Advance Layoff Notices and Aggregate Job Loss*

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LERA ASSA Session: Job Quality and Job Loss

January 4, 2021

*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
  - 60 days' advance notice
- Research question: Can WARN data be a useful indicator of job loss?
- **Results:**
  1. **A national-level "WARN factor" is highly correlated with layoff data from Mass Layoff Statistics and JOLTS**
  2. **WARN layoffs perform well in an in-sample VAR and pseudo real-time forecasting of the unemployment rate**

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 required to provide 60 days notice prior to mass layoff
- 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
  - Three exceptions exist to 60 days' notice rule
    - E.g. Unforeseeable business circumstances such as COVID-19
  - Additional Details

WARN Data

Establishment-level data collected from state dislocated worker units

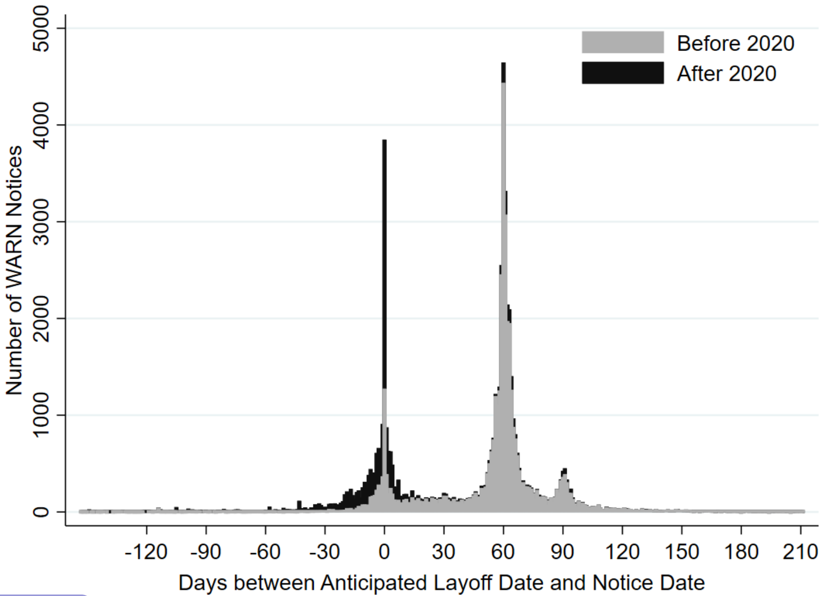
- Digitizing historical records, scraping state websites
- As of Nov 2020: about 75,000 notices affecting over 8 million workers
  - About 60k notices before 2020; about 15k during 2020
- Maintaining database and updating twice a month (middle and end)

Aggregated to state-level monthly panel

- Unbalanced panel
  - MI begins Jan 1990
  - 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)

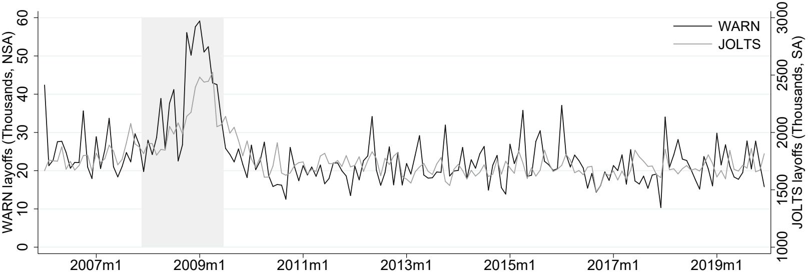
Coverage of WARN Data
WARN layoffs for 8 large states

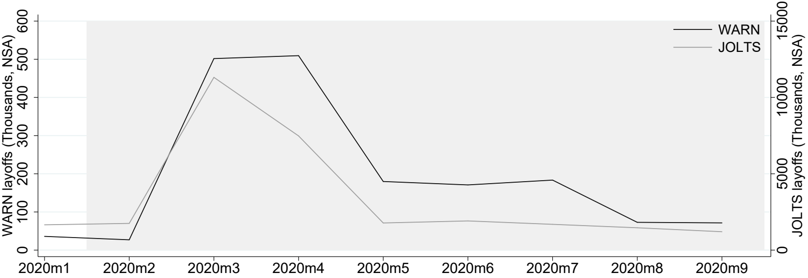
How Much Advance Notice in Practice?



Time series view

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 (unbalanced panel)
    - May limit history length of aggregate data
2. States update WARN data at different times ("jagged" / "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 s, we log and then standardize the data
  - $x_{s,t} = \ln(WARN_{s,t})$
  - $z_{s,t} = (x_{s,t} - \hat{\mu}_s)/\hat{\sigma}_s$
  - Vector of data described by DFM is $z_t = [z_{1,t}, \dots, z_{N,t}]'$
- The DFM is

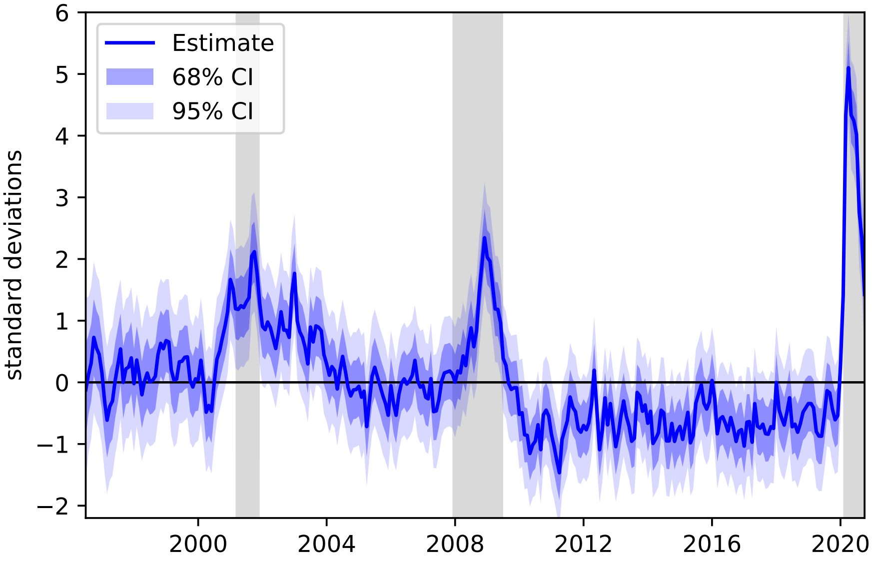
$$z_t = \Lambda f_t + e_t \tag{1}$$

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

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

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

The WARN Factor through October 2020



WARN Layoffs ($\widehat{WARN}_t$)

We use the factor model to obtain the implied number of workers affected by WARN layoffs:

- Products of loadings and factors give estimated $z_{s,t}$

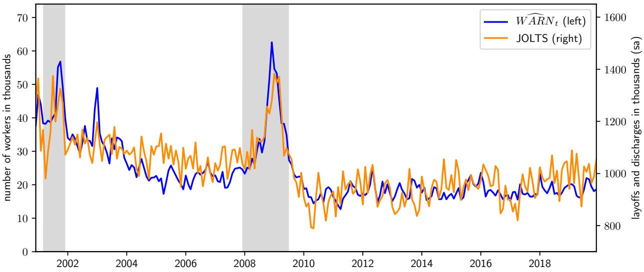
$$\hat{z}_{s,t} = \hat{\lambda}_s \hat{f}_t$$

- Undo standardization, take exponential, and sum to get number of workers

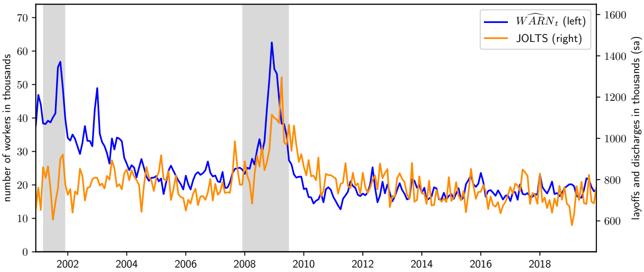
$$\widehat{WARN}_t = \sum_{s=1}^{N} \exp(\hat{\sigma}_s(\hat{\mu}_s + \hat{z}_{s,t}))$$

WARN Layoffs and JOLTS Layoffs

$\widehat{WARN}_t$ Compared to Layoffs and Discharges at Large Establishments



$\widehat{WARN}_t$ Compared to Layoffs and Discharges at Small Establishments



WARN and MLS

WARN Layoff Changes in a VAR

We estimate a VAR similar to Barnichon and Nekarda (2012):

$$Y_t = \Gamma_0 + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \zeta_t,$$

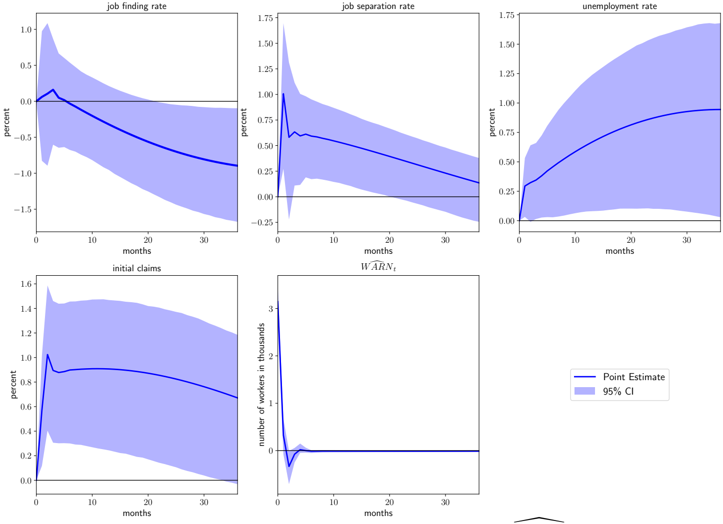
in which

$$Y_t = [100 \times \ln(g_{t-1}), 100 \times \ln(s_{t-1}), \Delta 100 \times \ln(ur_t), 100 \times \ln(uic_t), \Delta \widehat{WARN}_t/1000]'$$

and g_t and s_t are the job finding rate and the job separating rate from CPS data (Shimer, 2012)

IRFs to a surprise increase in $\Delta\widehat{WARN}_t$

Separation rate jumps and stays elevated. UR gradually rises.



Note: IRFs to a one-standard-deviation increase in the error of $\widehat{WARN}_t$.

VAR coefficient estimates

Forecasting the National Unemployment Rate (UR)

Forecasting UR with the VAR, which includes $\Delta \ln (ur_t)$, is easy:
Given data through periods $t - 1$, and estimates of the VAR coefficients, iterate VAR forward

- Total sample is July 1996 to December 2019
- We follow Barnichon and Nekarda (2012) closely

Details

Forecasting Results through December 2019

Table: Forecast Results and Comparisons to the VAR-4 Model

		$h=0$	$h=1$	$h=2$	$h=3$	$h=6$	$h=12$
(1)	VAR-4 RMSPE	0.16	0.23	0.31	0.40	0.69	1.29
Relative RMSPEs of Other VAR Models:							
(2)	VAR-f	0.99	0.99	0.98	0.98	0.97*	0.97
(3)	VAR-w	1.00	0.98	0.97	0.97**	0.96*	0.95
(4)	Sample size	144	143	142	141	138	132

- VAR-4 model includes $\ln(g_{t-1})$, $\ln(s_{t-1})$, $\Delta \ln(ur_t)$, and $\ln(uic_t)$
- VAR-f adds WARN factor changes
- VAR-w adds $\Delta \widehat{WARN}_t$

Conclusions and Future Work

Question: Is WARN data a useful job loss indicator?
Answer: Yes! WARN data are consistent with several indicators of job loss. Contain useful information in and out of sample.

In the future we plan to release updates of our data so that other researchers and analysts can:

1. Measure the effects of local demand shocks on various outcomes
2. Merge our WARN data with other microdata about workers/firms
3. Study the effects of state amendments to the federal WARN Act
4. Monitor labor market activity in real time

Appendix Slides

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
- Two other exceptions:
  1. Faltering company: in the process of obtaining capital
  2. Natural disaster: hurricane, flood, earthquake
- 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

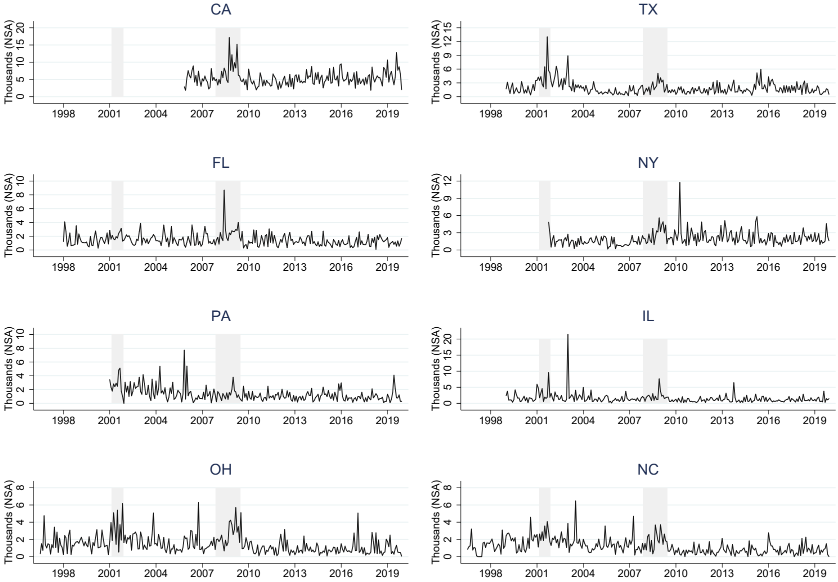
WARN Act

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

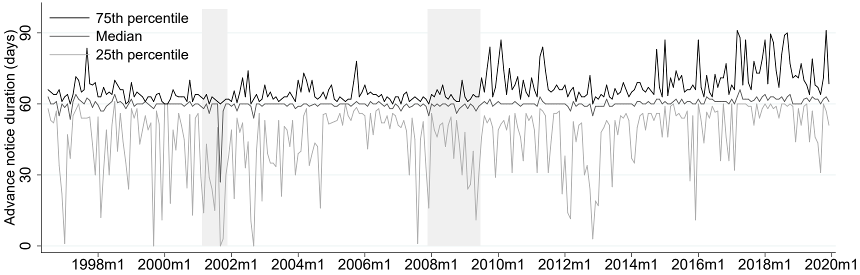
Warn Data

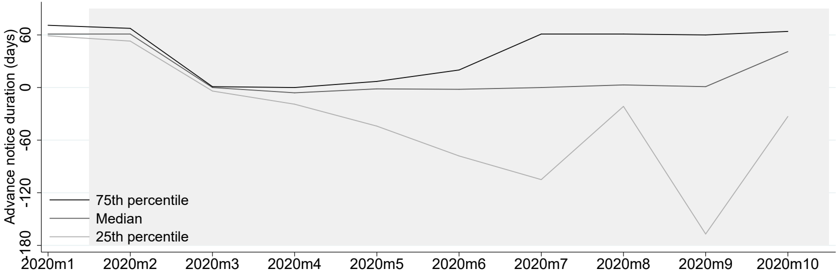
WARN Layoffs for 8 Large States



Warn Data

How Much Advance Notice in Practice?





Histogram

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:

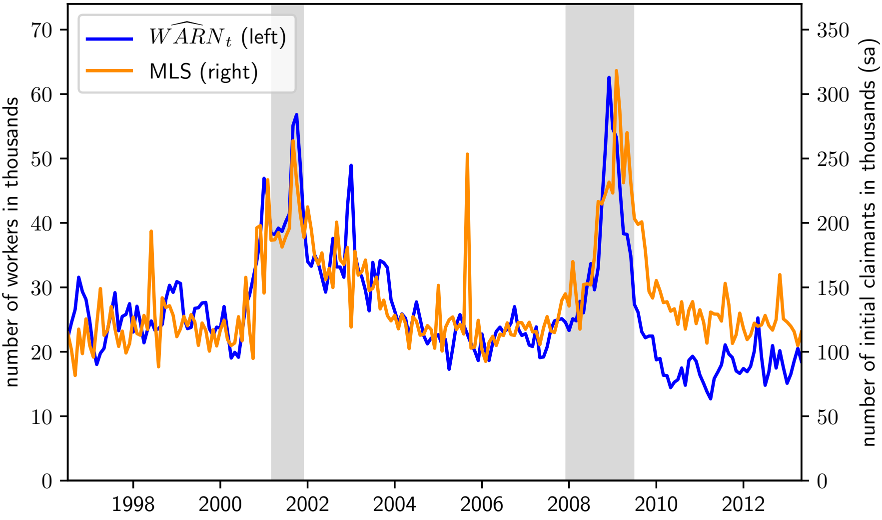
- Originally proposed by Dempster, Laird & Rubin (1977)
  - Iterative algorithm for maximum likelihood estimation
  - Increases log-likelihood with each iteration
- EM algorithm for missing data given by Shumway & Stoffer (1982)
- We follow more recent algorithm of Bańbura & Modugno (2014)

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

WARN Layoffs and MLS Layoffs



WARN and JOLTS

VAR Coefficient Estimates

The first lag of $\Delta\widehat{WARN}_t$ is statistically significant for the log separation rate even controlling for other regressors in a VAR:

Table: VAR regression coefficients on lags of $\widehat{WARN}_t$

	(1)	(2)	(3)	(4)	(5)
	$\ln(g_{t-1})$	$\ln(s_{t-1})$	$\Delta\ln(ur_t)$	$\ln(uic_t)$	$\Delta\widehat{WARN}_t$
$\Delta\widehat{WARN}_{t-1}$	0.02	0.32***	0.09**	0.18*	0.10
	(0.16)	(0.12)	(0.04)	(0.10)	(0.08)
$\Delta\widehat{WARN}_{t-2}$	-0.04	0.02	0.02	0.12	-0.13
	(0.14)	(0.09)	(0.04)	(0.09)	(0.09)

Note: VAR from Barnichon and Nekarda (2012). g_t and s_t are the job finding rate and the job separating rate from CPS data (Shimer, 2012). Sample is from July 1996 to December 2019.

IRFs

Details of UR Forecasting Exercise

- Use 11-year rolling windows to estimate Γ_is
- The sample period for the forecast errors is January 2008 to December 2019.
- Use real-time CPS data for estimation and forecasting
- Re-estimate DFM to the end of each rolling window
- In the paper we also consider the flows model in Barnichon and Nekarda (2012)

Forecasting UR