Opinions expressed herein are those of the author alone and do not necessarily reflect the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential data are disclosed. See U.S. Census Bureau Disclosure Review Board bypass numbers: DRB-B0073-CED-20190910, DRB-B0069-CED-20190725, DRB-B0037-CED-20190327, CBDRB-2018-CDAR-061.
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

\[ y = \log \text{ quarterly earnings} \]

\[ w = \log \text{ nominal wage} \]

\[ h = \log \text{ hours} \]
Quarterly earnings includes variable compensation

\[ y_{ikt} = w_{ikt} + h_{ikt} + v_{ikt} \]

\[
\begin{align*}
y &= \log \text{ quarterly earnings} \\
w &= \log \text{ nominal wage} \\
v &= \log \text{ variable compensation} \\
h &= \log \text{ hours}
\end{align*}
\]
Quarterly earnings includes payday weeks

\[ y_{ikt} = h_{ikt} + w_{ikt} + v_{ikt} + p_{ikt} \]

- \( y \) = log quarterly earnings
- \( w \) = log nominal wage
- \( v \) = log variable compensation
- \( p \) = 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 \( Var(y_{ik} - p_{ik}^{SX}) \)
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 \( \text{Var}(y_{ik} - p^{SX}) \)

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

\[ y_{ikt} - \hat{p}_{ikt} = w_{ikt} + h_{ikt} + v_{ikt} + p_{ikt} - \hat{p}_{ikt} \]

\[ \tilde{y}_{ikt} = w_{ikt} + h_{ikt} + v_{ikt} + \epsilon_{ikt} \]

\[ y = \text{log quarterly earnings} \]
\[ \nu = \text{log variable comp} \]
\[ w_t = \text{log wage in } t \]
\[ h = \text{log weekly hours worked} \]
\[ p = \text{log payday weeks} \]
\[ \hat{p} = \text{estimated log payday weeks} \]
Estimating persistent wage changes

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

\[ \tilde{y} = \text{payday-adjusted log earnings} \]
\[ w_1 = \text{log starting wage} \]
\[ w_t = \text{log wage in } t \]
\[ \Delta_s^w = \text{log wage change in } s \]
Estimating persistent wage changes

\[ \tilde{y}_{ikt} = \underbrace{\beta^1_{ik}}_{w_{ik1}} \ d^1_{ikt} + \sum_{s=2}^{T} \underbrace{\beta^s_{ik}}_{\Delta^w_{ik}} \ d^s_{ikt} + \epsilon_{ikt} \]

Salaried Worker

Hourly Worker

Lasso estimation:

\[ \min_{\hat{\beta}^1_{ik}, \ldots, \hat{\beta}^T_{ik}} \left( \sum_{t=1}^{T} \tilde{y}_{ikt} - \sum_{s=1}^{T} \hat{\beta}^s_{ik} d^s_{ikt} \right)^2 + \lambda_{ik} \left( \sum_{s=1}^{T} \| \hat{\beta}^s_{ik} \| \right) \]

\( \tilde{y} = \) payday-adjusted log earnings

\( w_1 = \beta^1 \) log starting wage

\( \Delta^w_s = \beta^s \) log wage change in \( s \)

\( \epsilon = \) error: hours, variable comp

\( d^s_{ikt} = 1 \) if \( s \leq t \)
Comparison of QoQ nominal wage change measures

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

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
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

<table>
<thead>
<tr>
<th></th>
<th>Taylor-style</th>
<th>Calvo-style</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual Staggering</td>
<td></td>
<td></td>
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<tr>
<td>Random Arrival</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nominal Cuts</td>
<td>None</td>
<td>Strong</td>
</tr>
<tr>
<td>Nominal Raises</td>
<td>Strong</td>
<td>Weak</td>
</tr>
</tbody>
</table>

- 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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