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Poverty in Forested Counties: An Analysis Based on Aid to Families with Dependent Children

ABSTRACT

The Sierra Nevada Forest Counties (SNFC) have persisting problems of poverty and low incomes. Over a forty-year period the forest counties have been consistently overrepresented in the bottom third of California counties in terms of per capita income and consistently underrepresented in the top third. Only 11% of the forest counties have ever experienced what might be characterized as an economic golden age. Poverty rates in the SNFC have tended to be higher than statewide averages and, for the most part, rose between 1980 and 1990. Similarly, Aid to Families with Dependent Children (AFDC) caseloads have tended to run above statewide averages. Time-series analysis provides no evidence that the loss of timber-related employment "Granger-caused" increases in AFDC caseloads at the county level, nor that its availability would cause the decline of AFDC caseloads at the county level. Nor is there evidence to suggest that lumber and wood-products employment affects AFDC indirectly through its effects on other employment. We found that lumber and wood-products employment Granger-caused" other employment in none of the forest counties. The growth rate of lumber and wood-products employment "Granger-caused" the growth rate of other employment in only one of the forest counties. These are strong findings, particularly in light of such strongly held popular beliefs to the contrary.

INTRODUCTION

The Sierra Nevada has historically been rich—rich in timber, gold, and scenery. That richness has made some of the people who use the region's resources wealthy, some very wealthy. But other residents of the region have been poor, some very poor.

Poverty in rural areas shouldn't be news to anyone. From fictional works like Grapes of Wrath to the classic photography and prose of Let Us Now Praise Famous Men (Agee and Evans 1941) and the stark testimony in The People Left Behind (U.S. National Advisory Commission on Rural Poverty 1967), life in rural areas has been portrayed as short and nasty more often than pastoral and bucolic. The Sierra Nevada is no exception. Kusel and Fortmann (1991) showed that the timber counties of California, including the Sierra Nevada counties, had poverty rates that sometimes equaled or exceeded inner-city rates.

This chapter addresses the issue of poverty in the Sierra Nevada Forest Counties (SNFC). These counties include Alpine, Amador, Butte, Calaveras, El Dorado, Lassen, Madera, Mariposa, Nevada, Placer, Plumas, Sierra, Tehama, Tulare, Tuolomne, and Yuba. These are Sierra Nevada counties that in 1980 had a forest cover of more than 50% or in which 3% or more of the 1980 wages came from forest-sector industries (not including tourism) and in which timber was cut commercially. It documents the extent to which these counties, like many other areas dependent on natural resources, are

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characterized by poverty and low incomes and explores some possible explanations.

Public Perceptions

Anecdotal explanations of economic well-being or the lack of it in the SNFC fall into four rough categories, all of which may be used by the same individuals in different contexts: The Golden Age of Timber, Environmentalism Run Amok, Corporate Greed Run Amok, and The Invasion of the Poverty Importers.

The Golden Age of Timber story suggests that when timber (and in a limited number of counties, gold) was king, towns were prosperous. The logging lifestyle was treasured:

> It's a good life to be able to work in the woods and make a good living. It really gets in your blood. It really does.[1]

The sequel to this story, Environmentalism Run Amok, implies that the golden age has disappeared, and its vanishing can be blamed directly on environmental regulation, which has "closed down the woods":

> And then came the spotted owl, and almost overnight the hauling jobs dried up and we had our electricity turned off and finally we received a foreclosure notice on this farm.
>
> —Unidentified Woman
> (California Forestry Association 1994)

> The amount of economic impact on small communities—devastating. It's going to ruin our lives to say the least. All our relatives are in the business.

> The loss is evident in the lines at the soup kitchens. And the loss is evident in the homes where unemployed workers, anxious, depressed, sunk in despair, lash out at their loved ones or find solace in alcohol or drugs. A culture, a way of life, prized and reverenced in our timber communities is dying.
>
> —Archbishop Thomas Murphy
> (California Forestry Association 1994)

The logical, and frequently expressed, corollary is that if increased and less-regulated timber harvesting were allowed, prosperity would once again reign in the SNFC. Interestingly, those who use these explanations are not unlikely to use a third, the Corporate Greed Run Amok story, summed up in the words of two timber fallers:

> We're just pawns in the hands of corporations—they don't care about us—you can be sure they won't lose any money. All they care about is their bonus. All they care about is making money. (Quoted in Kusel and Fortmann 1991, 56)

> All they see is dollar signs and profits. Timber fallers are making the same money as ten years ago, but timber has gone up so the profits are going elsewhere.

The fourth anecdotal explanation for poverty in the SNFC argues that it has been imported by undesirable outsiders over time. During the 1960s and 1970s people variously stereotyped as marijuana-growing and -smoking hippies and back-to-the-landers are described as having taken up residence in the region and gone on welfare. More recently, there has been a rise in anecdotal evidence of poor urban mothers moving to rural areas for cheaper housing and greater safety as well as for all the reasons that richer in-migrants move. A subtheme is that during the more temperate summer months, urban welfare recipients "vacation" (on welfare) in the Sierra along with the more standard form of tourist.

Finally, there is anecdotal evidence about the adverse effect on the affordable housing stock of in-migration by wealthier people, which aggravates the effects of poverty.

How Does This Issue Relate to Other Sierra Nevada Issues?

Land-use choices and economic strategies are likely to affect income levels and poverty rates. These choices should be made with as clear an understanding as possible of the potential consequences for poverty and low incomes and their alleviation.

Key Questions

Our questions arise out of Kusel and Fortmann's 1991 study of well-being in forest communities, to our knowledge the only systematic statistical study of poverty in the forest counties of California. Our questions are

- What is the incidence of poverty in the SNFC?
- How persistent has it been?
- How do trends in employment and specifically in timber-industry employment affect rates of AFDC, Unemployed Parent (AFDC UP)? The lack of sufficient poverty data led us to use AFDC UP as a poverty indicator. The shortcomings of this method are discussed in detail later in this chapter.

BACKGROUND

This review of the literature begins at the national level and then addresses regional and California studies. It includes both descriptive studies of who the poor are and analysis of why poverty exists.

Rural Poverty in the United States

The most recent comparison of metropolitan and non-metropolitan poverty rates shows both declining from 1959 (when nonmetropolitan rates were just under 35%) to the early 1970s when they began a slow (albeit uneven) rise to their 1993 rates of roughly 17% for nonmetropolitan and 15% metropolitan areas. (Definitions can be found in the "Methods" section. By convention, these cumbersome terms will hereafter be shortened to metro and nonmetro.) Throughout the entire thirty-four-year period, nonmetro poverty rates have exceeded metro rates (Nord 1995). The highest nonmetro poverty rates are found in the South; the second highest, in the West (Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming) (Nord 1995). In 1990, 44.4% of the U.S. nonmetro poor were in married couple families, 72.9% were white (Rural Sociological Society Task Force [hereafter RSS Task Force] 1993), and 64.7% of the families had at least one member who was formally employed (Deavers and Hoppe 1992). They were, in short, white, married, and working.

Working gets one less in nonmetro America than in metro America. McLaughlin and Perman (cited in RSS Task Force 1993) found that roughly two-thirds of the earning gap between nonmetro and metro white men is explained by the fact that education and experience result in lower incomes in nonmetro areas than in metropolitan areas. Workers in rural America are more likely to be poor than their urban counterparts with the same amount of education (Shapiro, cited in RSS Task Force 1993). The RSS Task Force on Persistent Rural Poverty (1993) concluded that "the fundamental problem resides in the low wages and inadequate employment opportunities found in rural America." We shall return to this point.

Rural Poverty in the Western Region

In 1993, among nonmetro poor households in the western region of the United States 21.8% had a full-time, full-year worker, 42.9% had part-time or part-year workers, 27.3% had no working member, and the remaining 8% had no family member of working age (that is, they were either too young or too old to work). Husband-wife families accounted for 46.8% of the nonmetro poor households, female-headed families for 32.5%, male-headed families for 1.3% and single men or women for 19.4%. Non-Hispanic whites constituted 64.9% of the nonmetro poor households in the western region. Whites made up 75% of the nonmetro poor in California. The most recent statistical data on poverty thus show that, as in the country as a whole, the nonmetro poor in the western region are likely to be white, married, and working at least part-time.

The Question of Welfare

As discussed later, we use AFDC caseloads as an indicator of poverty because of data constraints. The most exhaustive study of welfare dynamics in California (Albert 1988) does not disaggregate metro and nonmetro data. Hence, this literature offers no particular insights into rural poverty. Albert argues that expanding employment opportunities in low-skills, low-wage industries would decrease AFDC-Basic caseload. The alert reader will already have noticed that this approach is not wholly consistent with ending poverty if the RSS Task Force is correct about the causative nature of low wages.

Poverty in Natural-Resource Dependent Areas

Social scientists and economists have long since given up the search for a one-size-fits-all theory of poverty causation. We know that particular households fall in and out of poverty because of life-cycle changes such as marriage, divorce, the birth of children, the death of a breadwinner, or the onset of catastrophic illness. But we also know that systematic social and economic structures lead to prosperity for some and poverty for others. A particularly clear example is found in natural-resource dependent areas that generate substantial profits from high value products such as timber and minerals at the same time they are characterized by high rates of poverty.

The Working Group on Natural Resources of the RSS Task Force (without coming to a single, unified conclusion about causality) identified five factors affecting the creation of poverty in natural-resource dependent areas (RSS Task Force 1993):

1. rural deindustrialization (the closing of mills, employment cutbacks, the extraction of wage concessions)
2. the concentration of local political and economic power in the hands of resource-extraction firms, which may cause systematic underinvestment in human capital by restricting taxes and other measures to fund schools, and so on
3. control of state and national natural resource agencies by powerful clients (which often are large industrial concerns but, some argue, are increasingly bureaucratic national environmental interests)
4. segmented labor markets and core-periphery relations in which rural areas are the sites of low-paying, dangerous jobs while high-paying processing is located in urban areas (for a detailed discussion of this approach see Peluso et al. 1994)

5. moral exclusion from resource use through the social construction of what actually constitutes a resource (see Freudenburg and Gramling [1994] for a discussion of the moral-exclusion argument)

The group's conclusions thus simultaneously identify as poverty-generating factors both inadequate employment opportunities and low-wage employment opportunities.

Incomes and Livelihoods in California Forest Areas

Although Kusel and Fortmann's (1991) study is the only direct study of poverty in California's forest areas, the findings of studies of these areas' economies consistently suggest that the solution to poverty and low incomes is unlikely to be found in the timber industry.

Belzer and Kroll's (1986) study of the northern timber region included four forest counties (Lassen, Plumas, Sierra, and Tehama). In their argument for economic diversification in timber counties, they noted that in 1981 and 1982 timber industry employment in California was at its lowest level since the end of World War II, that California timber production had experienced an overall downward trend since 1955 despite rises in housing starts, and that from the 1950s the timber industry had tended toward concentration with smaller numbers of increasingly automated mills. They predicted permanent losses in timber employment and productive mills, with lower demands for labor.

Stewart (1993) found that significant losses of timber jobs were unrelated to changes in overall employment and that during the decline of the timber industry, per capita income in most forest counties increased because of the growing importance of public transfer payments and private capital payments in the form of interests, dividends, and rent.

Kusel and Fortmann (1991), based on a point-in-time analysis using 1980 county-level census data, found that contrary to the anecdotal "evidence" presented earlier, the greater the concentration of private timberland ownership, the lower the county median family income; the higher the percentage of public timberland, the higher the county poverty rate; and the higher the rate of in-migration between 1975 and 1980, the lower the county poverty rate.

McWilliams and Goldman (1994) tell a different story from Stewart for northern California (Butte, Del Norte, Humboldt, Lassen, Mendocino, Modoc, Nevada, Plumas, Shasta, Sierra, Siskiyou, Tehama, Trinity, and Yuba counties) where they find the forest-products industry in 1992 contributed a hefty 17.7% of the income and 22.8% of the jobs.

The Limitations of Point-in-Time Data

Piqued by the 1991 Kusel and Fortmann study, which revealed forest county poverty rates equaling or exceeding inner-city rates, we have asked a key question concerning poverty: How serious and how persistent is it in the SNFC, what causes it, and what can be done to reduce it? A preliminary attempt to update the Kusel and Fortmann study using 1990 census data suggested that the strength of the relationships found in that study had decreased considerably during the intervening decade. This change raised many questions. Did the changes reflect the declining importance of timber in the regional economy? Did in-migration act as a one-time jump start to incomes that then declined? Because income levels and poverty rates are affected by previous events, these questions cannot be answered with point-in-time data. Rather than the "snapshot" of point-in-time data, we found we needed the "movie" that time-series data can provide.

METHODS

We present two kinds of data in this study. We begin with descriptive data showing poverty-related characteristics of the SNFC. We then explore some causal relationships. Unfortunately, data on poverty rates usable at a county level are collected only once a decade, in the decennial census. The nearest surrogate for poverty rates reported monthly are AFDC caseloads. No other annual data exist. AFDC caseloads, however, are not identical to poverty rates. Not everyone who is poor receives AFDC for any number of reasons: They may not be eligible for welfare. (In 1985, California AFDC recipients who also received food stamps still fell 7% below the official poverty line [Albert 1988]. Maximum aid payments have declined 15% since 1991 [Barbara Snow, conversation with L. Fortmann, Spring 1995]). They may be eligible for welfare, but not for AFDC. They may be eligible and not know it. They may be eligible but be denied welfare nonetheless. They may be eligible but not apply because of the stigma of receiving AFDC. Thus, although AFDC is an indicator of poverty levels, it is not the same as the poverty level. Indeed, AFDC rates are likely to be below the poverty rate. Nonetheless, AFDC caseload is the best poverty indicator available across the SNFC at a frequency that was useful for time-series analysis. For this reason, we have used it.

Descriptive Statistics

Our descriptive data are taken from Nord (1995) and an analysis of the U.S. Census. The following definitions and explanations may be helpful.

Nonmetropolitan Counties

"Metropolitan statistical areas usually include an urbanized area with a population nucleus of 50,000 or more, as well as nearby communities that are economically and socially integrated with that nucleus. Nonmetropolitan counties are not linked with large cities nor with communities closely tied to large cities. This distinction is different from that between urban and rural devised by the Census Bureau (Duncan and Sweet 1992, xxvii).

Poverty Rates[2]

There are two sources of data for the 1989 poverty rates. The 1990 decennial census of population and housing is the only data source with a large enough sample to provide reliable estimates at the state and county level. The "long form" of the decennial census, filled in by about 5% of households, includes information on household composition, relationships, and income. The poverty income cutoff for each family is established based on family size and composition. The family's income for the year before the census is then compared with that poverty income cutoff level, and the people in the family are assigned the appropriate poverty status. What then shows up in the STF3C, the data file available to the public, is a total for each county of how many people had income above the poverty level, between .5 and 1.0 times poverty level, and below .5 times the poverty level. (Actually, there are a few more categories, but they are not relevant to this discussion.) These counts are also presented by race and ethnicity. The counts are population estimates based on the 5% sample. There is also a proportion of the population that is counted in the census, but for whom poverty status is not determined. The most important group is college students living in dormitories. They do not figure as either numerator or denominator in poverty-rate calculations.

The Current Population Surveys (for March 1990 and March 1994) were used to compare 1989 and 1993 data. This survey is similar to the long form of the decennial census (in terms of family and income data). It refers to income in the previous year. Like the decennial census, it calculates poverty status for each person based on the family composition and income and includes a weight variable to inflate the sample to population estimates. It is a large sample, about 55,000 households, but is not large enough to be reliable at the state level (except for states with very large populations). It is, however, done every year instead of once in ten years. It is useful, therefore, for regional estimates in the years between censuses.

Rural

"The decennial census classifies population as rural or urban . . . according to the classification of the place they live. In the West, urban places include places of 2500 or more population incorporated as cities, villages, boroughs (except in Alaska), and towns, but excluding rural portions of 'extended cities.' Also included are 'Census designated places' of 2,500 or more. All other areas are classified as rural" (Nord 1995).

Timber Harvest

Total annual timber harvest data for 1949–1993 were obtained from the Strategic Planning Program, California Department of Forestry and Fire Protection.

Causal Analysis

Data Sources

Monthly data were collected on the following variables for the period 1984–1993. Databases for the primary explanatory variable of interest, monthly employment in lumber and wood-products production (Standard Industrial Classification [SIC] code 24) in California, are not consistently available for years before 1984 and therefore limit the length of the time period examined. Fortunately, from a statistical point of view, the decade from January 1984 through December 1995 saw dramatic fluctuation in the level of SIC 24 employment. This variation allows us to test the hypothesis that changes in SIC 24 employment "Granger-cause" other county employment and AFDC caseload. (The term Granger cause is defined later in this section.)

AFDC Caseload

Data on AFDC caseload are gathered by the California Department of Social Services (various years). There are two categories of AFDC cases: AFDC Unemployed Parent (AFDC UP) and AFDC Family Group (AFDC FG). AFDC UP recipients consist of two-parent households, AFDC FG of one-parent (usually the mother) households. Both programs are means tested, that is, would-be recipients must demonstrate that their income and assets fall below a certain level. Recipients can keep the first $30 they earn, plus a third of their income before aid is reduced (Snow 1995a, 1995b). We have used AFDC UP caseload in our time series analysis because it should be more sensitive to changes in timber-related employment.

County Population

Data on county population were taken from California Department of Finance reports (February 1987, July 1991, and March 1994). County population is estimated as of July 1 of each year. A monthly time series was constructed from these annual data by assuming that population changed at a uniform rate throughout the year.

County Employment

County employment data are taken from the U.S. Bureau of Labor Statistics (BLS) series on employment covered by unemployment insurance (BLS ES-202 program data, also referred to as the "Bell" series), which is collected and maintained by the California Employment Development Department. This data series was used both because very few data were missing for the period of interest and because the series is one of the few monthly employment series that is not constructed from a sample. The data series is compiled from firm-level reports, filed to comply with unemployment insurance requirements. All firms with employees covered by unemployment insurance must report the number of workers on their payroll during the pay period including the twelfth day of the month to the California Employment Development Department. "Bell" series employment data were used in this study. BLS considers the ES-202 data series to be "the most complete universe of monthly employment and quarterly wage information by industry, county, and State [available]" (U.S. Department of Labor September 1992).

BLS ES-202 categorizes employment by Standard Industrial Classification (SIC) code. In counties where confidentiality considerations do not prevent it (that is, where individual firms cannot be identified from the data), employment is reported by four-digit SIC code. SIC categories are revised periodically to reflect changes in technology and industrial structure. Pre-1988 data used in this study are classified using the 1977 edition of the SIC. Data from 1988 on were classified using the 1987 edition of the SIC (U.S. Department of Labor September 1992). Changes to the industrial categories used in this study (SIC 08 and SIC 24) were not deemed extensive enough to raise any significant issues regarding data comparability.

The other major county-level employment series available is mid-March employment reported in the U.S. Department of Commerce, Bureau of the Census, County Business Patterns. These data are inadequate for examining forest-related industries because forest-related employment exhibits marked seasonality, peaking in mid-summer to mid-fall.

SIC 08 (forestry employment) includes employment in "establishments primarily engaged in the operation of timber tracts, tree farms, forest nurseries, and related activities such as reforestation services." Forestry services include establishments "primarily engaged in performing, on a contract or fee basis, services related to timber production, wood technology, forestry economics and marketing, and other forestry services, not elsewhere classified, such as cruising timber, firefighting, and reforestation" (Office of Management and Budget 1987). SIC 08 employment was not used in causality tests in this study primarily because data were unavailable for most counties and most months. In addition, based on the data that are available, SIC 08 employment represents an extremely small fraction of total county employment, rarely exceeding .5% of total county employment. This level of economic activity cannot drive other activity in an economy and therefore can be safely ignored in looking for factors causing total employment or poverty.

SIC 24 (lumber and wood-products employment) includes logging, sawmills and planing mills, and production of millwork, plywood and structural members, wood containers, mobile homes, prefabricated wood buildings, and furniture and fixtures (Office of Management and Budget 1987).

> This major group includes establishments engaged in cutting timber and pulpwood; merchant sawmills, lath mills, shingle mills, cooperage stock mills, planing mills, and plywood mills and veneer mills engaged in producing lumber and wood basic materials; and establishments engaged in manufacturing finished articles made entirely or mainly of wood or related materials. Certain types of establishments producing wood products are classified elsewhere. For example, furniture and office and store fixtures are classified in Major Group 25; musical instruments, toys and playground equipment, and caskets are classified in Major Group 39. Wood working in connection with construction, in the nature of reconditioning and repair, or performed to individual order, is classified in nonmanufacturing industries. Establishments engaged in integrated operations of logging combined with sawmills, pulp mills, or other converting activity, with logging not separately reported, are classified according to the primary product shipped. . . . Independent contractors engaged in estimating or trucking timber, but who perform no cutting operations, are classified in non-manufacturing industries (Office of Management and Budget 1987).

This series is available for all study counties except Alpine for nearly all months of the study period. We use SIC 24 to represent forest-related employment because of this consistent coverage and because of its possible economic importance.

We did not include SIC 26 (paper and paper-products employment) in the study primarily because the study counties have little pulp mill activity. Furthermore, in the study counties, data on pulp and paper-mill employment, which is closely linked to timber production could not be separated from employment in the manufacture of secondary paper products like paperboard containers, coated papers, paper bags, and stationery products, which may rely on imported pulp or recycled paper rather than on California timber harvest.

"Other employment" is total county employment less employment in SIC 24. This variable was also constructed using BLS ES-202 program data.

Monthly employment data were obtained from California Employment Development Department (1994). The data were censored to protect confidentiality of county businesses.

Granger Causality Tests

Granger causality tests are widely used to investigate statistical causality over time (Cromwell 1992; Gruidle and Pluver 1991; Hoffman 1991; and Schimmelpfennig and Thirtle 1994). They have been used to investigate the impact of U.S. Forest Service policy in Oregon on forest-related employment (Burton and Berck, in press). Granger causality tests check for a very specific form of statistical causation based on two basic ideas. The first is that x can cause y only if it precedes y in time. The second is that if x does cause y, then a regression of past values of x and y on current y should predict current y significantly better than a regression of only past values of y on current y. For example, we could ask the question, Does lumber and wood-products employment "Granger-cause" AFDC caseload in a county? This is asking whether current county AFDC caseload is explained better by past values of lumber and wood-products employment and AFDC caseload in the county than by past values of AFDC caseload alone.

Granger causality is also a specific kind of causality because it is not necessarily transitive. That is, if x "Granger-causes" y, and y "Granger-causes" z, then x may or may not "Granger-cause" z. Finally, Granger causality explores causality in a purely statistical sense. By itself, it does not imply that one phenomena causes another in an economy or society. However, it does provide evidence about the plausibility of hypotheses about causation drawn from experience, observation, or theory.

More formally, y fails to Granger-cause x if for all s > 0 the mean squared error (MSE) of a forecast of x_{t+s} based on (x_t, x_{t-1},...) is the same as the MSE of a forecast of x_{t+s} that uses both (x_t, x_{t-1},...) and (y_t, y_{t-1},...). The test is conducted by comparing two regressions: one of (x_t, x_{t-1},...) and (y_t, y_{t-1},...) regressed on x_{t+s}, and the other of (x_t, x_{t-1},...) regressed on x_{t+s}. For small samples, like those used in this study, an F-statistic is used on the results of the restricted and unrestricted regressions to test the hypothesis that (y_t, y_{t-1},...) contributes significantly to the explanation of x_{t+s} (Hamilton 1994).

Studies have found that the results of Granger causality tests can be sensitive to the number of lagged (past) values used in running the regressions and can be sensitive to the way nonstationarity (nonconstant mean or variances over time) is handled (Hamilton 1994). Said and Dickey (1984) have shown that lag lengths equal to the cube root of the number of observations used in the regressions usually provide as much information as can be obtained with greater lag lengths. The issue of whether and how to deal with nonstationarity in the underlying time series is unresolved.

In this study, transformations that increase stationarity in the observed time series materially change the interpretation of the test. Twelve-month-differencing the natural log of our observed data induces stationarity but transforms a monthly series of observations into a series made up of the annual growth rate of the variable calculated each month. This is quite different from a time series of observed past values of each variable. As a result, we have run Granger causality tests using both the raw observed time series and twelve-month differenced values of the natural log of the observed data. Granger causality tests were run using six lags of transformed series. The raw series exhibit yearly seasonal cycles. As a result, Granger causality tests on the raw observed data were run using eighteen lags (twelve months + six lags). To see how these transformations affect the interpretation of results, consider the test of whether lumber and wood-products employment Granger-causes AFDC caseload. The resulting tests on raw data can be interpreted as asking whether a combination of the past eighteen months of AFDC caseload and the past eighteen months of lumber and wood-products employment predicts current AFDC caseload significantly better than the past eighteen months of AFDC caseload alone. Tests on the transformed data ask whether the annual rate of growth in AFDC caseload in the current month is predicted significantly better by a combination of the annual growth rates of AFDC and lumber and wood-products employment for the last six months than by the annual growth rate for the past six months of AFDC caseload alone.

Granger Causality Models

The following is provided for those who desire a formal discussion of the model. Others should skip this section. Granger causality is a vector autoregressive test that defines causation so that for the time series of any two variables x and y, x fails to Granger cause y if

$$\begin{aligned} &\text{MSE}\,[\hat{E}(y_t \mid y_{t-1}, y_{t-2}, \ldots)] \\ &= \text{MSE}\,[\hat{E}(y_t \mid y_{t-1}, y_{t-2}, \ldots, x_{t-1}, x_{t-2}, \ldots)] \end{aligned} \tag{1}$$

The reasoning behind this definition is that for event x to cause event y, it must precede event y. Another way to say this is that "x is exogenous to y in the time series sense" if equation (1) holds (Hamilton 1994).

We ran Granger causality tests using two types of data: raw data and twelve-month differenced natural log transformations of the raw data. With both sets of models, the number of lags was chosen because it was sufficient to induce stationarity and made sense as a representation of the information firms use for employment decisions.

We used ordinary least squares (OLS) on eighteen monthly lags of raw data to estimate

$$\begin{aligned} \mathbf{y}_t = c &+ ß_1\mathbf{y}_{t-1} + ß_2\,\mathbf{y}_{t-2} + \ldots + ß_{18}\,\mathbf{y}_{t-18} + ß_{19}\mathbf{x}_{t-1} \\ &+ ß_{20}x_{t-2} + \ldots + ß_{36}\mathbf{x}_{t-18} + \mathbf{e}_t \end{aligned} \tag{2}$$

The test for Granger causality is then simply an F-test of the null hypothesis

$$H_o\!: ß_{19} = ß_{20} = \ldots = ß_{36} = 0 \tag{3}$$

For each county in the study, tests were conducted of the hypotheses that lumber and wood-products (SIC 24) employment Granger-caused non-SIC 24 employment, that SIC 24 employment Granger-caused AFDC UP caseload, and that non-SIC 24 employment Granger-caused AFDC UP caseload.

To test for Granger causality of rates of growth, we used OLS on six monthly lags of natural log transformed data to estimate

$$\begin{aligned} d(\ln(\mathbf{y}))_t = c &+ ß_1 d(\ln(\mathbf{y}))_{t-1} + \ldots + ß_6\, d(\ln(\mathbf{y}))_{t-6} \\ &+ ß_7 d(\ln(\mathbf{x}))_{t-1} + \ldots + ß_{12} d(\ln(\mathbf{x}))_{t-12} + \mathbf{e}_t; \end{aligned}$$

where

$$d(\ln(\mathbf{y}))_t = \ln(\mathbf{y})_t - \ln(\mathbf{y})_{t-12}$$

and

$$d(\ln(\mathbf{x}))_t = \ln(\mathbf{x})_t - \ln(\mathbf{x})_{t-12} \tag{4}$$

The annual rate of growth in a variable is the change in its natural log over a twelve month period. This is the discrete counterpart to the instantaneous rate of growth of a variable being the derivative of its natural log.

The test for Granger causality is then an F-test of the null hypothesis

$$H_o: ß_7 = ß_8 = ... = ß_{12} = 0 \tag{5}$$

For each county in the study, tests were conducted of the hypotheses that the annual rate of growth of lumber and wood products (SIC 24) employment Granger-caused annual rate of growth of non-SIC 24 employment, that the annual rate of growth of SIC 24 employment Granger-caused the annual rate of growth of AFDC UP caseload, and that the annual rate of growth of non-SIC 24 employment Granger-caused the annual rate of growth of AFDC UP caseload.

FINDINGS

We have presented our data in two different ways. To ensure that graphs can be read and to allow geographic comparisons, graphed data are presented in small geographic clusters of counties. Tabular data are presented for the entire data set in alphabetical order.

Sierra Nevada Forest County Poverty: Descriptive Data

The Golden Age of Timber may have been a reality for some individual households. But, as can be seen in the following tables, incomes and livelihoods in the forest counties of the Sierra Nevada currently and historically compare unfavorably with the state as a whole. However, it is important to note that no forest county is included among the 24% of nonmetro counties nationally that are persistently poor, that is, counties with 20% or more of people in poverty in each of the years 1960, 1970, 1980, and 1990. Such counties are concentrated in the South, Southwest, and Alaska (Cook and Mizer 1994).

Data on the comparative rank of SNFC in terms of average per capita income are presented in table 14.1.[3] All counties in the state were ranked from one to fifty-eight. The county with the highest average per capita income is ranked number one, and the lowest is ranked number fifty-eight. As can be seen in table 14.2, which summarizes table 14.1, the SNFC are disproportionately found among the poorer counties in California. Although they account for 28% of the counties, from 1950 to 1992 the SNFC have made up only 5% to 11% of the wealthiest third of counties, 16% to 32% of the middle third, and 45% to 60% of the poorest third. In other words, although individual households may have experienced a bonanza, since 1950, only 11% of the forest counties has experienced what might be characterized as a golden age. Furthermore, the SNFC have also been disproportionately represented among the least affluent of California counties, within the bottom third. As can be seen in table 14.1, since 1950 the SNFC have constituted between 40% and 71% of California counties with average per capita income 25% or more below the state average and (with the exception of zero in 1970) between 42% and 75% of counties averaging less than 30% of the state average.

The data presented in these tables, which show an apparent rise in the relative aggregate income levels of the SNFC while their percentage of the lowest income counties remains high, are consistent with Stewart's (1993) finding about the increasing economic importance of public transfer payments and private capital payments in the form of interest, dividends, and rent.

Data on poverty rates in SNFC presented in table 14.3 show poverty to be a persisting, indeed, increasing, problem in the forest counties. As is typical for both the United States as a whole as well as for the western region, nonmetro poverty rates exceeded metro rates. In both 1980 and 1990, half of the SNFC had poverty rates exceeding the state average. In five forest counties in 1990, nearly one in five persons fell below the poverty level. In 1990, 67% of the forest counties classified as metro had poverty rates exceeding the statewide average for metro counties, while 20% of the nonmetro counties exceeded the nonmetro average. This imbalance may, as will be seen in table 14.4, be due to the high rates of rurality in the forest metro counties, because nonmetro poverty rates are typically higher than metro rates. It is worth noting that the three foothill counties (Placer, Nevada, and El Dorado), which emerged as having relatively higher per capita income by 1992, also have some of the lowest poverty rates. (See Duane 1996 for additional insights into the foothill counties.)

Deep poverty is defined as a family income of less than 50% of the poverty level. In 1989 the average nonmetro deep poverty rate in California was 5.2% (Nord 1995). That is, 5.2% of the people in California's nonmetro areas were in deep poverty. Only two (12.5%) of nonmetro forest counties had deep poverty rates approaching or exceeding the state nonmetro average. Thus, while people in the forest counties often suffer from low incomes, most do not suffer from the deprivations of deep poverty.

The data in table 14.4 show persisting rurality in the metropolitan forest counties. As can be seen in tables 14.1 and 14.4, the 1970 census was the first to record a metro county (Placer) among the SNFC, and by 1993 six (38%) of the SNFC

TABLE 14.1

Relative rank of Sierra Nevada Forest Counties among California counties of average per capita income 1950–92 (Goldman and Hetland 1995).

County	1950	1960	1970	1980	1986	1992
Alpine	28	58[a]	52[b]	56[b]	46[b]	20
Amador	52[b]	55[a]	31	37	26	43
Butte	44	45	51	**51**[c]	**45**[b]	**44**[b]
Calaveras	57[a]	53[b]	55[b]	53	36	39
El Dorado	29	32	19	30	**17**	**18**
Lassen	31	37	48	54[b]	53[a]	53[a]
Madera	55[b]	52[b]	54[b]	27	50[a]	51[a]
Mariposa	46	24	16	52	37	41
Nevada	58[a]	56[a]	44	42	23	24
Placer	48[b]	49[b]	**29**	**16**	**14**	**12**
Plumas	22	28	23	44	34	32
Sierra	19	11	47	46	29	29
Tehama	53[b]	35	40	55	54[a]	54[a]
Tulare	51[b]	40	56[b]	**45**	**52**[a]	**48**[a]
Tuolumne	40	47[b]	53[b]	50	42[b]	37
Yuba	20	8	50	**58**[a]	**56**[a]	**56**[a]
SNFC as a percentage of counties 25% below average	64%	54%	71%	60%	47%	40%
[state total]	[11]	[13]	[7]	[5]	[17]	[15]
SNFC as a percentage of counties 30% below average	67%	75%	0%	50%	42%	45%
[state total]	[3]	[4]	[2]	[2]	[12]	[11]

[a]At least 30% below state average per capita income.
[b]At least 25% below state average per capita income.
[c]Bold indicates classification as a metro county.

were classified as metro counties. However, only one metro county, Butte, had less than 25% of its population living in rural areas. Five counties (31%) were 75%–100% rural.

Nord (1995) defines underemployment as working less than thirty-five hours a week or less than forty weeks a year. In California the average rate of underemployment among nonmetro working males in 1989 was 35.5%. As can be seen in table 14.4 in half of the nonmetro counties the underemployment rate nearly equaled or exceeded the state average.

Tables 14.1–14.4 show that the SNFC have a long history of relatively low incomes and persisting poverty. The question is why. In beginning to address this question, we have examined the relationships among AFDC Unemployed Parent caseload, lumber and wood-products employment and other employment in the SNFC.

Sierra Nevada Forest County Timber Harvest, Employment, and AFDC Caseloads: Descriptive Data

Timber Harvest

As is shown quite clearly in appendix 14.1, figure 14.A1, the timber harvest in the SNFC has been steady in comparison to the state harvest levels since the mid 1960s with a decline during the nationwide recession of the early 1980s and a recovery in the late 1980s and early 1990s. This trend contrasts with the general decline in the California timber harvest as a whole since 1955 (Belzer and Kroll 1986). Appendix 14.1, figure 14.A2 plots the SNFC timber harvest on a scale that reveals year-to-year variation more clearly. Individual county graphs are more volatile and varied (appendix 14.1, figures 14.A3–14.A6). Timber harvest is not included as a causal vari-

TABLE 14.2

Distribution of SNFC within California counties by per capita income (Goldman and Hetland 1995).

Tier	Ranking	1950	1960	1970	1980	1986	1992
1	Top 19	1 (5%)[a]	2 (11%)	2 (11%)	1 (5%)	2 (11%)	2 (11%)
2	Middle 19	5 (26%)	5 (26%)	3 (16%)	3 (16%)	6 (32%)	6 (32%)
3	Bottom 20	10 (50%)	9 (45%)	11 (55%)	12 (60%)	8 (40%)	8 (40%)

[a]Percentage rates refer to SNFC as a percentage of all California counties in the relevant tier.

TABLE 14.3

Poverty rates in Sierra Nevada Forest Counties (Bureau of the Census 1983; Nord 1995).

County	Metro/Nonmetro	Poverty Rate 1980 (State Average, 11.8%)	Poverty Rate 1990 (State Average, 12.5%; Metro Average, 12.4%; Nonmetro Average, 14.9%)	Deep Poverty 1989[a] (Nonmetro Average, 5.2%)
Alpine	Nonmetro	18.8	18.1	5–7%
Amador	Nonmetro	9.0	8.4	<5%
Butte	Metro	15.0	18.9	—
Calaveras	Nonmetro	10.1	10.1	<5%
El Dorado	Metro	8.7	7.7	—
Lassen	Nonmetro	10.3	13.3	<5%
Madera	Metro	15.7	17.5	—
Mariposa	Nonmetro	11.5	12.7	<5%
Nevada	Nonmetro	8.7	7.7	<5%
Placer	Metro	8.6	7.1	—
Plumas	Nonmetro	9.7	11.9	<5%
Sierra	Nonmetro	12.9	9.2	<5%
Tehama	Nonmetro	12.9	15.3	5–7%
Tulare	Metro	16.5	22.6	—
Tuolumne	Nonmetro	11.9	9.1	<5%
Yuba	Metro	16.1	19.5	—

[a]Nonmetro counties only. Deep poverty is defined as a family income of less than 50% of the poverty level.

able in the following statistical analysis since its effect is not direct but is mediated through employment.

Total Monthly Employment

Total monthly employment (that is, all employment, not just lumber and wood-products employment) is shown in appendix 14.2, figures 14.A7–14.A12. As in shown figure 14.A 7 (which demonstrates seasonal fluctuations), total employment in the SNFC has risen since 1984, leveling off in the 1990s well above 1984 levels. Figures 14.A8–14.A11 show employment levels in individual counties to be rising or steady.

TABLE 14.4

Rurality and underemployment of Sierra Nevada Forest Counties (Nord 1995).

County	Metro/ Nonmetro 1993	Percentage of Population Living in Rural Areas 1990[a]	Percentage of Underemployed Working Males 1989[b] (State Average, 35.5%)
Alpine	Nonmetro	75–100	<30
Amador	Nonmetro	50–75	>35
Butte	Metro	<25	—
Calaveras	Nonmetro	75–100	30–35
El Dorado	Metro	50–75	—
Lassen	Nonmetro	50–75	>35
Madera	Metro	25–50	—
Mariposa	Nonmetro	75–100	30–35
Nevada	Nonmetro	50–75	30–35
Placer	Metro	25–50	—
Plumas	Nonmetro	75–100	>35
Sierra	Nonmetro	75–100	30–35
Tehama	Nonmetro	50–75	>35
Tuolumne	Nonmetro	50–75	>35
Tulare	Metro	25–50	—
Yuba	Metro	25–50	—

[a]Overlapping categories are in the original.
[b]Nonmetro counties only.

Lumber and Wood Products Employment

SIC 24 employment includes logging, sawmills and planing mills, and production of millwork, plywood and structural members, wood containers, mobile homes, prefabricated wood buildings, wooden furniture, and fixtures. A more detailed description of this variable can be found earlier in the "Methods" section.

Absolute levels of lumber and wood-products employment are presented in appendix 14.3, figures 14.A12–14.A16. Again, seasonal fluctuations figure prominently in some of these graphs. The timber-cutting boom of the late 1980s and early 1990s also is reflected in many of these graphs. As can be seen in figure 14.A12, lumber and wood-products employment in the whole region rose during the mid to late 1980s, falling off sharply in the early 1990s. Most counties followed this general pattern, with these exceptions: Sierra was relatively stable throughout. Madera showed a much earlier drop. Plumas showed a steady decline throughout the entire period.

SIC 24 Employment as a Percentage of Total County Employment 1984–1994[4]

We have already seen that during the 1980s and early 1990s both SNFC timber harvest and SNFC lumber and wood-products employment rose and fell markedly (see appendix 14.1, figure 14.A2; and appendix 14.3, figure 14.A12). But this cycle does not appear to have had an effect on lumber and wood-products employment relative to total regional employment (see appendix 14.4, figure 14.A17). During the 1980s and early 1990s, SNFC employment in the lumber and wood products sector made up roughly 3% of total employment in the SNFC as a whole. One would not expect employment of this relative magnitude to drive a regional economy. Furthermore, while lumber and wood products employment as a percentage of SNFC total employment fell slightly relative to total SNFC employment, it fell steadily in a pattern that does not evidence the rise and fall in timber employment during the decade (see figure 14.A17). This reasonably stable regional employment picture is at variance with the dramatic stories of catastrophe with which we began this chapter. It is important to remember that stories based on real and painful individual experience are not necessarily indicative of larger trends. We shall return to this point below. It is also important to remember the point of the RSS Task Force that employment can involve low wages and poor working conditions. Our data do not address this issue.

As expected, the picture at the county level is more variable. Graphs of lumber and wood products employment as a percentage of total county employment are presented in appendix 14.4, figures 14.A17–14.A21. Again, seasonal fluctuations figure prominently in some of these graphs, as does the timber boom of the late 1980s and early 1990s. Throughout the decade, lumber and wood-products employment was consistently at or below 4% in eight counties: Butte, El Dorado, Nevada, Placer, Calaveras, Madera, Mariposa, and Tulare. These counties included all the southernmost tier of SNFC (figure 14.A21) and two of the four counties in the next tier to the north (figure 14.A20). Five of these counties (El Dorado, Nevada, Placer, Calaveras, and Mariposa) fell into the first or second tier for per capita income in 1986 and 1992. Double-digit levels of lumber and wood-products employment (roughly 10%–25%) occurred throughout most of the decade in Amador, Plumas, Sierra, and Tehama, with all but Sierra experiencing steep downward trends after 1988. Sierra experienced an upward trend, ending the decade with a slightly higher percentage of lumber and wood-products employment.

AFDC Unemployed Parent

If timber unemployment drives welfare, AFDC Unemployed Parent cases are the most likely to reflect timber employment trends. Data for AFDC UP cases per capita from 1970 to 1993 are presented in appendix 14.5, figures 14.A22–14.A26. Again, AFDC UP cases show strong seasonal fluctuations. This is consistent with Albert's (1988, 57) statewide finding that "many of the cases that open in the winter close in the spring." The SNFC are compared with California in figure 14.A22. Two features of this graph should be given particular attention. First, the per capita figures are higher for the SNFC than for the state as a whole, consistent with the income and poverty figures presented in tables 14.1–14.3. Second, at the very time that statewide AFDC caseloads were dropping and the timber industry was booming, the SNFC caseloads were rising. Why this was so will be explored in the following Granger causality analysis. Again, county trends vary. It is worth noting that four of the five counties with per capita incomes at least 30% below the state average in 1986 and 1992 (Lassen, Madera, Tulare, and Yuba) also had the highest per capita AFDC UP caseloads in 1993.[5]

Although we did not use them in the statistical analysis, data on 1970–93 AFDC Family Group caseloads are presented in appendix 14.6, figures 14.A27–14.A32. (AFDC FG households have only one parent, usually the mother, present.) In contrast to AFDC UP, AFDC FG caseloads for the SNFC briefly fell below statewide levels in the early 1980s. However, for the remainder of the period, SNFC caseloads exceeded state levels.

Tests of Causality

The remainder of this chapter explores causal relationships between variables that social science theory or popular anecdote suggest cause good or bad economic outcomes in the SNFC. We have used Granger causality tests to do this. Because of federal rules protecting confidentiality, we were not able to include data from Alpine County in these tests.

In reporting our findings we use the verb phrase "Granger-cause," a term of art in time-series analysis, because we want to be precise and clear about the limits of our findings. If we say x "Granger-causes" y, we mean that past values of x and y predict the current value of y better than the past values of y alone. Granger causality implies that the variable x_t, does not occur later in time than the variable y_t that it "Granger-causes." To repeat our caution in the Methods section, Granger causality explores causality in a purely statistical sense. By itself, it does not imply that one phenomena causes another in an economy or society. However, it does provide evidence about the plausibility of hypotheses about causation drawn from experience, observation, or theory.

Because "Granger-cause" is an awkward term, we have used "cause," within quotation marks, as a shorthand for "Granger-cause." The reader should bear in the mind the limitations on the meaning of "cause" signaled by the quotation marks.

Although we have presented diagnostic statistics for these tests, the lay reader need look only in the final column labeled Prob >F in the following tables. If there is a footnote reference beside the beside the number in that column, then, in lay terms, it is likely that x does "Granger-cause" y in that county. It is important to know that the preferred and more precise interpretation is that the question "Does x Granger-cause y" cannot be answered "no" with any statistical confidence for that county. The precision involved in the term "Granger-cause" reflects scientific method in which hypotheses can be disproved but not proved.

Tables 14.5–14.7 were calculated using eighteen months of lagged raw data. In these tables the question "Does x 'cause' y?" should be interpreted as meaning "Do the past eighteen months of x and y predict current y better than the past eighteen months of y alone?" If the answer is yes, then x "Granger-causes" y.

Table 14.5 shows that lumber and wood-products employment fails to "cause" other employment in any of the forest counties over time. More precisely, given that one can predict

TABLE 14.5

Does SIC 24 employment Granger-cause other county employment?[a]

County	Restricted R-Square	DW	F-Test Statistic	Prob >F ($F_{18, 52}$)
Amador	0.98	1.99	0.78	0.711
Butte	0.98	1.99	1.04	0.432
Calaveras	0.96	1.98	0.89	0.589
El Dorado	0.99	1.94	1.14	0.338
Lassen	0.84	2.06	1.28	0.230
Madera	0.89	1.92	1.56	0.098
Mariposa	0.93	1.91	0.55	0.924
Nevada	0.99	1.98	0.89	0.596
Placer	1.00	2.00	1.40	0.161
Plumas	0.97	1.95	0.42	0.978
Sierra	0.79	2.00	0.49	0.953
Tehama	0.97	1.98	0.62	0.869
Tulare	0.95	2.07	1.39	0.165
Tuolumne	0.96	2.01	0.93	0.552
Yuba	0.87	2.02	1.04	0.432

[a]Time series: raw data, eighteen lags.

current other employment in the county from the previous eighteen months of such employment, knowing what the lumber and wood-products employment has been during the last eighteen months will not improve ability to predict current other employment. In lay terms, employment variation in the lumber and wood-products industry over time does not cause variation in other employment. This is consistent with Stewart's (1993) finding.

Table 14.6 shows that other employment "causes" AFDC UP caseload over time in seven of the forest counties. More precisely, if one knows only what the AFDC UP caseload has been for the past eighteen months, one cannot predict the current AFDC UP caseload as well as if one also knows the past eighteen months of other employment. In lay terms, variations in other employment causes variations in the AFDC UP caseload in seven of the fifteen counties. These findings for these seven counties are consistent with Albert's (1988) findings that employment affects aggregate levels of AFDC in California as whole.[6]

The lack of such a causal relationship in the remaining eight counties may be explained in two basic ways. First, Albert (1988) found that aggregate employment predicted AFDC case closures but not case accessions, while employment in specific industries was an accurate predictor of both. It may be that employment levels in specific industries have greater predictive power. Second, these counties may be reflecting the persisting effects of particular economic structures. Five of the counties (Amador, Calaveras, Nevada, Sierra, and Tulare) have relatively low poverty rates. It is possible that these low rates reflect poverty that persists for structural reasons, such as age distribution of the population or the wage structure of particular industries, that would not necessarily be affected by variations in employment. Similarly, since 1980 Lassen and Yuba counties have experienced average per capita incomes 30% or more below the state average. This again suggest that these low incomes persist for structural reasons and are not affected by changes in available employment. An important lesson of table 14.6 is that whatever ecological or geographical unity the Sierra Nevada may have emphatically does not translate into socioeconomic unity. These are very heterogeneous counties with differential social, political, and economic ties to state, national, and global systems.

If Albert's (1988) finding that employment levels in specific industries make a difference in predicting AFDC accession and termination, then the obvious industry to investigate in the SNFC is lumber and wood products. The data in table 14.7 show that lumber and wood-products employment fails to "cause" AFDC UP caseload over time in any of the forest

TABLE 14.6

Does other employment Granger-cause AFDC Unemployed Parent caseload?[a]

County	Restricted R-Square	DW	F-Test Statistic	Prob >F ($F_{18, 52}$)
Amador	0.86	2.05	1.08	0.389
Butte	1.00	1.97	2.05	0.019[b]
Calaveras	0.93	2.04	0.73	0.769
El Dorado	0.96	1.90	1.95	0.026[b]
Lassen	0.86	1.98	1.19	0.295
Madera	0.99	1.99	2.47	0.004[b]
Mariposa	0.94	1.94	1.82	0.041[b]
Nevada	0.96	1.99	0.99	0.480
Placer	0.99	2.08	2.08	0.017[b]
Plumas	0.91	2.04	1.63	0.078
Sierra	0.69	1.98	0.64	0.851
Tehama	0.96	1.98	2.39	0.006[b]
Tulare	1.00	1.94	2.91	0.001[b]
Tuolumne	0.94	1.99	1.51	0.115
Yuba	0.97	1.97	0.96	0.514

[a]Time series: raw data, eighteen lags.
[b]Significant at d = .05, that is, one cannot reject the hypothesis that other employment Granger-causes AFDC UP caseload.

TABLE 14.7

Does SIC 24 employment Granger-cause AFDC Unemployed Parent caseload?[a]

County	Restricted R-Square	DW	F-Test Statistic	Prob >F ($F_{18, 52}$)
Amador	0.86	2.03	0.91	0.566
Butte	1.00	1.93	1.62	0.081
Calaveras	0.94	2.00	1.43	0.147
El Dorado	0.96	1.99	1.89	0.033[b]
Lassen	0.87	1.94	0.14	0.170
Madera	0.99	2.04	1.06	0.411
Mariposa	0.93	1.94	1.46	0.121
Nevada	0.96	2.00	1.42	0.152
Placer	0.98	1.94	1.42	0.151
Plumas	0.93	1.96	3.21	0.000[b]
Sierra	0.75	1.94	1.58	0.101
Tehama	0.96	1.95	1.33	0.192
Tulare	1.00	1.94	0.68	0.814
Tuolumne	0.94	1.95	1.43	0.146
Yuba	0.98	2.02	1.71	0.060

[a]Time series: raw data, eighteen lags
[b]Significant at d = .05, that is, one cannot reject the hypothesis that SIC 24 employment Granger-causes AFDC UP caseload.

counties except El Dorado and Plumas. More precisely, if one can predict current AFDC UP caseload from the previous eighteen months of AFDC UP caseload, knowing what the lumber and wood-products employment has been during the last eighteen months will not improve ability to predict current AFDC UP per capita caseloads except in El Dorado and Plumas counties. In lay terms, employment variation in the lumber and wood-products industry over time does not cause variation in AFDC caseload except in El Dorado and Plumas counties.

Tables 14.8–14.10 address the same questions as tables 14.5–14.7, except that they use the annual difference in the natural log of raw monthly data.[7] The annual change in the natural log of a variable is the annual growth rate in the variable itself. The regression results reported in these tables use six-month lags of this transformed variable. In essence, they ask whether the annual growth rate of y from, for example, January to January is better predicted by the annual growth rate of y for the previous six months or by the annual growth rate in both x and y during the previous six months.

Table 14.8 shows that the annual growth rate of lumber and wood-products employment fails to "cause" the annual growth rate of other employment in any of the forest counties except Tulare. More precisely, if one can predict the annual growth rate of current other employment from the annual growth rate of other employment for the previous six months, then also knowing what the annual growth rate of lumber and wood products employment was during the past six months will not improve your ability to predict the current annual growth rate of other employment except in Tulare County.

In lay terms, the combination of tables 14.5 and 14.8 shows that lumber and wood-products employment fails to "cause" other employment in the long term (defined as eighteen months) in any of the forest counties and that annual growth in lumber and wood-products employment "causes" annual growth in other employment only in Tulare County.

In Tulare County, the ability to predict the current annual growth rate of other employment will be better if one knows the annual growth rates of both lumber and wood-products employment and other employment for the past six months. Tulare is a high poverty, persistently low-income county with the percentage of total employment accounted for by lumber and wood products employment consistently running less than 2%. The fact that results for all three Granger causality tests on annual growth rates were significant for Tulare County suggests that something distinguishes it from other forest counties.

Table 14.9 shows that the annual growth rate of other employment does not "cause" the annual growth rate of AFDC UP caseload in any of the forest counties except Tulare and Tuolumne. More precisely, if one can predict the annual growth rate of AFDC UP caseload from the annual growth rate of the AFDC UP caseload in the previous six months, then also knowing the annual rate of growth of other employment for the past six months ago does not improve ability to predict the annual growth rate in AFDC UP caseload except in Tulare and Tuolumne counties.

We have discussed Tulare County earlier. Tuolumne County has an underemployment rate of more than 35%, but a low poverty rate. Lumber and wood-products employment has accounted for roughly 2% to 6% of total employment over time.

Table 14.10 shows that the annual rate of growth of lumber

TABLE 14.8

Does the annual growth rate of SIC 24 employment Granger-cause the annual growth rate of other county employment?[a]

County	Restricted R-Square	DW	F-Test Statistic	Prob >F ($F_{6, 89}$)
Amador	0.74	2.03	1.10	0.368
Butte	0.80	1.92	1.83	0.102
Calaveras	0.60	2.00	0.60	0.733
El Dorado	0.81	1.90	0.68	0.662
Lassen	0.66	2.00	0.70	0.648
Madera	0.40	2.00	1.61	0.153
Mariposa	0.77	1.96	1.72	0.126
Nevada	0.67	1.98	0.19	0.979
Placer	0.86	1.84	1.77	0.114
Plumas	0.71	1.97	0.64	0.696
Sierra	0.58	1.95	0.27	0.948
Tehama	0.56	1.96	0.68	0.667
Tulare	0.74	2.01	2.83	0.014[b]
Tuolumne	0.72	1.97	0.64	0.699
Yuba	0.75	1.98	1.01	0.421

[a]Time series: twelve-month differences of the natural log of raw data, six lags.
[b]Significant at d = .05, that is, one cannot reject the hypothesis that other employment Granger-causes AFDC UP caseload.

TABLE 14.9

Does the annual growth rate of other employment Granger-cause the annual growth rate of AFDC Unemployed Parent caseload?[a]

County	Restricted R-Square	DW	F-Test Statistic	Prob >F ($F_{6, 89}$)
Amador	0.79	2.01	2.02	0.071
Butte	0.71	2.01	1.69	0.134
Calaveras	0.74	2.13	1.21	0.310
El Dorado	0.85	1.88	1.94	0.084
Lassen	0.70	1.98	1.69	0.133
Madera	0.94	1.99	1.13	0.353
Mariposa	0.84	2.00	1.44	0.207
Nevada	0.90	1.99	2.00	0.074
Placer	0.92	2.03	1.05	0.397
Plumas	0.81	2.07	2.03	0.070
Sierra	0.53	2.00	1.44	0.209
Tehama	0.85	2.07	1.70	0.131
Tulare	0.97	1.91	3.93	0.002[b]
Tuolumne	0.80	2.02	3.06	0.009[b]
Yuba	0.91	1.92	1.08	0.378

[a]Time series: twelve-month differences of the natural log of raw data, six lags.
[b]Significant at d = .05, that is, one cannot reject the hypothesis that other employment Granger-causes AFDC UP caseload.

TABLE 14.10

Does the annual growth rate of SIC 24 employment Granger-cause the annual growth rate of AFDC Unemployed Parent caseload?[a]

County	Restricted R-Square	DW	F-Test Statistic	Prob >F ($F_{6, 89}$)
Amador	0.78	1.99	1.39	0.226
Butte	0.69	1.98	0.71	0.645
Calaveras	0.74	2.08	1.43	0.204
El Dorado	0.86	1.90	3.87	0.002[b]
Lassen	0.70	1.99	1.62	0.152
Madera	0.94	2.05	1.75	0.120
Mariposa	0.84	1.96	0.87	0.523
Nevada	0.89	1.99	1.09	0.377
Placer	0.92	1.97	0.90	0.501
Plumas	0.81	1.99	1.86	0.096
Sierra	0.57	2.06	2.84	0.015[b]
Tehama	0.88	2.06	4.97	0.000[b]
Tulare	0.97	1.83	2.26	0.045[b]
Tuolumne	0.78	1.98	1.50	0.187
Yuba	0.90	1.93	0.67	0.673

[a]Time series: twelve-month differences of the natural log of raw data, six lags.
[b]Significant at *d* = .05, that is, one cannot reject the hypothesis that other employment Granger-causes AFDC UP caseload.

and wood-products employment "causes" the annual growth rate of AFDC UP caseload in four of the forest counties. More precisely, if one knows only the annual growth rate of the AFDC UP caseload during the last six months, one cannot predict the annual growth rate of AFDC UP caseload in the current month as well as if one also knew the annual growth rate of lumber and wood-products employment during the last six months. In lay terms, variations in the growth rate of lumber and wood-products employment in the last six months does cause variations in the growth rate of AFDC UP caseload in four of the fifteen counties.

Again, we have discussed Tulare County earlier. El Dorado County has a low poverty rate, a rising rank in average per capita income, and only 2% to 4% total employment accounted for by lumber and wood products. In Sierra County, although poverty is relatively low, lumber and wood-products employment fluctuates around 20% of total employment, which may account for the effect shown here. Tehama is a low-income county with high underemployment, high poverty, and high deep poverty. Lumber and wood-products employment has dropped from roughly 15% to 7% of total employment. In this vulnerable county, it is perhaps not surprising that short-term shocks are registered quickly.

CONCLUSIONS

The most obvious policy implication of our findings is clear-cut. Poverty and low incomes are persisting problems in the Sierra Nevada and need to be addressed. A second and equally obvious conclusion of this study is the difficulty of studying poverty.

This study had its origins in an attempt to use 1990 census data to update Kusel and Fortmann's (1991) study of poverty in California forest counties, which used 1980 census data. When the variables that predicted poverty levels in 1980 turned out to be no longer statistically significant, two interrelated explanations seemed likely. First, the descent into poverty is not necessarily instantaneous. Rather, the onset of poverty may lag behind the occurrence of a causal event, be it job loss, divorce, pay cut, or death of a spouse. Second, during the decade the structure and economic importance of the California timber industry had continued to change. Our point-in-time data could not capture the effects of these dynamic processes.

We therefore undertook a time-series analysis, which is sensitive to ongoing dynamic processes and delayed effects. We immediately encountered the data availability problems described earlier. For obvious political reasons domestic poverty is not tracked closely by the state or federal government. Lacking data on poverty suitable for time-series analysis, we used monthly AFDC UP caseloads as the closest and most accurate substitute. The limitations of this measure have been detailed earlier. Nor, although we intended to, were we able to assess the effects of employment in agriculture and tourism because reliable data suitable for county level time-series analysis were not available. We discuss alternative approaches later in the section.

Despite our inability to conduct all the analyses we had hoped to, this analysis does provide valuable policy insights. Poverty and low incomes, persisting problems in the SNFC, need to be addressed. One means of relieving poverty and increasing incomes suggested by the timber industry and supported by popular perceptions of the economy in forest counties is to increase lumber and wood-products employment in general and timber harvesting in particular.

Albert (1988) found that for California as a whole aggregate employment predicted AFDC case termination but not accessions, while employment in specific industries accurately predicted both. We therefore tested the hypothesis that lumber and wood-products employment cause AFDC UP in the SNFC either directly or indirectly by causing other employment.

Lumber and wood-products employment directly "Granger-caused" AFDC caseload in only two of fifteen forest counties. The growth rate of lumber and wood-products employment Granger-caused the growth rate of AFDC caseloads in only four of the forest counties. Although this is not as strong a finding as the absence of impact on other employment or other employment growth discussed later, it provides a marked contrast to anecdotal evidence such as the very localized stories that began this chapter. Still, these findings indicate that on a regional level a policy that attempts to increase lumber and wood-products employment or its growth rate will do little to reduce AFDC caseload or—to the extent that AFDC is a good poverty indicator—by extension, regional poverty.

Other employment appears to have more effect on AFDC caseload than does lumber and wood-products employment, whether looking at either level or growth rate. It is not possible, however, to conclude on this basis that simply increasing employment would significantly decrease AFDC caseload or poverty in the SNFC.

There is also no evidence to suggest the lumber and wood-products employment affects AFDC indirectly through its effects on other employment. We found that lumber and wood-products employment "Granger-caused" other employment in none of the forest counties. The growth rate of lumber and wood-products employment "Granger-caused" the growth rate of other employment in only one of the forest counties. These are strong findings, particularly in light of such strongly held popular beliefs to the contrary. They differ from the implications of McWilliams and Goldman's (1994) input-output analysis because input-output analysis does not account for changes in economic conditions. Input-output analysis asks what might happen if there were a decrease in sales by forest-related industries in the very short run and labor in all sectors were employed in fixed proportion to output. Time-series analysis reflects the adjustments that result from changes in economic conditions. That is, it asks what actually happened in the long run.[8]

It is clear from these findings that increasing lumber and wood-products employment is not likely to have a significant long-run impact either on other employment or on AFDC caseloads in the SNFC. That is, we have no evidence that the loss of timber-related employment "caused" increases in AFDC caseloads at the county level, nor that its availability would cause the decline of AFDC caseloads at the county level. It seems safe to conclude that policies which might increase lumber and wood-products employment in general and timber harvesting in particular would provide a crude and probably ineffective lever for addressing these issues. It must be borne in mind that this analysis has nothing to say directly about impact on household or individual income. In addition, it must be kept in mind that these are regional trends, and individual experiences in local communities may be different. Understanding what policy efforts would decrease poverty requires a broad understanding of the process that causes poverty in these counties. This is beyond the scope of the study reported in this chapter.

The analysis presented here leaves many questions unanswered. In particular, our understanding of what drives poverty in the region is not clear enough to make specific policy suggestions. In addition, many questions are beyond the scope of available data suitable for time-series analysis. This chapter does not address the dynamics of how or why people fall into poverty or the welfare system, or how they avoid doing so, or how families who lose timber-based livelihoods cope. It is important to remember that real people do lose real jobs, and to these people aggregate trends offer little consolation.

Understanding the dynamics of poverty and welfare will require systematic interviews with people in the SNFC, specifically former timber workers and former and current welfare recipients. Questions that might be asked include

- Are people staying employed by taking lower-paying jobs?
- Are people more willing to go on welfare than they used to be?
- Are people leaving the SNFC for jobs in urban areas? Who leaves? Who stays?
- Are welfare recipients moving into the SNFC? Where do they come from? Do they stay?
- Is poverty becoming "harder" as nonstandard housing becomes scarcer?

What this study does make clear is that different levels of analysis reveal different, sometimes conflicting, pictures, of poverty and economic well-being and their causes.

ACKNOWLEDGMENTS

This study has benefited from the assistance of a number of people. Professor Henry Brady, Department of Political Science, and Professor Peter Berck and Professor Irma Adelman, Department of Agricultural and Resource Economics, University of California, Berkeley, provided generous tutelage in the intricacies of time-series analysis. Professor Brady and staff at the University of California Data Archives and Technical Assistance (UC DATA) also provided poverty data and insights from their studies of poverty programs in California. Professor Keith Gilless, Department of Environmental Science, Policy, and Management; Vicky Albert, George Goldman, and Norman Hetland, Department of Agricultural and Resource Economics, University of California, Berkeley; and Russell Henly, California Department of Forestry and Fire Protection, provided insights and data. Arvis Cury and other staff of the Labor Market Information Division/Area Services Group, Employment Development Department were generous in helping us understand the limitations of California data and in providing monthly employment data. Barbara Snow, UC DATA, provided AFDC definitions. Rowan Rountree, Pacific Southwest Research Station, was helpful in many ways. Jodi Bailey helped us assemble this chapter in compliance with the guidelines of the Sierra Nevada Ecosystem Project.

NOTES

1. Quotations without attribution are from unpublished field notes. Some of the stories in Brown's (1995) sophisticated and nuanced presentation of local narratives in an Oregon timber county reveal these same themes.

2. The following discussion of the calculation of poverty rates is taken from an email communication from M. Nord, Economic Research Service, PLIB, May 24, 1995.
3. We are grateful to George Goldman and Norman Hetland, Department of Agricultural and Resource Economics, University of California, Berkeley, for making available the data on which this table is based. The actual percentages can be found in their appendix 1.
4. County SIC 24 employment does not necessarily mean that timber is being harvested in that county. A gyppo logger who lives and pays a crew from his county of residence may actually be logging elsewhere. However, milling and wood-products manufacturing would take place almost exclusively in the county.
5. Alpine County also had a high per capita caseload.
6. Albert's choice of "urban" indicators such as nonagricultural work should be borne in mind.
7. This transformation appears to increase the stationarity of each data series. There are conflicting schools of thought on whether raw or transformed data are more appropriate in tests of Granger causality (Hamilton 1994). For this reason, and because the raw and transformed data series are interpreted differently, both data types are used in this study.
8. Input-output analysis is very useful in providing a picture of the current linkages between economic sectors. However, in projecting how a change in supply or demand will affect the economy depends on a number of strong assumptions about technology and human resources. These include no substitution by firms among possible inputs, no change in relative prices, fixed proportion technologies, no labor mobility between industrial sectors, and no regional migration. In short, the input-output model does not adjust to changes in demand or supply except through unemployment and idling of production plants. As a result, input-output analysis is well known to predict higher multiplier effects than are actually experienced. Unlike input-output analysis, Granger causality makes no assumptions about production technologies or people's response to economic change. It allows the data to reveal what has occurred. Its shortcoming is that, alone, it cannot explain structurally how adjustment occurs. Its strength is that it does not base estimates of economic impact on assumptions about the structure of the economy. It measures how the economy did in fact respond.

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APPENDIX 14.1

Aggregate and County-Level Timber Harvest

FIGURE 14.A1

Timber harvest for Sierra Nevada Forest Counties and state.

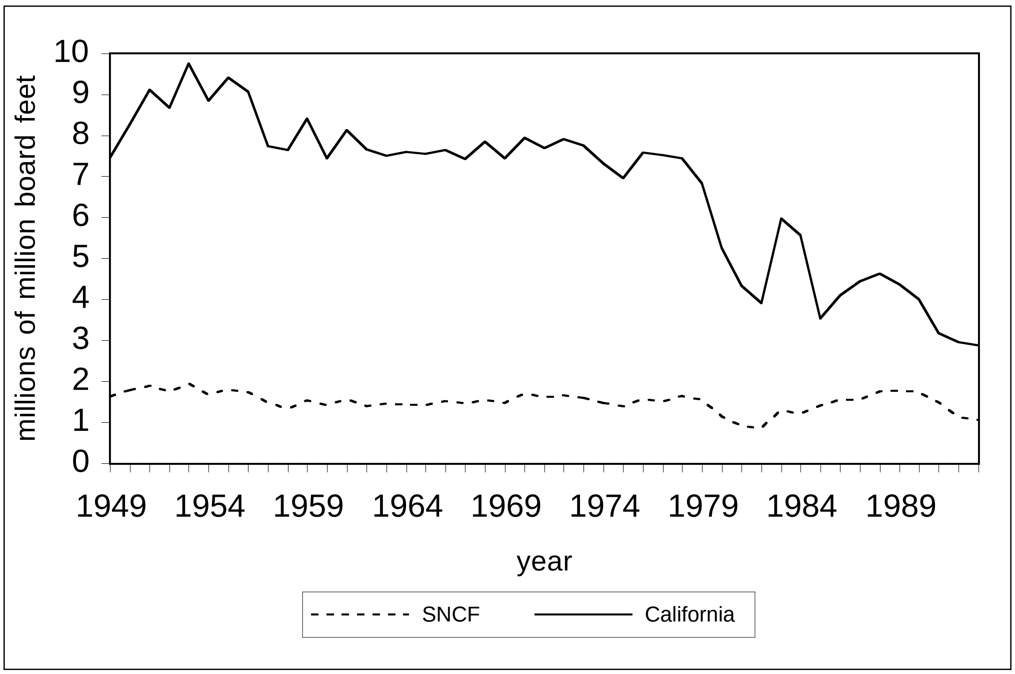


FIGURE 14.A2

Timber harvest for SNFC.

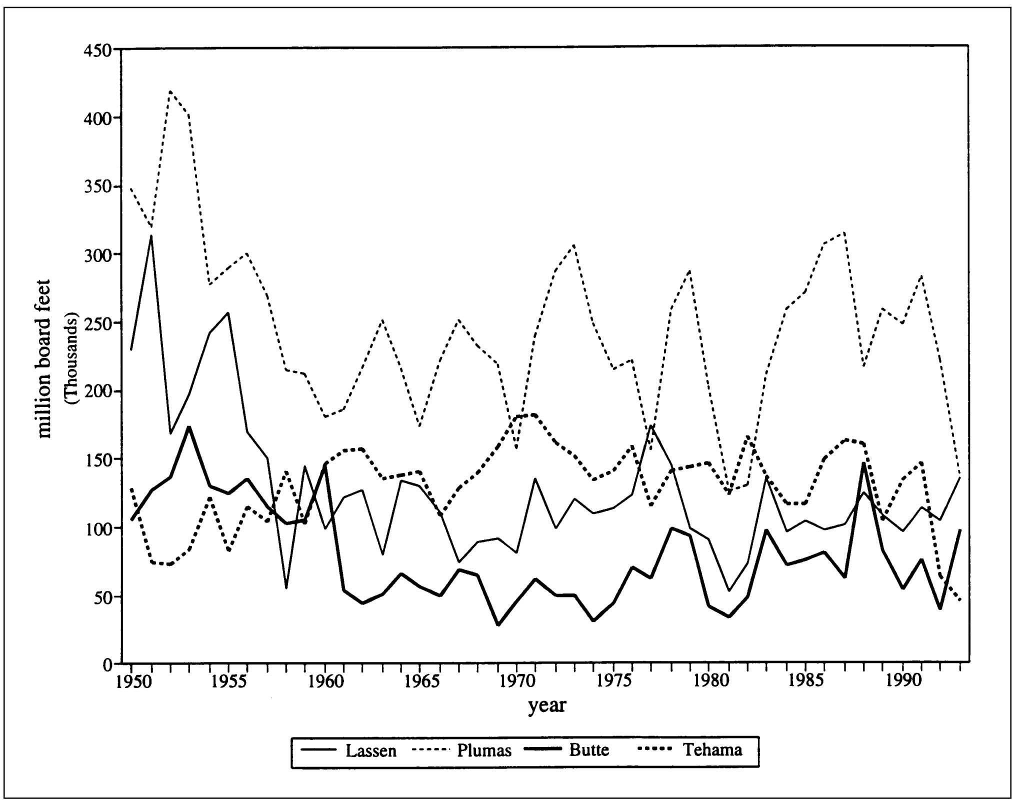


FIGURE 14.A3

Timber harvest 1949–93 for Lassen, Plumas, Butte, and Tehama counties.

FIGURE 14.A4

Timber harvest 1949–93 for Sierra, Nevada, Yuba, and Placer counties.

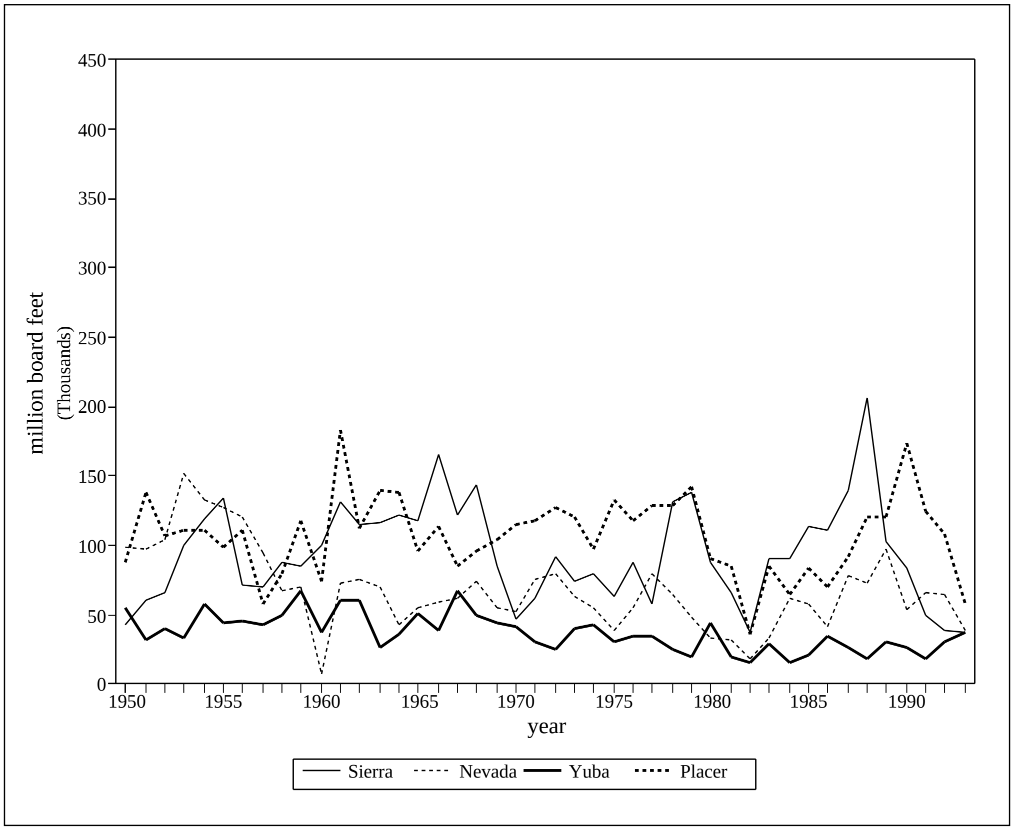
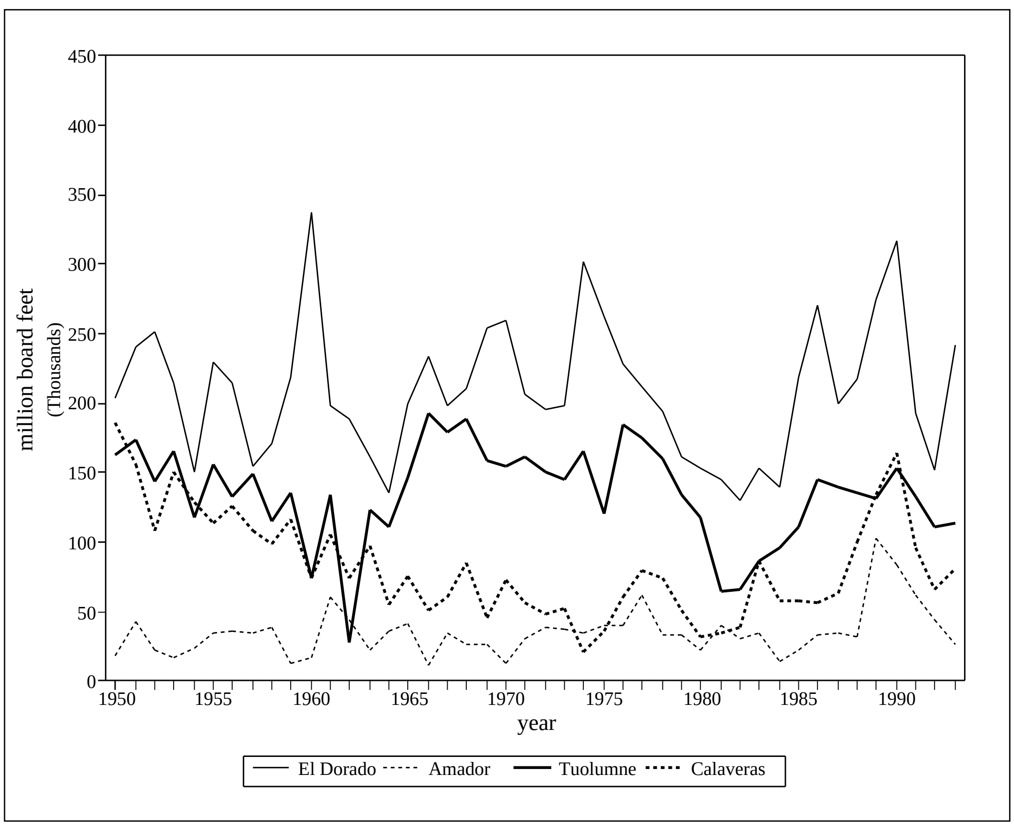


FIGURE 14.A5

Timber harvest 1949–93 for El Dorado, Amador, Tuolumne, and Calaveras counties.



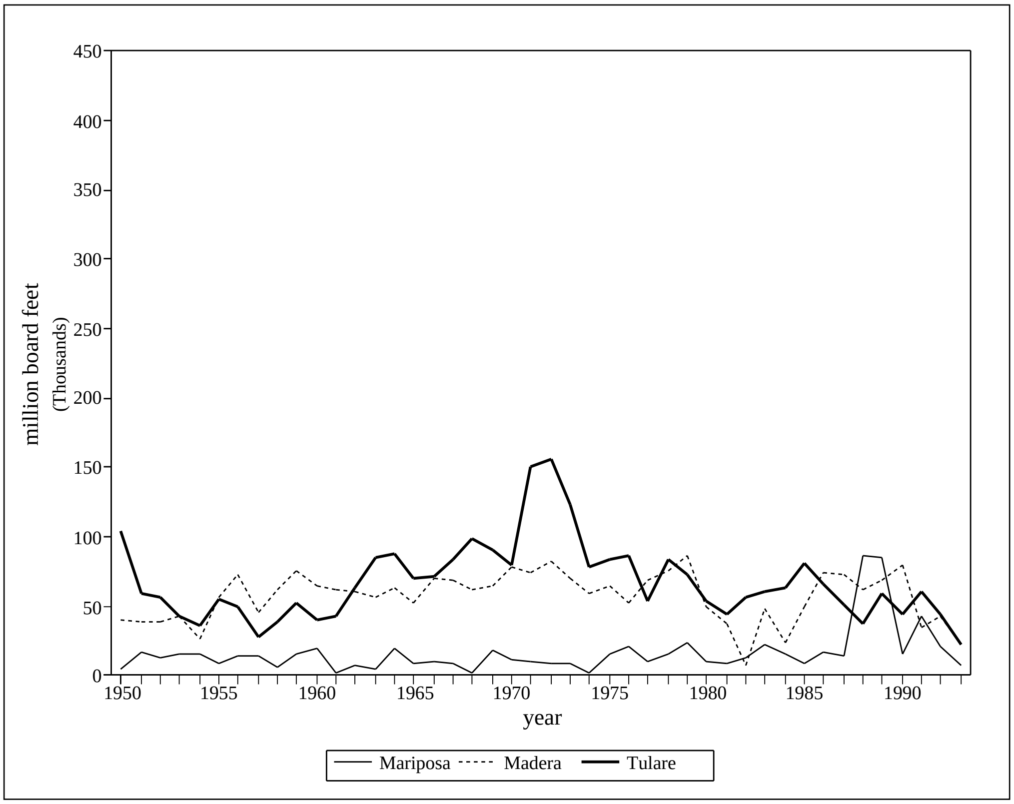


FIGURE 14.A6

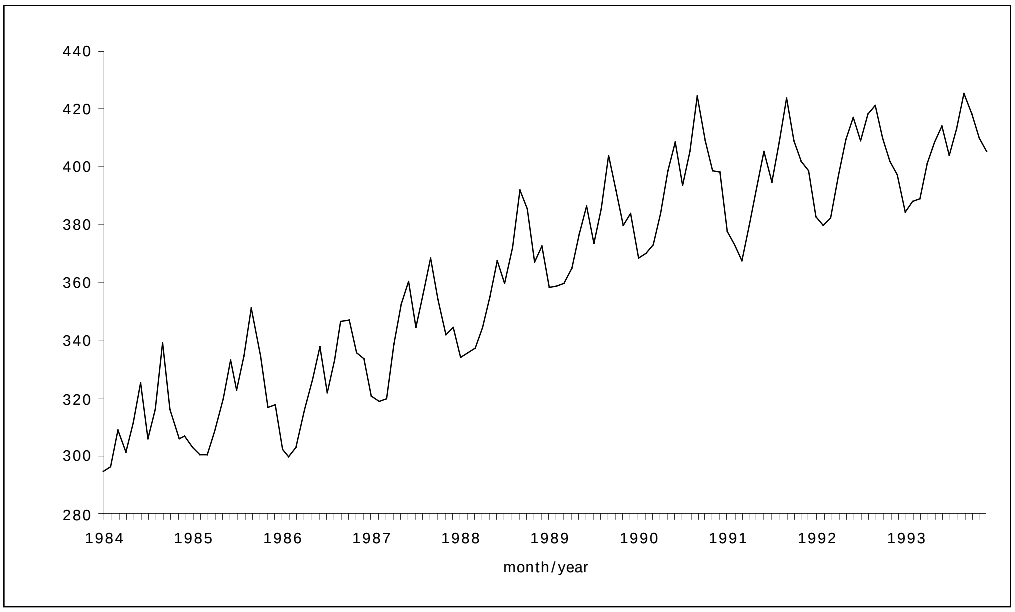
Timber harvest 1949–93 for Mariposa, Madera, and Tulare counties.

APPENDIX 14.2

Aggregate and County Total Monthly Employment

FIGURE 14.A7

Total monthly employment for SNFC.



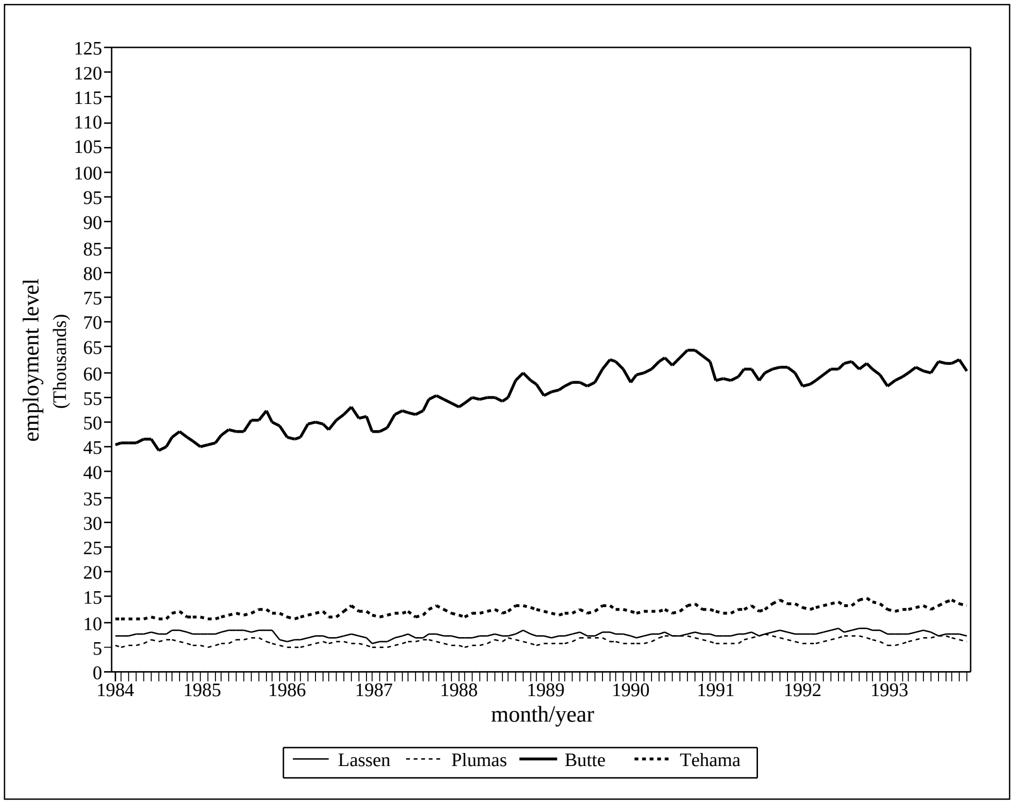


FIGURE 14.A8

Total monthly employment for Lassen, Plumas, Butte, and Tehama counties.

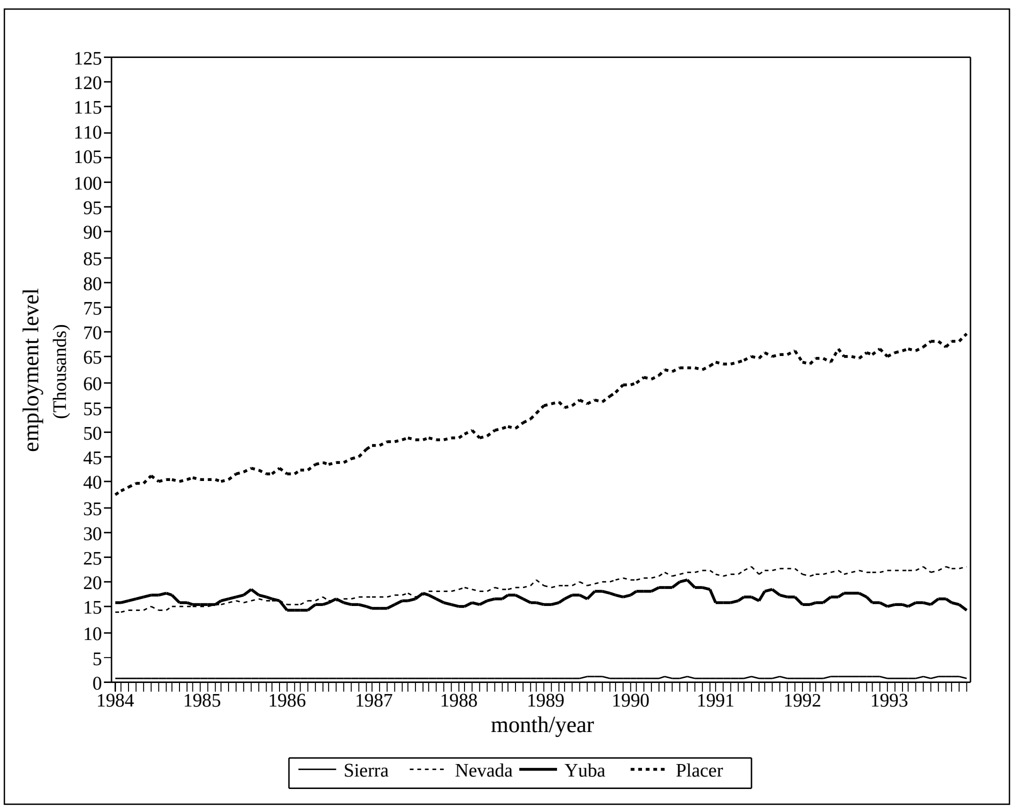


FIGURE 14.A9

Total monthly employment for Sierra, Nevada, Yuba, and Placer counties.

FIGURE 14.A10

Total monthly employment for El Dorado, Amador, Tuolumne, and Calaveras counties.

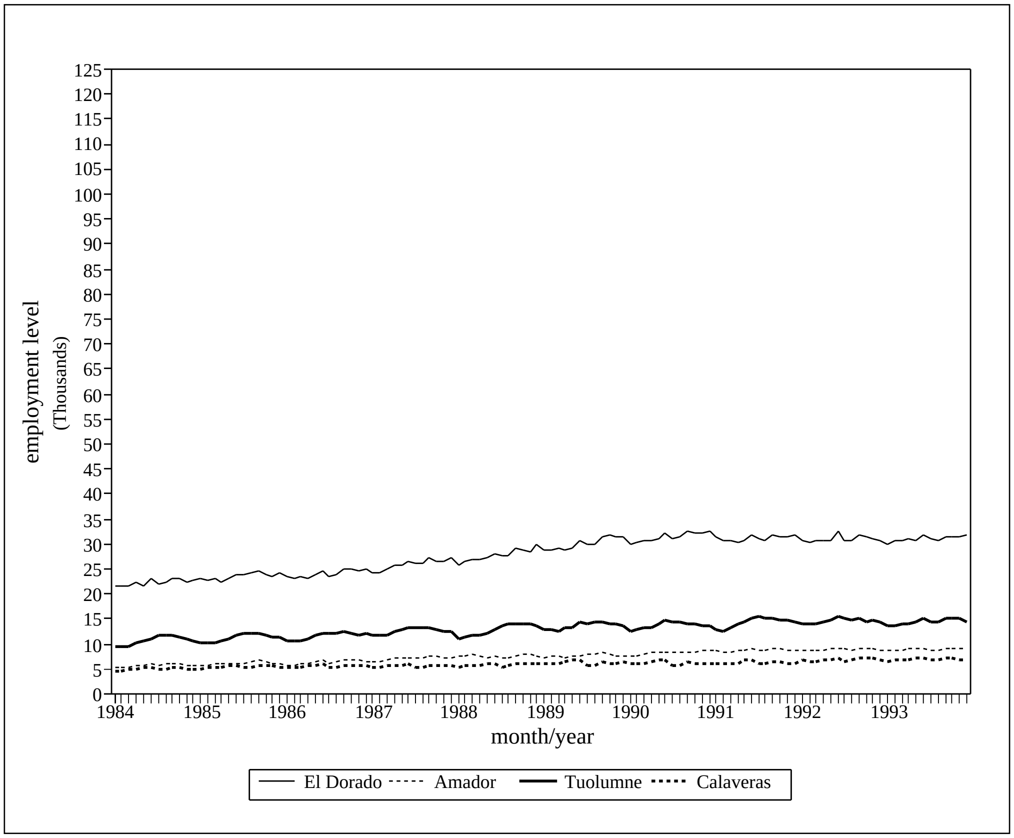
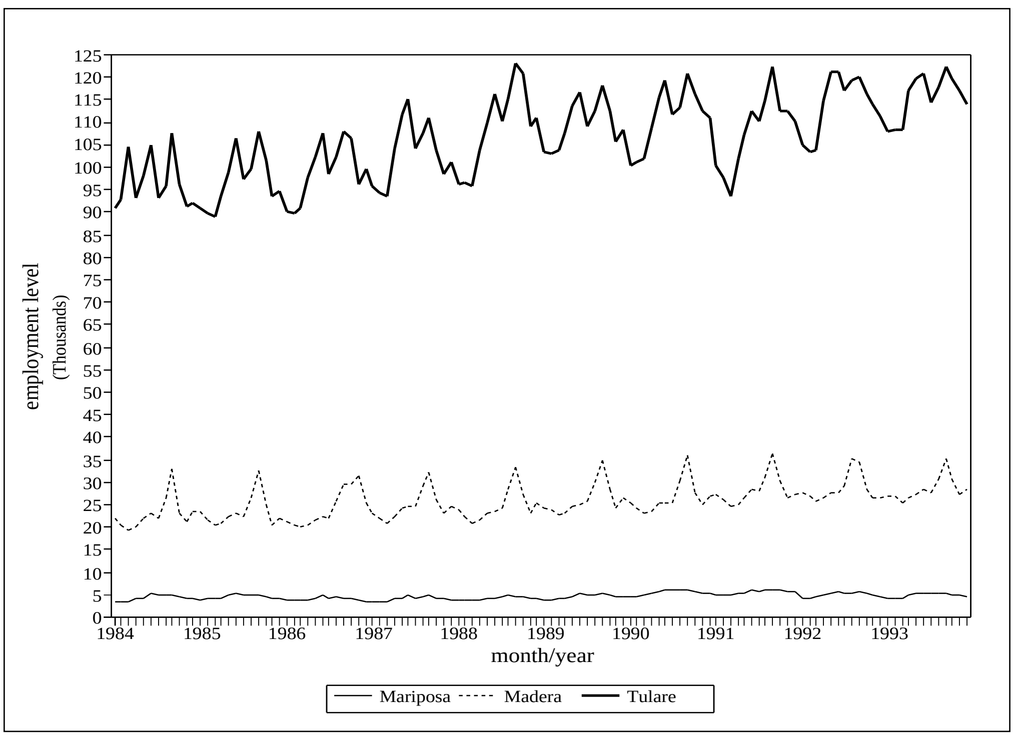


FIGURE 14.A11

Total monthly employment for Mariposa, Madera, and Tulare counties.



APPENDIX 14.3

Aggregate and County Lumber and Wood-Products Employment

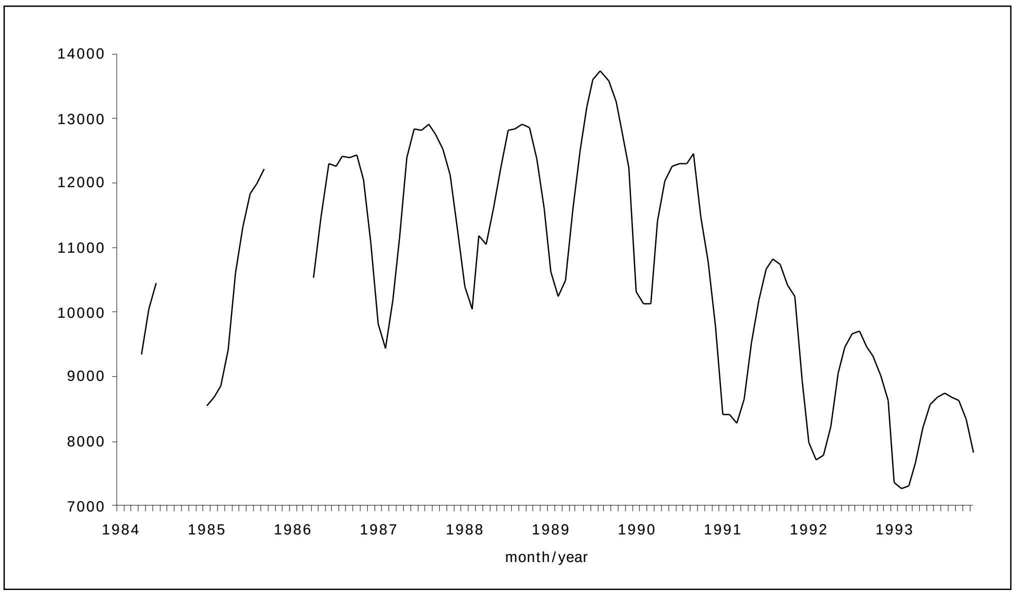


FIGURE 14.A12

Lumber and wood-products employment for SNFC.

FIGURE 14.A13

Lumber and wood-products employment for Lassen, Plumas, Butte, and Tehama counties.

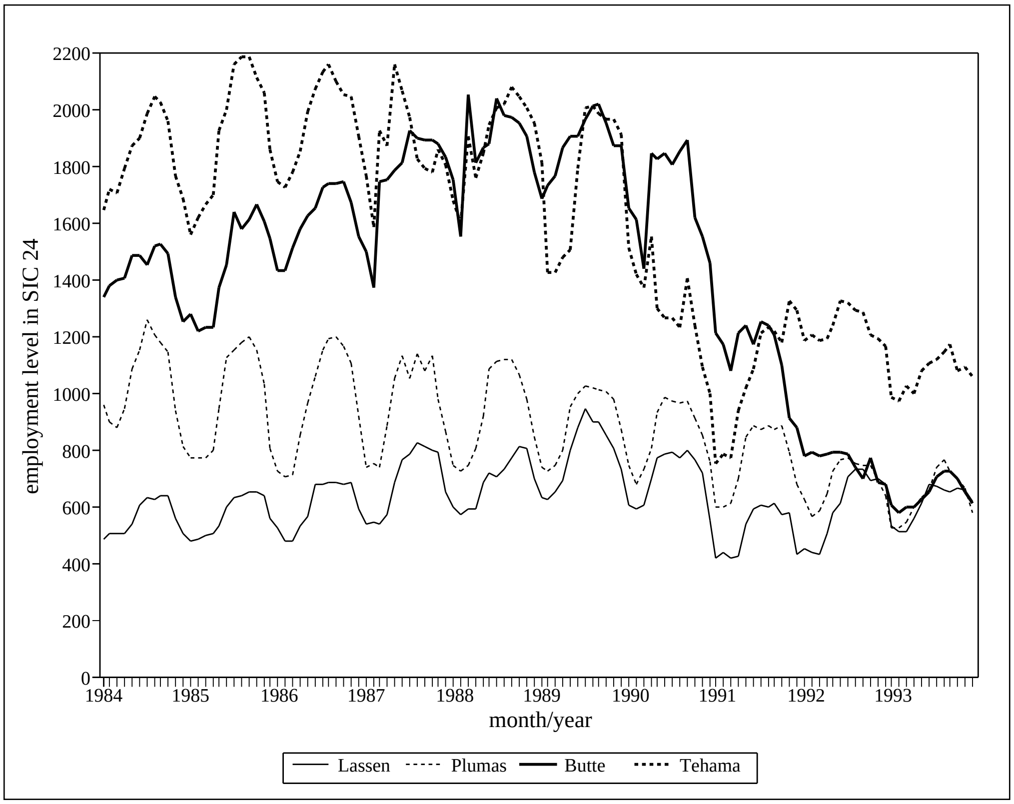
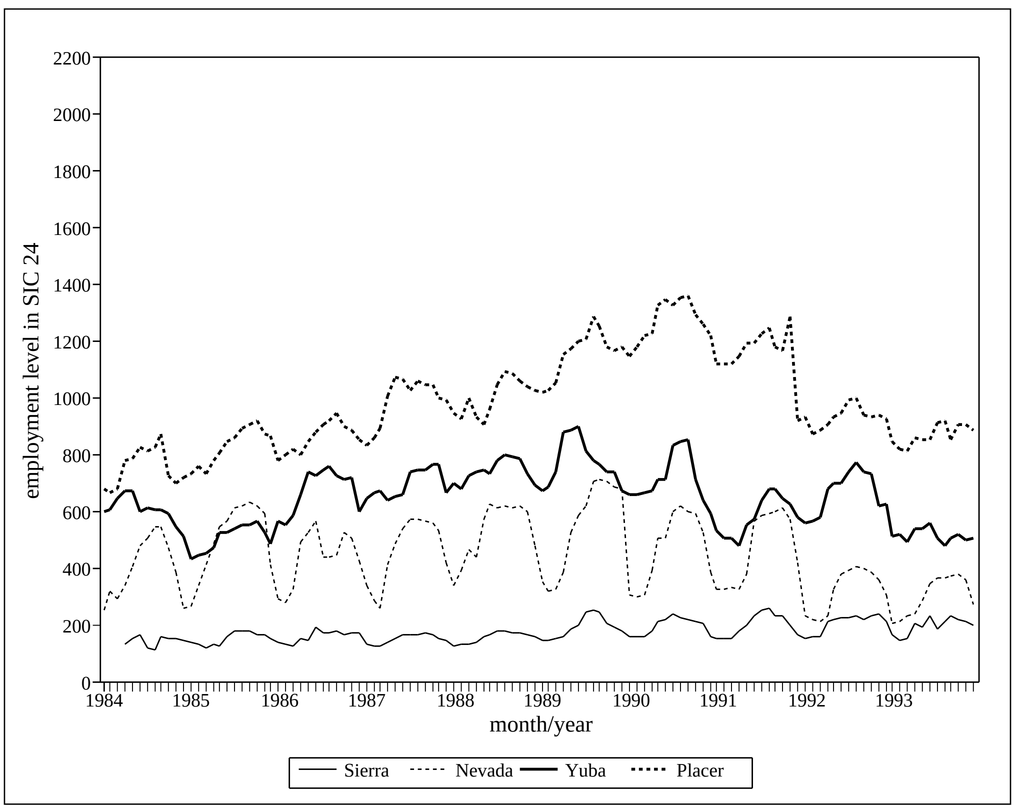


FIGURE 14.A14

Lumber and wood-products employment for Sierra, Nevada, Yuba, and Placer counties.



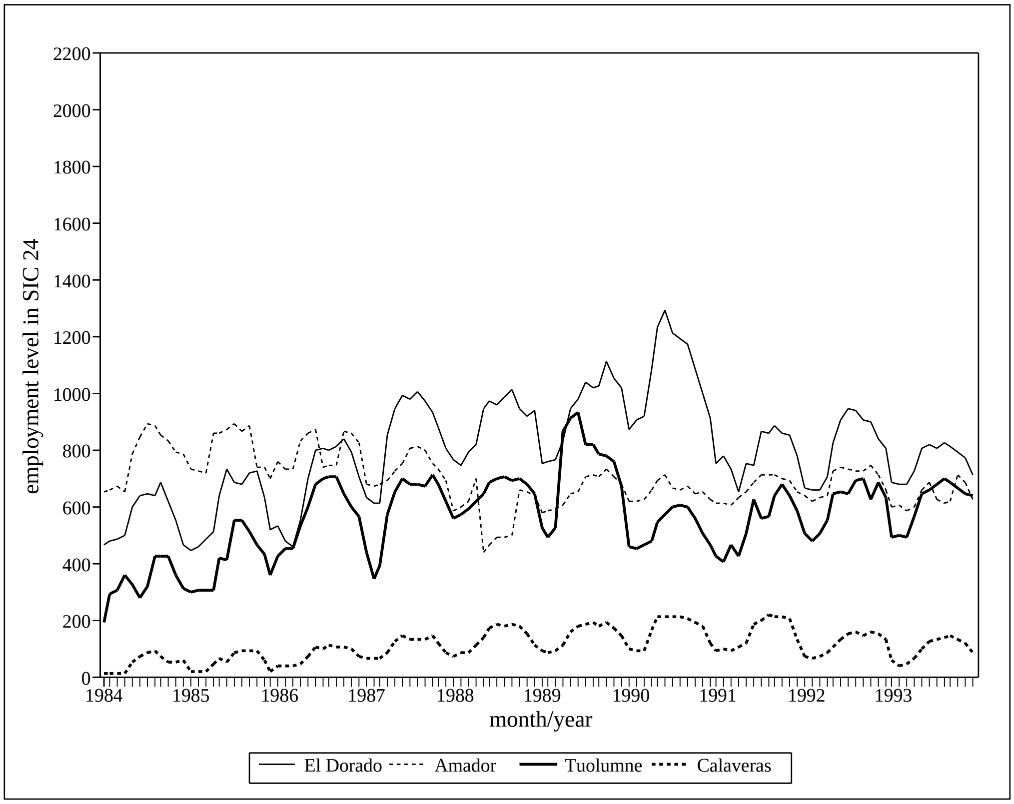


FIGURE 14.A15

Lumber and wood-products employment for El Dorado, Amador, Tuolumne, and Calaveras counties.

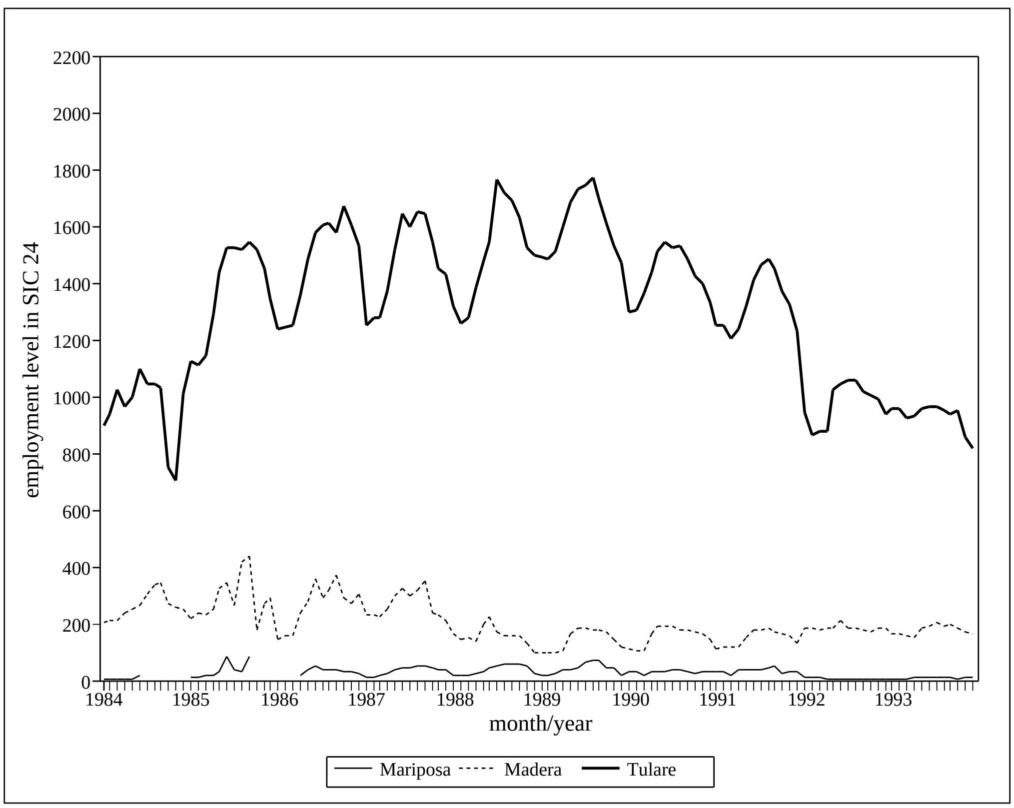


FIGURE 14.A16

Lumber and wood-products employment for Mariposa, Madera, and Tulare counties.

APPENDIX 14.4

Aggregate and County SIC 24 Employment as a Percentage of Total Employment

FIGURE 14.A17

Total SNFC SIC 24 employment as a percentage of total SNFC employment.

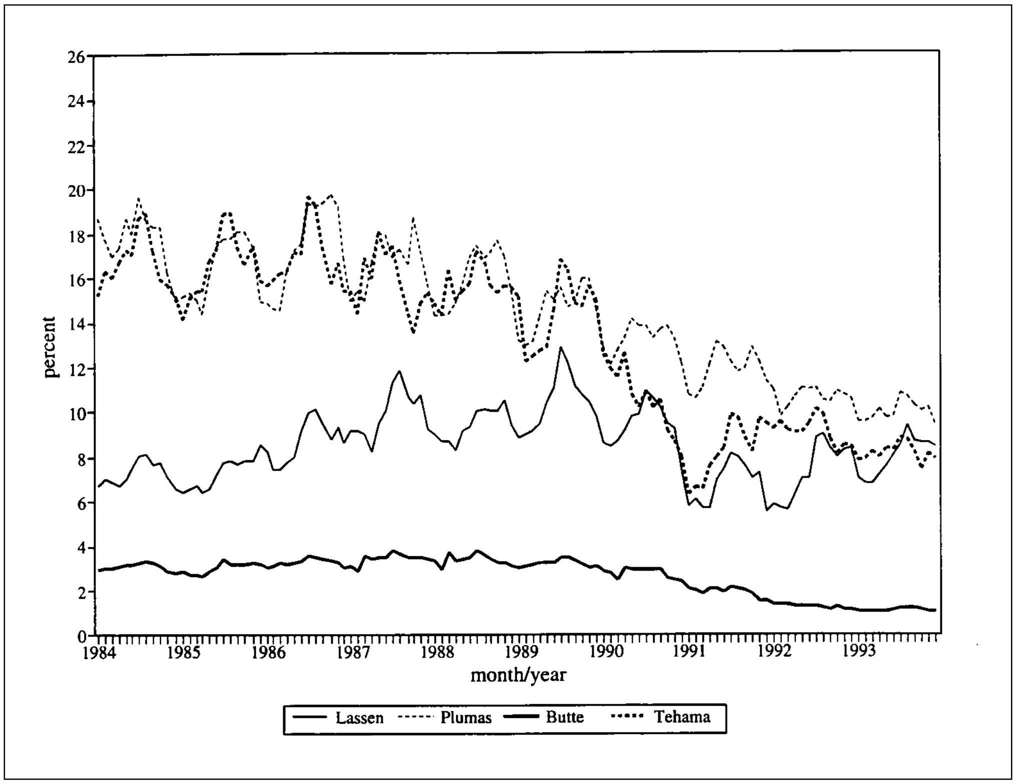


FIGURE 14.A18

SIC 24 employment as a percentage of total county employment for Lassen, Plumas, Butte, and Tehama counties.

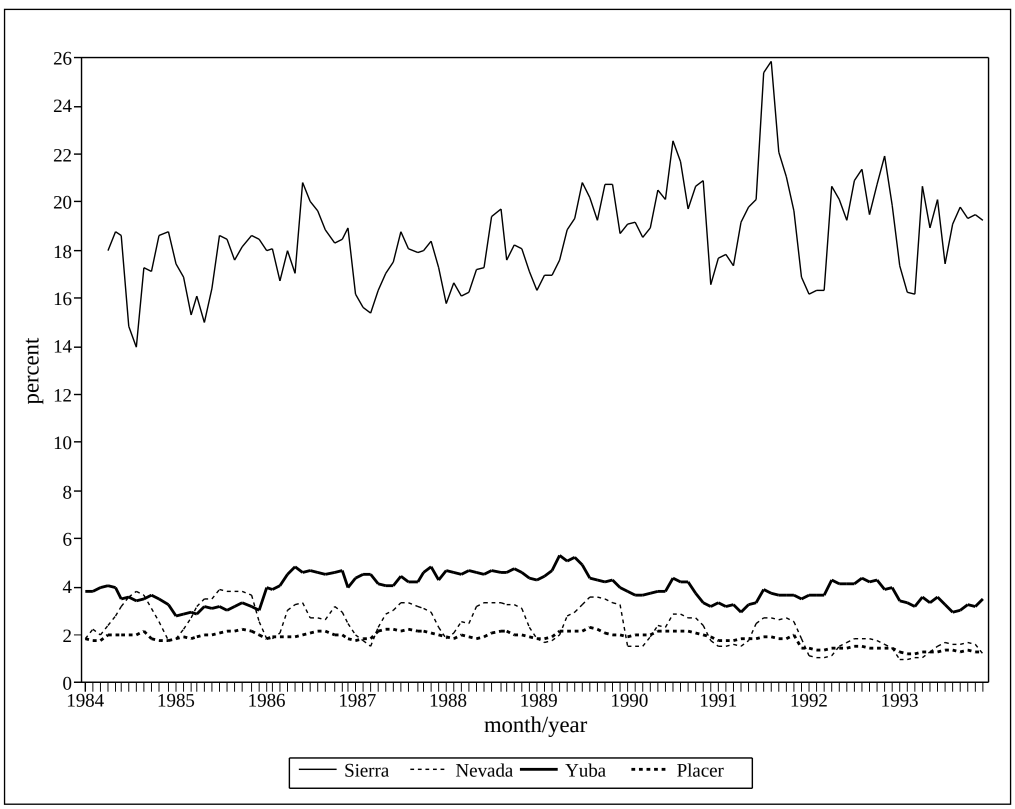


FIGURE 14.A19

SIC 24 employment as a percentage of total county employment for Sierra, Nevada, Yuba, and Placer counties.

FIGURE 14.A20

SIC 24 employment as a percentage of total county employment for El Dorado, Amador, Tuolumne, and Calaveras counties.

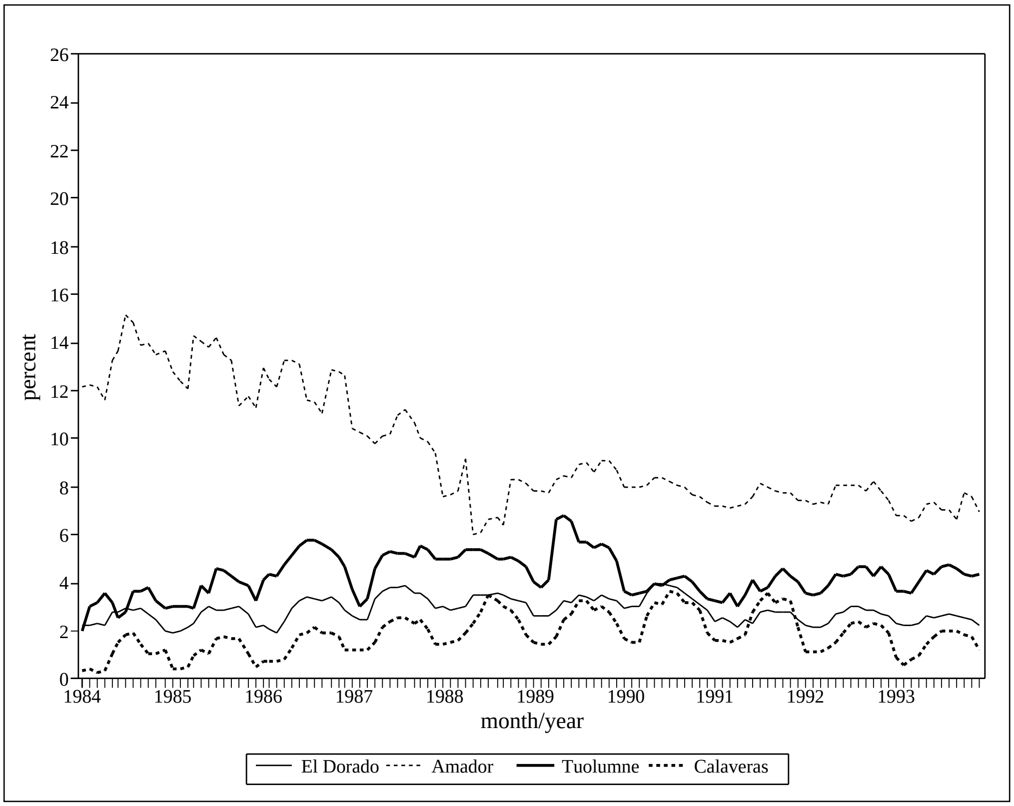
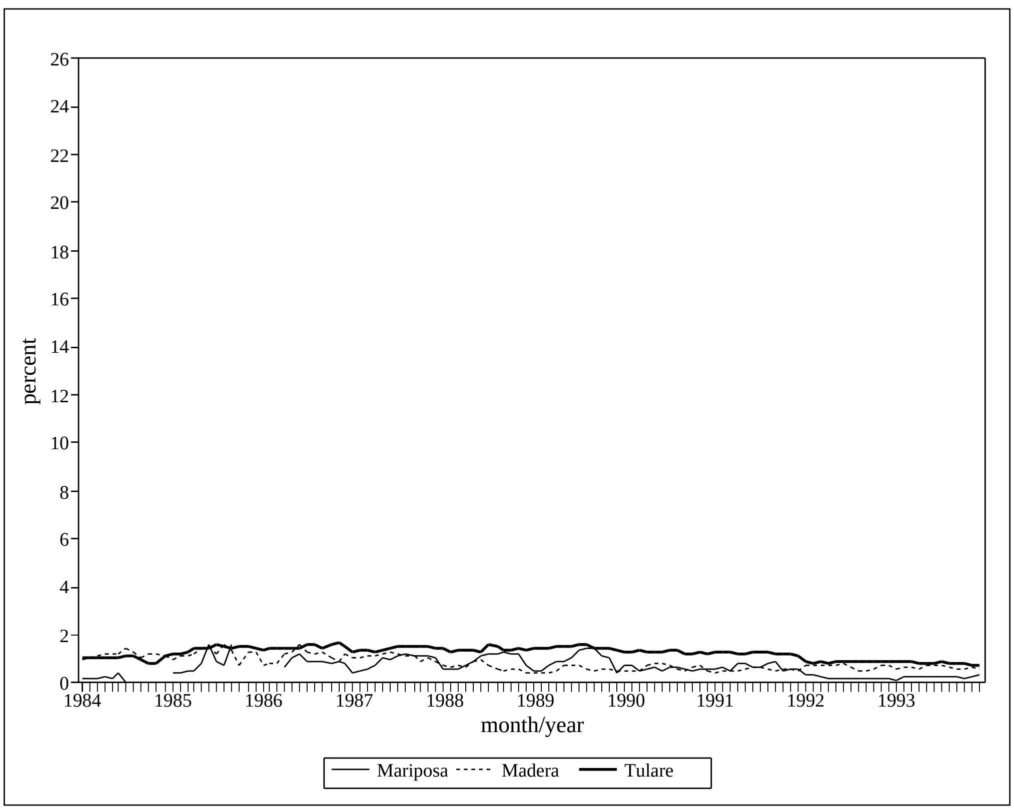


FIGURE 14.A21

SIC 24 employment as a percentage of total county employment for Mariposa, Madera, and Tulare counties.



APPENDIX 14.5

Aggregate and County AFDC Unemployed Parent Caseload

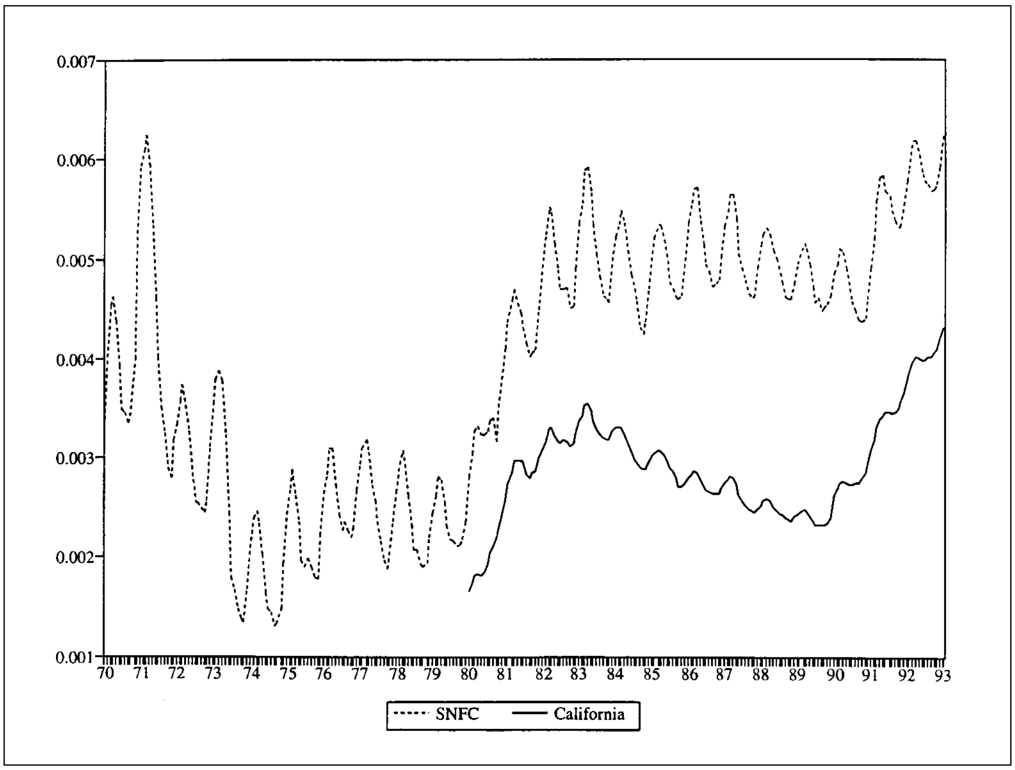


FIGURE 14.A22

AFDC Unemployed Parent program cases per capita for SNFC and state.

FIGURE 14.A23

AFDC Unemployed Parent program cases per capita for Lassen, Plumas, Butte, and Tehama counties.

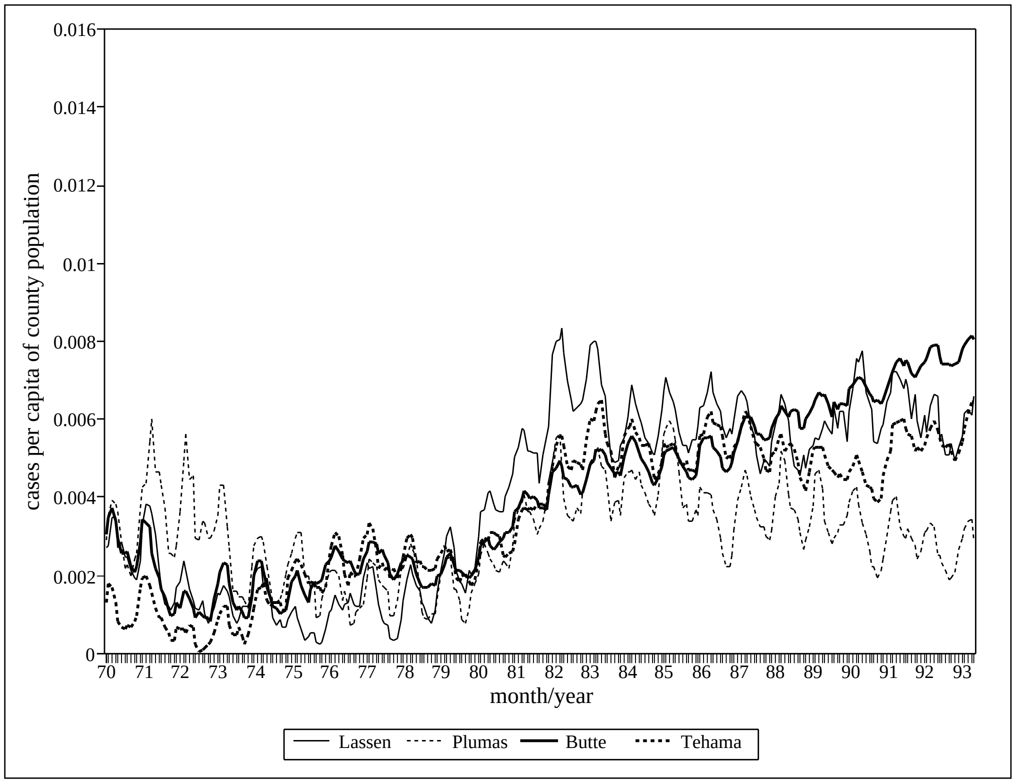
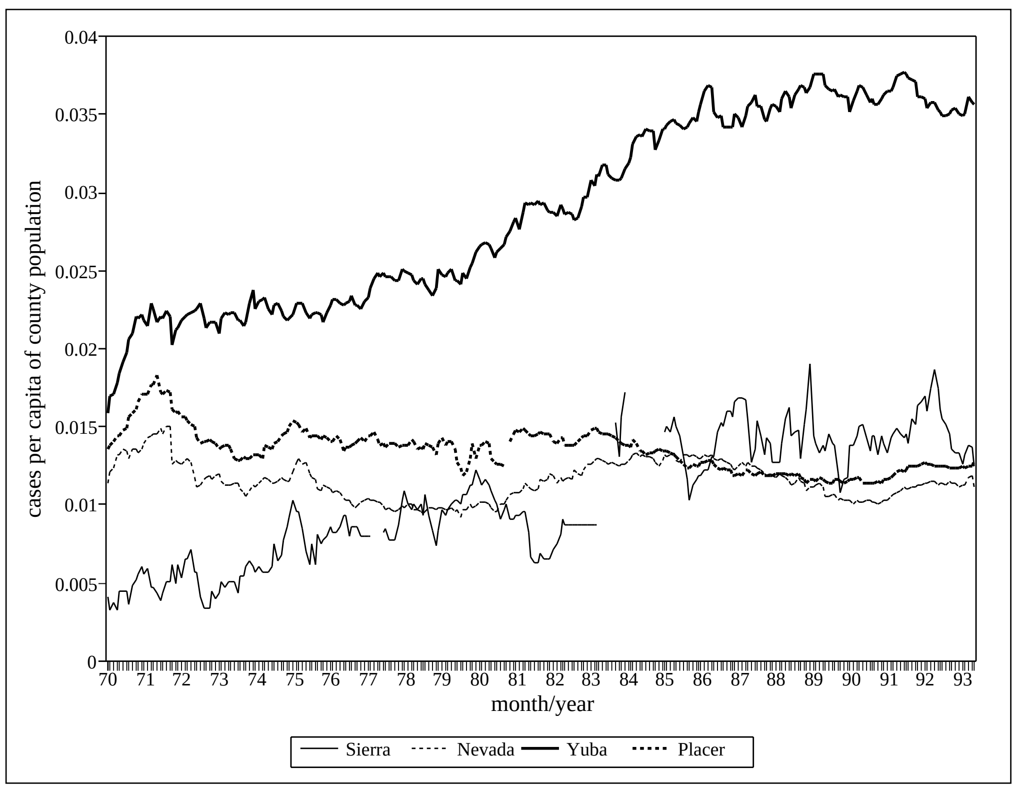


FIGURE 14.A24

AFDC Unemployed Parent program cases per capita for Sierra, Nevada, Yuba, and Placer counties.



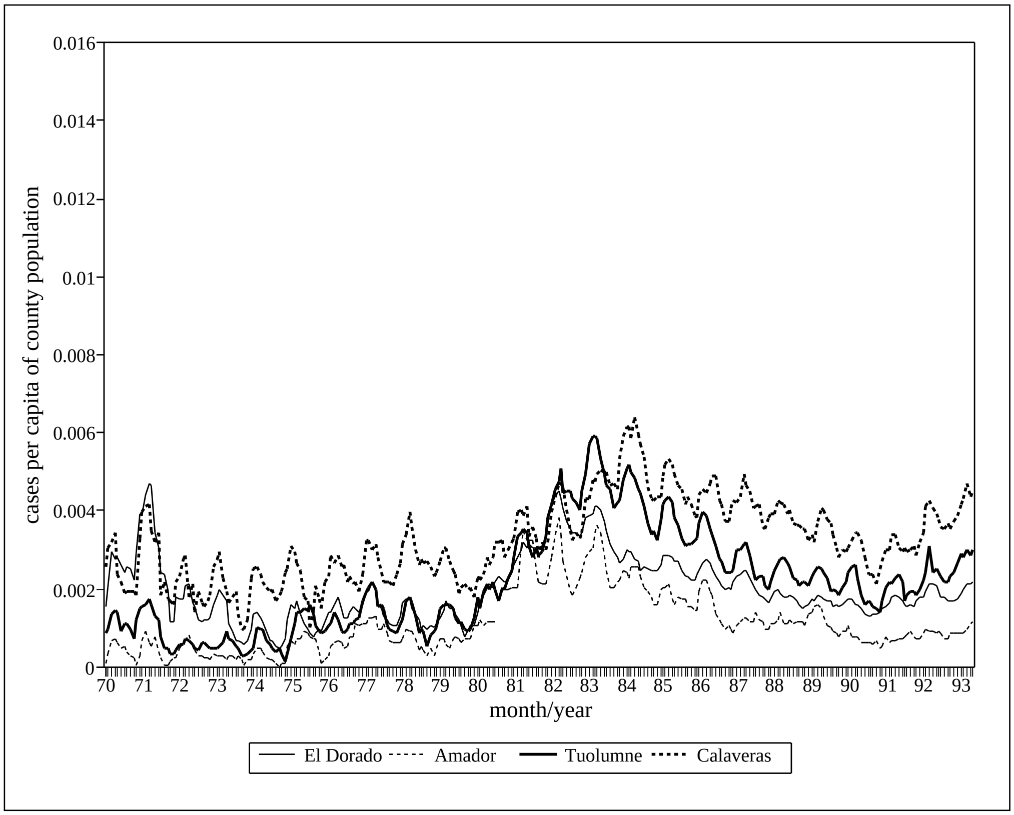


FIGURE 14.A25

AFDC Unemployed Parent program cases per capita for El Dorado, Amador, Tuolumne, and Calaveras counties.

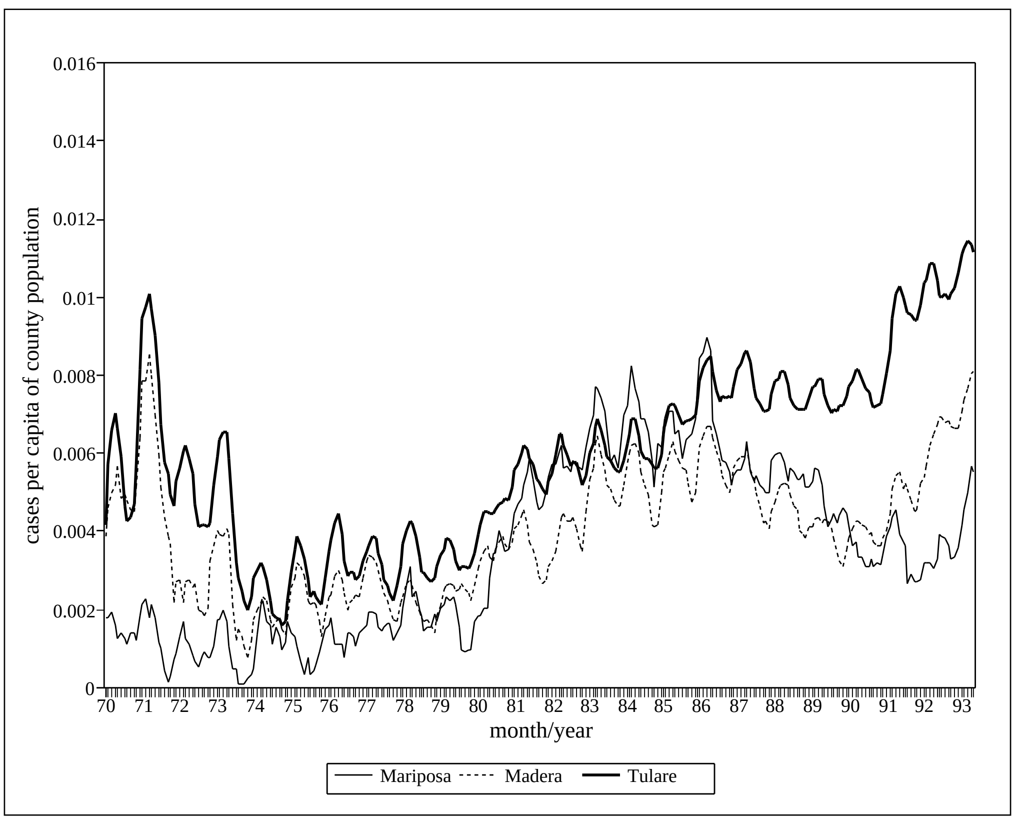


FIGURE 14.A26

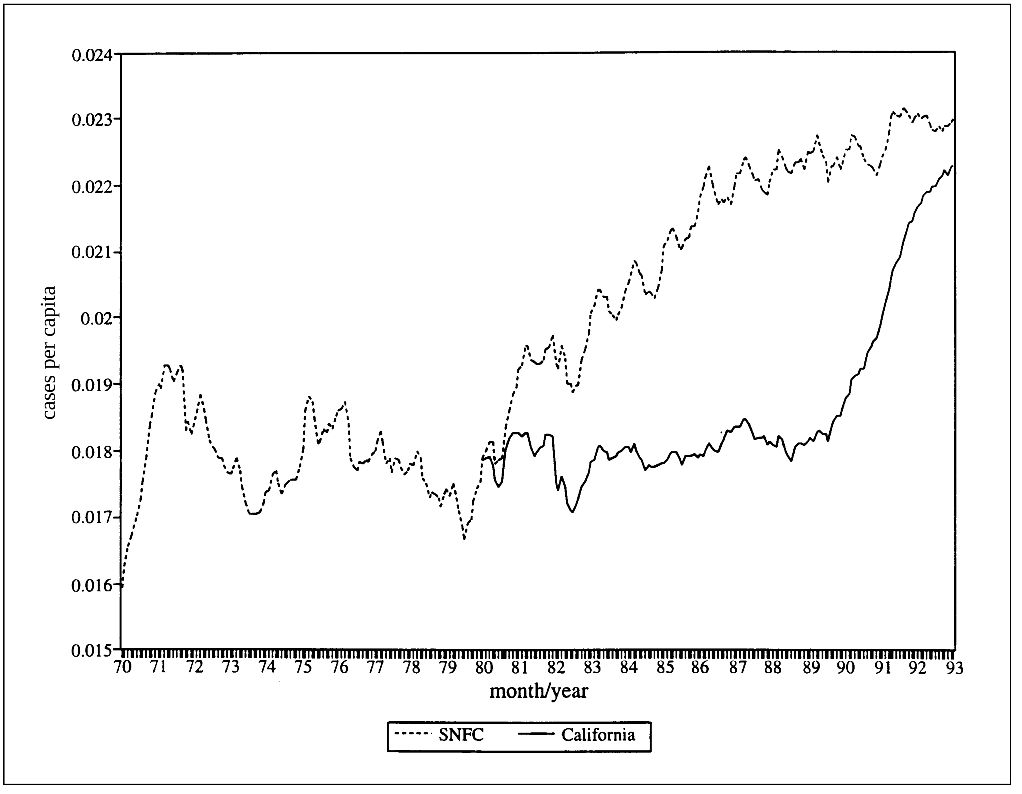
AFDC Unemployed Parent program cases per capita for Mariposa, Madera, and Tulare counties.

APPENDIX 14.6

Aggregate and County AFDC Family Group Caseload

FIGURE 14.A27

AFDC Family Group program cases per capita for SNFC and state.



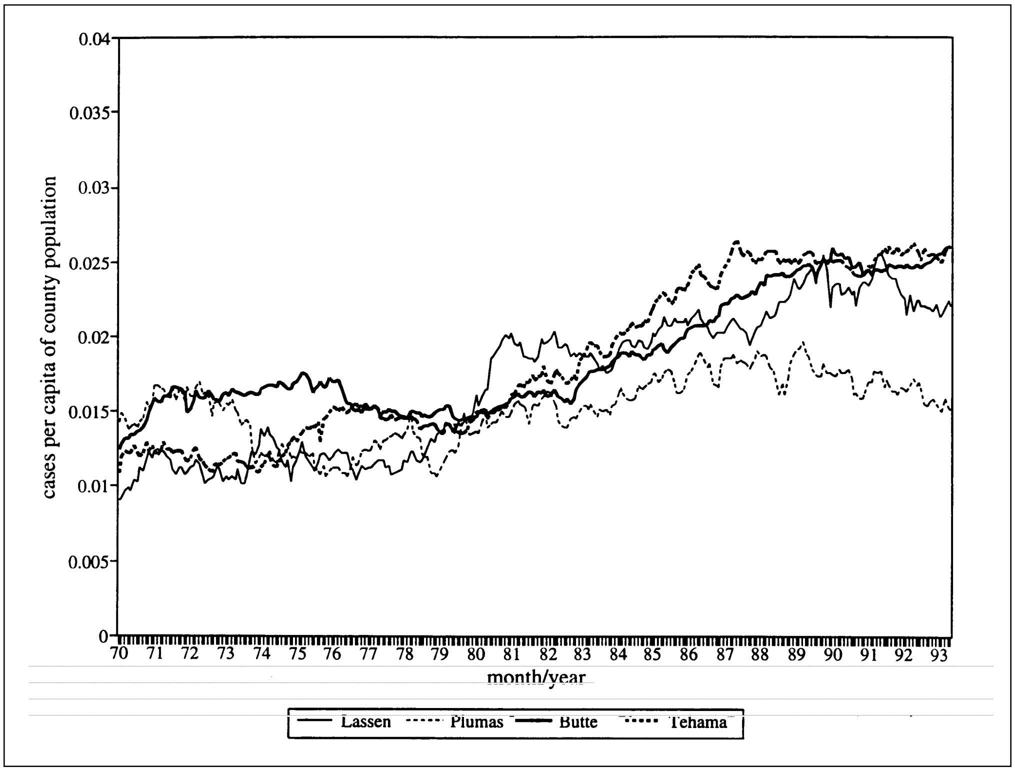


FIGURE 14.A28

AFDC Family Group program cases per capita for Lassen, Plumas, Butte, and Tehama counties.

FIGURE 14.A29

AFDC Family Group program cases per capita for Sierra, Nevada, Yuba, and Placer counties.

FIGURE 14.A30

AFDC Family Group program cases per capita for El Dorado, Amador, Tuolumne, and Calaveras counties.

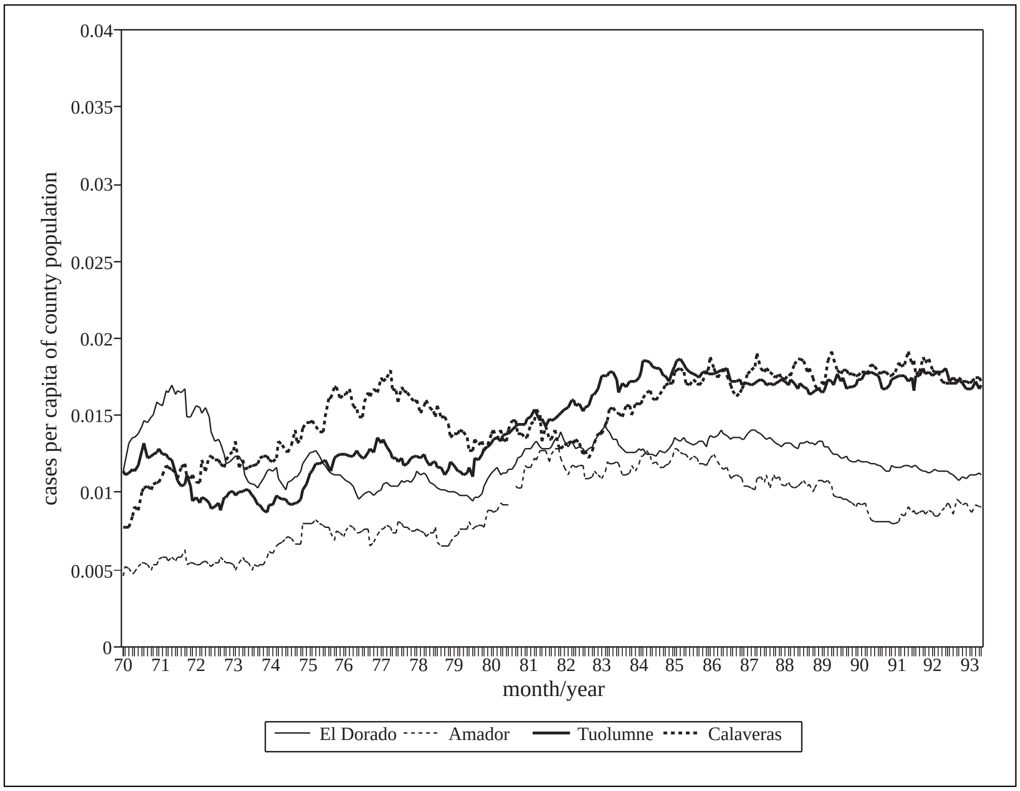
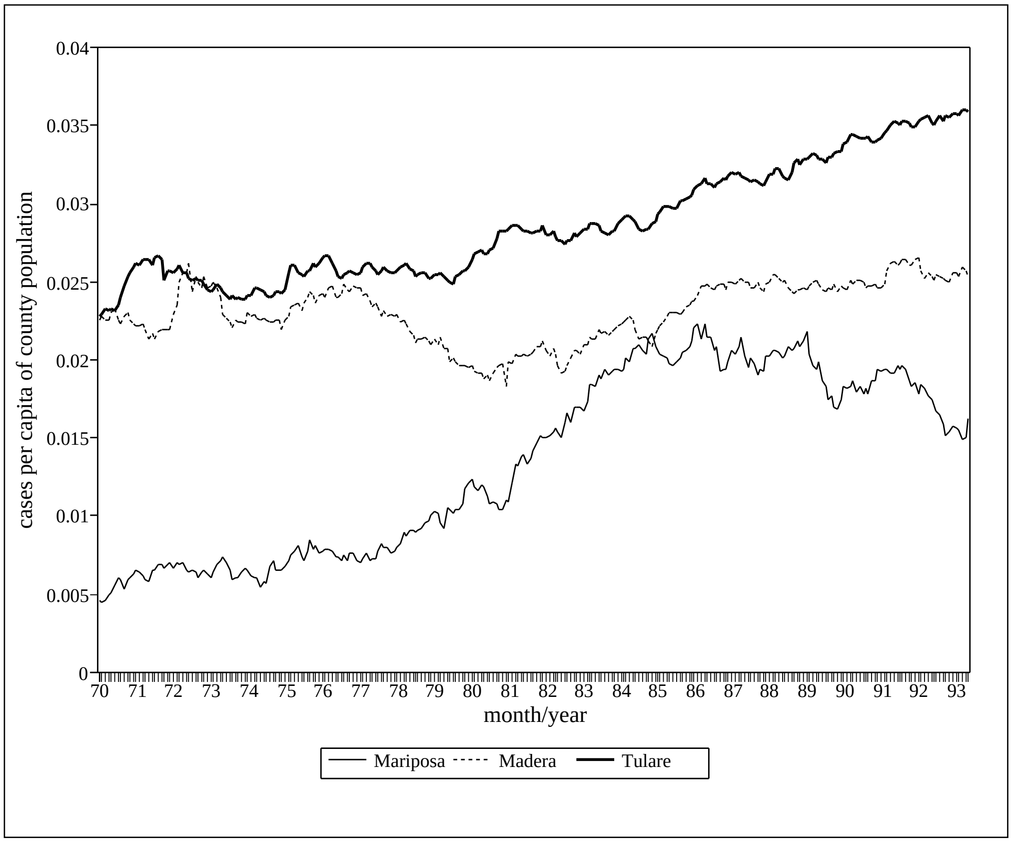


FIGURE 14.A31

AFDC Family Group program cases per capita for Mariposa, Madera, and Tulare counties.



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