

Poverty and Employment in Timber-Dependent Counties

Peter Berck, Christopher Costello,
Louise Fortmann, and Sandra Hoffmann

November 2000 • Discussion Paper 00–52



Resources for the Future
1616 P Street, NW
Washington, D.C. 20036
Telephone: 202–328–5000
Fax: 202–939–3460
Internet: <http://www.rff.org>

© 2000 Resources for the Future. All rights reserved. No portion of this paper may be reproduced without permission of the authors.

Discussion papers are research materials circulated by their authors for purposes of information and discussion. They have not necessarily undergone formal peer review or editorial treatment.

Poverty and Employment in Timber-Dependent Counties

Peter Berck, Christopher Costello, Louise Fortmann, and Sandra Hoffmann

Abstract

One of the most controversial aspects of federal and state policies aimed at protecting old-growth ecosystems has been the potential impact of job losses on local economies. A fundamental question for historically timber-dependent communities is whether these policies will result in local economic stagnation and enduring pockets of poverty. In this paper, we examine the long-run impact of changes in timber-related employment on other types of employment and participation in major federal poverty programs. We use monthly, multi-county time series data to estimate a vector autoregressive model of the experience of northern California counties during the 1980s and 1990s. We find that employment base multiplier effects of timber employment on other types of employment in each county are small, and state economic conditions rather than local employment conditions are the principal driver behind local poverty.

Key Words: forest policy, poverty, employment, time series

JEL Classification Numbers: Q23, O15, R11, R15

Contents

1 Introduction	1
2 The California Timber Region: Economics and Environmental Policy	3
3 Past Research: Employment, Unemployment, and Poverty	4
4 Model	5
5 Data	7
6 Estimation	9
6.1 Testing Hypotheses: The Theory	12
7 Results	13
7.1 Timber Employment and Poverty	14
7.2 Impact of Timber vs. Nontimber Employment	15
7.3 Do State Variables Matter?	16
8 Conclusion	16
Appendix 1 Structural and VAR Modeling	23
References	25

Poverty and Employment in Timber-Dependent Counties

Peter Berck, Christopher Costello, Louise Fortmann, and Sandra Hoffmann*

Mills don't run, men don't work and families don't eat when politicians cannot give us the assurance that we can log in the nonwilderness areas (Vincent 1988).

1 Introduction

The 1989 announcement of a federal court order protecting the northern spotted owl and President Clinton's subsequent 1994 forest plan marked the end of a decade-long boom in California's timber harvests and the beginning of a decade of transformation in California's timber industry (Tuchman 1995). In California, area residents and state officials have been concerned that a loss of timber jobs could transform northern California into a stagnating economy (California Senate 1996). They have argued that increased levels of timber harvesting are essential to prevent not only job loss but also increased poverty in these forest-dependent local economies (California Senate 1996; California Forestry Association 1994; Vincent 1988). The question of how old-growth forest protection is changing local economies remains controversial, as demonstrated by recent exchanges between Oregon environmental groups and timber-industry representatives over the employment impact from harvest restrictions in Oregon (Associated Press 1999).

This paper examines the influence that timber employment and statewide economic conditions have had on other employment and on poverty program participation in California's timber-dependent counties. We pose three specific questions. First, does a decrease in county

* Peter Berck is a professor in the Department of Agricultural and Resource Economics, University of California, Berkeley. Louise Fortmann is Rudy Grah Professor of Forestry and Sustainable Development in the Department of Environmental Sciences, Policy and Management, University of California, Berkeley. Christopher Costello is an Assistant Professor in the Bren School of Environmental Science and Management, University of California, Santa Barbara. Sandra Hoffmann is a fellow at Resources for the Future.

The authors would like to thank Vicky Albert, Henry Brady and the staff at UC Data Archives for advice on poverty measures, and Arvis Cury and other staff of the Labor Market Information Division/Areas Services Group, California Employment Development Department, for providing monthly employment data. This research was funded in part by The California Department of Forestry and Fire Protection. The views expressed and errors remaining are solely those of the authors.

timber employment result in a long-run decrease in other types of county employment and an increase in county poverty program caseloads? Second, are county timber jobs better in the short-run at reducing county poverty program caseload or inducing county employment growth than other county jobs? And third, is there a long-run relationship between state economic activity and county employment or county poverty program caseloads?

In contrast to most work on the economic impact of timber employment, this study utilizes co-integrated vector autoregressive (VAR) time-series analysis to examine short- and long-run relationships between changes in timber-related employment, other county employment, and poverty in California's major timber-producing counties. Most commonly, structural models such as input-output or computable general equilibrium models have been used to analyze the local impact of change in sectoral demand. These models depend on strong assumptions about factor mobility and openness to trade. Hoffmann, Robinson, and Subramanian (1996) show that the size of economic-impact multipliers from structural models is strongly affected by assumptions about local factor market adjustment. An alternative to making such assumptions is to use time-series methods that directly capture this adjustment (e.g., Lesage and Reed 1989, Lesage 1990, Kraybill and Dorfman 1992). By using time-series methods, we avoid the need to make assumptions about the unmeasured, but potentially large, interactions between California's timber counties and nearby metropolitan areas.

This study examines the relationship between poverty program participation levels and employment by county and multi-county region. Use of program data as a poverty indicator follows recent U.S. Census Bureau practice (U.S. Bureau of the Census 2000). This analysis is county-based and describes the situation in a county or small region of adjacent counties. This situation obviously can differ from the experience of an unemployed individual, because an individual can relocate. It is also different from the relationship between unemployment rates and poverty program caseloads, as discussed in the section 3. In policy terms, it is designed to determine whether decreasing timber employment leads to persistent geographical pockets of poverty.

The next section of this paper briefly describes economic conditions in California's timber industry from the 1980s through the early 1990s. Section three reviews national, state, and metropolitan-area studies of the relationship between employment, unemployment, and poverty. This review indicates a need for research that examines the extent to which local poverty is driven by local labor-market conditions, as opposed to state or national economic conditions. Section four discusses the relationship between our VAR model and a structural model representing these local economies. These models are formally developed in Appendix 1.

In section five, we describe the data used to operationalize this model. We also discuss recent U.S. Census Bureau efforts to estimate county-level poverty rates and show that administrative program data provides a reasonable indicator variable for poverty at the county level. In section six, we explain how we estimated cointegrated VARs, which represent economic processes in the study counties and in pooled sets of adjacent counties. In section seven, we discuss the results of formal tests and simulations of relationships among time series. on county timber and nontimber employment, county poverty program caseload, and state-level time series. We conclude with a brief summary and discussion of these results.

2 The California Timber Region: Economics and Environmental Policy

Over the past 40 years, the eleven counties included in this study¹ have produced 70-80% of California's annual timber harvest. During the 1980s, lumber and wood-products industries provided 10–20% of total employment in these counties (McWilliams and Goldman 1994). Timber harvests and timber-related employment in California went through a pronounced boom and bust cycle during the 1980s. Total timber harvests in the study counties peaked at almost 3.4 million thousand board feet (mbf) in 1987, up from 1.8 million mbf in 1984. However, by 1994, harvest in these counties had dropped back to 2 million mbf. Despite growing labor productivity, average monthly wood products sector employment in the study counties increased from a low of 16,102 in 1985, to a high of 17,072 in 1988, before falling steadily to 13,213 in 1993 (California Department of Finance 1983–1993).

California timber harvests during the 1980s were affected by the forest planning process mandated by the National Forest Management Act (NFMA 1976) and the Resource Planning Act (RPA 1974). Timber harvests in national forests in California were maintained at historically high levels, exceeding federal nondeclining even flow requirements throughout the 1980s (Yaffee 1994). From 1989 on, a series of federal and state judicial and administrative actions aimed at protecting endangered bird and fish species forced reconsideration of the harvest plans for national forests and private land, and resulted in a rapid decline in California timber harvests.²

¹ The eleven counties are: Amador, Del Norte, Humboldt, Lassen, Mendocino, Plumas, Shasta, Siskiyou, Tehama, Trinity, and Tuolumne.

² See volume 62 *Federal Register* pages 49397-49411 (September 1997) for the proposed listing of the McCloud River redband trout and the bull trout. See also *California Code of Regulations* Title 133, Natural Resources, Division 1, Subdivision 3, Chapter 3, Section 670.5 for state listings of salmonids.

Total county employment grew steadily in the study counties during the 1980s, paralleling statewide employment growth. Yet when statewide employment stagnated in the early 1990s and local timber-related employment declined, total employment in these counties continued to grow (California Department of Finance 1983–1993).

In contrast, poverty in the study counties worsened relative to state poverty rates. The average poverty rate in 1979 for the study counties was slightly lower than that of the state as a whole (11.5% compared to 11.8%). By the 1990 census, the average study county poverty rate of 13.8% exceeded the statewide rate of 12.5% by 1.3 percentage points (U.S. Bureau of the Census 1980).

Geographic proximity and transportation linkages affect the ease of labor market adjustment. In general, California's timber counties are not remote from major urban areas. The major service centers for the northern timber counties, Eureka and Redding, are each within a four- to five-hour drive of San Francisco and Sacramento. The central Sierra study counties, Amador and Tuolumne, are within a two-hour drive of Sacramento and San Francisco. These central Sierra counties lie partially in California's Central Valley, and their economies are dominated by the Valley's agricultural and commercial activities.

3 Past Research: Employment, Unemployment, and Poverty

The logic behind the concern that old-growth forest protections lead to increased local poverty is based on belief in a strong inverse relationship between local labor market conditions and local poverty. A substantial body of literature has identified a strong, positive relationship between unemployment rates and both poverty rates and poverty program participation at a state and national level (Blank and Blinder 1986; Sawhill 1988; Blank and Card 1993; Blank 1997; Wallace and Blank 1999; Blank 2000). Studies using state-level panel data estimate that one-third to two-thirds of the decline in Aid to Families with Dependent Children (AFDC) in the early 1990s was due to macroeconomic factors (for a recent review see Blank 2000). Tobin (1994) found that states with chronically high unemployment and low wage rates also have chronically high poverty rates that can persist over time despite employment growth. Using state-level caseload data, Wallace and Blank (1999) estimated that declining unemployment rates accounted for 28-44% of the decline in Food Stamp caseload from 1994 through 1998. Using a dynamic model of state-level caseload data, Wilde et al. (2000) found that 35% of the decline in Food Stamp caseload from 1994-1998 was explained by state unemployment rates and per capita employment growth.

Using monthly cross-sectional time series data on state unemployment rates, AFDC Family Group (FG) caseloads, and Unemployed Parent Program (UP) caseloads from 1976 to 1996, Blank (1997) found that a 1% rise in the unemployment rate was associated with a 3.5% increase in AFDC FG caseload and a 20% increase in AFDC UP caseload. AFDC FG, the better known of the pre-1996 welfare reform AFDC programs, was available to children in single-parent households. AFDC UP was a smaller program for children in households with two unemployed parents who have a history of recent employment. Blank also found that although the changes in AFDC UP caseloads induced by changes in unemployment rates were large, they were not as permanent as those induced in AFDC FG caseloads.

The question addressed in this paper, which is the relevant question for federal and state forest management, is to what extent does this relationship between poverty and employment hold at the local or at least sub-state regional level. Theoretically, it is not clear that such a relationship must hold for small, open, local economies. Existing empirical evidence is mixed. For example, Bartik (1993) found that local residents retained 10-40% of employment growth within Metropolitan Statistical Areas (MSAs). In contrast, Blanchard and Katz (1992) found that in-migrants absorb all MSA job growth within five to seven years. Recent research has begun to examine urban and rural differences in the relationship between the business cycle and participation in poverty programs (Joint Centers for Poverty Research 2000).

It is also important to understand the relative efficacy of different types of employment in promoting local employment and thereby indirectly reducing poverty. According to economic base theory, growth in exporting sectors, like lumber production, should have a greater impact on local economic growth than growth in non-exporting sectors (see Krikelas (1992) for a recent review). We specifically test the hypothesis that forest-related employment plays a role in local poverty reduction that is distinct from the that of employment growth in other sectors.³

4 Model

The questions addressed in this study are examined in a cointegrated VAR framework. Interest has grown in using time-series models to estimate regional economic multipliers

³ While this paper is related to recent work using VAR models to identify basic and nonbasic economic activity, it is not an economic-base model (Lesage and Reed 1989; Lesage 1990 Kraybill and Dorfman 1992). Instead, it asks how a change in a particular export sector, such as timber and wood products, affects other local employment and local income distribution.

(Fawson and Criddle 1994; Wozniak and Babula 1992; Krikelas 1992). Recent poverty literature emphasizes the use of dynamic models in estimating the contribution of macroeconomic conditions to welfare caseload reductions (Figlio and Ziliak 1999). In this study, we use cointegration tests to examine long-run relationships among local and state poverty-program and employment variables. Brown, Coulson, and Engle (1992) also use cointegration methods to estimate MSA-level employment multipliers. We use county-level VARs to estimate the multiplier impact of county timber and nontimber employment on poverty program participation.

Time-series models, such as a VAR model, can be viewed as the solution to a dynamic structural model, like those in the I-O/CGE class of models. There is a trade-off in choosing between these two representations of a regional economy. Structural models, like the I-O/CGE class of models, incorporate significant sectoral and structural richness, but impose assumptions regarding economic adjustment. Time-series models measure the actual empirical impact of the adjustment process but ignore sectoral detail and structural information for which good evidence may be available. The relationship between structural and VAR models, and the case for preferring VAR models to structural models in a macroeconomic setting, is discussed by Sims (1980). Because our focus is on gaining an empirical understanding of the actual adjustment process in the study counties, we use time-series analyses.

The VAR that we estimate can be viewed as a solution to a two-sector, structural model. The structural model represents economic relationships that would be expected to determine the impact of changes in local employment and state economic conditions on local poverty. It includes equations representing: (1) equilibrium in county timber and nontimber labor markets, (2) county poverty program caseload as a function of employment and other variables, (3) total state employment and state poverty program caseload as a function of other state-level variables, and (4) county-level migration as a function of county and state variables. Solving this simple structural model yields a VAR model defined over five variables: local (county or multi-county) timber-related employment (T), local nontimber-related employment (N), local poverty program participation (POV), state employment (SE), and state poverty program participation (SPOV). A formal presentation of the derivation of the VAR from a structural model can be found in Appendix 1.

The VAR estimated in this study allows us to test the relative role that activity in timber-related industries, a major local export sector, and activity in other sectors have on participation in local poverty programs. At a more macro level, this model allows us to test hypotheses about the relative roles of local versus state economic conditions on local employment and poverty program participation.

5 Data

The need to focus this study on small, rural counties severely constrains data availability. Conventionally, county-level economic analysis uses national or state data that is then disaggregated to the county level. This disaggregation is based on assumptions about the relationship between county economic activity and state or national activity. These include relationships that we seek to measure. Use of these assumptions distorts the signal the data provides about fluctuations in the level of county economic activity over time. Administrative data for anti-poverty and unemployment programs, in contrast, are collected monthly at the county level—far more frequently than county-level poverty rate data, which is measured only during the decennial census. The primary source of economic data that is collected at a county level on a more frequent basis than the decennial census is administrative data for major government programs such as the federal anti-poverty programs, or unemployment insurance programs. As a result, this study relies on monthly administrative data collected at the county level from 1983 through 1993.⁴

Recent federal legislation on poverty-targeted school funding has stimulated considerable research interest in small area poverty estimation (Improving America's Schools Act of 1994, P.L. 103-382). Directly measured county-level poverty rates for most rural counties are available only from the decennial census. The Current Population Survey offers intercensal estimates of poverty and income statistics, but its sample is designed to provide accurate estimates only at the national, not county, level. Yet the geographic distribution and level of poverty, employment, and unemployment can vary markedly in intercensal periods (U.S. Bureau of the Census 2000). As a result, studies by the U.S. Bureau of Census and the National Science Foundation have recommended the use of administrative data on poverty program participation in estimating county-level poverty during intercensal periods (Siegel 1997; National Research Council 1999). In keeping with these recommendations, we use data on county-level participation in three major federal poverty programs—Food Stamps, AFDC FG, and AFDC UP—as indicators of county-level poverty.

Eligibility in all three major, pre-1996 federal anti-poverty programs was tied to federal poverty guidelines and household asset tests (U.S. House of Representatives 1992). During the

⁴ Preliminary analysis using comparisons of 1980 and 1990 U.S. Census data led to inconclusive results, which further motivated us to approach the question using time series analysis (Fortmann et al. 1991).

study period, all California counties used the same eligibility requirements in administering these programs. The three programs differed in their requirements for labor force participation. AFDC UP was established in 1961 as an anti-recessionary program for two-parent families with minor children, financial need, and unemployed fathers with a recent work history (U.S. House of Representatives 1992). Requiring recent work force participation by the family's primary earner distinguished AFDC UP from the more familiar AFDC FG and Food Stamps programs (U.S. House of Representatives 1992). Food Stamps are available to households with low income, regardless of employment history or status, including households whose members are collecting unemployment insurance. In 1992, 10.4% of U.S. Food Stamp participants were also receiving unemployment compensation (U.S. House of Representatives 1994). All households receiving AFDC were eligible for Food Stamps. Recent studies of state and national data indicate a strong relationship between both Food Stamp and AFDC UP caseload and unemployment rates and a weaker relationship between unemployment rates and AFDC FG (Blank 1997).

County timber and nontimber employment levels are taken from the U.S. Bureau of Labor Statistics (BLS) series on employment covered by unemployment insurance (BLS ES-202 series) (California Employment Development Department 1983–1993).⁵ Timber-related employment is represented by employment in lumber and wood-products industries [Standard Industrial Classification (SIC) 24]. Employment in forest management (SIC 08) is not used in the study. It represents less than 2% of total timber-related employment (SIC 24 + SIC 08) in California and is blocked in most study counties for reasons of business confidentiality (California Employment Development Department 1983–1993). Employment in the pulp and paper (SIC 26 1-3) was also excluded. There is only one pulp and paper mill in all of the study counties, and data on employment in this mill is also blocked for reasons of business confidentiality (Gilless 1999). Total monthly state employment is also taken from the BLS ES-202 series (California Employment Development Department 1983–1993). Total state employment provides a proxy for state output of goods and services, which are believed to be significant factors driving demand for local employment and, ultimately, the willingness of unemployed

⁵ County employment data were obtained by personal communication with California Employment Development Department personnel responsible for collection and maintenance of employment and hours data for individual counties. Decisions on county-level record retention are made on a county-by-county basis by personnel responsible for that particular county. The longest series available began in January 1983, creating a limit on the length of our time series.

workers in forest counties to migrate to other areas for employment. Data on alternative state-level measures of economic activity, such as gross state product (GSP), are ultimately constructed from employment data and assumptions regarding the ratio of value added to employment. Again, the use of GSP figures would distort the signal that employment provides about fluctuations in statewide economic activity over time.

6 Estimation

Three cointegrated VARs—one for each poverty program, Food Stamps (FS), AFDC UP (UP), and AFDC FG (FG) caseload—were estimated for each county in the study and for pooled sets of contiguous counties. County analysis is included because counties are a natural unit of analysis for this study of local economic impact. Counties are the administrative units for welfare programs and other local government policy decisions. The multi-county analysis provides regions large enough to account for inter-county commuting and for employment data being reported by employer rather than employee address. Tests involving these cointegrating relationships provide evidence on the long-run relationships between county (or multi-county) timber employment, other employment, poverty program participation, and statewide variables.

Following Engle and Granger (1987), the VAR model is written in error correction form using first differences of lagged variables:

$$\Delta \mathbf{y}_t = \boldsymbol{\phi} + \boldsymbol{\Gamma}_1 \Delta \mathbf{y}_{t-1} + \cdots + \boldsymbol{\Gamma}_{k-1} \Delta \mathbf{y}_{t-k+1} + \boldsymbol{\Pi} \mathbf{y}_{t-1} + \boldsymbol{\Psi} \mathbf{D}_t + \boldsymbol{\varepsilon}_t, \quad (1)$$

where \mathbf{y}_t is a 5x1 column vector of the model's endogenous variables included in the study at time t . \mathbf{y}_t is the vector of observations on the variables—county nontimber employment (N_t), county timber employment (T_t), county poverty program participation (POV_t), state employment (SE_t), and state poverty program participation ($SPOV_t$)—at time t , i.e., $\mathbf{y}_t' = (N_t, T_t, POV_t, SE_t, SPOV_t)$. Δ indicates the first difference of monthly observations on each of the variables (e.g., $\Delta \mathbf{y}_t = \mathbf{y}_t - \mathbf{y}_{t-1}$). Variables are transformed to natural log form, so that $\Delta \mathbf{y}_t$ represents the monthly growth rate in the variables in \mathbf{y} . The $\boldsymbol{\Gamma}_t$ are 5x5 matrices of parameters of the t -times lagged difference of \mathbf{y} . \mathbf{D}_t is a vector of 11 monthly dummy variables at time, t , and $\boldsymbol{\Psi}$ is a 5x11 matrix of corresponding parameters. The parameters $\boldsymbol{\Gamma}$ and $\boldsymbol{\Psi}$ capture the short-run behavior of the model. $\boldsymbol{\Pi}$ is a 5x5 parameter matrix containing information about the cointegrating relationships among the variables in \mathbf{y} . The parameters, $\boldsymbol{\Pi}$, capture information about long-run behavioral relationships. Finally, $\boldsymbol{\phi}$ is a vector of constant terms and $\boldsymbol{\varepsilon}$ is a vector of mean zero errors.

The parameters of (1) are estimated in a three-step statistical analysis. First, iterative likelihood ratio tests are used to determine the number of lagged difference terms to be included

in the estimated equations. Next, cointegration tests are used to find the number of cointegrating vectors, that is, the rank, r , of the cointegrating space. Finally, the values of the parameter matrices are estimated.

Two or more time series that are individually nonstationary, and integrated of order one are cointegrated if a linear combination of them is stationary. Intuitively, this means that the series move in tandem over time (Rao 1994). The rank of the cointegrating spaces, r , in any of the VAR models is the number of linearly independent cointegrating relationships among the p (in this case five) time series in the model. The elements of \mathbf{y}_t are cointegrated of rank r when the rank, r , of $\mathbf{\Pi}$ from equation (1) is greater than zero but less than the number of endogenous variables, p (Johansen and Juselius 1990).

To conduct hypothesis tests about the long-run relationships between series, it is useful to decompose $\mathbf{\Pi}$ as $\mathbf{\Pi} = \mathbf{\alpha}\mathbf{\beta}'$, where $\mathbf{\alpha}$ and $\mathbf{\beta}$ are $p \times r$ and $r \times p$ matrices of full rank respectively. The matrix $\mathbf{\beta}$ captures information regarding whether variables are included in stationary long-run relationships among other variables. In this representation, $\mathbf{\beta}$ is the matrix of coefficients for r stationary cointegrating relationships, $\mathbf{\beta}'\mathbf{y}_t = \mathbf{0}$, which are interpreted as stationary relationships among nonstationary variables. This is the sense in which cointegration represents long-run relationships among variables. The matrix $\mathbf{\alpha}$ captures information about the rates at which the variables in \mathbf{y}_t adjust toward these stationary long-run relationships or, more precisely, the cointegrating space. Some variables may adjust quickly while others may not change at all. Weighted elements of $\mathbf{\alpha}$ measure the average speed of convergence towards long-run equilibrium.

Johansen and Juselius (1990) derive two useful tests for the hypothesis of r cointegrating vectors. The first, the trace statistic, is a likelihood ratio test for the hypothesis that the rank of $\mathbf{\Pi}$ is r . The null hypothesis for this test is $H_0: \text{rank}(\mathbf{\Pi}) \leq r$ (or, equivalently, that the system has $p-r$ unit roots) versus the alternative that the rank is greater than r . The second test, the maximum eigenvalue test, computes the λ_{\max} statistic, and is based on the ratio of the likelihood of r cointegrating vectors versus $r+1$ cointegrating vectors. The null hypothesis for this test is that the rank of $\mathbf{\Pi}$ is r or less, while the alternative is that the rank is $r+1$ or less.⁶ The

⁶ In practice, determining the cointegration rank is an iterative process, in which one starts with the hypothesis of $r=0$ cointegrating vectors. If this test is rejected by either test at the .95 significance level, the test is repeated for $r=1, 2, \dots, p-1$ cointegrating vectors. There were several counties where the estimate of cointegrating rank would increase if the .90 level of significance were used. In no county would the extreme hypotheses of no cointegration or stability

asymptotic distributions of the rank and trace test statistics for these tests are nonstandard and depend on deterministic components included in the model (Johansen 1995). The first accepted rank is reported as the estimate of rank in Table 1. Finally, parameter matrices, Γ_t and Ψ , were estimated given the number of lags, k , found in step one and the cointegrating rank found in step two.

Model appropriateness was assessed by testing for residual autocorrelation and by examining R^2 . The R^2 of the equations for nontimber jobs, averaged across counties and regions, was just over 78% for all three sets of VARs. For timber jobs, it was approximately 61%. The average R^2 for AFDC FG was 36%, for AFDC FG 54%, for AFDC UP, and 58% for Food Stamps. Of the state variables, the lowest R^2 was for Food Stamps (62%), and the highest was for AFDC UP (80%). On the whole, the VAR models fit well with the poorest fits being for AFDC FG, which is not surprising since this poverty program was least influenced by employment conditions in state and national studies.

Two different Lagrange multiplier tests were used to test for residual autocorrelation (Hansen and Juselius, 1995). In general, there was little evidence of autocorrelation in the residuals of the cointegrated models. No counties or regions tested positive for residual autocorrelation using AFDC-UP as the poverty indicator variable. When AFDC-FG was used, only one county and no region displayed residual autocorrelation. Autocorrelation was detected in only one county and one region when Food Stamps program caseload was used as the poverty indicator.

Out-of-sample model validity was assessed using one-step-ahead predictions. The model was first estimated using data from the first 72 months of the study period. We then calculated one-month-ahead forecasts and found that the resulting out-of-sample fit was nearly the same as the in-sample fit. Finally, the constancy of the Π matrix over the last four years was tested using methods developed by Hansen and Johansen (1993). On average, the hypothesis of constancy was rejected in only three of the 48 forecast periods for each county. There were no patterns to these rejections, indicating that there is sufficient stability to the model.

(five cointegrating vectors) be supported. Parameter matrices are too voluminous to present and are available from the authors on request.

6.1 Testing Hypotheses: The Theory

We examined long-run economic relationships in the study counties through three sets of hypotheses. The first is a set of exclusion hypotheses. Can county poverty, timber jobs, or state variables be excluded from the system's long-run (cointegrating) relationships? If either county timber employment or poverty is not part of any long-run relationship, then county poverty is not affected in the long-run by changes in timber employment. If state variables are excluded from long-run relationships with county variables, then state variables do not influence county employment or poverty program participation. The second "set" is the single hypothesis is that county-level participation in poverty programs is weakly exogenous to these long-run relationships. A positive finding here implies that, in the long-run, county poverty program participation does not respond to changes in the other variables.

The third set of hypotheses examines specific long-run relationships among particular variables in the system. Three specific long-run relationships are of particular interest. First, county timber and nontimber jobs and poverty program participation could grow in proportion to one another in the long run. This is a test for balanced growth in the county. Accepting this test suggests that more people work in all types of employment. To the extent that increased employment draws new residents into the county these new residents have the same long-run incidence of poverty as the existing residents. Second, a one-job increase in timber and nontimber jobs could have the same long-run impact on the other variables. This is a finding that timber jobs do not play a special role in the local economy, a "job is a job". In essence, this tests whether timber employment is part of the region's economic "base." Finally, there may be three cointegrating relationships among the county variables. If the two state variables are held constant, and there are three cointegrating relationships among the 5 variables in the VAR, then the values of county variables must return to their original values following a perturbation. In such a county, employment growth is totally determined by conditions in the larger state economy.

The cointegrating relationships captured in $\Pi = \alpha\beta'$ are used to test for these long-run relationships. The three sets of hypotheses are formalized as linear restrictions on α and β and are tested using likelihood ratio tests that follow a χ^2 distribution (Johansen 1995). Specific long-run relationships among particular variables in the system are tested as linear restrictions on β , formalized by an appropriate matrix R' in equation (2) below. For example, the test for exclusion of the i^{th} variable (N, T, POV, SE, or SPOV) in y from a cointegrating relationship is:

$$H_0: \mathbf{R}'\beta = 0, \quad (2)$$

where \mathbf{R}' is a vector of zeros with a one in the i^{th} position. For instance, if the hypothesis that poverty is excluded from the cointegrating vectors (or long-run relationships) is accepted, then it could not be that changes in employment have a long-run effect on poverty. Similarly if timber employment is excluded, there could be no long-run relationship between poverty and timber.

The hypothesis of weak exogeneity of the i^{th} variable in \mathbf{y} is tested as linear restrictions on α , formalized by an appropriate matrix \mathbf{J}' in equation (3):

$$H_0: \mathbf{J}'\alpha = 0, \quad (3)$$

where \mathbf{J}' is a vector of zeros except for the i^{th} position, which is one. This tests whether the i^{th} variable adjusts to a cointegrated relationship with the other variables in \mathbf{y} at a rate of zero. If poverty doesn't adjust to changes in employment, then decreases in employment again do not affect poverty.

Even if there is a long-run relationship between poverty and employment, it could be one in which increases (not decreases) in employment are associated with poverty increases. One possibility is that timber, nontimber jobs, and poverty grow in proportion to one another. (Recall that the variables used in the estimation are in natural log form.) More exactly, the hypothesis is that if $\beta\mathbf{y}^* = \mathbf{0}$, and \mathbf{y}^* is a possible long-run equilibrium of the cointegrated system, then so is a vector \mathbf{y} with its first three (county specific) elements increased proportionately and its remaining two (state specific) elements left unaltered. The long-run equilibria of this system would then include proportionate growth in poverty and employment. Of course, this is exactly the opposite of the theory that decreasing employment is associated with increasing poverty.

The last hypothesis that is tested is called “a job is a job.” This is the hypothesis that increasing timber jobs by one job and decreasing nontimber jobs by one job can leave the equilibrium value of jobs and poverty the same.

Table 2 describes the specific form of the \mathbf{R}' and \mathbf{J}' matrices that formalize these six hypotheses.

7 Results

These hypothesis tests, together with the short-run dynamics of the estimated VAR, provide evidence that addresses three important economic questions raised in the ongoing debate over timber policy in California. First, does a decrease in local timber employment result in a long-run increase in local poverty? Second, are timber jobs better in the short-run at reducing

poverty or inducing county employment growth than other jobs? And third, are state or county factors the long-run determinants of county employment and poverty? These results improve our understanding of the impact of timber policy in California's major timber counties.

7.1 Timber Employment and Poverty

As expected, evidence on the long-run impact of county timber employment on poverty program participation in the study area varies by program. We use five tests to rule out the possibility that decreasing timber employment is associated with increased poverty in the long-run: 1) the exclusion of poverty from any long-run relationships, 2) the exclusion of timber employment, 3) weak exogeneity of poverty, 4) proportionality of employment and poverty, and 5) a cointegrating rank of three. Results of these tests are in Tables 3A, B, and C, which give the p-values for each test for each county and region and each of the three sets of VARs. Failure to reject any of these hypotheses (exclusion, etc.) is evidence that timber employment does not have a long-run impact on poverty program participation. For instance, for Amador county, AFDC FG—the poverty indicator—has a p-value of .25 for the weak exogeneity test (see Table 3A). Therefore weak exogeneity is not rejected and timber employment does not cause (in the sense of weak exogeneity) AFDC FG participation in Amador county. Failure to reject these hypotheses does not, however, rule out short-run effects, nor does it rule out migration out of the region caused by unemployment.

AFDC FG participation has been found to be the least sensitive of all major poverty programs to changes in macroeconomic conditions at the state and national levels (Blank 2000). It is not surprising, then, that county timber employment had little impact on AFDC FG participation in the study area (Table 3A). Using a 10% level of significance, in no county or multi-county region is there evidence that decreasing employment increases long-run poverty. (In all but Lassen and Tuolumne counties, poverty is weakly exogenous. The link between timber employment and poverty in the long-run is broken in Lassen county because poverty and employment increase together in the long-run; in Tuolumne county the cointegrating rank is three.)

In contrast, state and national studies indicate that AFDC UP participation was strongly counter-cyclical (Blank 1997). As a result, it is significant that there is also little evidence that timber employment had a long-run relationship with AFDC UP participation in the study counties or multi-county regions. No multi-county area and only two counties, Amador and

Humboldt, survive all five tests for a long-run relationship between timber employment and AFDC UP caseload (Table 3B).

Food Stamp participation also has been shown to be strongly counter-cyclical in state and national studies (Wallace and Blank 1999). There is some evidence from our hypothesis tests that Food Stamp participation in our study area is sensitive to timber employment cycles. A long-run relationship between timber employment and Food Stamp participation could not be ruled out in four of the study counties (Plumas, Shasta, Tehama, and Tuolumne) or in the northwest multi-county region (Del Norte, Humboldt, Mendocino, and Siskiyou counties), although there was no relationship between timber employment and Food Stamp participation in counties in the northwest region taken individually.

Actual and simulated model forecasts also provided evidence on the relationship between county employment and poverty in the form of expected program participation conditional on employment. These conditional expectations were estimated by first, making a 24-month forecast using the actual values of all variables. Second, the number of jobs (either timber or nontimber) was increased by 100 jobs in the last period before the forecast. Then the system was forecasted out 24 months. The difference between these two forecasts gives the expected short-run job increases or poverty program caseload decreases conditional on an increase in 100 timber or nontimber jobs. Table 4 gives the average of these conditional expectations across counties for the programs for which there was some evidence of long-run responsiveness. With 100 additional timber jobs, one expects 61 fewer Food Stamp cases and essentially no change in AFDC UP participation. AFDC FG participation was even less responsive than AFDC UP participation.

In summary, there is mixed evidence for timber employment decreases being associated with Food Stamp program participation increases and little evidence of timber employment decreases being associated with increases in either AFDC UP or AFDC-FG program participation in the either the long- or short-run.

7.2 Impact of Timber vs. Nontimber Employment

The next question to be addressed is whether timber and nontimber employment plays the same role in the county or multi-county regional economy. The null hypothesis is that the combination of one additional timber job and one less nontimber job has no effect on the set of stable outcomes for the county in the long run. That is, one timber job and one nontimber job both have the same effect on the long-run relationships, and timber jobs are not the driving

economic base of these counties to any greater degree than other jobs. As is shown in Table 3, this hypothesis is largely rejected. Again Table 4 can be used to get a sense of the magnitude of the effects involved. In the AFDC UP model, with 100 additional timber jobs one can expect 139 more total county jobs. With the Food Stamps model, one can expect 58 more total jobs in the county.

7.3 Do State Variables Matter?

In all eleven study counties, employment and caseload in all of the poverty programs are influenced by statewide economic conditions. An exclusion test is again used to determine whether statewide variables affect long-run levels of county employment and poverty. Exclusion of state variables is rejected in all counties and multi-county regions for all poverty programs, suggesting that a long-run relationship does exist between state and county variables.

8 Conclusion

This analysis uses county-level monthly data on major anti-poverty programs to examine the impact of changes in timber employment on poverty in rural California counties from 1983–1993. Our analysis finds mixed evidence that changes in timber employment have a long-run impact on poverty in California's timber country. For AFDC FG, there is no evidence that decreasing timber employment leads to a higher caseload. For AFDC UP, there are only a few counties for which decreasing timber employment leads to a higher caseload. The conditional expectation of the number of increased cases if timber employment were decreased by 100 jobs is 2 cases. In the case of Food Stamps, the long-run evidence is mixed and the conditional expectation for Food Stamp caseload decrease is quite large. In comparison with the national evidence for the effects of employment on AFDC UP or Food Stamp participation, the effect of county-level employment seems much less pronounced. This may reflect the ability of laid off workers to move to new locations and new jobs.

This study does find statistical evidence that timber jobs have a different effect on the long-run make-up of employment and poverty than nontimber jobs do. However, results from the two most sensitive models (Food Stamps and AFDC UP) do not suggest large "multipliers" in these counties. In neither model does adding a timber job lead to anything close to an induced additional job in the nontimber sector, a frequent assumption in the spotted owl impact studies cited by Sample and Le Master (1992). Thus, timber has a base-multiplier effect, but it is likely to be rather small.

Perhaps the strongest result of this analysis is that state employment levels and state poverty program caseloads do have a strong, significant long-run relationship with *county* poverty program participation. Taken together, these results suggest a picture of rural economies with reasonably close ties to the rest of California's economy. One likely explanation is that there may be a fair amount of mobility between labor markets in California's timber region and those elsewhere in the state. Given the relatively close proximity of these counties to northern California's major metropolitan areas, coupled with good transportation and communication, this explanation seems plausible.

This is a place-based analysis. It looks at the local economic impact of changes in timber employment in rural California. It does not address the question of how these changes affect individual workers or the state economy. It is perfectly possible, for example, that individual residents of these counties are affected by cuts in timber employment and migrate from the region to find employment or experience poverty outside the region. Our multi-county analysis suggests that this is not the case, at least for multi-county regions within California's timber region.

At best, then, the relationship between county timber employment and poverty, at least as reflected in participation in major anti-poverty programs, is tenuous. Timber extraction is not a strong expansionary force in California, even in its major timber counties. Solutions to rural unemployment and poverty in these counties are unlikely to be found in expanded timber harvests. To the extent that these counties are concerned about reducing poverty program caseloads, it appears that changes in statewide economic conditions and poverty program structures themselves will have a greater impact than employment growth in timber-related industries.

Table 1. Rank of the Cointegrating Space for Models Run with Alternative Poverty Indicators

Model	Rank							
	County or Multi-County Region							
	Amador	Del Norte	Humboldt	Lassen	Mendocino	Plumas	Shasta	
AFDC UP	2	2	2	1	2	3	2	
AFDC FG	2	1	1	1	2	2	1	
Food Stamps	1	2	1	1	1	2	2	
	Siskiyou	Tehama	Trinity	Tuolumne	NW	NE	SE	
AFDC UP	1	2	2	2	2	2	1	
AFDC FG	2	2	1	3	1	2	3	
Food Stamps	1	2	3	2	2	2	2	

Poverty indicator variables include the following: Aid to Families with Dependent Children–Unemployed Parent caseload (AFDC UP); AFDC–Family Group caseload (AFDC FG); and Food Stamps. Multi-county regions are: NW (Del Norte, Humboldt, Trinity, Mendocino); NE (Lassen, Plumas, Siskiyou, Shasta, Tehama); and SE (Amador, Tuolumne).

Table 2. Hypothesis Tests

Test	Description	Econometric Formulation
Exclude NT	Tests whether it is appropriate to exclude county nontimber jobs (NT) from the cointegrating space	$\mathbf{R}' = [1\ 0\ 0\ 0\ 0]$
Exclude T	Tests whether it is appropriate to exclude county timber jobs (T) from the cointegrating space	$\mathbf{R}' = [0\ 1\ 0\ 0\ 0]$
Exclude P	Tests whether it is appropriate to exclude county poverty (P) from the cointegrating space	$\mathbf{R}' = [0\ 0\ 1\ 0\ 0]$
Exclude SPOV	Tests whether it is appropriate to exclude state poverty (SPOV) from the cointegrating space	$\mathbf{R}' = [0\ 0\ 0\ 0\ 1]$
Exclude Both State Variables	Tests whether it is appropriate to exclude both state variables (employment and poverty) from the cointegrating space	$\mathbf{R}' = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Proportionality	Tests whether county jobs and poverty grow in proportion to one another	$\mathbf{R}' = [1\ 1\ 1\ 0\ 0]$
Job Is a Job	Tests whether, in the long run, a one job increase in county timber jobs is exactly offset by a one job decrease in county nontimber jobs	$\mathbf{R}' = [1\ -N/T\ 0\ 0\ 0]$ Where N/T is the average proportion of non-timber to timber jobs in a county.
Exogeneity of P	Tests whether county poverty is weakly exogenous to the cointegrating space	$\mathbf{J}' = [0\ 0\ 1\ 0\ 0]$

\mathbf{R}' and \mathbf{J}' test restrictions on the vector of explanatory variables $\mathbf{y}' = [N, T, POV, SE, SPOV]$.

Table 3a. Results of Tests on Hypotheses about Long-Run Relationships among County and State Variables in Models Using Aid to Families with Dependent Children Unemployed Parent Caseload as a Poverty Indicator Variable

Null Hypothesis	p Value							
	County or Multi-County Region							
	Amador	Del Norte	Humboldt	Lassen	Mendocino	Plumas	Shasta	
Exclude P	0	0.01	0.03	0.02	0.01	0.40	0.01	
Exclude T	0	0.96	0.08	0.08	0.04	0	0.54	
Exogeneity of P	0	0.01	0.10	0	0.17	0.74	0.94	
Job Is a Job of P	0	0.50	0.03	0.05	0.01	0	0.71	
Proportionality	0	0	0.02	0.62	0	0.05	0.01	
	Siskiyou	Tehama	Trinity	Tuolumne	NW	NE	SE	
Exclude P	0.50	0.68	0	0.04	0.65	0.50	0	
Exclude T	0.02	0	0.27	0.07	0.24	0	0.72	
Exogeneity of P	0.61	0.05	0.20	0.01	0.01	0.10	0.01	
A Job Is a Job	0	0	0.08	0.16	0.03	0	0.96	
Proportionality	0	0.03	0.71	0.09	0.01	0.02	0	

Table 3b. Results of Tests on Hypotheses about Long-Run Relationships among County and State Variables in Models Using Aid to Families with Dependent Children Family Group Caseload as a Poverty Indicator Variable

Null Hypothesis	p Value							
	County or Multi-County Region							
	Amador	Del Norte	Humboldt	Lassen	Mendocino	Plumas	Shasta	
Exclude P	0.04	0.28	0	0.03	0.03	0.86	0	
Exclude T	0	0.65	0	0	0	0	0	
Exogeneity of P	0.25	0.39	0.56	0.08	0.57	0.49	0.38	
Job Is a Job of P	0	0.85	0.06	0	0	0	0	
Proportionality	0	0.97	0.01	0.77	0	0.14	0.79	
	Siskiyou	Tehama	Trinity	Tuolumne	NW	NE	SE	
Exclude P	0	0.72	0.02	0	0.23	0.18	0.01	
Exclude T	0	0.02	0	0	0	0	0.04	
Exogeneity of P	0.92	0.99	0.44	0	0.25	0.29	0.07	
Job Is a Job of P	0.01	0.02	0	0	0	0	0.02	
Proportionality	0	0	0	0	0.51	0.01	0	

Table 3c. Results of Tests on Hypotheses about Long-Run Relationships among County and State Variables in Models Using Food Stamp Caseload as Poverty Indicator Variable

Null Hypothesis	p Value							
	County or Multi-County Region							
	Amador	Del Norte	Humboldt	Lassen	Mendocino	Plumas	Shasta	
Exclude P	0.01	0	0.01	0.96	0.22	0.02	0	
Exclude T	0.90	0.20	0.04	0	0	0	0.01	
Exogeneity of P	0.01	0	0.53	0.15	0.27	0.09	0	
Job Is a Job of P	0.90	0.12	0.05	0	0	0	0.01	
Proportionality	0.78	0	0.22	0.01	0.07	0.01	0	
	Siskiyou	Tehama	Trinity	Tuolumne	NW	NE	SE	
Exclude P	0.31	0	0	0.01	0	0.02	0.08	
Exclude T	0	0.04	0	0.07	0.01	0	0	
Exogeneity of P	0.50	0	0.03	0	0.03	0.02	0	
Job Is a Job of P	0	0	0	0.02	0.02	0	0	
Proportionality	0.02	0.01	0	0.04	0.01	0.21	0.38	

P= county poverty indicator variable; T= county timber employment. Multi-county regions are: NW (Del Norte, Humboldt, Trinity, Mendocino); NE (Lassen, Plumas, Siskiyou, Shasta, Tehama); and SE (Amador, Tuolumne).

Table 4. Expected Outcomes Conditional on 100 Additional Jobs Using VAR Models with Alternative Poverty Indicator Variables

Condition	AFDC UP Model			Food Stamp Model		
	Expected Additional Jobs or Cases:			Expected Additional Jobs or Cases:		
	nontimber jobs	timber jobs	AFDC UP cases	nontimber jobs	timber jobs	Food Stamp cases
Add 100 timber jobs	34.6	104.6	-1.7	-55.1	113.2	-61.5
Add 100 nontimber jobs	76.6	7.6	0.73	68.8	-1.6	3.1

Appendix 1 Structural and VAR Modeling

The VAR that we estimate can be viewed as a solution to a two-sector, structural model. The model includes five equations representing: equilibrium in county timber (1) and non-timber (2) labor markets, county poverty program caseload as a function of employment and other variables (3), total state employment (4), state poverty program caseload as a function of other state-level variables (5), and county-level migration as a function of county and state variables (6).

County timber industry labor markets are assumed to clear:

$$T^d(w_T, SE) = T^s(\text{pop}, w_T, w_N). \quad (1)$$

County timber industry labor demand (T^d) is a function of wage in that industry (w_T), and state employment (SE). State employment shifts demand for timber and, therefore, demand for county timber workers. The supply of labor to county timber firms depends upon county population (pop), and both timber and non-timber wages (w_N).

County nontimber sector labor markets also clear. Here, however, both state employment and county timber employment shift demand. According to export-base theory, the local timber sector (T), a primary exporting (basic) industry, should drive total local labor demand in these timber-dependent counties. Assuming markets clear,

$$N^d(SE, T, w_T) = N^s(\text{pop}, w_T, w_N), \quad (2)$$

where N^d and N^s are demand and supply, respectively, for county workers in nontimber industries.

The third equation of the structural model defines the relationship between a county poverty program caseload (POV) and other variables in the system. We want to test the hypothesis of a relationship between county poverty and county employment rates (N, T, pop). Since emigration from the county is an alternative to unemployment, county net migration (mig) should also be a determinant of caseload. County migration is defined below in equation (7). State poverty program caseload (SPOV) is a proxy for noncounty factors influencing caseload in the county poverty program, including factors such as state-wide changes in benefits levels or eligibility requirements. As discussed below, all counties in California applied the same eligibility and benefits rules in the poverty programs examined in this study. Thus,

$$\text{POV} = \text{POV}(N, T, \text{pop}, \text{mig}, \text{SPOV}). \quad (3)$$

The state-level variables are not of primary interest here and are simply modeled as a vector autoregressive process.

$$SE = SE(SE_{t-1}, SE_{t-2}). \quad (4)$$

$$SPOV = SPOV(SE_{t-1}, SE_{t-2}, SPOV_{t-1}, SPOV_{t-2}). \quad (5)$$

By definition, county population is

$$pop_t = g \bullet pop_{t-1} + mig_t, \quad (6)$$

where g is an exogenously determined net rate of county population growth. Equation (6) can be solved for current population as a function of initial population and a growth-rate weighted sum of past migration.

$$pop_t = pop_0 + g \bullet \sum_t mig_t. \quad (6a)$$

From the point of view of this study, initial population is a constant. As a result, lagged values of migration can be substituted for population wherever it appears in the model. Finally, net county immigration depends on state and county employment and on state and county poverty:

$$mig = mig(SE, N, T, POV, SPOV). \quad (7)$$

Substituting migration (7) into the population equation (6a) gives pop_t as a function of initial population and $SE, N, T, POV,$ and $SPOV$. Substituting pop_t into equations (1), (2), (3), and (5) leaves a vector autoregressive model in which $N, T, SE, SPOV,$ and POV are each a function of current and lagged values of all five of these variables. While the estimation of this time-series model will not permit reconstruction of the structural model, it does allow explicit empirical testing of hypotheses about the long-run relationship between poverty program participation and employment.

References

- Associated Press. 1999. Logging Cutbacks Helped, Not Hurt, Economy, 22 Oct.
- Bartik, Timothy J. 1993. Who Benefits from Local Job Growth: Migrants or the Original Residents? *Regional Studies* 27: 297-311.
- Blanchard, Olivier J., and Lawrence F. Katz. 1992. Regional Evolutions. *Brookings Papers on Economic Activity*. Washington, DC: Brookings Institution, 1-61.
- Blank, Rebecca M. 1997. What Causes Public Assistance Caseloads to Grow? Working Paper No. 6343. National Bureau of Economic Research, Cambridge, MA.
- . 2000. Fighting Poverty: Lessons from Recent U.S. History. *Journal of Economic Perspectives* 14: 2–19.
- Blank, Rebecca M., and Alan Blinder. 1986. Macroeconomics, Income Distribution and Poverty. In *Fighting Poverty: What Works and What Doesn't?*, edited by Sheldon H. Danziger and Daniel H. Weinberg. Cambridge, MA: Harvard University Press.
- Blank, Rebecca M., and David Card. 1993. Poverty, Income Distribution, and Growth: Are They Still Connected? *Brookings Papers on Economic Activity*. Washington, DC: Brookings Institution, 285-325.
- Brown, Scott J, N. Edward Coulson, and Robert F. Engle. 1992. On the Determination of Regional Base and Regional Base Multipliers. *Regional Science and Urban Economics* 22: 619-635.
- California Department of Finance. 1983–1993 (annual report). *California Statistical Abstract*. Sacramento, CA.
- California Department of Social Services. 1983–1993 (annual report). *Social Welfare in California*. Sacramento, CA.
- California Employment Development Department. 1983–1993 (annual report). Bureau of Labor Statistics Employment Series-202 (BLS ES-202 “Bell Series”). Sacramento, CA.
- California Forestry Association. 1994. *California's Changing Forests: A Case for Management*. Sacramento, California. Videocassette.
- California Senate. 1996. Office of Research. *Myths of Jobs vs. Resources: Environmental Protections and Economic Growth*. By A. Gordon. Sacramento, CA.

- Engle, Robert F., and Clive W. J. Granger. 1987. Co-integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* 55: 251-276.
- Fawson, Christopher, and Keith Criddle. 1994. A Comparative Analysis of Time Series Approaches to Modeling Intersectoral and Intercounty Employment Linkages in Rural Regional Labor Markets. *Journal of Regional Science* 34: 57-74.
- Figlio, David N. and James P. Ziliak. 1999. Welfare Reform, the Business Cycle, and the Decline in AFDC Caseloads. In *Economic Conditions and Welfare Reform*, edited by Sheldon H. Danziger. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.
- Fortmann, Louise, Jonathan Kusel, Yoshio Kawamura, Martin Olson and Cecilia Danks. 1991. Study 1: The Effects of Forest Control and Use on County Well-Being. In *Well-Being in Forest Dependent Communities*, Vol. 1. University of California, Department of Forestry and Resource Management, Berkley, 49-75.
- Gilles, Keith. 1999. Conversation with the authors. Department of Environmental Science, Policy and Management, University of California, Berkeley, Fall 1999.
- Hansen, Henrik, and Soren Johansen. 1993. Recursive Estimation in Cointegrated VAR-Models. Copenhagen, Sweden: University of Copenhagen, Institute of Mathematical Statistics.
- Hansen, Henrik, and Katarina Juselius. 1995. *CATS in RATS: Cointegrated Analysis of Time Series*. Evanston, Illinois: Estima.
- Hoffmann, Sandra, Sherman Robinson, and Shankar Subramanian. 1996. The Role of Defense Cuts in the California Recession: Computable General Equilibrium Models and Interstate Factor Mobility. *Journal of Regional Science* 36: 571-95.
- Johanssen, Soren. 1995. Likelihood-Based Inference in Cointegrated Vector Auto-Regressive Models. Oxford, England: Oxford University Press.
- Johansen, Soren, and Katarina Juselius. 1990. Maximum Likelihood Estimation and Inference on Cointegration—With Applications to the Demand for Money. *Oxford Bulletin of Economics and Statistics* 52: 169-210.
- Joint Centers for Poverty Research. Rural Dimensions of Welfare Reform Conference. <http://www.jcpr.org> (accessed May 2000).
- Kraybill, David S., and Jeffrey Dorfman. 1992. A Dynamic Intersectoral Model of Regional Economic Growth. *Journal of Regional Science* 32: 1-17.

- Krikelas, Andrew C. 1992. Why Regions Grow: A Review of Research on the Economic Base Model. *Federal Reserve Bank of Atlanta Economic Review* 77: 16-29.
- Lesage, James P. 1990. Forecasting Metropolitan Employment Using an Export-Base Error-Correction Model. *Journal of Regional Science* 30: 307-23.
- Lesage, James P., and David Reed. 1989. The Dynamic Relationship between Export, Local, and Total Area Employment. *Regional Science and Urban Economics* 19: 615-36.
- McWilliams, Bruce, and George Goldman. 1994. The Forest Industries in California: The Impact on the State Economy. Publication Number CNR002. Berkeley, CA: University of California.
- National Research Council. 1999. Interim Report 3: Evaluation of 1995 County and School District Estimates for Title I Allocations, edited by Constance Citro and Graham Kalton. Washington, D.C.: National Research Council.
- Rao, Bhaskara. 1994. Cointegration for the applied economist. New York: St. Martin's Press.
- Sample, Alaric V., and Dennis C. Le Master. 1992. Economic Effects of Northern Spotted Owl Protection. *Journal of Forestry* 90: 31-35.
- Sawhill, Elizabeth. 1988. Poverty in the U.S.: Why Is It So Persistent? *Journal of Economic Literature* 26: 1073-1119.
- Siegel, Paul. 1997. Developing Postcensal Income and Poverty Estimates for all U.S. Counties. In American Statistical Association, Proceedings of the Section on Government Statistics and Section on Social Statistics, 177-191.
- Sims, Christopher. 1980. Macroeconomics and Reality. *Econometrica* 48: 1-48.
- Tuchman, E. Thomas. 1995. Timber Supply and the President's Forest Plan. *Journal of Forestry* (July): 6-10.
- U.S. Bureau of the Census. 1980. U.S. Census of Population. U.S. Government Printing Office, Washington, D.C.
- . 1990. U.S. Census of Population. U.S. Government Printing Office, Washington, D.C.
- . Small Area Income and Poverty Estimates Program, <http://www.census.gov/hhes/www/saipe.html> (accessed July 2000).

- U.S. House of Representatives, Ways and Means Committee. 1992. *Green Book. Overview of Entitlement Programs Background Material and Data on Programs*. Washington, D.C.: U.S. Government Printing Office.
- . 1994. *Green Book. Overview of Entitlement Programs Background Material and Data on Programs*. Washington, D.C.: U.S. Government Printing Office.
- Vincent, Bruce. 1988. It's OK to Be a Logger. *Evergreen*, Number 2, (September): unpaginated.
- Wallace, Geoffrey, and Rebecca M. Blank. 1999. What Goes Up Must Come Down. Explaining Recent Changes in Public Assistance Caseloads. In *Economic Conditions and Welfare Reform*, edited by Sheldon Danziger. Kalamazoo, MI: W.E. Upjohn Institute.
- Wilde, Parke, Peggy Cook, Graig Gundersen, Mark Nord, and Laura Tiehen. 2000. The Decline in Food Stamp Program Participation in the 1990's. Food Assistance and Nutrition Research Report No. 7. Washington, D.C.: USDA Economic Research Service.
- Wozniak, Gregory D., and Ronald A. Babula. 1992. Dynamic Relationships Among Regional and Nationwide Manufacturing. *Growth and Change* 23: 16-36.
- Yaffee, Steven L. 1994. *The Wisdom of the Spotted Owl: Policy Lessons for a New Century*. Washington, D.C.: Island Press.