

# Measurement of Nominal Wages and Payroll Schedules in Administrative Earnings Data

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Conference on Research in Income and Wealth  
July 13, 2020

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## Today's talk

### Methods for administrative earnings records that identify:

- Persistent wage changes
- Payroll schedules

### Evidence of distinct adjustment patterns for nominal wage raises and cuts

- Nominal wage raises follow a Taylor-style annual adjustment pattern
- Pattern of nominal wage cuts is consistent with a Calvo-style random arrival of opportunities to cut nominal wages

# Longitudinal Employer-Household Dynamics (LEHD) Dataset

U.S. Census Bureau employer-employee linked dataset

## Key LEHD features

- Quarterly earnings from administrative UI records
- Covers  $\approx 96\%$  of employment in any state

## Sample Used:

- 10% random sample of firms from 30 states from 1998:Q1 to 2017:Q1

Measuring Wage Changes

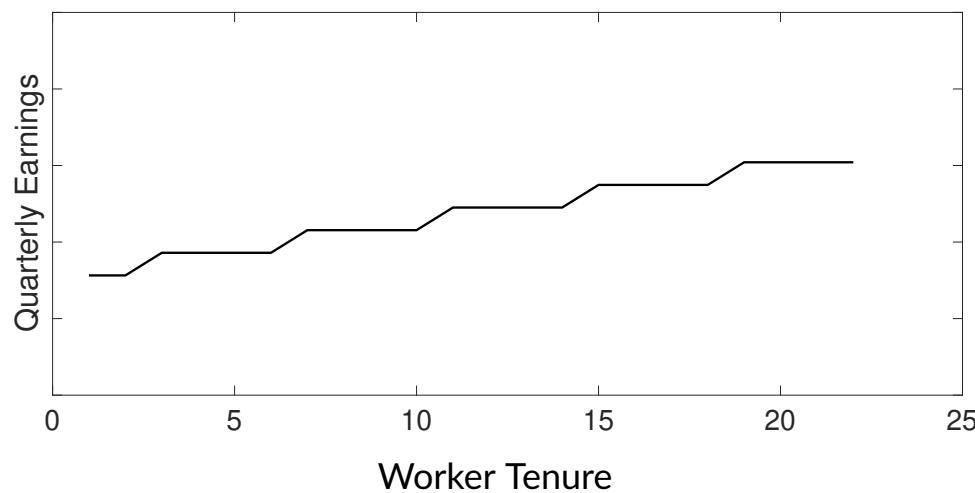
from

Quarterly Earnings Data

Quarterly earnings includes base wage + hours paid

$$y_{ikt} = w_{ikt} + h_{ikt}$$

Salaried Worker



Hourly Worker



$y = \log$  quarterly earnings

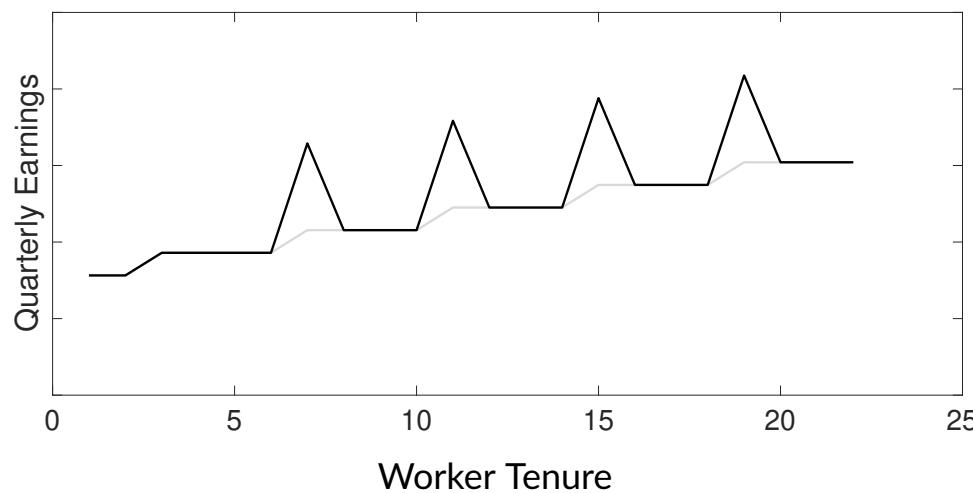
$w = \log$  nominal wage

$h = \log$  hours

## Quarterly earnings includes variable compensation

$$y_{ikt} = w_{ikt} + h_{ikt} + v_{ikt}$$

Salaried Worker



Hourly Worker



$y = \log$  quarterly earnings  
 $v = \log$  variable compensation

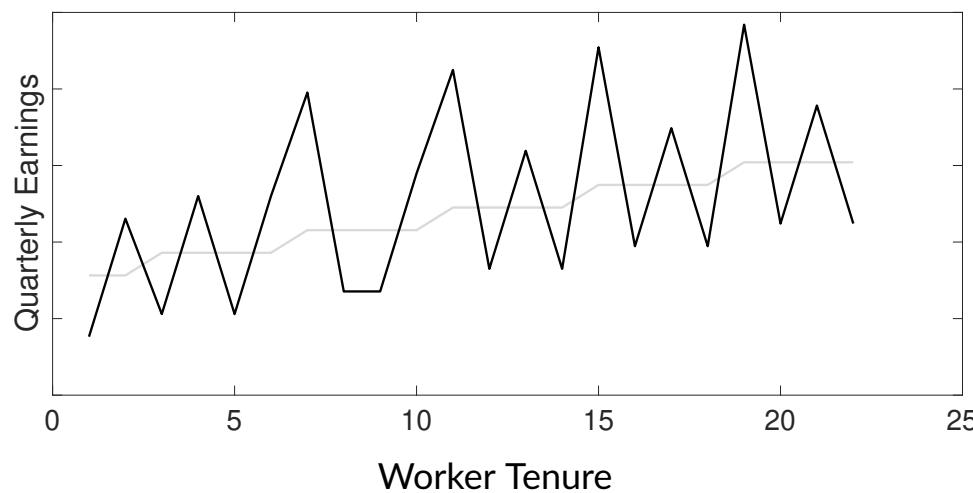
$w = \log$  nominal wage

$h = \log$  hours

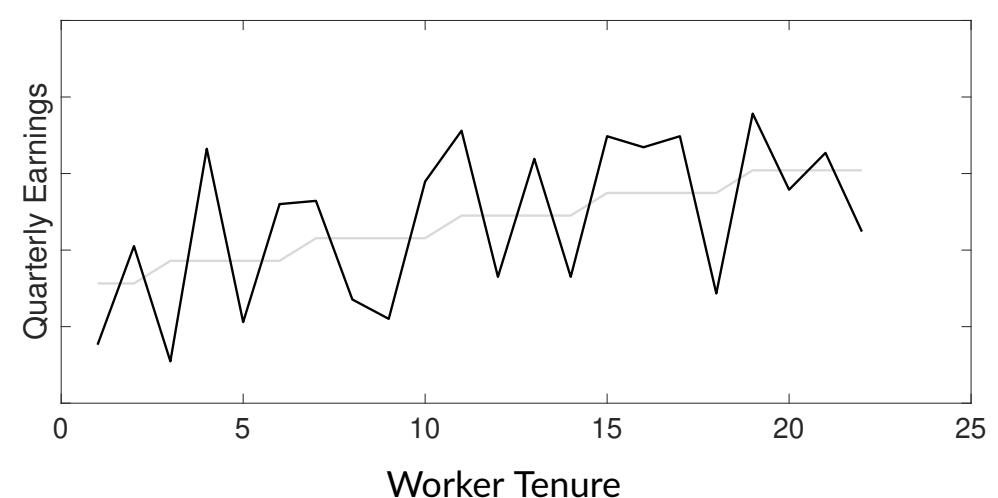
## Quarterly earnings includes payday weeks

$$y_{ikt} = h_{ikt} + w_{ikt} + v_{ikt} + p_{ikt}$$

Salaried Worker



Hourly Worker



$y = \log$  quarterly earnings  
 $v = \log$  variable compensation

$w = \log$  nominal wage  
 $p = \log$  payday weeks

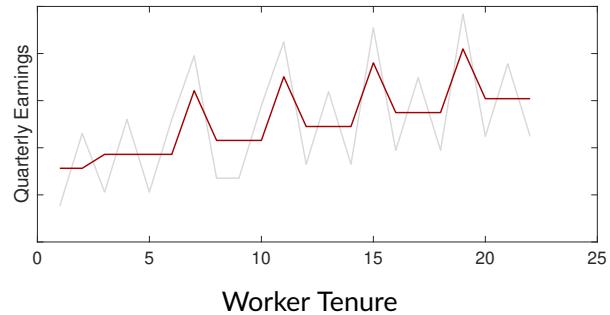
$h = \log$  hours

## Estimating payday weeks

$$y_{ikt} - p_t^{SX} = w_{ikt} + h_{ikt} + v_{ikt} + p_{ikt} - p_t^{SX}$$

1. Limited set of potential payday schedules (S1-S22)
2. Each potential payday schedule has a known number of payday weeks in each quarter ( $p_t^{S1} - p_t^{S22}$ )

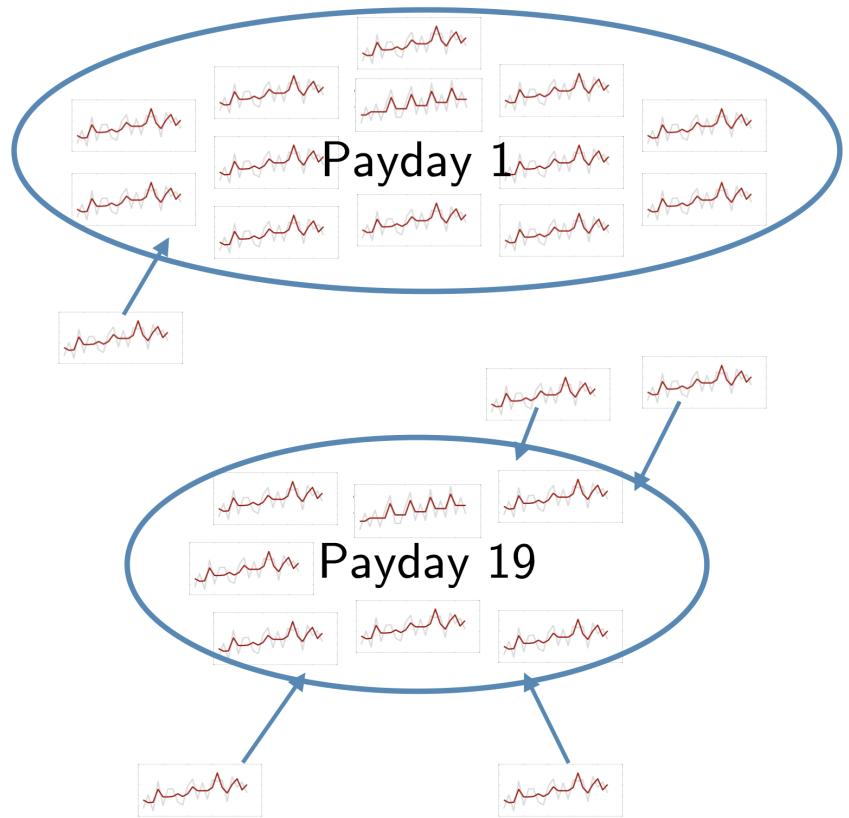
⇒ For each worker, analyze all 22 potential payday schedules to identify the payday schedule that minimizes  $Var(y_{ik} - p^{SX})$



## Estimating payday weeks

$$y_{ikt} - p_t^{SX} = w_{ikt} + h_{ikt} + v_{ikt} + p_{ikt} - p_t^{SX}$$

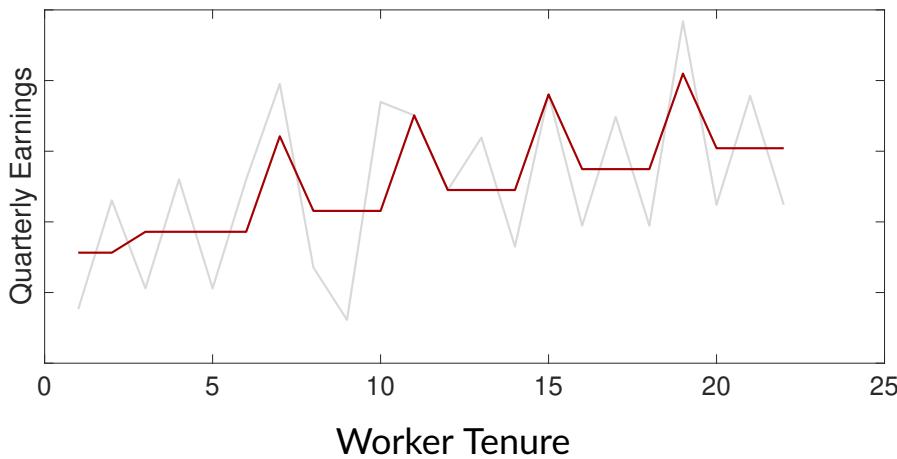
1. Limited set of potential payday schedules (S1-S22)
2. Each potential payday schedule has a known number of payday weeks in each quarter ( $p_t^{S1} - p_t^{S22}$ )
  - ⇒ For each worker, analyze all 22 potential payday schedules to identify the payday schedule that minimizes  $Var(y_{ik} - p^{SX})$
3. A firm has a small number of payday schedules that are common to many workers
  - ⇒ Clustering algorithm selects the payday(s) that minimizes this objective function for the most workers at the firm



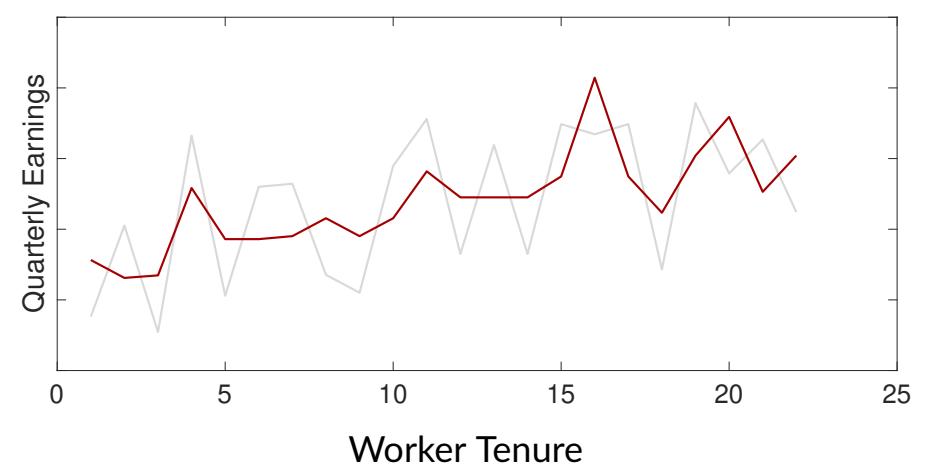
## Estimating persistent wage changes

$$\underbrace{y_{ikt} - \hat{p}_{ikt}}_{\tilde{y}_{ikt}} = w_{ikt} + \underbrace{h_{ikt} + v_{ikt} + p_{ikt} - \hat{p}_{ikt}}_{\epsilon_{ikt}}$$

Salaried Worker



Hourly Worker



$y = \log$  quarterly earnings  
 $v = \log$  variable comp

$w_t = \log$  wage in  $t$   
 $p = \log$  payday weeks

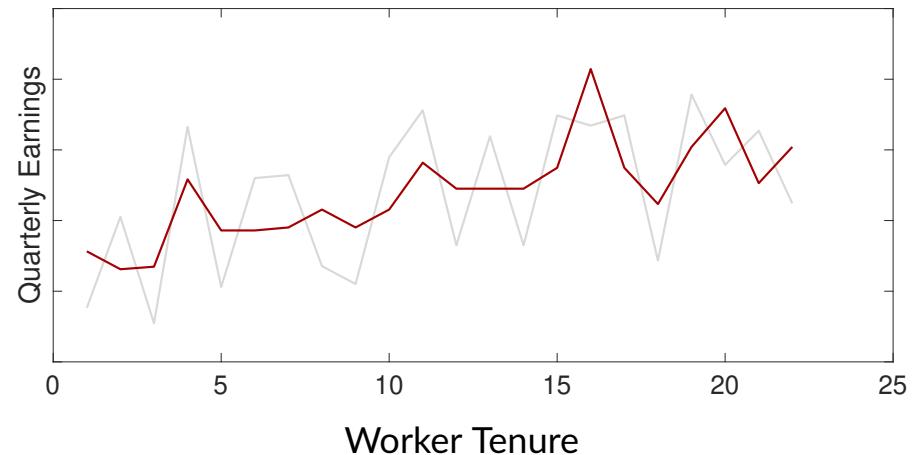
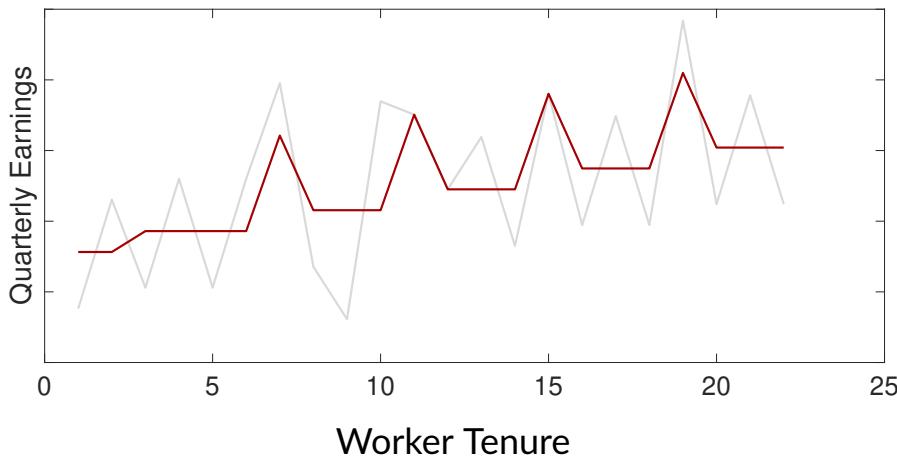
$h = \log$  weekly hours worked  
 $\hat{p} = \text{estimated log payday weeks}$

## Estimating persistent wage changes

$$\tilde{y}_{ikt} = w_{ik1} + \underbrace{\sum_{s=2}^t \Delta_{iks}^w}_{w_{ikt}} + \epsilon_{ikt}$$

Salaried Worker

Hourly Worker



$\tilde{y}$  = payday-adjusted log earnings  
 $\epsilon$  = error: hours, variable comp

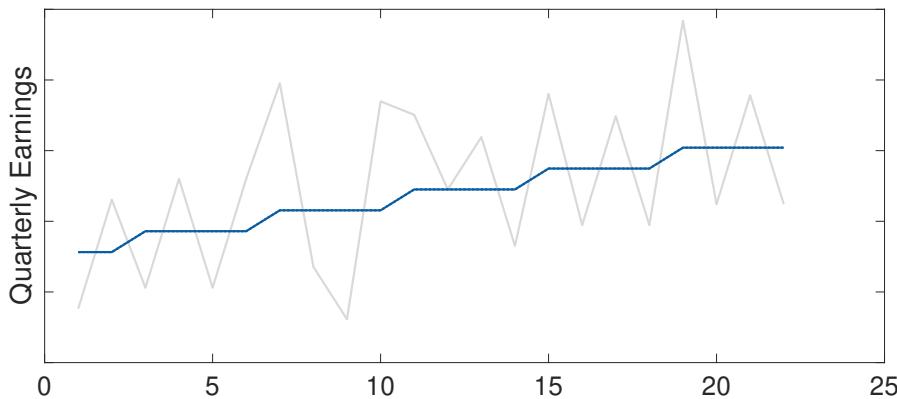
$w_1$  = log starting wage  
 $w_t$  = log wage in  $t$

$\Delta_s^w$  = log wage change in  $s$

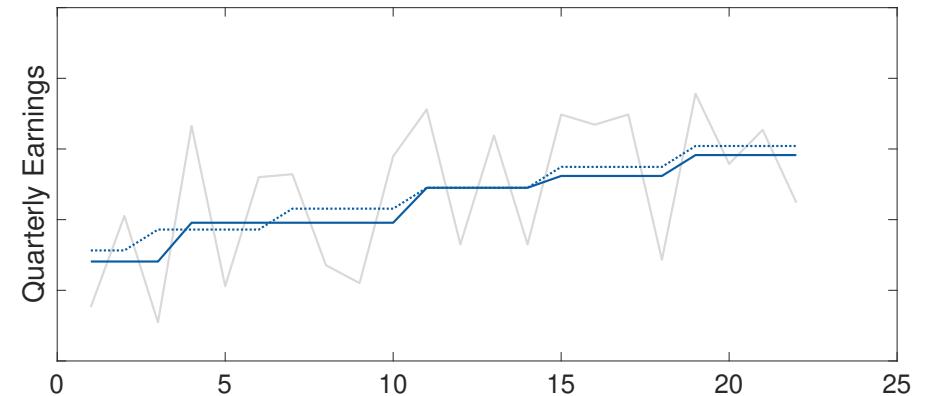
## Estimating persistent wage changes

$$\tilde{y}_{ikt} = \underbrace{\beta_{ik}^1}_{w_{ik1}} d_{ikt}^1 + \sum_{s=2}^T \underbrace{\beta_{ik}^s}_{\Delta_{iks}^w} d_{ikt}^s + \epsilon_{ikt}$$

Salaried Worker



Hourly Worker



Lasso estimation:

$$\min_{\hat{\beta}_{ik}^1, \dots, \hat{\beta}_{ik}^T} \left( \sum_{t=1}^T \tilde{y}_{ikt} - \sum_{s=1}^T \hat{\beta}_{ik}^s d_{ikt}^s \right)^2 + \lambda_{ik} \left( \sum_{s=1}^T \|\hat{\beta}_{ik}^s\| \right)$$

$\tilde{y}$  = payday-adjusted log earnings  
 $\epsilon$  = error: hours, variable comp

$w_1 = \beta^1$  log starting wage  
 $d_{ikt}^s = 1$  if  $s \leq t$

$\Delta_s^w = \beta^s$  log wage change in  $s$

## Comparison of QoQ nominal wage change measures

	Source Data	Raise	Freeze	Cut
Barattieri Basu Gottschalk (2014)	SIPP		78.4-84.8%	
Grigsby Hurst Yildirmaz (2019)	ADP 50+	18.5%	80.6%	0.9%
<b>Persistent base wage</b> (Payday Adjusted Post-Lasso Estimate)	LEHD30	13.6%	84.9%	1.6%

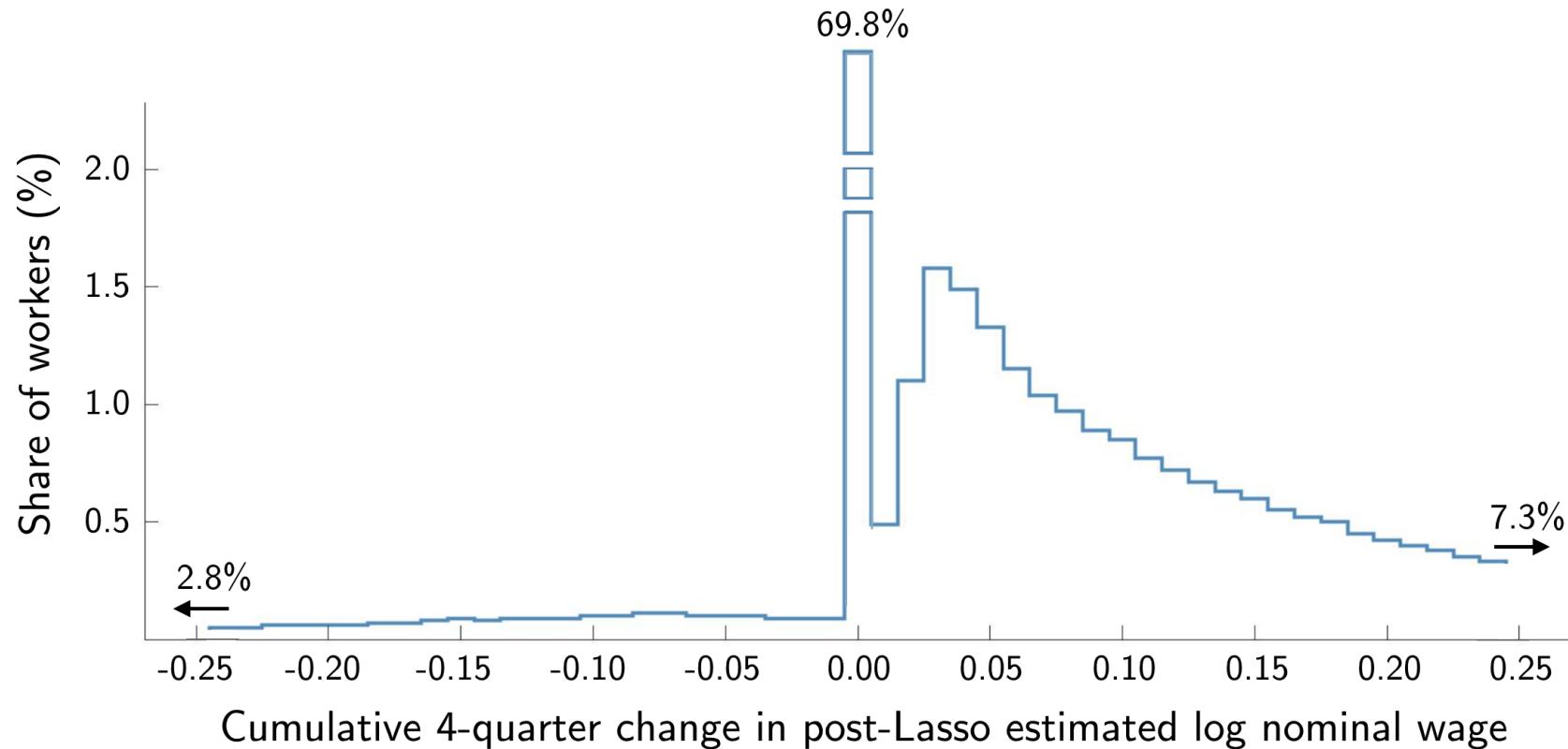
Annual wage changes

Minimum wage changes

Persistence of changes

Evidence on  
Taylor- and Calvo-style  
Wage Adjustment

## Nominal wages exhibit downward rigidity

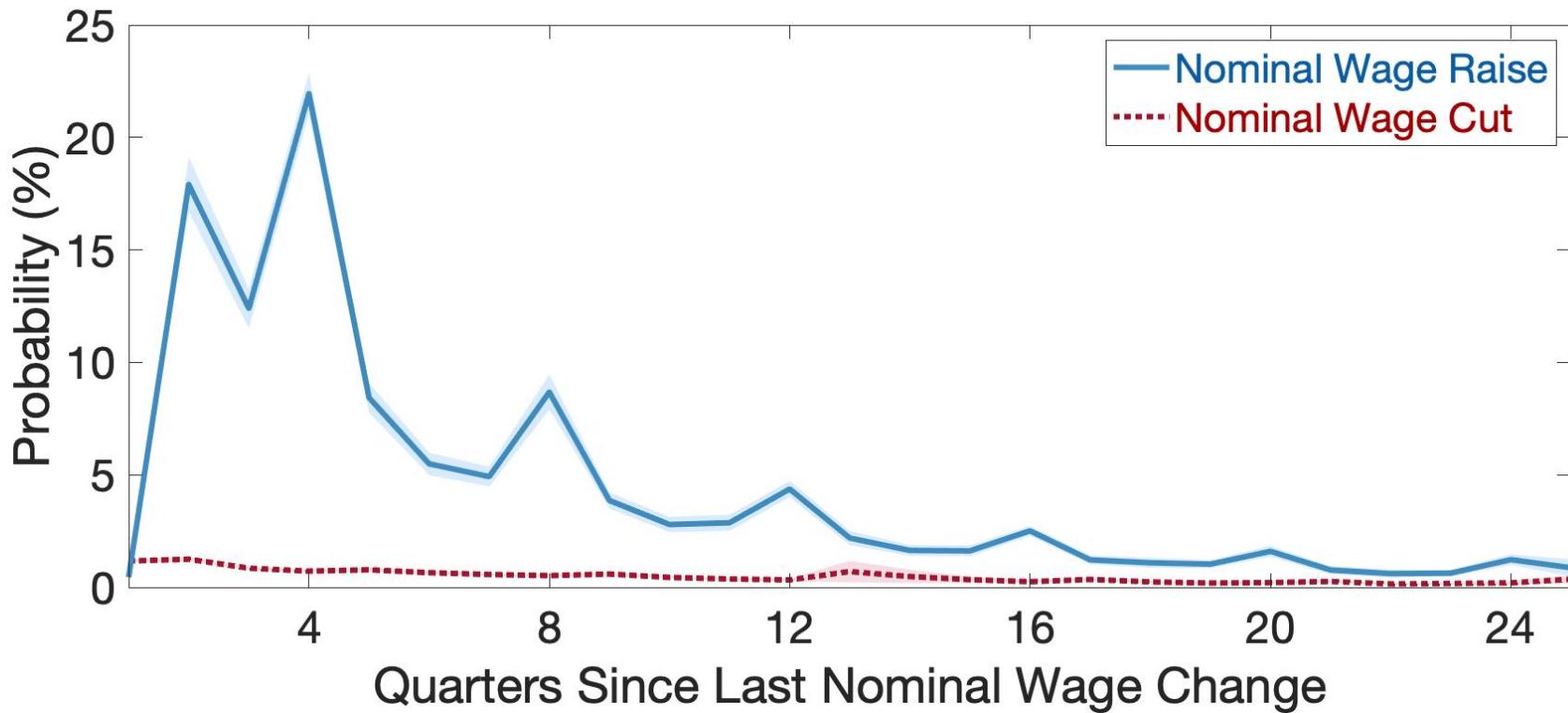


Source: U.S. Census Bureau LEHD, 10% random sample of firms from 30 states between 1998:Q1 and 2017:Q1

RD at Nominal Zero

Nominal Cut Suppression

## Nominal wage change probability by wage spell duration



Probability of a nominal wage change in the persistent base wage given the wage spell age. Shaded areas correspond to 95% confidence intervals using robust standard errors clustered at the SEIN level.

# Implications for macro modeling of wage adjustment

## Evidence on Wage Adjustment Patterns

	Taylor-style Annual Staggering	Calvo-style Random Arrival
Nominal Cuts	None	<b>Strong</b>
Nominal Raises	<b>Strong</b>	Weak

- Consider models with **distinct wage adjustment regimes** if an optimal real wage change requires a **nominal cut (Calvo)** versus **nominal raise (Taylor)**
  - ⇒ **State-dependent wage adjustment**: the incidence of nominal wage cuts and nominal wage freezes rise during downturns
  - ⇒ **Asymmetric persistence** of positive versus negative shocks: persistence of shocks is higher in Calvo models

# Thank you

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