Advance Layoff Notices and Labor Market Forecasting*

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*The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System.

Introduction

- Worker Adjustment Retraining and Notification (WARN) Act
  - Large firms provide layoff notices to workers and state governments
  - Typically 60 days' advance notice
- Research question: Can WARN Act data help assess the state of the aggregate labor market?
- **Results:**
  - **When aggregated, WARN Act data moves with other labor market data over the business cycle**
  - **"WARN factor" predicts changes in manufacturing employment better than unemployment claims and ISM indexes**

Introduction

This project:

- Collect WARN Act data from state government websites
- Organize data into state-month unbalanced panel
- Create national-level WARN factor from dynamic factor model (DFM)
- Use WARN factor for forecasting

The Worker Adjustment and Retraining (WARN) Act

- Seeks to provide workers with sufficient time to begin new job searches or obtain necessary training for a new job
  - Employers provide workers 60 days written notice prior to layoff
- Notice given to workers and to state dislocated worker unit
- What each notice must include:
  - Name and address of affected employment site, date of notice, expected date of first separation, anticipated number of affected employees
- Caveats:
  - Only applies to large employers and mass layoffs
  - Exceptions exist where firms can provide less than 60 days' notice
    - Unforeseeable business circumstances such as COVID-19
  - Not all employers comply
  - Additional Details
- Question: Will these data provide a useful labor market indicator?

WARN Data

Establishment-level data collected from state dislocated worker units

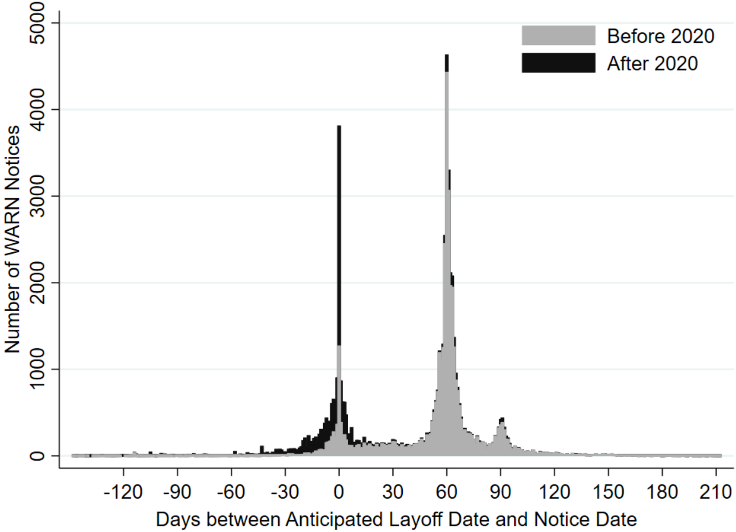
- Scraped from websites
- Contacted state officials
- As of Oct 2020: about 75,000 notices affecting over 8 million workers

Aggregated to state-level monthly panel

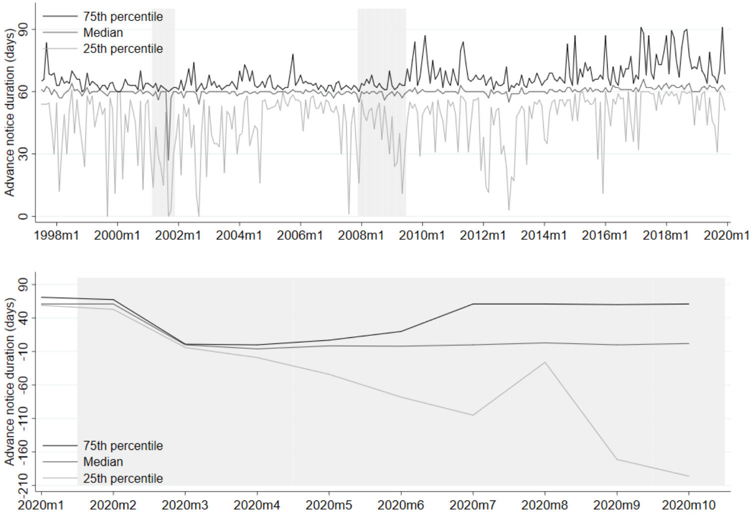
- Unbalanced panel
  - MI begins Jan 1990
  - PA begins Jan 2001
  - CA begins Jan 2006
  - TX, FL, IL, OH, NC, VA begin between Jul 1994 and Jan 1999
- 33 states: includes 23 of 25 largest states (not GA or MA)

Coverage of WARN Data

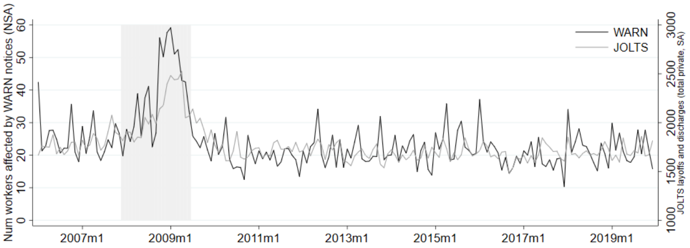
How Much Advance Notice in Practice?

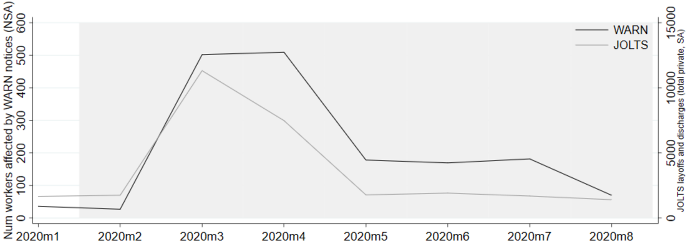


How Much Advance Notice in Practice?



WARN versus Job Openings and Labor Turnover (JOLTS)





Note: WARN includes 21 states. JOLTS is national.

Aggregating to National Level

Two problems:

1. Different history lengths for each state
   - MI begins Jan 1990
   - PA begins Jan 2001
   - CA begins Jan 2006
   - May limit history length of aggregate data
2. Not all states update WARN data at same time
   - "jagged" or "ragged" edge problem
   - May limit real-time availability of aggregate data

Solution: Use dynamic factor model (DFM) to estimate "WARN factor"

The Dynamic Factor Model

- For each state, indexed by j, we log and then de-mean the data
  - $y_{j,t} = \ln(WARN_{j,t})$
  - $z_{j,t} = y_{j,t} - \bar{y}_j$
  - Vector of data described by DFM is $z_t = [z_{1,t}, \ldots, z_{N,t}]$
- The DFM is

$$z_t = \Lambda f_t + e_t \tag{1}$$

$$f_t = A f_{t-1} + u_t \tag{2}$$

$$e_t \overset{iid}{\sim} N(0, R), \quad u_t \overset{iid}{\sim} N(0, Q) \tag{3}$$

- f_t is scalar unobserved WARN factor
- Unknown parameters of model given by Λ, A, R, Q
- Want to estimate $f_1, \ldots, f_T$ given $z_1, \ldots, z_T$
- Use Expectation Maximization (EM) algorithm for estimation with unbalanced panel EM Algorithm

The Dynamic Factor Model

Two additional details:

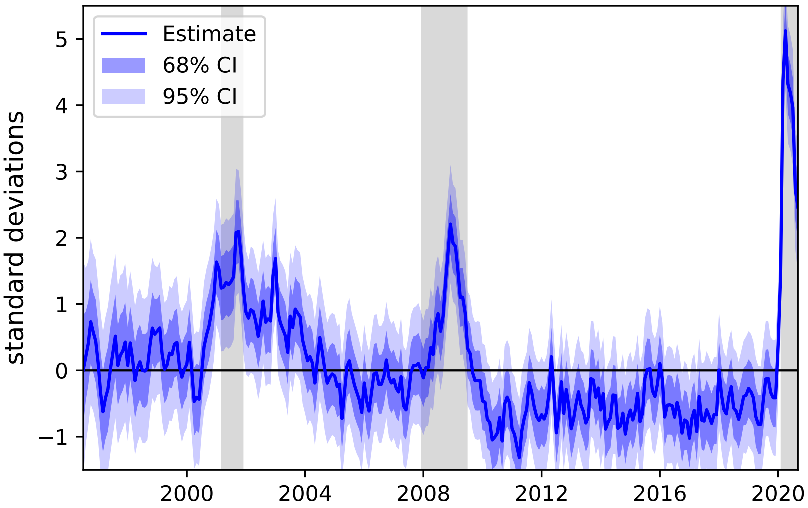
1. The WARN factor has no observable units
   - Scale of Λ and f_t not identified
   - We normalize the variance of f_t to be 1
2. Can use factor model to convert back to "number of worker" units
   - Products of loadings and factors give estimate $z_{j,t}$

   $$\hat{z}_{j,t} = \hat{\lambda}_j \hat{f}_t$$

   - Include means, take exponential, and sum to get number of workers

   $$\widehat{WARN}_t = \sum_{j=1}^{N} \exp(\bar{y}_j + \hat{z}_{j,t})$$

The WARN Factor through October 2020



Forecasting Manufacturing Employment

- Baseline forecasting model is AR(2) with direct estimation:

$$\Delta E_{man,t+h} = \beta_{h,0} + \beta_{h,1}\Delta E_{man,t-1} + \beta_{h,2}\Delta E_{man,t-2} + \xi_{t+h}$$

- Competing model includes an additional predictor (x_t)

$$\begin{aligned}\Delta E_{man,t+h} = \gamma_{h,0} + \gamma_{h,1}\Delta E_{man,t-1} + \gamma_{h,2}\Delta E_{man,t-2} \\ + \delta_{h,1}x_{t-1} + \delta_{h,2}x_{t-2} + \zeta_{t+h}\end{aligned}$$

- Additional predictors are UI claims, ISM employment index, ISM new orders index, WARN factor, WARN factor in number of worker units
- Total sample is July 1996 to December 2019
  - Use 10-year rolling windows to estimate βs, γs, and δs
  - Use real-time employment data for estimation and forecasting
  - Re-estimate DFM to the end of each rolling window

Forecasting Results through December 2019

Table: Forecast results for changes in manufacturing employment

	$h = 0$	$h = 1$	$h = 2$	$h = 6$	$h = 12$
(1) Baseline RMSPE	26.1	31.2	35.1	48.5	56.2
Relative RMSPEs with an Additional Predictor:					
(2) UI Claims	0.99	0.97	0.97	0.98	0.99
(3) ISM Emp	0.94	0.94	0.95	0.98	1.00
(4) ISM New Order	0.97	0.97	0.99	1.02	1.01
(5) $\hat{f}_t$	0.92	0.91	0.91	0.90	0.95
(6) $\widehat{WARN}_t$	0.86**	0.86*	0.86*	0.92	0.99

Note: Row (1) shows the root mean squared prediction errors (RMSPEs) of the baseline AR(2) forecasting model. The units can be interpreted as the number of employees in thousands. The sample of forecast errors is July 2006 to December 2019. Rows (2) to (6) show the ratios of the RMSPEs from the corresponding model to the baseline model. Values less than 1 indicate lower RMSPEs than the baseline model. Stars, * and **, indicate statistical significance at the 10 and 5 percent levels using Giacomini & White (2006).

Conclusions

Question: Is WARN notice data useful as a labor market indicator?

This paper:

- Collected WARN notice data for 33 states
- Aggregated to national-level indicator with DFM
- WARN factor is a countercyclical labor market indicator
- WARN factor is a useful predictor of manufacturing employment

To be done: Further explore the predictive properties of the WARN factor

WARN Act Details

- Additional details:
  - Employers with 100 or more full-time workers
  - Triggered for layoffs exceeding 6 months
  - Triggered for reductions of 50 or more employees
  - Covers private and quasi-public employers, including nonprofits
  - Does not cover federal, state, local government
  - Does not cover temporary employment, temporary facilities, or strikes
- Enforcement:
  - Employer owes back pay and benefits up to 60 days
  - Employer has civil penalty of $500 per day
  - No pecuniary penalty for not carrying out layoffs
- Some states and localities have stricter rules
  - NY state requires 90 days notice

Takeaway: Employers may not be covered, alter behavior, or simply not comply. Not clear *ex ante* if data will be useful as a labor market indicator.

WARN Act

Coverage of WARN Act

- From 1990 to 2014, 60% to 65% of employment located in firms with 100 or more employees
- WARN notices cover
  - About 1.5% of all private-sector layoffs and discharges (JOLTS)
  - About 2% of all initial UI claims

Warn Data

The Dynamic Factor Model

Problem: Some of the data, $z_1, \ldots, z_T$, have missing elements

Solution: Use expectation maximization (EM) algorithm

- Estimates parameters of DFM by maximum likelihood
- Get estimates of $f_1, \ldots, f_T$ from Kalman filter and smoother
- Algorithm is iterative
- Expectation (E) step
  - Given estimates of parameters and data, get expectation of log-likelihood
  - Also get expected moments of $f_1, \ldots, f_T$
- Maximization (M) step
  - Use data and expected moments of $f_1, \ldots, f_T$ to estimate parameters
- Can account for missing data in both steps: References and Inference

Back to DFM

EM Algorithm: References and Inference

EM Algorithm:

- Originally proposed by Dempster, Laird & Rubin (1977)
  - Iterative algorithm for maximum likelihood estimation
  - Increases log-likelihood with each iteration
- EM algorithm for missing data given by Shumway & Stoffer (1982)
- We follow more recent algorithm of Bańbura & Modugno (2014)

Confidence bands computed by bootstrap:

- Simulate DFM using maximum likelihood estimates of parameters
- Drop observations from simulated data in accordance with actual data
- Run the EM algorithm to get bootstrapped estimate of $f_1, \ldots, f_T$
- Repeat many times
- Use mean squared error estimator from Pfeffermann & Tiller (2005)

EM Algorithm