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Spatial aggregation and forecast accuracy in a functional economic area and its component counties

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Abstract. This research addresses an issue related to economic forecasting in a functional economic area (FEA) and its component counties, spatial aggregation and forecast accuracy. Exponential smoothing models are applied to time series of monthly total employment data for the Spokane FEA and its 18 component counties. The models are multiplicative Winters in form and are estimated with Forecast Pro for Windows software. Top-down and bottom-up approaches are applied to both FEA-level and county forecasts. Data series are generated for counties of eastern Washington and northern Idaho from 1990 through 1995. The series are universally trended and seasonal and often have increasing variability through time. The models generally fit the data well. One in-sample mean absolute percent error is over 3 percent, and only two are over 2 percent. For Spokane County and the FEA the in-sample mean absolute percent error is .5 percent. Out-of-sample forecasts with top-down and bottom-up methods are similar. In all but two months forecast errors are of the same sign, and the mean absolute percent error is low for both methods. Both methods forecast FEA and component county total employment accurately in this time period.

1. Introduction

This research addresses one of many issues related to economic forecasting in a functional economic area and its component counties, spatial aggregation and forecast accuracy. Because FEA data are aggregated from data of component political regions (namely counties), forecasters have at least two options regarding a FEA forecast. A FEA aggregate can be forecasted directly or component county forecasts can be summed to form a FEA forecast. Likewise, individual county forecasts can be derived form direct forecasts at the county

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level or can be obtained from an aggregate FEA forecast using proportionality constants. The forecasting literature is far from unified on the appropriate method to use.

As shown in Figure 1, the specific spatial context of this research is a large, well-defined region comprising 18 counties in eastern Washington and northern Idaho. It is one of 172 BEA economic areas delineated by the U.S. Bureau of Economic Analysis (U.S. Department of Commerce 1995). Because the BEA blankets the country with contiguous economic areas, some areas make more economic sense than others do. *Economic sense* is defined metaphorically as a glue that binds a region together economically. An economic region should have a central, dominant node providing functions not found in the hinterland. It should be a well-defined market area in terms of trade in goods and labor. A regional culture should also be present. The Spokane FEA is just such an economic region. Before imperialism fell from grace in modern times, the region was referred to as the *Inland Empire* (e.g., see London 1990). The region has a dominant economic center in Spokane County (WA), a metropolitan statistical area, and its rapidly growing Idaho neighbor, Kootenai County (Coeur d'Alene). Much of its area is rural and remote, with agriculture, wood products, and recreation the major basic industries. A common market area is also suggested by newspaper circulation (*Spokesman-Review*) and television reception (KHQ, KXLY, and KREM). [See Preston (1978).]

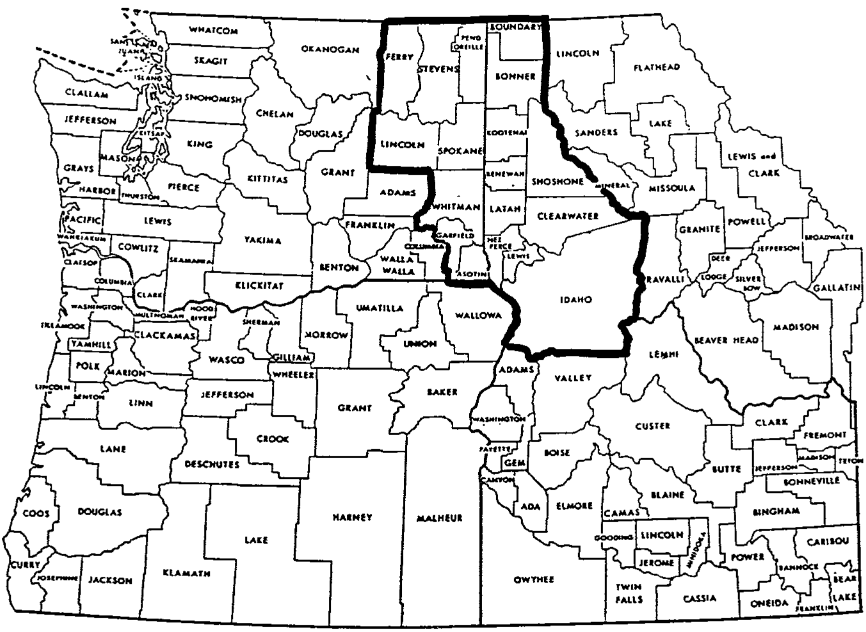
2. Related literature

Little literature exists on the issue of aggregation and forecast accuracy in a univariate time series and spatial context. But work in related areas is instructive, as it demonstrates that little theoretical or empirical consensus exists on whether top-down or bottom-up methods are superior. In three different areas of inquiry, researchers have addressed the issue of aggregation and forecast accuracy. These three areas (aggregation in econometrics, business forecasting, and regional forecasting) are addressed briefly in the following pages.[1]

The early econometrics literature on aggregation addressed multivariate, causal econometric models only (Theil 1954; Orcutt, Watts, and Edwards 1968; Edwards and Orcutt 1969; Zellner 1969; Aigner and Goldfeld 1974). Because of this trend, econometricians were interested not only in forecasting and forecast accuracy, but also in the precision of estimates of parameters in microeconomic relationships. No consensus emerged regarding aggregation and forecast accuracy.

[1]For a more detailed discussion of the forecasting literature on aggregation and forecast accuracy and the related literature in spatial econometrics, see Miller (1998).

Figure 1. Location of the Spokane functional economic area in the Pacific Northwest



In the business forecasting literature, results of empirical work lean toward a disaggregated approach. For example, Kinney (1971) and Collins (1976) conclude that aggregating forecasts done at the sub-firm level is more accurate than forecasting aggregated firm-level data. Schwartzkopf, Tersine, and Morris (1988) and Dangerfield and Morris (1992) conclude that disaggregation improves accuracy of forecasts of sub-aggregate series.

In regional economic forecasting, the results are again mixed. Some advocate aggregation prior to estimation. Grunfeld and Griliches (1960) conclude that if explanation of an aggregate economic relationship is desired, aggregation of the disaggregated relationships prior to estimation can lead to improved goodness of fit, if specification error in the disaggregated relationships outweighs the aggregation error. Likewise, Harris (1973) concludes that it would be appropriate that "regional forecasts be allocations of national forecasts" (p. 71). Milne, Glickman, and Adams (1980) argue that the need for national consistency in regional projections and the relative lower quality of data at the regional level suggest a top-down approach. In a sectoral (not spatial) context, Kurre and Weller (1989) conclude that univariate time series forecasts of metropolitan total employment are more accurate than the sum of forecasts of industrial sectors. Similarly, Miller (1998) concludes that direct state-level forecasts are slightly more accurate than the aggregation of substate, economic region forecasts, and that direct sub-state economic region forecasts are less accurate than forecasts derived by disaggregating state-level forecasts with proportionality constants.

By contrast, other regional researchers favor a bottom-up or disaggregated approach. Ballard and Wendling (1980) argue that constraining the sum of growth in regions to a predetermined national growth rate ignores regional causes of national growth. Dunn, Williams, and DeChaine (1976) analyze local area telephone demand and conclude that aggregating subaggregate univariate forecasts is more accurate than forecasting the aggregate area directly. Finally, Taylor and Charney (1983) argue that the aggregation rule should depend on many factors, including data quality and model specification.

Given the lack of consensus in the literature on the proper approach with respect to aggregation in general, and spatial aggregation in particular, we are left with a case by case assessment of rules for handling spatial aggregation in regional forecasting. The next section describes the methods used in a case study of regional employment forecasting in the FEA/county spatial context.

3. Methods

Exponential smoothing models are applied to time series of monthly total employment data for the Spokane FEA and its 18 component counties. The top-down and bottom-up question is addressed for both FEA-level and county forecasts. Exponential smoothing models are chosen for their proven accuracy and their ease of application.[2] A univariate cousin of exponential smoothing, the autoregressive, integrated moving average (ARIMA) method, can give similarly accurate forecasts, but the method is much more data-hungry (in terms of number of observations) and is much more analytically complex. Likewise, multivariate methods are more data-hungry in terms of number of data series that need to be obtained and maintained. By using exponential smoothing methods, however, we abandon hope of doing 'what-if' simulation analysis that is possible with causal, multivariate regression methods. Tradeoffs exist.

[2]For a discussion of the accuracy of extrapolative methods in general, and exponential smoothing in particular, see Makradakis, *et al.* (1982).

The models here are multiplicative Winters in form and estimated with the software package Forecast Pro for Windows (Winters 1960 and Stellwagen and Goodrich 1994).[3] Models are defined as follows:

$$Y_t(m) = (S_t + mT_t)I_t(m) \qquad (1)$$

where:

$Y_t(m)$	=	Forecast for time t+m from base t;
S_t	=	Smoothed level at end of time t;
m	=	Forecast lead time;
T_t	=	Smoothed trend at end of time t; and
I_t	=	Smoothed seasonal index at end of time t

Level, trend, and seasonal values are obtained from the following equations:

$$S_t = a(Y_t/I_{t-p}) + (1-a)(S_{t-1} + T_{t-1}) \qquad (2)$$

$$T_t = g(S_t - S_{t-1}) + (1-g)T_{t-1} \qquad (3)$$

$$I_t = d(Y_t/S_t) + (1-d)I_{t-p} \qquad (4)$$

where:

p	=	The number of periods per year; and
a, g, and d	=	Smoothing parameters for level, trend, and seasonal indexes, respectively.

The purpose of smoothing is to take account of (sic) changes in all series characteristics, level, trend, and seasonality. Choosing not to smooth one of these characteristics of the series would be an implicit assumption that the characteristic is constant over time.

All smoothing parameters occur in the interval [0, 1]. If a smoothing parameter is close to one, the method is weighting recent values in level, trend, or seasonality heavily and discounting past values. As the smoothing parameter approaches 0, the method uses more distant past information in the computation of the forecast. To estimate model parameters, the Forecast Pro program uses an iterative search to minimize the sum of squared errors over the historic data.

Two FEA-level forecasts are compared. The first comes from a direct forecast of the FEA-level time series. The second, a bottom-up approach, is an aggregation of individual forecasts performed on the 18 component counties. Likewise, two alternative forecasts are considered for each county in the region, a direct forecast on county data, and a forecast created as the product of the FEA-level forecast and a proportionality constant determined as the proportion of monthly FEA employment occurring in the county in that month in the final year in the historical sample period. Figure 2 illustrates the relationship of these different forecasts.

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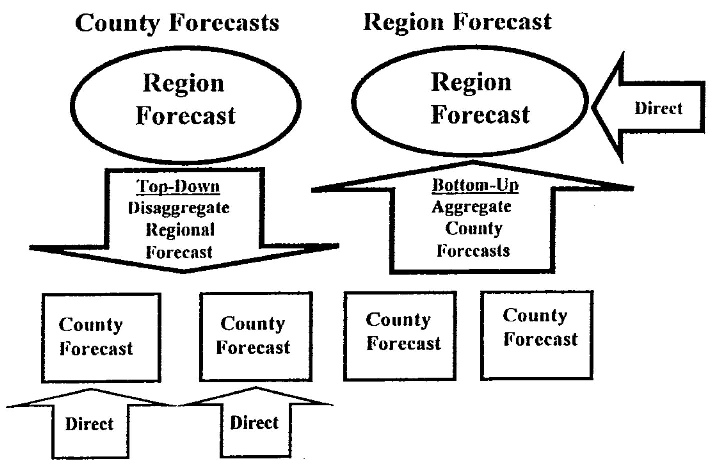
[3] The software program used here, while comprehensive and user-friendly, is only one among many such programs available for time series analysis. Other popular programs include, among others, Micro TSP, E-Views, and RATS.

Figure 2. Direct, top-down, and bottom-up forecasts



Forecast accuracy is measured on the basis of out-of-sample forecasts of monthly data for the 12 months of 1995. Models are estimated using data from January 1990 to December 1994. The resulting models are used to make monthly forecasts for the 12 months of 1995. MAPE is the accuracy measure.

4. The Data

The series are generated from monthly total employment data for counties of eastern Washington and northern Idaho from 1990 through 1995. Total employment is the broadest employment measure and is available on a timely basis at the county level. It is by person (not job) and by place of residence. Total employment data are presently used to compute the unemployment rate for county, state, and national political jurisdictions. In all time periods the FEA total employment is the sum of the county total employment numbers. These employment series are interesting and challenging from a forecasting standpoint. They are universally trended and seasonal and often have increasing variability through time.

In a perfect world employment would most likely not be the measure of choice for regional economic performance. Broader measures of economic activity, such as personal income or gross regional product, would be superior. Gross product data are not available at the county level. Personal income data appear with a long lag and only for annual time periods, characteristics that are not good for short-term forecasting.

5. Results

The basic forecasting results for the 18 counties and the Spokane FEA appear in Table 1. The first two columns identify the areas and their corresponding mean total employment for the estimation period. Note the wide variation in county size, from Garfield with a mean employment barely over 1,000, to nearly 170,000 in Spokane County, which accounts for over 52 percent of FEA employment. The next four columns contain in-sample measures of

Table 1. Statistics for exponential smoothing models of monthly total employment for the Spokane functional economic area and its component counties[a] (n = 60, 1990-1 through 1994-12)

County	MEAN	MAD[b]	RMSE[b]	R^2	In-sample MAPE[b]	Out-of-sample, cumulative average MAPE[c]
Asotin	9,445	95.8	132.0	.95	1.0	1.0
Benewah	3,336	48.8	64.7	.95	1.5	0.5
Bonner	12,190	171.5	228.9	.97	1.4	0.7
Boundary	3,386	51.5	71.4	.95	1.5	0.6
Clearwater	3,407	62.2	72.7	.84	1.8	1.3
Ferry	2,439	39.4	50.0	.83	1.6	1.4
Garfield	1,012	21.9	25.7	.89	2.2	2.1
Idaho	5,621	102.1	133.2	.88	1.8	1.1
Kootenai	36,700	557.9	730.6	.98	1.5	1.0
Latah	13,900	315.2	415.0	.87	2.3	1.6
Lewis	1,418	25.1	31.8	.91	1.8	.9
Lincoln	4,065	61.1	76.1	.94	1.5	1.3
Nez Perce	19,870	219.2	307.0	.92	1.1	1.8
Pend Orielle	3,124	50.2	63.8	.90	1.6	3.1
Shoshone	5,585	180.2	317.6	.47	3.5	1.9
Spokane	169,900	804.9	1,034.0	.98	0.5	1.0
Stevens	13,280	123.5	155.2	.98	0.9	1.1
Whitman	17,200	180.4	242.5	.93	1.0	0.9
Spokane FEA	325,900	1770.0	2301.0	.98	0.5	0.5

[a]All models are multiplicative Winters in form, with linear trend and multiplicative seasonality. Models are estimated with the software Forecast Pro for Windows, version 2.0. See Stellwagen and Goodrich (1994)

[b]MAPE is mean absolute percent error. MAD is mean absolute deviation. RMSE is root mean square error

[c]Out-of-sample forecast statistics are based on a rolling base evaluation with a twelve-month hold out sample. The initial base period is 1994-12 (December 1994). After initial monthly forecasts from the base period, the model is rolled forward one month and forecasts are made again. Model parameters are not reestimated. The cumulative out-of-sample MAPE is computed over 78 forecasts, twelve one-period, eleven two-period, ten three-period, ... , and one twelve-period forecast

model fit, mean absolute deviation (MAD), root mean square error (RMSE), R^2, and mean absolute percent error (MAPE), respectively. In general the models fit the data well. Only one in-sample MAPE is over 3 percent, and only two are over 2 percent. For Spokane County, and the FEA, the in-sample MAPE is 0.5 percent. The last column of Table 1 contains cumulative out-of-sample MAPE statistics. These columns indicate that the models forecast well for the 12 months of 1995, data points not included in the estimation sample.

Table 2 contains information on the relative forecast accuracy of FEA-level and aggregated county forecasts. As noted in the discussion of related literature above, this method is often referred to as a *bottom-up forecast.* The forecasts with the two methods are similar. In all but two months the forecast errors are of the same sign, and the MAPE is low for both methods. The FEA-level approach wins the competition, but by a margin so small that it is of no practical importance. The dominant result is that both methods forecast FEA total employment extremely accurately in this time period.

Table 2. Comparison of bottom-up and aggregate monthly total employment forecasts for the Spokane functional economic area

Time period	Actual	Bottom-up forecast	% Error	Aggregate forecast	% Error
1995-1	351,314	352,016	0.02	352,959	0.47
1995-2	352,495	351,477	-0.29	352,618	0.03
1995-3	355,277	353,069	-0.62	354,189	-0.31
1995-4	359,185	357,491	-0.47	358,441	-0.21
1995-5	366,411	362,798	-0.99	363,397	-0.82
1995-6	363,974	360,843	-0.86	361,273	-0.74
1995-7	364,224	363,159	-0.29	363,299	-0.25
1995-8	366,396	363,578	-0.77	363,962	-0.74
1995-9	363,841	361,197	-0.73	361,346	-0.69
1995-10	368,019	366,369	-0.45	366,296	-0.47
1995-11	368,057	367,411	-0.18	367,343	-0.19
1995-12	364,551	366,189	0.45	366,546	-0.55
MAPE[a]			0.52%		0.46%

[a]This is a standard MAPE (mean absolute percent error) computed over 12 forecasts, one for each month of 1995, not a cumulative MAPE as in Table 1

Relative forecast accuracy at the county level is addressed in Table 3. The question is whether direct county forecasts are more accurate than disaggregated FEA-level forecasts. The results in Table 3 are mixed. The average MAPE over 18 counties is somewhat lower for the direct approach, even including the large value (7.11 percent) for Pend Orielle County. But this number masks a much larger amount of inconclusive information. For Bonner, Garfield, Kootenai, Latah, Pend Orielle, and Shoshone Counties, top-down forecasts of county total employment are decidedly more accurate than their direct counterparts. On the other hand, for Benewah, Boundary, Clearwater, Ferry, Idaho, Lewis, Lincoln, and Nez Perce Counties, direct forecasts are more accurate. No other discernable patterns emerge.

Table 3. Comparison of the accuracy of direct and top-down forecasts of monthly total employment for counties of the Spokane FEA

County	Direct MAPE[a]	Top-Down MAPE[b]
Asotin	0.68	0.46
Benewah	0.39	0.98
Bonner	1.71	0.98
Boundary	0.38	0.99
Clearwater	1.01	2.86
Ferry	1.35	2.77
Garfield	4.69	2.84
Idaho	1.09	4.84
Kootenai	2.20	0.98
Latah	2.45	1.30
Lewis	1.36	4.84
Lincoln	1.37	2.59
Nez Perce	1.51	3.13
Pend Orielle	7.11	2.17
Shoshone	1.79	0.98
Spokane	1.65	1.58
Stevens	0.85	1.37
Whitman	0.94	0.96
Average (18 counties)	1.81	2.03

[a]This is a standard MAPE computed over 12 forecasts, one for each month of 1995, not a cumulative MAPE as in Table 1
[b]Top-down forecasts are derived as the product of the FEA forecast for the period and the county's proportion of total FEA employment in the same month of 1994. MAPE is mean absolute percent error

6. Concluding Comments

One main point should not be overshadowed by the comparison of the accuracy of the forecast methods here. Whether we want a short-term forecast of total employment at the FEA level or forecasts of total employment for the counties that make up the FEA, exponential smoothing models applied to a relatively short data series of monthly total employment can yield accurate forecasts. MAPEs (for direct forecasts) less than 2 percent are the rule rather than the exception.

Forecasts of FEA total employment are in general more accurate than forecasts for its component counties. No in-sample MAPE is lower than the 0.5 obtained for the Spokane FEA. No cumulative out-of-sample MAPE is lower. The percent error for each of the monthly out-of-sample forecasts for the FEA is never greater than 1 percent and averages about 0.5 percent in both the direct and bottom-up approaches. This fact should be comforting to those who see the landscape as a collection of economic rather than political regions.

These results have implications for short-term employment forecasts by government agencies. Given the accuracy demonstrated with the methods discussed in this paper and the importance ascribed to labor force developments in general, methods such as those used here could be used in estimating county or FEA-level employment and unemployment. Local department of employment personnel publish preliminary labor force information with only about one and one-half months lag time. These estimates are later revised and then revised again (*benchmarked*). Six months ahead forecasts of labor force data, from a base of benchmarked data, may be more accurate than preliminary data now published, or may be used to improve preliminary estimates. This could be a fruitful line of future research.

While the research here concerns spatial aggregation and employment forecasting in a specific regional context, there is nothing sacred about regional employment as a measure of regional economic activity or about the Spokane FEA as a case study. Other measures of regional performance exist, and other regions are worthy of consideration. For example, as mentioned in the data section above, data on a superior measure of regional economic performance, personal income, are available, but with inferior timing and inferior temporal aggregation. Nonetheless, another fruitful line of research might involve the use of extrapolative methods to forecast, or at least update, regional personal income data in several regions and to examine accuracy and spatial aggregation issues in this context.

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