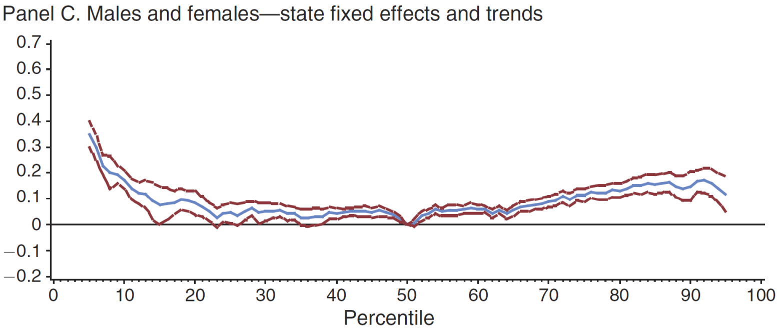


FIGURE 3. OLS ESTIMATES OF THE RELATIONSHIP BETWEEN $\log(p) - \log(p50)$ AND $\log(\text{MIN}) - \log(p50)$ AND ITS SQUARE, 1979–2012

- From Autor, Manning and Smith (2016)

Removing time fixed effects

Back

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel A: Regions differ only in location, stable distribution				
True average causal effect	-0.010	0.019	0.006	-0.004
Effective min. wage	-0.010	0.020	0.006	-0.004
	(0.001)	(0.003)	(0.000)	(0.000)
Eff. min. wage, no time FE	-0.010	0.019	0.006	-0.004
	(0.000)	(0.001)	(0.000)	(0.000)
Panel B: Regions differ in location and dispersion				
True average causal effect	-0.010	0.020	0.006	-0.004
Effective min. wage	-0.007	0.034	0.015	-0.023
	(0.004)	(0.023)	(0.013)	(0.028)
Eff. min. wage, no time FE	-0.007	0.052	0.024	-0.041
	(0.001)	(0.006)	(0.003)	(0.007)

Percentile 90 as the deflator

Back

	Outcome			
	Emp.	p10 - p90	p25 - p90	p50 - p90
Panel A: Regions differ only in location, stable distribution				
True average causal effect	-0.010	0.023	0.009	0.000
Effective min. wage, p90	-0.010	0.024	0.009	0.000
	(0.001)	(0.003)	(0.001)	(0.000)
Panel B: Regions differ in location and dispersion				
True average causal effect	-0.010	0.023	0.009	0.000
Effective min. wage, p90	0.009	0.219	0.176	0.000
	(0.003)	(0.026)	(0.021)	(0.000)
Panel C: Model from Haanwinckel (2023)				
True average causal effect	-0.046	0.211	0.090	0.000
Effective min. wage, p90	0.025	0.384	0.306	0.000
	(0.012)	(0.015)	(0.021)	(0.000)

State-level variation and IV approaches

Back

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel A: No regional variation in minimum wage.				
True average causal effect	-0.010	0.020	0.006	-0.004
Effective min. wage	-0.002	0.076	0.040	-0.075
	(0.004)	(0.021)	(0.012)	(0.026)
Panel B: 20% of regions with local min. wage				
True average causal effect	-0.015	0.035	0.008	-0.005
Effective min. wage	-0.015	0.050	0.014	-0.018
	(0.003)	(0.009)	(0.005)	(0.012)
Two instruments	-0.016	0.036	0.009	-0.006
	(0.004)	(0.013)	(0.008)	(0.017)
Three instruments (AMS)	-0.017	0.041	0.008	-0.005
	(0.003)	(0.010)	(0.006)	(0.013)

Diagnosing with upper tail spillovers

Back

Subject to false positives:

- Models such as Engbom and Moser (2023) and Haanwinckel (2023) have mechanisms that generate spillovers high into the wage distribution, such as reallocation to higher-wage firms (as in Dustmann et al. 2021)

Subject to false negatives:

- Estimator may be biased for employment and lower-tail spillovers, but unbiased for upper-tail spillovers (especially after combining effects of issues discussed here with measurement error-induced bias from Autor, Manning, and Smith 2016).

Canonical model

Back

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
Panel A: Initial minimum wage is low, sigma = 3.0				
True average causal effect	-0.009	0.017	0.005	-0.004
Eff. min. wage, no region FE	-0.009	0.018	0.003	0.044
	(0.000)	(0.002)	(0.001)	(0.003)
Panel B: Initial minimum wage is low, sigma = 1.4				
True average causal effect	-0.009	0.016	0.005	-0.003
Eff. min. wage, no region FE	-0.010	0.002	-0.007	0.078
	(0.000)	(0.003)	(0.002)	(0.003)
Panel D: Initial minimum wage is high, sigma = 1.4				
True average causal effect	-0.039	0.054	0.019	-0.016
Eff. min. wage, no region FE	-0.045	0.042	0.008	0.067
	(0.001)	(0.002)	(0.002)	(0.003)

Model from Haanwinckel (2023) ◂ Back

	Outcome			
	Emp.	p10 - p50	p25 - p50	p90 - p50
True average causal effect	-0.046	0.198	0.077	-0.013
Effective min. wage	-0.015	0.218	0.122	0.070
	(0.012)	(0.011)	(0.013)	(0.037)
Effective min. wage, no region FE	-0.073	0.196	0.088	-0.016
	(0.006)	(0.005)	(0.006)	(0.014)
Effective min. wage, no time FE	0.113	0.212	0.121	-0.139
	(0.004)	(0.003)	(0.004)	(0.012)
AMS, no time FE	0.125	0.211	0.121	-0.159
	(0.005)	(0.003)	(0.003)	(0.011)

Fraction affected design ◂ Back

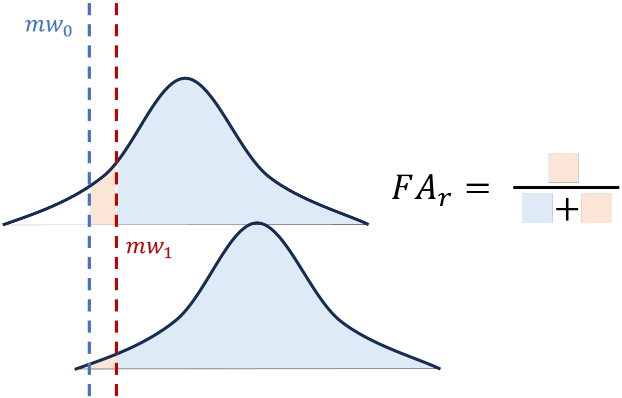
$$y_{o,r,t} = \alpha_{o,r} + \delta_{o,t} + \beta_o FA_r \cdot \mathbf{1}\{t = 1\} + \epsilon_{o,r,t}$$

- Each outcome o is a separate regression
- FA_r: share of workers i with $mw_0 \leq w_i < mw_1$ at time $t = 0$
- $\hat{\mathbf{ATE}}_o$ is the product of average FA and β_o
- Typical application: one-time mw hike following years of stability
  - Can test for differential pre-trends

Fraction affected design

◂ Back

$t = 0$



Gap design ◂ Back

$$
\begin{aligned}
y_{o,r,t} =& \alpha_{o,r} + \delta_{o,t} + \beta_o Gap_r \cdot \mathbf{1}\{t = 1\} + \epsilon_{o,r,t} \\
Gap_r =& \frac{\sum_{i=1}^{I_r} \max\{\exp(mw_1) - \exp(w_{i,0}), 0\}}{\sum_{i=1}^{I_r} \exp(w_{i,0})}
\end{aligned}
$$

- Introduced by Card and Krueger (1994) at the firm level; later used at the regional level (e.g., Dustmann et al., 2021)

Issue #1: misspecification biases
Back

- Fraction affected and gap designs define "susceptibility to treatment" based on a theoretically-inspired measure
  - But not the reduced form of some popular economic model
- Simulations show biases even in "ideal" applications
  - Attenuation seems more prevalent for employment and wage effects in the lower tail, when the minimum wage is strongly binding

Normal-markdown model, 1/2 Back

Regions differ only in time-invariant location parameter μ_r

	Outcome				
	Emp.	p10	p25	p50	p90
Panel A: Initial min. wage is small, $m = 0.7$					
True average causal effect	-0.006	0.016	0.008	0.004	0.002
Fraction affected	-0.008	0.020	0.010	0.005	0.003
	(0.000)	(0.002)	(0.001)	(0.002)	(0.002)
Gap measure	-0.006	0.015	0.007	0.004	0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Initial min. wage is small, $m = 0.9$					
True average causal effect	-0.018	0.043	0.022	0.012	0.006
Fraction affected	-0.019	0.038	0.022	0.013	0.006
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
Gap measure	-0.015	0.029	0.017	0.010	0.005
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)

Normal-markdown model, 2/2 Back

Regions differ only in time-invariant location parameter μ_r

	Outcome				
	Emp.	p10	p25	p50	p90
Panel C: Initial min. wage is large, $m = 0.7$					
True average causal effect	-0.042	0.162	0.049	0.028	0.013
Fraction affected	-0.053	0.153	0.063	0.036	0.018
	(0.001)	(0.021)	(0.005)	(0.002)	(0.002)
Gap measure	-0.037	0.101	0.044	0.025	0.013
	(0.001)	(0.017)	(0.003)	(0.002)	(0.002)
Panel D: Initial min. wage is large, $m = 0.9$					
True average causal effect	-0.079	0.126	0.084	0.053	0.027
Fraction affected	-0.073	0.071	0.067	0.052	0.030
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Gap measure	-0.052	0.050	0.048	0.037	0.021
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)

Issue #2: Regression to the mean ◂ Back

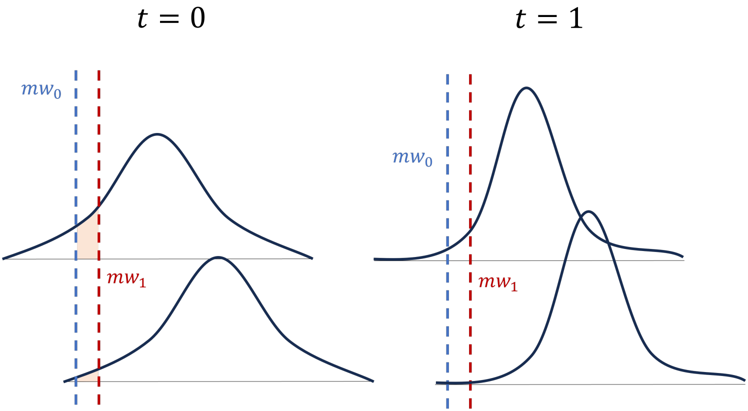
- Treated regions selected on extreme outcomes
  - Sampling variation (if low-wage regions have small samples)
  - Regional TFP (Caliendo et al. 2017; Gennaioli et al. 2014)
- May be captured by tests for pre-trends...
  - ... but not if treatment is defined by averaging the fraction affected over all pre-treatment years
- Controlling for a linear trend does not help

Normal-markdown model ◂ Back

	Outcome				
	Emp.	p10	p25	p50	p90
Panel A: Only permanent differences in location					
True average causal effect	-0.010	0.026	0.012	0.007	0.003
Gap measure	-0.009	0.027	0.011	0.006	0.003
	(0.000)	(0.003)	(0.001)	(0.001)	(0.001)
Panel B: Adding location shocks, stable distributions					
True average causal effect	-0.010	0.026	0.012	0.007	0.003
Gap measure	-0.007	0.043	0.031	0.027	0.024
	(0.001)	(0.010)	(0.012)	(0.012)	(0.013)
Panel C: Adding dispersion differences and shocks, stable distributions					
True average causal effect	-0.010	0.026	0.013	0.007	0.003
Gap measure	-0.007	0.052	0.034	0.024	0.008
	(0.002)	(0.012)	(0.012)	(0.012)	(0.018)

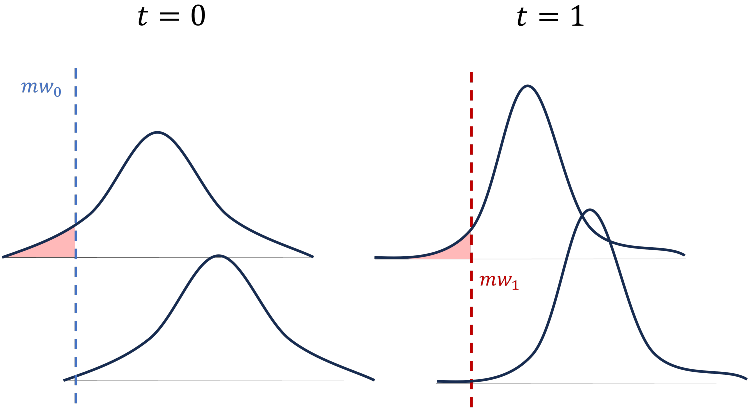
Issue #3: Trends in dispersion of latent wages

Back



Issue #3: Trends in dispersion of latent wages

Back



Normal-markdown model ◂ Back

	Outcome				
	Emp.	p10	p25	p50	p90
Panel C: Adding dispersion differences and shocks, stable distributions					
True average causal effect	-0.010	0.026	0.013	0.007	0.003
Gap measure	-0.007	0.052	0.034	0.024	0.008
	(0.002)	(0.012)	(0.012)	(0.012)	(0.018)
Panel D: Average dispersion falls over time					
True average causal effect	-0.010	0.026	0.013	0.007	0.003
Gap measure	-0.004	0.046	0.032	0.023	0.009
	(0.002)	(0.013)	(0.013)	(0.013)	(0.019)