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The Information Content of Regional Employment Data for Forecasting Aggregate Conditions*

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Abstract

We consider whether disaggregated data enhances the efficiency of aggregate employment forecasts. We find that incorporating spatial interaction into a disaggregated forecasting model lowers the out-of-sample mean-squared-error from a univariate aggregate model by 70 percent at a two-year horizon. [JEL: C21, C53]

Keywords: forecasting, aggregation, spatial econometrics

Employment is a commonly used indicator of the state of the economy, and forecasts of employment are often used to signal the end of recessions. However, forecasts of aggregate employment typically ignore the information provided by geographically disaggregated data.¹ Possibly, this is because it is assumed that aggregate data are merely summed regional data, leaving the information content essentially equivalent.² Using a technique

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¹Lütkepohl (1984), for example, develops a theoretical framework for assessing the efficiency of some regional forecasting models.

²Another alternative explanation of the apparent dearth of regional analysis is the differences in the manner in which the aggregate and regional data are collected. Gross state product, for example, is collected annually and at a two-year lag making it virtually worthless for meaningful econometric analysis. While we do not address these issues directly, we posit that once the benefit of exploiting the information content of regional information is realized, more resources may be shifted toward the accumulation of such data.

that exploits the spatial interactions found in regional data, we consider whether using disaggregated data can enhance the efficiency of aggregate employment forecasts.

Recently, Owyang, Piger, and Wall (2003) used coincident indices constructed primarily from employment data in order to date state-level recessions. They suggest that information in the *spatial pattern* of disaggregated recession propagation can be informative to policymaking at an aggregate level. The spatial interaction observed through the cross-autocorrelation of regional employment may be significant and predictable. But can incorporating this information significantly improve the quality of the aggregate forecast? We address the following two questions: (i) How important is the spatial (i.e., regional) component in forecasting aggregate employment? and (ii) To what degree does incorporating regional information affect the accuracy (i.e., efficiency) of the aggregate forecast?

A recent paper by Giacomini and Granger (2004) addresses the second question in a theoretical framework. They consider forecasting an aggregate variable with four alternative models: (A) a univariate aggregate forecast, (B) the sum of univariate regional forecasts, (C) the sum of regional VAR forecasts, and (D) the sum of the forecasts from an (p, q) -order Space-Time autoregressive (henceforth ST-AR(p, q)) model. The ST-AR(p, q) model includes p temporal lags and q spatially distributed lags—that is, lags of the other regional series weighted by spatial proximity. Thus, the ST-AR(p, q) exploits spatial correlations and the information content in the disaggregated series. Giacomini and Granger argue that model (D) leads to a more efficient forecast of the aggregate variable than even the regional VAR. We show that model (D) yields much more efficient forecasts of aggregate employment.

1 The Models

We address our two questions by conducting an out-of-sample “horse race” between the four alternative forecasts of aggregate employment mentioned above. The four forecasting models used in this exercise are outlined below. Suppose first that period- t log-level of aggregate employment is denoted Y_t and can be written as the sum of its n regional counterparts y_{it} . Let $\widehat{Y}_{t+\tau}$ be the τ -period-ahead forecast of Y . A univariate aggregate AR(p) forecast of the change in $\widehat{Y}_{t+\tau}$ has the form

$$\Delta\widehat{Y}_{t+\tau} = c + \sum_{j=1}^p \Phi_j \Delta Y_{t+\tau-j}, \quad (1)$$

where p is the number of lags, c is a constant, and Φ_j are scalar coefficients.

A similar univariate model can be employed to forecast the τ -period-ahead forecast of region i 's employment, $\widehat{y}_{i,t+\tau}$. The aggregate forecast is the sum of the n regional forecasts

$$\Delta\widehat{Y}_{t+\tau} = \sum_{i=1}^n \Delta\widehat{y}_{i,t+\tau}^{uni} = \sum_{i=1}^n \left[c_i + \sum_{j=1}^p \phi_{ij} \Delta y_{i,t+\tau-j} \right], \quad (2)$$

where $\widehat{y}_{i,t+\tau}^{uni}$ is region i 's employment forecast from the univariate AR(p) model, the c_i s are region-specific constants, and ϕ_{ij} are scalar coefficients.

One criticism of (2) might be that it does not capture the interaction between regions. An alternative is a VAR forecasting model of regional employment. The aggregate forecast obtained from such a model is

$$\Delta\widehat{Y}_{t+\tau} = \sum_{i=1}^n \Delta\widehat{y}_{i,t+\tau}^{var} = \sum_{i=1}^n \left[c_i + \sum_{k=1}^n \sum_{j=1}^p \Gamma_{ikj} \Delta y_{k,t+\tau-j} \right], \quad (3)$$

where $\widehat{y}_{i,t+\tau}^{var}$ is the region i 's employment forecast and Γ_{ikj} is the (scalar) lag- j effect of region k on region i 's employment taken from the VAR coefficient matrices.

Finally, we consider the forecast obtained from the space-time-autoregressive model with p autoregressive lags and q spatial lags (ST-AR(p, q)). The ST-AR(p, q) model explicitly accounts for spatial dependence between neighbors.³ Given a definition of these neighbors, a spatial-lag operator is defined as the weighted average of the observations in a region's neighbors in a specific time period. The spatial weights are chosen *a priori* and reflect geographic characteristics of the regions under consideration. Thus, interaction between regions is governed by an exogenously chosen weighting matrix $W = \{w_{ik}\}$ satisfying $w_{ik} \geq 0$, $w_{ii} = 0$, and $\sum_{k \neq i} w_{ik} = 1$.⁴ The ST-AR model restricts the autoregressive coefficients for each region to be identical, pushing the idiosyncratic fluctuations into the spatial interaction terms or the residual. This model has the form:

$$\Delta \widehat{Y}_{t+\tau} = \sum_{i=1}^n \Delta \widehat{y}_{i,t+\tau}^{star} = \sum_{i=1}^n \left[c_i + \sum_{j=1}^p \phi_j \Delta y_{i,t+\tau-j} + \sum_{k=1}^n \sum_{l=1}^q \psi_l w_{ik} \Delta y_{k,t+\tau-l} \right], \quad (4)$$

where ϕ_j and ψ_l are scalar autoregressive and scalar spatial lag coefficients, respectively.

Under parameter certainty, the VAR forecast (3) weakly dominates the three alternative models (1), (2), and (4). However, Giacomini and Granger show that forecasting from an estimated VAR (3) is less efficient than forecasting from the ST-AR (4) model.⁵ Because the ST-AR model is a restricted form of the VAR, the error associated with pa-

³We do not allow for contemporaneous influence from a region's neighbors' neighbors, because these effects are propagated indirectly through the time dimension.

⁴We consider two sets of weights: the first takes into account distance between the centroids of economic regions, and the second considers geographic contiguity as a categorical qualification. Under the first definition, $w_{ij} = (1/d_{ij}) / (\sum_{j \neq i} 1/d_{ij})$ and d_{ij} is the distance between the geographic centroids of regions i and j . Under the second definition, $w_{ij} = (\eta_{ij}) / (\sum_{j \neq i} \eta_{ij})$ and $\eta_{ij} = 1$ if regions i and j are geographically adjacent, and $\eta_{ij} = 0$ otherwise.

⁵Under certain conditions, the univariate aggregate model yields a lower mean squared error. For a discussion of these conditions, see Giacomini and Granger (2004).

parameter uncertainty decreases.^{6,7} They are, however, unable to determine whether the ST-AR model or the univariate model is more theoretically efficient, i.e., whether interaction between regions yields significant information for forecasting. In the following section, we investigate whether accounting for spatial interaction in regional employment data is sufficiently elucidative to warrant the use of disaggregate data in forecasting.

2 The Horse Race

For our experiment, we use monthly employment data for the eight BEA regions for the period 1960:01 to 2003:11. Each BEA region is composed of between five and eleven states. Models are estimated in log differences and each respective employment series is forecasted in levels.⁸ Aggregate employment is the sum of the levels forecasted for the eight regions. Our measure of forecast efficiency is the monthly mean squared error (MSE) out to a three-year horizon. We estimate a version of each model using in-sample data from the beginning of the sample through 1990:01 and generate aggregate employment forecasts using each of the four models out to a horizon of 36 months.⁹ We then augment the dataset with the next vector of realizations and generate forecasts at the same horizons. This recursive estimation procedure is continued until the end of the forecast horizon which coincides with the end of the full sample. From this procedure, we obtain a collection of

⁶The unrestricted VAR(p) estimates pn^2 coefficients and n constants while the ST-AR(p, q) model estimates $p + q$ coefficients and n constants. For large numbers of regions, the error introduced by parameter uncertainty in the VAR swamps the efficiency gain from more completely modelling the system.

⁷In principle, we could test (in-sample) the restrictions on the VAR implied by the ST-AR model. However, we believe tests of this sort are implicitly tests of the validity of the restrictions in a theoretical sense. Our forecasting exercise is not a test of theory *per se* and our objective is not to maximize in-sample fit.

⁸We conducted augmented Dickey-Fuller tests on the aggregate and each regional employment series and could not reject the null hypothesis of nonstationarity at the 5 percent level.

⁹We chose the lag length to minimize the MSE of the out-of-sample forecasts. Both the aggregate and disaggregated AR models and the VAR were estimated with seven lags. The ST-AR model was estimated with six autoregressive lags and one spatial lag.

τ -step-ahead forecasts, where $\tau = 1, 2, \dots, 36$. For each of the four models, we calculate the MSE from the out-of-sample data at each forecast horizon. Finally, we compute the efficiency improvement of the ST-AR model as a function of the ratio of the MSEs of the ST-AR model to that of each alternative model i :

$$\Psi_i = 1 - \frac{MSE_{ST-AR}}{MSE_i}. \quad (5)$$

The metric (5) reveals the percentage reduction in MSE of using the ST-AR model relative to each other alternative model. The results out to 36 months are illustrated in Figure 1.

Figure 1 about here.

A number of lessons can be ascertained from Figure 1. Consistent with the theoretical predictions of Giacomini and Granger, the VAR forecasts are the least efficient of the four models. In particular, disaggregation appears to significantly enhance forecast performance at horizons between 6 months and three years. At very short horizons, the ST-AR model's performance is virtually identical to both AR models. However, incorporating regional interaction via the ST-AR model yields the most efficient of the four models, yielding an 80 percent reduction of the MSE from the VAR and a 70 percent reduction of the MSE from both AR models at a two-year forecast horizon. At long horizons, the ST-AR model's efficiency gains begin to disappear as the forecasts become dominated by reversion to the trend.¹⁰

Improved efficiency of the ST-AR model over the VAR was anticipated from the theo-

¹⁰We note here that diminishing long-horizon efficiency of the ST-AR model can be mitigated by reducing the number of autoregressive lags at the expense of short-horizon efficiency. A ST-AR(1,1) model has a 70 percent efficiency gain at a three-year horizon but forecasts worse than either AR model at horizons less than 6 months. We postulate that the efficiency loss of the ST-AR(6,1) exhibited in Figure 1 at longer horizons is, in part, caused by estimation uncertainty.

retical results of Giacomini and Granger. However, the vast improvement of the ST-AR model forecasts over the univariate AR models reveals the importance of exploiting regional interactions. Disaggregation alone yields negligible efficiency gains; accounting for spatial interaction, however, significantly increases forecasting efficiency.

These spatial effects may result from the propagation of idiosyncratic regional employment shocks. Variation in the rate of propagation across regions may occur because the distance between locations affects the behavior of firms and consumers. For example, households' location and labor supply decisions, as well as firms' location and labor demand decisions, may depend on local market conditions relative to the conditions in other nearby regions. Relevant market conditions may include fiscal and regulatory environments, as well as the state of locally available technology and infrastructure. Thus, changes in employment in one region may have predictive power in forecasting future conditions in not only that region but its neighbors. At the national level, these interactions are obfuscated by aggregation, reducing forecast efficiency.

3 Conclusion

In this note, we have investigated the relevance of disaggregation for forecasting aggregate employment. We find that exploiting regional interaction reduces the aggregate forecast MSE at horizons between six months and three years. We argue that this may warrant increased utilization of regional economic data in macroeconomic policymaking. While anecdotal information may be useful, the collection and refinement of local and state-level economic data may be an important step to help more accurately predict the volatile macroeconomy.

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Efficiency Gain for the ST-AR(6,1)

