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Advance Layoff Notices and Aggregate Job Loss*

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Abstract

We collect data from Worker Adjustment and Retraining Notification (WARN) Act notices and establish their usefulness as an indicator of aggregate job loss. The number of workers affected by WARN notices ("WARN layoffs") leads state-level initial unemployment insurance claims, and changes in the unemployment rate and private employment. WARN layoffs move closely with aggregate layoffs from Mass Layoff Statistics and the Job Openings and Labor Turnover Survey, but are timelier and cover a longer sample. In a vector autoregression, changes in WARN layoffs lead unemployment rate changes and job separations. Finally, they improve pseudo real-time forecasts of the unemployment rate.

JEL codes: C32, E24, E27, J63, J65

Keywords: WARN Act, mass layoffs, unemployment, dynamic factor model

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1 Introduction

The unemployment rate is one of the most widely recognized business cycle indicators. In turn, job separations are important for understanding unemployment fluctuations, especially during economic turning points.[1] Therefore, policymakers and economists benefit from high-frequency and timely measures of job separations.[2]

In this paper, we develop and maintain a timely measure of layoffs using daily establishment-level data from Worker Adjustment and Retraining Notification (WARN) Act notices. Further, we present evidence that supports the use of WARN data for monitoring job separations in real time and for predicting unemployment fluctuations.

We collect data from advance layoff notices filed under the WARN Act. This act requires larger employers to notify affected workers at least 60 days before a potential mass layoff. We assemble about 75,000 WARN notices from 33 US states. For many large states our data begin in the 1990s. We update these data twice a month and aggregate them into an unbalanced monthly panel of state-level "WARN layoffs," defined as the number of workers affected by WARN notices. We make the real-time data publicly available on openICPSR at https://doi.org/10.3886/E155161 (Krolikowski and Lunsford, 2022). WARN data are timely as we obtain initial measures of WARN layoffs for the previous month about two weeks after the end of that month.

Four findings establish that these WARN data are a useful indicator of aggregate job loss. First, in-sample state-month panel regressions show that increases in WARN layoffs predict increases in initial unemployment insurance (UI) claims and the unemployment rate,

[1] Elsby, Michaels, and Solon (2009) and Barnichon (2012) find that separations account for about 40 percent of unemployment fluctuations on average and the role of separations is more pronounced at the onset of recessions. Coles and Moghaddasi Kelishomi (2018) present a model in which job separations drive "the large variation in unemployment over the cycle."

[2] The need for high-frequency and timely labor market data was highlighted during the onset of the 2020 recession, as discussed in Cajner et al. (2020a), Chetty et al. (2020), Coibion, Gorodnichenko, and Weber (2020), Forsythe et al. (2020), and Kurmann, Lalé, and Ta (2021). Our paper focuses on job separations and complements this work.

and decreases in employment. The strongest predictions occur over the two-month horizon, consistent with the 60 days' notice required by the WARN Act.

Second, aggregated WARN data track published layoffs well but are timelier and cover a longer period. We aggregate the unbalanced state-level data to a national-level indicator of job loss (the "WARN factor") using a dynamic factor model that we estimate with the algorithm in Bańbura and Modugno (2014). WARN layoffs implied by our factor are highly correlated with the number of initial UI claimants from the defunct Mass Layoff Statistics (MLS) program and the number of layoffs and discharges among large establishments from the Job Openings and Labor Turnover Survey (JOLTS). Further, WARN layoffs lead these two other indicators during the 2008-09 recession. Our data also extend beyond May 2013 (when the MLS program was eliminated) and before December 2000 (when JOLTS began), and they are timelier than JOLTS data, which are published with a two-month lag.

Third, in the vector autoregression (VAR) from Barnichon and Nekarda (2012), changes in WARN layoffs implied by our factor lead changes in the unemployment rate and the job separation rate from the Current Population Survey (CPS). Impulse response functions (IRFs) from this VAR show that a surprise increase in WARN layoffs causes an immediate increase in the separation rate and initial UI claims that also persists beyond the mandated 60 days' notice. Consistent with these IRFs, a surprise increase in WARN layoffs also causes the unemployment rate to rise for about three years. A surprise increase in WARN layoffs has no short-term effect on the job finding rate, consistent with the notion that WARN data inform job separations.

Fourth, changes in WARN layoffs improve forecasts of the national unemployment rate. We use the VAR on its own and incorporated into Barnichon and Nekarda's (2012) flows model of the unemployment rate, for forecasting the unemployment rate in pseudo real time. From 2008 through 2019, the inclusion of changes in WARN layoffs implied by our factor improves forecast accuracy at horizons of more than two months. WARN layoffs also improve forecasts of the unemployment rate during the onset of the 2020 recession.

Our findings support the recent use of WARN data by other researchers, although none of that work evaluates WARN notices as an indicator of aggregate job loss. For example, Hall and Kudlyak (2020) use WARN notices from three states to measure mass layoffs. Kudlyak and Wolcott (2020) use WARN announcements from several states to document the nature and timing of layoffs at the onset of the 2020 recession. Hernández-Murillo and Krolikowski (2020) study advance notice and the industry and geography of job loss in four Midwestern states during the recent crisis. WARN data also provide a timely indicator that complements initial UI claims, which has shortcomings as a measure of layoffs. During the pandemic, processing delays, duplicate claims, and fraud made initial UI claims less accurate than in the past (Cajner et al., 2020b). More generally, initial claims do not measure layoffs because the UI take-up rate is well below 100 percent and moves over the cycle.[3]

Our collected data could support future work in at least four areas. First, our data could be merged with other microdata to update the literature about WARN notice incidence and the outcomes for notified workers.[4] Second, the geographic granularity of our data allows us to measure concentrated local demand shocks and could be used in work related to that of Autor, Dorn, and Hanson (2013), Foote, Grosz, and Stevens (2019), Notowidigdo (2019), and Acton (2020). Third, our data could be used to study the effects of state amendments to the federal WARN Act on notice provision and timing. Fourth, our data could complement future data collection efforts related to the Fair Warning Act of 2019 (US Congress, 2019a,b), which proposes creating a publicly available database of layoff notices.

Section 2 describes the WARN Act and our process for collecting the data and aggregating them to a monthly panel of states. This section also presents summary statistics, including the coverage of WARN notices, and describes the distribution of advance notice and how it varies over time. Section 3 provides in-sample evidence that state-level WARN layoffs move

[3]See Blank and Card (1991), Vroman (2009), and Auray, Fuller, and Lkhagvasuren (2019) for evidence about and discussion of the former. Hobijn and Şahin (2011) find that the UI take-up rate rose during the 2008–09 recession.

[4]For example, Addison and Blackburn (1994a,b) study how the incidence of notices changed around the passage of the WARN Act. Swaim and Podgursky (1990), Ruhm (1992), and Addison and Blackburn (1997) study advance notice and post-displacement non-employment.

closely with MLS and JOLTS layoffs and that WARN layoffs lead other state-level labor market indicators. Section 4 aggregates the unbalanced state panel to a national WARN factor using a dynamic factor model. Section 5 compares national-level WARN layoffs with MLS and JOLTS data and shows that WARN layoffs are highly correlated with the CPS separation rate, even controlling for other indicators in a VAR. Section 6 shows that WARN data improve pseudo out-of-sample forecasts of the unemployment rate. Section 7 concludes.

2 The WARN data

2.1 The WARN Act

The WARN Act seeks to provide workers with sufficient time to begin new job searches or to obtain necessary training. The act requires employers with 100 or more employees to provide their workers with at least 60 days' written notice prior to layoff. WARN notification is triggered by large, permanent reductions in the labor force at individual employment sites, defined in two ways. First, a "plant closing" is when an employment site is shut down and 50 or more full-time workers lose their jobs. Second, a "mass layoff" happens when employment is reduced by 500 or more full-time workers at a given site, or by 50 to 499 full-time workers if they make up at least one-third of the employer's workforce.[5] The act also applies when an employer announces that a temporary layoff (less than 6 months) becomes a permanent one. The act requires notices to include the name and address of the affected employment site, the expected date of the first separation, and the anticipated number of affected employees.

The penalty for issuing too little notice can be severe. In particular, if a covered employer fails to give workers 60 days' notice for a qualifying WARN event, they are liable to each employee for back pay and benefits for the period of violation, up to 60 days. We provide further requirements of the act and discuss the non-pecuniary costs associated with unrealized WARN notices in Appendix A.1.

Employers can issue notices with less than 60 days' notice. For example, the "unforesee-

[5] The one-third rule exempts many large layoffs from coverage by the act according to the GAO (1993) and, as a result, employers are more likely to issue notices of plant closures than mass layoffs (GAO, 2003).

able business circumstances" exception applies when business circumstances change suddenly and unexpectedly. During the onset of the 2020 recession, employers often cited this reason when issuing less than 60 days' notice. Even when employers file with an exception, however, the Department of Labor insists that notices must be given as soon as is "practicable" and the employer must provide a statement of the reason for reducing the notification period. We discuss two other narrow exceptions in Appendix A.1.

Some states and localities have passed legislation that expands the federal WARN Act. For example, since February 2009, New York state requires that employers provide 90 days' advance notice and it requires WARN notices from smaller firms and in anticipation of smaller layoff events (NY WARN, 2019).

2.2 Data collection, revisions, and creating a monthly panel

We collect establishment-level WARN notices from state employment offices, via websites and contacting state officials. We often extend publicly available WARN data by using digital archives of the internet and documents from state officials. We discuss details about our data collection efforts and missing data in Appendix A.2.

We currently update our WARN database in the middle of the month and at the end of the month. We stop counting the number of workers affected by WARN notices in a given state and a given month when we observe a WARN notice for that state in a subsequent month. We observe the most recent WARN notices at different times for each state because of different WARN release schedules and infrequent WARN notices for smaller states. In Appendix A.2 we discuss extending historical data and our updating schedule, and we highlight the timeliness of our data relative to other labor market information.

We remove revisions of original WARN notices from our data because including original and revised notices would overcount the number of workers affected by WARN notices. And we prefer to use original notices over revised notices because the former improve the timeliness of our data and minimize data revisions. Only some states in our sample differentiate revised notices from original notices. For other states, we identify revised notices with an algorithm described in Appendix A.2. Our algorithm does not remove more than 3 percent of any state's notices.

To obtain a monthly state panel we sum the expected number of affected workers by WARN notices across individual establishments in each state-month cell and seasonally adjust this series for each state using the model in Wright (2013, pg. 80), as discussed in Section 4. The timing of these notices is based on the notice date. We refer to the number of workers affected by WARN notices in a given state and month as "WARN layoffs" for brevity, although firms do not have to follow through with the announced layoffs, as discussed in Section 2.1. We drop several states from our analysis due to restrictions on WARN information and we use several published data sets in our analysis, like the defunct Mass Layoff Statistics (MLS, 2022), as discussed in Appendix A.2.

2.3 Monthly panel summary statistics

As of December 30, 2021, our WARN data have almost 75,000 WARN notices affecting over 8 million workers, which implies that the average WARN notice affects about 110 workers.[6] About 55,000 notices occurred before January 2020 and about 20,000 occurred afterwards. Over the years 2014 to 2019, when the sample of states did not change, there were roughly 270,000 workers affected by 2,600 WARN notices each year.

Table 1 presents our baseline sample of states and some summary statistics about WARN layoffs in these states. We collect and post WARN layoffs for 33 states, as mentioned in Section 1, but we drop ID, KY, OK, UT, and WV because they contain many months with zero WARN layoffs. Our final sample includes 28 states, with an average of about 18 years of monthly observations for each state, yielding 6,103 state-month observations. Michigan is the first state to enter our sample in January 1990, and by January 2000, we have 13

[6] We find that about 40 (25) percent of employers filing WARN notices in our sample anticipate fewer than 50 (25) layoffs, which is below the federally mandated threshold for issuing a WARN notice. This is partly due to variation in legislation by locality (some states require WARN notices when fewer than 50 workers are laid off), as mentioned in Section 2.1, and partly because employers may be confused about when a WARN notice is required, as documented by the GAO (1993, 2003). Ehrenberg and Jakubson (1990) find that Pennsylvania employers filed notices with their state even when WARN did not apply.

states; by January 2006, we have 23 states; and by January 2019, we have 27 states in our sample (SC enters our sample in 2009 but drops out by the end of our sample).[7] States do not publish their most recent data at the same time, as discussed in Section 2.2. Hence, the end date for each state can differ, although most large states completed reporting WARN data through November 2021 when we collected the data at the end of December. Table A1 presents summary statistics through December 2019 for WARN layoffs along with summary statistics for several other published data sets.

The number of workers affected by WARN notices in each state is counter-cyclical, but the data are somewhat noisy, as shown for some large states in Figure 1. WARN layoffs rise during the 2001 and 2008-09 recessions and fall subsequently. (WARN layoffs rose sharply at the onset of the 2020 recession, peaked in March or April 2020 in almost all of the large states, and have declined since then, as depicted in Figure A1.) Sharp increases in the number of WARN layoffs outside of recessionary periods typically reflect large layoff events. For example, on January 1, 2003, United Airlines filed two WARN notices affecting almost 20,000 workers in the Chicago area. In Section 4 we aggregate these state-level panel data to show that they contain important information about national job loss.

2.4 WARN data coverage

The WARN Act covers the majority of firms and our recent sample of states with WARN data covers most of the United States. In particular, according to the Business Dynamics Statistics from the US Census Bureau (Census, 2019), between 1990 and 2019, 60 to 67 percent of employment has been located in firms with at least 100 workers, which is the firm size restriction in the federal WARN Act. As a result, the act covers up to two-thirds of all employment relationships.[8] In addition, the initial UI claims in our sample of states in 2018 cover almost 85 percent of national initial UI claims.

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[7] WARN data for the eight most populous states in our sample—CA, TX, FL, NY, PA, IL, OH, and NC—start in 1/2006, 1/1999, 1/1998, 10/2001, 1/2001, 1/1999, 7/1996, and 5/1996, respectively.

[8] Some employment is temporary and some involves seasonal workers, who are not covered by the WARN Act, but this employment is a relatively small part of the economy (OECD, 2020).

Additionally, these WARN data cover a small but non-trivial fraction of aggregate job loss, as measured by various other related indicators. First, for state-month observations in our sample, using seasonally adjusted data, the median number of workers affected by WARN notices is about 10 percent of the median number of initial UI claimants from plants in the MLS (Table A1, rows 1 and 2). This suggests that about 10 percent of all workers affected by mass layoffs and plant closures are subject to, and comply with, the act.[9] Second, if all WARN notices end in actual layoffs, then WARN notices cover about 1.5 percent of all private-sector layoffs and discharges in the United States as measured by the Job Openings and Labor Turnover Survey (JOLTS, 2022). Over the years 2014 to 2018, annual layoffs and discharges among private employers were about 17 million per year. Third, WARN notices cover about 2 percent of all initial UI claims, which were roughly 13 million over the years 2014 to 2018 (Claims, 2022).

2.5 How much advance notice do employers give?

Our WARN data will help assess current and future labor market conditions only if employers issue timely WARN notices. In this section we assess how much advance notice employers give their workers and how this notice period varies over the business cycle. To measure advance notice we use the number of days between the date a notice was filed and the anticipated layoff date for each establishment-level WARN notification.

Advance notice data before 2020 have three features that suggest that WARN notices provide substantial advance layoff notice, largely consistent with the structure of the WARN Act, as shown in Figure 2 (grey bars). First, there is a large spike at 60 days, consistent with the 60 days' advance notice required by law. Second, almost two-thirds of all notices provide 40 to 80 days of advance notice. Third, there is a substantial number of WARN notices with about 90 days' advance notice because New York has required 90 days' advance notice since February 2009, as discussed in Section 2.1. The spike at 0 days reflects employers that file the WARN notice the same day they start laying off workers.

[9] This is consistent with the GAO (2003), which finds that about 25 percent of all mass layoffs and plant closures are subject to the act and employers provide WARN notices for about one-third of these events.

Most employers issued little advance notice during 2020 and 2021, as shown in Figure 2 (black bars). The vast majority of notices provided about 0 days of notice, and only a small fraction provided 60 days or more. This short advance notice suggests that the pandemic was unexpected by businesses (Hernández-Murillo and Krolikowski, 2020).

The median advance notice does not vary much over the business cycle, and the advance notice distribution is skewed to the left, as shown in the top panel of Figure 3. The figure shows the 75th, 50th, and 25th percentiles of the advance notice distribution for each month from July 1996 to December 2019. The median number of days between the notice date and the anticipated layoff date is typically no less than about 60 days during this period, which is the advance notice required by the WARN Act. (The median notice duration fell abruptly to 7 days in September 2001 because many businesses filing WARN notices were adversely affected by the unexpected terrorist attacks.) The advance notice distribution is skewed to the left: the 75th percentile almost never goes above 90 days and the 25th percentile often falls to about 30 days and sometimes close to 0 days.

In March 2020, at the onset of the recent crisis, median advance notice fell to about zero, as shown in the bottom panel of Figure 3. This advance notice suggests that the median business was issuing WARN notices about the same day it started laying off workers, consistent with the unexpected nature of the COVID-19 pandemic. After remaining close to zero through September 2020, median advance notice began to rise in October 2020, and since January 2021 it has remained about 60 days. The 25th percentile fell well below zero in September 2020 because many businesses filed WARN notices for temporary layoff events that happened in March, once they realized these layoffs would become permanent.

3 WARN as a labor market indicator

3.1 Preliminary evidence

We present preliminary evidence that WARN notices move together with, and slightly lead, initial UI claims from the MLS program and layoffs and discharges from JOLTS. The slight lead time is consistent with the 60 days' notice required by law and our evidence about advance notice in Section 2.5.

Figure 4 shows the seasonally adjusted aggregate number of workers affected by WARN notices and the number of initial UI claimants as covered by the MLS program for each month since January 2006. We begin in January 2006 and include only those states that have data available on WARN notices during that month to maintain a balanced sample of states.[10] The figure shows that the number of individuals affected by WARN notices tends to move with MLS initial claims, but the latter is noisier than the former. Moreover, during the 2008-09 recession, WARN layoffs rose sharply in October 2008, three months before the sharp rise in MLS initial claims. Toward the end of that recession, WARN layoffs peaked in December 2008 and was on a clear decline before MLS initial claims peaked in May 2009.

WARN layoffs and the number of layoffs and discharges from JOLTS display similar patterns. During the 2008-09 recession, the number of workers affected by WARN notices rose sharply in October 2008, two months before the sharp rise in JOLTS layoffs in December 2008, as shown in the top panel of Figure 5. The number of layoffs and discharges in JOLTS rises through April 2009, whereas the number of individuals affected by WARN notices peaks in December 2008 and declines considerably by April 2009. During the 2020 recession WARN layoffs rise sharply in March, similar to JOLTS layoffs, as shown in the bottom panel of Figure 5. Both series have since declined, and in November 2021, JOLTS and WARN layoffs were below pre-pandemic levels.

3.2 State-level evidence with regression analyses

In this section we present evidence that WARN notices help predict several labor market indicators at the state level. To assess the predictive content of WARN information, we estimate the following equation:

$$y_{s,t} = \alpha_s + \sum_i \beta_i WARN_{s,t-i} + \sum_i \eta_i X_{s,t-i} + \epsilon_{s,t} \tag{1}$$

[10] We start in January 2006 because CA enters our sample then and we have 23 states in our sample.

in which s denotes state and t denotes month; $y_{s,t}$ is initial UI claims, the change in the unemployment rate, or the change in private employment; α_s are state fixed effects; $WARN_{s,t-i}$ is the number of workers in state s affected by WARN notices in month t and its lags; and $X_{s,t-i}$ controls for lags of the left-hand-side variable, $y_{s,t-i}$, and the other variables of interest. Because WARN requires 60 days' notice, and in Section 2.5 we find that most notices occur about two months before the anticipated layoff event, we include two lags, so that $i = 1, 2$. We weight the regressions by state employment in each state in each month because a regression of squared residuals on the inverse of state employment, as suggested by Solon, Haider, and Wooldridge (2013), indicates significant heteroskedasticity in our data.

The number of workers affected by WARN notices leads state-level labor market indicators by one to two months. Table 2 presents the results. Column (1) suggests that if the number of workers affected by WARN notices rises by 1,000 this month (almost a one-standard-deviation increase) in state s, we expect initial claims in state s to rise next month by about 270 ($\approx 63 \times 4.3$), after controlling for lags of initial UI claims and changes in the state-level unemployment rate and private employment. Although this effect is statistically significant, this magnitude is small as the monthly average of state-level initial UI claims in our sample is about 10,000. If the number of workers affected by WARN notices rises by 1,000 this month in state s, we expect the change in the unemployment rate to increase by about 0.005pp and employment growth to slow by about 2,100 over the next two months. Because the standard deviation of changes in the unemployment rate is 0.1pp, the magnitude of the effect of WARN layoffs for the unemployment rate is small. But the mean change in state-level private employment over our whole sample is about 2,600, so the predictive content of WARN notices is economically large for this indicator.

4 National-level aggregation with a dynamic factor model

In this section, we aggregate our state-level panel data to a national-level labor market indicator. The challenge for aggregating our data is that the state-level panel is unbalanced in two ways. First, as discussed above and as shown in Table 1, the state-level data do not all begin at the same time. For example, MI enters our sample in 1990 but CA enters in

2006. Second, as discussed in Section 2.2, states do not publish their most recent data at the same time. Some state-level data are available within a few days of the end of the previous month, while data from some smaller states may not be available for several months. Hence, the real-time data flow is unsynchronized, leading to a "jagged" or "ragged" edge problem (Bańbura et al., 2013).

Our unbalanced panel prevents us from being able to sum up our WARN data across states as one could, for example, with initial UI claims. We could restrict our sample to those states that are available at a point in time, such as January 2006, and simply sum those particular states going forward. Indeed, this is what we do for Figures 4 and 5. While this is a useful expository approach, it limits both the historical time-series and the cross-sectional number of states that can be used for more formal statistical analysis. Further, the jagged/ragged edge problem remains and limits the real-time usefulness of the data.

To manage these data challenges, we model our unbalanced panel with a dynamic factor model (DFM), which we estimate with the expectation maximization (EM) algorithm in Bańbura and Modugno (2014). This modeling and estimation approach is commonly used to handle unbalanced panels with jagged/ragged edge problems. We give an overview of the DFM and EM in this section and provide additional details in Appendix B.

If $WARN_{s,t}$ is observed and non-zero, then $x_{s,t} = \ln(WARN_{s,t})$. Otherwise, we treat $x_{s,t}$ as missing.[11] We use $\mathcal{T}_s \subseteq \{1, \ldots, T\}$ to denote the set of periods in which $x_{s,t}$ is observed.[12] As in Bańbura and Modugno (2014), we standardize the data with $\hat{z}_{s,t} = (x_{s,t} - \hat{\mu}_s)/\hat{\sigma}_s$, in which $\hat{\mu}_s$ and $\hat{\sigma}_s$ are the sample average and standard deviation of $\{x_{s,t}\}_{t\in\mathcal{T}_s}$.

We model $\hat{z}_{s,t}$ for $t \in \mathcal{T}_s$ and $s = 1, \ldots, N$, with a DFM as follows. Let $z_t = [z_{1,t}, \ldots, z_{N,t}]'$

[11] We do not take logs if $WARN_{s,t} = 0$; rather, we treat these observations as missing. As with the jagged/ragged edge problem at the end of our sample, the EM algorithm handles these missing observations within our sample. Because zeros typically occur in smaller states, treating these observations as missing puts more weight on larger states for estimating the WARN factor in the corresponding months.

[12] We follow Camacho, Lovcha, and Pérez Quirós (2015) and seasonally adjust $\{x_{s,t}\}_{t\in\mathcal{T}_s}$ for each state individually before running the DFM. We use the state-space model on page 80 of Wright (2013) and an EM algorithm to handle missing observations, with details in Appendix B.1.

be an N-dimensional process, which follows

$$z_t = \Lambda f_t + e_t, \quad e_t \overset{iid}{\sim} N(0, R), \tag{2}$$

in which f_t is an unobserved scalar factor, $\Lambda = [\lambda_1, \ldots, \lambda_N]'$ is an $(N \times 1)$ vector of factor loadings, $e_t = [e_{1,t}, \ldots, e_{N,t}]'$ is an N-dimensional process of disturbances, and R is a diagonal matrix with all diagonal elements being strictly positive. Then, $\hat{z}_{s,t} = z_{s,t}$ if $\hat{z}_{s,t}$ is observed.

We interpret f_t as being the national-level "WARN factor" that affects all states through the factor loadings. We assume that f_t follows an AR(1) process,

$$f_t = A f_{t-1} + u_t, \quad u_t \overset{iid}{\sim} N(0, Q), \tag{3}$$

in which A is the autoregression slope coefficient, u_t is the autoregression innovation, and $Q > 0$. This AR(1) structure allows the WARN factor to be persistent, similar to other national-level labor market variables. Equations (2) and (3) compose our DFM.

We use $\hat{z}_{s,t}$ for $t \in \mathcal{T}_s$ and $s = 1, \ldots, N$ to jointly estimate the DFM parameters and the WARN factor with maximum likelihood, using the EM algorithm in Bańbura and Modugno (2014). In doing so, we normalize the unconditional variance of the WARN factor to be 1 and discuss the WARN factor in terms of its standard deviation.[13] We use the parametric bootstrap in Pfeffermann and Tiller (2005) to compute the mean-squared errors for the confidence intervals. We give details of the EM algorithm and confidence intervals in Appendix B.2. We find that the estimated state factor loadings increase with average employment and manufacturing shares, as discussed in Appendix B.3.

We use a sample of July 1996 to November 2021 for the 28 states in Table 1 to estimate our WARN factor. We start our sample in July 1996 to balance having a long time series with having many states in the initial cross-section. On the one hand, we want the longest

[13]Formally, we impose the condition that the unobserved factor f_t has an unconditional variance equal to 1. The estimate of $\{f_t\}_{t=1}^{T}$, which we display below, has a variance less than 1. For ease of discussion, we discuss our estimated WARN factor in terms of standard deviation units.

sample possible to get the best sense of the WARN data's aggregate properties. On the other hand, we want a moderate number of states in our sample to get a good estimate of the WARN factor. We balance these two concerns by starting the sample in July 1996 when we observe data for five states: MI, NC, OH, VA, and WI.

Our WARN factor has three noteworthy features. First, it rises just before or in recessions, falls during the initial parts of expansions, and is relatively flat during later parts of expansions, as shown in the top panel of Figure 6. While it is typically near or below zero outside of recessions, it is significantly above zero for the 2001 recession, the subsequent slow labor market recovery, and the 2008-09 and 2020 recessions. Second, the peak of the WARN factor is higher in the 2008-09 recession than in the 2001 recession, and higher in the 2020 recession than in the 2008-09 recession. These peaks are consistent with the relative severity of these recessions. Third, the WARN factor has few false positives: When it is one standard deviation or more above zero, it indicates increasing slack in the labor market.

While we normalize the WARN factor and interpret it in terms of its standard deviation, it may be useful to have an aggregate measure of WARN notice data with economically interpretable units. Toward this end, we provide an aggregate measure of WARN layoffs implied by our WARN factor. Using $\{\hat{f}_t\}_{t=1}^T$ and $\hat{\Lambda} = [\hat{\lambda}_1, \ldots, \hat{\lambda}_N]$ to denote the maximum likelihood estimates of the WARN factor and the factor loadings, we compute $\hat{x}_{s,t} = \hat{\mu}_s + \hat{\sigma}_s \hat{\lambda}_s \hat{f}_t$ for $s = 1, \ldots, N$ and $t = 1, \ldots, T$. We then construct

$$\widehat{WARN}_t = \sum_{s=1}^{N} \exp(\hat{x}_{s,t}) \tag{4}$$

to be the estimated number of WARN layoffs implied by the WARN factor.

The bottom panel of Figure 6 shows $\widehat{WARN}_t$ from July 1996 to November 2021. It is highly correlated with the WARN factor (correlation of 0.86). However, because we take exponentials in equation (4), $\widehat{WARN}_t$ displays more skewness than the WARN factor with larger peaks in recessions. This asymmetry better matches US labor market data (for example, see Ferraro, 2018), which may help explain why $\widehat{WARN}_t$ improves unemployment rate forecasts more than the WARN factor in Section 6.

5 In-sample properties of the WARN factor

In this section, we discuss some in-sample properties of $\widehat{WARN}_t$.[14] In Section 5.1, we visually compare $\widehat{WARN}_t$ to MLS and JOLTS layoff data. These comparisons extend the results in Figures 4 and 5 and show the usefulness of the DFM in expanding the data sample. In Section 5.2, we show that changes in $\widehat{WARN}_t$ have a statistically significant impact on the job separation rate, the unemployment rate, and initial UI claims in the VAR from Barnichon and Nekarda (2012).

5.1 Comparison to MLS and JOLTS

Figure 7 shows $\widehat{WARN}_t$ and the number of initial claimants from the MLS from July 1996, when $\widehat{WARN}_t$ begins, to May 2013, when the MLS data end. The two series are highly correlated (correlation of 0.64) and have similar business cycle properties. Both series increased in the second half of 2000, leading up to the 2001 recession, and both series have spikes in September 2001 associated with the September 11, 2001, terrorist attacks. Both series also have a slow decline from 2002 to 2004, coinciding with a slow labor market recovery. $\widehat{WARN}_t$ slightly leads the MLS data in the 2008-09 recession, as in Figure 4. Overall, when filtered through the DFM, the WARN data align well with the aggregate properties of the MLS data despite fewer states reporting WARN data earlier in our sample.[15]

Figure 8 shows $\widehat{WARN}_t$ and the number of JOLTS private layoffs and discharges from December 2000, when the JOLTS data begin, to December 2019.[16] We display the JOLTS data in two panels by establishment size. The top panel shows layoffs and discharges at

[14] We focus on $\widehat{WARN}_t$ in this section because it improves forecasts of the unemployment rate more than the WARN factor.

[15] The large spike in the MLS series in September 2005 reflects the impact of Hurricane Katrina in Louisiana and Mississippi (BLS, 2005). Theses states enter our sample in 2007 and 2010, respectively, so the WARN series does not reflect the impact of that hurricane.

[16] We do not show data for 2020 because the scale is so large that data fluctuations prior to 2020 become difficult to see, as shown in Figure A2.

establishments with 50 employees or more. The bottom panel shows layoffs and discharges at establishment with 49 employees or less. The top panel shows that $\widehat{WARN}_t$ correlates highly with layoffs and discharges at larger establishments (correlation of 0.81). In addition, layoffs and discharges at larger establishments have a general downward trend over this sample and are generally lower from 2010 to 2019 than from 2002 to 2007. This matches a downward trend in the WARN data and is consistent with evidence about the secular decline in job loss rates over the last 40 years (Davis, 2008; Elsby, Michaels, and Solon, 2009; Shimer, 2012). As with the MLS data, the WARN data do a good job of matching the aggregate properties of JOLTS layoffs and discharges at larger establishments.

The bottom panel of Figure 8 shows that $\widehat{WARN}_t$ correlates less highly with layoffs and discharges at smaller establishments (correlation of 0.38). This result is consistent with the WARN Act only applying to relatively large firms.

5.2 A VAR with unemployment flows

The results in the previous section indicate that the WARN data align well with similar labor market indicators, MLS and JOLTS layoffs and discharges at larger establishments, over a relatively long period. In this section, we provide more formal evidence that WARN data are a useful labor market indicator by including them in the VAR from Barnichon and Nekarda (2012), henceforth BN.

We first introduce some additional notation and data. Let g_t and s_t be the job finding rate and the job separating rate between month $t-1$ and month t. We compute g_t and s_t as in BN and Shimer (2012), with details in Appendix C. The vector of the data in the VAR is

$$Y_t = [100 \times \ln(g_t), 100 \times \ln(s_t), \Delta 100 \times \ln(ur_t), 100 \times \ln(uic_t), \Delta\widehat{WARN}_t/1000]',$$

in which ur_t denotes the unemployment rate and uic_t denotes initial UI claims. The VAR is

$$Y_t = \Gamma_0 + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \zeta_t, \tag{5}$$

in which Γ_0 is a (5×1) vector and Γ_1 and Γ_2 are (5×5) matrices. The use of logs and differences in the first four rows of this VAR match BN. In addition, we scale the first four rows by 100 so that data can be interpreted in terms of percent or percent changes. We also use two lags to match BN. The substantive difference between this VAR and the VAR in BN is the fifth row, in which we include the change in $\widehat{WARN}_t$ divided by 1,000.[17]

We estimate the VAR from July 1996 to December 2019. Ending the sample in 2019 will give better intuition for the forecasting results in Section 6.2.1. Table 3 shows the regression coefficients on the lags of $\Delta\widehat{WARN}_t$. It shows that the first lag of $\Delta\widehat{WARN}_t$ is statistically significant for the log separation rate even controlling for the other regressors in the VAR. Consistent with the patterns in Figures 7 and 8, this result shows that WARN data provide a useful indicator of aggregate job loss. We also note that we construct the separation rate, s_t, from CPS data. Hence, our WARN data correlate highly with job loss data from three separate sources: MLS, JOLTS, and CPS. Consistent with our earlier research (Krolikowski, Lunsford, and Yang, 2019), Table 3 also shows that the first lag of $\Delta\widehat{WARN}_t$ is statistically significant for the log change in the unemployment rate and log initial claims even controlling for the other regressors in the VAR.

To facilitate interpretation of these VAR results, we show impulse response functions (IRFs) to a surprise increase in $\widehat{WARN}_t$ in Figure 9. We do this by assuming that there is a one standard deviation increase in the element of ζ_t in the fifth row of the VAR, while all other elements of ζ_t are zero. We then use the VAR coefficients (excluding Γ_0) to iterate Y_t forward. These IRFs display the marginal effect of an increase in $\widehat{WARN}_t$ on the future path of all variables in the VAR. In Figure 9, month 0 on the horizontal axis shows the initial increase in $\widehat{WARN}_t$ and all subsequent months show the effects on the other variables. The shaded region in each panel shows the 95 percent confidence intervals.[18]

[17] BN use the change in the log of the help wanted index (HWI) from Barnichon (2010). We have found that this HWI is only updated sporadically and so do not use it.

[18] Our bootstrap follows Runkle (1987). We resample the VAR residuals with replacement to produce bootstrapped VAR innovations. We use these innovations with the estimates of Γ_0, Γ_1 and Γ_2 and the initial conditions $Y_0^* = Y_0$ and $Y_{-1}^* = Y_{-1}$ to recursively produce an artificial sample $\{Y_t^*\}_{t=-1}^{T}$. We use

Consistent with the results in Table 3, a surprise increase in $\widehat{WARN}_t$ in month 0 causes increases in the job separation rate, the unemployment rate, and initial claims in month 1. There is noise in the job separation rate in month 2, but the separation rate stays persistently elevated after that. To aid interpretation, we accumulate the unemployment rate IRF and show it in percent rather than percent changes. After month 1, the unemployment rate gradually rises by about 0.59 percent at one year and 0.88 percent at three years. As with the separation rate, the confidence interval around the unemployment rate widens in month 2 but the IRF is statistically significantly different from zero after that. In contrast, initial claims peak at month 1, fall slightly after that, but stay persistently elevated. Finally, a surprise increase in $\widehat{WARN}_t$ has no discernible short-run impact on the job finding rate, but leads to a fall in the job finding rate after about 20 months.

The IRFs show that a surprise change in WARN layoffs provides useful information about future job separations, initial UI claims, and the unemployment rate. Further, job separations, initial UI claims, and the unemployment rate have non-zero responses at horizons extending well beyond the WARN Act's 60-day advance notice period. These longer-horizon responses occur because the VAR is a system of equations that allow the non-WARN variables to continue to affect each other after the initial change in WARN layoffs, which is short-lived. Hence, while the WARN Act only requires 60 days' advanced layoff notice, the IRFs indicate that WARN layoffs can help forecast the labor market at longer horizons.

One caveat is that our IRFs are in-sample estimates and do not necessarily indicate that WARN layoffs are useful in real time. This caveat is especially material because the WARN factor and $\widehat{WARN}_t$ are produced from the Kalman smoother, which uses information through November 2021 and may provide a more accurate estimate of WARN layoffs than is available in real time. In the next section, we address this concern with a pseudo real-time forecasting exercise and show that WARN layoffs are indeed informative in real time.

this artificial sample to estimate new IRFs, including a new estimate of the standard deviation of the fifth element of ζ_t. We repeat this process 5000 times, sort the bootstrapped IRFs at each horizon, and show the 125th and 4875th sorted IRFs as the confidence intervals.

Further, the IRFs in Figure 9 provide useful intuition for the horizons at which WARN layoffs improve forecasting ability.

6 Pseudo real-time forecasting

6.1 Forecasting models

We use two methods for forecasting the unemployment rate. The first method produces forecasts directly from the VAR in equation (5). Given data through period $t-1$, which implies that flow rates are known through period $t-2$, and estimates of the VAR coefficients, we can iterate the VAR forward to produce forecasts of $\Delta \ln(ur_t), \Delta \ln(ur_{t+1}), \ldots$. These forecasts along with the realized value ur_{t-1} allow us to compute forecasts of the unemployment rate, which we denote with $\widehat{ur}_{t|t-1}, \widehat{ur}_{t+1|t-1}, \ldots$.

The second method uses BN's labor market flows model. This model uses

$$ur_t = \left[1 - e^{-(g_t+s_t)}\right] ur_t^* + e^{-(g_t+s_t)} ur_{t-1}, \tag{6}$$

in which $ur_t^* = s_t/(g_t + s_t)$ is the so-called "steady-state unemployment rate" or SSUR. Equation (6) establishes a relationship between flow rates, the lagged unemployment rate, and the current unemployment rate. To produce forecasts from this model, BN use forecasts of g_t and s_t from the VAR, which we denote with $\hat{g}_{t|t-1}, \hat{g}_{t+1|t-1}, \ldots$ and $\hat{s}_{t|t-1}, \hat{s}_{t+1|t-1}, \ldots$. They then recursively produce unemployment rate forecasts with

$$\widehat{ur}_{t+j|t-1} = \left[1 - e^{-(g_{t+j|t-1}+s_{t+j|t-1})}\right] \widehat{ur}^*_{t+j|t-1} + e^{-(g_{t+j|t-1}+s_{t+j|t-1})} \widehat{ur}_{t+j-1|t-1}, \tag{7}$$

in which $\widehat{ur}^*_{t+j|t-1} = s_{t+j|t-1}/(g_{t+j|t-1}+s_{t+j|t-1})$. We use ur_{t-1} in place of $\widehat{ur}_{t-1|t-1}$ to initialize the recursion.

We produce six collections of unemployment rate forecasts. The first three collections are directly from the VAR model: one collection uses only the first four variables in the VAR, a second collection adds the change in the WARN factor to the VAR, and a third collection adds the change in $\widehat{WARN}_t$ to the VAR. We refer to these forecasting models as VAR-4, VAR-f, and VAR-w. We produce the next three collections of forecasts with the flows model, using three different ways to forecast g_t and s_t: one way uses only the first four variables in the VAR, a second way adds the change in the WARN factor to the VAR, and a third way adds the change in $\widehat{WARN}_t$ to the VAR. Given the very good forecasting performance of the flows model that BN document, we take the flows model with the four-variable VAR to be the baseline forecasting model. We refer to this model as SSUR-baseline, and the other two flows models as SSUR-f and SSUR-w.

We use each model to produce forecasts at 13 monthly horizons, $h = 0, 1, \ldots, 12$. We produce our first collection of forecasts for January 2008 to January 2009, using data through December 2007. We then move one month forward and produce forecasts for February 2008 to February 2009, using data through January 2008, and so on. At each point in time, t, we use all available WARN data through period $t - 1$ for each state with at least 24 months of WARN data for seasonal adjustment.[19] Then, we use the seasonally adjusted WARN data from July 1996 through period $t - 1$ to estimate the DFM and produce pseudo real-time estimates of the WARN factor and $\widehat{WARN}_{t-1}$. Finally, we use these pseudo real-time estimates of the WARN factor and $\widehat{WARN}_{t-1}$ along with real-time CPS data to estimate the parameters of the VAR model and compute the forecasts.[20] We estimate the VAR parameters using a rolling 11-year sample size. BN use 15-year rolling samples; however, we are limited to 11 years because the WARN factor only goes back to July 1996 and our first collection of forecasts uses data through December 2007.

6.2 Forecasting results

We present two sets of results. The first set compares the predictive accuracy of the forecasting models at all horizons made for January 2008 to December 2019. This forecast

[19]For example, referring to Table 1, the start date for CA is 2006m1. Hence, we have 24 observations for CA as of December 2007. We then seasonally adjust CA and include it in the DFM to make forecasts for January 2008 and later.

[20]Following Barnichon and Nekarda (2012) and Meyer and Tasci (2015), we use the most recent vintage, not the real-time vintages, of initial unemployment insurance claims.

sample includes the 2008-09 recession but not the COVID-19 pandemic. Our second set of results compares the forecast accuracy of nowcasts, horizon $h = 0$ forecasts, made in 2020 and 2021. We separate the pre- and post-2020 period for two reasons. First, we do not believe it is reasonable for any forecasting model or data series to have predicted the unemployment rate fluctuation in 2020 at a multi-step horizon and so only consider $h = 0$ forecasts. Second, the unemployment rate fluctuations in 2020 are so large that conventional forecast evaluation statistics based on squared forecast errors are overwhelmed by the 2020 observations.

Because we began collecting the WARN notices in March 2019, we do not know the real-time nature of the ragged edge problem for much of our forecasting sample. For forecasts from 2008 through 2019, we use all WARN data through period $t-1$ when making forecasts of periods $t, t+1, \ldots$. For forecasts in 2020 and 2021, we use the real-time WARN vintages, including the real-time ragged edge, when making our forecasts.

6.2.1 Results for 2008 to 2019

Table 4 shows the forecast accuracy results for January 2008 to December 2019. Row (1) shows the root mean squared prediction errors (RMSPEs) of the SSUR-baseline model.[21] The units in row (1) can roughly be interpreted as the unemployment rate in percentage points. For forecast horizon $h = 0$, this implies that the SSUR-baseline model's forecast errors average about 0.17 percentage points. Row (1) shows that these errors grow with the forecast horizon.

Rows (2) through (6) of Table 4 show the RMSPEs from the competing forecasting models divided by the RMSPEs from the SSUR-baseline model in row (1). Values less (greater) than 1 indicate that the competing model is more (less) accurate than the SSUR-baseline model.

[21] We compute the RMSPEs as follows. First, let $\widehat{ur}_{t+h|t-1}$ denote the forecasted unemployment rate at horizon h. Then, $\hat{d}_{h,t} = ur_{t+h} - \widehat{ur}_{t+h|t-1}$ is the estimated forecast error, in which ur_{t+h} is the most recent vintage of the $t+h$ unemployment rate. Then, the RMSPE is $\sqrt{K^{-1}\sum_{t=1}^{K}\hat{d}^2_{h,t}}$, in which K is the number of available forecast errors. Because we only evaluate the forecasts through December 2019 in Table 4, the number of available forecast errors in row (10) shrinks with the forecast horizon.

Rows (2) and (3) show the SSUR models that include either the WARN factor or $\widehat{WARN}_t$ when forecasting the labor market flows. The results in rows (2) and (3) indicate that including either the WARN factor or $\widehat{WARN}_t$ in the SSUR model can give statistically significant improvements at longer forecasting horizons.[22] Overall, the model with $\widehat{WARN}_t$ performs slightly better than the model with the WARN factor. We acknowledge that our RMSPE reductions are modest and that many of our improvements are only statistically significant at the 10 percent level. However, we are evaluating our forecasts over a relatively short sample, which limits our statistical power. For example, BN used 36 years of forecasts (1976 to 2011) while we only use 12 years of forecasts (2008 to 2019). In addition, we only have one recession in our sample, which limits the variation in the data and opportunities for forecast improvements. Nevertheless, forecast improvements are apparent.

Intuition for the horizon of the forecast improvements can be drawn from the IRFs in Figure 9. The SSUR models use the labor market flows to construct unemployment rate forecasts. In Figure 9, a surprise change in $\widehat{WARN}_t$ begins to have consistently statistically significant effects on the job separation rate at horizon 3 and after. It is at this horizon that statistical significance shows up for the SSUR-w model in row (3) of Table 4. Further, Figure 9 shows that a surprise increase in $\widehat{WARN}_t$ begins to have negative effects on the job finding rate at horizon 7. It is at this horizon and later that the largest RMSPE reductions show up for the SSUR-w model in row (3) of Table 4.

Rows (4), (5) and (6) show the relative RMSPEs of the VAR models. All of the VAR models have lower RMSPEs than the SSUR-baseline model. Further, the VARs with the WARN factor and $\widehat{WARN}_t$ in rows (5) and (6) produce larger RMSPE reductions than the the VAR without any WARN information in row (4). However, of the 39 forecast comparisons

[22] As in BN, we follow Giacomini and White (2006) to test statistical significance. Let $d_{h,t}^{base}$ and $d_{h,t}^{alt}$ denote the forecast errors from the baseline model and some alternative model, respectively. We test the null hypothesis $\mathbb{E}[(d_{h,t}^{base})^2 - (d_{h,t}^{alt})^2|\mathcal{I}_{t-1}] = 0$ against the alternative $\mathbb{E}[(d_{h,t}^{base})^2 - (d_{h,t}^{alt})^2|\mathcal{I}_{t-1}] \neq 0$, in which $\mathcal{I}_{t-1}$ denotes that the forecaster's information set runs through period $t-1$ when making the forecasts in month t. Following the recommendation in Clark and McCracken (2013), we test the null hypothesis with the modified Diebold and Mariano (1995) test statistic proposed by Harvey, Leybourne, and Newbold (1997).

(3 comparison models in rows (4), (5) and (6) by 13 forecast horizons), only one comparison has a statistically significant difference and only at the 10 percent level.

In addition to comparing the VAR models to the SSUR-baseline model, we also compare the VAR models to themselves in Table 4. Row (7) shows the RMSPEs of the four-variable VAR model. Rows (8) and (9) show the relative RMSPEs when either the WARN factor or $\widehat{WARN}_t$ is included in the VAR. The results in rows (8) and (9) show that including WARN data improves the forecast accuracy of the VAR models, and that $\widehat{WARN}_t$ improves the accuracy slightly more than the WARN factor. The statistically significant forecast improvements occur at horizon $h = 3$ and beyond. This roughly aligns with the in-sample IRFs in Figure 9. In that figure, an increase in $\widehat{WARN}_t$ in month 0 causes an increase in the unemployment rate in month 1 and a continued gradual rise in the unemployment rate after that. However, the confidence interval around the unemployment rate IRF widens in month 2 and only consistently excludes 0 in months 3 and beyond.

6.2.2 Results for 2020 and 2021

The magnitudes of the economic fluctuations in 2020 due to the COVID-19 pandemic present challenges for estimating macroeconomic forecasting models. In particular, the fluctuations in macroeconomic variables are large enough to materially change the estimates of forecasting models, such as our VAR in equation (5). Lenza and Primiceri (2021), Schorfheide and Song (2020), and Carriero et al. (2021) provide further discussion. To handle the COVID-19 pandemic in our forecasting models, we change the VAR in equation (5) to be

$$Y_t = \Gamma_0 + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \Gamma_3 d_{Mar2020,t} + \Gamma_4 d_{Apr2020,t} + \Gamma_5 d_{May2020,t} + \zeta_t, \tag{8}$$

in which $d_{Mar2020,t}$, $d_{Apr2020,t}$, and $d_{May2020,t}$ are dummy variables that equal 1 in March 2020, April 2020, and May 2020, respectively, and equal zero in every other month. Γ_3, Γ_4, and Γ_5 are the corresponding (5×1) vectors of parameters. To forecast unemployment in period t, we use data through period $t-1$ to estimate equation (8). Then, we only use the estimates of Γ_0, Γ_1, and Γ_2, but *not* Γ_3, Γ_4, and Γ_5, to produce the forecasts. We do this whether or not the VAR includes any WARN data. In the words of Lenza and Primiceri (2021), we are "dummying out" March, April and May 2020, which allows us to continue to use 11-year rolling sample sizes for estimation but without the estimates of Γ_0, Γ_1, and Γ_2 being dominated by the extreme COVID-19 observations.

Figure 10 shows the realized unemployment rate and the $h = 0$ unemployment rate forecasts for 2020 and 2021 in the top panel. It also shows the absolute forecast errors in the bottom panel. Figure 10 includes forecasts from the SSUR-baseline and VAR-4 models, neither of which includes WARN information, as well as forecasts from SSUR and VAR models that include $\widehat{WARN}_t$. Because the forecasts from all of the models are very similar in 2021, we limit our discussion to 2020.

For 2020, the SSUR-baseline model has an RMSPE of 11.3 and the SSUR-w model has an RMSPE of 10.5. The VAR-4 model has an RMSPE of 11.6 and the VAR-w model has an RMSPE of 11.4 percent. That is, including WARN layoffs lowers the 2020 RMSPE in both the SSUR and the VAR models. Figure 10 shows that the forecasting improvement from including WARN layoffs occurs in April, May and June 2020, which have particularly large changes in the unemployment rate. In April and May 2020, WARN layoffs pull the SSUR and VAR forecasts up toward the realized unemployment rate. In June, WARN layoffs pull the SSUR model down toward the realized unemployment rate.

7 Conclusion

Previous research has documented that job loss is an important margin for understanding aggregate unemployment fluctuations. We compile a unique database that includes about 75,000 establishment-level WARN notifications. Our data cover 33 US states, and, for many large states, our data begin in the 1990s.

We aggregate these data to the state level and establish that they are a useful indicator of aggregate job loss. We find that the number of workers affected by WARN notices ("WARN layoffs") leads other labor market indicators, such as initial UI claims and changes in the unemployment rate and private employment. The lead relationship is strongest in the two months following WARN announcements, consistent with the 60 days' notice required by the WARN Act. Using a dynamic factor model, we aggregate the unbalanced state-level data to a national-level indicator of job loss (the "WARN factor"). WARN layoffs implied by our factor correlate highly with MLS and JOLTS layoffs. IRFs from an in-sample VAR show that a surprise increase in WARN layoffs implied by our factor causes immediate and persistent increases in the job separation rate and the unemployment rate from the CPS, as well as initial UI claims. A pseudo real-time forecasting exercise shows that changes in WARN layoffs implied by our factor improve the accuracy of unemployment rate forecasts from both a VAR and the flows model in Barnichon and Nekarda (2012). From 2008 to 2019, these forecast improvements occur at multi-step forecast horizons. In 2020, changes in WARN layoffs implied by our factor improve nowcast accuracy, particularly in the volatile months of April, May, and June.

We update state-level WARN layoffs and the WARN factor twice a month and make these real-time data publicly available (Krolikowski and Lunsford, 2022). Policymakers and economists can use our data to monitor job loss in real time and to predict unemployment fluctuations. Researchers can use our data to study the effects of advance notice and concentrated labor demand shocks.

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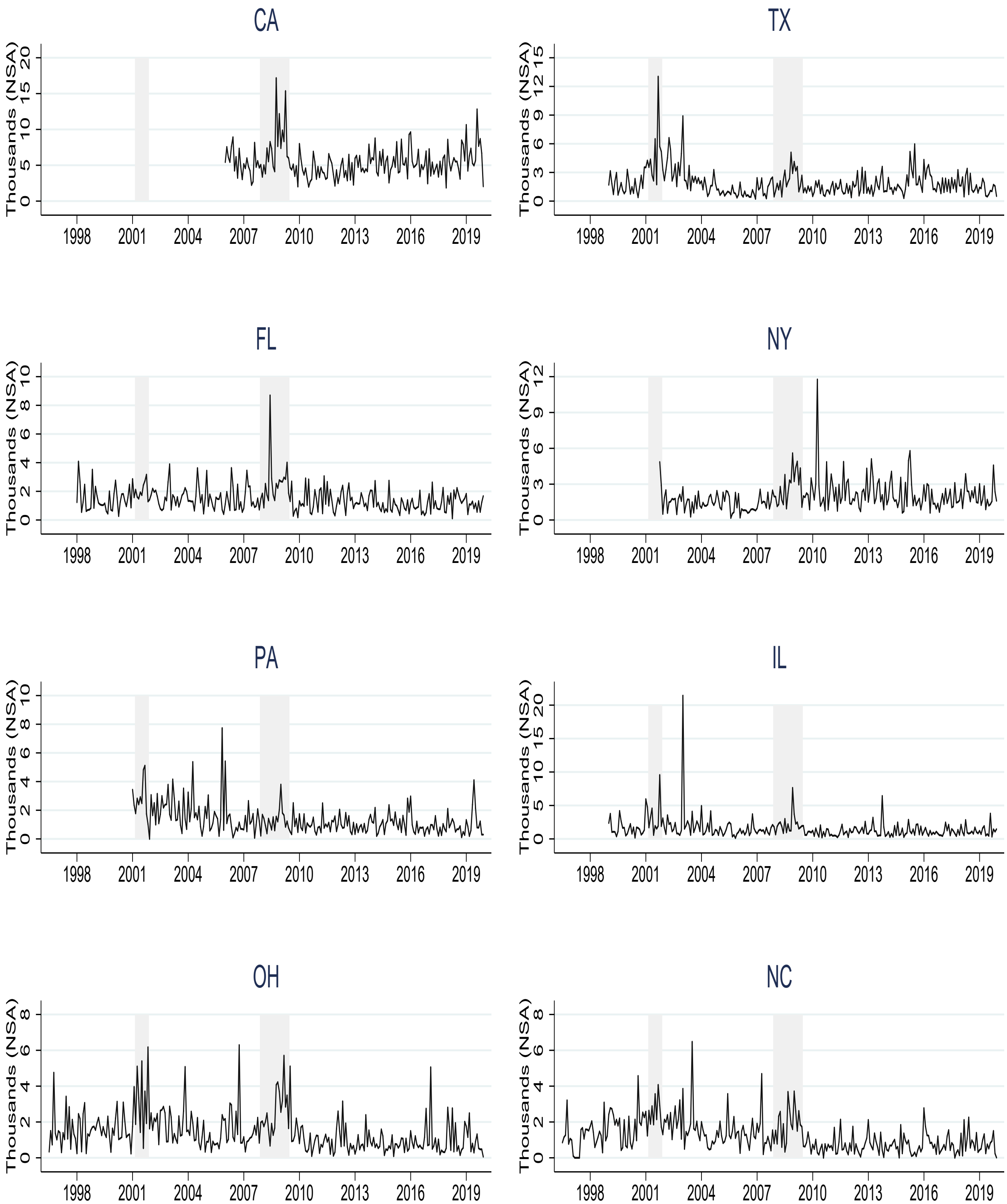

Figure 1: Number of workers affected by WARN notices for eight large states, 1996 to 2019

Note: The unbalanced panel data of WARN layoffs by state exhibit cyclical fluctuations. Horizontal axes start in July 1996 and end in December 2019. Vertical axes differ from panel to panel. Shading represents NBER recession dates. See Section 2.3 for details.

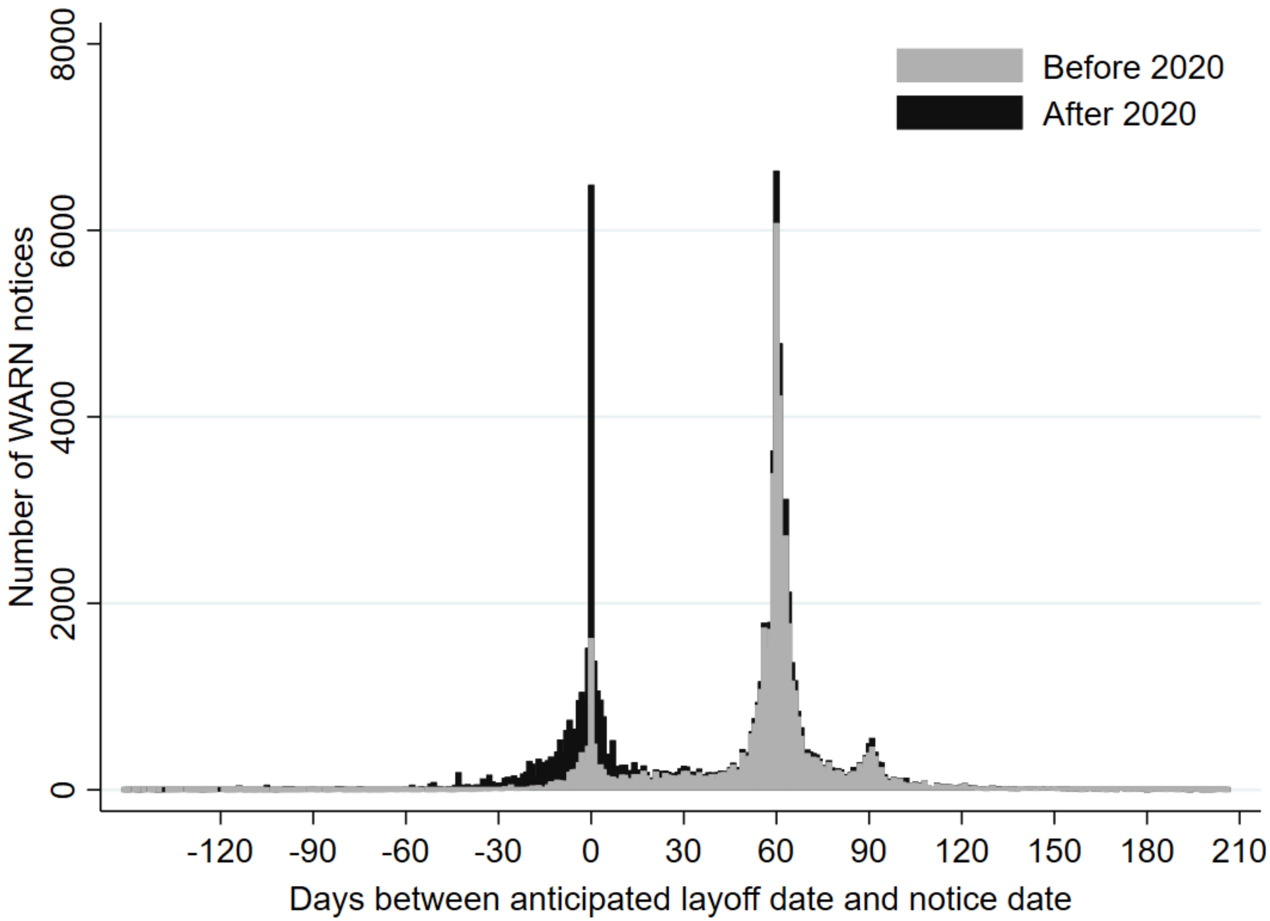

Figure 2: Number of WARN notices by the number of days of advance notice

Note: Establishment-level WARN notice data from January 1990 to November 2021. This histogram excludes Arizona (2019m7 and on), Kansas, Minnesota, New Jersey, and Pennsylvania, from our sample because we do not have the difference between layoff and notice dates. Total number of observations is 85,023 of which 26,925 have notice dates after 2019. Outliers are dropped at the 1 percent level on both sides of the advance notice distribution. See Section 2.5 for details.

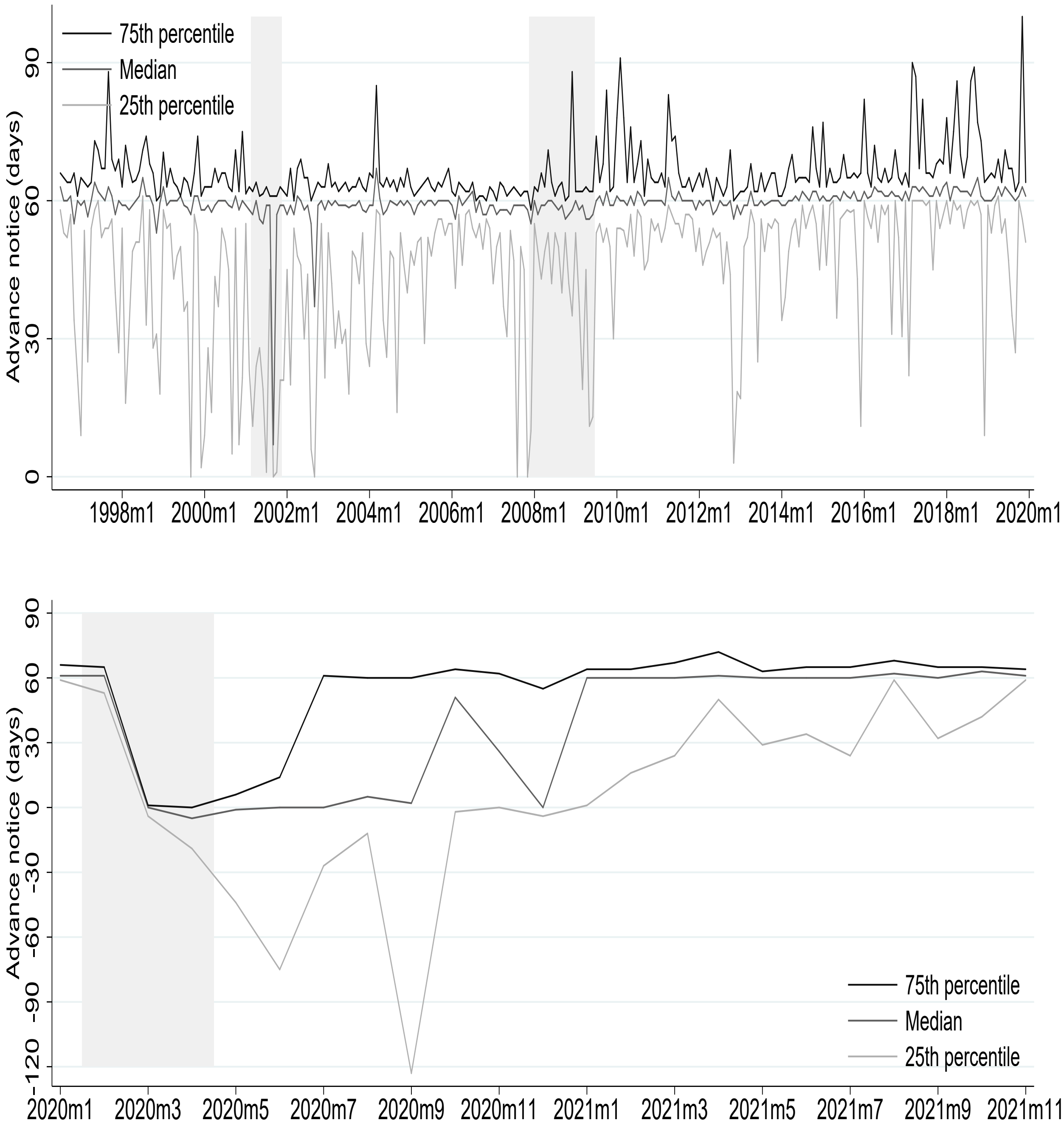

Figure 3: 75th, 50th, and 25th percentile of the advance notice distribution

Note: The top panel shows percentiles of the advance notice distribution from July 1996 to December 2019 and the bottom panel since January 2020. Vertical axes differ in the two panels. The median number of days between the notice date and the anticipated layoff date is about 60 days prior to 2020, except during the September 2001 terrorist attacks. Advance notice fell substantially during the onset of the previous recession and the median remained about zero through September 2020. Since January 2021, median advance notice has returned to its usual 60 days. Shading represents NBER recession dates. See Section 2.5 for details.

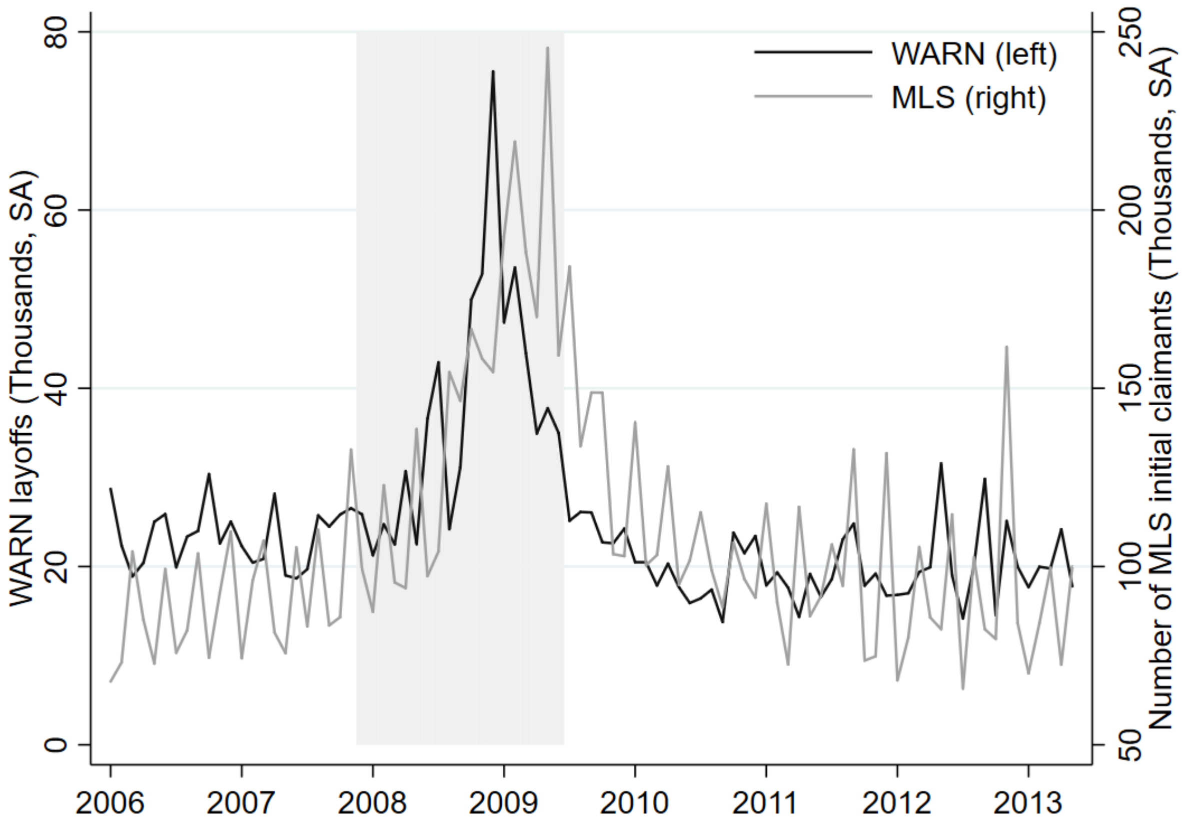

Figure 4: Number of workers affected by WARN notices and MLS initial claimants

Note: The number of seasonally adjusted individuals affected by WARN notices leads the number of MLS initial claimants during the 2008-09 recession. WARN data are for a balanced panel of states as of January 2006. MLS data are for the same set of states. Initial claimant data from MLS end in May 2013. Data are seasonally adjusted using the procedure in Wright (2013, pg. 80). Shading represents NBER recession dates. See Section 3.1 for details.

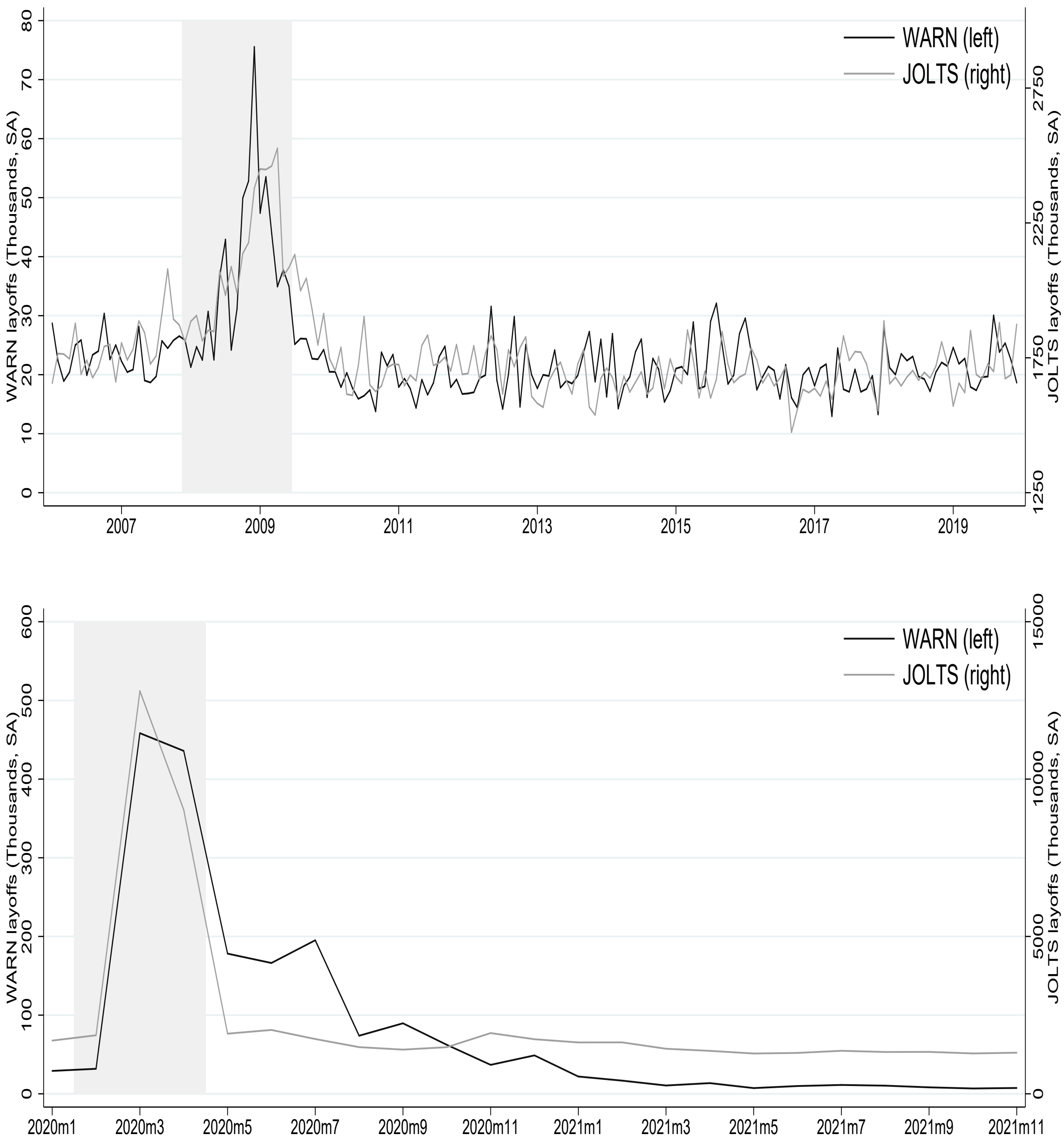

Figure 5: Number of workers affected by WARN notices and JOLTS layoffs and discharges

Note: The number of seasonally adjusted individuals affected by WARN notices and the number of layoffs and discharges in JOLTS (total private) move together. Both series are in thousands. In the top panel the sample is January 2006 to December 2019 and in the bottom panel it is since January 2020. Vertical axes differ in the two panels. WARN data are for a balanced panel of states as of January 2006. JOLTS data are for the nation. JOLTS seasonally adjusted data are from the BLS. Shading represents NBER recession dates. See Section 3.1 for details.

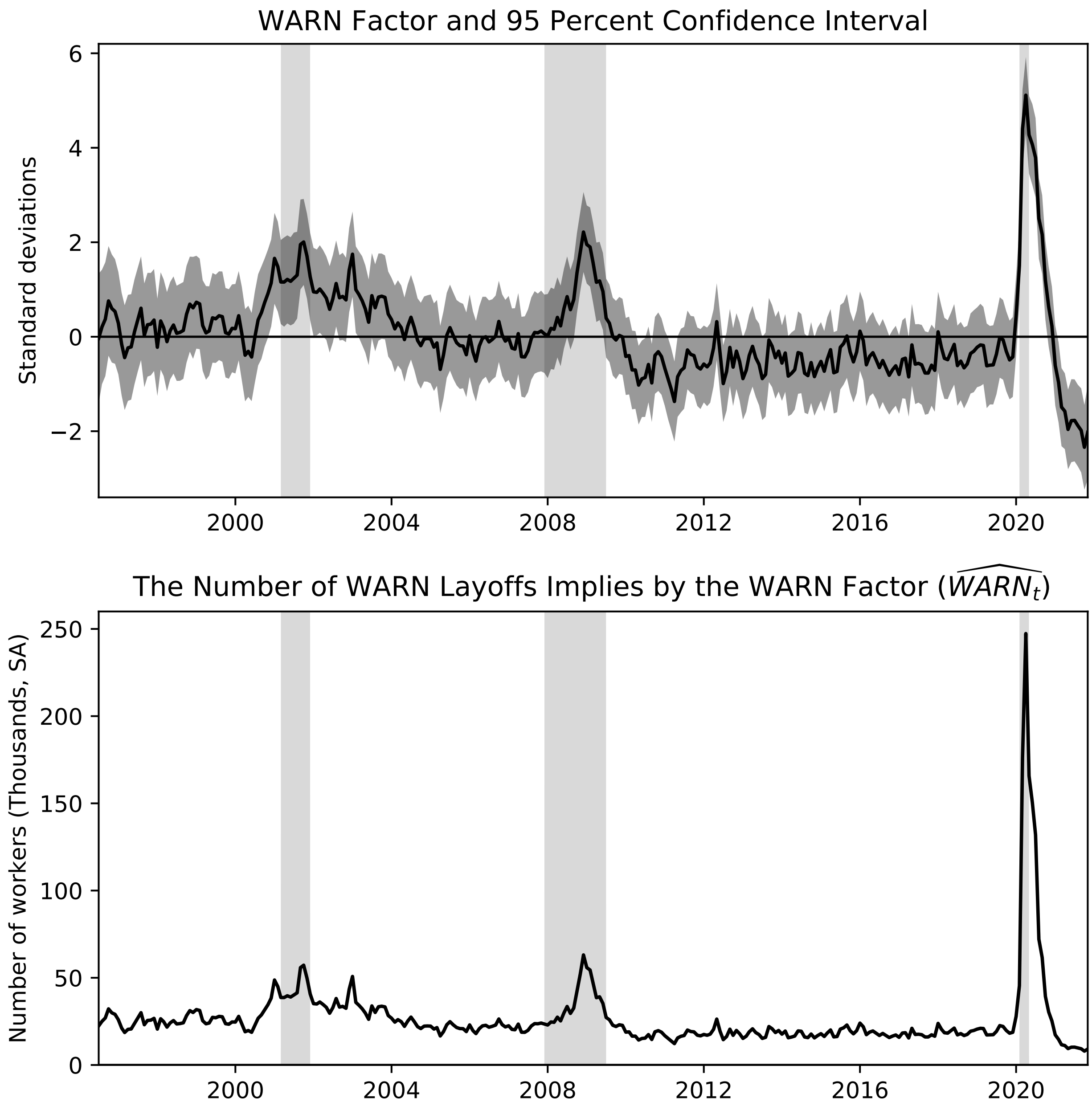

Figure 6: The WARN factor and $\widehat{WARN}_t$

Note: The top panel has the estimated WARN factor from July 1996 to November 2021 with 95 percent confidence intervals. The factor is estimated using the method in Bańbura and Modugno (2014). Standard errors are computed using the parametric bootstrap approach in Pfeffermann and Tiller (2005). The bottom panel has $\widehat{WARN}_t$, the number of WARN layoffs implied by the WARN factor, from July 1996 to November 2021. Vertical grey bars in both panels indicate NBER recession dates. See Section 4 for details.

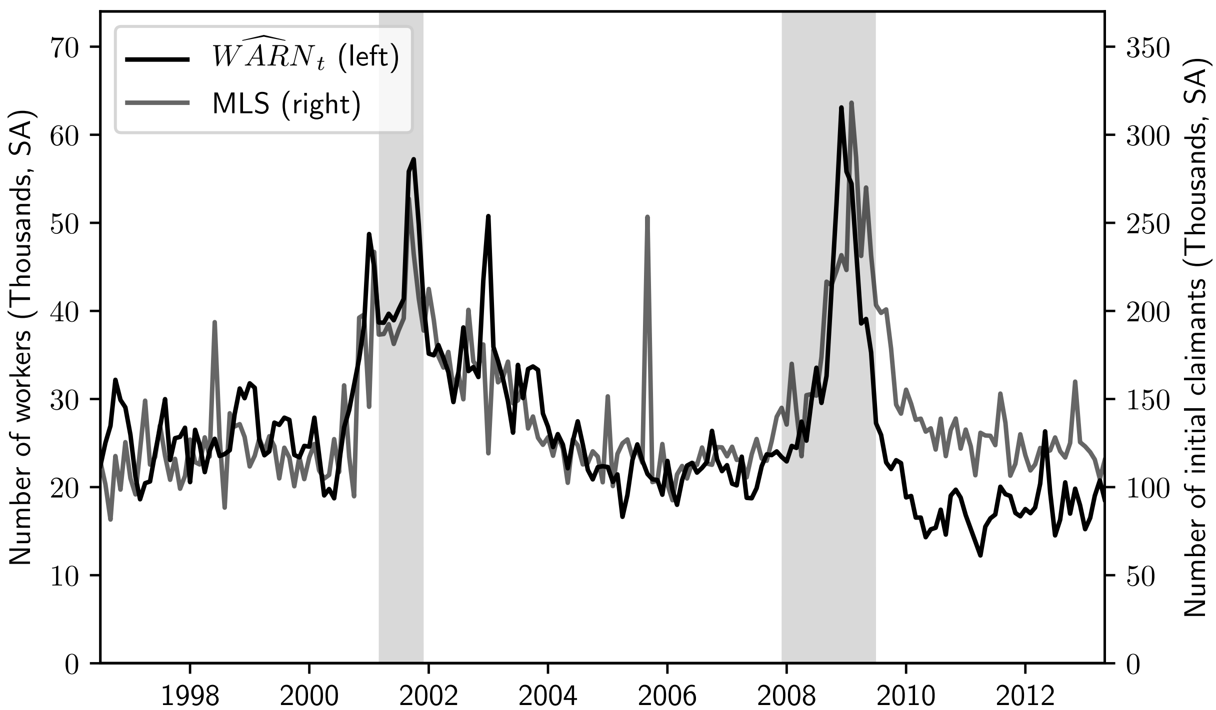

Figure 7: Comparing $\widehat{WARN}_t$ and MLS

Note: $\widehat{WARN}_t$ is in number of workers in thousands on the left scale. MLS number of initial claimants in thousands is on the right scale. The sample is July 1996 to May 2013 when MLS was discontinued. Shading represents NBER recession dates. See Section 5.1 for details.

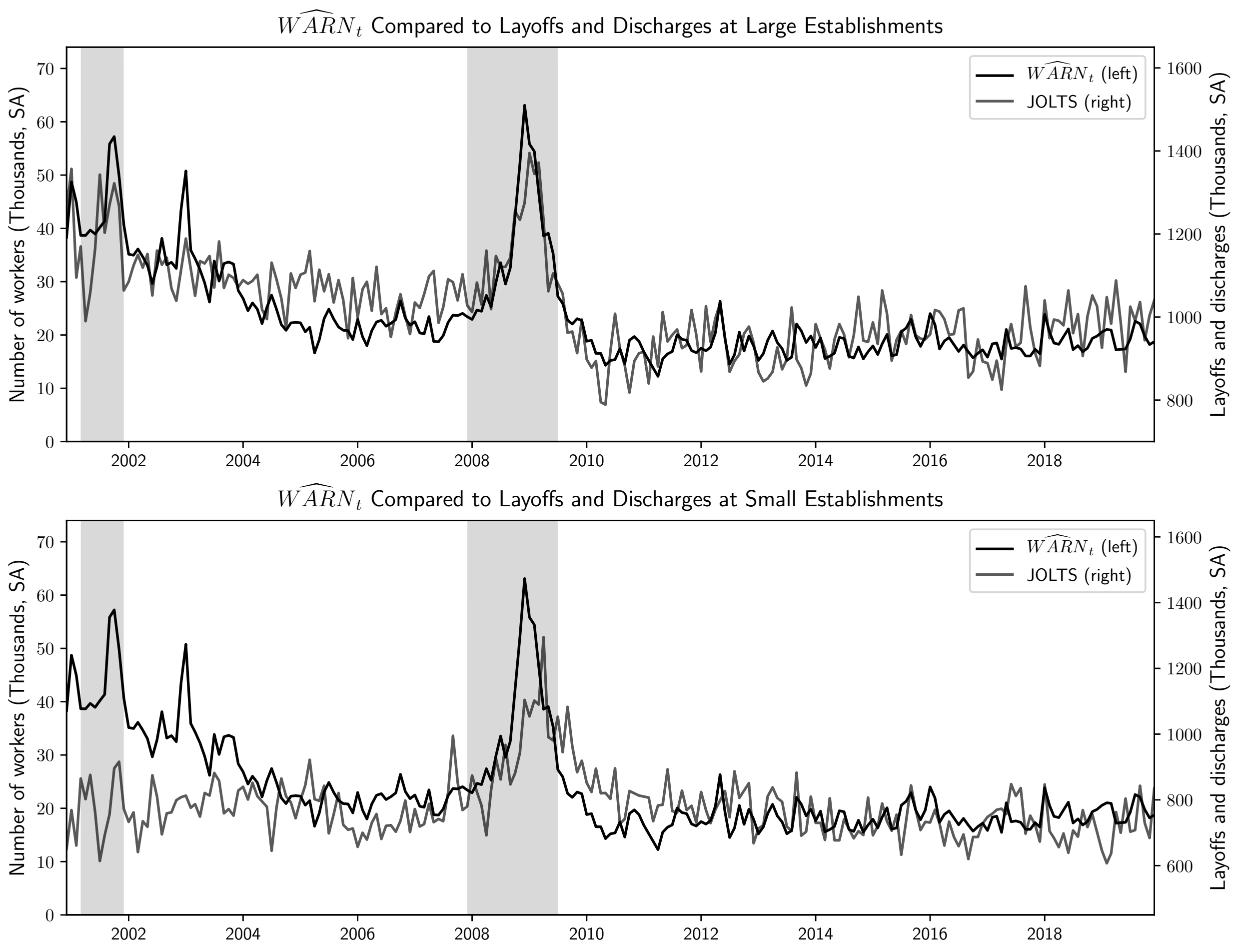

Figure 8: Comparing $\widehat{WARN}_t$ and JOLTS

Note: $\widehat{WARN}_t$ is in number of workers in thousands on the left scale. It is the same in both panels. In the top panel, JOLTS private layoffs and discharges in thousands are for establishments with 50 workers or more and are on the right axis. In the bottom panel, JOLTS private layoffs and discharges in thousands are for establishments with 49 workers or less and are on the right axis. The sample is December 2000 to December 2019 in both panels. Shading represents NBER recession dates. See Section 5.1 for details.

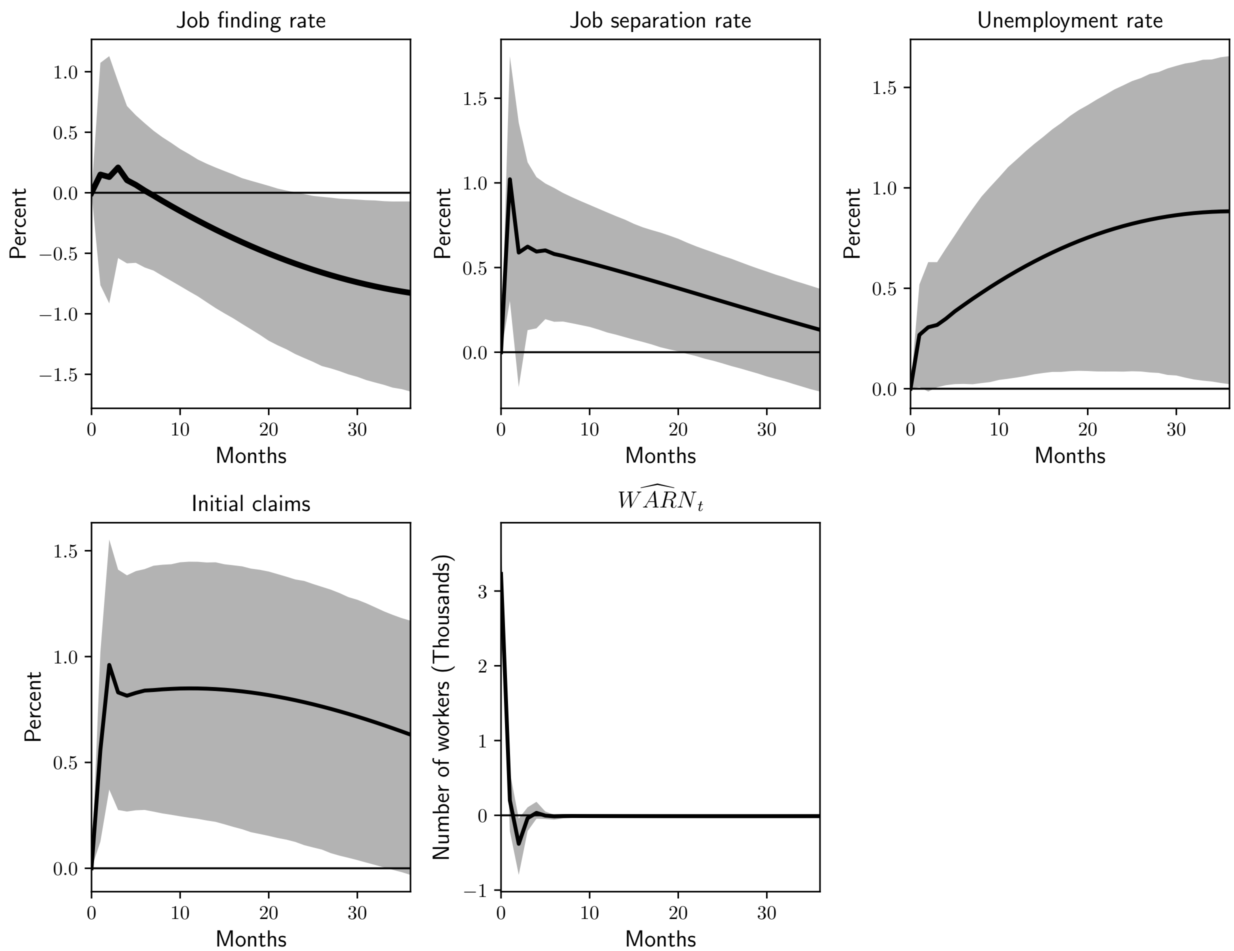

Figure 9: IRFs to a surprise increase in $\widehat{WARN}_t$

Note: IRFs produced iteratively from the estimated VAR in equation (5). Solid lines show the point estimates and shaded regions show the 95 percent confidence intervals. Confidence intervals are produced with a bootstrap. See Section 5.2 for details.

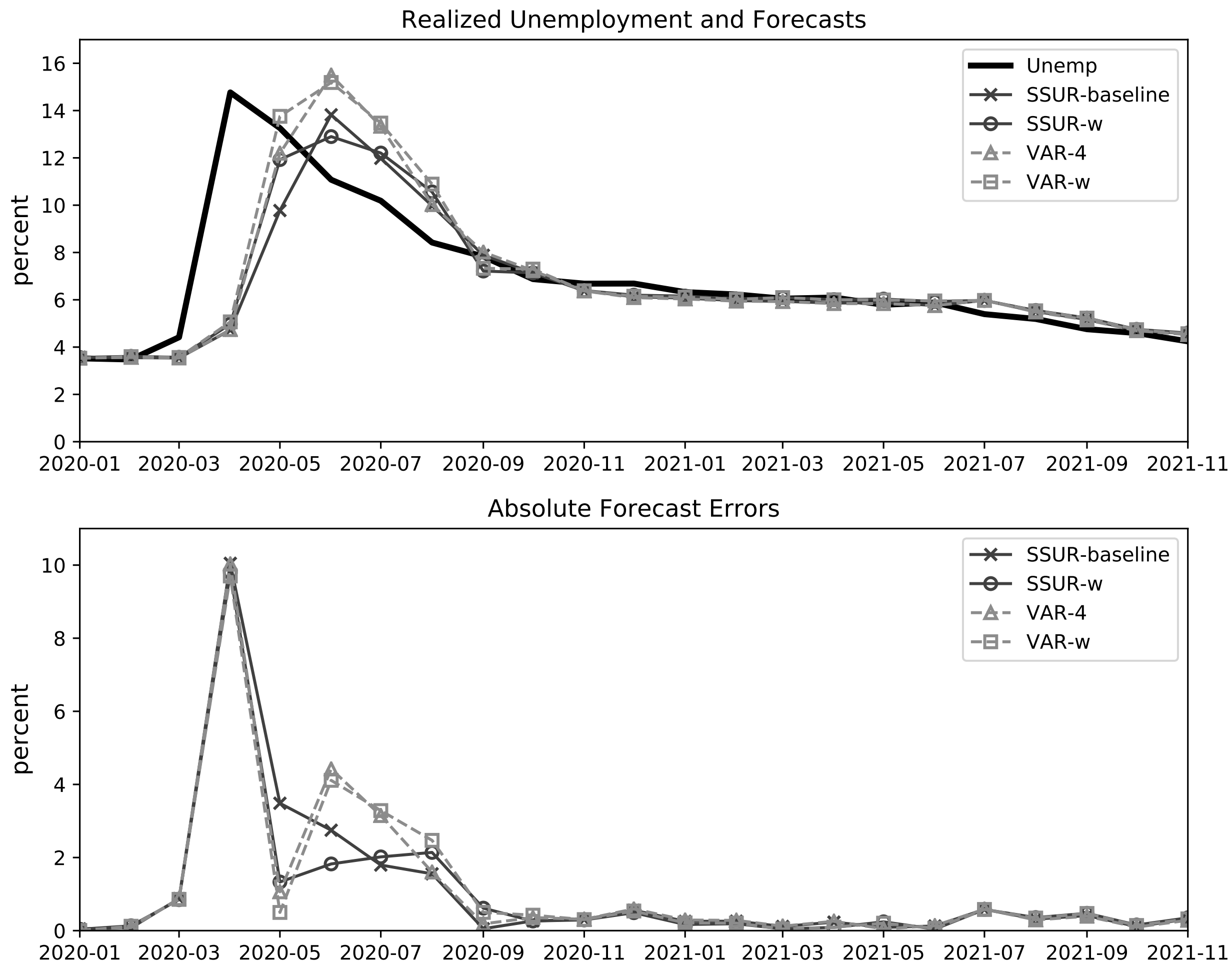

Figure 10: Unemployment rate forecasts and absolute forecast errors in 2020 and 2021

Note: All forecasts are at the $h = 0$ horizon. The forecasting models correspond to those in Table 4. See Section 6 for details.

State	Start date	End date	Avg. # of affected workers	Median # of affected workers	Std. dev	# of months with 0 # of affected workers
AL	1998m7	2021m7	594	405	655	31
AZ	2010m4	2021m11	487	215	1,030	20
CA	2006m1	2021m11	9,129	5,024	26,047	0
CO	2006m1	2021m11	574	325	1,098	15
CT	1998m1	2021m10	388	269	397	17
FL	1998m1	2021m11	2,014	1,356	3,738	0
IA	2005m7	2021m9	247	171	243	24
IL	1999m1	2021m10	1,664	1,178	2,012	0
IN	1997m1	2021m11	845	620	973	6
KS	1998m8	2021m9	403	198	606	35
LA	2007m1	2021m10	418	207	728	28
MD	2000m1	2021m11	551	347	733	17
MI	1990m1	2021m9	1,052	697	1,343	5
MN	2000m6	2021m9	344	227	430	43
MO	2000m7	2021m10	686	471	909	6
MS	2010m7	2021m8	269	147	433	36
NC	1996m5	2021m11	1,237	1,001	1,047	7
NJ	2004m1	2021m11	1,428	913	2,252	2
NY	2001m10	2021m11	2,597	1,756	4,506	0
OH	1996m7	2021m11	1,492	1,087	1,496	1
OR	2005m1	2021m9	342	179	558	36
PA	2001m1	2021m11	1,495	1,096	1,689	2
SC	2009m1	2012m11	658	535	414	0
TN	2012m1	2021m11	748	506	966	3
TX	1999m1	2021m11	2,078	1,561	2,476	0
VA	1994m7	2021m10	906	644	853	9
WA	2004m1	2021m11	691	386	1,222	6
WI	1996m1	2021m11	850	643	766	1

Table 1: Summary statistics of state-month panel of the number of workers affected by WARN notices

Note: There are 28 states in our final sample. From the 50 US states we drop AR, DE, HI, ME, MT, NH, NV, SD, VT, and WY due to data accessibility restrictions. We drop GA and NE because they did not have notice dates. We drop MA because we could not obtain historical data. We drop AK, ND, NM, and RI because the time series could not be seasonally adjusted. Finally, we drop ID, KY, OK, UT, and WV because they contain many months with zero workers affected by WARN notices. SC is the only state that has data for some period and then drops out of our sample. SC drops out because subsequent to November 2012, no notice month is available. Data are as of the end of December 2021. Summary statistics for seasonally adjusted data. See Section 2.3 for details.

	(1)	(2)	(3)
	$uic_{s,t}$	$\Delta ur_{s,t}$	$\Delta e_{s,t}$
$WARN_{s,t-1}$	63**	0.0028*	-1,278***
	(28)	(0.0014)	(172)
$WARN_{s,t-2}$	-48	0.0019	-843***
	(43)	(0.0014)	(283)
p-value $WARN_{s,t-i} = 0$	0.026	0.15	0.0000020
Observations	6,047	6,047	6,047
R-squared	0.98	0.61	0.47

Table 2: WARN as a leading state-level indicator

Note: WARN notices lead state-level initial UI claims, changes in the unemployment rate, and changes in private employment. The sample is January 1990 to December 2019. All columns include state fixed effects and controls for two lags of initial UI claims ($uic_{s,t}$), changes in the unemployment rate ($\Delta ur_{s,t}$), and changes in private employment ($e_{s,t}$). Initial UI claims represent the average weekly claims in a month. Therefore, to obtain the approximate effect of WARN layoffs on monthly initial UI claims, we multiply the coefficients in column (1) by 4.3. The number of observations in columns (1) and (2) is 56 less than in Table A1, rows 4 and 6, respectively, because equation (1) includes two lags and we have 28 states in our sample. Weighted by employment. Standard errors clustered at the state level. ***p<0.01, **p<0.05, *p<0.1. See Section 3.2 for details.

	(1) $\ln(g_t)$	(2) $\ln(s_t)$	(3) $\Delta\ln(ur_t)$	(4) $\ln(uic_t)$	(5) $\Delta\widehat{WARN}_t$
$\Delta\widehat{WARN}_{t-1}$	0.05	0.32***	0.08**	0.17*	0.06
	(0.15)	(0.12)	(0.04)	(0.09)	(0.08)
$\Delta\widehat{WARN}_{t-2}$	-0.04	0.04	0.03	0.11	-0.14*
	(0.14)	(0.09)	(0.04)	(0.08)	(0.08)

Table 3: VAR regression coefficients on lags of $\Delta\widehat{WARN}_t$

Note: Regression coefficients for equation (5) estimated by least squares. Standard errors are in parentheses and are heteroskedasticity robust. ***p<0.01, **p<0.05, *p<0.1. See Section 5.2 for details.

		$h = 0$	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$	$h = 7$	$h = 8$	$h = 9$	$h = 10$	$h = 11$	$h = 12$
	Panel A: Forecast Results of and Comparisons to the SSUR-baseline Forecasting Model													
(1)	SSUR-baseline RMSPE	0.17	0.24	0.32	0.41	0.50	0.60	0.70	0.81	0.92	1.03	1.13	1.23	1.33
Relative RMSPEs of Other Forecasting Models:														
(2)	SSUR-f	1.00	1.01	1.00	1.00	0.99	0.99	0.98	0.97*	0.97*	0.97*	0.96*	0.96*	0.96
(3)	SSUR-w	1.00	1.00	0.99	0.99**	0.98*	0.98	0.97*	0.97**	0.96**	0.95*	0.95*	0.95*	0.95
(4)	VAR-4	0.97	0.95	0.96	0.97	0.98	0.98	0.99	0.98	0.98	0.98	0.98	0.98	0.97*
(5)	VAR-f	0.97	0.95	0.95	0.95	0.95	0.96	0.95	0.94	0.94	0.94	0.93	0.93	0.93
(6)	VAR-w	0.97	0.95	0.94	0.94	0.94	0.95	0.94	0.93	0.93	0.93	0.92	0.92	0.92
	Panel B: Forecast Results of VAR Models and Comparisons to the VAR-4 Model													
(7)	VAR-4 RMSPE	0.16	0.23	0.31	0.40	0.49	0.59	0.69	0.80	0.90	1.01	1.11	1.21	1.29
Relative RMSPEs of Other VAR Models:														
(8)	VAR-f	1.01	1.00	0.99	0.98	0.97	0.97	0.97*	0.96*	0.96*	0.95*	0.95*	0.95	0.95
(9)	VAR-w	1.01	1.00	0.98	0.97***	0.96**	0.96*	0.96*	0.95**	0.95**	0.94*	0.94*	0.94*	0.94
(10)	Sample size	144	143	142	141	140	139	138	137	136	135	134	133	132

Table 4: Predictive accuracy of unemployment rate forecasting models

Note: Row (1) shows the root mean squared prediction errors (RMSPEs) of the SSUR-baseline forecasting model for each forecasting horizon, h. The units can be interpreted as unemployment rate percentage points. The sample period for the forecast errors is January 2008 to December 2019. Rows (2) to (6) show the ratios of the RMSPEs from the corresponding model to the SSUR-baseline model. Values less than 1 indicate lower RMSPEs than the SSUR-baseline model. Row (7) shows the root mean squared prediction errors (RMSPEs) of the four-variable VAR model. Rows (8) and (9) show the relative RMSPEs for five-variable VARs that include either the WARN factor or $\widehat{WARN}_t$ to the four-variable VAR model. Stars, *, **, indicate statistical significance at the 10 and 5 percent levels. See Section 6 for details.

A Data appendix

This is an appendix to Section 2 of the paper.

A.1 Details about the WARN Act

The act was passed on August 4, 1988, and became effective on February 4, 1989. The act was legislated partly in response to a report by the US Government Accountability Office (GAO, 1987), which found that few laid-off workers had enough notice to obtain job-related assistance. The act covers employers that have 100 or more employees, not counting employees who have worked less than 6 months in the last 12 months and not counting employees who work an average of less than 20 hours a week (part-time workers), or 100 or more workers who work at least a combined 4,000 hours a week, exclusive of overtime. The act covers private and quasi-public employers, including for-profit and non-profit employers, but regular federal, state, and local government employers are not covered.[23] The act does not cover job loss if employment occurred with the understanding that it was temporary.

The act is also triggered if the plant closing or mass-layoff definitions are met by the number of employment losses for two or more groups of workers during any 90-day period. The act also applies when hours of work for 50 or more individual employees are reduced by more than 50 percent for each month in any 6-month period. While part-time employees are not considered in determining whether plant closing or mass layoff thresholds are reached, such workers are due notice. Workers who are offered a transfer to another site within a reasonable commuting distance before the plant closing or mass layoff occurs are not counted as having suffered an employment loss under WARN. During the sale of a business, the seller (buyer) is responsible for issuing the WARN notice if the covered event occurs before (after) the sale becomes effective.

[23]Prior to the potential January 2013 sequestration, federal contractors were encouraged not to issue WARN notices given the uncertainty as to whether the sequestration would occur, the speculative nature of any possible layoffs, how contracts would be affected, and how reductions might occur. Moreover, federal contractors could likely not issue legally sufficient WARN notices because they would not have specific information required by the act (DOL, 2012; GAO, 2013).

WARN notices must be provided to the affected workers, to the state dislocated worker unit (SDWU),[24] and to the chief elected official of the unit of local government in which the employment site is located (e.g., the mayor). In addition to the non-compliance penalties described in Section 2.1, the employer is subject to a civil penalty of at most $500 per day, but this fine may be waived if the employer settles liabilities with employees promptly. Relevant cases are brought to federal courts by workers, their representatives, or units of local government. The US Department of Labor is not responsible for enforcing the act.

The act does not impose the condition that firms carry out their expected layoffs, but there are likely non-pecuniary costs to issuing unrealized WARN notices. It is possible that firms issue WARN notices and then do not undergo a mass layoff.[25] Nevertheless, issuing a WARN notice might reveal something about the employer's financial health to employees, which might encourage some workers, especially the most productive ones with outside options, to seek alternative employment, as in Schwerdt (2011). This adverse selection, together with only a slight increase in lengthy written notices around the enactment of WARN, suggests that employers likely do not issue WARN notices without some cause.

Some states had voluntary advance notice programs prior to the act (Ehrenberg and Jakubson, 1990), and before WARN took effect approximately half of all displaced workers received some sort of advance notice, most of which took place "informally" (Addison and Blackburn, 1994a).

Addison and Blackburn (1994a,b) provide succinct summaries of the legislation, and Ehrenberg and Jakubson (1988) and Addison and Portugal (1991) provide more historical context.

There are three exceptions to issuing a notice with less than 60 days' notice, which are

[24]SDWUs aim to minimize disruptions associated with job loss, often providing on-site services, such as career counseling, assistance with job search, and job training (DOLETA, 2022a).

[25]To quantify how often this might happen, we searched for media coverage of mass layoff events announced in WARN notices in Ohio in 2018. We found that many WARN announcements were not followed by media coverage of the mass layoff event. This lack of media coverage could be because many WARN notices are not realized or because the media does not cover many WARN events.

purposefully construed narrowly. First, "faltering company" applies when a company is in the process of obtaining capital or business that would allow it to avoid or postpone a shutdown and believes that the advance notice would prevent it from obtaining this capital or business. Second, "unforeseeable business circumstances" applies when business circumstances change suddenly and unexpectedly, such as the unexpected cancellation of a major order. Third, "natural disaster" applies when the workforce reduction is the direct result of, among others, hurricane, flood, or earthquake.

A.2 Details about creating the monthly WARN panel

We discuss two common examples of extending the time series of states' WARN data. First, California's Employment Development Department website includes WARN notices back to 2014 (EDD, 2020b), but using digital archives of the internet, we extend the California sample back to 2006. We use a similar approach to collect WARN notices from New York, but we use web scrapers because these data are not available in convenient formats. Second, the Virginia Employment Commission posts WARN notices back to 2011 on its website (VEC, 2020), but we extract data from PDFs sent to us by state officials to extend the sample to 1994.

We began collecting real-time data in March 2019, and we currently update our WARN database in the middle of the month and at the end of the month. This updating schedule coincides with the updating schedule of California's WARN notices, which occurs on the 10th and 25th of each month and is published within three business days thereafter (EDD, 2020a). We stop counting the number of workers affected by WARN notices in a given state and a given month when we observe a WARN notice for that state in a subsequent month. For some smaller states, this means that we may not have a measure of workers affected by WARN notices in a given month until several months later when a subsequent WARN notice is filed. In this situation, we treat the most recent data for these states as unavailable. Also, when we observe a WARN notice in t and then a subsequent month, say $t + 4$, we deduce that there were zero WARN layoffs in the intervening months. In practice, data for most states for month $t - 1$ are available by the middle of month t. For example, data for

December 2019 were available for 23 of 27 states (not counting SC) as of January 15, 2020, and included essentially all of the large states: CA, FL, IL, MI, NJ, NY, OH, PA, TX, VA and WA.

Our updating schedule is timely relative to other prominent labor market information. Our update in the middle of the month lags the employment report (BLS, 2022) by 5 to 10 days. But our data cover the entire previous month, whereas the employment report covers the reference week that includes the 12th of the month (Current Population Survey) and the pay period that includes the 12th of the month (Current Employment Statistics). Our data are slightly less timely than weekly initial UI claims data.

As mentioned in Section 2.1, each notice typically includes the name and address of the employer, the date the notice was filed, the anticipated layoff date, and the estimated number of affected workers, but there are some exceptions. For example, we can obtain the month of notice but not the exact day of notice for several states, including KS, NJ, and PA. For some notices we do not have the estimated number of affected workers, likely due to uncertain business conditions. For some notices we have an associated city or county, but we do not have a street address. In some states, notices include additional information, such as the cause of the layoff,[26] whether the layoff is temporary or permanent, the number of workers affected by occupation, and the establishment industry code. We do not exploit this additional information in the present paper.

From our sample of states, CT, IA, IN, NY, PA, and WI differentiate revised notices from original notices and we remove revisions to original notices. Because of its long history and size, we use original and revised notices from the state of WI to develop an algorithm that identifies notice revisions for states that do not differentiate revisions from original notices. We find that two criteria work well for identifying revisions to WARN notices. First, we identify as a revision any notice that is filed by the same company on the second of two subsequent days. This procedure removes any notices that alter the number of affected

[26]For example, in some states notices differentiate between a layoff and a plant closure and sometimes they provide the cause of the layoff, such as “economic downturn,” “financial,” or “September 11th tragedy.”

workers or the anticipated date of the layoff. Second, we identify as a revision any notice that has exactly the same amount of affected workers as a previous notice from the same establishment. This criterion removes any notices that change the anticipated layoff date but leave the number of affected workers the same.

We drop several states from our analysis due to restrictions on WARN information. First, we have difficulty obtaining and updating complete WARN notice information from several (mostly) smaller states—AR, DE, HI, ME, MT, NH, NV, SD, VT, and WY—so we omit these states from our sample. Second, GA's and NE's WARN records do not have a notice date (or month) so we could not include these states in the analysis, and a similar issue arises for SC before 2009 and after 2012. Third, the panel of WARN information for AK, ND, NM, and RI is too short to allow for seasonal adjustment so we drop these states. Fourth, we drop ID, KY, OK, UT, and WV because they contain many months with zero WARN layoffs. Finally, we could not obtain historical WARN data for MA.

We also use several other data sets in our analysis. We use published seasonally adjusted (SA) data where available. The data sets we use are as follows. First, we use NSA data from the defunct Mass Layoff Statistics (MLS, 2022) program run by the Bureau of Labor Statistics (BLS). The MLS program published statistics between April 1995 and May 2013 from establishments that had at least 50 initial claims for UI filed against them during a 5-week period. We seasonally adjust these data using the model in Wright (2013, pg. 80). Second, we use SA data from the BLS on layoffs and discharges at private employers from the Job Openings and Labor Turnover Survey (JOLTS, 2022). Third, we obtain SA state-level unemployment rates from the Local Area and Unemployment Statistics (LAUS) program at the BLS (LAUS, 2022). Fourth, we use estimates of SA state-level private employment from the State and Metro Area Employment program (SAE, 2022), although using total employment data from LAUS does not change our conclusions. Finally, we use SA weekly initial UI claims from the Employment and Training Administration (DOLETA, 2022b). To aggregate the weekly initial UI claims data to the monthly level, we compute the monthly averages.

B DFM and EM algorithm appendix

This is an appendix to Section 4 of the paper.

B.1 Seasonal adjustment

We seasonally adjust the log of the number of workers affected by WARN notices for each state before estimating the DFM. To do this univariate seasonal adjustment, we use the state space model that Wright (2013) recommends for seasonally adjusting employment data. We use the notation $x_{s,t} = \ln(WARN_{s,t})$ when $WARN_{s,t}$ is observed and non-zero. If $WARN_{s,t}$ is missing or equal to zero, then we treat $x_{s,t}$ as missing. Because of these missing observations, we estimate the seasonal adjustment state space model with an EM algorithm in the spirit of Shumway and Stoffer (1982) that can handle missing observations. In this section, we describe the seasonal adjustment model and the associated EM algorithm. For the rest of this section, we suppress the state-level index s for notational convenience.

We assume that the scalar process x_t follows

$$x_t = \tau_t + \gamma_t + \nu_t,$$

in which τ_t is a stochastic trend, γ_t is a stochastic seasonal, and ν_t is an irregular component. The stochastic trend follows

$$\tau_t = \tau_{t-1} + \kappa_{t-1} + \varepsilon_{1,t},$$

in which κ_t is a slope component that follows

$$\kappa_t = \kappa_{t-1} + \varepsilon_{2,t}.$$

The stochastic seasonal follows

$$\gamma_t = -\sum_{j=1}^{11} \gamma_{t-j} + \varepsilon_{3,t}.$$

This seasonal adjustment model can be written with a state equation and an observation equation. The state equation is

$$\begin{bmatrix} \tau_t \\ \kappa_t \\ \gamma_t \\ \gamma_{t-1} \\ \gamma_{t-2} \\ \vdots \\ \gamma_{t-9} \\ \gamma_{t-10} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & -1 & -1 & -1 & \cdots & -1 & -1 \\ 0 & 0 & 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ \kappa_{t-1} \\ \gamma_{t-1} \\ \gamma_{t-2} \\ \gamma_{t-3} \\ \vdots \\ \gamma_{t-10} \\ \gamma_{t-11} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix},$$

and the observation equation is

$$x_t = \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & \cdots & 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_t \\ \kappa_t \\ \gamma_t \\ \gamma_{t-1} \\ \gamma_{t-2} \\ \vdots \\ \gamma_{t-9} \\ \gamma_{t-10} \end{bmatrix} + \nu_t.$$

We assume that the innovations ν_t, $\varepsilon_{1,t}$, $\varepsilon_{2,t}$, and $\varepsilon_{3,t}$ are mutually and serially independent normal random variables with mean zero. The variances of these innovations are the only unknown parameters, and we estimate the variances by maximum likelihood using an EM algorithm.

To ease notation, we write the state vector as $S_t = [\tau_t, \kappa_t, \gamma_t, \gamma_{t-1}, \dots, \gamma_{t-10}]'$. Then, we write the state and observation equations as

$$S_t = \Phi S_{t-1} + \varepsilon_t \tag{B9}$$

and

$$x_t = MS_t + \nu_t, \tag{B10}$$

in which $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t}, 0, \ldots, 0]'$, $\nu \overset{iid}{\sim} N(0, \sigma_\nu^2)$, and $\varepsilon_t \overset{iid}{\sim} N(0, \Sigma_\varepsilon)$. Note that all elements of Σ_ε are zero except for the elements in the (1,1), (2,2) and (3,3) positions.

As with the DFM in Appendix B.2, we need to distinguish between the process x_t, generated by equations (B9) and (B10), and the observed data, which may contain missing observations. Borrowing notation from Appendix B.2, we use Ω_T to denote the observed values of x_t, which may be a subset of $\{x_t\}_{t=1}^T$.

To initialize the EM algorithm, we first compute the variance of x_t. Let $\mathcal{T}$ be the subset of $\{1, \ldots, T\}$ in which x_t is observed. We estimate the mean and variance of the observed values of x_t with $\hat{\mu} = (\sum_{t \in \mathcal{T}} 1)^{-1} \sum_{t \in \mathcal{T}} x_t$ and $\hat{\sigma}^2 = (\sum_{t \in \mathcal{T}} 1)^{-1} \sum_{t \in \mathcal{T}} (x_t - \hat{\mu})^2$. We then guess that σ_ν^2 equals $\hat{\sigma}^2$ divided by 1.5 and guess that the (1,1), (2,2) and (3,3) elements of Σ_ε each equal $\hat{\sigma}^2$ divided by 50. Let $\theta(0)$ denote this initial collection of parameters.

With this initialization, the EM algorithm is as follows:

Expectation Step: Using $\theta(j)$, we compute $\mathbb{E}_{\theta(j)}(S_t|\Omega_T)$,

$$P_t^{(j)} = \mathbb{E}_{\theta(j)}[(S_t - \mathbb{E}_{\theta(j)}(S_t|\Omega_T))(S_t - \mathbb{E}_{\theta(j)}(S_t|\Omega_T))'|\Omega_T],$$

and

$$P_{t,t-1}^{(j)} = \mathbb{E}_{\theta(j)}[(S_t - \mathbb{E}_{\theta(j)}(S_t|\Omega_T))(S_{t-1} - \mathbb{E}_{\theta(j)}(S_{t-1}|\Omega_T))'|\Omega_T]$$

using the Kalman filter and smoother equations in the appendix of Shumway and Stoffer (1982). Note that $\mathbb{E}_{\theta(j)}(S_t|\Omega_T)$ and $P_t^{(j)}$ are available over $t = 0, \ldots, T$. $P_{t,t-1}^{(j)}$ is available over $t = 1, \ldots, T$. We also use the Kalman filter to compute the innovations form of the log likelihood of the state-space model as in equation (18) of Shumway and Stoffer (1982). If the observation of x_t is missing in period t, then we set $K_t = 0$ when computing equations (A6) and (A7) of Shumway and Stoffer (1982) and we do not include period t in the computation of the log likelihood.

Maximization Step: Let

$$A(j) = \sum_{t=1}^{T} (P_{t-1}^{(j)} + \mathbb{E}_{\theta(j)}(S_{t-1}|\Omega_T)\mathbb{E}_{\theta(j)}(S'_{t-1}|\Omega_T)),$$

$$B(j) = \sum_{t=1}^{T} (P_{t,t-1}^{(j)} + \mathbb{E}_{\theta(j)}(S_{t}|\Omega_T)\mathbb{E}_{\theta(j)}(S'_{t-1}|\Omega_T)),$$

and

$$C(j) = \sum_{t=1}^{T} (P_{t}^{(j)} + \mathbb{E}_{\theta(j)}(S_{t}|\Omega_T)\mathbb{E}_{\theta(j)}(S'_{t}|\Omega_T)).$$

Then,

$$\tilde{\Sigma}_{\varepsilon}(j+1) = T^{-1}(C(j) - B(j)\Phi' - \Phi B(j)' + \Phi A(j)\Phi')$$

and we update the (1,1), (2,2) and (3,3) elements of $\Sigma_{\varepsilon}(j+1)$ with the (1,1), (2,2), and (3,3) elements $\tilde{\Sigma}_{\varepsilon}(j+1)$. To update σ_{ν}, we use

$$\sigma_{\nu}(j+1) = T^{-1} \sum_{t=1}^{T} c_t^{(j)}$$

in which

$$c_t^{(j)} = (x_t - M\mathbb{E}_{\theta(j)}(S'_t|\Omega_T))^2 + MP_t^{(j)}M'$$

if x_t is observed in period t and c_t equals $\sigma_n u(j)$ if x_t is missing in period t.

We repeat the expectation and maximization steps until the change in the log likelihood converges. For the first pass through the expectation step, we set $\mathbb{E}_{\theta(0)}(S_0)$ equal to the zero vector. For each expectation step after that, we set it equal to $\mathbb{E}_{\theta(j-1)}(S_0|\Omega_T)$ from the previous iteration's Kalman smoother. To compute the unconditional variance of S_0, we define

$$\tilde{\Phi} = \begin{bmatrix} 0.98 & 1 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0.98 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & -0.98 & -0.98 & -0.98 & \cdots & -0.98 & -0.98 \\ 0 & 0 & 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 1 & 0 \end{bmatrix}.$$

Then, the vectorized unconditional variance of S_0 equals $(I - \tilde{\Phi} \otimes \tilde{\Phi})^{-1}\text{vec}(\Sigma_\varepsilon)$, where Σ_ε is either computed in the previous maximization step or in the initialization.

When the log likelihood does converge, we keep the third element of $\mathbb{E}_{\theta(J)}(S_t|\Omega_T)$ as the estimated seasonal, using J to denote the number of loops until convergence. When x_t is observed, we subtract this estimated seasonal from x_t to seasonally adjust the data. If x_t is unobserved, then we leave it as unobserved.

B.2 The EM algorithm for the DFM

In this appendix, we give the details of the expectation maximization (EM) algorithm that we use to compute the WARN factor. We use the EM algorithm in Bańbura and Modugno (2014), which builds on Dempster, Laird, and Rubin (1977) and Shumway and Stoffer (1982).

We start the algorithm by seasonally adjusting each state's observed WARN layoffs (Camacho, Lovcha, and Pérez Quirós, 2015). We describe the seasonal adjustment algorithm in Appendix B.1. Let $WARN_{s,t}$ be the seasonally adjusted observation for state s in period t. We note that some observations of $WARN_{s,t}$ are missing. Then, $x_{s,t} = \ln(WARN_{s,t})$ when $WARN_{s,t}$ is observed and non-zero. If $WARN_{s,t}$ is missing or equal to zero, then we treat $x_{s,t}$ as missing. Let $\mathcal{T}_s$ be the subset of $\{1, \ldots, T\}$ in which $x_{s,t}$ is observed. We estimate the mean, variance and standard deviation of the observed values of $x_{s,t}$ with $\hat{\mu}_s = (\sum_{t\in\mathcal{T}_s} 1)^{-1} \sum_{t\in\mathcal{T}_s} x_{s,t}$, $\hat{\sigma}^2_s = (\sum_{t\in\mathcal{T}_s} 1)^{-1} \sum_{t\in\mathcal{T}_s}(x_{s,t} - \hat{\mu}_s)^2$, and $\hat{\sigma}_s = \sqrt{\hat{\sigma}^2_s}$. We then standardize $x_{s,t}$ with $\hat{z}_{s,t} = (x_{s,t} - \hat{\mu}_s)/\hat{\sigma}_s$.

We assume that the N-dimensional process $z_t = [z_{1,t}, \ldots, z_{N,t}]'$ follows

$$z_t = \Lambda f_t + e_t, \quad e_t \overset{iid}{\sim} N(0, R) \tag{B11}$$

in which f_t is an unobserved scalar factor, $\Lambda = [\lambda_1, \ldots, \lambda_N]'$ is an $(N \times 1)$ vector of factor loadings, $e_t = [e_{1,t}, \ldots, e_{N,t}]'$ is an N-dimensional process of disturbances, and R is a diagonal matrix with all diagonal elements being strictly positive. The factor follows an AR(1) process,

$$f_t = A f_{t-1} + u_t, \quad u_t \overset{iid}{\sim} N(0, Q), \tag{B12}$$

in which A is the autoregression slope coefficient, u_t is the innovation, and $Q > 0$.

For the EM algorithm below, we distinguish between the N-dimensional process, z_t, which follows equations (B11) and (B12), and the standardized data, $\hat{z}_{s,t}$, which is not always observed. When $\hat{z}_{s,t}$ is observed, we assume that it equals $z_{s,t}$; however, we do not observe all elements in $\{z_t\}_{t=1}^T$. As in Bańbura and Modugno (2014), we will use Ω_T to denote the observed data, which is a subset of $\{z_t\}_{t=1}^T$.

Let $\theta = \{\Lambda, A, R, Q\}$ denote the collection of model parameters. We compute an initial guess of θ, denoted with $\theta(0) = \{\Lambda(0), A(0), R(0), Q(0)\}$, and an initial sequence for the WARN factor, denoted with $\{f_t^{(0)}\}_{t=1}^T$, using principal components as follows. First, we define $\tilde{z}_{s,t}$ as equal to $\hat{z}_{s,t}$ when $\hat{z}_{s,t}$ is observed and equal to 0 when $\hat{z}_{s,t}$ is missing. Then, we use $\tilde{z}_t = [\tilde{z}_{1,t}, \ldots, \tilde{z}_{N,t}]'$ and $\tilde{Z} = [z_1, \ldots, z_T]'$. Second, let d_1 denote the largest eigenvalue of $T^{-1}\tilde{Z}'\tilde{Z}$ and let p_1 denote the corresponding $(N \times 1)$ eigenvector. We use $[\tilde{f}_1^{(0)}, \ldots, \tilde{f}_1^{(T)}]' = d_1^{-1/2}\tilde{Z}p_1$ and $\tilde{\Lambda}(0) = p_1 d^{1/2}$. Third, we compute $A(0)$ by estimating $\tilde{f}_t^{(0)} = A\tilde{f}_{t-1}^{(0)} + u_t$ with ordinary least squares, and $\tilde{u}_t^{(0)} = \tilde{f}_t^{(0)} - A(0)\tilde{f}_{t-1}^{(0)}$ is the corresponding residual. Then, $\tilde{Q}(0) = (T-1)^{-1}\sum_{t=1}^T \tilde{u}_t^{(0)}$. Fourth, let $\tilde{v}(0) = \tilde{Q}(0)/(1 - A(0)^2)$. Then, we compute $f_t^{(0)} = \tilde{v}(0)^{-1/2}\tilde{f}_t^{(0)}$ for $t = 1, \ldots, T$, $\Lambda(0) = \tilde{v}(0)^{1/2}\tilde{\Lambda}(0)$, $Q(0) = \tilde{v}(0)^{-1}\tilde{Q}(0)$. Fifth, we use $e_t^{(0)} = \tilde{z}_t - \lambda(0)f_t^{(0)}$, and $R(0)$ is computed from the diagonal elements of $T^{-1}\sum_{t=1}^T e_t^{(0)}e_t^{(0)\prime}$.

With this initialization, the EM algorithm is as follows:

Expectation Step: Using $\theta(j)$, compute $\mathbb{E}_{\theta(j)}(f_t|\Omega_T)$, $P_t^{(j)} = \mathbb{E}_{\theta(j)}[(f_t - E_{\theta(j)}(f_t|\Omega_T))^2]$ and $P_{t,t-1}^{(j)} = \mathbb{E}_{\theta(j)}[(f_t - E_{\theta(j)}(f_t|\Omega_T))(f_{t-1} - E_{\theta(j)}(f_{t-1}|\Omega_T))]$ using the Kalman filter and smoother equations in the appendix of Shumway and Stoffer (1982). Note that $\mathbb{E}_{\theta(j)}(f_t|\Omega_T)$ and $P_t^{(j)}$ are available over $t = 0, \dots, T$. $P_{t,t-1}^{(j)}$ is available over $t = 1, \dots, T$. With these expectations, we then compute $E_{\theta(j)}(f_t^2|\Omega_T) = P_t^{(j)} + [\mathbb{E}_{\theta(j)}(f_t|\Omega_T)]^2$ for $t = 0, \dots, T$ and $E_{\theta(j)}(f_t f_{t-1}|\Omega_T) = P_{t,t-1}^{(j)} + \mathbb{E}_{\theta(j)}(f_t|\Omega_T)\mathbb{E}_{\theta(j)}(f_{t-1}|\Omega_T)$ for $t = 1, \dots, T$ to be used in the maximization step. Following Bańbura and Modugno (2014), if elements of z_t are missing, then we skip the corresponding rows of z_t, $\Lambda(j)$, and $R(j)$ in the Kalman filter equations. We compute the log likelihood function with the innovations form in equation (18) of Shumway and Stoffer (1982).

Maximization Step: We use equations (6), (8), (11) and (12) in Bańbura and Modugno (2014), which rely on $R(j)$ from the previous iteration and $\mathbb{E}_{\theta(j)}(f_t|\Omega_T)$ and $\mathbb{E}_{\theta(j)}(f_t^2|\Omega_T)$ for $t = 0, \dots, T$ and $\mathbb{E}_{\theta(j)}(f_t f_{t-1}|\Omega_T)$ for $t = 1, \dots, T$ from the expectation step, to compute $A(j+1)$, $\tilde{Q}(j+1)$, $\tilde{\Lambda}(j+1)$, and $R(j+1)$. We then compute $\tilde{v}(j+1) = \tilde{Q}(j+1)/(1-A(j+1)^2)$, $\Lambda(j+1) = \tilde{v}(j+1)^{1/2}\tilde{\Lambda}(j+1)$, $Q(j+1) = \tilde{v}(j+1)^{-1}\tilde{Q}(j+1)$. This last step normalizes the unconditional variance of f_t to be 1.

We repeat the expectation and maximization steps until the log likelihood converges. For the first pass through the expectation step, we use $\mathbb{E}_{\theta(0)}(f_0) = 0$ and $\mathbb{E}_{\theta(0)}[(f_0 - \mathbb{E}_{\theta(0)}(f_0))]^2 = 1$ to initialize the Kalman filter. For each subsequent pass through the expectation step, we use $\mathbb{E}_{\theta(j-1)}(f_0|\Omega_T)$ from the previous iteration's Kalman smoother and keep $\mathbb{E}_{\theta(0)}[(f_0 - \mathbb{E}_{\theta(0)}(f_0))]^2 = 1$ to initialize the Kalman filter.

We now briefly discuss the normalization that the unconditional variance of f_t is 1. Without further restrictions, the scale of the factor loadings and the factor are not separately identified. Intuitively, because the WARN factor is not observed, its units are unknown and not identified from the WARN data. We can rewrite equation (B11) to be $z_t = \Lambda c^{-1} c f_t + e_t$ for any scalar $c \neq 0$ and define $\tilde{f}_t = c f_t$, $\tilde{\Lambda} = \Lambda c^{-1}$, and $\tilde{Q} = c^2 Q$. The expected log likelihood of the DFM conditional on the observed data is the same when using Λ and Q or $\tilde{\Lambda}$ and

$\tilde{Q}$. Dempster, Laird, and Rubin (1977) note that the log likelihood of a factor model has a ridge of local maxima, and Bańbura and Modugno (2010) also discuss identification in DFMs. Hence, our choice of normalization simply scales the factor but does not change how the factor affects z_t.

When the log likelihood does converge, we keep $\hat{f}_t = \mathbb{E}_{\theta(J)}(f_t|\Omega_T)$ for $t = 1, \ldots, T$ as the estimated WARN factor, using J to denote the number of loops computed until convergence. We also keep $\hat{\theta} = \theta(J)$ as the estimated model parameters and $\hat{P}_t = P_t^{(J)}$ for $t = 1, \ldots, T$ in order to compute confidence intervals.

To compute confidence intervals around $\hat{f}_t$, we use the parametric bootstrap in Pfeffermann and Tiller (2005). We use the estimates $\hat{\Lambda}$, $\hat{A}$, $\hat{R}$, and $\hat{Q}$ in place of Λ, A, R, and Q in equations (B11) and (B12) to compute B simulations of $\{z_t\}_{t=1}^{T}$. Let $\{z_t^b\}_{t=1}^{T}$ denote the bth set of simulated values. We then compute $x_{s,t}^b = \hat{\mu}_s + \hat{\sigma}_s z_{s,t}^b$ and treat $x_{s,t}^b$ as missing whenever $x_{s,t}$ is missing. We then compute new values of $\hat{\mu}_s$ and $\hat{\sigma}_s$, normalize $x_{s,t}^b$ with those values, re-compute the principal components initialization, and re-compute the EM algorithm to get $\{\hat{f}_t^b\}_{t=1}^{T}$. In addition, we keep $\hat{P}_t^b = \mathbb{E}_{\theta(J^b)}[(f_t - E_{\theta(J^b)}(f_t|\Omega_T^b))^2]$ for $t = 1, \ldots, T$, in which Ω_T^b denotes the observed simulated data. Then, we compute the mean squared error of $\hat{f}_t$ with

$$\widehat{MSE}_t = B^{-1} \sum_{b=1}^{B} (\hat{f}_t^b - \hat{f}_t)^2 - B^{-1} \sum_{b=1}^{B} \hat{P}_t^b + 2\hat{P}_t \tag{B13}$$

We compute 95 percent confidence intervals with $\hat{f}_t \pm 1.96 \times \widehat{MSE}_t^{1/2}$.

B.3 Analysis of the factor loadings

In this appendix, we provide a simple analysis of the DFM factor loadings that are estimated by the EM algorithm. We show the loading estimates in Table A2 along with the number of observations used in the DFM, average employment in thousands, and average manufacturing percent, which is the percent of a state's employment in manufacturing. These are the variables we will use to study the estimated factor loadings. The state-level employment data are from the Bureau of Economic Analysis's state and metro area employment, hours, and earnings database (SAE, 2022).

We start by discussing the loading estimates. SC has the highest loading value, followed by CA, OH, IL, and IN. We discuss the high loadings on CA, OH, IL and IN in the subsequent analysis. However, we first note that the high loading on SC is likely because we treat SC differently from the other states in the DFM. As shown in Table 1 in the body of the paper, we begin observing SC data in January 2009. However, we only observe SC data through November 2012, giving SC 47 observations in Table A2. Hence, we observe SC in the middle of the 2008-09 recession and in the beginning of the subsequent expansion. This sample is highly correlated with many other states, yielding a high loading for SC. However, because we are not observing new WARN data for SC, we have treated SC as missing since December 2012 and it has essentially no effect on current values of the WARN factor. In contrast, we continue to collect new WARN data for all other states in Table A2. Because of this different treatment of SC, we show all subsequent statistics in this appendix with and without SC in the sample.

We begin by showing simple correlations in Table A3. We first note that we take the natural logarithm of employment before computing the correlation to parallel how we take logs of WARN layoffs before estimating the DFM. Table A3 shows that, with or without SC in the sample, factor loadings have high correlations with employment and low correlations with average manufacturing percent. In contrast, the correlation between factor loadings and number of observations is sensitive to the inclusion of SC. Without SC, there is a high correlation between factor loadings and number of observations.

The simple correlations in Table A3 only consider the bivariate relationships between the estimated factor loadings and the other variables. To study all of the variables jointly, we next use a linear model:

$$\begin{aligned}\text{loading}_s = \phi_0 + \phi_1 \# \text{ of obs}_s + \phi_2 \text{Log avg. employment}_s \\ + \phi_3 \text{Avg. manufacturing percent}_s + e_s.\end{aligned} \tag{B14}$$

We estimate ϕ_0, ϕ_1, ϕ_2, and ϕ_3 with ordinary least squares, and show the results in Table A4.

Table A4 shows that the inclusion of SC has a meaningful impact on the relationship between factor loadings and number of observations, as in Table A3. With SC, the coefficient on the number of observations is negative and not statistically significant. Without SC, the number of observations is positive and statistically significant, and an additional 100 observations are associated with an increased factor loading by 0.06.

Table A4 shows that SC has little influence on the relationship between factor loadings and employment size, as in Table A3. The coefficient on employment size is positive and statistically significant in both cases. Without SC, a one unit increase in log average employment (roughly the difference between CA and IL) is associated with an increased factor loading by 0.15.

Table A4 shows that SC does have a material impact on the relationship between factor loadings and number of observations. With SC, this relationship is negative but statistically insignificant. Without SC, this relationship is positive and statistically significant. However, the effect is not particularly large. Without SC, an additional 100 observations are associated with an increased factor loading by 0.04.

Finally, Table A4 shows that SC has a moderate influence on the relationship between factor loadings and average manufacturing percent, as in Table A3. The coefficient on average manufacturing percent falls from 0.14 to 0.09 if SC is excluded. However, these coefficients are statistically significant with or without SC. That is, average manufacturing percent has a statistically significant relationship with estimated factor loadings after controlling for the number of observations and employment size. While average manufacturing percent is statistically significant, the marginal effect is small. Without SC, a 1 percent increase in average manufacturing percent is associated with an increased factor loading by 0.009.

Returning to the loadings of CA, OH, IL, and IN, CA appears to have a high factor loading because it has by far the most employees. OH and IL have high numbers of employees compared to most states in the sample, and they also have long samples. OH has a high manufacturing percent, and IN has a combination of a long sample and a high manufacturing percent.

C Computing job finding and separation rates

In this appendix, we describe how we measure the job finding rate, g_t, and the job separation rate, s_t, that we use for forecasting in the VAR in Section 5.2. Our measurement approach follows Barnichon and Nekarda (2012) and Shimer (2012). We begin by defining $G_t \in [0, 1]$ as the job finding probability and $S_t \in [0, 1]$ as the job separation probability.

We compute the job finding probability as

$$G_t = 1 - \frac{u_t - u_t^s}{u_{t-1}}, \tag{C15}$$

in which u_t is the level of unemployment, series code UNEMPLOY in the FRED database, and u_t^s is the number of people unemployed for less than 5 weeks, series code UEMPLT5 in the FRED database, multiplied by 1.1549. We follow Barnichon and Nekarda (2012) in multiplying the FRED series UEMPLT5 by 1.1549 to adjust for the change in the Current Population Survey that occurred in 1994. See also Appendix A of Shimer (2012). Then, the job finding rate is $g_t = -\ln(1 - G_t)$. We compute G_t directly from equation (C15) and then compute g_t.

Next, we compute the job separation rate. We define $s_t = -\ln(1 - S_t)$. Then, we use

$$u_t = \frac{(1 - e^{-g_t - s_t})}{g_t + s_t} l_{t-1} + e^{-g_t - s_t} u_{t-1}, \tag{C16}$$

in which $l_t = u_t + e_t$ is the labor force with e_t being the level of employment, series code CE16OV in the FRED database. We solve equation (C16) for s_t, given u_t, u_{t-1}, g_t and l_{t-1}, using the method of bisection.

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D Appendix figures and tables

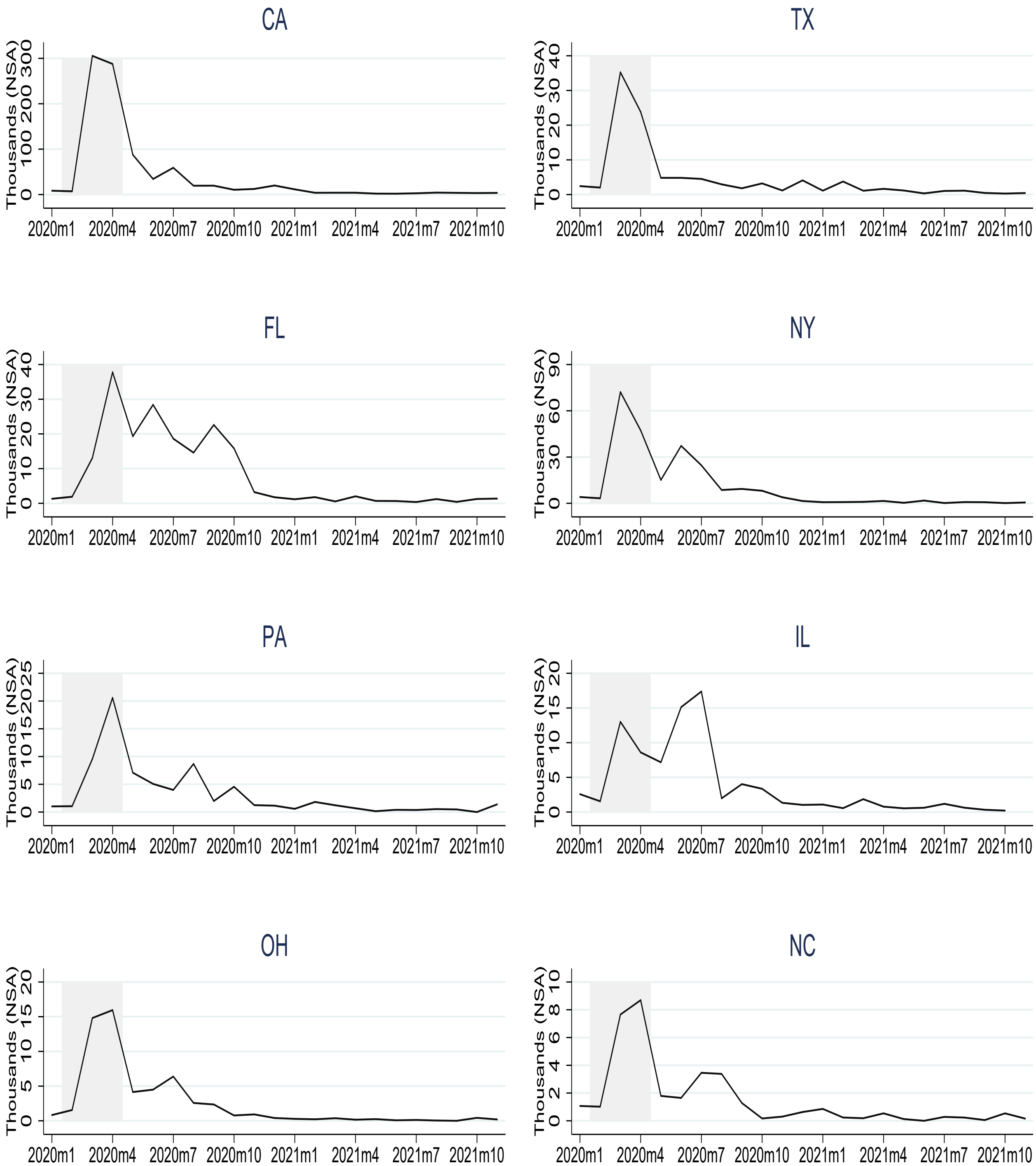

Figure A1: Number of workers affected by WARN notices for large states since January 2020

Note: WARN layoffs rose sharply at the beginning of the 2020 recession and have declined since then. Horizontal axes start in January 2020 and end in November 2021. Vertical axes differ from panel to panel. Shading represents NBER recession dates. See Section 2.3 for details.

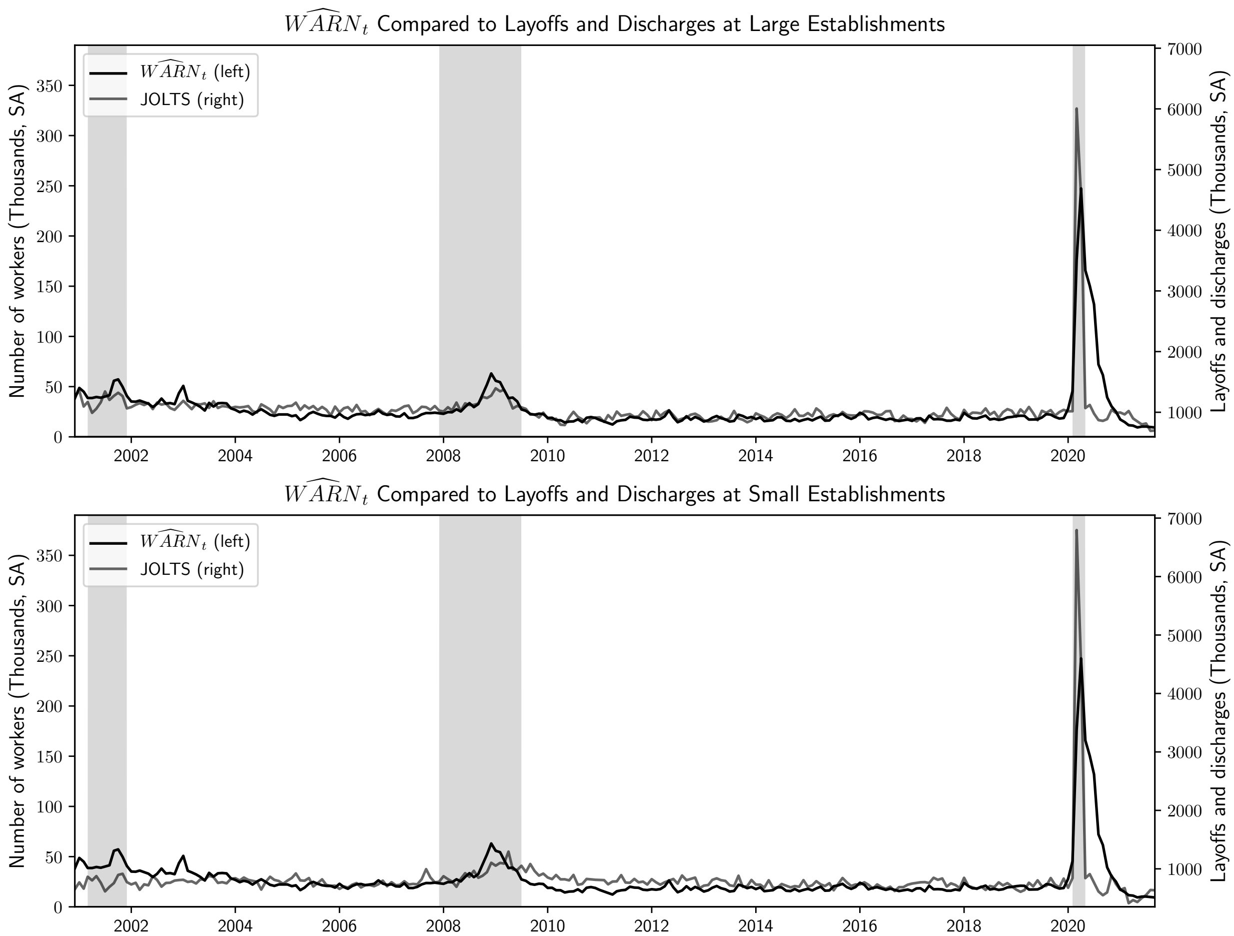

Figure A2: Comparing $\widehat{WARN}_t$ and JOLTS through November 2021

Note: $\widehat{WARN}_t$ is in number of workers in thousands on the left scale. It is the same in both panels. In the top panel, JOLTS private layoffs and discharges in thousands are for establishments with 50 workers or more and are on the right axis. In the bottom panel, JOLTS private layoffs and discharges in thousands are for establishments with 49 workers or less and are on the right axis. The sample is December 2000 to December 2019 in both panels. Shading represents NBER recession dates.

	Mean	Median	Std. dev	Min	Max	Observations
(1) $\text{WARN}_{s,t}$ (lvl)	997	612	1,264	0	16,746	6,103
(2) MLS initial $\text{claims}_{s,t}$ (lvl)	6,324	4,673	6,708	0	69,157	2,628
(3) JOLTS $(\text{LDs})_{s,t}$ (k)	1,765	1,721	175	1,474	2,527	168
(4) $uic_{s,t}$ (lvl)	10,336	7,394	9,704	978	79,340	6,103
(5) $ur_{s,t}$ (%)	5.7	5.2	2.1	2.0	14.0	6,103
(6) $\Delta ur_{s,t}$ (pp)	-0.01	0	0.12	-0.8	2.3	6,103
(7) $e_{s,t}$ (k)	3,541	2,546	2,568	845	14,961	6,103
(8) $\Delta e_{s,t}$ (k)	2.8	2.4	12.0	-172.3	192.2	6,102

Table A1: Summary statistics of state-month panel of labor market indicators

Note: Summary statistics for seasonally adjusted data since January 1990, when we first have state WARN notice information, to December 2019 for the states in our sample. "$\text{WARN}_{s,t}$" stands for the number of individuals affected by WARN notices in state s in month t. "MLS" stands for Mass Layoff Statistics, "JOLTS" stands for Job Openings and Labor Turnover Survey, "LDs" stands for layoffs and discharges, "uic" stands for initial UI claims, "ur" stands for the unemployment rate, and "e" stands for private employment. The last row has one fewer observation than the four rows above because state-level employment data begin in January 1990, whereas the other series have longer histories. As a result, the first difference for this series is missing in January 1990. The MLS program started in April 1995 and ended in May 2013 and therefore there are fewer observations in row (2). JOLTS data are for the nation (total private), and all other series are for our sample of states when WARN information is available. JOLTS seasonally adjusted data are from the BLS, and all other series are seasonally adjusted using the model in Wright (2013, pg. 80). The UI claims data are monthly averages of weekly data. "lvl" stands for levels, "pp" stands for percentage points, and "k" stands for thousands. See Section 2.3 for details.

State	Loading	# of obs	Avg. emp. (in thousands)	Avg. manuf. percent
AL	0.36	277	1,953	14.8
AZ	0.35	140	2,492	7.2
CA	0.72	191	15,170	9.8
CO	0.39	191	2,345	6.6
CT	0.40	286	1,663	11.2
FL	0.59	287	7,642	5.2
IA	0.22	195	1,500	15.0
IL	0.64	274	5,876	11.5
IN	0.61	299	2,963	18.6
KS	0.41	278	1,357	13.0
LA	0.40	178	1,918	7.9
MD	0.41	263	2,554	5.3
MI	0.59	303	4,294	15.1
MN	0.34	256	2,738	12.4
MO	0.48	256	2,755	10.8
MS	0.33	134	1,129	14.9
NC	0.57	305	4,047	13.9
NJ	0.39	215	3,965	7.8
NY	0.53	242	8,782	6.4
OH	0.66	305	5,387	14.5
OR	0.37	201	1,695	11.6
PA	0.52	251	5,715	11.6
SC	0.81	47	1,912	13.8
TN	0.45	119	2,789	13.8
TX	0.56	275	10,613	8.9
VA	0.51	304	3,684	7.7
WA	0.55	215	2,945	10.1
WI	0.56	305	2,823	17.8

Table A2: Factor loading estimates and other state-level statistics

Note: "Loading" is the estimated factor loading from the EM algorithm, "# of obs" is the number of observations available for estimating the DFM, "Avg. emp" is average nonfarm employment (in thousands) from July 1996 to September 2021, and "Avg. manuf. percent" is the percent of nonfarm employees in the manufacturing industry, averaged from July 1996 to September 2021.

	# of obs	Log avg. emp.	Avg. manufacturing percent
(1) with SC	0.09	0.60	0.12
(2) without SC	0.47	0.78	0.06

Table A3: Correlations with estimated factor loadings

Note: See notes to Table A2.

	Intercept	# of obs	Log avg. emp.	Avg. manufacturing percent
(1) with SC	-0.91	-0.0004	0.16	0.014
	(0.16)	(0.0005)	(0.02)	(0.005)
(2) without SC	-0.94	0.0004	0.15	0.009
	(0.14)	(0.0001)	(0.02)	(0.003)

Table A4: Coefficient estimates of equation (B14)

Note: See notes to Table A2. Standard errors are in parentheses.