Journal of Forest Economics 20 (2014) 305–315

Contents lists available at ScienceDirect

Journal of Forest Economics

journal homepage: www.elsevier.com/locate/jfe

Projecting county pulpwood production with historical production and macro-economic variables☆

Consuelo Brandeis[a,*], Dayton M. Lambert[b]

[a] USDA Forest Service, Southern Research Station, 4700 Old Kingston Pike, Knoxville, TN 37919, United States
[b] University of Tennessee Institute of Agriculture, Department of Agricultural and Resource Economics, Knoxville, United States

ARTICLE INFO

Article history:
Received 18 November 2013
Accepted 9 September 2014

Keywords:
County pulpwood forecast
Vector autoregressive
Spatial panel VAR

ABSTRACT

We explored forecasting of county roundwood pulpwood production with county-vector autoregressive (CVAR) and spatial panel vector autoregressive (SPVAR) methods. The analysis used timber products output data for the state of Florida, together with a set of macro-economic variables. Overall, we found the SPVAR specification produced forecasts with lower error rates compared to CVAR specifications. Nonetheless, high forecast errors across counties revealed the uncertainty associated with projecting volumes of county pulpwood production.

Published by Elsevier GmbH. on behalf of Department of Forest Economics, Swedish University of Agricultural Sciences, Umeå.

Introduction

Developing econometric models for relatively small regions such as counties or mill procurement zones requires disaggregated data that may be difficult and/or expensive to obtain. Yet transportation costs constrain primary wood-using mills to localized markets, justifying the need for small scale supply and demand models. Vector autoregressive (VAR) models require less disaggregated data, offering

* Corresponding author. Tel.: +1 8658622028; fax: +1 8658620262.
E-mail address: cbrandeis@fs.fed.us (C. Brandeis).

http://dx.doi.org/10.1016/j.jfe.2014.09.002
1104-6899/Published by Elsevier GmbH. on behalf of Department of Forest Economics, Swedish University of Agricultural Sciences, Umeå.

an alternative to fully specified supply-demand econometric models. In a VAR setting, a variable's movement is estimated in terms of past information for all variables in the system including itself.

Pulpwood forecasts can provide valuable information to primary mills for planning timber procurement, and to state extension foresters for directing management efforts to critical areas. Without adequate forest management, counties experiencing higher demand for pulpwood may be challenged in the future with respect to roundwood supply. Ex-ante identification of these areas may be useful to forests managers and timberland owners for planning forest management activities.

This study evaluated the performance of different VAR specifications forecasting pulpwood production for a set of Florida counties. The main specifications investigated include a cross-sectional VAR specification (CVAR) and a specification which models the effects of geographic spillover between counties on pulpwood production (SPVAR).

Literature review

A number of published studies use time series models to forecast the short-term performance of the forest products sector using macroeconomic variables as predictors of demand and or supply. Hetemäki et al. (2004) analyzed the effect of import demand on forecasts of Finnish lumber exports and Finland's demand for saw-logs. Alavalapati et al. (1996) examined the effect of shocks to Canada's exchange rate on the domestic demand for pulp. Jennings et al. (1991) forecasted Canada's lumber industry using gross national product, exchange rates, and housing starts.

Research comparing the forecast performance of vector autoregressive (VAR) to other time series models proves mixed. Hetemäki et al. (2004) found no significant forecast improvement between a first order autoregressive process and a more complex VAR system. Similarly, Malaty et al. (2007), evaluating forecasted stumpage prices for pine saw-logs in Finland, found a VAR model had the largest forecast error among the methods evaluated. In contrast, forecasting stumpage prices for U.S. pine saw-timber, Mei et al., (2010) found VAR model predictions to be more accurate than other methods, including an autoregressive moving average (ARMA) model, a vector error correction (VEC) model, and a state space representation of price movements. Likewise, Hetemäki and Mikkola's (2005) analysis of paper imports in Germany found that a VAR model with exogenous regressors (VARX) generated more accurate forecasts compared to other methods. Most studies of forest product forecasts target large geographic or administrative areas. Buongiorno et al. (1988) study is an exception, using macroeconomic variables to predict harvests within a county. The authors used housing starts, lumber prices, and information on cut saw-timber volumes to forecast saw-logs harvests by major land ownership type (private and public).

Methods

Vector autoregressive (VAR) models allow for the analysis of interrelated time series data by making use of lagged observations. In a VAR, variables affect each other's past and current outcomes. Because of this feedback, the structural VAR cannot be estimated directly without specific identifying restrictions. Instead, one typically estimates the reduced form (or standard VAR) which excludes contemporaneous feedback. A two-variable (y and z) first-order standard VAR system with time periods $t = 1, \ldots, T$ is

$$\begin{aligned} y_t &= \beta_{10} + \beta_{11} y_{t-1} + \beta_{12} z_{t-1} + \varepsilon_{1t}, \\ z_t &= \beta_{20} + \beta_{21} y_{t-1} + \beta_{22} z_{t-1} + \varepsilon_{2t}, \end{aligned} \tag{1}$$

where β are coefficients to be estimated for equations $j = 1, \ldots, J$ system variables and ε_{jt} are the error terms. Provided both equations include the same set of regressors, the standard VAR can be estimated consistently using equation-by-equation ordinary least squares (OLS) (Enders, 2003; Hamilton, 1994).

Combining observational units into a panel provides an augmented sample which controls for unit specific effects and time effects. Unit specific effects account for heterogeneity across units while time fixed effects capture exogenous shocks that affect all units simultaneously. Identifying neighboring units allows for the inclusion of a spatial component to model geographic spillover. If significant spatial interaction exists, omitting the spatial lag of the dependent variables would result in inconsistent estimators (Anselin, 1988). Moreover, including information pertaining to spatial interactions may improve forecast accuracy (Baltagi et al., 2011).

Considering a first-order spatial autoregressive panel with cross-sections units $i = 1, \ldots, N$; and time periods $t = 1, \ldots, T$, a first-order two-variable spatial panel VAR system is

$$\begin{aligned} y_{it} &= \rho_1 \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_{11} y_{it-1} + \beta_{12} z_{it-1} + \gamma_{1i} f_i + \varphi_{1t} d_t + \varepsilon_{1it}, \\ z_{it} &= \rho_2 \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_{21} y_{it-1} + \beta_{22} z_{it-1} + \gamma_{2i} f_i + \varphi_{2t} d_t + \varepsilon_{2it}, \end{aligned} \tag{2}$$

where ρ_1 and ρ_2 are spatial autoregressive coefficients and $\sum_{j=1}^{N} w_{ij} y_{jt}$ the spatial lag. The weights, w_{ij}, correspond to elements of an $N \times N$ weight matrix W; f_i represents the unobserved individual effects of unit i; d_t is the unobserved time effects; β, γ, and φ are coefficients to be estimated; and ε_{1it}, ε_{2it} are the error terms.

Estimating the equations in (2) including the individual effects as additional parameters can induce an incidental parameters problem (when the number of parameters increases with N) and consequently biased estimates. A common practice to avoid the incidental parameter problem is to transform the variables to eliminate fixed effects from the equation, usually by taking first-differences. However, applying first-differences to the dynamic panel results in correlation between the lagged variables and the first-differenced error term. Under these conditions, the generalized method of moments (GMM) appears to be a preferred estimation method. For the dynamic spatial panel estimation, research finds Blundell and Bond's (1998) system of generalized method of moments (system GMM) exhibits the best sample properties (Monteiro and Kukenova, 2009). When the system GMM estimator is used, estimation of the level and differenced equations occurs jointly, with lags of the differenced variables the instruments for the level equation, and vice versa. However, the system GMM estimator is most appropriate for panels with large N and small T. Considering that instruments increase at a quadratic rate in T, a data set with a large time dimension will generate a sizable number of instruments, which may lead to bias estimates and affect instrument validity tests (Roodman, 2009).

For panels with a large time dimension, two alternatives to the system GMM estimator include the bias corrected least squares dummy variable (LSDV) and the Anderson and Hsiao (AH) first-difference estimator. The least squares dummy variable technique (estimation that either includes or removes the fixed effects by mean-differencing) can result in significant bias even under relatively large time dimensions (Judson and Owen, 1999). A biased corrected LSDV, however, performs well irrespective of time dimensions (Judson and Owen, 1999). Unfortunately, bias correction methods for LSDV apply only under the assumption of strictly exogenous covariates. The AH approach offers more flexibility for dealing with endogenous variables. The method involves working with the variables in first differences to eliminate fixed effects. Estimation proceeds by instrumental variables using as instruments the second lag of the endogenous variables in levels. Although the AH method is not as efficient as the system GMM estimator, it does provides consistent estimates even when the time dimension is relatively large (Judson and Owen, 1999).

Data sources and model specification

We used the CVAR and SPVAR specifications to project county pulpwood production for Florida's Northwest FIA survey unit (Fig. 1). These 16 counties comprised 41 percent of the state's timberland (Brown et al., 2012), included close to 30 percent of the mill capacity (based on total number of mills), and accounted for 38 percent of the roundwood produced by the state during 2009 (Johnson and Nowak, 2011).

The CVAR and SPVAR systems included three system variables – the county pulpwood production, the U.S. real gross domestic product (GDP) hypothesized to capture the demand for pulpwood products, and the producer price index for pulpwood products (PPI), a proxy for timber prices. Additionally, we assumed that temporal external shocks affecting pulpwood production resulted mostly

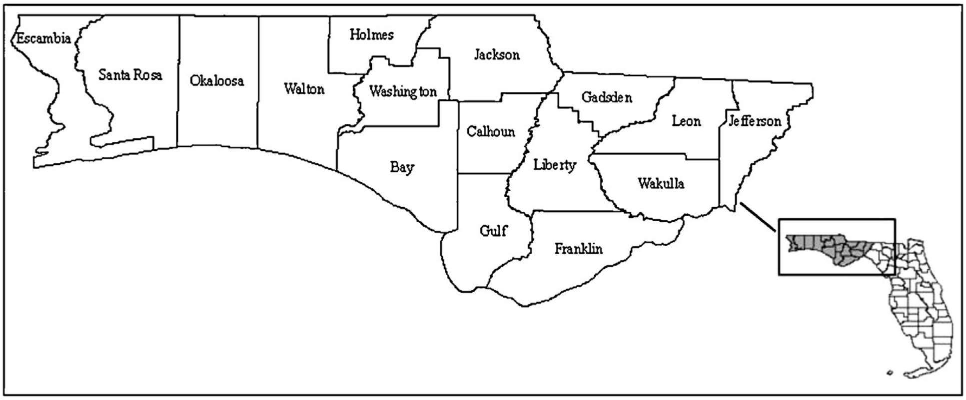

Fig. 1. Florida's FIA Northwest Unit.

from shocks to the economy. Therefore, we used a binary variable denoting U.S. economic recession years, representing business cycles expansions and contraction (FRED, 2012).

We used county pulpwood production data collected by the USDA Forest Service (FS) Forest Inventory and Analysis Timber Products Output (TPO) program. The TPO program performs periodic surveying of all active primary wood processing mills to estimate volume and flow of wood harvests. Mill survey frequency varies across the FS regional units, with the FS southern region collecting information biannually for all primary mills except pulp mills, which are surveyed annually. Part of the information gathered from pulp mills includes volume of roundwood consumed by tree species and by county of origin. The volume of pulpwood produced by a county corresponds to the sum of volumes reported by pulp mills procuring roundwood from that county.

Data on GDP are from the U.S. Department of Commerce, Bureau of Economic Analysis (BEA, 2012) and the PPI for pulp and paper products data are published by the Bureau of Labor Statistics (BLS, 2012). The recession indicator used is published by the Federal Reserve Bank based on data provided by the National Bureau of Economic Research (FRED, 2012). All series included annual data from 1947 to 2011.

We first-differenced the log transformed variables to obtain stationary series and moderate heteroskedasticity. The untransformed county pulpwood production series are displayed in Fig. 2. To assess the accuracy of a short-term forecast we reserved the last two years of data, resulting in a sample with $T = 62$ years and $N = 16$ cross-sectional units (counties). However, to evaluate forecast accuracy over longer horizons we estimated SPVAR using a recurring rolling window. Using a recurring rolling window parameters are estimated repeatedly, each time using a sample increased by one year of data.

Both CVARs and SPVAR included two lags of the system variables. We based the lag length selection on the akaike information criterion (AIC) as recommended in Enders (2003). Additionally, we tested for unit roots using the Augmented Dickey-–Fuller test for CVARs and the Levin–Lin–Chu test (Levin et al., 2002) for SPVAR. The Levin–Lin–Chu test applies to cases where the number of panels is small in relation to the number of time periods. We tested for cointegration among the system variables using the Engle–Granger test (Schaffer, 2010) for CVARs and the Westerlund panel cointegration tests (Persyn and Westerlund, 2008) for SPVAR. Tests failed to reject the null of no cointegration on both specifications. However, in the panel model we failed to reject the null of no cointegration only after controlling for cross-sectional dependence. Consequently, we report standard errors clustered on the time variable.

We specified the panel using county fixed effects, considering the sample includes a group of counties representing a region of the state opposed to a random sample of counties. Specifying a time effect indicator, however, would result in multicollinearity with GDP and PPI (the macroeconomic

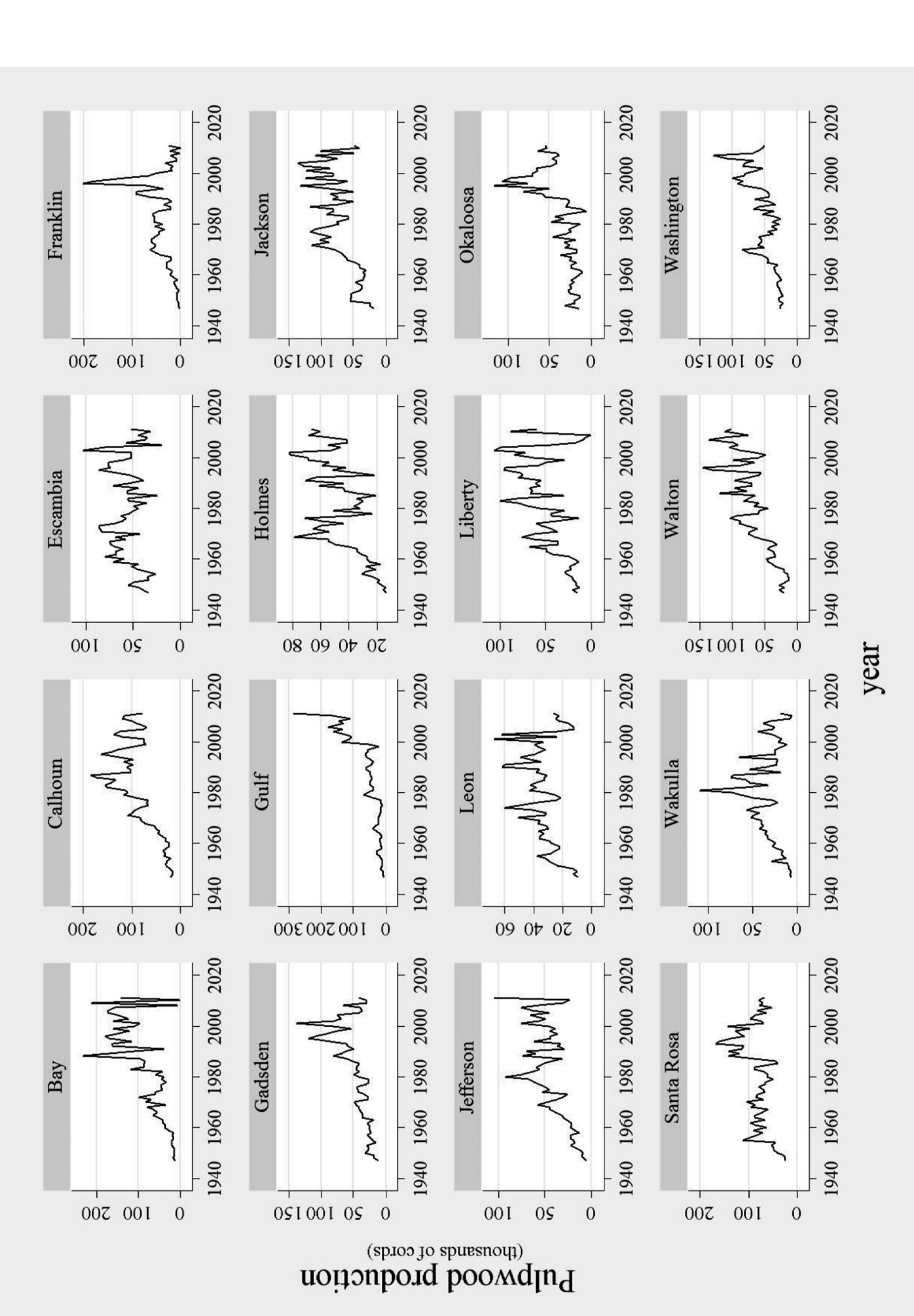

Fig. 2. County pulpwood production series.

variables vary only across time, not across units). Moreover, we specified the panel VAR including spatial lag components of the dependent variable to capture spillover effects of pulpwood production among neighboring counties. We also included a temporal spatial lag, assuming that current production ensues in part from information on the past production of neighboring counties. Spillover effects from local production were introduced into the model using an inverse distance weighting matrix (W), with the Euclidean distance between county centroids measuring distance. The row sums of the neighborhood matrix were normalized to one such that spillover effects are scale neutral (Anselin, 1988). Each element w_{ij} ($i \neq j$) of W corresponded to the inverse distance from county i to county j, with elements of the matrix diagonal set to zero. This weighting scenario reflects the expected higher influence from nearby counties. The region essentially represents one or perhaps two markets. However, natural advantages in terms of soil fertility are likely shared across county borders. Forest composition and timber tract ownerships span county delineations as well. Roads and rail connect inter-county commerce. We cannot directly discern these relationships, but modeling spatial interactions proxy the neighborhood effects of shared similar natural and physical advantages on pulpwood output.

Instead of solving the equations for pulpwood production, GDP, and PPI simultaneously we focused on the pulpwood supply equation,

$$V_t = \rho_v WV_t + \gamma_v WV_{t-1} + \sum_{p=1}^{2} \beta_{vv}^p V_{t-p} + \sum_{p=1}^{2} \beta_{vg}^p G_{t-p} + \sum_{p=1}^{2} \beta_{vq}^p Q_{t-p} + \beta_v D_t + f_v + \varepsilon_{vt}, \tag{3}$$

where, V, G, and Q are $N \times 1$ vectors of the transformed variables (county pulpwood volumes, GDP and PPI, respectively); W is the neighborhood relational matrix; D is an $N \times 1$ vector indicating U.S. economic recession years ($D = 1$ if the year corresponds to an economic recession year and $D = 0$ otherwise); f_v are county fixed effects; ρ_v and γ_v are the spatial autocorrelation and the spatial temporal autocorrelation coefficients for the pulpwood volume equation; β_{vm}^p are the temporal coefficients of order p to be estimated ($p = \{1, 2\}$) for the pulpwood volume equation, v, and variable m ($m = \{v, g, q\}$); and ε_{vt} is an $N \times 1$ vector of error terms. The error terms were hypothesized to be correlated within panels and heteroskedastic. When $\rho_v = \gamma_v = 0$, the above reduces to a panel VAR and estimating by cross-sectional unit results in the standard VAR specification (CVARs).

We estimated the CVARs using ordinary least squares. In selecting the estimation method for SPVAR, however, we considered the characteristics of both the data and the model specification. Specifically, we have a data set with a large time dimension in relation to number of cross-sectional unit and a dynamic panel with an endogenous variable (spatial lag). To address these issues we followed AH and worked with the equation in first-differences,

$$\Delta V_t = \delta_1 \Delta WV_t + \delta_2 \Delta WV_{t-1} + \sum_{p=1}^{2} \delta_{vv}^p \Delta V_{t-p} + \sum_{p=1}^{2} \delta_{vg}^p \Delta G_{t-p} + \sum_{p=1}^{2} \delta_{vq}^p \Delta Q_{t-p} + \delta_v \Delta D_t + \Delta \varepsilon_{vt}.$$

We instrumented the endogenous variable with the first available lag of the corresponding variable in levels. We instrumented ΔWV_t and ΔWV_{t-1} using the second order of the variable's second and third lags in levels ($W^2 V_{t-2}$ and $W^2 V_{t-3}$). The first-lag of the predetermined variables (ΔV_{t-1}, ΔG_{t-1}, and ΔQ_{t-1}) were instrumented with their third lag in levels. To test the validity of the instruments, we included the second lag of the recession indicator (D_{t-2}) as an additional instrument. The above equation was estimated using GMM.

To evaluate the accuracy of the forecasts, pulpwood projections from CVARs and SPVAR estimations were compared with observed values using the mean absolute percent error (MAPE) calculated as,

$$\text{MAPE} = \frac{100}{h} \times \sum_{S}^{S+h} \left| \frac{y_{t+1} - \hat{y}_{t+1}}{y_{t+1}} \right|$$

where S represents the start point for forecast, h corresponds to the number of forecast periods, y_{t+1} is the observed value at time $t+1$, and $\hat{y}_{t+1}$ the predicted value at time $t+1$. The CVAR and SPVAR forecasts were also compared to the ad-hoc step forward (SF) methodology to evaluate potential gains from the added complexity of VAR specifications. When using the SF method, the value observed in period t is used as the forecast for period $t+1$. Accuracy of projections from CVARs was evaluated using the last two years of data. The SPVAR was evaluated using a recursive rolling window which allowed estimating forecasts over longer horizons.

Results and discussion

Pulpwood productions exhibits positive spatial clustering, as evidenced by the positive and significant coefficient of the spatially lagged dependent variable (Table 1); pulpwood production in a county is affected by output from nearby counties. From the perspective of input demands of mills, the observed positive spillover effects may be present due to similar forest composition characteristics, or forest ownerships spanning across county borders. The temporal spatial lag coefficient was not statistically significant; a county's production is not influenced by past activity in neighboring counties. Both the first and second lags of pulpwood production were statistically significant and negative. The negative coefficients on pulpwood production reflect the reduced volumes expected after a county's continuous harvest. Results also suggest a negative and significant effect of PPI on pulpwood production. Gross domestic product and the economic recession indicator were uncorrelated with supply. The lack of statistical significance suggests a more complex relationship between county pulpwood production and general indicators of the economy's health. Various unobserved factors such as policies, markets for final products, and mill procurement practices might contribute to weaken pulpwood production's response to GDP and recession years. For instance, recessions affecting the demand for sawn wood products could, in some instances, promote increased pulpwood harvests. Pulp mills procure wood inputs from roundwood and from sawmill residues. With lower residues available, resulting from lower sawmill activity, pulp mills would need to substitute residues with pulpwood.

We found the SPVAR specification improving the forecasts, although not consistently across counties. The CVAR estimation provided a lower average MAPE in comparison to the other methodologies (CVARs MAPE of 126 for the one-year forecast, compared to 317 and 467 on the SF and SPVAR, respectively). However, the high regional average MAPE from SPVAR resulted from an outlier data point evident in Washington County (Table 2). Excluding Washington County we find the one-year forecast average MAPE improved by eight percent when using SPVAR (104 and 113 average MAPE for SPVAR and CVAR, respectively).

Comparing MAPE values for each county on the one-year forecast, we found SPVAR generated more accurate predictions than CVAR for forty percent of the counties. Examining the two-year forecast,

Table 1
Spatial panel VAR, pulpwood equation.

Variable	Coefficient	Standard error
ΔWV_t	0.699***	0.231
ΔWV_{t-1}	−0.201	0.218
ΔV_{t-1}	−0.218***	0.070
ΔQ_{t-1}	−0.124*	0.555
ΔG_{t-1}	0.564	0.290
ΔV_{t-2}	−0.133**	0.056
ΔQ_{t-2}	−0.632	0.494
ΔG_{t-2}	0.140	0.263
ΔD	−0.0001	0.015
Constant	−0.002	0.009
Number of observations = 870		
Wald chi2(9) = 13.10		

Notes: *** *1 percent;* ** 5 percent; * 10 percent significance.

Table 2
Mean absolute percent error (MAPE) by county and estimation method.

County	FIPS	1-year ahead			2-years ahead		
		SF	CVAR	SPVAR	SF	CVAR	SPVAR
Bay	12005	164	73	85	186	83	86
Calhoun	12013	564	301	62	327	193	93
Escambia	12033	174	128	35	171	117	43
Franklin	12037	144	93	91	171	96	92
Gadsden	12039	2039	76	79	1062	96	131
Gulf	12045	169	96	191	99	96	186
Holmes	12059	301	35	47	267	124	89
Jackson	12063	179	92	70	404	143	70
Jefferson	12065	123	79	49	121	89	76
Leon	12073	182	16	180	178	53	155
Liberty	12077	152	109	98	823	74	90
Okaloosa	12091	331	214	28	529	463	59
Santa Rosa	12113	189	135	322	174	117	298
Wakulla	12129	153	201	71	146	156	87
Walton	12131	204	49	150	382	54	164
	Average	338	113	104	336	130	115
Washington	12133	9	312	5913	106	188	3231

SPVAR (excluding Washington County) yielded smaller MAPE values as well, improving the average forecast by 12 percent compared to CVAR. Compared to the SF projection, both CVAR and SPVAR provide significant improvement to prediction accuracy.

The recurring rolling window estimation allowed us to compare MAPE values over longer forecast horizons. We present results from the forecast of 2010 values using SPVAR projections varying from five to one-year ahead (Table 3). As expected, forecast errors decreased significantly when projecting over a shorter term. Findings reveal county pulpwood production that is not fully captured by the model, resulting on some counties displaying zero forecast accuracy even on a one-step ahead projection (*i.e.* Gulf, Leon, Santa Rosa, and Walton counties).

On average, the forecast methods over-predicted the change in county production on the one-year forecast and under-predicted the two-year values (Fig. 3). While SPVAR first-year forecasts overestimated the change in volume of pulpwood production in 10 of the 16 counties, two-year projections overestimated only 4 of the 16 counties.

Table 3
MAPE for the forecast of 2010 values using a rolling window, SPVAR model.

County	FIPS	2005 → 2010	2006 → 2010	2007 → 2010	2008 → 2010	2009 → 2010
Bay	12005	745	161	96	97	85
Calhoun	12013	4849	456	75	46	62
Escambia	12033	1606	145	43	81	35
Franklin	12037	284	128	93	96	91
Gadsden	12039	1172	126	138	103	79
Gulf	12045	1443	31	151	127	191
Holmes	12059	7024	561	268	133	47
Jackson	12063	713	149	84	95	70
Jefferson	12065	2419	163	134	123	49
Leon	12073	3967	325	197	91	180
Liberty	12077	767	121	137	101	98
Okaloosa	12091	1957	194	63	91	28
Santa Rosa	12113	2931	84	166	142	322
Wakulla	12129	1027	106	100	105	71
Walton	12131	1887	170	133	126	150
	Average	2186	195	125	104	104

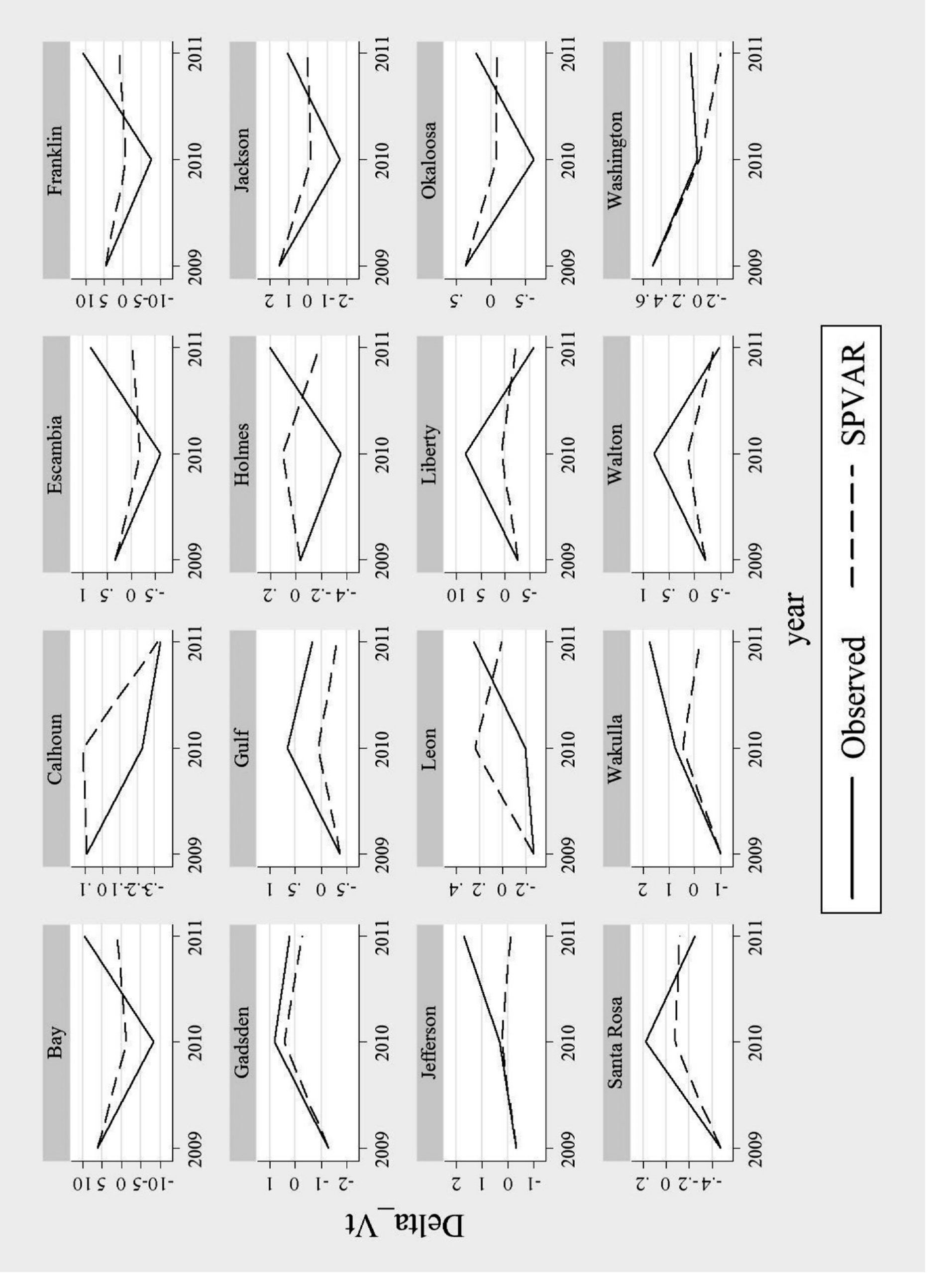

Fig. 3. Observed values versus the SPVAR forecasted figures.

Conclusions

Initial examination of the performance of CVAR and SPVAR models to forecast future timber production at the county level revealed a mixed picture, with SPVAR estimation exhibiting improved forecast accuracy relative to CVAR models and the naïve step-forward approach. Yet forecast accuracy varied considerably between counties. In effect, the flow of pulpwood differs considerably across counties and across time. Controlling for county heterogeneity and spatial interaction with SPVAR improves the forecasts but the gap between observed and projected values remained relatively high for a number of counties.

Rapidly expanding wood energy industries, such as wood pellet mills, pose increased demand for small-size logs and suggest likely competition with pulp mills. Under increasing potential resource competition, timely information of county pulpwood production represents a valuable commodity. However, pulpwood production data collected by TPO are released to the public with an approximate two-year lag. Forecasts using historical TPO information can provide interim information bridging the gap between data collection and publication. Results from this research provide information to guide future forecasting efforts of the pulpwood sector with a method to incorporate geographic spillover effects into predictions. The forecasting exercise provides evidence of the large errors associated with a simple step forward methodology, revealing the potential improvement in accuracy resulting from a formal specification.

However, these results justify exploration of alternative methods using spatial effects that could further improve forecast accuracy. For instance, future research comparing SPVAR performance with the Bayesian spatial prior VAR developed in LeSage and Krivelyova (1999) and/or exploring an augmented state space model incorporating the spatial spillover effect.

Acknowledgements

I would like to add our thanks to reviewers and information to acknowledge partial funding for co-author. A version of this paper was resented at the 2013 Southern Forest Economics Workers Annual meeting in Auburn, Alabama. The authors wish to thank Donald G. Hodges and Christian Vossler for their valuable comments on earlier research leading to this paper as well as the anonymous reviewers for their helpful comments and suggestions. Lambert's research was partially funded by USDA Hatch Project Funds, NE-1049.

References

Alavalapati, J., Luckert, M., Adamowicz, W., 1996. Short-term influences on Canadian wood pulp prices and exports: a vector autoregression analysis. Can. J. For. Res. 26 (4), 566–572.
Anselin, L., 1988. Spatial Econometrics: Method and Models. Kluwer Academic Publishers, London.
Baltagi, B.H., Fingleton, B., Pirotte, A., 2011. Estimation and forecasting with a dynamic spatial panel data model. Spatial Economics Research Centre, discussion paper 95. Available at (http://www.spatialeconomics.ac.uk/textonly/SERC/publications/download/sercdp0095.pdf) (accessed March 2012).
Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econometrics 87, 115–143.
Brown, M.J., Nowak, J., Johnson, T.G., Oswalt, S.N., Chamberlain, J.L., Barnard, E.L., 2012. Florida's Forests, 2007. U.S. Department of Agriculture Forest Service, Southern Research Station, SRS-188.
Buongiorno, J., Kang, Y., Connaughton, K., 1988. Predicting the effect of macro-economic variables on timber harvest in small regions: methods and application. Agric. Syst. 28, 241–257.
BEA, Bureau of Economic Analysis. 2012. Table 1.1.5. Gross Domestic Product. U.S. Department of Commerce. Available at (http://www.bea.gov/iTable) (accessed March 2012).
BLS, Bureau of Labor Statistics, 2012. Producer Price Index—Pulp and Paper Products. BLS, Available at ⟨http://data.bls.gov/data/⟩ (accessed March 2012).
Enders, W., 2003. Applied Econometric Time Series, 2nd ed. John Wiley & Sons, Hoboken.
FRED, Federal Reserve Bank of St Louis, 2012. NBER based Recession Indicators for the United States from the Peak through the Trough. FRED, Available at ⟨http://research.stlouisfed.org/fred2/series/USRECM⟩ (accessed March 2012).
Hamilton, J., 1994. Time Series Analysis. Princeton University Press, Princeton.
Hetemäki, L., Hanninen, R., Toppinen, A., 2004. Short-term forecasting models for the Finnish forest sector: lumber exports and sawlog demand. For. Sci. 50 (4), 461–472.
Hetemäki, L., Mikkola, J., 2005. Forecasting Germany's printing and writing paper imports. For. Sci. 51 (5), 483–497.

Jennings, S., Adamowicz, W., Constantino, L., 1991. The Canadian lumber industry and the macroeconomy – a vector autoregression analysis. Can. J. For. Res. 21 (3), 288–299.
Johnson, T.G., Nowak, J., 2011. Florida's Timber Industry – An Assessment of Timber Product Output and Use, 2009. U.S. Department of Agriculture Forest Service, Southern Research Station, SRS-180.
Judson, R.A., Owen, A.L., 1999. Estimating dynamic panel data models: a guide for macroeconomists. Econ. Lett. 65, 9–15.
LeSage, J.P., Krivelyova, A., 1999. A Spatial prior for Bayesian vector autoregressive models. J. Reg. Sci. 39 (2), 297–317.
Levin, A., Lin, C.-F., Chu, C.-S., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. J. Econometrics 108 (1), 1–24.
Malaty, R., Toppinen, A., Viitanen, J., 2007. Modeling and forecasting Finnish pine sawlog stumpage prices using alternative time-series methods. Can. J. For. Res. 37 (1), 178–187.
Mei, B., Clutter, M., Harris, T., 2010. Modeling and forecasting pine sawtimber stumpage prices in the US South by various time series models. Can. J. For. Res. 40 (8), 1506–1516.
Monteiro, J.A., Kukenova, M., 2009. Spatial Dynamic Panel Model and System GMM: A Monte Carlo Investigation. IRENE working papers 09-01, IRENE Institute of Economic Research.
Persyn, D., Westerlund, J., 2008. Error-correction-based cointegration tests for panel data. Stata J. 8 (2), 232–241.
Roodman, D., 2009. A note on the theme of too many instruments. Oxford Bull. Econ. Statist. 71 (1), 135–158.
Schaffer, M., 2010. Egranger: Engle–Granger and Augmented Engle–Granger Cointegration Tests and 2-step ECM Estimation, Available at (http://ideas.repec.org/c/boc/bocode/s457210.html) (accessed March 2012).