Predicting US State Employment Growth in Realtime

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Outline

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  - State (and metro) data in the US are subject to substantial revisions
  - Example: Illinois employment growth in 2015

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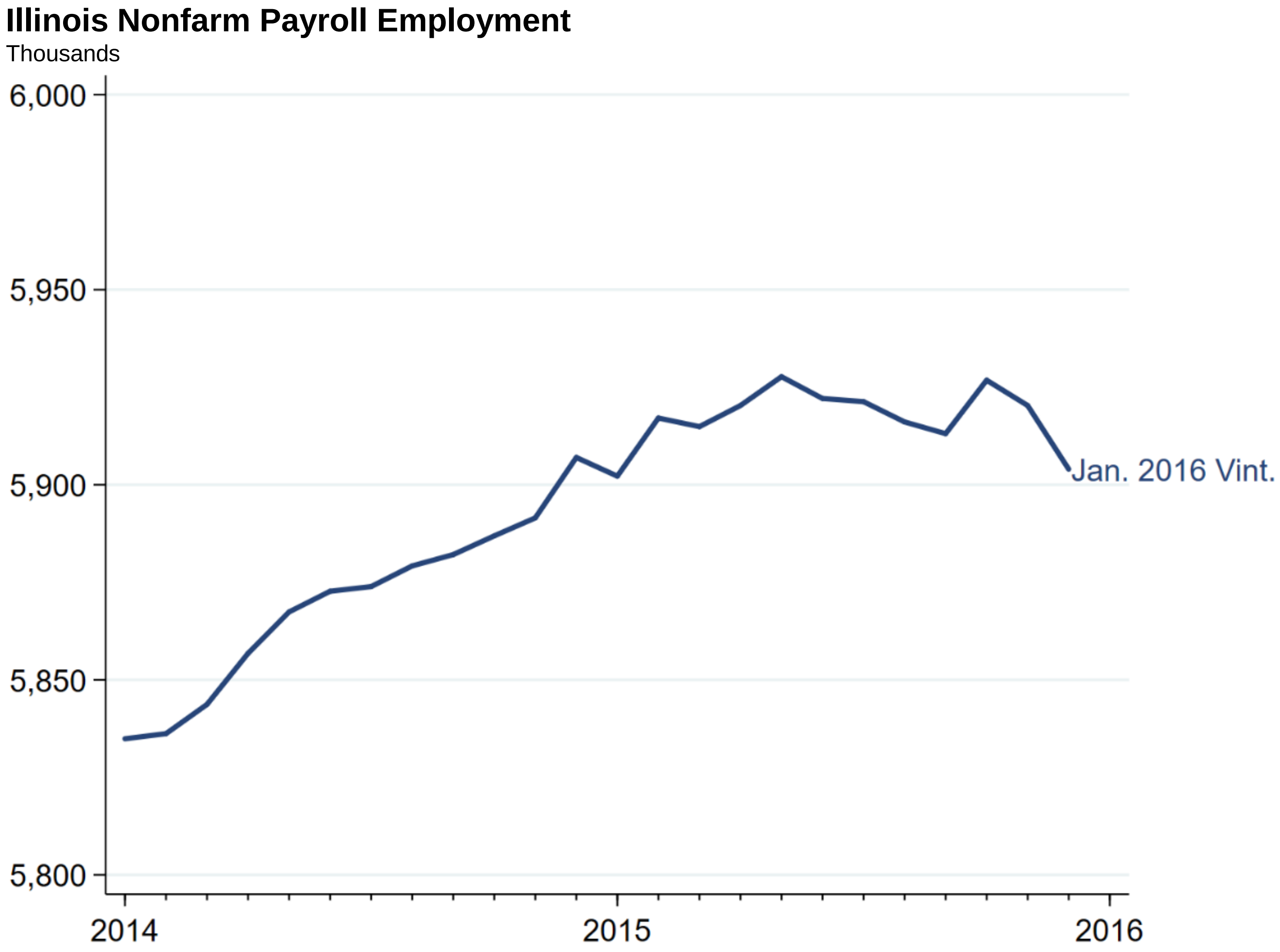
    - Modeling the revision process
    - Incorporating external data
- We find
  - We can successfully forecast the revisions for most states
  - Both components of the model contribute

State employment data are revised substantially



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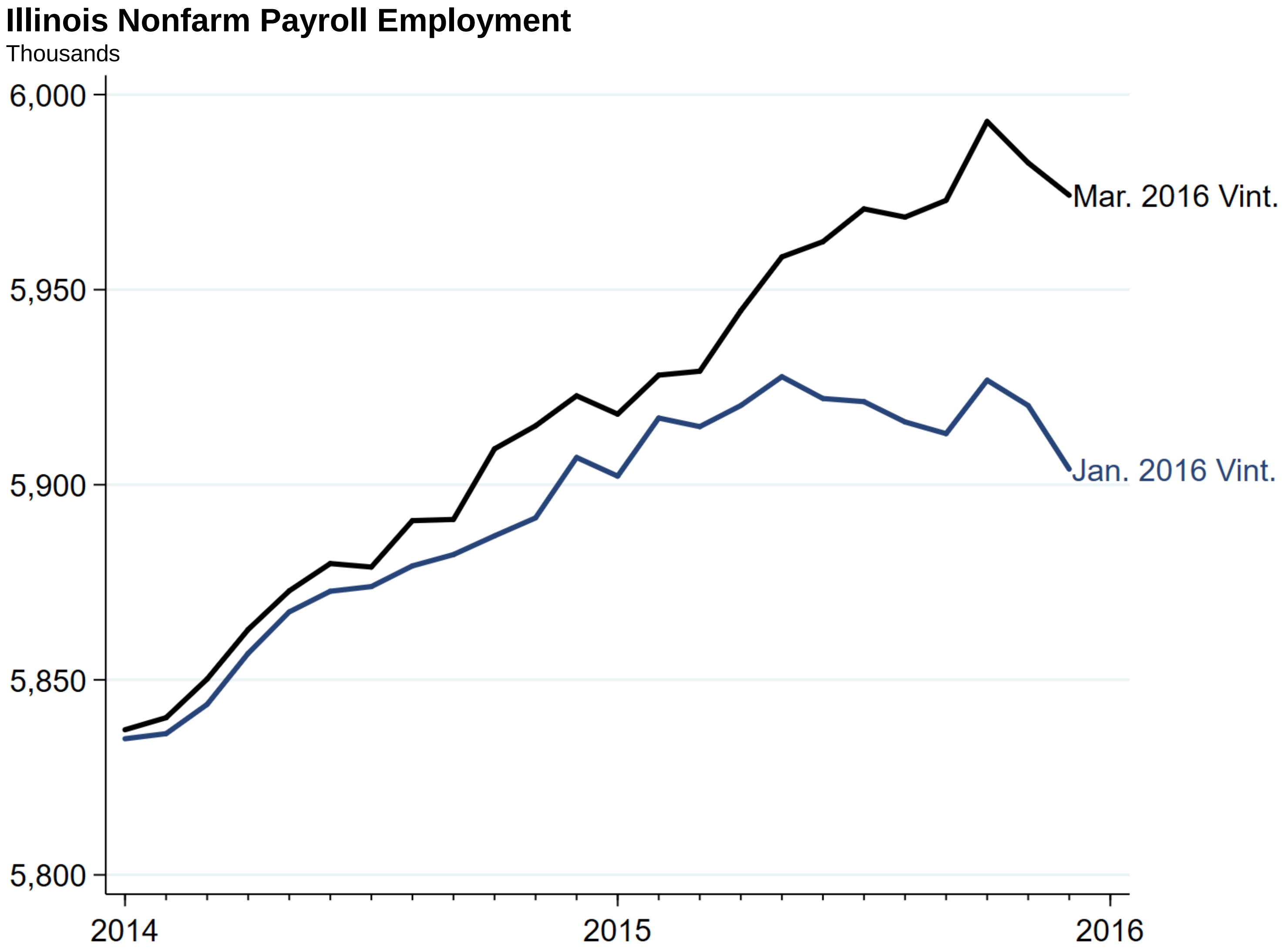

- For Illinois in 2015, employment growth was revised from −3,000 to +51,000

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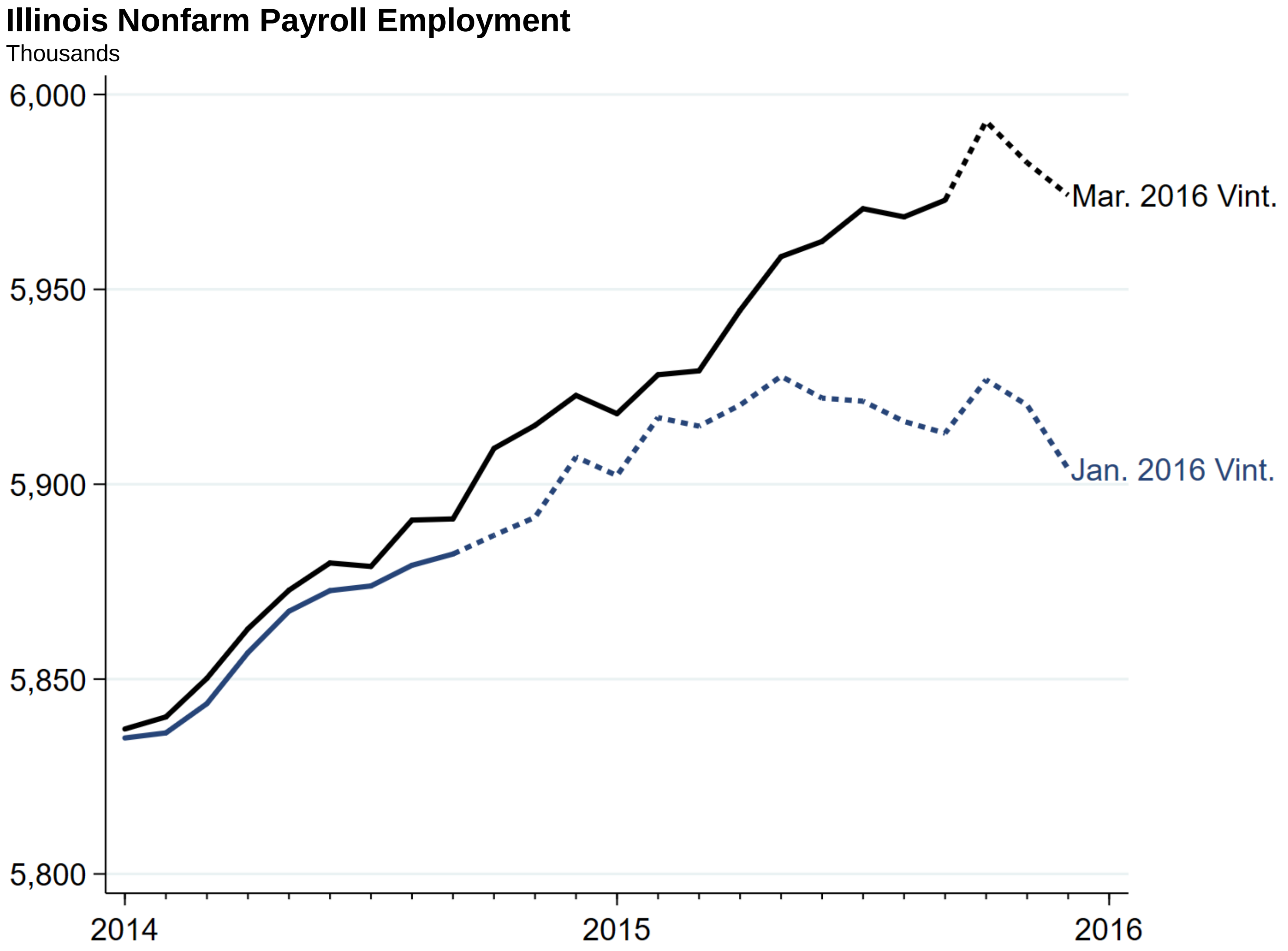

- Once-a-year revision is known as the "rebenchmark"
- Survey data are revised using administrative data

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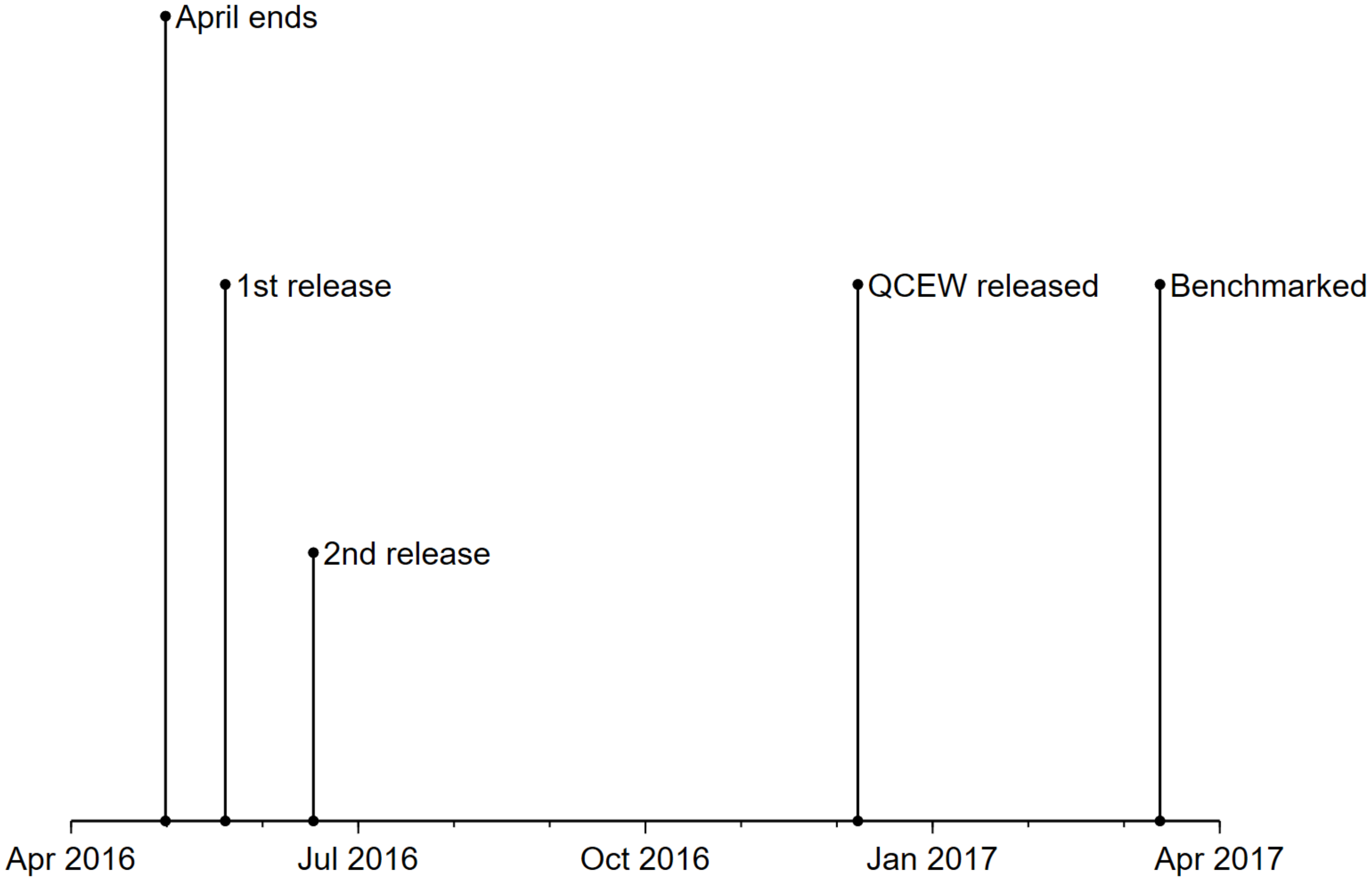
- We develop a state-space model that incorporates
  - An explicit model of the revision process
    - Incorporates releases of closely-related administrative data called the QCEW
  - External indicators of state employment growth
    - Via a dynamic factor model

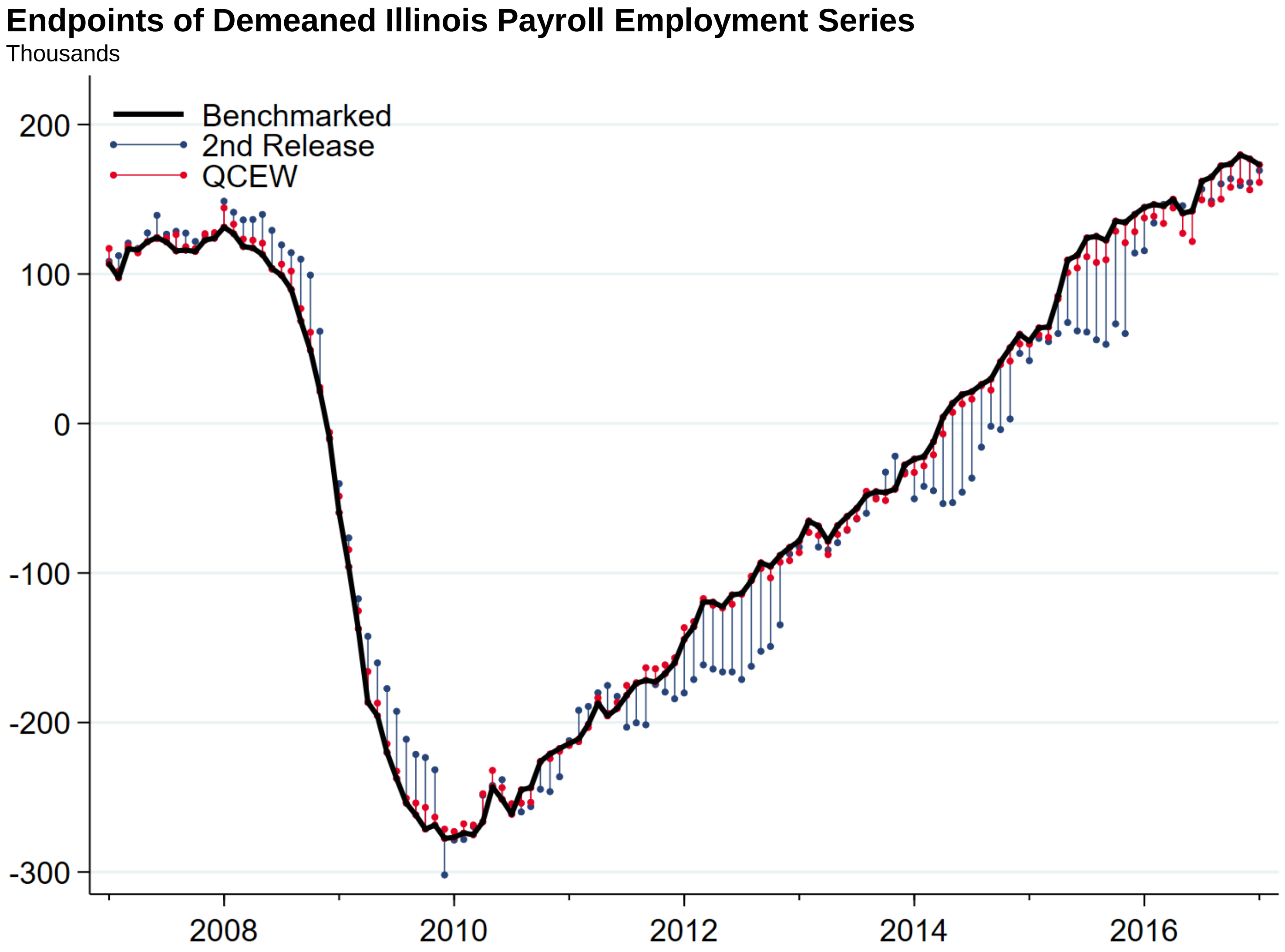
A full timeline of the revision process

Data releases for April 2016



- 1st release 3 weeks after reference period
- 2nd release 1 month after 1st release
- QCEW 5–7 months after reference period
- Data benchmarked 5–13 months after reference period

QCEW usually close, 2nd release can be quite far



- 2nd release misses can be quite persistent

A state-space model of the revision process

$CESPost_t = E_t$

$QCEW_t = E_t + W_t$

$CESRev_t = E_t + B_t$

$CESInit_t = E_t + B_t + R_t$

$\Delta E_t = \alpha + \sum_i \gamma_i \Delta E_{t-i} + \chi_{it}$

$W_t = \delta + \sum_i \lambda_i W_{t-i} + \nu_t$

$B_t = \kappa + \rho B_{t-1} + \eta_t$

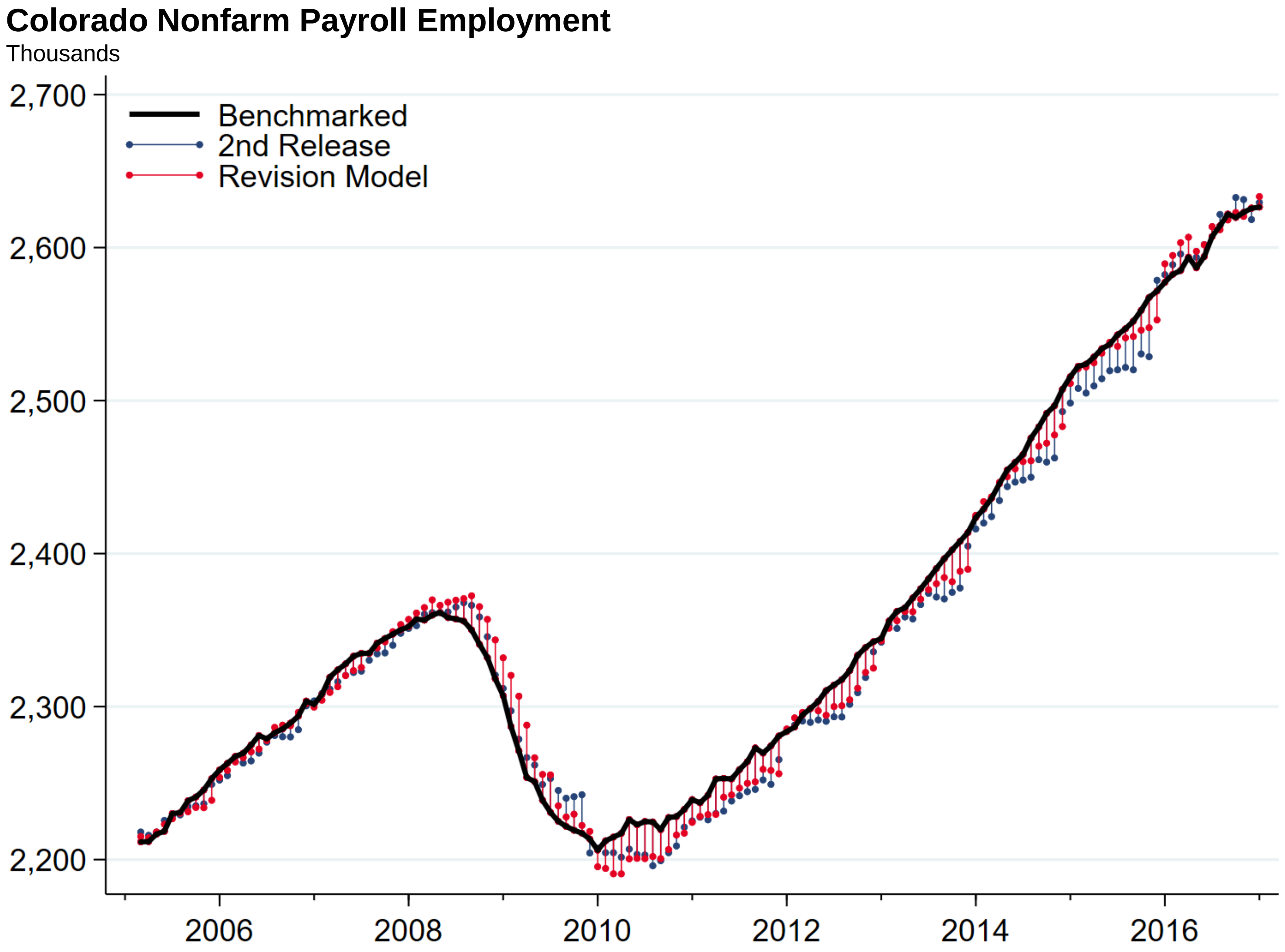
$R_t = \omega_t$

- Spliced series of realtime values for each release version
- Target is E_t, the benchmarked employment value

Standard approach to estimating and evaluating the model

- Estimation
  - Maximum likelihood with the Kalman Filter
- Evaluation
  - Test out-of-sample forecast of a series's level
  - Sample period: March 2005–September 2017

By itself, the revision model makes a difference



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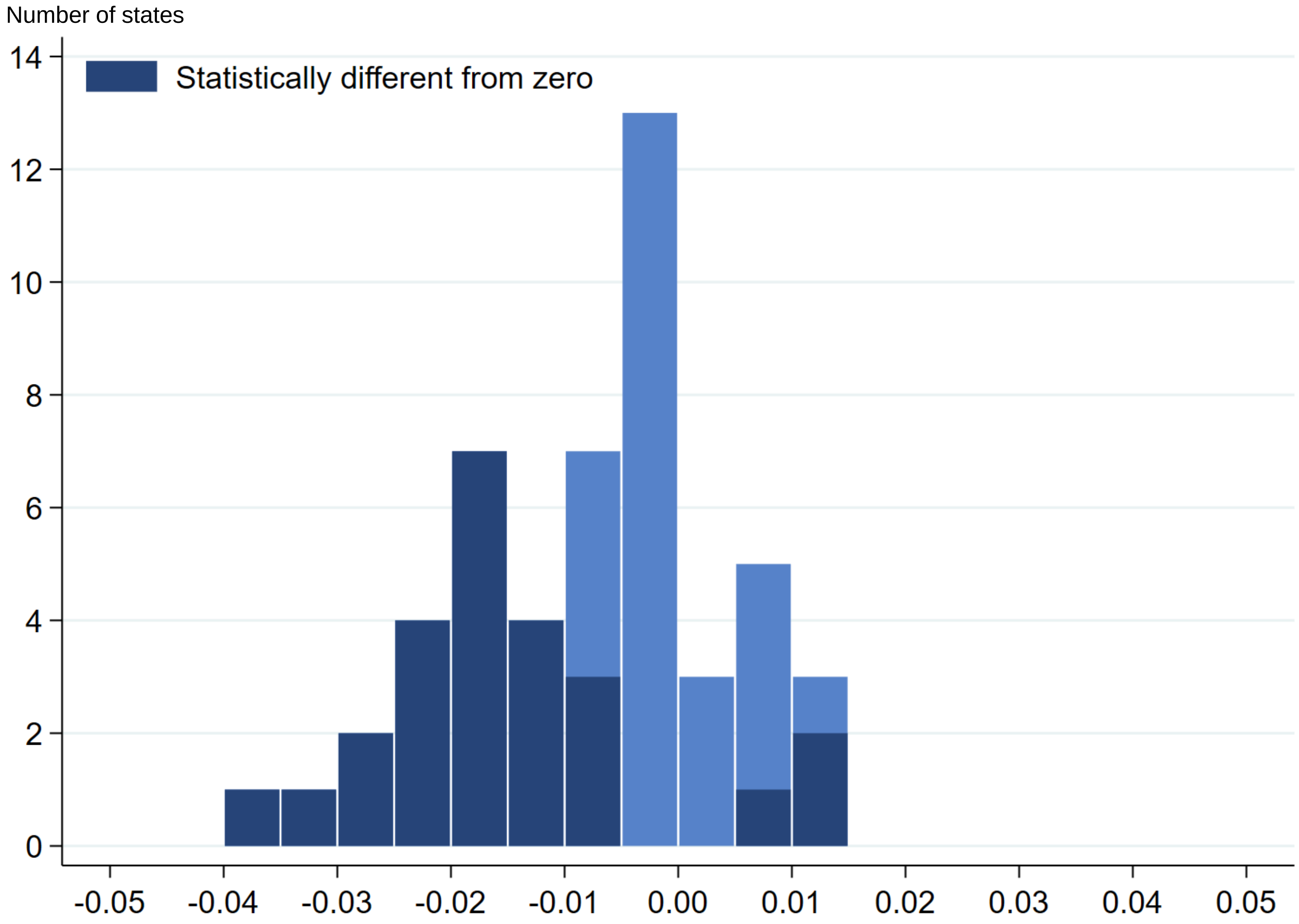
Distribution of difference in mean absolute percent errors (Model − 1st Release)



Difference in mean absolute percent error (Model − 1st Release)	
10th Percentile	−0.025
Median	−0.007
90th Percentile	0.008

Number of states better	39/50
Statistically significantly better	22/50

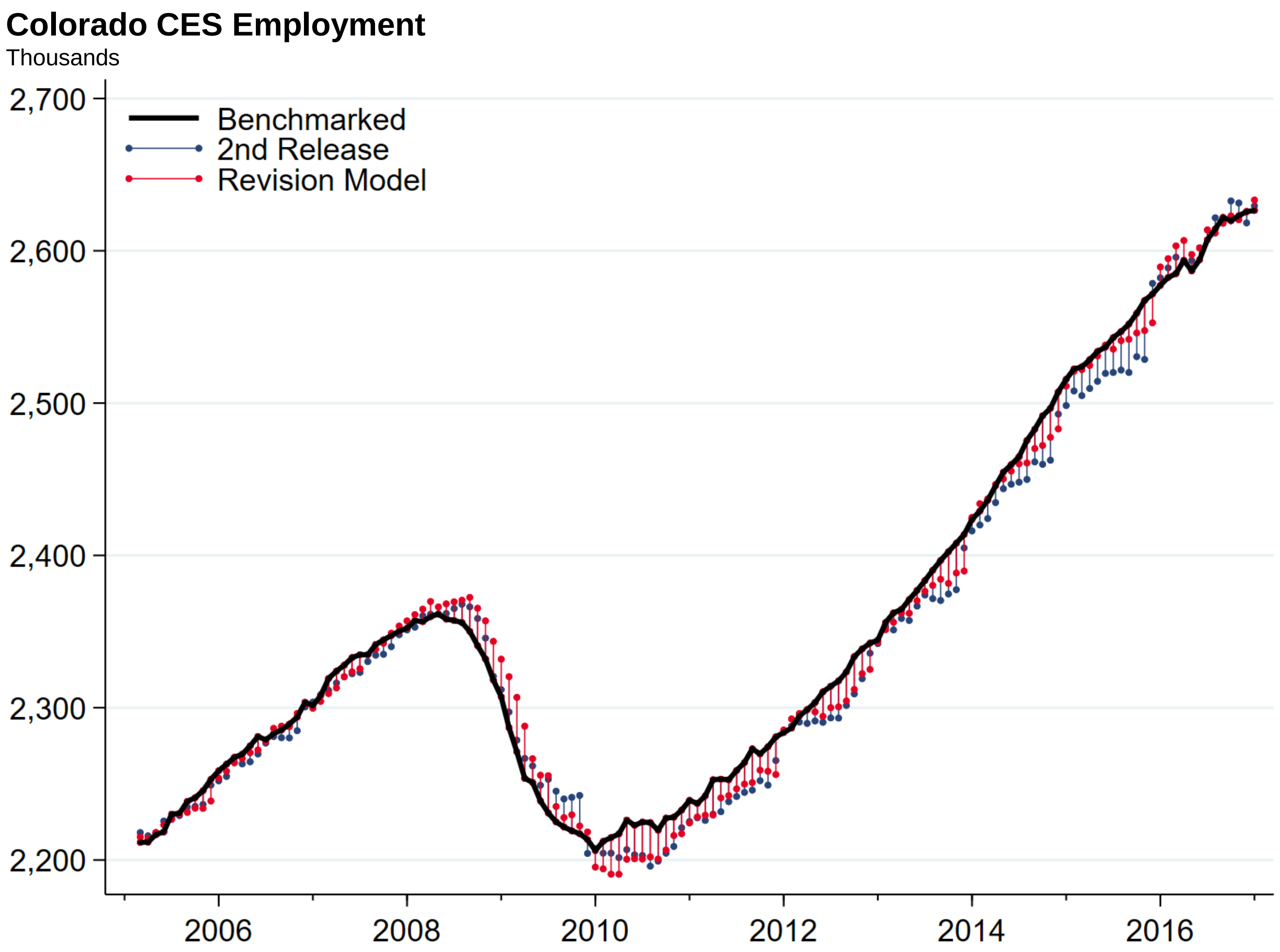
Incorporating external data via a dynamic factor model

$$CESPost_t = E_t \qquad \Delta E_t = \alpha + f_t + \zeta_t \qquad f_t = \theta f_{t-1} + \varepsilon_t$$

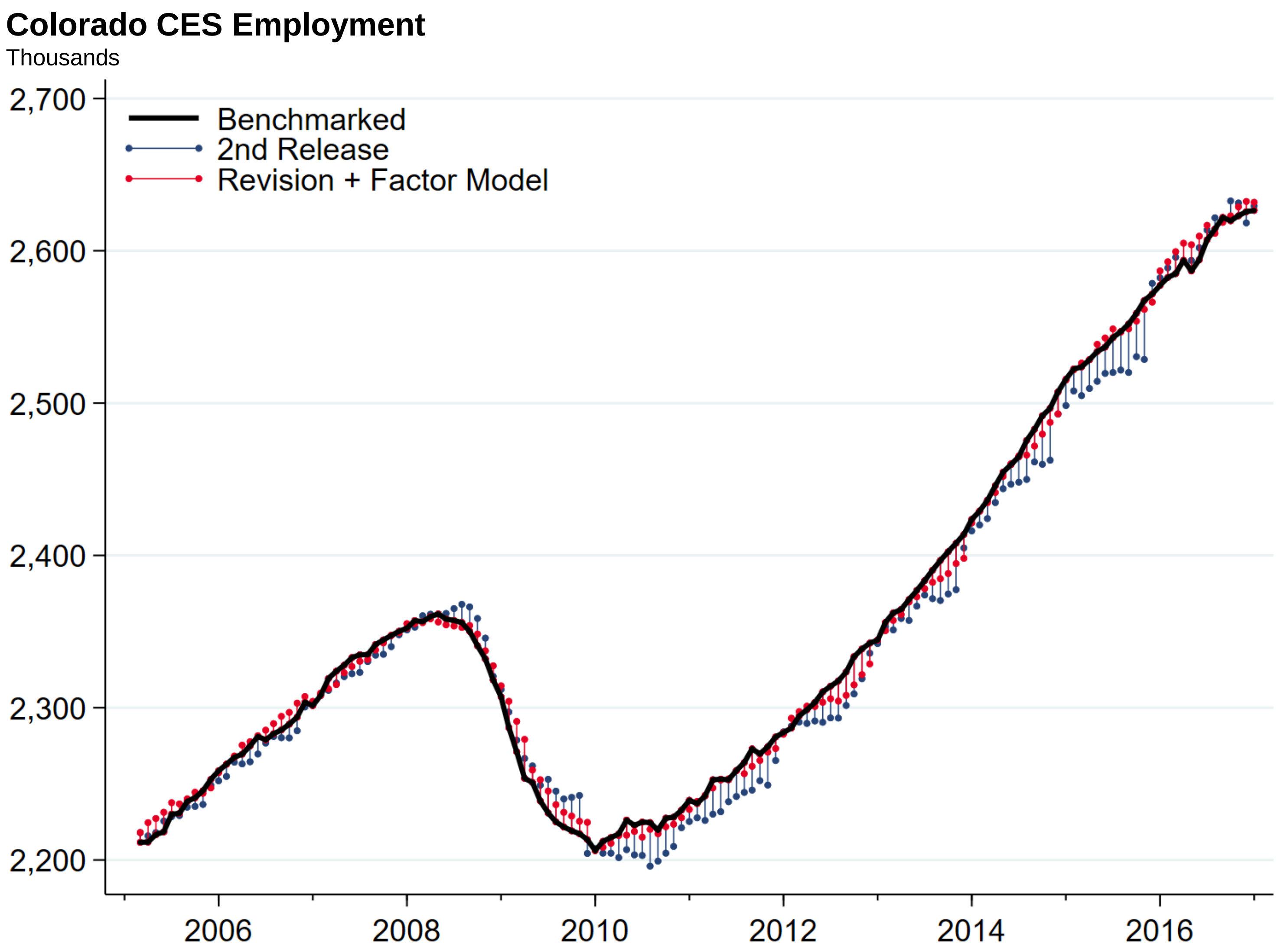
$$\Delta Y_{it} = \gamma_i + \Gamma_i f_t + \upsilon_{it} \qquad \upsilon_{\boldsymbol{it}} = \psi_i \upsilon_{\boldsymbol{it}-1} + \vartheta_{\boldsymbol{it}}$$

- Y_{it} (all realtime vintages)
  - National CES
  - Shift-share CES (based on a state's industrial composition)
  - Household employment from the CPS
  - Unemployment Insurance Claims

Incorporating external data helps in most states (before)



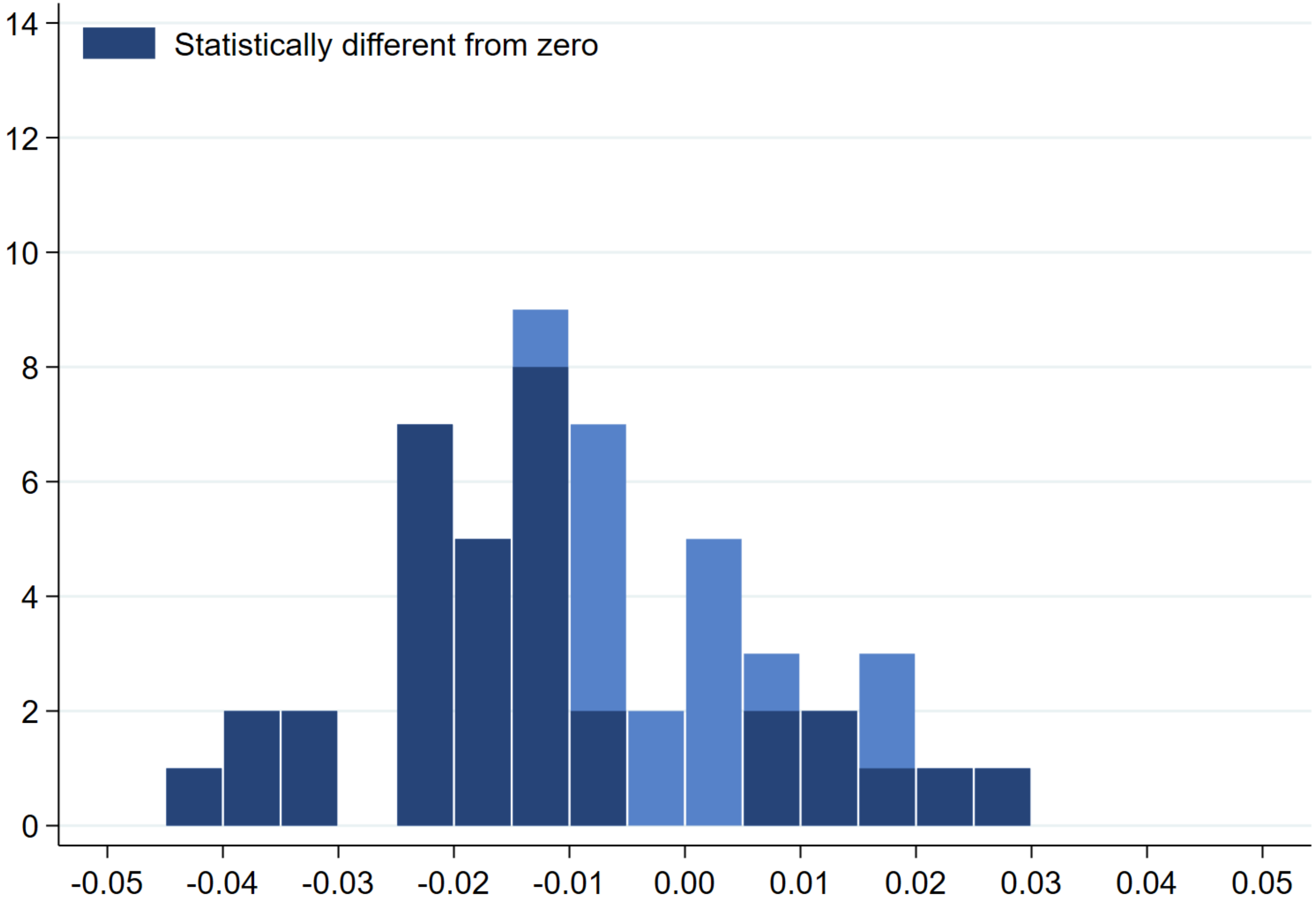
Incorporating external data helps in most states (after)



Incorporating external data helps in most states

Distribution of difference in mean absolute percent errors (Model − 1st Release)

Number of states

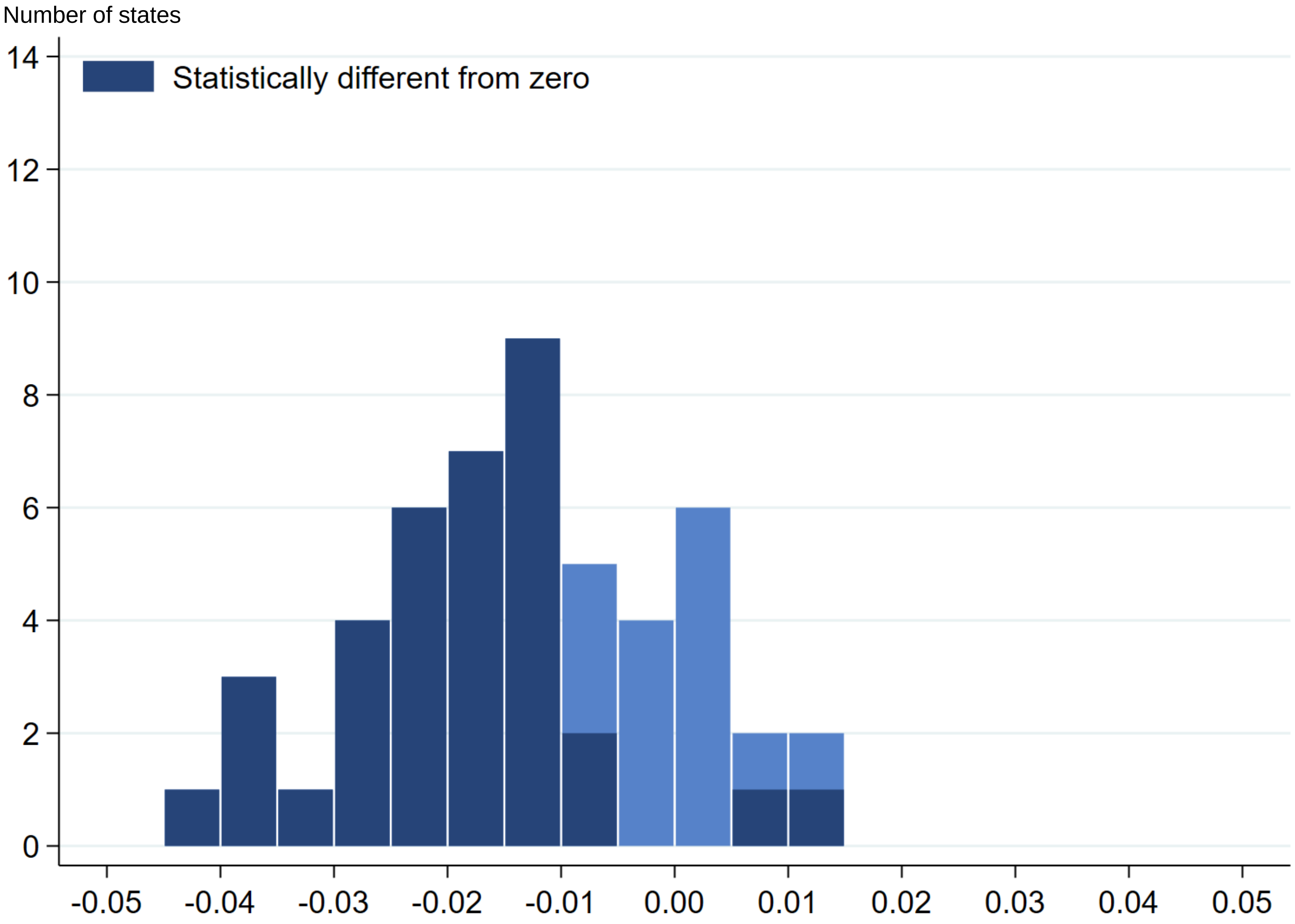


Difference in mean absolute percent error (Model − 1st Release)	
10th Percentile	−0.036
Median	−0.012
90th Percentile	0.015

Number of states better	35/50
Statistically significantly better	27/50

What if we pick a state's best result?

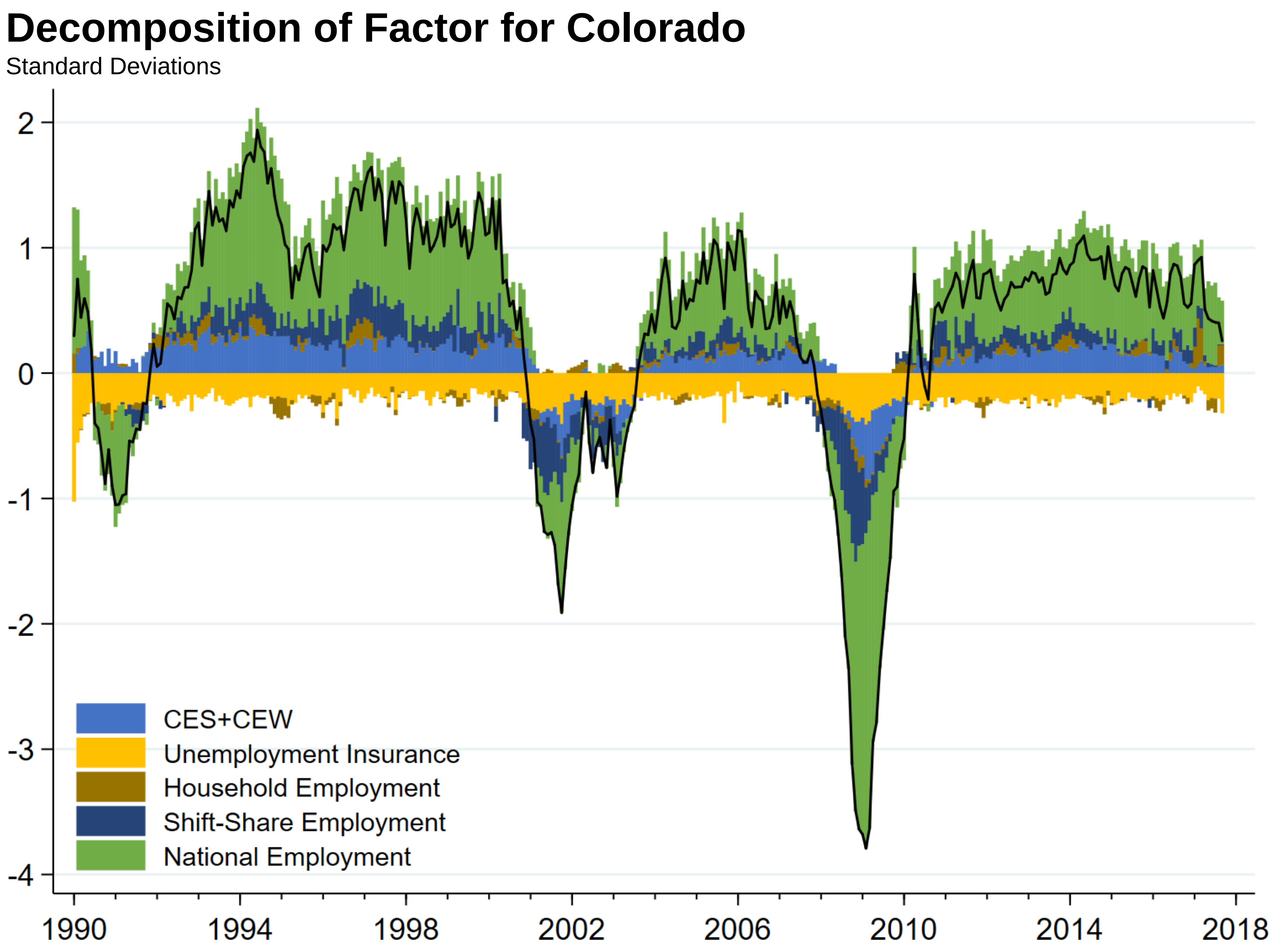
Distribution of difference in mean absolute percent errors (Model − 1st Release)



Difference in mean absolute percent error (Model − 1st Release)	
10th Percentile	−0.036
Median	−0.014
90th Percentile	0.005

Number of states better	40/50
Statistically significantly better	33/50

Contributions of external data are widespread



Next steps

- Evidence that the lag structure of the factor differs across states
  - Should increase the performance gains from the factor model
- Take into account later benchmark revisions?
- Incorporate unstructured data?