Measuring the Effects of National Activity Shocks on State Economies: A Factor-Augmented Vector Autoregressive (FAVAR) Approach

Introduction. The economic literature does not put forth a unified approach to quantitatively model disaggregated labor market response to the financial crisis. The National activity shock, from the financial services industry, disrupted a diverse set of State level economies with various magnitudes and persistence. Forecasts of State level labor dynamics are thin, and fiscal policy was applied like an even blanket to all of them. This is no fault of dynamic factor modeling techniques, which have been used to measure both National and State level activity (Stock and Watson 1989; Orr et al. 1999). Industry specific shocks in the National aggregate have not been mapped to disaggregated State level industry and labor dynamics.

The Coincident Economic Indicator (CEI) of Stock and Watson (1989) is generated from National data including: industrial production, manufacturing, income, and employment hours. Orr et al (2001) follows with a single dynamic factor generated with use of the Kalman filter, producing State level CEI measures for New Jersey and New York from 4 series in the Quarterly Census of Employment & Wage (QCEW) and Bureau Labor Stat. (BLS) datasets; employment, average hours, wages, and unemployment rate. The pure labor data CEI of Orr et al. (1999) relies on the well-documented relationship between output activity and employment. Carlino and DeFina (2004) find evidence of cross-industry co-movements in State level employment. Meanwhile, the cross-industry variance of National activity with State activity explains between 10-60% of the total fluctuation in State level employment (Rissman 1999). Of late, Chung and Hewings (2014) append the Chicago Fed National Activity Index (CFNAI) to Metropolitan Statistical Area (MSA) activity factors in attempts to disentangle National from MSA activity.

Data and Methodologies. I propose constructing National and State level CEI, in the spirit of Orr et al. (2001), omitting unemployment rate (does not exist in disaggregated industries).

Total-industry CEI: $X_{\{Emp,\ Hrs,\ Wage\}tj} = CEI_{tj}\lambda_j + \varepsilon_{tj}$ j={National, State} CEI_{tj} =[Tx1] λ_j=[1x3]

An industry cycle factor is extracted from a sufficiently disaggregated set of Employment(E), Hours(H), and Wage(W) data at the National and State level. Industry cycle factors $F\{E,H,W\}_{i,j}$ for the i={1,2,3,4} below. The QCEW 6-digit industry disaggregation (NAICS codes):

1. Goods Producing (101) excl. Manufacturing (1013)	={6-digit disaggregated industries}
2. Manufacturing (1013)	={6-digit disaggregated industries}
3. Service-Providing (102) excl. Financial Activities (1023)	={6-digit disaggregated industries}
4. Financial Activities (1023)	={6-digit disaggregated industries}

The process is a simple factor extraction on the data for the National(N) level. For State(S) level industry factors, the National factor of the same industry and QCEW data type{E,H,W} is regressed on the State level data (i.e. $F\{E\}_{2,N}$ on $X\{E\}_{[\text{6-digit Manufacturing data,State}]}$). Once the State level data is conditioned/purged on/of the National cycle, we can extract State level factors for each QCEW data type{E,H,W} and each underlying industry type i={1,2,3,4}. For the National industry factor extraction $v_{t,i,j}$ represents 6-digit data. For the State level industry factor extraction $v_{t,i,j}$ equals the residual from our regression of National factor on State data.

$$\hat{F}_{t,i,j} \text{ solves } \min_{\lambda,F_{t,i,j}} \sum_{t,i,j} (v_{t,i,j} - \lambda'_{i,j} F_{t,i,j})^2 \quad \lambda_{i,j} \epsilon [1 \times m_{i,j}] \quad \text{Important:} \forall\, i \text{ the span of data } m_{i,j} \text{is large}$$

As in Hatzius et al. (2010), for both the National and State level, we use the expectation maximization algorithm above as the likelihood estimator, which allows for missing data across our 6-digit disaggregated factor extraction. The high dimension of the 6-digit data within each factor extraction should provide a robust estimate of the underlying cycle for each industry factor drawn. At this point we have National factors for each $F\{E,H,W\}_{i,N}$ i={1,2,3,4}, as well as $F\{E,H,W\}_{i,S}$ for State idiosyncratic to National cycle.

Model & Identification. We now implement a structural VAR on the National and State QCEW industry cycle factors $F\{E,H,W\}_{i=[1,2,3,4],j}$. The $F_{t,j=National}$ in equation (below) will stack only vectors from the National cycles, while $F_{t,j=State}$ will stack National and State industry cycles.

$$F_{t,j} = \phi_j(L)F_{t-1,j} + u_{t,j}$$

i.e. $F\{E\}_{t,j=State} = [F\{E\}_{1,S}\ F\{E\}_{2,S}\ F\{E\}_{3,S}\ F\{E\}_{4,S},\ldots\ F\{E\}_{1,N}\ F\{E\}_{2,N}\ F\{E\}_{3,N}\ F\{E\}_{4,N}]$

The FAVAR(lags=p) of $F_{t,j=State}$ formulates an explicit dynamic relationships between National industry shocks and State industry response; novel compared to infrequent input-output models.

We model the {E,H,W} separately (i.e $F\{E\}_{t,j=State}$) and can independently identify the State level response of National shocks for each feature of activity (levels{E}, pressure{H}, and price{W}). We can pool {E,H,W} dynamics back together using λ_j from the total-industry CEI.

The model, through projection of the factor dynamics to 6-digit disaggregation, can detail summed-responses at industry disaggregation of 6,5,4,3,2-digits to display headwinds for pivotal businesses. For example, agriculture may be experiencing drag from dated manufactured machinery on the market, or from inadequate investment funding for expansion. Disentangling the industry dynamics following the National financial crisis, the model would recommend targeted subsidies to stimulate either the manufacturing sector or support financial investments.

These exercises require a shock decomposition of the $u_{t,j}$, using either Cholesky orthogonalization of shocks or general structural shocks on the full-sample. Determining proper identification we can use a combination of pseudo-out-sample impulse responses (Bernanke et al. 2007), and root mean square error of forecasts at various horizons (Diebold and Mariano 1995).

Extensions. With full-sample shock decomposition we can qualitatively map National shock magnitudes relating to Trade, Fiscal, and Monetary policy with local labor market response. This type of National policy mapping to shock magnitude, allows empirical measurement of State level labor response from trade pacts like the Trans-Pacific Partnership; $F\{E,H,W\}_{i=2,N}$ shock.

The model provides an extendible framework for analyzing Counties with $F_{i,S}$:

$[F\{E\}_{i=\{1,2,3,4\},N}\ F\{E\}_{i=\{1,2,3,4\},S}]$ on $X\{E\}_{[6\text{-digit data } i=\{1,2,3,4\},County]}$

$F\{E\}_{t,j=County} = [F\{E\}_{i=\{1,2,3,4\},C}\quad F\{E\}_{i=\{1,2,3,4\},S}\quad F\{E\}_{i=\{1,2,3,4\},N}]$

Broader Impacts. State and County municipalities are frequently affected by adverse National shocks. Localities cannot float municipal debt to foreign markets, as easily as Federal Treasuries (most buyers are domestic with tax incentives), and they must protect against revenue shortfalls. The municipal pension systems in this Nation are highly exposed to labor and associated taxable income shortfalls. A major step in municipal financial reform is empirical attention to regional spillover from National shocks and policies. The proposed model empirically relates local labor and income dynamics from a National shock, allowing municipal agencies to assess weakness in pension finances and other spending given a national shock scenario.

References

Bernanke B, Boivin J., and Eliasz P. "Measuring the effects of monetary policy: a Factor-Augmented Vector AutoRegressive (FAVAR) approach." *Quarterly Journal of Economics*, 2005.

Carlino G., and R. DeFina. " How strong is co-movement in employment over the business cycle? Evidence from state/sector data." *Journal of Urban Economics,* 2004.

Chung S., and G. Hewings. "Assessing the regional business cycle asymmetry in a multi-level structure framework: a study of the top 20 U.S. MSAs." *Regional Economics Applications Laboratory*, 2014.

Diebold F. and R. Mariano. "Comparing predictive accuracy." *Journal of Business & Economic Statistics*, 1995.

Hatzius J., Hooper P., Mishkin F., Shoenholtz K., and M. Watson. "Financial conditions indexes": a fresh look after the financial crisis." *NBER: Working Paper Series*, 2010.

Orr J., Rich R., and Rosen R."Two indexes offer broad view of economic activity in theNY,NJregion."*FRBNY*,1999.

Rissman E. "Regional employment growth and the business cycle." FRBCH: Economic Perspectives, 1999

Stock J., and M. Watson. "New indexes of coincident and leading economic indicators." *Macro. Annual*, 1989.